Three Essays on Outbound Open Innovation and Intellectual Property Protection

by

Said Matr

A dissertation submitted by in partial fulfillment of the requirements for the degree of Doctor of Philosophy in

Business and Finance

Universidad Carlos III de Madrid

Advisor(s):

Eduardo Melero
Neus Palomeras

Tutor:

Neus Palomeras

June, 2020

To my parents.

ACKNOWLEDGEMENTS

Firstly, I would like to express my gratitude to my advisors, Neus Palomeras and Eduardo Melero, for their continuous guidance and encouragement. Their knowledge, scientific intuitions, and their way of thinking have been of great support to me. The mentoring and the effort they exerted inspired me and guided my improvement as a researcher and scientist. I would also like to thank Andrea Fosfuri for sponsoring my research visit at Bocconi University. I am grateful for his hospitality and his insights and suggestions that helped me improve my research.

Special thanks go to my family, whose love and support have been my source of inspiration. Without them, I would not be the person I am now, so I forever indebted and lucky to have them in my life and I devote my success to them. I would like also to thank my friends and PhD fellows at the business department at UC3M for sharing with me the journey during its happy and sad times. Special gratitude goes to Akram Khalilov, Araks Ayvazyan and Irina Gazizova. I would like thank Araks more specifically for being my co-author and working with me on our research.

This thesis benefited from the financial support from the Spanish Ministry of Education and Science FEDER (UNC315-EE-3636) and (PGC2018-096316-B-I00) and from the department of Business Administration at UC3M. All the errors are mine.

PUBLISHED AND SUBMITTED CONTENT

Chapter 1 of the Thesis is partially based on a published article.

- Reference for this article: Ayvazyan, A. & Matr, S. (2019, July). Sharing is Caring: Outbound Open Innovation and the Subsequent Innovation Process. In ***Academy of Management Proceedings*** (Vol., 2019, No., 1, p., 18182). Briarcliff Manor, NY 10510: Academy of Management. https://journals.aom.org/doi/10.5465/AMBPP.2019.254

The material from this source included in this thesis is not singled out with typographic means and references.

Chapter 1 of the Thesis was wholly or partially submitted to the following conferences:

- May 2019: EITC Doctoral School.
- June 2019: DRUID19: https://conference.druid.dk/acc_papers/y0e3r96i2gw5d357579s47kcbmi6c3.pdf
- Aug., 2019: 79th Annual Meeting of the Academy of Management.

The material from these sources included in this thesis is not singled out with typographic means and references.

Chapter 2 of the Thesis was wholly or partially submitted to the following conferences:

- May 2018: 5th Annual IE Doctoral Consortium.
- June 2019: DRUID19: https://conference.druid.dk/acc_papers/5hfh7kcdjo4bbfubefmu2uwaqtagrw.pdf
- June 2019: Brownbag Seminar at Department of Management and Technology at Bocconi University.
- Aug., 2019: 79th Annual Meeting of the Academy of Management.
- Sep., 2019: Strategy, Entrepreneurship & Innovation (SEI) Doctoral Consortium (20-21 September 2019, KU Leuven)

The material from these sources included in this thesis is not singled out with typographic means and references.

Table of Content:

Abstract

This thesis consists of three chapters studying topics related to the corporate innovation management. More specifically, the first two chapters discuss the outbound open innovation phenomenon and its relationship with the firm's behavior in technology and labor markets, respectively. The last chapter links the firm's litigiousness with its collaborative activities.

The thesis starts with the first chapter (co-authored with Araksya Ayvazyan) studying the firm\s decision to adopt outbound openness in its IP strategy. We propose two channels through which a firm can potentially capitalize on a decision of adopting an outbound open approach in its intellectual property (IP) strategy for no direct financial benefits in return. The first channel involves selling subsequent intellectual assets in markets for technology to meet the demand resulting from the increased engagement of third parties in the liberated knowledge. The second one refers to bringing the subsequent external knowledge in-house via buying intellectual assets or building upon it internally. We capture the variation in IBM's IP strategy toward more openness, using the decision of IBM to pledge 500 of its patents to the public in 2005. The results from implementing a difference-in-differences approach between 1999 and 2010 provide support for the proposed mechanisms.

The second chapter explores how a firm's move towards outbound open innovation strategy via opening up the firm's intellectual property (IP) affects inventor mobility from the firm. Interestingly, the answer is not straightforward because there are arguments to expect both an increase as well as a decrease in inventor mobility as a consequence of the move towards openness. The key argument relies on the degree of complementarity or

substitutability between the codified knowledge and the inventors' tacit knowledge, and how it is altered by outbound openness. Using IBM's 2005 patent pledge, to capture the firm's shift towards outbound openness, I empirically investigate its consequences on the likelihood of IBM's inventors to leave the firm. The findings, on average, favors the proposition that outbound openness decreases the firm's labor mobility.

In the third chapter (co-authored with Eduardo Melero, David Wehrheim), we study the effect of the strength of the IP enforcement on firm's collaborative activities. We argue that there are two potential contradicting forces driving the effect, namely, the expected return from learning during a collaborative project, and the expected cost of any unintended potential knowledge leakage during that project. Our results from a quasi-natural experiment, exploiting the reduction of the IP enforcement due to a recent landmark event in the U.S. patent system (the ruling in eBay v. MercExchange), show that weaker property rights, on average, lead to fewer collaborations and alliances. To get additional insights, we also investigate the effect on particular types of collaborations, as well as in settings where the two mechanisms may be strengthened or weakened.

Chapter 1
What's There to Gain? Outbound Openness and markets for technology

(co-authored with Araksya Ayvazyan)

1.1 INTRODUCTION

Over the past years, the practice of outbound open innovation[1] has become increasingly popular among big players in the software, semiconductors, pharmaceuticals, and automobile industries (West, Salter, Vanhaverbeke, & Chesbrough, 2014). Prominent examples are Johnson & Johnson's innovation lab in La Jolla, California, IBM's industry solution lab in Zurich Rüschlikon, or patent pledges of Red Hat (2002, 2017), IBM (2005), Google (2013), and many others. According to Linux Magazine, the 500 patents pledged by IBM "cost $10,000,000 to obtain (just in the U.S.) and are worth an unknown amount in licensing revenue"[2]. Interestingly, many such voluntary commitments to openness require no formal agreements to use the unlocked knowledge, meaning that outsiders can freely access it, without giving anything in return.

Firms' tendency toward making their knowledge or part of it available for free to outsiders (i.e. outbound open innovation[3]) in traditionally intellectual property (IP)

---

[1] There are three main types of open innovation: outbound (inside-out knowledge flows), inbound (outside-in knowledge flows), and combined (both inside-out and outside-in knowledge flows) (Chesbrough, 2003; Chesbrough 2006a, 2006b). In this paper, we interchangeably use the terms outbound open innovation, outbound openness, and strategic openness to refer to the inside-out type of open innovation.

[2] http://www.linux-mag.com/id/1975/

[3] In this study, by outbound open innovation we refer to the non-pecuniary type of outbound open innovation, following the definition by Dahlander & Gann (2010, p. 704), "This [non-pecuniary outbound] type of openness refers to how internal resources are revealed to the external environment. In particular, this approach deals with how firms reveal internal resources without immediate financial rewards…" The second, pecuniary type of outbound open innovation, distinguished by the authors, refers to dealing with external commercialization of internal inventions and technologies via selling, licensing out or partnerships.

intensive industries represents a "departure in strategy to say the least" (Fortune, 2016)[4]. Indeed, the conventional premise from the resource-based view strongly associates resource ownership with the ability of a firm to appropriate value (e.g. Barney, 1991; Collis & Montgomery, 1998). Thus, by granting free access to proprietary assets, thereby allowing for imitability, firms may risk losing competitive advantage over rivals (Dahlander & Gann, 2010). Then, why do corporate firms engage in outbound openness, especially without direct financial gains in exchange? In this paper, we suggest two main mechanisms that the firm may use to capitalize on its practice of outbound openness. These channels primarily concern strategic openness' facilitating inward and outward knowledge flows, which in turn, induces the focal firm's engagement in markets for technology, in terms of transactions for IP rights. This may give rise to potential externalities for the opening up firm.

We complement to existing research that discusses possible incentives for firms to grant free access to their proprietary assets. These incentives comprise creating and obtaining returns from standards and their development (West, 2003; Henkel, 2006), advancing collective innovation (Levin et al., 1987), increasing the demand for their still proprietary assets that are complementary[5] to the opened-up ones and saving costs (e.g. Raymond, 1999; Alexy & Reitzig, 2013; Alexy, West, Klapper & Reitzig, 2018), or pursuing social goals (Raymond, 1999; Contreras, 2015). While these studies posit that other players in the market get more involved and contribute more to the opened-up intellectual assets (e.g. Parker & Van Alstyne, 2017), to the best of our knowledge, there is little research on whether and how the focal firms capitalize on and incorporate the newly created knowledge

[4] http://fortune.com/2016/07/22/the-radical-experiment-thats-changing-the-way-big-pharma-innovates/

[5] These are often "razor and blade" (Tripsas & Gavetti, 2000) or "hardware and software" type of complementarities between the opened-up and still proprietary assets.

by others into their innovation processes. According to the literature on competitive dynamics, firms consider the possible reactions from other actors in the market, when making important strategic decisions. Therefore, arguably, following the practice of strategic openness, the way they manage their innovation processes will subsequently be altered due to the increased involvement and knowledge availability from third parties.

An important element in our theoretical arguments is that outbound openness reduces transaction and negotiation costs, as well as litigation threats (Wen, Ceccagnoli, & Forman, 2016). Due to the decrease in access costs and litigation risks, other firms get encouraged to become more involved (Boudreau, 2010) and subsequently build more knowledge. Further, the focal firm can respond to the advances in innovation in different ways: by selectively buying innovations that other firms have developed via relying on the liberated knowledge, or by making further internal developments through combining its expertise with the new knowledge created by others in a specific technology. At the same time, because strategic openness indirectly enforces the outsiders' commitment to the liberated knowledge and technologies, as they create more complementary assets, thereby increasing their demand for the subsequent knowledge, the focal firm gets more opportunities for selectively selling its other internally developed knowledge.

Our study makes use of IBM's patent pledge of 2005 as a shock to the level of openness in the IP strategy of IBM (Wen et. al, 2016). Having the sample period from 1999 to 2010 allows us to implement a difference-in-differences approach to explore the consequences of the openness decision on the firm's engagement in markets for technology and the degree to and channels through which IBM utilizes the follow-on spillovers. Our results show that after 2005, IBM buys and sells more patents, proportionally to the level of openness in its IP strategy. However, we find stronger evidence for increased selling, rather than buying

activities by IBM. We also find that IBM continues to create further knowledge developments, building upon external sources of subsequent knowledge more than on its own subsequent knowledge.

This study provides a new perspective on the firm's decision to waive its exclusivity rights and uncovers an indirect mechanism that firms may exploit for potentially profiting from opening up, especially in the presence of a well-developed market for technology. Naturally, this advantage should be weighed against the potential negative effects in terms of competition that may be imposed by the loss of property rights. In this sense, opening up may be a particular suitable alternative when (in countries/technological areas) there are well-developed markets for technology allowing the firm to trade on the subsequently created knowledge.

We contribute to the open innovation literature by providing a novel motivation and discussing potential indirect returns for the firms that adopt outbound openness pursuing no direct financial benefits. This link between open innovation and markets for technology has not been explored before, to the best of our knowledge. Put together, outbound open innovation could be viewed as complementary with trading in markets for technology. We also contribute to the literature on open innovation more broadly, by focusing on the effects of the outbound type of openness untangled from the inbound openness. While much of the prior research on open innovation has primarily focused on inbound open innovation, the outbound type of open innovation has received significantly less attention (Chesbrough, 2003). Importantly, however, our knowledge on the effects of inbound open innovation does not substitute that of outbound open innovation, and many studies have called for investigations on outbound open innovation effects (e.g. West et al., 2014). In this paper, we suggest that outbound openness is not necessarily something marginal in the firm's

technology policy, but an important stepping stone for the subsequent development of innovation.

1.2 THEORY AND HYPOTHESES

1.2.1 Closed and Open Models of Innovation

Unlike in the traditional "closed" approach of innovation, where firms largely focus on in-house research and development (R&D), whilst constraining outsiders from using their technology (Cohen et al., 2000), in "open" innovation models, firms tend to employ fewer boundaries on the use, development, and commercialization of the technology (Chesbrough, 2003). In this paper, we focus on a setting of purely outbound open innovation practices, where a firm explicitly grants the proprietary rights of its technology to the public domain (Katz & Shapiro, 1986; Boudreau, 2010). As patents or copyrights have long served as important mechanisms to protect firms from competitors by providing exclusive property rights for their innovations (Cohen et al., 2000; Hall & Ziedonis, 2001), without these rights, competitors, for instance, may be better placed in terms of their complementary assets or/and production facilities to utilize the opened-up knowledge by the focal firm (Dahlander & Gann, 2010). Therefore, one of the main challenges for firms practicing outbound open innovation is the risk of not being able to appropriate benefits from their decision (Helfat, 2006). Nonetheless, firms are increasingly adopting openness in their innovation approaches, and therefore, we briefly discuss the prior literature on the motives for adopting strategic openness in the next subsection.

1.2.2 Motives for Adopting Outbound Open Innovation

We mentioned in the introduction some of the studies that extend the understanding of the underlying reasons why firms choose to open up their knowledge (e.g. von Hippel, 1998, 2005; von Hippel & von Krogh, 2003; West, 2003; Henkel, 2006; Alexy & Reitzig, 2013; Alexy et al., 2018). The theoretical premise from the previous literature is that opening up is not always detrimental for appropriating benefits from an innovation (von Hippel, 1998, 2005; Henkel, 2006; von Hippel & von Krogh, 2003). Several works link openness with appropriation benefits in return from resource complementarities. For instance, primarily addressing the question of who opens up their knowledge, Alexy & Reitzig (2013) suggest that by doing so, firms can enhance the demand for their complementary resources controlled by the firm. In the context of open source software (OSS), Fosfuri, Giarratana, & Luzzi (2008) find that the possession of complementary assets increases the likelihood of introducing OSS products. The authors argue that the control over complementary resources helps the firm to appropriate value from OSS development (Arora, 1995), and gives the firm a bargaining power to reduce potential litigation risks from other entities against OSS products (Ziedonis, 2004). Building on the resource-based view, Alexy et al. (2018) provide contexts when openness can help/harm firms, their competitors or both. In particular, the paper argues that when the cost of production is high for an innovation and it is strongly positioned with complementary assets, the firm may decide to open it up and utilize those complementary assets to internalize the benefits from the opened-up knowledge.

Other explanations for engaging in openness include the following. A study by Henkel, Schöberl, & Alexy (2014) suggests that firms' deliberate waiving of some of their IP rights

can be explained by the consumer demand pull for openness and that such behavior brings in a positive feedback loop, eventually making openness become another dimension of competition. Alexy, George, & Salter (2013) propose that firms may also engage in strategic openness to increase collaborative activities with others in the market. The authors argue that firms will be more prone to openness, especially when there is a high partner uncertainty, high coordination costs, and when potential known partners are unwilling to collaborate. Other reasons for which firms may decide to grant access to their proprietary knowledge include endorsing product interoperability via standards creation or pursuing social goals (Contreras, 2015).

Though a common assumption in these studies is that outbound openness induces third parties' involvement in the opened-up technologies, to the best of our knowledge, there is still little research that has focused on whether and how the firms that decide to open up, can internalize the involvement from other entities in their further innovation processes. Focusing on the effect on outsiders, Wen et al. (2016) analyze how strategic openness affects new product introductions by start-up firms. The authors find that on average, more new product introductions occur by startups in areas of knowledge with higher rather than lower degrees of openness. Murray et al. (2016) find a positive impact of the level of openness associated with unlocked research tools on the subsequent innovations' amount and type in a context of academic researchers. However, neither of these papers consider the consequences for the opening firm (IBM and Dupont, respectively) on its innovation strategy, which is key in this paper.

One primary focus of this study is on how the level of openness in the IP strategy of a firm affects the opening firm's participation in markets for technology. Hence, we further

link the adoption of strategic openness to being on the supply and demand sides of markets for technology, following Arora & Gambardella (2010).

1.2.3 Outbound Openness and Markets for Technology

While developing new products and technologies is essential for survival and growth in today's business environment (Swink, 2003), the possibility of purchasing technological assets can also provide firms with strategic flexibility to utilize on market opportunities (Cesaroni, 2004). Markets for technology, where inventors (organizations, individual inventors, etc.) trade knowledge assets, have grown substantially over the past decades (Arora, Fosfuri, & Gambardella, 2001; Chesbrough, 2003; Arora & Gambardella, 2010) and have received considerable attention from business and economics scholars, despite the general assumption of being underutilized. Prior literature provides mixed evidence on the relationship between markets for technology and IP protection (Arora & Gambardella, 2010). Some studies find a positive association (e.g. Arora, 1995; Anand & Khanna, 2000; Gans, Hsu, & Stern, 2002), while other works find that weak or ineffective patent regimes are likely to increase trades in technology markets, or else, that IP protection has no effect on these markets (e.g. Veugelers & Cassiman, 1999; Smith, 2001; Nagaoka, 2002; Fosfuri, 2004). Our paper adds to this stream of research by investigating the link between outbound openness (i.e. explicitly giving up IP protection for some pieces of knowledge) and markets for technology. In the next section, we hypothesize on possible mechanisms through which the focal firm can capitalize on its practice of outbound openness, and Figure (1) depicts the hypotheses that we discuss in the following subsections.

Insert Figure 1 about here.

1.2.4 Internalization Mechanisms of Outbound Openness: Selling in Markets for Technology

Outbound openness and selling in markets for technology. As a firm waives the proprietary rights to its technology, other players in the market are per se exposed to more "usable" knowledge[6]. Exposure to external knowledge sources increases the likelihood that other firms will seek to make use of the external knowledge (Huber, 1991), especially if the contribution is significantly large. This can be explained by the fact that the voluntarily liberated knowledge translates into decreased transaction and negotiation costs and litigation threats (Boudreau, 2010; Wen et al., 2016) for others, which encourages them to incorporate the opened-up knowledge into their internal innovation processes. If before, third parties had to pay royalty fees or else, buy the proprietary rights to incorporate it without infringing, now these entities can freely access and make use of this knowledge.

To be able to exploit the liberated knowledge, outside actors are likely to create other supporting assets. These supporting assets can take the form of complementary downstream resources, as such resources related to manufacturing, marketing, or distributing the products that use the opened-up knowledge. This, in turn, will tend to increase third parties' valuations of future inventions and further advancements of the opened-up knowledge. Consequently, the demand for the subsequent innovations based on the specific pieces of knowledge will tend to increase. In other words, as outsiders incorporate the opened-up knowledge into their internal innovation processes, by investing in complementary assets to support the knowledge usage and commercialization, they will tend to have a higher

[6] As patents are public, anyone can access the information provided in the patent. In this context, by "usable" knowledge, we mean that for the opened-up patent, the inventor is given the right to use the relevant knowledge without the need to pay any royalty fees. Additionally, the inventor is exempt from a litigation threat for using the knowledge in the patent. Therefore, the usability of the knowledge is per se increased with strategic openness.

demand for related inventions. Hence, the focal firm practicing strategic openness, will obtain more opportunities for selling its other proprietary knowledge to outsiders[7].

Two main factors can help explain that the focal firm could indeed translate these increased selling opportunities into supplying the demanded pieces of knowledge following its practice of outbound openness. First, due to its prior experience with the opened-up knowledge, one could argue that the firm is naturally equipped with a stock of relevant knowledge, which would make it possible for the firm to satisfy the increased demand. Second, for the increased demand to be actually satisfied by the focal firm, the gains from selling opportunities would arguably need to exceed the costs from losing ownership and control over its other proprietary assets. As the probability of engaging in beneficial selling transactions would plausibly increase with higher demand and involvement from outside parties, in the hypothesis below, we expect the focal firm to sell more of its still-proprietary knowledge after the decision to open up.

Hypothesis 1. The more openness the firm adopts in its IP strategy, the more knowledge it sells in the markets for technology.

1.2.5 Internalization Mechanisms of Outbound Openness: Using the Subsequently Created Knowledge via Buying in Markets for Technology or Building upon it

Outbound openness and buying in markets for technology. Another logical reaction from outside parties to the reduction in the costs and risks of incorporating the liberated

[7] Though outside the scope of the current study, the increase in the demand for relevant inventions will not necessarily only benefit the focal firm. Since outbound openness can also induce other firms to create their own advancements of knowledge (see further development of the hypotheses; and for a more detailed discussion, see Ayvazyan & Matr, 2019), the increased demand for the subsequent knowledge can be satisfied by external parties as well.

knowledge is to engage in creating subsequent developments[8], for instance, by building upon it or/and by recombining it with their pre-existing stocks of knowledge. In the context of platform development, Parker & Van Alstyne (2017) argue that platform openness stimulates third-party developers to build upon the made-free knowledge and generate R&D spillovers. As others having diverse capabilities innovate and contribute to these opened-up technologies, the possibilities of knowledge recombination and new knowledge creation increase. Galasso & Schankerman (2015) document an increase in the follow-on inventive activities in the aftermath of *involuntary* waivers of exclusivity rights, i.e. patent invalidation decisions from the court. Despite the decision of patent invalidation, follow-on innovators are still required to recognize prior art, though now, without the need for paying any royalty fees (i.e. reduced costs for using the knowledge). Similarly, in the context of *voluntary* waivers of exclusivity rights (i.e. outbound openness), third-party engagement in advancing the liberated knowledge will tend to increase.

The increased involvement from outside parties in developing new knowledge will be reinforced by the increased demand for the subsequent knowledge from those engaging in creating complementary assets, as a response to strategic openness (as hypothesized previously). From the focal firm's point of view, the advancements of the liberated knowledge by others will, in turn, represent opportunities for internalizing these spillovers through two main channels. First, the focal firm could selectively buy from the new knowledge. Second, it could incorporate the further developments by building upon them within the limits of non-infringement of property rights.

[8] Building complementary assets and engaging in creating further knowledge are not necessarily mutually exclusive. Third parties may do both and this could depend on various factors (e.g. the degree of their upstream and downstream capabilities).

These two mechanisms (at least partially) can be explained through the lens of the concept of absorptive capacity (Cohen & Levinthal, 1989, 1990). Having the privilege of familiarity and a likely considerable experience with the previously proprietary knowledge, the focal firm will possess important absorptive capacities for identifying and evaluating the follow-on inventions (Arora & Gambardella, 1994). These abilities will facilitate the firm's engagement in buying transactions of the subsequent external pieces of knowledge, which can potentially be more value-enhancing in terms of their suitability with the firm's innovative needs. In addition, being familiar and experienced in the liberated knowledge, focal firms would likely be equipped with the necessary complementary assets to be able to incorporate the outside knowledge into their internal innovation processes. These two factors, namely absorptive capacities and complementarities between internal and external knowledge are, in fact, two of the three main drivers of the demand side of markets for technology, as identified by Arora & Gambardella (2010). The third driver relates to the so-called "Not-Invented-Here" (NIH) syndrome, which largely refers to the irrational bias against outside sources of knowledge/technology. This syndrome may, at the extreme case, lead to an exclusively internal recombination of knowledge, thereby potentially putting the firm into a competency trap (Levitt & March, 1988; Levinthal & March, 1993). However, it is less likely to be dominant in firms that adopt open innovation approaches, since these firms are supposedly more "open-minded" towards outside-in or inside-out knowledge flows[9]. Thus, while absorptive capacities will tend to help the focal firm to identify and evaluate knowledge developments from third parties for buying decisions, the complementarities between internal knowledge and external knowledge advancements,

[9] See Cassiman and Valentini (2016) for a discussion on the complementarities between outbound and inbound open innovation and, in particular, on the role of reductions in cognitive, organizational and transaction costs.

together with a low propensity that the firm suffers from the NIH syndrome, will tend to mitigate the generally assumed underutilization of knowledge acquisitions in markets for technology.

Taken together, the above-mentioned arguments support the premise that with strategic openness, the focal firm will get more opportunities for engaging in buying transactions in markets for technology. Hence, we hypothesize:

Hypothesis 2. The more openness the firm adopts in its IP strategy, the more knowledge it buys in the markets for technology.

Outbound openness and building upon the knowledge spillovers. The second channel through which the firm may internalize the knowledge spillovers from the opened-up knowledge is via building upon these external knowledge advancements. This is especially relevant for situations, where directly incorporating others' follow-on knowledge with the help of the firm's complementary assets via buying in markets for technology (see the discussion above) is likely not an optimal choice for the firm. For instance, with the increased availability of subsequent knowledge due to outbound openness, it is possible that some of this externally developed knowledge is simply not yet commercializable and further technical developments are still required to ultimately take the knowledge to market. Considering that the focal firm can use its absorptive capacities of identifying and evaluating external pieces of knowledge from the pool of sequential inventions (due to its existing experience and know-how with the liberated knowledge), with increased available

knowledge, the firm will be provided with new possibilities for further recombining and advancing the technology without infringing on others'[10].

Prior research has argued that building upon the subsequent technical developments for generating new knowledge is, in fact, beneficial for the focal inventing firm, as it may allow for capitalizing on the firm's previous inventive efforts (Belenzon, 2012). The intuition behind is that by "reabsorbing" the subsequent knowledge, the firm may mitigate the potential negative effects of (involuntary) knowledge spillovers[11] and sustain its long-run earnings. Then one could argue that building on the follow-on knowledge would be especially important, when practicing outbound openness, where the firm itself allows for knowledge spillovers. This is the case, since with more involvement from others in creating developments of the opened-up knowledge, the competitive environment becomes more dynamic, increasing the need for the focal firm for developing and renewing prevailing capabilities to match the changing requirements of the environment (Teece et al., 1997). The increased "competition" anticipated by the firm's adoption of outbound openness implies that the firm should protect its market position and continuously develop new knowledge to be able to compete in these fields. Thus, as illustrated in Figure 2, we argue that the increased subsequent inventive output due to outbound openness would lead to more opportunities for the firm for internalizing those externalities. Hence, our third hypothesis:

Hypothesis 3. The more openness the firm adopts in its IP strategy, the more knowledge it builds upon the subsequently created knowledge.

---

[10] Importantly, the newly created knowledge by the focal firm should be sufficiently differentiated from and not infringing on others' inventions. Otherwise, the risks and costs of infringement could cancel out the potential benefits from building upon the external follow-on developments of the liberated knowledge.

[11] For a discussion on the negative effects of knowledge spillovers, see e.g. Spence (1984), Aghion & Howitt (1992).

1.3 RESEARCH SETTING

Studies on knowledge transfer among firms and on innovation have relied on the outcomes of technology licensing transactions (e.g. Arora & Ceccagnoli, 2006; Fosfuri, 2006; Nagaoka & Kwon, 2006; Gambardella, Giuri, & Luzzi, 2007) or collaborations (e.g. Singh, 2005; Schilling & Phelps, 2007; Jugend et al., 2018). We argue that these proxies do not allow disentangling the effect of outbound open innovation for the following reasons. Firms engaging in licensing or collaborations remain in control, at least partially, of the flow of knowledge in terms of who can use the knowledge or how often they can use it. Specifically, in case of licensing, the firm chooses to whom to license, while getting royalties in return. On the one hand, this naturally limits the number of users, who can benefit from the knowledge, and on the other hand, the firm still holds the ownership of the knowledge. Similarly, in case of a collaboration, the firms remain the owners of the knowledge, and the knowledge flows in both directions, as the collaborating firms make their knowledge available to each other. As a result, the effect of outbound and inbound openness appears combined and separately undistinguishable.

We deviate from these studies, by testing our hypotheses in a different setting, namely patent pledges. Specifically, our research context is IBM's IP strategy and its consequences for innovation-related outcomes for IBM itself during the period from 1999 to 2010. In 2005, IBM announced that it had decided to donate 500 of its patents to the public in support of the development of the OSS community. Being royalty-free, IBM's patent pledge did not require any formal agreement for anybody to use the patents in the pledge. This means that anybody could use the opened-up knowledge without, for instance, a requirement of giving up their own IP rights. These properties make the setting of IBM's

pledge a pure form of outbound openness. In addition, IBM made the decision of pledging these patents considering their substantial economic importance, as well as their ample coverage of technological classes. According to Linux Magazine, the 500 patents "cost $10,000,000 to obtain (just in the U.S.) and are worth an unknown amount in licensing revenue"[12]. IBM's patent pledge announcement (2005) claimed that that patent pledge was by far the biggest contribution to the OSS, in terms of the number of patents. The announcement (2005) also stated that "Fostering Innovation, Interoperability and Open Standards" were the goal of the pledge.

Nevertheless, several alternative motives behind IBM's pledge have been discussed in various academic and non-academic sources. For instance, IBM pledge was suspected to be motivated by the dispute between IBM and Santa Cruz Operation (SCO) Group in 2003, where IBM was accused of infringing SCO's UNIX code (Goettsch, 2003). After its counterclaim against SCO in 2004, IBM decided to offer the 500 patents in the pledge for free, arguably, to provide the OSS community with insurance about Linux, the open-source operating system IBM supported. Meanwhile, Alexy & Reitzig (2013) note that the patent pledge could have been reasoned to stimulate the demand for IBM's complementary assets and the sales of its hardware products. Another speculation regarding this pledge refers to the debate about European software patent laws. Some observers doubted that IBM's move was aimed at signaling to the European legislators that software patents did not necessarily hinder the innovation process. Altogether, we argue that these speculations do not seem to be directly related to IBM's strategy in markets for technology. Thus, IBM pledge appears to be a suitable context to address our research question.

[12] http://www.linux-mag.com/id/1975/

1.3.1 Identification Strategy

Empirically, we perform difference-in-differences analyses incorporating IBM's pledge of 2005 at two different levels. The first set of analyses includes the level of knowledge domain, represented by technological classes, according to The United States Patent Classification (USPC). We use these class-level analyses (with class-year type of observations) to explain the temporal variation outcomes of patent trading (i.e. selling and buying) activities (for hypotheses 1 and 2), using a score of openness for each technological class. To understand the construction of this score (see "Independent Variables" subsection), we next explain our identification strategy at this level. First, we identify the treated group of technological classes, if the class includes any of the 500 patents that IBM pledged in 2005. There are 50 such technological classes. The classes without any pledged patent, to which IBM had significantly contributed up until 2005 – that is IBM patents counted for more than 2.5% of all the patents in the class or IBM had more than 200 patents in the class[13] - serve as the control group of technological classes. There are 127 control classes, leaving us with 177 classes in total. Assigning an openness score to each of these technological classes allows us to explore whether IBM tends to buy or sell more patents in areas of knowledge in related to their levels of openness.

In the second set of analyses, we use data at the patent-level (with patent-year observations). The goal of these analyses is to track the effect of the patent pledge on patent trading in a more detailed and direct manner and to test the impact on building upon the subsequently created external knowledge (Hypothesis 3), by examining the pledged patents and their spillovers, e.g. citing patents, in comparison to similar non-liberated patents and

[13] The choice of the 200 patents allows us to avoid losing technological classes that have a substantial absolute number of IBM patents, however, a smaller percentage than 2.5%.

the latter's spillovers. In these difference-in-differences analyses, we compare the pledged patents, i.e. treated group, to a selected group of similar patents, i.e. control group, which we construct by matching each pledged patent with other patents using a text matching algorithm to measure technological similarity, following Arts, Cassiman, & Gomez (2017). We ask for a minimum similarity score of 15% and require the control patents to have the same filing year and to belong to the same technological class. Eventually, we are left with 1351 patents in the control group with an average of about three control patents for each patent in the pledge[14]. These treated and control patents represent the "Initial" patents illustrated in Figure 2.

For each group (i.e. treated and control), we extend the number of patents by considering their spillovers, which we capture with "Level-one" and "Level-two" patents (see Figure 2). To do so, we draw on prior studies that argue for the proximity between citations and knowledge flows, despite possible noisiness[15] (Jaffe, Trajtenberg, & Fogarty, 2000; Duguet & Mac Garvie, 2005; Gay & Le Bas 2005), and use *initial* treated and control patents' forward citations to proxy related knowledge flows (i.e. spillovers). Importantly, we differentiate between direct and indirect citations received by the *initial* patents. A patent that cites any of the initial patents (treated or control) represents a direct citation. We refer to this patent as *level-one* patent. Accordingly, depending on whether the level-one patent cites the pledged patent or a control patent, we consider it as treated or control, respectively. Further, a patent that cites the patent citing any of the initial patents (level-one

[14] Note that there are duplications in the control patents for the treated patents (i.e. two different pledged patents can share the same control patent).

[15] The noisiness of this measure (using forward citations to capture knowledge flows) is mostly related to the fact that during the patent application process, citations from patent examiners, who are responsible for checking for prior art, may be added to the original references in the patent application. However, citations are still a valid empirical proxy, especially in industries, where knowledge creation is cumulative, and are widely used in extant related literature.

patent) represents an indirect citation. We refer to this patent indirectly citing an initial patent as *level-two* patent (Figure 2 provides a graphical representation of the discussion above)[16]. This distinction between *level-one* and *level-two* patents is especially relevant for testing our third hypothesis, where we look at whether an external patent (i.e. a patent that was not created by IBM) is more likely to be cited by IBM (*level-two*) if that patent (external *level-one*) has built upon any of IBM's pledged patents after 2005. As for Hypotheses 1 and 2, we test for whether being related to the pledge (*level-one* or *level-two* patents in the treated group), increases the likelihood of being traded by IBM. Not surprisingly, then, in the analyses related to Hypothesis 1 (selling) at the patent-level, we limit the sample to only IBM patents.

Insert Figure 2 about here.

1.3.2 Pledged Patents

Before we turn to data description and results discussion, we further examine the differences between the pledged and control patents (at the initial level), to corroborate the suitability of our empirical exercise. In their study on the effect of IBM 2005 patent pledge on new product introductions, Wen et al. (2016) compare the patents in IBM's pledge to a randomly selected group of similar patents in the market and conclude that the pledged patents have, in general, similar backward and forward citations, and that the pledged patents have lower number of claims. Similarly, they compare the pledged patents to other

[16] Although intuitively, indirect citations are not limited to only level-two patents (they can include patents at level three and more), for methodological reasons associated with the data characteristics, we consider only up until the patents in the second level. However, we believe that this restriction should not distort our results, as the higher the so-called level of the citation, the farther and less related, in principle, the newly created knowledge from the original invention in the focal patent. And what we are interested in capturing, are the "relevant" knowledge flows.

IBM patents, and find that the pledged patents have similar forward citations, but lower backward citations (indicating lower derivativeness) and lower claims (indicating narrower scope). In the current study, we compare the patents in the pledge (500 patents) to the control group (1351 patents). Table 1 presents our own tests of the differences between the treated and control groups in terms of the following observables: *Forward citations*, *Forward citations up to 2005*, *Backward citations*, *Non-patent references*, *Claims*, *and Independent claims*. Both groups of patents seem to have received a similar number of *Forward citations* and *Forward citations before 2005* and they both seem to have relied on a similar number of references. On the other hand, the patents in IBM's pledge seem to use more non-patent references, which suggests more closeness to science and a higher level of basicness. Our control group has a higher number of claims, similar to Wen et al. (2016), and a higher number of independent claims, which indicates a wider scope of knowledge. Overall, this evidence also rules out the argument that IBM could have pledged patents that were not valuable[17].

Insert Table 1 about here.

1.4 DATA AND METHODS

1.4.1 Data

To build the variables related to patent trading (i.e. selling and buying) activities, we rely on the Patent Assignment Dataset (PAD) from the United States Patent and Trademark Office (USPTO) website (www.uspto.gov). Importantly, unlike licensing or alliance

[17] Similar to the patent-level comparisons, Ayvazyan & Matr (2019) compare the treated and control groups in terms of the amount of patents by IBM and the total number of patents in the technological classes and do not find any drastic differences in the trends before 2005.

transactions, most patent ownership transfers are recorded by parties with the database, since legally, for the (re)assignment to be considered as legally binding[18], it has to be filed with the USPTO. A typical transaction includes information on the buyer and the seller, the dates of recording, executing or signing, the number of patents/patent applications transacted per assignment, and the assignment type (Marco et al., 2015). Although the majority of the reassignments constitute an inventor-to-employer transfer of rights, we mainly consider inter-firm assignments of patents, as the latter are more reflective of markets for technology. Other types of patent reassignments that we do not consider as a buying or selling activity include name correction, government interest, and name change of the assignee. Since the assignee names are not disambiguated in the Patent Assignment Database, we follow the name standardization procedure from the NBER patent data project[19] to identify possible IBM transactions. Finally, after identifying the bought and sold patents, we are able to link these data with other relevant data on patent characteristics from the USPTO database PatentsView[20] that we use to construct our independent and control variables. This data is disambiguated for patents, inventors, assignees (firms/individual inventors).

1.4.2 Empirical Model

For the class-level analyses, we run the regressions under the specification of a linear estimator:

$$Y_{jt} = \alpha + \beta\, Openness_{jt} + \delta\, Openness_{jt} * After\ 2005_j + \mu * Controls_{jt} + u_j + \mu_t + \varepsilon_{jt},$$

[18] Marco et al. (2015) note that whether the recorded transfers accurately represent the population of the assignments remains an open question, since it is not mandatory to record the transfer of patent rights at the USPTO. However, interested parties do have incentives to record an assignment with the USPTO, as only those patent transfers that are recorded serve as evidence of ownership transfer in courts.
[19] Available at https://sites.google.com/site/patentdataproject.
[20] Available at www.patentsview.org.

where j indicates the technological class, and t indicates time. For the error components, u_j indexes a technological-class-specific effect and ε_{jt} is an idiosyncratic error term. Our baseline regressions take the relevant trading intensity as dependent variables (Y_{jt}). We regress these variables on the degree of openness of IBM in the corresponding technological class, as measured by the class' presence in the patent pledge. To capture the extra effect of the decision of opening up this knowledge, we interact the openness measure with a dummy variable for the years from 2005 to 2010. This approach involves a difference-in-differences with a non-dichotomous treatment variable (*Openness*) and dichotomous time variable (*After 2005*). In order to accurately estimate the precision of the regression coefficients, we cluster the standard errors at the level of the treatment assignment, technological class level. Since the variable *Openness* is time invariant, adding it as an explanatory variable is equivalent to adding the group means of this variable as a separate predictor. This approach is similar to the correlated random effects approach of Mundlak (1978). Moreover, we add to the model year fixed effects to control for the time trends in a flexible manner.

We use an analogous setting for the patent level analysis, where the openness measure is captured with a dichotomous indicator (*Pledge-Related Patent*[21]) denoting if the focal patent cites any pledge patent, directly or indirectly. In these patent-level analyses, we use a difference-in-differences design with dichotomous treatment group and dichotomous treatment time and with standard errors clustered at the patent level.

[21] For variable descriptions, see Table 1.

1.4.3 Dependent Variables

IBM Selling $_{class}$ ***and IBM Buying*** $_{class}$. We build these variables for our class-level analyses (see Identification Strategy subsection above), to account for patent acquisitions in a specific technological class in a specific year. As noted previously, when identifying patent acquisitions, we exclude within-firm reassignments of rights – recorded reassignments from an inventor employee to an employer assignee (Employee Assignments) or reassignments due to changes in the assignee name or name corrections –, in addition to agreements of governmental interest. By verifying whether IBM is on the buying or selling side of the patent trade, we determine the number of patents sold or bought in each of the transactions, and then aggregate these values per year at the technological-class level. Hence, *IBM Selling class* (*IBM Buying class*) represents the total number of patents that IBM sold (bought) in a specific technological class in a given year. In some analyses, we also include the variable *IBM Trading* $_{class}$, which we create by summing up the yearly bought and sold patents by IBM per technological class, to account for the firm's aggregate participation in markets for technology.

IBM Selling $_{patent}$ ***and IBM Buying*** $_{patent}$. In the analyses at the patent level, our dependent variables related to the participation in markets for technology, are (binary) dummies that simply record whether IBM bought or sold the focal patent in a given year.

Citations from IBM. We build the variable *Citations from IBM* at the patent-level to test our third hypothesis. This is a yearly measure, counting the number of citations made by IBM to level-one patents. To construct this variable, for each level-one patent in a given year, we simply aggregate the total citations received from IBM.

1.4.4 Independent Variables

Openness. As remarked in our empirical model, the effect of outbound openness at the technological-class level, is captured by the interaction term between an openness measure, *Openness*, and the dummy *After 2005*. The variable *Openness*, represents the claims-weighted count of the pledged patents in each of the technological classes[22]. Weighting these patents by their number of claims, rather than simply using patent counts, allows us to better reflect on the scope/breadth of the opened-up knowledge in technological classes (Allison, Lemley, Moore, & Trunkey, 2004; Novelli, 2015). Accordingly, the technological classes without any pledged patents obtain a value of zero in their openness score.

Pledge-related Patent. To account for "openness" in our patent-level analyses, we create the (binary) dummy variable *Pledge-related Patent*, which indicates whether the patent is a level-one or level-two citation to any of the initial 500 pledged patents. In some cases (for Hypothesis 3), we specify *Pledge-related Level-one Patent* to refer to the level-one pledge-related patent (i.e. taking a value of 1 if the level-one patent is pledge-related, and 0 otherwise).

In Table 2, we describe all the variables used in our analyses at both levels.

Insert Table 2 about here.
---

[22] This approach is similar to Wen et al. (2016) measure of openness, called "Commons".

1.5 RESULTS

1.5.1 Descriptive Statistics

Descriptive statistics for selected variables at the class level appear in Panel A in Table 3. For our sample period between 1999 and 2010, we have 1969 class-year observations belonging to 177 technological classes, in total, 50 out of which were to some extent opened up due to IBM's pledge in 2005. The average *Openness* score in our panel data is 80.5 claims and the maximum score is 2184 claims. On average, IBM files for 118 patents yearly in the average technological class with a maximum of 2020 patents in a class. The average technological class has 19045 patents yearly from all the firms in the market. From the same class in the same year, IBM buys slightly more than 11 patents, on average, while it sells around 24 patents. In Panel A in Table 4, we present the statistical correlations between our main variables at the technological class level. Analogously, Panels B in Tables 3 and 4 show the descriptive statistics and the correlation matrix, respectively, for the main variables at the patent level.

Insert Tables 3 and 4 about here.

Further, we provide some simple and preliminary statistics, exploring the differences between the pledge-related patents that IBM sold and bought in our sample, to get some initial insights on the characteristics of the patents in IBM's trading decisions. We compare these two groups of patents, 549 sold and 453 bought patents, in terms of observables, like patent's *Forward Citations*, *Backward Citations*, *Non-patent References,* and *Independent Claims* (see Table 5). While the forward citations received by the bought patents seem to be higher than the ones received by the sold patents, in terms of the backward citations, both

groups seem to be statistically similar. The two groups seem to be statistically similar also in terms of the number of the *independent claims*, indicating that these patents seem to have similar breadths/scopes. More interestingly, the difference in *Non-patent References* is extremely statistically significant, where, on average, the bought patents have higher numbers of non-patent references. In later analyses, we notice that the buying probability increases when the patent has more non-patent references, yet the opposite happens for the selling probability in the corresponding model (see Table 7).

Insert Table 5 about here.

The pre- and post-trends of IBM's participation in markets for technology, in terms of patent buying and selling activities in opened-up (treated) versus close (control) technological classes are shown in Figure 3. This figure suggests that IBM's decision to open up its IP strategy was associated with an increased buying and selling tendencies in the opened-up technological classes. Arguably, the figure provides a preliminary support for the use of difference-in-differences analyses in our empirical approach, pointing out at acceptably similar pre-treatment trends for both variables of interest. Interestingly, one can note that the association between IBM patent trading and openness may seem to be lagged. We speculate that these "lagged" effects can be explained by the time that may be needed for the pledge to facilitate a market creation, which will in turn enable IBM to buy (sell) subsequent inventions from (to) others. In other words, time is needed for the demand and supply of technology to be developed so that IBM can internalize the externalities of its strategic openness. Our additional analyses (see Results section below) formally test for this effect over time. Taken together, these graphs suggest that IBM's trading in markets for

technology experienced a boost after the firm's decision to adopt outbound open innovation, as proxied by employing the 2005 patent pledge.

Insert Figure 3 about here.

1.5.2 Class-level Results

We begin with investigating how the aggregate trading activities of IBM are associated with the variation in its strategic shift toward openness. Then, we study how *IBM Selling* $_{Class}$ or *IBM Buying* $_{Class}$ change with the openness level. Table 6 reports the main results for this part of the analysis. The positive and significant coefficient of the interaction term in column (1) in Table 6 suggests that additional 100 claims in an opened technological class are associated with 3.7 extra traded patents, either bought or sold, in that technological class after the pledging time, year 2005[23]. Column (2) indicates that the total number of patents sold by IBM after 2005 in affected technological classes, increases by 1.6 patents with each additional 100 claims contributed to the pledge. Analogously, the third column shows that the number of patents that IBM buys also increases with the firm's outbound openness. More specifically, IBM buys 0.4 patents per class with an increase of 100 claims to the openness of the technological class. The second and third models point at the direction that IBM gets more involved in trading activities, in general, after its decision to waive its exclusivity rights of its intellectual assets. However, IBM seems to be keen on selling more patents in comparison to buying patents. In relative terms, a one-standard-deviation increase in *Openness* leads, on average, to a 0.053 (80×0.016/24) standard-

[23] Considering that each pledged patent includes, on average, 16.72 claims, this numbers imply that, on average, one more pledged patent leads to 0.61 additional traded patents.

deviation increase in selling and a 0.03 (80×0.004/11) standard-deviation increase in buying after 2005. These findings provide support for our Hypotheses 1 and 2.

Insert Table 6 about here.

1.5.3 Patent-level Results

To investigate the effect of the patent pledge on IBM's behavior in markets for technology in a more direct way (for the first two hypotheses), we conduct patent-level analyses, where we check for the likelihood of a patent being sold or bought by IBM (*IBM Selling* $_{Patent}$ or *IBM Buying* $_{Patent}$), depending on whether or not the patent is related to the pledge. We construct two different samples of patents to study the buying and selling possibilities separately. The sample for testing the probability of buying consists of both the level-one and level-two patents (both the pledge-related and control patents). For the analysis of the probability of selling, we build the sample from IBM's level-one and level-two (both treated and control) patents. The effect of interest is represented by the interaction term between the dummies *Pledge-related Patent* and *After 2005*. We control for citations received by the patent (*Forward Citations*), since that can be a signal of quality and potentially can increase the probability of being traded. Other controls are *Backward Citations*, *Non-patent References*, and *Independent Claims*, which can account for the patent scope and value. In addition, we control for the total number of patents IBM files in the focal patent's technological class (*IBM Total Patents* $_{Class}$). The results in column (2) in Table 7 imply that after 2005, IBM is significantly more inclined to sell patents that are related to the pledge. The probability of IBM selling a patent increases after 2005 by 0.02% for the pledge-related patents. Column (4) shows that being related to the pledged patents

does not seem to affect the probability of being bought by IBM. Overall, the results presented in Tables 6 and 7 give a strong support for our first hypothesis and a partial support for the second one.

Insert Table 7 about here.

To test Hypothesis 3, which states that the focal firm internalizes the knowledge created by other players through building upon it, we analyze the effect on *Citations from IBM* to level-one patents before and after the practice of strategic openness. To do so, we first identify the pledge-related and the corresponding control group of level-one patents (*Pledge-related Level-one Patent*), after which we simply distinguish between whether or not the level-one patent belongs to IBM (*Non-IBM Level-one Patent*). The idea behind these classifications is to allow for empirically testing whether IBM will build upon the external subsequent knowledge more, in comparison to its own subsequent knowledge, which we will be able to capture by interacting the dummies *Pledge-related Level-one Patent, Non-IBM Level-one Patent*, and *After 2005*. Table 8 comprises a three-way interaction approach with the corresponding two-way interaction terms. We are particularly interested in the coefficient of the interaction term between *Level-one Pledge-related Patent* and the *After 2005* dummy, as well as in the three-way interaction term. The first of these two coefficients of interest is negative and statistically significant, suggesting that IBM depends less on its own level-one pledge-related patents after 2005 in comparison to non-pledge-related ones (i.e. level-one control patents). More interestingly, the three-way interaction is significantly positive, which means that IBM seems to internalize the spillovers created by others using its liberated knowledge more than it uses its own subsequent knowledge. Taken together, these results provide evidence to confirm our third

hypothesis positing that the opening up firm will draw on the knowledge others create using its opened-up knowledge.

Insert Table 8 about here.

1.5.4 Robustness Checks and Additional Analyses

The potential confounding effect of OIN. In 2005, IBM, Novell, Philips, Red Hat, and Sony launched the Open Invention Network (OIN) with the aim to advance Linux and other OSS programs. To become a member of this network, firms are required to offer their patents for royalty-free licenses and agree not to assert their own patents against the Linux innovators. The patents that OIN acquires from the outsides are also offered royalty-free to the members. This way, OIN's goal is to create a collaborative ecosystem, a patent-non-aggression community and protect its members from litigation and other types of patenting risks (OIN official website[24]). Since both the creation of OIN and IBM's patent pledge took place in 2005, and both events represented a liberation of knowledge for the OSS community, one could argue that the results presented earlier in the paper could be driven by the launch of the shared defensive patent pool, OIN, rather than IBM's pledge. Therefore, it is reasonable to address the potential confounding effect of the OIN's establishment on IBM's internalization strategies after 2005.

In order to do so, we follow a similar approach used for our (original) *Openness* measure and create the variable *OIN Openness* at the class level, to capture the knowledge scope/breadth liberated by OIN in each of the technological classes. More specifically, this measure indicates the claims-weighted patent count of OIN patents related to a

[24] https://www.openinventionnetwork.com/

technological class *j*. While OIN owns more than 1300 global patents, we only consider the 660 patents registered at the USPTO when constructing our proxy.

To disentangle the impact of the OIN launch from IBM patents' pledge, we run the main analyses with incorporating *OIN Openness*. In particular, in models (1), (3), and (5) in Table 9, we examine the effect of *OIN Openness* isolated from IBM's pledge, while in models (2), (4), and (6), we consider both events simultaneously. We perform these analyses for the main variables of interest regarding IBM's trading activities. The results show that the effect of the patent pledge is robust to accounting for the impact of OIN liberated patents. In models (1), (3), and (5), *OIN openness* seems to have no effect on the number of patents IBM sold, bought, or traded, respectively, after 2005. More importantly, the effect of *Openness* on the variables of interest in models (2), (4), and (6) does not seem to change when considering *OIN openness*, which provides additional evidence that the 2005 patent pledge influences the changes in the firm's behavior in markets for technology and its effect does not seem to be mixed with the effect of OIN launch.

Insert Table 9 about here.

The development of the openness effect over time. During our sample period, IBM did not add to the 500 patents in the pledge after 2005, which means that the shock was unstaggered and concentrated in the few years after 2005. To study the development of the effect of IBM's pledge over time in more details, we break down the effect over the years following the firm's decision. In our sample, there are five years after the announcement of the patent pledge, 2005-2010, with the first (second) block of analysis being the years 2006 and 2007 (2008 and 2009), and the last one, being the year 2010. For all of these blocks, we create dummy variables, each of which we interact with the openness measure. We do this

to reflect on the concentration of the effect of openness, in terms of the closeness from the shock. The results in Table 10 show that the effect of the patent pledge on the variables of interest related to trading is concentrated in the second block, years 2008 and 2009. Overall, these results may suggest that the impact of openness takes some time to show up in the firm's patenting and IP trading activities and fades away after a few years.

Insert Table 10 about here.

Economic effects. To get further insights on the economic effect of the patent pledge, we investigate the intensity of IBM's inventive activities, as proxied by the number of patents filed by IBM, and its ability to create radical inventions, proxied by the number of radical patents. To construct the latter variable, we follow Eggers & Kaul (2018) measure of radicalness. Both of these aspects can help quantify the economic returns to adopting an open IP strategy, as these have been positively linked to firm value, firm future earnings, etc. (e.g. Mitchell, 1989). The results in Table 11 show that IBM experienced an increase in its inventive output in the technological classes, proportionally to their degree of openness. Analogously, the radicalness of IBM's patents also increased after the firm's decision to open up its IP strategy. An increase in a specific technological class openness by 100 claims is associated with an increase in the number of patents produced by IBM by 9.64 patents and 0.8 more radical patents after the firm's shift toward openness in 2005. This positive association between the adoption of an open IP strategy and the number of total patents and the number of radical patents can be an indicator of firm's value and its future earnings (Mitchell, 1989; Bessen, 2009).

Insert Table 11 about here.

1.6 DISCUSSION AND CONCLUSIONS

Our paper sheds light on a new possible angle for investigating a firm decision to allow for inside-out knowledge flows for no direct financial benefits, i.e. strategic openness, prominent examples of which are patent pledges by various multinational giants. This behavior seems to contradict the traditional management theories that emphasize the role of ownership and protection of intellectual assets in ensuring value appropriation from the firm's innovation. In this paper, we study certain actions of a firm after its adoption of outbound open innovation, in order to improve our understanding of possible internalization mechanisms. Mainly, we claim that the firm can capitalize on the externalities resulting from its decision to grant free access for its knowledge to the outsiders through two channels. The first channel involves selling intellectual assets in markets for technology to meet the hypothesized demand resulting from the increased engagement of third parties in the liberated knowledge. The second one refers to bringing the subsequent external knowledge in-house via buying intellectual assets in markets for technology or building upon them internally. We test our hypotheses using IBM's pledge of 500 patents to the OSS community in 2005 during the period 1999-2010. Our results suggest that IBM exploited the markets for technology options in the research lines related to the liberated knowledge after its shift toward outbound openness via selling intellectual assets. In addition, IBM seems to have kept valuing the subsequent knowledge in the opened-up fields created by others, evidenced by increased building on external patents and by increased involvement in buying transactions of patents in markets for technology.

Overall, this study contributes to the literature on open innovation by investigating how firms may internalize on their practice of (non-pecuniary) outbound openness through the

proposed two channels. To the best of our knowledge, we provide a novel link between open innovation and markets for technology. While prior research has proposed that outbound openness may trigger a demand boost in the firm's complementary assets (e.g. Alexy et al., 2018), in this paper, we show an augmented demand for the firm's other relevant knowledge, which can be met through markets for technology. However, one should also analyze the costs of this practice and the forgone opportunities that the firm could achieve if it did not decide to involve in this practice. Such costs and opportunities can be related to potential licensing revenues the firm could make or possible benefits from blocking potential competitors from using its knowledge.

Our study is subject to limitations. As we empirically examine the effect solely for IBM, the external validity of this study is limited, which means that one should be careful when implementing our findings in different contexts and for other firms. Nevertheless, we believe that studying a firm as big as IBM is still useful as a case from which other firms can learn. IBM is a big firm that provides a great variety for aspects to be explored and other firms thinking of adopting openness can infer a lot from it. These findings are expected to be more relevant and beneficial for firms with substantial resources and capabilities that allow them to employ the suggested mechanisms, especially in the markets for technology. Another related limitation for our study could be linked to the fact that we do not observe heterogeneity in terms of factors, such as firm's size and capabilities, financial and intellectual, which may be essential when deciding to open up the firm's IP strategy. Next, one other factor that we cannot account for due to our empirical setting, is the timing of openness adoption (e.g. earlier adopter vs follower) and how it could change the dynamics of our mechanisms. These could provide opportunities for future research. Finally, we assume that openness in one area of knowledge has no impact on the effect of

openness in another knowledge area. Since the fields of knowledge can be interrelated and therefore, dependent on each other at different degrees, one can think of considering the interactions among classes' openness, especially the ones that are closely related to each other, for future research.

1.7 Chapter 1 Tables

Table 1: Tests of the differences between the treated and control groups of patents.

	Pledged Patents (500 patents)			**Control Group** (1351 patents)			**Difference**
VARIABLES	Mean (SE)	Min	Max	Mean (SE)	Min	Max	Mean (SE)
Forward Citations	39.900 (6.230)	1	357	36.621 (1.449)	1	540	3.278 (2.771)
Forward Citations *up to 2005*	38.685 (6.032)	1	341	35.356 (1.435)	0	540	3.328 (2.733)
Backward Citations	9.900 (0.994)	1	56	12.249 (0.469)	1	263	-2.349 (1.210)
Non-patent References	3.510 (1.263)	0	177	2.723 (0.204)	0	107	0.787* (1.211)
Claims	16.724 (1.440)	1	57	19.583 (0.359)	1	120	-2.859*** (1.341)
Independent Claims	3.594 (0.323)	1	17	3.905 (0.073)	0	28	-0.311*** (0.630)

Note: The column "Difference" represents the value from subtracting the mean of the control group from the treated group of patents. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

Table 2: Variable descriptions.

Variable name	**Variable description** *(all variables are yearly measures)*	**Level of analysis**
Dependent variables	***Data source*: Patentsview.org (patents, citations), USPTO (reassignments)**	
IBM Buying $_{Class}$	Number of patents IBM buys in a given technological class.	*Class*
IBM Selling $_{Class}$	Number of patents IBM sells in a given technological class.	*Class*
IBM Trading $_{Class}$	Number of patents IBM buys or sells in a given technological class.	*Class*
IBM Total Patents $_{Class}$	Number of patents that belong to IBM in a given technological class.	*Class*
IBM Rad. Patents $_{Class}$	Number of radical patents (following Eggers & Kaul (2018)) that belong to IBM in a given technological class.	*Class*
IBM Buying $_{Patent}$	A level-two patent that is bought by IBM.	*Patent*
IBM Selling $_{Patent}$	A level-two patent that is sold by IBM.	*Patent*
Citations from IBM	Number of citations each level-one patent receives from IBM.	*Patent*
Independent variables	***Data source:* Patentsview.org (patents, citations)**	
Openness	Summation of the claims of the patents that were pledged by IBM in a given technological class in 2005.	*Class*
After 2005	1 if the (application) year (of the patent) is after 2005, 0 otherwise.	*Both*
Total Patents $_{Class}$	Number of patents in a given technological class.	*Class*
Number of Patenting Firms $_{Class}$	Number of firms that patent in a given technological class.	*Class*
Pledge-Related Patent	Pledge-related level-one or level-two patent (binary).	*Patent*
Pledge-Related Level-one Patent	Pledge-related level-one patent (binary).	*Patent*
Non-IBM Level-one Patent	1 if the level-one patent does not belong to IBM (binary).	*Patent*
Patent age	The difference between the application year and the given year.	*Patent*
Forward Citations	Number of forward citations received by the patent.	*Patent*
Backward Citations	Number of backward citations made by the patent.	*Patent*
Claims	Number of claims of the patent.	*Patent*
Independent Claims	Number of independent claims of the patent.	*Patent*
Non-patent References	Number of backward citations made by the patent to references that are not patent.	*Patent*

Note: This table describes the variables at class- and patent-levels used in our analysis.

Table 3: Descriptive statistics of the main variables at the class and patent levels.

VARIABLES	Mean	Std. Dev.	Min	Max
A.		**Class-level**		
Openness	80.560	267.172	0	2184
IBM Total Patents $_{Class}$	118.294	225.438	1	2020
IBM Selling $_{Class}$	24.043	72.601	0	2468
IBM Buying $_{Class}$	11.280	22.466	0	511
Total Patents $_{Class}$	19045.890	18759.940	35	96356
Number of Patenting Firms $_{Class}$	288.825	274.233	1	1639
VARIABLES	Mean	Std. Dev.	Min	Max
B.		**Patent-level**		
IBM Buying $_{Patent}$	0.0004	0.020	0	1
IBM Selling $_{Patent}$	0.0005	0.023	0	1
Forward Citations	22.980	45.442	1	1083
Backward Citations	35.423	53.281	1	500
Non-patent References	10.627	17.676	0	100
Claims	23.717	16.924	1	539
Independent Claims	3.737	2.744	0	136

Note: Panel A includes the descriptive statistics of the variables defined at the class level. The number of class-year observations is 19,045. Panel B includes the descriptive statistics of the variables defined at the patent level. These statistics consider both the level-one and level-two patents. *IBM Buying* $_{Patent}$ and *IBM Selling* $_{Patent}$ are binary variables. The number of patent-year observations is 308,307. All variables are defined in Table 2.

Table 4: Correlation matrix for the main variables at the class and patent levels.

	VARIABLES	1	2	3	4	5	6	7
	A.			**Class-level**				
1	Openness	1						
2	IBM Total Patents $_{Class}$	0.374	1					
3	IBM Selling $_{Class}$	0.025	0.101	1				
4	IBM Buying $_{Class}$	0.225	0.240	0.184	1			
5	Total Patents $_{Class}$	0.157	0.661	0.192	0.383	1		
6	Number of Patenting Firms $_{Class}$	0.118	0.354	0.153	0.395	0.843	1	
	VARIABLES	1	2	3	4	5	6	7
	B.			**Patent-level**				
1	IBM Buying $_{Patent}$	1						
2	IBM Selling $_{Patent}$	0.165	1					
3	Forward Citations	-0.005	-0.006	1				
4	Backward Citations	-0.006	-0.008	0.096	1			
5	Non-patent References	-0.005	-0.008	0.056	0.540	1		
6	Claims	0.003	0.000	0.149	0.102	0.120	1	
7	Independent Claims	-0.001	0.001	0.103	0.023	0.038	0.450	1

Note: Panel A includes the correlations between the variables defined at the class level. Panel B includes the correlations between the variables defined at the patent level. All variables are defined in Table 2.

Table 5: Comparisons between the pledge-related bought and sold patents by IBM.

VARIABLES	Mean		Std. Dev.		Min		Max	
	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy
Forward Citations	24.290	30.320	34.690	57.150	1	1	265	800
Backward Citations	16.880	47.290	18.070	62.030	1	1	234	323
Non-patent References	5.610	27.290	16.700	71.190	0	0	355	360
Independent Claims	3.620	3.790	2.340	2.490	0	1	22	20

Note: This table provides the preliminary statistics of the patents that IBM bought and sold during the sample period. All variables are defined in Table 2.

Table 6: IBM's total traded patents and total bought and sold patents in each technological class.

VARIABLES	(1) IBM Trading $_{Class}$	(2) IBM Selling $_{Class}$	(3) IBM Buying $_{Class}$
Openness	0.154	0.103***	0.018
	(0.257)	(0.010)	(0.011)
After 2005	-0.340*	0.280	-0.305
	(0.138)	(0.698)	(0.241)
After 2005 x Openness	0.037***	0.016**	0.004***
	(0.009)	(0.008)	(0.001)
Total Patents $_{Class}$ (×1000)	0.540	-0.096	0.006
	(1.150)	(0.087)	(0.031)
Number of Patenting Firms $_{Class}$	0.003*	-0.002	-0.002
	(0.001)	(0.008)	(0.002)
IBM Total Patents $_{Class}$	-0.015	0.007	0.015
	(0.014)	(0.010)	(0.009)
Year FE	Yes	Yes	Yes
Constant	-0.834***	-0.669	0.281
	(0.620)	(0.618)	(0.247)
Observations	1,969	1,969	1,969
Number of Tech. classes	177	177	177

Note: This table provides the estimates based on the class-level analyses under the specification of a random-effect linear estimator. Robust standard errors clustered at the technological class level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

Table 7: The effect of being related to the pledged patents on the probability of IBM selling or buying.

VARIABLES	(1) IBM Selling $_{Patent}$	(2) IBM Selling $_{Patent}$	(3) IBM Buying $_{Patent}$	(4) IBM Buying $_{Patent}$
Pledge-Related Patent		0.035***		0.005***
		(0.003)		(0.000)
After 2005		-0.086***		-0.004***
		(0.002)		(0.000)
Pledge-Related Patent x After 2005		0.008**		0.0001
		(0.004)		(0.001)
Forward Citations (×1000)	0.488***	0.268***	0.019***	0.009***
	(0.023)	(0.029)	(0.003)	(0.003)
Backward Citations (×1000)	0.029***	-0.075***	-0.007***	-0.007***
	(0.010)	(0.011)	(0.000)	(0.000)
Independent Claims (×1000)	1.950***	1.110***	0.004	-0.006
	(0 200)	(0., 193)	(0.046)	(0.047)
IBM Total Patents $_{Class}$ (×1000)	-0.001***	-0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Non-patent References (×1000)	-0. 361***	-0., 265***	0.007**	0.006**
	(0.019)	(0.018)	(0.003)	(0.003)
Constant	-0.006***	0.000	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes
Observations	181,794	181,794	263,215	263,215

Note: This table provides the estimates based on the patent-level analyses under the specification of a random-effect linear estimator. The sample in columns (3) and (4) consists of IBM patents only, hence, the difference in the number of observations. Robust standard errors clustered at the patent level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

Table 8: IBM citations to the patents created using the pledged patents (level-one patents).

VARIABLES	(1) Citations from IBM	(2) Citations from IBM	(3) Citations from IBM
Pledge-related Level-one Patent		0.060	-0.030
		(0.039)	(0.066)
Non-IBM Level-one Patent		-0.034	-0.147***
		(0.039)	(0.053)
After 2005		0.0261	0.281**
		(0.069)	(0.126)
Pledge-related Level-one Patent x Non-IBM Level-one Patent			0.194**
			(0.082)
Pledge-related Level-one Patent x After 2005			-1.088***
			(0.162)
Non-IBM Level-one Patent x After 2005			-0.039
			(0.148)
Pledge-related Level-one Patent x After 2005 x Non-IBM Level-one Patent			0.958***
			(0.203)
Patent Age	0.093***	0.092***	0.091***
	(0.007)	(0.008)	(0.008)
Forward Citations (×1000)	7.430***	7.430***	7.430***
	(0.746)	(0.746)	(0.747)
Backward Citations (×1000)	6.910***	6.890***	7.000***
	(0.276)	(0.277)	(0.277)
Independent Claims (×1000)	-2.720	-2.780	-3.120
	(5.940)	(5.940)	(5.940)
Non-patent References (×1000)	7.430***	7.430***	7.430***
	(0.746)	(0.746)	(0.747)
Year FE	Yes	Yes	Yes
Constant	1.948***	1.932***	1.984***
	(0.088)	(0.097)	(0.099)
Observations	48,051	48,051	48,051
Number of level-one patents	16,773	16,773	16,773

Note: This table provides the estimates based on the patent-level analyses under the specification of a random-effect linear estimator. Robust standard errors clustered at the patent level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

Table 9: The effect of IBM's patent pledge when considering the effect of OIN patents.

VARIABLES	(1) IBM Selling Class	(2) IBM Selling Class	(3) IBM Buying Class	(4) IBM Buying Class	(5) IBM Trading Class	(6) IBM Trading Class
Openness		0.009***		0.004		0.013**
		(0.003)		(0.003)		(0.006)
OIN Openness	-0.003	-0.005	-0.003	-0.003	-0.005	-0.007
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)
After 2005 x Openness		0.003**		0.003*		0.005**
		(0.001)		(0.001)		(0.002)
After 2005	-0.089	-0.181*	-0.052	-0.145	-0.142	-0.325*
	(0.080)	(0.096)	(0.067)	(0.100)	(0.138)	(0.179)
After 2005 x OIN Openness	0.001*	-0.0004	0.001	-0.007	0.003	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Total Patents $_{Class}$ (×1000)	-0.023	-0.021	0.030	0.032	-0.007***	-0.006***
	(0.035)	(0.035)	(0.023)	(0.024)	(0.001)	(0.001)
Number of Patenting Firms $_{Class}$	0.001	0.001	-0.001	-0.002	0.000	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
IBM Total Patents $_{Class}$	0.005	0.004	0.007	0.005	0.011	0.009
	(0.005)	(0.005)	(0.005)	(0.004)	(0.009)	(0.009)
Year FE	YES	YES	YES	YES	YES	YES
Constant	-0.0772	0.0425	-0.226	-0.106	-0.304	-0.0631
	(0.109)	(0.0967)	(0.190)	(0.132)	(0.293)	(0.215)
Observations	1,969	1,969	1,969	1,969	1,969	1,969
Number of Tech. classes	177	177	177	177	177	177

Note: This table provides the estimates based on the class-level analyses under the specification of a random-effect linear estimator. Robust standard errors clustered at the technological-class level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

Table 10: The development of the openness effect over time after the pledge.

VARIABLES	(1) IBM Selling $_{Class}$	(2) IBM Buying $_{Class}$
Openness	-0.001	-0.001
	(0.003)	(0.003)
Years 2006&2007 x Openness	0.002	-0.001
	(0.002)	(0.000)
Years 2008&2009 x Openness	0.006***	0.008**
	(0.002)	(0.003)
Year 2010 x Openness	-0.000	-0.000
	(0.000)	(0.000)
Total Patents $_{Class}$ (×1000)	-0.028	0.017
	(0.031)	(0.015)
Number of Patenting Firms $_{Class}$	0.001	-0.002
	(0.002)	(0.001)
IBM Total Patents $_{Class}$	0.002	0.004
	(0.004)	(0.003)
Year FE	Yes	Yes
Constant	0.109	0.0558
	(0.091)	(0.093)
Observations	1,969	1,969
Number of Tech. Classes	177	177

Note: This table provides the estimates based on the class-level analyses under the specification of a random-effect linear estimator. Robust standard errors clustered at the technological-class level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

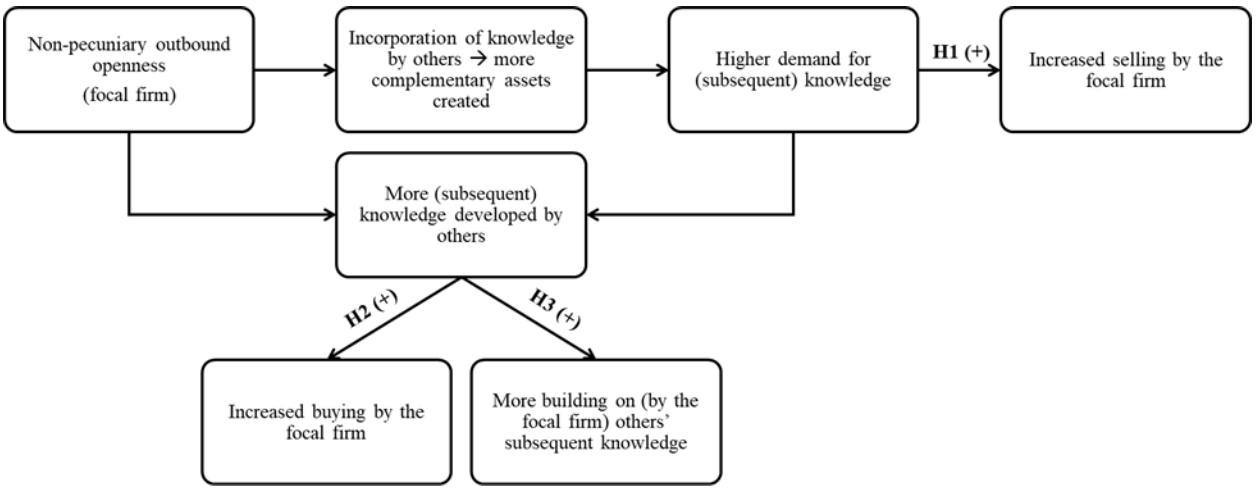
Table 11: IBM's total patents and total radical patents in each technological class.

VARIABLES	(1) IBM Total Patents $_{Class}$	(2) IBM Rad. Patents $_{Class}$
Openness	0.960***	0.018***
	(0.082)	(0.006)
After 2005	-12.450*	-1.618***
	(7.342)	(0.593)
After 2005 × Openness	0.096***	0.008**
	(0.037)	(0.003)
Total Patents $_{Class}$ (×1000)	-6.170***	0.102***
	(1.190)	(0.033)
Number of Patenting Firms $_{Class}$	0.426***	-0.005**
	(0.010)	(0.002)
IBM Total Patents $_{Class}$		0.064***
		(0.006)
Year FE	Yes	Yes
Constant	8.537	0.890*
	(8.456)	(0.475)
Observations	1,969	1,969
Number of Tech. Class	177	177

Note: This table provides the estimates based on the class-level analyses under the specification of a random-effect linear estimator. Robust standard errors clustered at the technological-class level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

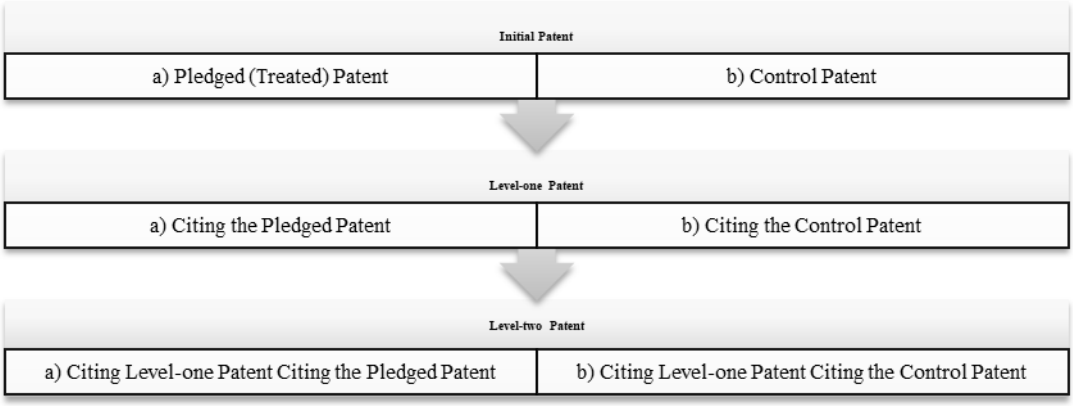
1.8 Chapter 1 Figures

Figure 1: Consequences of the focal firm's adoption of outbound openness.



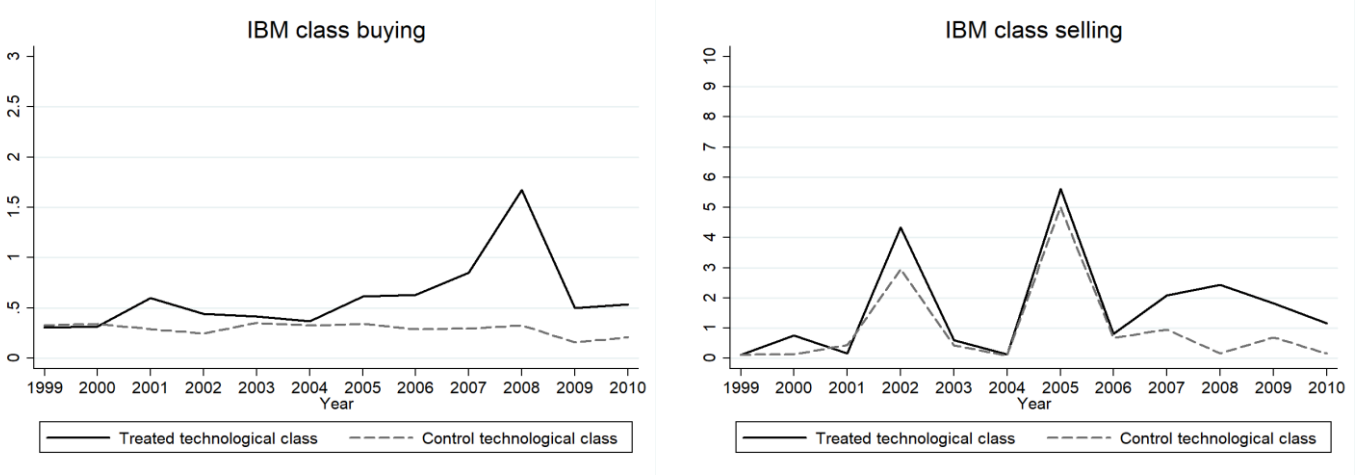
Note: This figure summarizes the three hypotheses developed in the paper.

Figure 2: Illustration for the levels of patents.



Note: This figure depicts the discussion on the use of the pledged 500 patents for the construction of treated and control groups for patent-level analyses. The matching procedure is performed at the initial step, where we match the pledged patents (i.e. treated) with a randomly selected group of non-pledged patents that comply with certain criteria (i.e. control), according to textual similarity scores between the pledged and non-pledged patents' abstracts, their application years and technological classes. In the next two steps, we create "Level-one" and "Level-two" patents, according to the citations received to the pledged (or pledge-related, i.e. the left side of the figure) and initial control (or initial-control-related; the right side of the figure) patents.

Figure 3: Average Number of Patents Bought/Sold by IBM from 1999 to 2010 for the Treated vs Control Technological Classes.



Note: A technological class is considered as treated (control), if it includes (does not include) a patent that was opened-up by IBM in 2005. In addition, the control group of technological classes is restricted to those, where IBM had patented in significantly before 2005. IBM class buying (selling) represents the average number of patents bought (sold) in all the treated/control technological classes.

Chapter 2
Opening Up Intellectual Property Strategy: Implications for Inventor Mobility

2.1 INTRODUCTION

The search for new ideas is an essential part of the innovation process. Besides investing in traditional internal sources of knowledge, firms also exploit external sources of knowledge in their search for new innovative opportunities. The channels to access external sources of knowledge include strategic alliances and acquisitions (e.g. Rosenkopf & Almeida, 2003; Mawdsley & Somaya, 2016). In addition, firms often recruit outside inventors to overcome geographical and technological boundaries in their search for new ideas (e.g. Song, Almeida, & Wu, 2003; Palomeras & Melero, 2010; Singh & Agrawal, 2011). In fact, labor mobility facilitates the transfer of knowledge and potentially enhances the ability of the firm to exploit the outside knowledge. However, from the point of view of the firm that loses its inventors, that loss of human and social capital can have reverse effects on the firm (Hausknecht & Trevor, 2011). For instance, competitors may "learn by hiring" from the firm and later use the acquired knowledge to compete with it. Therefore, to prevent the involuntary knowledge leakage via inventor mobility, firms have been employing various mechanisms, such as patents, secrecy, and litigation actions (Agrawal, Ganco, & Ziedonis, 2009; Ganco, Ziedonis, & Agrawal, 2015).

Surprisingly, with the growing prevalence of outbound open innovation in the recent years, more firms, including big players, like IBM, Google, Microsoft, Tesla, Red Hat, and others, have been voluntarily granting access to their (intellectual) assets to outsiders. This practice represents an example of the so-called “non-pecuniary” type of outbound open innovation, which *“...refers to how internal resources are revealed to the external*

environment... without immediate financial rewards" Dahlander & Gann (2010, p. 704). Seemingly contradicting the proposition of the resource-based view regarding the importance of ownership and control of resources for appropriation (Alexy et al., 2018), these actions go against the knowledge protection mechanisms employed by firms. Therefore, understanding their implications on labor mobility represents an intriguing research question. The question of what consequences these practices may bring to the labor mobility of the firm opening up its intellectual properties (IP) is not quite straightforward and the literature provides little theoretical and empirical understanding on the direction of the effect. In this paper, I study whether the practice of outbound openness makes the inventors of the firm more or less mobile. Specifically, I focus on the effect of the firm's openness level in a field of knowledge on the mobility of its inventors that have expertise in this field.

Arguments can be made both for a reduction and for an increase in inventor mobility, following the facilitation of knowledge out-flow via opening up firm's IP strategy. On the one hand, scholars argue that aggressiveness in IP rights' use and enforcement can reduce employee turnover (Kim & Marschke, 2005; Ganco et al., 2015). Then, by considering the practice of granting access to the firm's knowledge to outsiders as a "soft" strategy, the firm's inventors will become more, rather than less mobile. The reason is that with more openness, the perceived risks and costs of recruiting the firm's knowledge labor will be reduced, resulting in increased likelihood that more inventors will leave the firm. In addition, it has been shown that openness in the innovation process increases the involvement of the outsiders, due to a reduction in costs and risks in using or implementing the opening up firm's knowledge (Murray et al., 2016; Wen, Ceccagnoli, & Forman, 2016). Therefore, with more engagement in the knowledge fields, the demand for the experienced

labor in the liberated technologies will increase. On the other hand, allowing for inside-out flows of knowledge may make the firm's inventors less mobile. The underlying logic is the following. By voluntarily granting access to proprietary knowledge, the focal firm reduces the incentives for outsiders to recruit the firm's inventors. Thereby, the voluntary leakage of information can serve firms as a tool to reduce the drain of skilled labor embodying such information (Lewis & Dennis, 2001; Guarino & Tedeschi, 2006).

As the theoretical arguments from the prior literature provide conflicting conjectures, I decide to look closely at the factors driving the effect. In this paper, I draw on arguments linking the degree of complementarity or substitutability of the inventors' tacit knowledge with the codified opened-up knowledge. Specifically, I suggest that in the presence of complementarity (substitutability) between the inventors' knowledge and the opened-up knowledge, the mobility of inventors outside the firm is likely to increase (decrease). The main rationale I propose is that outsiders' demand for the inventor will increase (decrease), when the inventors' knowledge is perceived as necessary (replaceable) for exploiting the opened-up knowledge. I elaborate on the potential situations and scenarios where outsiders perceive the two types of knowledge, i.e. the inventor's tacit knowledge and the opened-up knowledge, as substitutable or complementary. As such, I discuss instances when outsiders a) practiced inventing around before the decision of the firm to open up (part of) its knowledge, b) seek to commercially implement the opened-up knowledge, or c) aim to internally develop follow-up innovations. Section III provides reasons for why the substitutability mechanism is more likely to dominate. First, outbound openness per se reduces the outsiders' need to invent around the liberated knowledge, which provides a substitute to hiring inventors from the opening up firm. And second, unlike the knowledge and the experience of the inventors that created the opened-up knowledge, those of the

inventors with general expertise in the field (the focus of the current study), are not deemed complementary to the codified liberated knowledge in the contexts of commercial implementation or building upon practices. The reason is that these inventors do not necessarily possess specific information on how to commercially exploit or advance the opened-up knowledge. Thus, I expect that inventors with general knowledge in the field will experience lower turnover rates after their employers' decision to open up their IP strategy. To gain further insights on the suggested direction of the effect, I investigate inventors' knowledge characteristics that may moderate the effect of outbound openness on inventors' mobility. Specifically, I hypothesize that a) when the inventors' knowledge is more basic, b) when the inventors work with lower number of co-inventors, and c) when the inventors' knowledge is in areas characterized with higher technological cumulativeness, the negative effect of outbound openness will be strengthened.

In order to address my hypotheses, I utilize the decision by International Business Machines Corporation (IBM) to (partially) open up its IP at a specific point in time to analyze whether and how this decision changed labor mobility patterns. IBM is as a very good case, since it used to be known for a strict adherence to the closed model of innovation (Mayle, 2006). However, IBM made a radical shift to the open innovation model (Chesbrough, 2003), by supporting open-source software (OSS) through many actions, as such pledging 500 patents in 2005. I use this patent pledge as a proxy for IBM's adoption of openness in its IP strategy in multiple areas of knowledge. By extracting information about IBM's inventors and their patents from the USPTO database, I detect inventor mobility and investigate the implications of IBM shift to open governance of their IP's on the leaving of their inventors. I use a special version of difference-in-differences, with a continuous treatment variable, in order to capture the variations in the levels of the

inventors' knowledge openness. The results suggest that opening up the corporate innovation strategy, on average, lessens the chances of outbound labor mobility.

This paper provides several contributions to the literature. First, by considering the complementarity and substitutability mechanisms between the codified knowledge and the inventor's (tacit) knowledge, this study presents a new angle of looking at the dynamism between the knowledge flow and the inventor mobility. The main finding of this study suggests that strategically practicing outbound openness can bring along benefits of retaining knowledge workers for the focal firm. In addition, my findings support the proposition that firms "learn by hiring" where the knowledge is a driver for recruiting external inventors. Finally, this study contributes broadly to the literature on open innovation. Since the seminal work of Chesbrough (2006a), firms have started to acknowledge the importance of the so-called "outside-in" (i.e. inbound) and "inside-out" (i.e. outbound) knowledge flows (Tranekjer & Knudsen, 2012). The academic literature, however, has mainly focused on the inbound type of open innovation. By disentangling the effect of outbound openness from inbound open innovation, I attempt to provide a deeper and better understanding of open innovation phenomenon (Schroll & Mild, 2011).

2.2 THEORETICAL FRAMEWORK

By the end of the 20th century, the closed model of innovation has become less and less popular in the innovation management field. This innovation model is based on the premise that in order to innovate and remain competitive, firms should create and develop their inventions internally. In his book, "Open Innovation: The new imperative for creating and profiting from technology", Chesbrough (2003) discusses factors and phenomena that contributed to the erosion of the closed innovation model. These factors include the

increasing labor mobility, the enhancing popularity of venture capital, the ease of knowledge dissemination between public and private institutions, and the increase in competition. These changes in the business environment have made it more difficult for organizations to exclusively and entirely rely on themselves in doing R&D, and, thus, have urged them to make the firm's R&D boundaries permeable, as the potential solution for their innovation practices, the open innovation model. In this model, profits and benefits from R&D investments are achieved by improving products and services in product markets, meanwhile the technology markets stay free and open, with the companies contributing to the growth of the pool of the common knowledge and even make profit from trading the firm's IP rights (West & Gallagher, 2006). Dahlander & Gann (2010), in their paper where they re-conceptualize the idea of open innovation, define two types of outbound open innovation, "pecuniary" and "non-pecuniary". The main difference is about the existence of direct financial benefits for the firm when revealing it knowledge. The focus of interest in the current paper is on the non-pecuniary outbound open innovation when the firm does not ask directly for any immediate financial returns for the liberated assets but that does not mean that the firm cannot seek indirect benefits.

2.1.1 Labor Mobility and Knowledge Flow

Labor mobility has recently received extensive attention in the literature and its impacts have been studied at different levels: individual, organizational, industry, societal, and global. For instance, employees' inter-organizational movements have been linked to knowledge transfer and organizational learning, organization's relational aspects, market entry, innovative capabilities and other sources of competitive advantages. Most of the research studying the relationship between labor mobility and knowledge transfer focuses

on a single direction of the effect; namely that labor mobility affects knowledge transfer (e.g. Hoisl, 2007; Hoisl 2009; Kim & Marschke, 2005; Agrawal et al., 2009; Ganco et al., 2015). The predominant findings suggest that labor mobility contributes to an increase in knowledge transfer and an improvement of the quality of the innovation process (Fosfuri & Ronde, 2004; Moen, 2005; Agrawal, Cockburn, & McHale, 2006). However, the effect of voluntary knowledge flow via outbound openness on outbound labor mobility is an underexplored side of the process. The direction of this effect is not clearly intuitive and arguments can be made to support both possible directions of the effect, i.e. firms adopting more openness could face higher rates of turnover, or else, they could be more able to keep their inventors from leaving. Next, I discuss the potential answers that the prior literature provides for the direction of the effect of outbound openness on the inventor mobility.

Tough enforcement of the IP and labor mobility. Scholarly work on the effect of IP enforcement on the inventor's exit decision established a negative effect. Mainly, the research in this area explores how actions, such as patenting and litigation actions, reduce the likelihood of skilled labors leaving the firm through building the reputation of toughness and increasing the perceived risk of poaching the firm's inventors and using its knowledge (Kim & Marschke, 2005; Agrawal et al., 2009; Ganco et al., 2015). Melero, Palomeras, & Wehrheim (2017) claim that "*patent protection turns the innovation-related skills of the R&D workers into patent-holder-specific human capital and therefore decreases inventor mobility*" (p., 2). Therefore, one can extrapolate that openness, as a "softer" IP strategy and via reducing the risk of recruiting the firm's inventors, will lead to an increase in employees' switching jobs to other firms.

Outbound openness and innovative activities in the market. Another argument supporting the previous prediction of outbound openness increasing the mobility of the

knowledge labor is related to the demand for talents in the labor market. Specifically, due to the reduction of transaction and negotiation costs and the reduction of the risk of infringement and litigation threats too, the market entries increase (Murray et al., 2016; Wen et al, 2016), which means that companies are getting more involved in the opened-up areas of knowledge. This increase in the innovative activities may result in a demand increase for the specialized labor in the liberated fields. Accordingly, the inventors of the firm opening up its IP strategy might be more attractive for the outsiders in the labor market as their knowledge and experience are more related and closer to the liberated knowledge.

Knowledge as a driver for labor mobility. One of the main arguments to infer that the adoption outbound open innovation decreases the rate of the employees leaving their employer is related to the learning by hiring stream of research. Following the resource-based view of the firm, recruiting inventors from outside the company has been recognized as a mean to grow beyond what internal R&D would allow the firm to do. Moving inventors tend to utilize the knowledge they learnt from their previous employer (Song et al., 2003). However, recruiting external employees is associated with transactions costs and risks, besides; there are alternative competing channels, such as, alliances, networks and geographic spillovers, and acquisitions, through which the firm can get access to other firms' knowledge (Mawdsley & Somaya, 2016). Therefore, in the case of outbound openness and opening up the firm's IP strategy, the firm facilitates the knowledge transfer for the outsiders via granting free and riskless access to part of their intellectual assets, which in turn makes the other firms less keen to recruit the focal firm's inventors. Lewis &

Yao (2001) [25] and Guarino & Tedeschi (2006) [26] suggest that firms, in fact, can use knowledge sharing/openness, as a response to losing key inventors.

In the next section, I attempt to explain how openness in the firm's IP strategy could potentially lead to these contradictory predictions. In the development of the hypotheses, I claim that the degree of complementarity and the substitutability between the inventor's (tacit) knowledge and the liberated (explicit) knowledge is the factor deciding the direction of the effect of opening up the firm's IP strategy on labor mobility.

2.2 HYPOTHESES DEVELOPMENT

This research addresses how liberation of knowledge affects mobility of the inventors, who have general (tacit) knowledge and experience in the liberated knowledge fields. I suggest that the effect of outbound openness on inventors' mobility depends on the extent to which the inventors' (tacit) knowledge is required and essential for exploiting and making use of the liberated explicit (codified) knowledge (e.g. in a patent). Accordingly, my main prediction in this paper relies on arguments related to the degree of complementarity or substitutability between the codified knowledge and the inventors' tacit knowledge and how it is altered by the outbound openness.

---

[25] Lewis & Yao (2001) show through their model that even if the company adopts a closed model for R&D with no knowledge disclosure, there is a chance for information leakage from the company to its rivals, especially through poaching of the inventors. The authors also argue that openness can be a possible way to decelerate inventors' poaching by other firms. They claim that there are opposing preferences for openness between the firms and skilled labor, and that firms prefer more closed approaches to earn their share of rents and to protect their knowledge capital. On the contrary, inventors generally prefer to share their inventions. However, due to contractual incompleteness, the authors show that it is efficient for the firms to settle for a certain degree of openness in their R&D environment and to accept a certain level of turnover, which they call "Efficient Open-Constrained Equilibria". In Lewis & Yao (2001) model, this is the 2nd best solution due to inability to attain the 1st best solution of maximum information flow.

[26] Guarino & Tedeschi (2006) claim "*knowledge transmission is a way to avoid labor poaching*". They argue that, in equilibrium, some firms may choose to share their knowledge with the outside parties, as a mechanism to attenuate the "stealing" of their specialized workers. The argument is based on the assumption that information leakage, spillovers, can happen voluntarily, – by opening firm borders, – or involuntarily, – by labor movement; – and these are not necessarily mutually exclusive. In other words, by opening up their knowledge, firms may avoid further losing their valued employees.

On the one hand, when the explicit knowledge opened up by the focal firm can be a good substitute to the tacit knowledge of the firm's inventors, the external firms are able to realize benefits from the liberated knowledge without the need to hire the inventor. The liberation of knowledge provides outsiders with the opportunity of accessing the knowledge freely, while avoiding the costs and risks of poaching external inventors, which would hardly be possible had the knowledge not been liberated. In this scenario, then, outbound openness would have a substitution effect on inventor mobility, meaning that the inventors would be less likely to be hired outside the focal firm. In other words, with reduced external value of the inventor's (substitutable) knowledge due to outbound openness, the inventor is expected to become less mobile, the higher the level of her knowledge's openness. On the other hand, if the inventor's (tacit) knowledge complements the liberated (codified) knowledge, outbound openness is expected to increase labor mobility. In this context, not only would external firms need to pay royalties for using the knowledge, had it not been opened up, but they would also need to poach the inventor to be able to generate returns. For these firms, therefore, the reduced transaction and negotiation costs and risks of litigation with freely available knowledge would mean a decline in the total costs of using the knowledge. Hence, the demand for the inventors with complementary (tacit) knowledge is likely to increase after outbound openness.

Further, I suggest that the demand for the inventor's (tacit) knowledge after outbound openness depends on the ultimate use of the codified knowledge by others. This will determine whether the inventor's tacit knowledge complement or substitute the opened up codified knowledge. One of the situations in which outsiders might need the tacit knowledge of the focal firm's inventors is when they are "*inventing around*" a protected intellectual asset or technology. Prior literature has long recognized that *inventing around*

rivals' protected inventions (i.e. patented) may bear substantial costs and risks (e.g. Nordhaus, 1969; Scherer, 1972; Levin et al., 1987, etc.). Despite these risks and costs, inventing around offers outsiders the possibility to create similar inventions, while sidestepping the focal firm's protection. Hiring inventors from the firm that created the original knowledge in the presence of such knowledge protection means could be considered a feasible way to decrease the costs of imitation and overcome the appropriation mechanisms employed by the firm. These inventors are typically equipped with skills and knowledge, acquired via training and experience with their employer. Arguably, then, their tacit knowledge is highly valuable for outside firms willing to *invent around* the protected inventions. As the inventor's tacit knowledge is viewed as a substitute to the protected codified knowledge, once the explicit knowledge is opened up, the need to hire the inventors will diminish due to the diminution of the need to invent around. In other words, when the focal firm practices outbound openness, outsiders no longer view inventors' tacit knowledge as very complementary or highly valuable for inventing around, since they simply no longer need to invent around. Following this logic, outbound open innovation would make the inventors less mobile.

The tacit knowledge of the inventor that created the knowledge has been viewed as complementary to the explicit knowledge, when firms aim at *commercially implementing* the specific invention (Hegde, 2014; Maurseth & Svensson, 2015). The reason is that this stage often requires more information on the invention, in terms of more explanations and demonstrations for learning and testing the inventions, than one can extract from the codified explicit knowledge (e.g. patents). Thus, the "creator" inventor, who simply knows more about the invention, is especially valuable for those who are willing to transform inventions into marketable products or services. From the outsiders' point of view, although

outbound openness diminishes the barriers preventing the use of the inventions themselves, it does not in fact remove the need for the "creator" inventor's knowledge when they seek for commercial implementation. This is due to the above-mentioned complementarities between the "creator" inventor's knowledge and the explicit knowledge. However, for an inventor in the focus of this study whose (tacit) knowledge is general in the field and is not directly related to the specific liberated invention that the outside firms seek to commercialize, the demand for her tacit knowledge would not be as high. Hence, I expect that outbound openness will not increase the mobility of these inventors in these scenarios.

One could argue that outsiders might be interested in the focal firm's explicit knowledge for *building upon/advancing* purposes, rather than *commercializing* or *inventing around* motives. In those cases, the same logic as in the case of commercial implementation can apply. The inventors who created the knowledge are specifically complementary to the codified knowledge in the case of advancing the knowledge. However, the focal firm's other inventors who have expertise in the same areas of the codified knowledge are not specifically irreplaceable for outsiders. Moreover, the importance and dependence on the creating inventors' general tacit knowledge is relatively lower than in case if the outsiders are interested in commercial implementation or else, inventing-around. This is mainly because these firms have their own stock of (tacit) knowledge that they can combine with the codified knowledge and they may have their own trajectories and plans for the future development of the acquired knowledge. The latter, however, need not necessarily conform and fit the skills and the training of the focal firm's inventors.

Altogether, once the knowledge is opened up, from the outsiders' point of view, there is even less need of bearing the risks and costs of recruiting the focal firm's inventors, considering the direct open access to the firm's codified knowledge. Hence, it seems logical

to expect that the substitution effect of outbound opening up dominates the complementarity effect for the group of inventors with expertise in the fields of the liberated knowledge (e.g., not the authors of the liberated inventions in particular). Consequently, openness in the IP strategy will make these inventors less mobile. Hence, I state the main hypothesis of this study as following:

Hypothesis (1): The higher the openness degree of the company's IP strategy in a field is, the less likely the firm's inventors specialized in this field are to leave.

2.2.1 Interactions of Knowledge Openness with Other Knowledge Characteristics

In order to provide more insights about the effect of openness on labor mobility, I examine, more deeply, specific situations by considering moderators that might accentuate the complementarity or the substitutability mechanism of the effect of outbound openness. For the labor mobility, the difference between the value of the inventor for her employer and for the other potential employers plays a big role in the exit decision (Palomeras & Melero, 2010). The contextual variables that play a role in the labor mobility process are multilevel including individual inventor, firm (previous and current employer), and environmental and industry levels (Mawdsley & Somaya, 2016). Therefore, I explore specific situations that may affect the intensity of the substitutability and/or the complementarity mechanisms for further understanding of the relationship between outbound openness and labor mobility. For this purpose, I investigate the following moderators: the basicness of the inventor's knowledge, the average number of co-inventors, and knowledge cumulativeness.

Knowledge basicness. Basicness of the inventor's knowledge, which generally captures its closeness to science, can be viewed as opposite to how close the inventor's knowledge is

to "applied knowledge". Being usually at its early stages of development and reflecting on the generality of the knowledge (Jaffe, Trajtenberg & Henderson, 1993; Zucker, Darby & Armstrong 2002), the basic knowledge can provide third parties with more flexibility of combining it with their own stock of knowledge. While the field of knowledge and the type of the industry can affect the importance of basic versus applied knowledge, general predictions can also be made regarding the substitutability or complementarity between the inventor's knowledge type and the codified knowledge.

The next arguments suggest that in the presence of outbound openness there is a higher degree of substitutability between the inventor's basic knowledge and the codified knowledge. Inventors with basic knowledge are more capable of helping the outside firms to invent around a protected knowledge, as the generality and the wider breadth of their knowledge enable them to create an alternative version of the protected knowledge without infringement. Then, when the need to invent around is reduced with more openness introduced in the field of knowledge, the drop in the value of the inventor's external value, especially relative to the internal value, will be higher with more basicness of her knowledge. Since inventing around, as explained earlier, favors the substitutability mechanism, I expect that the degree of substitutability for the firm's inventors with basic knowledge will be higher, once the firm decides to adopt openness in its IP strategy, in comparison to the inventors with applied knowledge.

Subsequently, I argue that the complementarity with the codified knowledge is higher for inventors with more applied knowledge. These inventors are significantly more essential for knowledge exploitation and commercialization. Since her (tacit) knowledge is closer to the market aspect of the innovation process, she has specific knowledge about how to transform the knowledge of the invention into a marketable innovation. In contrast,

inventors with more basic knowledge have lower potential input for sooner commercialization. Overall, therefore, after the decision of the firm to open up its explicit knowledge, inventors with more applied knowledge will be more likely to leave their firm due to the complementarities between their and the opened-up knowledge.

Thus, I claim that the basicness of the inventor's knowledge exaggerates the negative effect of her knowledge openness on the chances of leaving the firm and I state the negative moderation effect of knowledge basicness in the following hypothesis:

Hypothesis (2): The higher the inventor's knowledge basicness is, the stronger (more negative) the effect of outbound openness on the inventor's outbound mobility is.

Co-inventors. Knowledge complementarity can be achieved through labor division among inventors, where dependencies are created on each other's knowledge in the process of replicating and producing new knowledge. Ways of capturing labor division include measuring the extent of using teams of inventors, which represents an informal appropriability mechanism, and the size of the teams producing the firm's inventions (Ahuja, 2007). As the inventive knowledge of an individual depends on other scientists' knowledge, exploiting her knowledge outside her original firm becomes difficult (Ahuja, Lampert, & Novelli, 2013). Consequently, the decision to leave the firm for inventors working in teams becomes less probable.

Next, I argue that the knowledge of the inventors that work in smaller teams is more likely to be substituted by the liberated codified knowledge than that of the inventors working in larger teams. In smaller teams, i.e. with a lower number of co-inventors, inventors generally cover a bigger part of the invention process, which reflects on the broadness of their knowledge. Being knowledgeable of multiple perspectives of the innovation process, these inventors can be valuable for inventing around purposes for

outsiders. As a case in point, consider the case of a solo inventor, i.e. the inventor that works alone. As the only creator of the invention, this inventor possesses specific information about the whole procedure of developing the invention, from its idea formation to the implementation, as well as alternative ways of creating the invention. Therefore, for outsiders, hiring this specific inventor, rather than an inventor that is only responsible for a specific part of the invention, i.e. the case of an inventor working in larger teams, may be especially desirable, if they intend to invent around the protected knowledge. It follows, then, that when the codified knowledge becomes available, the substitutability with the inventor's knowledge will increase for the solo inventor. Keeping this logic in mind, hence, the degree of substitutability between the liberated codified knowledge and an inventor with a lower number of co-inventors should, on average, be higher, than for an inventor with a higher number of co-inventors.

In addition, considering the situation, where outsiders intend to hire the focal firm's inventors for commercial implementation purposes, complementarities can exist between the liberated codified knowledge and the knowledge of the inventors working in both smaller and larger teams. On the one hand, inventors with a lower number of co-inventors can be essential for commercially exploiting the knowledge, due to their relatively wider coverage of the codified knowledge. On the other hand, inventors with a higher number of co-inventors can be valuable due to their networks developed while working in larger teams, as well as their experience in arguably more complex fields of knowledge. Indeed, firms tend to allocate more resources, including more inventors, when tasks are more complex. These two perspectives lead to the prediction that both "types" of inventors may be complementary to the codified knowledge, once it is opened up. However, in the broader picture, I argue that the reduction of the relative value of the inventors with a lower number

of co-inventors is greater. While the substitutability mechanism explained above seems to prevail for inventors working in smaller teams, the mechanism of complementarity does not appear to be obviously stronger for inventors working in smaller versus larger teams. Overall, then, I expect that the effect of outbound openness on outbound inventor mobility would, on average, be more articulated for the inventors with a higher the number of co-inventors. Hence, I hypothesize a positive moderation effect of the average number of co-inventors:

Hypothesis (3): The higher the number of average co-inventors whom the inventor worked with is, the weaker (less negative) the effect of outbound openness on inventor's outbound mobility is.

Knowledge cumulativeness. Knowledge cumulativeness is defined as the extent to which an innovation relies on the previous knowledge of its own technological area (Green & Scotchmer, 1995; Scotchmer, 2004). It captures, at least partially, knowledge complexity and system embeddedness (Weigelt, 2009). Unlike areas with low technological cumulativeness, those with high cumulativeness are characterized by higher values of prior art. Here, previous innovations implemented internally remain significant with knowledge advancements in the field, as by definition, the new knowledge needs to gradually develop on the existing knowledge (Lee, Park, & Bae, 2017). This feature, in turn, is associated with higher costs of inventing around and more possibilities of infringing on prior art (Scotchmer, 1991; Grindley & Teece, 1997). Analogously, less cumulative fields of knowledge represent fewer dependencies on prior art, hence, there are lower chances of infringement and less difficulties in inventing around.

In this section, I argue that inventors with knowledge in highly cumulative areas are more likely to be substituted by the opened-up codified knowledge, than those, whose

knowledge is essentially in areas characterized by a low level of cumulativeness. Inventors with highly cumulative knowledge are usually more acquainted and familiar with the prior state of art, which makes them more equipped for helping outsiders to invent around a protected knowledge. Due to the broadness of their knowledge, these inventors, unlike inventors with knowledge in less cumulative fields, can help reduce the risk of infringing on the previous inventions in the field, whilst creating and developing new alternative knowledge. It follows, then, that while in the absence of outbound openness, outsiders may view them as essential for inventing around purposes, if the firm decides to open up (part of) its knowledge, the need for inventing around and therefore, for these inventors' knowledge, will arguably be reduced. This is not necessarily the case for inventors with knowledge in less cumulative fields, due to their lower importance for inventing around practices. As a result, outsiders would view inventors with highly cumulative knowledge as more substitutable by the liberated codified knowledge, suggesting a stronger mechanism of substitutability for those inventors.

Further, I argue that when outsiders are considering hiring external inventors for commercialization purposes, there is a higher complementarity between the codified knowledge and the inventors, whose knowledge is essentially in areas characterized by lower cumulativeness. The commercialization process does not in principle require extensive knowledge on the prior art, rather, it generally demands knowledge on relatively more recent advancements and their practical applications. With prior inventions becoming less significant at a faster rate over time in areas with lower cumulativeness (Lee, Park, & Bae, 2017), inventors with knowledge in these fields are more likely to be focused on the later inventions in their field of expertise. Thus, for commercially exploiting and implementing the inventions, the knowledge of these inventors would likely be more

relevant, than that of the inventors who have worked in areas with higher cumulativeness. This implies a higher (lower) degree of complementarity between the codified knowledge and the inventors with knowledge in low (highly) cumulative fields. Consequently, the effect of openness in the firm's IP strategy would be stronger for the inventors with knowledge in low cumulative areas. Hence, I hypothesize a negative moderation effect of knowledge cumulativeness in the following way:

Hypothesis (4): The higher the cumulativeness of the inventor's knowledge is, the stronger (more negative) the effect of outbound openness on inventor's outbound mobility is.

2.3 RESEARCH SETTING

The majority of studies on outbound openness has focused on the outcome of collaborations and/or licensing transactions where the knowledge transfer flows in both inward and outward the firm simultaneously (Collaboration case) or the firm has full control on who can benefit from its knowledge and it is not free. Therefore, the current study focuses on a purer form of outbound openness, which can enhance our understanding of open innovation via disentangling the effect of outbound from the inbound open innovation. To address the research question proposed in this paper, I use IBM's 2005 patent pledge as a proxy of its strategic shift toward a significantly higher level of outbound openness in its IP strategy. Through this pledge, where IBM granted an open access to the community of open source software, I track the mobility of IBM's R&D workers during the period from 1999 to 2010, in the middle of which the 2005 patent pledge took place.

There are several reasons why the case of IBM provides a good setting to study the effect of openness on labor mobility. IBM is one of the biggest research-based companies

in the world and until now, IBM continues to be committed to open governance and in general, to the open-source community. A number of events in IBM's history have eased the shift of the company's strategy toward more openness. In fact, IBM used to be known for its strict adherence to a closed model of innovation (Mayle, 2006). However, the company made a radical shift to the open innovation model (Chesbrough, 2003) by supporting open-source software (OSS), initiating programs and communities, such as Apache and Eclipse. As a response to the market share losses to UNIX and Microsoft Windows NT operating system (Chesbrough, 2006b), IBM started to license its relatively underused technologies, and that served the company as a significant source of revenues over many years. However, the patent pledge of 2005, when IBM pledged free access to 500 software patents for the open source community, was IBM's most remarkable step toward openness. This event was dramatically different from any other major projects, due to the fact that the pledged patents were made public explicitly taking into account their considerable economic importance, as well as their coverage of multiple technological classes. According to Linux Magazine, the 500 patents "cost $10,000,000 to obtain (just in the U.S.) and are worth an unknown amount in licensing revenue"[27]. Besides, pledging the patents meant that no formal agreement was required for anybody to use them. IBM's patent pledge announcement (2005) claimed that its patent pledge was by far the biggest contribution to the OSS, in terms of the number of the patents. The announcement (2005) also stated that "Fostering Innovation, Interoperability and Open Standards" were the goal of the pledge.

[27] http://www.linux-mag.com/id/1975/

2.3.1 Endogeneity Issues

There have been many speculations about IBM pledge regarding its timing, the areas it covers, its size, and the real intentions behind it. For the timing, this pledge came after Santa Cruz Operation (SCO) group sued IBM in 2003 for infringing its UNIX code (Goettsch, 2003) and, consequently, IBM responded with a counterclaim against SCO group and initiating a legal defense fund for Linux in 2004. In 2005, they pledged their 500 patents to provide more security and guaranties to the OSS community. Despite the pledge goals stated in IBM announcement, "Fostering Innovation, Interoperability and Open Standards", other motivations were suspected to play a role in this decision. Another potential driver for the patent pledge was the competition between Microsoft operating system, Windows, and Linux operating system, which IBM uses and installs on its hardware products. Therefore, IBM supporting OSS can also be interpreted as an indirect way to compete with Microsoft and its proprietary operating system. Another incentive for IBM adoption of outbound openness is related to the demand of the complementary assets. This big donation to the OSS community is an investment from IBM to increase the demand for its complementary assets and to boost the sales of its hardware products (Alexy & Reitzig, 2013). One more surmise about IBM's patent pledge is linked to the debate in Europe about software patents, in which IBM was supporting software patents. Specialists suggested that the 2005 pledge was a signal from IBM to justify to European legislators that software patents are not an obstacle for innovation neither for the OSS community. Overall, though it is undebatable that opening up the firm's IP strategy was an internally motivated decision, none of these actual or potential motives refer to mobility, which could otherwise pose a concern for the design of this study. Thus, researcher's turnover does not

seem to be among the proposed triggers of the decision. Furthermore, it is safe to assume that IBM's patent pledge was fairly exogenous for the other firms in the labor market who are on the other side of employees' job switching.

One concern regarding the endogeneity of this research question is that the firm can decide to open up parts of its IP rights selectively in areas where the firm has a significantly high or low market power, which can affect also the probability of its inventors' movement. In order to account for the issue of this omitted factor, I account for the firm's power in each field of knowledge. Another internal factor that might affect the analysis is the simultaneous strategic actions the firm takes when deciding to open up its IP strategy. For instance, the firm can decide to offer the inventors with expertise in the fields of the liberated knowledge more incentives to stay with the firm, such as higher salary. However, if markets are competitive enough compensation offers should reflect the marginal value of the inventor for each company, and therefore mobility decisions should be mainly driven by the relative difference between the internal and external value of the inventor. This type of information about the internal incentives is difficult to obtain and control for. Yet, I include a variable reflecting on how much of the firm's resources are devoted to each fields of knowledge in order to capture, at least partially, the change of the firm's priorities among its fields. For the previous concerns, I cannot claim causality in my study regardless of the potential association.

One interesting event, related to this study topic, is the crisis that the company faced in the early 90's. IBM, close to becoming bankrupt, decided to hire a new CEO, Louis V. Gernstner Jr., from outside the company for the first time in eight decades. The urgent restructuring and cost cutting in the first few years of her tenure were associated with massive layoffs of employees (see Figure (1)), and write-off of corporate assets. By the end

of the 90's, the company reached the sought stability and recovered its leadership in the industry. This sequence of events is especially important for the current study, as technically speaking, it allows to check for the effect of the openness of R&D on inventors' mobility, without much of noise from restructuring programs done by the company. In other words, the fact that IBM finished its short-term massive restructuring earlier than the treatment (the pledge of 500 patents for the sake of supporting the open source community) took place, makes my analysis of the effect of openness on outbound mobility less contaminated by the company's economic contingencies. Hence, this study uses the patent pledge as a proxy for IBM's dramatic change in its IP strategy towards supporting and adopting open innovation approach.

Insert Figure 1 about here.

2.4 DATA, VARIABLES, AND METHODS

2.4.1 Data

Due to the lack of direct measures, it is not easy to detect the events of labor movements between firms. Many researchers have used patent data to detect mobility (Almeida & Kogut, 1999; Song et al., 2003; Corredoira & Rosenkopf, 2010; Palomeras & Melero, 2010). Alternative sources for measuring mobility that have been used in the prior works include surveys and public data from LinkedIn website. In the present paper, I use the United States Patent and Trademark Office (USPTO) database from PatentsView (www.patentsview.org) to collect the patent applications and citation data for IBM, as it is incorporated and headquartered in the U.S. This data is disambiguated for patents, inventors as well as companies (assignees). The time period ranges between 1975 and

2010. I analyze the dependent variable, mobility, for the period from 1999 to 2010 and I build the rest of the variables using the whole sample period. In my analyses, the observations represent an inventor of IBM filing a patent, which means that my unit of observation is an inventor-application year.

Existing literature has recognized some shortcomings for using patent data to measure mobility. One of these shortcomings is the potential truncation of inventor's patenting behavior (Palomeras & Melero, 2010). Truncation of inventor's patenting behavior means the inventor is not recognized as a mover unless she files a patent with the new employer. Using patent data, the year of the inventor's mobility cannot be accurately specified, since no information is available for whether he/she files a patent in the first or the coming years in her new job. In other words, the use of patent data can affect the accuracy of determining the exact point in time when moves take place (Ge, Huang & Png 2016; Melero, Palomeras, & Wehrheim, 2017). However, the fact that the inventor moved is the interest in my study more than the exact year of mobility. Another downside of using patent data to observe mobility is that the leaving inventors, who stop patenting after moving, are not observed in the sample. For instance, the entrepreneurs, who start their own companies, are unlikely to file patents, and therefore, will not be captured as leavers in this sample. After applying the restrictions and processing the data, eventually, the final sample consists of 453,575 inventor-filing year observations for the period 1999-2010. It includes 116,557 inventors from IBM and its wholly owned subsidiaries. For the cases, when an inventor has more than one patent filed on the same year, I aggregate all patents of the same inventors in the same year in one observation since the effect of the inventor's knowledge openness after 2005 is the focus of interest.

2.4.2 Variables

Dependent variable

Outbound labor mobility. In the current study, I detect mobility by following the patenting history of the inventors and the assignees, with which these inventors have patent applications. I manually collected the assignees of IBM and those of its subsidiaries to determine the inventors working for IBM. Technically speaking, the inventor is considered as leaving, once she starts patenting with another company for a long period of time, 2-3 years, without appearing to patent with IBM anymore. To assure higher accuracy, I consider inventors that appear more than once in the patent records. Besides, I identify as "false" mobility the cases of cooperation patents, where the patents are recorded under multiple assignees, including IBM as assignee together with another firm, and I do not consider them as moving out events.

Independent variables

Degree of openness of inventors' knowledge.

To the best of my knowledge, there is no study measuring the openness of knowledge at the inventor-level. In order to create this measure, I rely on the openness indicator of the technological classes that the inventor's innovations belong to. I use two different class-level measure of openness.

1. *Openness (Unweighted)*: First, I identify the technological classes of the 500 patents pledged in 2005. I refer to these technological classes as the liberated or open classes. Then, for each patent, I create a dummy variable, indicating whether the patent belongs to one of the open classes. For each inventor, I compute the percentage of his/her

patents that belong to the open technological classes at each point in time when the inventor files a patent.

2. *Openness (Weighted):* I construct the openness score at the technological class level, similar to Wen et al. (2016) method. I follow a similar measure using independent-claims-weighted patents count related to each technological class as a better proxy for capturing patent value, scope and breadth (Cohen & Lemely, 2001; Allison et al., 2004; Marco, Sarnoff & deGrazia 2016). This way helps representing the level of openness of IBM in each field more accurately. In details, I count the total number of independent claims of all the patents in each technological class included in 2005 patent pledge. It is important to notice that the technological classes that are not present in the pledged patents score a zero in the openness measure. For each patent in an inventor's portfolio, I identify its technological class and filing year, and assign to the patent an "openness score" accordingly. Afterwards, for each inventor, I calculate the average of her knowledge openness at each year of patent filing. Finally, for the simplicity of analysis and the interpretation of the coefficients, I use a standardized version of the variable.

Moderating variables

Knowledge basicness. The basicness of a patent and its closeness to science have been linked to the number of citations made to scientific references, i.e. papers (Agrawal & Henderson, 2002; Ahmadpoor & Jones, 2017). Therefore, I measure the basicness at the patent level by counting the number of non-patent references in its backward citations. Next, I calculate the basicness for each inventor at each year of filing a patent as the average of the number of backward scientific references in of her patents.

Co-inventors. I use the number of co-inventors in each patent of the focal inventor listed in as measure of inventor's knowledge complementarity (Palomeras & Melero,

2010). Next, I take the average of the number of co-inventors for the inventor's patents up to each year of the latest patent application. This variable captures the difference between the inventors over time in terms of the number of co-inventors. This partially captures how much of a team player the inventor is.

Cumulativeness. Cumulativeness of innovation refers to the extent to which the current innovations in a specific class are dependent on the previous knowledge of their own class (Caballero & Jaffe, 1993). Studies claim that cumulativeness of knowledge is a factor that may affect mobility (Clarkson, 2005). Usually, the patent "i" categorized in a specific class "j" in a certain year "t" backwardly cites other patents as references. These cited patents can belong to the same class as the focal patent, "n_{ijt}", or to other technological classes. The patents cited in the same class represent a proportion of all the previous patents in that specific class, "N_{ijt}". For each patent, I calculate the proportion of "n_{ijt}/N_{ijt}", after which I standardize it by the application year. Clarkson, 2005, has a slightly different approach, which is used in Wen et al. (2016), too, mainly correcting for the fact that older patents tend to have higher cumulativeness, which might be for the reason that N_{ijt} is smaller. In the current paper, the correction mechanism is simply done by standardizing with respect to the application year. After establishing an annual measure of cumulativeness for each class, I assign a number to each patent, according to its technological class and the application year. Afterwards, for each inventor, I take the mean of her cumulativeness of knowledge at each point in time of her filing a patent.

Control variables

Involvement. IBM class involvement encapsulates the relative importance of the technological class for IBM itself. This factor may affect the labor mobility, as suggested by Song et al. (2003) and Palomeras & Melero (2010) who refer to it as "core" knowledge.

As a matter of operationalization, I create this variable by simply calculating the percentage of IBM's yearly patent applications in a specific technological class from the total number of IBM's patent applications. This step results in an annual indicator at the technological class level. Subsequently, I transform it into the inventor's level via assigning a value for each patent according to its application year and its technological class and calculating the average for each inventor over time.

Dominance. Inventor's IBM Class Dominance measures the importance of IBM in each related technological class. Following a similar approach as in Shane, 2001, and Palomeras & Melero, 2010, I create this variable by calculating the percentage of IBM's yearly patent applications per technological class from the total number of patent applications in that technological class. This index represents the firm's class dominance at the technological class level. Subsequently, for each patent, I assign the firm's dominance measure according to its technological class and the year of application. Then for each inventor, I calculate the average of the inventor's IBM class dominance at every year in the sample.

Experience. Most of the research in the labor mobility area includes individual's experience as a relevant factor. Studies on labor mobility are no exception. The variable *Inventor's Experience* is measured as the difference between the first time of ever filing a patent that was eventually granted, and the time of the current patent application. To account for non-linear effects, I also introduce the squared term of this variable into the analyses.

Number of patents. This variable is the summation of all the patents registered under the inventor's name up to any specific moment in time. Number of patents is generally related to the characteristics of the inventor's knowledge. Many studies use it as a measure of quality and productivity of the inventors.

Geographical location and time. The literature on labor mobility has established a strong link between labor mobility and geographical location (Almeida & Kogut, 1999). As IBM has facilities in many different locations across the U.S., I introduce location dummies, by states. To control for other time changes, not accounted for in this study, I introduce dummies for the application years into the model. These factors that are time related can be internal or external, as such are factors related to the industry, the legislation process, or any macroeconomic factors.

2.4.3 Methods

The main goal of the current study is to check whether the increase in the openness level of the inventor's knowledge is associated with an increase or a decrease in the likelihood of the outbound mobility of the company's inventors. Following the approach from Palomeras & Melero (2010) the dataset produced is an unbalanced panel, where each inventor "j" has T_j events of patenting, when she is at the risk of moving out. Consequently, the hazard function can be written as:

$$\delta\ (t+1, Z) = \delta\ (t, Z_t\ (t) \mid u, \mu),$$

where δ is the generic expression for the hazard rate of moving between t and $(t+1)$. The functional form chosen for the baseline hazard function is logarithmic. The term Z_t is the vector of time variant explanatory variables observed at time "t". The term μ is the vector of parameters to be estimated, and u is a random variable that adds unobserved heterogeneity to the model and is distributed independently of Z and t. The term u captures the impact of omitted variables, particularly the inventor's personal characteristics (i.e., ability, education, age, gender, marital status, number of children, etc.). To model the hazard rate in discrete time with time-dependent covariates, I use a binary response model

(Yamaguchi 1991). In my models, I use a linear probability model (LPM) with inventor fixed effects, in order to control for the individual unobserved time-invariant characteristics, caused by individual-specific omitted variables. The linear relationship between the probability of the inventor "*j*" moves (Y_{jt}) and the *Openness* of her knowledge is described by the following equation:

$$Y_{jt} = \alpha + \beta_1\, Openness_{jt} + \beta_2\, Moderators_{jt} + \beta_3\, Openness_{jt} \times After\ 2005_j + \beta_4\, Moderators_{jt} \times After\ 2005_j + \beta_5\, Moderators_{jt} \times Openness_{jt} \times After\ 2005_j + \rho\, Controls_{jt} + u_j + \varepsilon_{jt}$$

,

The coefficient of interest for the main hypothesis is "β_3" as it captures the extra effect resulting from the firm's decision to open up its IP strategy. "β_1" refers to "hypothetical openness" for observations before 2005. Therefore, my model is a specific version of difference-in-differences model with a continuous treatment variable, "*Openness*". For the moderation hypotheses, "β_4" is the coefficient to look at to infer about the corresponding moderator in each analysis.

Generally, the linear probability models, unlike the nonlinear model, such as logit and probit models, have the advantage of simplicity of the interpretation of the coefficients. More importantly, the interaction terms are less complicated to understand and explain in terms of their significance and magnitude. One of the concerns regarding the use of a panel data is the issue of heteroscedasticity, for which I use robust standard error estimates.

2.5 RESULTS AND ANALYSIS

2.5.1 Descriptive Statistics

Before testing my hypotheses, I compare the pledged patents with different sets of similar patents from the market and the focal firm, IBM. In their study on the effect of IBM

2005 patent pledge on new product introductions, Wen et al. (2016) compare the patents in IBM's pledge to a randomly selected group of similar patents in the market and conclude that the pledged patents have, in general, similar backward and forward citations, and that the pledged patents have lower number of claims. Similarly, they compare the pledged patents to other IBM patents, and find that the pledged patents have similar forward citations, but lower backward citations (indicating lower derivativeness) and lower claims (indicating less resistance to invalidation). In the current study, I perform other comparisons, whereas I find that the pledged patents seem to have higher forward citations until 2005 in contrast to IBM's patent portfolio. The results are consistent both when using the normalized citations by the year of application and technological class, and when using the total number of citations. This comparison indicates that the pledged patents were of importance and quality, even before 2005, the year of the pledge. Thus, IBM's pledging valuable and significant patents for the OSS community can be interpreted as a sign of its strong commitment to the community.

The classes, in which IBM chose to pledge patents, represent in total around 35% of IBM total patents with different percentages ranging from 0.06% to 3.42% per class. Wen et al. (2016) provide a comparison of the distribution of the pledged patents over the technological classes and the distribution of the total IBM's patents portfolio over the same classes and they tend to be very similar, which suggests that IBM's support to the OSS community is consistent with its IP right portfolio. In terms of the number of inventors, the pledged patents have on average 2.71 (SD = 1.5) inventors, while IBM's other patents in the same technological classes before 2005 have 2.32 (SD = 1.8) inventors. By conventional criteria, this difference is considered statistically not significant. The pledged patents are collaborative, similar to IBM's other comparable software patents, and the

inventors of these patents started patenting with IBM at different rates at different points in time between 1988 and 2000. In IBM, 1086 inventors worked on the 500 patents in the pledge, with the majority of them contributing with one patent and the biggest contributing inventor appears on nine patents in the pledge.

The sample consists of 1,178,491 of patent-year observations for 116,557 inventors who have worked for IBM at some point in their career. In Table (1), I provide some descriptive statistics on the variables used for the analysis at the inventor level for the pooled sample. As for the correlations among the independent variables, most of them seem to be normal and harmlessly low (see Table (2)). However, the Dominance variable seems to be correlated with the openness measures which points at the possibility that IBM decided to open areas where they have a high power and a strong position. Therefore, I control for this confounding variable.

Insert Tables 1 and 2 about here.

2.5.2 Main Results

Using linear probability regressions, I tested the main hypotheses regarding the conditions under which the inventor's knowledge openness is more likely to facilitate or hamper their mobility. In this study, I proposed two measures for the knowledge openness at the inventor-level; therefore, I performed the same set of analyses with both measures, separately, in order to confirm the results.

Results with the unweighted measure of openness. Table 3 depicts a set of specifications designed to scrutinize the main effect of outbound openness on mobility and the moderating factors through five models that represent different settings and variables included. I first estimated a baseline model including the moderating and the control

variables only (Model 1). Each subsequent model represents an essential modification over the baseline model. Model 2 includes the addition of the variable of interest, *Openness*, and its interaction with the *After 2005* dummy variable. This model indicates that, in the case of IBM and its shift to openness, the average effect of inventor's knowledge openness on her exit probability is significantly negative (significance level of 1%). As explained before, this observation is drawn from the coefficient of the interaction term between *Openness* and *After 2005* dummy, which captures the extra effect of having patenting expertise in the liberated fields after the openness adoption time, 2005. In more details, the coefficient of the variable *Openness* reflects on the effect of increasing the proportion of the inventor's experience in the liberated technological classes before 2005 and it seems to be insignificant. However, after the announcement of the pledge, inventors specialized in the areas of the liberated knowledge experienced a relative decrease in the likelihood of leaving the firm. In quantitative terms, the inventor increasing her proportion of knowledge in the liberated technological classes by 10% will be associated with an extra reduction of 3.36% in the probability of exiting IBM after 2005. Keeping in mind that IBM inventors have on average 53.76% of their knowledge in the liberated technological classes with a standard deviation of 40.13% (Table (1)), one SD increase in the inventor's knowledge composition in favor of the open classes after 2005 will make this inventor less mobile by 15% in comparison to the same change before 2005. The results shown in Model 2 provide support for Hypothesis 1, which means that the negative effect mechanisms are expected to outweigh the positive effect ones. In other words, IBM's decision to open up its knowledge, in general, results in the outsiders becoming less keen on hiring IBM's inventors and IBM retaining its researchers specialized in the liberated technologies.

Among the implications of these findings, one can firstly think that the relationship found in the literature for the creating inventors of the innovation cannot be extrapolated to other inventors in the area who, lacking the innovation-specific implementation knowledge, may have skills to invent around. Second, this finding supports the proposition that one of the main drivers for the recruitment of external talents is the knowledge of the inventors that they acquired in their previous employer. Further, both types of knowledge, explicit and tacit, seem to play a role in this relation and this observation is driven from the finding that granting access to the explicit knowledge reduces the employee turnover rate. As an empirical implication, these results propose that openness can be one of the options to deal with the knowledge spillovers through labor mobility.

In the next three models, I incorporate the moderation effects (Knowledge Basicness, Average Number of Co-Inventors, and Knowledge Cumulativeness) separately in each model. In Model 3, I find a statistical support for the negative moderation effect of the inventor's knowledge Basicness. The three-way interaction coefficient is statistically significant and negative. For the inventor with applied knowledge (*Basicness* = 0), the knowledge openness does not seem to affect her probability of leaving IBM, however, with each non-patent reference increase in the average basicness of the inventor's knowledge, the effect of knowledge openness on reducing the likelihood of her leaving IBM after 2005 is amplified by 0.025%. In short, there is evidence confirming Hypothesis 2.

According to the results in Model 4, *Co-inventors* seems to have a positive moderation effect of the *Openness* on labor mobility. In this case, again, the focus is on the three-way interaction term, while controlling for the corresponding two-way interactions. Mainly, the number of *Co-inventors* seems to favor the positive effect of openness, which is inferred from the significantly positive coefficient of the three-ways interaction. According to the

results of Model 4, knowledge openness reduces the mobility of solo inventors significantly more than that of the average inventors who used to work in teams. The effect of increasing the inventor's experience in the open classes on her mobility is about three times stronger for the solo inventors (*Co-inventors* = 0) than the average inventor, according to a comparison of β_3 in Model 2 and 4 (-0.00336 vs -0.00517). For instance, all else equal, a solo inventor with a certain level of *Openness* after 2005 will become less likely to leave IBM by 9.39% if she increases her specialty in the liberated technologies by 10% after 2005 with keeping working solo. However, holding everything else equal, if the very next research project in the open technological classes includes her with other co-inventors so that *Co-inventors* increases from 0 to 1, then, the effect of the same *Openness* change on reducing her mobility chances after 2005 will be reduced to 7.59% (-9.39 + 1.8) due to the increase of her average number of *Co-inventors* by one.

These results provide support for the second moderation hypothesis where the mobility of inventors working in bigger teams appear to be less negatively affected by their knowledge *Openness* in comparison to the inventors with the same *Openness* level but with tendency to work solo or in smaller teams. With these considerations, one can argue that the internal value of the inventors, who are less protected by more *Co-inventors*, increases after the firm adopts more openness in its R&D strategy and the firm tends to keep these inventors.

When examining the results in Model 5, which test the moderation effect of the Knowledge Cumulativeness, the three-way interaction coefficient is statistically negative and significant at 99% level of confidence. The effect of the inventor's knowledge openness on her mobility possibility is significantly negative for the inventors with a zero level of Knowledge Cumulativeness (*Cumulativeness* = 0) where 10% increase of her

Openness after 2005 results in an extra reduction of 5.17% of her chances to leave IBM, all else equal. For a corresponding inventor with only one difference in her *Cumulativeness* level, the effect of 10% increase in her *Openness* after 2005 is stronger by an extra 1.74% of reduction on her turnover possibility after 2005 for each one unit increase of her *Cumulativeness*. The results presented in Model 5 support the fourth hypothesis regarding the negative moderation role of knowledge cumulativeness in the effect of openness on mobility. Practically speaking, the adoption of outbound openness makes the employees working on the highly cumulative fields even less mobile if they are specialized in the liberated technologies.

Results with the weighted measure of openness. By running the same previous procedures of the analyses, I create another five models with the weighted *Openness* variable (See Table 4). Taking into consideration that the two measures of openness are very correlated at the patent-inventor level with $\rho = 0.637$, it is not surprising that the results are very similar. The results from these settings (Table (4)) support the observations made previously. The main effect of outbound openness on the firm's inventors is generally making them less mobile. In more detail, a one SD increase after 2005 in the inventor's openness measured by the independent-claims-weighted patents count will result in an extra reduction of mobility by 3.17%. The average number of *co-inventors* seems to be positively moderating the main effect of openness, as shown before. However, one of the major differences between the two sets of results is that the moderation effect of knowledge *Basicness* is insignificant which does not confirm the second hypothesis of the negative moderation effect of *Basicness* through this analysis, as the three-way interaction coefficient is statistically insignificant. Therefore, the moderation effects of firm's *Basicness* is partially supported by one of the two versions of openness measures. The

negative moderation effect of knowledge *Cumulativeness* is also supported by this analysis. These findings point at the direction of the supposition that the decision of openness of the IP strategy helps to reduce the hazard of inventors' moving out of the company when they invent in the more opened classes.

Insert Tables 3 and 4 about here.

2.5.3 The Timing of the Outbound Openness Effect and Other Robustness Checks

As noted in the Endogeneity Issues section, IBM took other steps to support the OSS community in the years between 2003 and 2005 and the pledge arguably was motivated by the law case against IBM by SCO in 2003. In addition, IBM pledge was not the first action from the frim to support the OSS community; however, I use the pledge as a proxy for the outbound openness because I believe it is a better proxy and a better indicator to reflect the adoption of outbound openness. Therefore, to validate using the 2005 pledge as a proxy for IBM's shift to outbound open innovation and understand the effect of these events happened in 2003 and 2004 on the labor mobility, I inspect the existence of "pre-trend" by interacting the openness measure with *After 2003* and *After 2004* dummies. I added these interactions separately and together in the Models 1-3 in Table 5 and the main take away from these analyses that the opposite and insignificant effect of these pre-trend indicators, the interactions of *Openness* with *After 2003* and *After 2004* dummies, does not confirm the existence of the pre-trend. These results validate the *After 2005* timing for the openness shock in my analyses, besides, confirm the direction of the effect to be negative.

In another robustness test, I check the continuation of the openness effect on the long-term. I run the main analysis for the years between 2010 and 2015 in Model 4. The *Openness* effect disappears on the longer term, especially as IBM did not repeat or increase

the size of the pledge after 2005. The results of Model 4 show that the effect of patenting in the liberated areas seems to fade away which emphasizes the effect around the shock time, 2005. I perform these robustness checks for the two different measures of openness and I present them in Table 5 for the unweighted measure and in Table 6 for the weighted measure.

As a robustness check and for additional support for the main findings, I used logit models for the main analyses. The results are consistent among all the methods. Moreover, the two different ways used to measure openness, besides the fact that I use panel data, even strengthen the robustness of my results. In addition, the inventor fixed effect controlled for in the analysis rules out the effect of the inventor's time invariant factors. As explained in the Endogeneity Issues section, I include the firm's involvement in each field of knowledge and its dominance as a proxy for the market power to account for specific concerns. The time and location fixed effects are also provided in the analyses to provide better estimations of the variables of interest. Clustering error at the treatment level controls for within-cluster error correlation in order to make sure that the model is robust to heteroscedasticity and autocorrelation. Lastly, I run the regression with a different measure of inventor's openness where I use a dummy that equals one for the inventors who either cited the pledged patents or cooperated with at least one of the inventors who created the pledged patents. It is an alternative way of measuring the inventor's involvement in the liberated areas. The results from this regression confirm the main finding that, after 2005, the inventors with related knowledge to the opened-up knowledge are less likely to leave IBM (Results can be provided upon request).

Insert Tables 5 and 6 about here.

2.5.4 The Effect of Openness on Labor Mobility over Time

The main finding of the study is that firm's openness of its IP strategy is associated with a reduction in the firm's inventors' outbound mobility. In order to study the effect development over time, I break down the impact into smaller periods after the firm's shift towards outbound openness. In more details, I consider each two years in the treatment period as a singular block, *Years 2005 & 2006, Years 2007 & 2008 and Years 2009 & 2010*. Next, I interact these time dummy variables with the openness measures, weighted and unweighted. Models 1 and 2 in Table 7 illustrate the results of this analysis. The effect of the firm's openness seems to be consistently reducing the outbound mobility over the period after the shock. This finding is supported by Figueres 2 and 3 where I present the coefficient of the interactions between openness measures and each year binary variable. The figures show that patenting in the fields that IBM decided to open up seem to be associated with increasing labor outbound mobility. However, after 2005 the intensity of this effect is substantially dropped. The change in the effect of inventor's knowledge openness from increasing labor mobility before 2005 to no effect or a smaller effect after 2005 confirm the main finding of this study that opening-up the firm's IP strategy tends to reduce the likelihood of its inventors to leave the firm.

Insert Table 7 about here.

Insert Figures 2 and 2 about here.

2.6 DISCUSION AND CONCLUSIONS

The current paper provides a novel perspective to look at the relationship between the restrictions to knowledge flow and inventor mobility by introducing the complementarity

and substitutability mechanisms between the codified knowledge and the inventor's (tacit) knowledge. This discussion help understanding the possible conflicting predictions of the effect of opening the firm's IP strategy on its skilled labor mobility. For the inventors with experience in the fields of the liberated knowledge, I argue that the substitutability mechanism dominates and the effect is in the direction of making these inventors less mobile proportionally with their experience in these fields of knowledge.

A***s*** a result of opening up the corporate innovation strategy, resources become available for free to the public. This creates an opportunity for other companies to make use of the made-free resources, such as intellectual property that are practically hard to defend and appropriate. This spillovers issue creates a misappropriation problem for the focal firm and makes their inventors more attractive for the outsiders. In practice, there are many different formal and informal mechanisms that firms use to deal with the problem of misappropriation, as such are the non-compete covenants, trade secrets, patents, trademarks, copyrights, confidentiality agreements, building reputation of toughness through litigiousness, and other methods (Kim & Marschke, 2005; Agrawal et al., 2009). R&D labor mobility among firms is recognized as one of the main channels of misappropriation. Firms, especially R&D-intense firms, make significant investments in their inventors, and these inventors usually carry the firms' tacit knowledge. This is why firms employ various mechanisms to prevent inventor mobility or at least to prevent the inventors from exposing firm specific knowledge.

In the current paper, I claim that opening up the corporate innovation strategy, generally, has the potential to increase, as well as, to decrease the labor outbound mobility. In the case of IBM and its 2005 patent pledge, the average effect found in the current paper is that outbound openness hinders outbound labor mobility. This finding provides firms

with another possibility for maintaining and protecting their skilled R&D labor. Traditionally, firms have gone for the aggressive options of enforcing their intellectual property, like patent litigation (Agrawal et al., 2009; and Ganco et al., 2015). Additionally, the results of this paper imply that firms may find it beneficial to share their knowledge and to open up their R&D borders, in order to keep their inventors for their special value to the firm.

I recognize that there could be alternative explanations for the results presented in this study. One potential explanation for the reduced mobility after openness is that the employees perceive the firm decision to adopt openness positively and they decide to stay with the firm. The employees may value this kind of practices from their employer and consider the social status of working for such a firm as a sort of compensation. Another potential explanation is related to the strategic planning of the focal firm. As the firm may anticipate that its decision to open up its IP's motivate the outsiders to create more innovation in these areas, then, the focal firm might decide to retain its inventors in these areas in order to be able to exploit these follow-up inventions by others. These possible mechanisms represent an opportunity for future work and an extension of this study.

The findings of this study contribute to the decision about which parts of the knowledge to open up, to be able to anticipate how and to what extent that openness will affect the firm. I contribute to this facet of the innovation model's openness by looking at how some characteristics of the inventor's knowledge moderate the effect of openness on the outbound labor mobility. The characteristics considered in this research cover general aspects of each area of knowledge, such as knowledge basicness, number of co-inventors, and cumulativeness. These characteristics, when reflected on the inventor's knowledge and experience, have different moderating effects on openness, hence, the firms that consider

adopting openness should consider them. When firms choose to incorporate more openness in their IP strategy, but at the same time want to protect their R&D labor, firms should choose to open up technological classes with low knowledge complementarity, high basicness, or/and high cumulativeness. As shown in the empirical analyses these moderators can alter and change the effect of openness on labor mobility, significantly.

Previous studies find that more protection and toughness in the IP approach reduces the likelihood of employees' exit decisions. However, this paper claims that more openness also reduces outbound labor mobility. Therefore, there are two possibilities to reduce inventors' movement out of the firm and the firm should decide which option to choose: going for more toughness or more openness. If the goal is to protect and maintain the human capital of the company, especially their stock of inventors, then the decision should consider the costs of the appropriability mechanisms, such as patent enforcements, litigiousness and other IP protection activities, versus the costs and hazards resulting from adopting more openness in the innovation model.

Considering the limitations of the current paper, this study cannot infer much about the effect of the adoption time (whether the company is an early adopter of openness in its industry or it is a late follower), and whether/how the adoption time would change the effect of openness on mobility. This is mainly due to the fact that I consider only one company in my analysis, which, additionally, limits the external validity of this study. Lastly, it is important to note that throughout this study I assume that openness in one class has no effect on the openness degree of the other classes. Thus, one can think of considering the inter-classes openness' interactions, especially the closely related classes, for future research.

2.7 Chapter 2 Tables

Table 1: Descriptive Statistics

Variable	Mean	S.D.	Min	Max
Labor mobility – pre 2005	0.0074	.0857	0	1
Labor mobility – post 2005	0.0073	.0854	0	1
Openness (Unweighted)	0.538	0.401	0	1
Openness (Weighted)	0.103	1.075	-0.6	4.789
Basicness	4.718	14.252	0	967
Co-inventors	2.871	1.829	0	62.500
Cumulativeness	-0.068	0.211	-0.401	16.251
Involvement	0.019	0.017	0	0.500
Dominance	0.142	0.083	0	0.757
Experience	8.402	8.262	0	57
No. of Patents	16.569	31.040	1	973

Note: These statistics are for the variables before standardizing

Table 2: Correlations between the main variables in the panel data

#	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	Openness (Unweighted)	1.000								
2	Openness (Weighted)	0.637	1.000							
3	Basicness	0.102	0.101	1.000						
4	Co-inventors	-0.004	0.059	0.115	1.000					
5	Cumulativeness	0.122	0.074	-0.011	-0.038	1.000				
6	Involvement	-0.101	0.232	-0.022	0.060	-0.354	1.000			
7	Dominance	0.396	0.713	0.022	0.038	0.076	0.482	1.000		
8	Experience	-0.091	-0.192	-0.052	-0.047	0.083	-0.222	-0.272	1.000	
9	No. of Patents	-0.067	-0.115	-0.016	-0.002	-0.002	-0.065	-0.127	0.521	1.000

Table 3: LPM Fixed Effect on the Probability of an Inventor's Exit with the Unweighted Openness Measure: Coefficients' Estimate

VARIABLES	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Openness		0.00232	0.00112	-0.00029	0.00154
		(0.00187)	(0.00168)	(0.00206)	(0.00168)
After 2005 × Openness		-0.00336***	-0.00256**	-0.00939***	-0.00517***
		(0.00129)	(0.00131)	(0.00223)	(0.00135)
Basicness	-4.50e-05	-4.25e-05	-3.88e-06	-4.26e-05*	-5.11e-05**
	(2.84e-05)	(2.84e-05)	(7.07e-05)	(2.57e-05)	(2.57e-05)
Co-inventors	-0.00129***	-0.00128***	-0.00118***	-0.00098**	-0.00119***
	(0.00023)	(0.00023)	(0.00020)	(0.00041)	(0.00020)
Cumulativeness	0.00078	9.88e-05	-0.00138	-0.00123	-0.00716**
	(0.00230)	(0.00233)	(0.00217)	(0.00217)	(0.00323)
After 2005 × Basicness			-8.44e-05		
			(7.96e-05)		
Openness × Basicness			0.00019**		
			(9.55e-05)		
After 2005 × Openness × Basicness			-0.00025**		
			(0.00011)		
After 2005 × Co-inventors				0.00040	
				(0.00045)	
Openness × Co-inventors				-0.00311***	
				(0.00047)	
After 2005 × Openness × Co-inventors				0.00179***	
				(0.00056)	
After 2005 × Cumulativeness					0.0110***
					(0.00403)
Openness × Cumulativeness					0.00808*
					(0.00427)
After 2005 × Openness × Cumulativeness					-0.01740***
					(0.00571)
Involvement	-0.32500***	-0.33600***	-0.35300***	-0.35000***	-0.34800***
	(0.03620)	(0.03720)	(0.03390)	(0.03380)	(0.03470)
Dominance	-0.02950***	-0.02930***	-0.01200	-0.01050	-0.01340*
	(0.00853)	(0.00859)	(0.00767)	(0.00767)	(0.00777)
Experience	0.00813***	0.00831***	0.00718***	0.00804***	0.00732***
	(0.00016)	(0.00018)	(0.00017)	(0.00021)	(0.00017)
Experience^2	-5.05e-05***	-5.16e-05***	-4.82e-05***	-4.97e-05***	-4.81e-05***
	(5.06e-06)	(5.09e-06)	(4.89e-06)	(4.87e-06)	(4.93e-06)
No. of Patents	-0.00017***	-0.00017***	-0.00018***	-0.00018***	-0.00018***
	(4.48e-05)	(4.49e-05)	(4.81e-05)	(4.73e-05)	(4.82e-05)
Year and State FE	Yes	Yes	Yes	Yes	Yes
Constant	-0.03170***	-0.03310***	-0.02890***	-0.03120***	-0.02950***
Observations	453,575	453,575	453,575	453,575	453,575
Number of Inventors	116,557	116,557	116,557	116,557	116,557

Note: Estimates based on the inventor-level analyses over a sample of inventor-year observations under the specification of a fixed-effect LPM. Robust standard errors clustered at inventor-level are in brackets. ***1% significance, **5% significance, *10% significance.

Table 4: LPM Fixed Effect on the Probability of an Inventor's Exit with the Weighted Openness Measure: Coefficients' Estimate

VARIABLES	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Openness		0.00425***	0.00327***	0.00292***	0.00324***
		(0.00064)	(0.00059)	(0.00069)	(0.00059)
After 2005 × Openness		-0.00317***	-0.00294***	-0.00430***	-0.00332***
		(0.00043)	(0.00045)	(0.00070)	(0.00046)
Basicness	-4.50e-05	-4.12e-05	-7.12e-05*	-4.22e-05	-4.98e-05*
	(2.84e-05)	(2.84e-05)	(4.22e-05)	(2.57e-05)	(2.57e-05)
Co-inventors	-0.00129***	-0.00127***	-0.00118***	-0.000782***	-0.00118***
	(0.00023)	(0.00023)	(0.00020)	(0.00023)	(0.00020)
Cumulativeness	0.00078	-0.00039	-0.00162	-0.00146	-0.00193
	(0.00230)	(0.00233)	(0.00216)	(0.00216)	(0.00227)
After 2005 × Basicness			2.01e-06		
			(1.85e-05)		
Openness × Basicness			3.02e-05		
			(4.10e-05)		
After 2005 × Openness × Basicness			-8.06e-06		
			(2.36e-05)		
After 2005 × Co-inventors				7.82e-05	
				(0.00014)	
Openness × Co-inventors				-0.00202***	
				(0.00026)	
After 2005 × Openness × Co-inventors				0.00047***	
				(0.00015)	
After 2005 × Cumulativeness					0.00161
					(0.00174)
Openness × Cumulativeness					-0.00121
					(0.00265)
After 2005 × Openness × Cumulativeness					-0.00584**
					(0.00236)
Involvement	-0.32500***	-0.35500***	-0.36100***	-0.35500***	-0.35900***
	(0.03620)	(0.03690)	(0.03360)	(0.03340)	(0.03460)
|Dominance	-0.02950***	-0.04770***	-0.02590***	-0.02480***	-0.02560***
	(0.00853)	(0.00912)	(0.00812)	(0.00812)	(0.00851)
Experience	0.00813***	0.00824***	0.00713***	0.00765***	0.00715***
	(0.00016)	(0.00016)	(0.00015)	(0.00017)	(0.00015)
Experience^2	-5.05e-05***	-5.55e-05***	-5.15e-05***	-5.29e-05***	-5.15e-05***
	(5.06e-06)	(5.14e-06)	(4.93e-06)	(4.91e-06)	(4.97e-06)
No. of Patents	-0.00017***	-0.00018***	-0.00018***	-0.00018***	-0.00019***
	(4.48e-05)	(4.51e-05)	(4.83e-05)	(4.76e-05)	(4.84e-05)
Year and State FE	Yes	Yes	Yes	Yes	Yes
Constant	-0.03170***	-0.02890***	-0.02610***	-0.02840***	-0.02640***
Observations	453,575	453,575	453,575	453,575	453,575
Number of Inventors	116,557	116,557	116,557	116,557	116,557

Note: Estimates based on the inventor-level analyses over a sample of inventor-year observations under the specification of a fixed-effect LPM. Robust standard errors clustered at inventor-level are in brackets. ***1% significance, **5% significance, *10% significance.

Table 5: Robustness Tests (Openness - Unweighted)

VARIABLES	Model (1)	Model (2)	Model (3)	Model (4)
Openness (Unweighted)	0.00180	0.00203	0.00180	0.00067
	(0.00193)	(0.00189)	(0.00193)	(0.00236)
After 2003 × Openness	0.00197		0.00135	
	(0.00150)		(0.00177)	
After 2004 × Openness		0.00224	0.00122	
		(0.00171)	(0.00201)	
After 2005 × Openness	-0.00450***	-0.00509***	-0.00509***	
	(0.00143)	(0.00171)	(0.00171)	
Basicness	-4.32e-05	-4.31e-05	-4.33e-05	-4.74e-05
	(2.84e-05)	(2.84e-05)	(2.84e-05)	(8.88e-05)
Co-inventors	-0.00128***	-0.00128***	-0.00128***	0.00105
	(0.00023)	(0.00023)	(0.00023)	(0.00089)
Cumulativeness	0.000278	0.00022	0.00029	-0.00328
	(0.00233)	(0.00233)	(0.00233)	(0.00388)
Involvement	-0.3330***	-0.3350***	-0.3330***	-0.1370***
	(0.0374)	(0.0373)	(0.0374)	(0.0523)
Dominance	-0.0296***	-0.0296***	-0.0296***	-0.0167
	(0.00860)	(0.00860)	(0.00860)	(0.0214)
Experience	0.00827***	0.00828***	0.00827***	0.00529***
	(0.00018)	(0.00018)	(0.00018)	(0.00038)
Experience2	-5.14e-05***	-5.15e-05***	-5.14e-05***	-2.85e-05***
	(5.09e-06)	(5.09e-06)	(5.09e-06)	(1.01e-05)
No. Of Patents	-0.00017***	-0.00017***	-0.00017***	-1.82e-05
	(4.49e-05)	(4.49e-05)	(4.49e-05)	(1.79e-05)
Year and State FE	Yes	Yes	Yes	Yes
Constant	-0.03270***	-0.03290***	-0.03270***	-0.04340***
Observations	453,575	453,575	453,575	141,431
Number of Inventors	116,557	116,557	116,557	64,514

Note: Estimates based on the inventor-level analyses over a sample of inventor-year observations under the specification of a fixed-effect LPM. Sample in model 4 differs because of the different time period. Robust standard errors clustered at inventor-level are in brackets. ***1% significance, **5% significance, *10% significance.

Table 6: Robustness Tests (Openness - Weighted)

VARIABLES	Model (1)	Model (2)	Model (3)	Model (4)
Openness	0.00469***	0.00476***	0.00467***	0.00182
	(0.00074)	(0.00070)	(0.00074)	(0.00168)
After 2005 × Openness	-0.00322***	-0.00250***	-0.00250***	
	(0.00050)	(0.00058)	(0.00058)	
After 2003 × Openness	-0.00036		0.00045	
	(0.00057)		(0.00068)	
After 2004 × Openness		-0.00122**	-0.00154**	
		(0.00061)	(0.00071)	
Basicness	-4.09e-05	-4.02e-05	-4.03e-05	-4.39e-05
	(2.84e-05)	(2.84e-05)	(2.84e-05)	(8.90e-05)
Co-inventors	-0.00127***	-0.00127***	-0.00127***	0.00104
	(0.00023)	(0.00023)	(0.00023)	(0.00089)
Cumulativeness	-9.68e-05	-0.00011	-0.00010	-0.00046
	(0.000492)	(0.000492)	(0.000492)	(0.00121)
Involvement	-0.3540***	-0.3530***	-0.3530***	-0.09850**
	(0.03690)	(0.03690)	(0.03690)	(0.04910)
Dominance	-0.04770***	-0.04760***	-0.04760***	-0.02850
	(0.00911)	(0.00912)	(0.00911)	(0.02290)
Experience	0.00821***	0.00822***	0.00821***	0.00512***
	(0.00016)	(0.00016)	(0.00016)	(0.00037)
Experience^2	-5.56e-05***	-5.59e-05***	-5.58e-05***	-2.67e-05***
	(5.16e-06)	(5.16e-06)	(5.16e-06)	(9.96e-06)
No. Of Patents	-0.00018***	-0.00018***	-0.00018***	-1.89e-05
	(4.52e-05)	(4.52e-05)	(4.52e-05)	(1.79e-05)
Year and State FE	Yes	Yes	Yes	Yes
Constant	-0.02840***	-0.02840***	-0.02840***	-0.04530***
Observations	453,575	453,575	453,575	141,431
Number of Inventors	116,557	116,557	116,557	64,514

Note: Estimates based on the inventor-level analyses over a sample of inventor-year observations under the specification of a fixed-effect LPM. Sample in model 4 differs because of the different time period. Robust standard errors clustered at inventor-level are in brackets. ***1% significance, **5% significance, *10% significance.

Table 7: Effect of openness on labor mobiity over time

VARIABLES	Model (1)	Model (2)
Openness (Unweighted)	0.000436	
	(0.000996)	
Years 2006&2007 x Openness (Unweighted)	-0.00165**	
	(0.000740)	
Years 2008&2009 x Openness (Unweighted)	-0.00159**	
	(0.000802)	
Year 2010 x Openness (Unweighted)	-0.00267***	
	(0.00101)	
Openness (Weighted)		0.00199***
		(0.000317)
Years 2005 & 2006 x Openness (Weighted)		-0.00115***
		(0.000228)
Years 2007 &2008 x Openness (Weighted)		-0.00159***
		(0.000252)
Year 2010 &2009 x Openness (Weighted)		-0.00168***
		(0.000363)
Basicness	3.38e-06	3.22e-06
	(8.49e-06)	(8.50e-06)
Co-inventors	-0.000891***	-0.000886***
	(0.000115)	(0.000115)
Cumulativeness	-0.000788**	-0.000825**
	(0.000338)	(0.000337)
Involvement	-0.00416***	-0.00424***
	(0.000337)	(0.000329)
Dominance	-0.000500	-0.00128***
	(0.000373)	(0.000394)
Experience	0.00473***	0.00466***
	(9.94e-05)	(8.37e-05)
Experience2	-5.71e-05***	-5.91e-05***
	(2.09e-06)	(2.14e-06)
No. Of Patents	-1.28e-05**	-1.31e-05***
	(5.00e-06)	(5.01e-06)
Year and State FE	YES	YES
Constant	-0.0311***	-0.0304***
	(0.000952)	(0.000748)
Observations	1,178,491	1,178,491
R-squared	0.012	0.012
Number of inventors	116,557	116,557

Note: Estimates based on the inventor-level analyses over a sample of inventor-year observations under the specification of a fixed-effect LPM. Robust standard errors clustered at inventor-level are in brackets. ***1% significance, **5% significance, *10% significance.

2.8 Chapter 2 Figures

Figure 1: IBM's total number of employees and gross income in the period 1985-2010.

Figure 2: The effects of inventor's knowledge (Unweighted) openness over the years before and after the treatment.

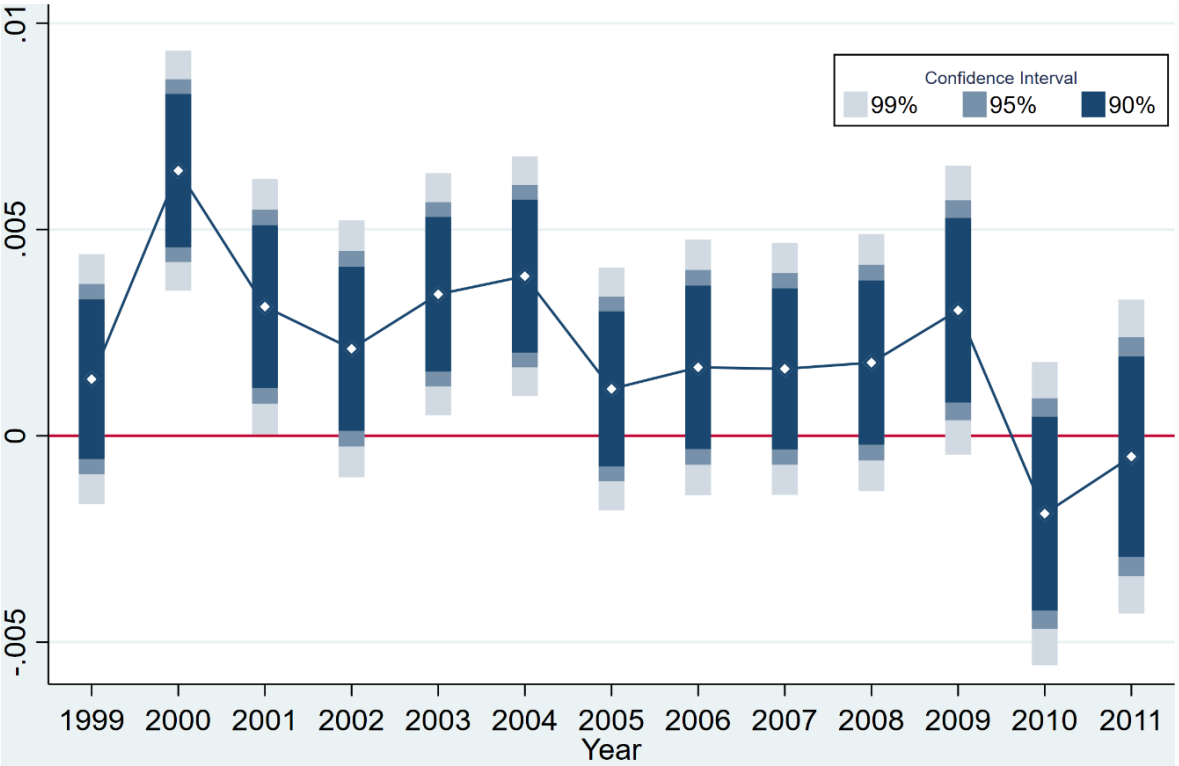
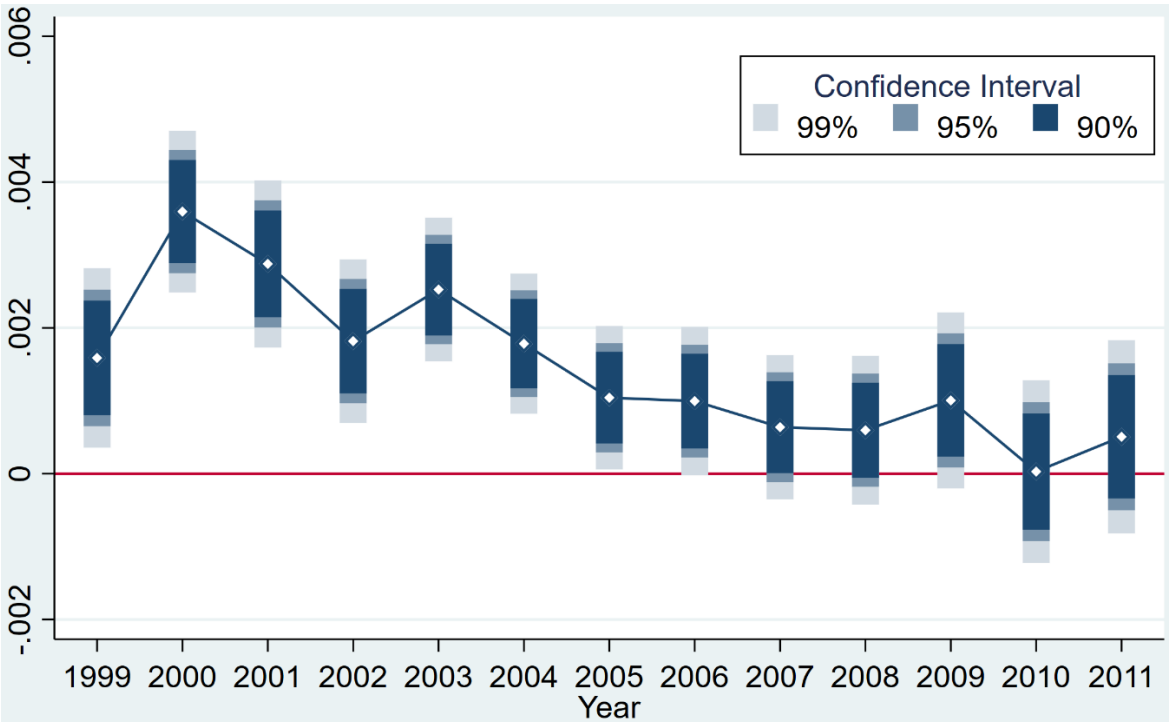


Figure 3: The effects of inventor's knowledge (Weighted) openness over the years before and after the treatment.



Chapter 3
Patent Enforcement Strength and Collaboration: The Effect of Firm's Litigiousness on Alliances Intensity

(co-authored with Eduardo Melero, David Wehrheim)

3.1 INTODUCTION

R&D collaborations play an important role in technological developments. They favor the creation of new technologies through the process of knowledge recombination, and spur the diffusion of existing ones (Rothaermel & Boeker, 2008). When considering the possibility of establishing a new collaboration with another organization, firms need to evaluate the tension between the added value that can be obtained from the project object of the alliance and the knowledge that can be absorbed as a consequence of working on it on the one hand, and, on the other hand, the potential damage caused by knowledge leakage during the collaboration (Oxley, 1999; Katila, Rosenberg & Eisenhardt, 2008; Diestre & Rajagopalan, 2012).

Past research has analyzed this trade-off, particularly for new entrepreneurial firms that have to make "swimming with the sharks" decisions (Katila et al., 2008). To a large extent, the literature on collaborations implicitly assigns an important enabling role to the enforceability of intellectual property (IP) rights in the balance of these decisions. In principle, a weak enforceability of those rights may keep innovators from sharing their knowledge in alliances, due to the fear of being expropriated by the partner, and thus may have a negative effect on collaborations (Oxley, 1999; Gans, Hsu & Stern 2002).

In this paper, however, we argue that a weaker enforcement of property rights generates two opposite forces on firms' research collaborations. Consequently, it may increase or reduce collaborations depending on the intensity of each of these forces. As implicit in previous research on alliances, weaker enforcement increases the expected cost of any unintended knowledge leakage that may happen during the partnership, thus discouraging it. On the other hand, to the extent that the patent system operates as a block-road to innovation by generating uncertainty and encouraging frivolous litigation (Lemley & Shapiro, 2005; Jaffe & Lerner, 2011; Mezzanotti, 2019), weaker enforcement increases the expected rewards to collaborative investments.

Within this framework, we analyze the consequences of recent moves in the U.S. patent system toward weaker patent enforcement on the prevalence of alliances, which will depend on the importance of the two opposed forces outlined above. Due to the ambiguity of these forces' dominance over each other, we do not hypothesize the main effect. Nonetheless, we hypothesize that weaker patent enforcement tends to decrease the formation of alliances between partners of different sizes more than alliances between partners of similar size. These asymmetric alliances are typically characterized by involving a small partner that is particularly concerned about knowledge leakage to the counterpart (Katila et al., 2008). Alliances between partners of a similar size, on the other hand, are not expected to be discouraged, since they develop in a less unbalanced context. Secondly, we expect a relative increase in the prevalence of collaborations between relational partners, i.e., partners with a history of past collaboration together. Relational partners are likely to have developed mechanisms to avoid opportunistic appropriation of knowledge, and consequently experience less concerns of knowledge leakage (Deeds & Hill, 1999). Therefore, they are only affected by the "bright" side of a weaker patent enforcement,

through a reduced legal uncertainty regarding the outcome of the alliance. Finally, we also predict that the positive aspects of a weaker enforcement for R&D collaboration agreements will tend to be relatively more important than the negative ones for firms performing more basic-science research activities. The reason is that because basic-science-related knowledge is idiosyncratically more difficult to absorb by potential partners (Lane & Lubatkin, 1998), weaker enforcement imposes fewer risks on collaborations for these companies.

To test these hypotheses, we exploit the legal change in the treatment of patent infringement created by the U.S. Supreme Court decision "*eBay v. MercExchange*" in 2006, which terminated the practice of automatically issuing an enduring injunction after proving a patent violation. There is a consensus among legal scholars that this decision effectively weakened the enforcement of patent protection (Tang, 2006; Bessen & Meurer, 2008). We examine the impact of such a decision on firm's decision to collaborate by exploiting heterogeneity among companies in their tendency to litigate as the treatment variable, and combining data from Securities Data Company (SDC) Platinum for alliances, patent litigation data from Marco, Tesfayesus, & Toole (2017), patent data from Patentview dataset for co-patenting measures, data on the scientific references from Kevin A. Bryan, Yasin Ozcan, & Bhaven N. Sampat (2019), and control variables from Arora, Belenzon & Sheer (2019). Overall, our analysis suggests that the decrease in the patent protection enforcement leads companies in our sample to engage in fewer alliances. The results support our main predictions regarding the symmetric alliances in comparison to asymmetric alliances and the relational alliances in comparison to alliances with de novo partners. The moderation effect of knowledge basicness is also supported by our analyses.

3.2 THEORETICAL BACKGROUND

When organizations consider establishing an R&D collaboration partnership, they have to confront a fundamental dilemma. The collaboration may offer important added value within the defined scope of the collaboration (e.g., the development of some specific technology), and beyond it (e.g., through learning about new processes and technologies). At the same time, the collaboration also exposes the company to the risk of misappropriation by its partner through knowledge leakage (Oxley, 1999; Gans, Hsu & Stern, 2002). Both elements of this tension are inherent to the knowledge exchange process. The existence of IP rights that protect knowledge could, in principle, help to delimit the scope of knowledge exchange in R&D collaborations, and should be therefore an enabling factor for these collaborations. In practice, however, the patent system is characterized by its probabilistic nature (Lemely & Shapiro, 2005) and its costly and noisy enforcement system (Jaffe & Lerner, 2011). This may impose substantial frivolous-litigation costs on successful innovators and decrease firm's incentives to invest in innovation (Mezzanotti, 2019).

Therefore, a decrease in the intensity of patent enforcement, such as the one that took place in the U.S. after 2006, does not have an unambiguous effect on the prevalence of inter-organizational collaborations. In principle, weaker property rights exacerbate the costs of knowledge leakage, as they increase the possibility of misappropriation by partners. On the other hand, weaker property rights decrease the expected costs associated with the implementation of knowledge acquired during the collaboration, either within or beyond the scope of the alliance (Dushnitsky & Lenox, 2005). First, it decreases the litigation costs that can be imposed by the partner in the event of a disagreement in the terms of the use of

such acquired knowledge. More generally, weaker property rights may also decrease the expected legal costs that may be imposed by third parties in the case of a successful development of the acquired knowledge (Mezzanotti, 2019).

From the previous theoretical analysis of the operating forces in the relationship between the IP protection and alliances ubiquity, we are not able to decide for an unequivocal effect. Thus, we basically consider the direction of the effect an empirical issue. Regardless of being agnostic regarding the balance of the two opposite forces affecting this relation, we propose next a series of hypotheses on the factors moderating such balance.

3.2.1 Symmetric and Asymmetric Collaborations

Even if a universal unequivocal statement on the effect of weakening property rights on R&D collaborations cannot be established, there are particular types of collaborations that may be incentivized or discouraged by the process, because they are particularly sensitive to the different channels described above. This is the case of *asymmetric* collaborations involving partners of different sizes. The paradigm of collaboration between a small start-up and a well-established incumbent has been common in past research on alliances. Previous literature underlines that the problem of knowledge misappropriation by the partner is particularly acute for the smaller company in this context (Katila et al., 2008; Diestre & Rajagopalan, 2012). The bigger company is likely to have the necessary stock of complementary assets and financial slack to exploit that knowledge. The smaller company has few options of reacting against misappropriation other than through the legal system if there has been some property right infringement. On the contrary, when two similarly sized companies engage in a collaboration, it is expected that the balance of power between the

two reduces the overall misappropriation concerns in the alliance to intermediate levels. Additionally, the positive effect of less strong property rights, which takes the form of fewer barriers to the development of the outcome of the partnership, is expected to be similar for both types of collaborations.

In consequence, a reduction in the strength of patent enforcement is expected to have a particularly detrimental effect on *asymmetric* collaborations between partners of different sizes, given the particularly acute concerns about knowledge misappropriation that take place in those types of collaborations.

Hypothesis 1: The effect of a reduction in patent enforcement on the establishment of collaborations is expected to be less strongly positive (more strongly negative) for asymmetric collaborations between partners of different sizes than for symmetric collaborations between partners of a similar size.

3.2.2 Relational Partners

A second interesting margin in which the effect of patent enforcement on collaboration may differ is the stability of relationships with the partner. Literature on Transaction Cost Economics has long established that (implicit) relational contracts between parties that interact frequently is an effective way to solve opportunism problems. Long-term (relational) partners involved in these contracts typically establish clear internal norms concerning the terms of the collaboration. In the case of R&D alliances, these norms are expected to affect, at the very least, the most important dimensions of the collaboration, namely those related to the knowledge exchange (Deeds & Hill, 1999). With clear internally-enforced rules for the knowledge exchange, knowledge misappropriation concerns are reduced to a minimum. Therefore, R&D alliances between long-term partners,

whose exchange is regulated by some type of relational contracts, are barely affected by the negative consequences of weaker IP rights. On the other hand, they are fully affected by the positive side of weaker patent enforcement, through the reduced legal uncertainty regarding the outcome of the alliance.

Hypothesis 2: The effect of a reduction in patent enforcement on the establishment of collaborations is expected to be more strongly positive (less strongly negative) for long-term partners with a history than for de novo collaborators.

3.2.3 Basic-Science-Related Research

A third contextual factor that may affect the impact of patent enforcement on R&D collaborations is the nature of the knowledge produced at the organizations that are considering the possibility of forming an alliance. Research on absorptive capacity has established that firms typically have to make explicit efforts in acquiring a substantial scientific knowledge base in their technological fields in order to be able to absorb further basic knowledge (Lane & Lubatkin, 1998). This also means that, on average, firms with a focus on basic-science research that are considering establishing an alliance are not particularly concerned with knowledge leakage. Since the type of knowledge that they hold is quite difficult to transfer, it is also quite unlikely to have it leaked involuntarily. Consequently, basic science-related knowledge tends to be less subject to misappropriation by partners. Thus, the negative impact of weaker patent enforcement for companies engaged in collaborations is less intense in the case of companies doing basic-science research. On the other hand, the expected benefits of weaker patent enforcement, in the form of decreased litigation-related uncertainty concerning the outcome of the alliance, are not likely to differ for basic- and applied-research firms. In consequence, we expect

collaborations involving basic-research firms to be relatively favored by weaker patent enforcement.

Hypothesis 3: The effect of a reduction in patent enforcement on the establishment of collaborations is expected to be more strongly positive (less strongly negative) for companies that do basic-science-related research.

3.3 THE "EBAY V. MERCEXCHANGE" CASE

In 2006, the Supreme Court ruled on the "eBay v. MercExchange" case, where the dispute between the companies was related to the infringement of one of MercExchange's patents related to the fixed-price auction feature. This is the main event that allows us to examine the research issue. The 2006 Supreme Court's decision put an end to the implementation of the rule of issuing an automatic and permanent injunction in case the patent found infringed and valid. Before that ruling, the infringed patent's owner could almost always obtain injunctive relief where the infringing firm is forced to stop making, using or selling any item related to the violated knowledge, despite the essence and size of the violation. However, the court in 2006 introduced a four-part test to decide if the injunctive relief is a necessary remedy for the plaintiff. According to the Supreme Court, the granting of an almost mandatory injunction is contradicting the premises of the Patent Act, which instead demands the application of equitable principles in deciding on the compensation mechanism in a patent infringement case.[28]

This significant ruling objective was mainly to limit abusive patent litigations and it achieved that by reducing the probability of obtaining an injunction for infringed patents and, therefore, remarkably reduced the patent enforcement strength in the U.S. (Ludlow,

[28] More details on the case background and its implications can be also found in Mezzanotti & Simcoe (2019).

2014). This ruling overturned the old presumption that the owner of a valid and infringed patent was granted the right of a permanent injunction, besides, the damage award which is a monetary compensation to the plaintiff for the caused damages. The presence of a strong litigation system with a near-mandatory injunction rule can lead to settlements that far exceed the costs that the potential infringer would pay in a negotiation before a case is filed, especially with minor infringements (Shapiro, 2010). In addition, the threat of injunction means that the firm can be forced to stop its operation before collecting returns from its investment in the specific technology that might be infringing. This large operational risk and the divergence of prices under pre- and post-infringement negotiation are factors in the hold-up problem originally described by Williamson (1979). Consequently, the bargaining position of the patent holders in the negotiations over patent disputes was strengthened due to the automatic injunction. In conclusion, eliminating automatic injunction is expected to decrease the hold-up costs of litigation, therefore amplifying the firms' motives and financial ability to generally invest in R&D projects (Mezzanotti, 2019) as firms active in high-litigation fields are forced to allocate a higher proportion of their resources for defensive and protective activities (Cohen et al., 2014).

Generally, the ruling in eBay v. MercExchange had an obvious effect on the use of injunction in court cases and patent enforcement more generally (e.g. Holte, 2015; Shapiro, 2010). In details, the probability of succeeding in enforcing an injunction over the infringer after the supreme court decision decreased to 75% of the before ruling likelihood (Chien & Lemley, 2012). And this reduction was even stranger in the cases of the disputes between non-competitors or cases involving a non-practicing entity (Seaman, 2016).

3.4 RESEARCH SETTING

3.4.1 Empirical Setting

The objective of our study is to analyze whether the change in the strength of the enforcement of patent rights (restriction of injunction cases) affects the prevalence of alliances. To examine this issue, we employ a quasi-natural experiment in which the patent enforcement strength in the U.S. was reduced by removing the automatic grant of permanent injunctions for proven patent infringement. The 2006 Supreme Court decision in "eBay v. MercExchange" case was a watershed where it stopped the practice of an automatically permanent injunction after proving a patent violation. By exploiting this shift in patent enforcement strength, we can explore the consequences on the firms' R&D activities (Mezzanotti, 2019) and especially their collaboration activities in American market. Generally, all firms patenting in the U.S. have been influenced by this legal change, and therefore it is not straight-forward to decide on the control group in this study (Mezzanotti, 2019).

We develop a research design that exploits a difference-in-difference approach around the main event, eBay v. MercExchange case. In order to exploit variation in firm's litigiousness before and after 2006, we run a firm's FE model to identify the firms that are more likely to be affected by the change in the strength of patent enforcement. We study how the firm's collaboration activities changes as a function of the firm's litigiousness before and after the shock. In other words, we estimate:

$$y_{jt} = \alpha_j + \alpha_t + \beta\ (litigiousness_j \times After\ 2006) + \gamma\ X_{jt} + \varepsilon_{jt}$$

where y_{jt} is an outcome of firm j at time t measuring its collaboration activities, which we measure by the alliances projects that the gets engaged in and by the co-patenting

activities that the firm files at the USPTO. After 2006 = 1{ time > decision}, (α_j , α_t) is a set of firm and time fixed effects, *litigiousness* $_j$ is the index of IP toughness by company j, measured prior to the shock, and X_{jt} is a matrix of controls. In an additional analysis, we add the knowledge basicness as moderator for the effect of litigiousness after 2006.

3.4.2 Data

The firms in our sample are the publicly traded U.S. firms with patenting history. The sample consists of about 2,800 firms over the period from 2000 to 2010, during which there were no major changes in the patent law except from the ruling on the "eBay v. MercExchange" case. Our panel consists of more than 20 thousand firm-year observations. We stopped the sampling by the end of 2010, because the America Invents Act, which introduced a significant change in the U.S. patent system, came into effect in 2011.

We start with the sample of publicly traded firms from Compustat and then we limit the sample to the firms that have a positive stock patents in studied period. This constraint represents the intuitive that the non-patenting firms do not have the possibility to be part of a patent dispute. We match these firms with the SDC platinum alliance database to capture the collaborative activities of the firm. After that we match the sample with the patent data from Patentview[29] dataset, which we used to create our co-patenting variables.

As mentioned above, we use the patent litigation data from Marco, Tesfayesus, & Toole (2017), in order to in order to measure the intensity of litigiousness to the reform. For the variable basicness, we use the public data on the scientific references of patents from Bryan, Ozcan, & Sampat, (2019). To calculate our control variables, we utilize the work of

[29] Available at https://www.patentsview.org/download/

Arora, Belenzon & Sheer (2019), where the database links patent data to Compustat firms and we use their publicly available datasets.[30]

3.4.3 Dependent Variables

Collaboration measures. We use two sets of measures to reflect on the intensity of the firm's collaboration activities. The first set utilize the R&D alliance projects the firm gets involved in. For this, we use the SDC Platinum alliances databases produced by Thomson Reuters[31]. The first measure indicates the probability of the firm to start at least one alliance project in each year. The second variable captures more variations in terms of the number of firm's alliances. Alliances can have different forms such as; joint ventures, strategic alliances, research and development agreements, sales and marketing agreements, manufacturing agreements, supply agreements, and licensing and distribution pacts.

Another categorization of alliances that we consider is the alliances asymmetry depending on the differences between the partners size and capabilities. We consider an alliance asymmetric if the partners are different in the size (total assets). Symmetry alliance happens when both companies have relatively similar size[32]. Moreover, we analyze two other types of alliances, the alliances with new partners and the relational alliances with partner whom firm has previous collaborative project with.

The second set of measures for the firm's collaborations is based on the co-patenting behavior. A co-patent is a co-owned patent that is registered with more than one assignee

---

[30] Available at https://zenodo.org/record/3594694#.XpN9mMgzavu

[31] Thomson Financial Joint Ventures and Strategic Alliances database defines the alliances as "Agreements where two or more entities have combined resources to form a new, mutually advantageous business arrangement to achieve predetermined objectives. All types of alliances are covered including: JVs, Strategic alliances, Licensing and exclusive licensing agreements, Research and development agreements, Manufacturing agreements, Marketing agreements, Supply agreements" (available at http://library.dialog.com/bluesheets/pdf/bl0554.pdf).

32 We consider firms having similar size if the big firm is less than 10 times bigger than the smaller partner. We check the results when the ratio between the firms' size is 5 or 15.

where both owners can exploit the invention on their own behalf. Thus, co-patenting means a joint ownership of collaborative outcomes (Hagedoorn, 2003). Analogously, the first of these measures reflects on the probability of having at least one co-patent in a specific year. The second measure focuses on the intensity of the co-patenting activities and it is computed by aggregating the number of co-patents the firm files in a specific year. Additionally, we build a measure for the collaborations with a relational partner or a new partner. We track the co-patenting history of firm to determine if it has a previous co-patent with a specific co-patentee or it is the first co-patent they file together. Then, we aggregate the total number of new co-patentees and the total number of old co-patentees at the firm-level for each year.

3.4.4 Independent Variables

Firm's Litigiousness measures. In order to capture the firm's *litigiousness*, we construct our measure based on the recent firm's history of initiating patent infringement lawsuits. In details, our measure consists of the moving sum of the number of unique lawsuits filed by the firm in the last recent three years. We exclude the lawsuits filed against the firm because we are interested in apprehending a firm-specific proxy for taking litigious actions. This moving sum over the years from t-1 to t-3 is a time-varying measure that captures the intensity of the firm's IP enforcement. This identification strategy has been used in literature to reflect on the firm's reputation of toughness (Agarwal, Ganco, & Ziedonis 2009; Ganco, Ziedonis & Agarwal, 2015). To build this proxy, we use the data from Marco, Tesfayesus, & Toole (2017). This USPTO paper introduces the patent litigation data from U.S. district court electronic data where they collect the information about the patent litigation cases in PACER and RECAP including the case identifier, parties

involved, filing date, court location, litigated patents, and more information. We extract all the patent disputes that were asserted by the plaintiff and then use this information to measure the intensity of the firm's litigiousness by computing the number of unique patent disputes in a specific year.

Using this identification, we can analyze whether the weaker/stronger enforcement of patent rights (restriction of injunction rule) affects how the firm's litigiousness impacts the prevalence of alliances. In conclusion, we identify the impact of the intensity of patent enforcement on the prevalence of alliances using a Differences in Differences approach where the intensity of the treatment is captured with tendency of the company to launch lawsuits of patent litigation.

3.4.5 Moderator

Knowledge basicness. We construct the knowledge basicness measure by building a proxy at the technological class level using the scientific references found in the in-text patent citations. We use the data provided by Kevin A. Bryan, Yasin Ozcan, & Bhaven N. Sampat, 2019. Instead of the front-page citation, they use the citations in the specification text itself. As the descriptive parts of patents are often mainly written by the inventors themselves, the authors argue that in-text citations should better measure the real knowledge inventors use to motivate and construct their inventions.

For each firm, we take their patents in the year between 2000 and 2005 and we computed the average number of scientific references per patent the firm has used. After that, we construct a binary indicator that considers that the firm does basic research if the average of scientific references per patent is above the mean, and non-basic research otherwise. This is a time invariant proxy for the basicness of the firm's knowledge.

3.4.6 Controls

We use the following variables as controls:

Firm's accumulated patents: This a variable that aggregate the patents that the firm has been granted up to a specific year *t*. As a control for the firm's innovation output, which reflects on the technological capabilities of the firm (Bachmann, 1998).

Return on assets: This is a control for the firm's profitability and it is constructed by dividing the firm's net income divided by the firm's total assets.

Growth Opportunities: we use the total assets proportional change with respect to the previous year total assets. This assets growth measure is associated with the firm's value (Lang & Stulz, 1994).

R&D intensity (R&D expenses adjusted by lagged total assets): This variable captures the investments that the firm makes in the innovation process weighted by the total assets from the previous year. Literature has argued for a positive relationship between internal R&D expenditures and external technology sourcing (Veugelers, 1997).

Sales: We use this variable that capture the firm's size and it absolute returns, which is a factor for the firm's engagement in alliances projects (Cohen, Levin & Mowery, 1987).

Employees: The firm's human resources play a role in the firm's ability to engaged in R&D alliances as the inventors of the firm work with the other firm's inventors. Also, this variable captures the firm size.

Cash: This variable controls for the firm financial liquidity.

Firm Age: This variable control for the firm's experience and it is measured as the difference from the first year that the company appears in the Compustat database.

Lerner Index: This index, formalized in 1934 by Abba Lerner, is a measure of a firm's market power. We calculate it based on the Lerner Index (see Lerner, 1934) by the difference between the output price of a firm and the marginal cost divided by the output price scaled by sales.

Firm and Year Fixed Effects: In order to control for time invariant variations specific to each firm, besides, any time/year specific influences, we use firm's and years fixed effects.

3.5 RESULTS

3.5.1 Descriptive Statistics

The main idea of this research in broad terms is to investigate the effect of firm patent litigiousness on the probability of engaging in technological alliances. This paper empirically studies the effect of the ruling by estimating a difference-in-difference model that exploits a variation in firm's litigiousness in 2006 to identify companies that are more likely to be affected by the eBay ruling in terms of their collaboration activities. Our sample consists of 17,227 firm-year observations. We start by providing some descriptive statics of the variables used in the analyses (See table (1)). table (2) illustrates the statistical correlations between these variables and the numbers do not suggest any harmless correlations.

Insert Tables 1 and 2 about here.

In figure 1, we present a preliminary picture of the firm's tendency to get engaged in relation to its litigiousness. We do so by comparing the patterns in alliances between the firms exposing high and low litigiousness (above and below the mean, respectively). We

calculate the average litigiousness of the firms in our sample and then we aggregate the number of alliances each year for the firms scoring above the mean litigiousness of our sample and for the firms scoring below the mean. The two series in the figure below suggest that the two types of firms having similar patterns in general. However, the gap is dramatically smaller in the last couple of years in our sample, 2009 and 2010. We notice the obvious decrease in the number of alliances in the years 2009 and 2010, which can be explained by the global and Eurozone recessions of 2009–2012 that followed the global financial crisis of 2007–2008 (Shijaku, Larraza-Kintana & Urtasun-Alonso, 2016). Next, we try to study these patterns through our models to statistically quantify these patterns.

3.5.2 Main Results

We perform multiple analyses to examine the predictions and propositions made in the theoretical part of our study. We start the analysis by studying the effect of litigiousness at the extensive margin of having any alliances project or a specific type of alliances. Table (3) represents the first set of analyses using an LPM where model 1 investigates the impact of the court ruling on the probability of having any alliances. By looking at the coefficient of the interaction term *After 2006 × litigiousness*, the firm's litigiousness after the no injunction ruling in the eBay v. MercExchange case seems to have a significantly negative effect on the probability of the firm to start any alliances. More specifically, the coefficient implies that an extra lawsuit in the last three years will increase the chances of the firm to get engaged in on alliances at least by 0.4%[33]. These results indicate the dominance of the negative effect of a weaker IP enforcement on alliances resulting from the possibility that

[33] Considering that litigiousness has a SD of 3.3.238, then one SD increase in the firm's litigiousness is associated with 1.3% less probability of engaging in one alliance at least.

weaker IP rights intensify the costs of knowledge leakage and raise the chances of misappropriation by partners as opposed to the positive effect that may rise because of the litigation costs and risks reduction. This finding also suggests that the focal firm (supply side) cautious behavior after the IP protection reduction overweight the potential increased demand for alliances from the outsiders due to the expected costs and threats decrease. In short, this model connotes that, for our sample, the reduction of the IP enforcement due to the ruling in eBay v. MercExchange has reduced the effect of litigiousness on the firm's number of alliances.

In models 2 and 3, we run the same analysis for the probability of having at least one alliance of a specific type, namely an alliance with a partner with similar size (A Symmetric Alliance) and with a partner with a significantly different size (An Asymmetric Alliance). The interaction term in model 3 is statically in significant denoting that the IP shock had no effect on the probability of the firm to start a symmetric alliance. However, model 4 demonstrate a significant negative association between the firm's litigiousness and the firm's asymmetric alliances. The difference between these two models support our second hypothesis stating that the effect of the reduction of IP protection is more strongly negative for asymmetric collaborations than for symmetric collaborations.

In models 4 and 5, we study the second hypothesis regarding the difference in the effect between alliances with long-term partners with a history and alliances with de novo collaborators. Model 4 shows a significant and negative effect of the shock on the *Alliances with New Partners Probability* while model 5 shows insignificant effect on *Alliances with Old Partners Probability*. These analyses support the prediction made in our hypothesis that the alliances with relational (old) partner are less negatively affected by the reduction of IP rights strength than the alliances with new partners with no prior history. Lastly,

model 6 addresses the moderation effect of knowledge basicness. The coefficient of three-way interaction term is statistically insignificant, which does not support our hypothesis about the difference of the effect on alliances for firms with basic knowledge.

Insert Table 3 about here.

We run the same set of analyses in table 2 for the effect on the number of alliance projects that the firm starts in a specific year. Model 1 in this analysis does not support the dominance of any of the two forces discussed above. Models 2-5, does not provide additional support for our first and second hypotheses. Nonetheless, model 6 provides support the statement in the third hypothesis where we predicted the firm's knowledge basicness to have positive moderation effect. The results reflect that the firms with basic knowledge is more strongly (positively) affected by the shock in terms of the number of alliance reduction. According to the three-way interaction term's coefficient, the firms with basic knowledge is expected to experience an increase of their alliances by 0.03 alliances for each lawsuit they launch after 2006 in comparison to insignificant effect for firms with non-basic knowledge. In other words, one SD increase in the firm's litigiousness is expected to have no impact on the firm's alliances if the frim works mainly on a more applied knowledge, while a similar firm with a difference of working on basic knowledge is expected to launch one more alliance due to that increase of its litigiousness.

Insert Table 4 about here.

For the second set of our measure for the firm collaborative activities, we perform a similar set of analyses for the effect on firm's co-patenting activities (See Tables 5). The first two models, 1 and 2, represent the results for the effect on the extensive marginal of having a co-patent and on the number of co-patents, respectively. Model 2 supports the

finding from table 3 about the average negative effect for our sample of firms. Numerically, one more lawsuit after 2006 is expected to decrease the firm's co-patents by 0.026 in the next three years. The effect of the firm's litigiousness after 2006 is significantly negative on the number of co-patents where one SD increase of the firm litigiousness after the ruling reduces the co-patents by 0.08. The comparison between the relational and de novo collaborators is displayed in the models 3-6 where we compare the probabilities as well as the absolute number of co-patents with these two different types of co-patentees. Analogously to our analysis in table 3 provides, at least partial, support for the first hypothesis. The last two models in table 5 represent the analysis of the moderation effect of the knowledge basicness on the litigiousness effect on the co-patenting activities. From model 7, we can conclude that, for firm's with non-basic knowledge, the reduction in the co-patents is statistically insignificant, however, for firms with basic knowledge, the effect increased to a reduction by 0.022 co-patent. This model provide evidence to support our third hypothesis.

Insert Table 5 about here.

3.5.3 Additional analysis and Robustness Checks

The case of eBay Inc. v. MercExchange was argued March 29th, 2006 and decided on May 15th, 2006. In our main analyses we consider the year 2006 as part of the after the shock period. However, as a robustness check we replicate all our analyses with excluding year 2006 from the after the treatment period. The results are presented in Appendix A and they support our main findings from the main analyses which shows the robustness of our analysis for the inclusion or exclusion of the year of the treatment to the after the shock period.

Moreover, we investigate the effect of the firm's litigiousness on the intensity of alliances over time. We compare the effect among the years in the sample by interacting the variable *litigiousness* with a dummy for each year. Table 6 presents the results of this analysis for our main variables for firm's collaborative activities, namely alliances and co-patenting. We examine the effect for our response variables at the extensive margin, models 1 and 3, and at the absolute effect, models 2 and 4. As we argued that the reduction patent protection does not have a clear-cut direction of its effect, we notice that the firm's toughness in enforcing its IP has generally positive effect on the firm's alliances, especially before 2006, and this effect turns to be insignificant few years after stopping the automatic injunction rule in 2006 (See models 1 and 2). As for the firm's co-patenting activities, we notice in model 3 that the firm's litigiousness does not have a statistically significant effect on the probability on filing a co-patent. However, when we look at the effect on the number of co-patents in model 4, we see that the effect becomes significantly negative for all the years after the change in the IP protection after the ruling in on the "eBay v. MercExchange" case. We also provide a visualization of these coefficients in figure 2 for the four models. These analyses show that generally the reduction of the IP protection tends to decrease the collaborative activities of the firms in our sample and it may take a year or two for the effect to show up.

Insert Table 6 and Figure 2 about here.

In order to examine the potential confounding effect of the financial crisis on 2007-2008 on our result, we replicate the main analysis excluding the years after 2008. As mentioned earlier, the market experienced a general drop in the number of alliances after the financial crisis due to the Eurozone recessions of 2009–2012 (Shijaku, Larraza-Kintana

& Urtasun-Alonso, 2016). The results presented in table 7 show that our baseline results only changed when considering the number of alliances as a response variable (See model 2). These results do not sharply exclude the potential confounding effect of the financial crisis however, the results hold when considering co-patents as a measure for firms' collaborative activities.

Insert Table 7 about here.

3.6 DISCUSSION CONCLUSIONS

To examine the paper's issue, we develop research settings that exploit a turning point in the corporate law recent history, the 2006 Supreme Court decision "eBay v. MercExchange." The ruling ended the near mandatory practice of granting a permanent injunction after a patent proven valid and infringed. Given this large operational risk, the presence of automatic injunction gave patent holders a very strong bargaining position in IP disputes and negotiations and the ruling has reduced the probability of granting the injunction and, therefore, reduced the bargaining power of the plaintiff.

In principle, this paper shows that changes in patent enforcement strength can have a significant impact on the incentives of firms to engage in R&D alliances. We argue that this is due to the consequent change in the balance between the learning opportunities and the litigation risks and costs. First argument that supports the negative effect prediction is that weaker enforcement increases the expected cost of any unintended knowledge leakage that may happen during the partnership, thus discouraging collaborations. The other argument at play is that, with strongly-enforced patent protection, the value of using a technology through an alliance with the counterpart increases vis a vis the value of doing it alone (and assume high expected litigation costs) with strong IPR enforcement. Thus, strong IPR

enforcement increases the relative attractiveness of alliances. Our results imply that the leakage-risk mechanism dominates, on average, the learning opportunities mechanism, at least for our sample of firms. In other words, weaker property rights (default injunction) leads on average to less collaborations and alliances.

Our study contributes to the management literature studying the relationship between legal aspects of the IP rights enforcement and economic activity represented by the alliances and collaboration activities. Moreover, by analyzing the two parties in an alliance in a specific legal system and the litigiousness of the partners, we contribute to the alliances literature through taking into account the expected return from the knowledge learning during a collaborative project, besides, the expected cost of any unintended potential knowledge leakage.

3.7 Chapter 3 Tables

Table 1: Descriptive statistics of the main variables

Variables	Mean	S.D.	Min	Max
Yearly number of alliances	0.109	0.602	0	32
Alliance Probability	0.047	0.212	0	1
Symmetric Alliances	0.013	0.116	0	3
Symmetric Alliance Probability	0.012	0.11	0	1
Asymmetric Alliance Probability	0.017	0.131	0	1
Asymmetric Alliances	0.020	0.170	0	6
Alliances with New Partners	0.102	0.508	0	18
Alliances with New Partners Probability	0.068	0.252	0	1
Alliances with Old Partners	0.007	0.176	0	14
Alliances with Old Partners Probability	0.004	0.063	0	1
Litigiousness	0.678	3.238	0	126
Patent Stock (log(x+1))	2.209	2.148	0	10.116
ROA	-1.019	48.988	-6309	1827
Growth Opportunities	1.281	73.666	-0.999	6785
R&D adjusted by Lagged TA (log(x+1))	0.128	0.216	-0.853	5.656
Sales (log(x+1))	4.753	2.608	-2.017	12.96
Employees (log(x+1))	0.928	1.146	0	6.059
Cash (log(x+1))	3.219	2.649	-6.908	11.321
Firm age (log(x+1))	2.834	0.663	0.693	4.127
Lerner Index	-9.873	273.839	-2.93E+04	358.211

Note: These observations for the full sample of 17,227 firm-year observations.

Table 2: Correlation matrix among of the main variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Yearly number of alliances	1																			
Alliance Probability	0.531	1																		
Symmetric Alliances	0.344	0.353	1																	
Symmetric Alliance Probability	0.34	0.355	0.98	1																
Asymmetric Alliance Probability	0.395	0.455	0.081	0.083	1															
Asymmetric Alliances	0.484	0.425	0.093	0.096	0.901	1														
Alliances with New Partners	0.964	0.586	0.354	0.353	0.414	0.493	1													
Alliances with New Partners Probability	0.659	0.75	0.374	0.381	0.45	0.409	0.743	1												
Alliances with Old Partners	0.641	0.127	0.156	0.146	0.157	0.232	0.415	0.114	1											
Alliances with Old Partners Probability	0.445	0.179	0.172	0.155	0.185	0.206	0.319	0.162	0.602	1										
Litigiousness	0.273	0.153	0.046	0.045	0.243	0.146	0.202	0.138	0.045	0.092	1									
Patent Stock (log(x+1))	0.135	0.104	0.065	0.065	0.08	0.083	0.145	0.138	0.045	0.094	0.258	1								
ROA	0.002	0	0	0	0.002	0.002	0.002	0.001	0.001	0.001	0.004	0.009	1							
Growth Opportunities	-0.003	-0.003	-0.001	-0.001	-0.002	-0.002	-0.003	-0.004	-0.001	-0.001	-0.003	-0.019	0	1						
R&D adjusted by lagged TA (log(x+1))	0.022	0.053	0.021	0.023	0.04	0.031	0.025	0.051	0.001	0.009	-0.035	-0.071	-0.09	0.116	1					
Sales (log(x+1))	0.083	0.029	0.03	0.027	0.022	0.033	0.087	0.054	0.032	0.06	0.211	0.551	0.031	-0.021	-0.413	1				
Employees (log(x+1))	0.122	0.048	0.037	0.033	0.038	0.05	0.127	0.084	0.052	0.093	0.241	0.592	0.016	-0.012	-0.287	0.86	1			
Cash (log(x+1))	0.119	0.096	0.059	0.056	0.077	0.079	0.129	0.125	0.035	0.076	0.204	0.573	0.051	-0.02	-0.159	0.69	0.602	1		
Firm age (log(x+1))	0.025	-0.016	-0.014	-0.014	-0.01	0.002	0.024	-0.013	0.016	0.034	0.113	0.238	0.005	-0.005	-0.271	0.427	0.464	0.145	1	
Lerner Index	0.001	0	0.003	0.003	0.002	0.002	0.001	0.001	0	0.001	0.007	0.007	0.004	-0.001	-0.075	0.069	0.026	0.005	0.028	1

Note: These observations for the full sample of 17,227 firm-year observations.

Table 3: LPM models' main results for the effect of litigiousness on the probability of having at least one (specific type of) alliance and the moderation effect of knowledge basicness.

VARIABLES	(1) Alliance Probability	(2) Symmetric Alliance Probability	(3) Asymmetric Alliance Probability	(4) Alliances with New Partners Probability	(5) Alliances with Old Partners Probability	(6) Alliance Probability
Litigiousness	0.006***	-0.001	0.003*	0.004***	0.001**	0.006***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
After 2006 × Litigiousness	-0.004***	0.000	-0.005***	-0.005***	-0.001	-0.004***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Firm with Basic Knowledge × After 2006 × Litigiousness						0.008
						(0.008)
Firm with Basic Knowledge × Litigiousness						0.002
						(0.004)
Firm with Basic Knowledge × After 2006						0.026
						(0.028)
Patent Stock (log(x+1))	-0.002	0.003	-0.004*	-0.010**	-0.001*	-0.003
	(0.003)	(0.002)	(0.002)	(0.004)	(0.001)	(0.004)
ROA	0.001	0.001	-0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Growth Opportunities	0.000	0.000*	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D adjusted by Lagged TA (log(x+1))	0.017	0.003	0.007	-0.006	0.004	0.014
	(0.016)	(0.007)	(0.012)	(0.018)	(0.005)	(0.018)
Sales (log(x+1))	0.000	-0.000	-0.001	-0.000	-0.001	0.001
	(0.004)	(0.002)	(0.003)	(0.005)	(0.001)	(0.005)
Employees (log(x+1))	-0.003	-0.001	0.004	-0.005	0.006	-0.005
	(0.014)	(0.006)	(0.008)	(0.018)	(0.004)	(0.014)
Cash (log(x+1))	-0.000	-0.001	0.000	0.001	-0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.002)	(0.000)	(0.002)
Firm age (log(x+1))	0.002	-0.014	-0.003	0.007	0.003	0.006
	(0.020)	(0.012)	(0.014)	(0.024)	(0.007)	(0.021)
Lerner Index	-0.000	0.000	0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.044	0.053	0.033	0.088	0.003	0.033
	(0.055)	(0.033)	(0.040)	(0.065)	(0.019)	(0.058)
Observations	17,227	17,227	17,227	17,227	17,227	15,033
Number of firms	2,566	2,566	2,566	2,566	2,566	2,121
Year FE	YES	YES	YES	YES	YES	YES

Note: Estimates based on the firm-level analyses over 10 years under the specifications of a fixed-effect LPM. Robust standard errors clustered at firm-level are in brackets. ***1% significance, **5% significance, *10% significance.

Table 4: Poisson models' main results for the effect of litigiousness on the number of (specific type of) alliance and the moderation of knowledge basicness.

VARIABLES	(1) Alliances	(2) Symmetric Alliances	(3) Asymmetric Alliances	(4) Alliances with New Partners	(5) Alliances with Old Partners	(6) Alliances
Litigiousness	0.011***	-0.009	0.012***	0.005	0.016	0.010***
	(0.003)	(0.011)	(0.005)	(0.004)	(0.021)	(0.003)
After 2006 × Litigiousness	0.001	0.005	-0.018	0.004	-0.003	-0.001
	(0.003)	(0.036)	(0.012)	(0.003)	(0.018)	(0.003)
Firm with Basic Knowledge × After 2006 × Litigiousness						0.030***
						(0.009)
Firm with Basic Knowledge × Litigiousness						0.012
						(0.010)
Firm with Basic Knowledge × After 2006						0.288
						(0.212)
Patent Stock (log(x+1))	-0.101	0.417**	-0.293*	-0.095	-0.554	-0.076
	(0.123)	(0.180)	(0.177)	(0.149)	(0.361)	(0.134)
ROA	0.001	0.325	-0.068	0.003	0.629	0.000
	(0.003)	(0.318)	(0.050)	(0.004)	(0.453)	(0.003)
Growth Opportunities	-0.003	-0.019	0.030	-0.050	-0.293	-0.008
	(0.026)	(0.040)	(0.050)	(0.032)	(0.279)	(0.026)
R&D adjusted by Lagged TA (log(x+1))	0.163	0.117	-0.019	0.082	-0.021	0.166
	(0.313)	(0.706)	(0.447)	(0.334)	(1.631)	(0.330)
Sales (log(x+1))	-0.047	-0.057	-0.064	-0.011	-0.250	-0.039
	(0.090)	(0.171)	(0.137)	(0.084)	(0.368)	(0.092)
Employees (log(x+1))	0.111	-0.002	0.098	0.111	1.617**	-0.058
	(0.322)	(0.419)	(0.453)	(0.242)	(0.704)	(0.365)
Cash (log(x+1))	0.012	-0.111	-0.004	0.017	-0.155	0.051
	(0.050)	(0.093)	(0.091)	(0.046)	(0.202)	(0.054)
Firm age (log(x+1))	-0.213	-0.936	0.200	-0.769**	-0.559	-0.140
	(0.351)	(0.954)	(0.703)	(0.384)	(1.766)	(0.330)
Lerner Index	-0.000***	0.003	0.003**	-0.000	0.002	-0.000***
	(0.000)	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)
Observations	3,806	1,415	1,722	4,759	369	3,481
Number of firms	446	158	201	555	40	405
Year FE	YES	YES	YES	YES	YES	YES

Note: Estimates based on the firm-level analyses over 10 years under the specifications of a fixed-effect Poisson models. Robust standard errors clustered at firm-level are in brackets. ***1% significance, **5% significance, *10% significance.

Table 5: The results of the effect of litigiousness on firm's co-patenting activities.

VARIABLES	(1) Probability of at least one co-patent	(2) Number of co-patents	(3) Probability of a co-patent with a new collaborator	(4) Probability of a co-patent with old collaborator	(5) Number of co-patents with a new collaborator	(6) Number of co-patents with an old collaborator	(7) Probability of at least one co-patent	(8) Number of co-patents
Litigiousness	-0.000	-0.008***	0.002**	0.001	-0.005	-0.003	-0.001	-0.007***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)	(0.005)	(0.002)	(0.002)
After 2006 × Litigiousness	-0.001	-0.026***	-0.004***	0.000	-0.018**	-0.010	-0.001	-0.026***
	(0.002)	(0.004)	(0.001)	(0.002)	(0.008)	(0.007)	(0.002)	(0.004)
Firm with Basic Knowledge × After 2006 × Litigiousness							0.022**	0.018
							(0.009)	(0.022)
Firm with Basic Knowledge × Litigiousness							0.002	-0.033**
							(0.005)	(0.014)
Firm with Basic Knowledge × After 2006							-0.032	-0.056
							(0.020)	(0.282)
Patent Stock (log(x+1))	0.001	-0.669***	0.000	-0.001	0.061	-0.218	0.001	-0.688***
	(0.002)	(0.115)	(0.001)	(0.001)	(0.313)	(0.338)	(0.002)	(0.119)
ROA	-0.000	-0.464*	-0.000	-0.000	-0.967*	0.030	-0.000	-0.436*
	(0.000)	(0.242)	(0.000)	(0.000)	(0.522)	(0.580)	(0.000)	(0.243)
Growth Opportunities	-0.000	0.057	-0.000	-0.000	-0.232	-0.061	-0.000**	0.053
	(0.000)	(0.089)	(0.000)	(0.000)	(0.256)	(0.120)	(0.000)	(0.090)
R&D adjusted by lagged TA (log(x+1))	-0.006	-2.711***	-0.000	-0.005	0.377	-2.657*	-0.007	-2.591***
	(0.006)	(0.870)	(0.004)	(0.004)	(1.390)	(1.466)	(0.006)	(0.875)
Sales (log(x+1))	0.006**	1.163***	0.004**	0.004	1.095***	0.554*	0.006**	1.173***
	(0.003)	(0.146)	(0.001)	(0.002)	(0.328)	(0.322)	(0.002)	(0.150)
Employees (log(x+1))	0.012	-0.433**	0.009	0.002	-0.363	0.259	0.013	-0.409*
	(0.009)	(0.214)	(0.006)	(0.007)	(0.552)	(0.521)	(0.009)	(0.216)
Cash (log(x+1))	-0.000	0.397***	-0.000	0.001	0.260*	0.180	0.000	0.391***
	(0.001)	(0.057)	(0.001)	(0.001)	(0.141)	(0.201)	(0.001)	(0.058)
Firm age (log(x+1))	-0.002	-0.192	0.004	0.013	-0.603	-0.004	-0.008	-0.241
	(0.014)	(0.470)	(0.013)	(0.011)	(1.355)	(1.311)	(0.016)	(0.478)
Lerner Index	-0.000	-0.023	-0.000	-0.000	-0.015	0.056	-0.000	-0.023
	(0.000)	(0.025)	(0.000)	(0.000)	(0.032)	(0.046)	(0.000)	(0.024)
Constant	-0.011		-0.022	-0.039			0.004	
	(0.041)		(0.034)	(0.033)			(0.043)	
Observations	17,227	1,540	17,227	17,227	1,214	782	15,033	1,520
Number of firms	2,566	162	2,566	2,566	125	83	2,121	159
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Estimates based on the firm-level analyses over 10 years under the specifications of a fixed-effect models. We use LPM in models 1, 3, 4, and 7. Poisson models are employed in the other models. Robust standard errors clustered at firm-level are in brackets. ***1% significance, **5% significance, *10% significance.

Table 6: The effect of firm's litigiousness over the years in the sample.

VARIABLES	(1) Alliance Probability	(2) Alliances	(3) Probability of at least one co-patent	(4) Number of co-patents
Litigiousness × Year 2000	0.008	-0.012	0.003	-0.047***
	(0.005)	(0.039)	(0.004)	(0.015)
Litigiousness × Year 2001	0.006	0.002	0.003	-0.002
	(0.004)	(0.030)	(0.003)	(0.009)
Litigiousness × Year 2002	0.009***	0.011	0.002	0.008
	(0.002)	(0.013)	(0.002)	(0.006)
Litigiousness × Year 2003	0.006***	0.009	-0.003	0.000
	(0.002)	(0.012)	(0.003)	(0.005)
Litigiousness × Year 2004	0.007***	0.016**	-0.000	-0.012***
	(0.002)	(0.008)	(0.002)	(0.004)
Litigiousness × Year 2005	0.007***	0.011**	-0.002	-0.012***
	(0.001)	(0.005)	(0.002)	(0.003)
Litigiousness × Year 2006	0.006***	0.001	0.001	-0.015***
	(0.002)	(0.008)	(0.002)	(0.004)
Litigiousness × Year 2007	0.011***	0.013	0.002	-0.050***
	(0.002)	(0.009)	(0.003)	(0.008)
Litigiousness × Year 2008	0.009***	0.005	-0.005	-0.080***
	(0.003)	(0.018)	(0.003)	(0.013)
Litigiousness × Year 2009	-0.003	-0.001	-0.005	-0.028***
	(0.003)	(0.018)	(0.004)	(0.008)
Litigiousness × Year 2010	-0.001	0.002	0.002	-0.026***
	(0.002)	(0.014)	(0.002)	(0.005)
Controls	YES	YES	YES	YES
Constant	0.049		0.001	
	(0.054)		(0.041)	
Observations	17,227	3,806	17,227	1,540
Number of Firms	2,566	446	2,566	162
Year FE	YES	YES	YES	YES

Note: Estimates based on the firm-level analyses over 10 years under the specifications of a fixed-effect models. We use LPM in models 1 and 3. Poisson models are employed in the other models. In these models, we include all the control variables used in the main analyses. Robust standard errors clustered at firm-level are in brackets. ***1% significance, **5% significance, *10% significance.

Table 7: The potential confounding effect of the 2007-2008 financial crisis of the IP protection strength relationship with collaborations prevalence.

VARIABLES	(1) Alliance Probability	(2) Alliances	(3) Probability of at least one co-patent	(4) Number of co-patents
Litigiousness	0.006***	0.009***	-0.001	-0.008***
	(0.001)	(0.003)	(0.001)	(0.003)
After 2006 × Litigiousness	0.003*	0.002	-0.002	-0.051***
	(0.002)	(0.003)	(0.002)	(0.008)
Patent Stock (log(x+1))	0.001	-0.094	0.001	-0.921***
	(0.004)	(0.127)	(0.002)	(0.149)
ROA	-0.000	-0.026**	-0.000	-0.547**
	(0.000)	(0.012)	(0.000)	(0.258)
Growth	0.000	-0.009	-0.000	-0.111
	(0.000)	(0.028)	(0.000)	(0.144)
R&D adjusted by Lagged TA (log(x+1))	0.014	0.282	-0.007	-1.877*
	(0.020)	(0.388)	(0.006)	(1.090)
Sales (log(x+1))	0.002	-0.072	0.005**	1.853***
	(0.006)	(0.095)	(0.002)	(0.183)
Employees (log(x+1))	-0.002	0.188	0.013	-1.292***
	(0.018)	(0.339)	(0.009)	(0.271)
Cash (log(x+1))	-0.000	0.031	-0.001	0.399***
	(0.002)	(0.053)	(0.001)	(0.068)
Firm age (log(x+1))	0.001	-0.317	-0.019	-0.305
	(0.027)	(0.377)	(0.018)	(0.572)
Lerner Index	-0.000	-0.000***	-0.000	-0.015
	(0.000)	(0.000)	(0.000)	(0.014)
Constant	0.032		0.040	
	(0.074)		(0.049)	
Observations	14,377	3,066	14,377	1,174
Number of firms	2,442	420	2,442	144
Year FE	YES	YES	YES	YES

Note: Estimates based on the firm-level analyses over 10 years under the specifications of a fixed-effect models. We use LPM in models 1 and 3. Poisson models are employed in the other models. Robust standard errors clustered at firm-level are in brackets. ***1% significance, **5% significance, *10% significance.

3.8 Chapter 3 Figures

Figure 1: The pattern of the number of alliances of firms with high and low litigiousness.

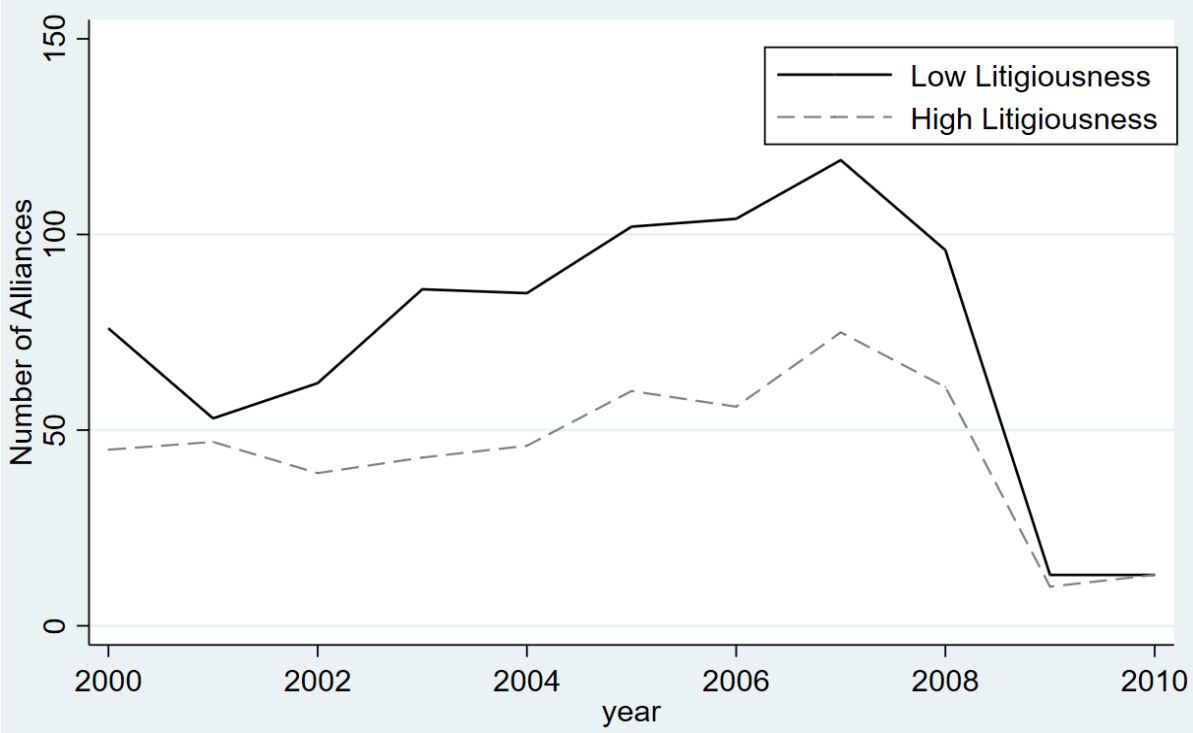
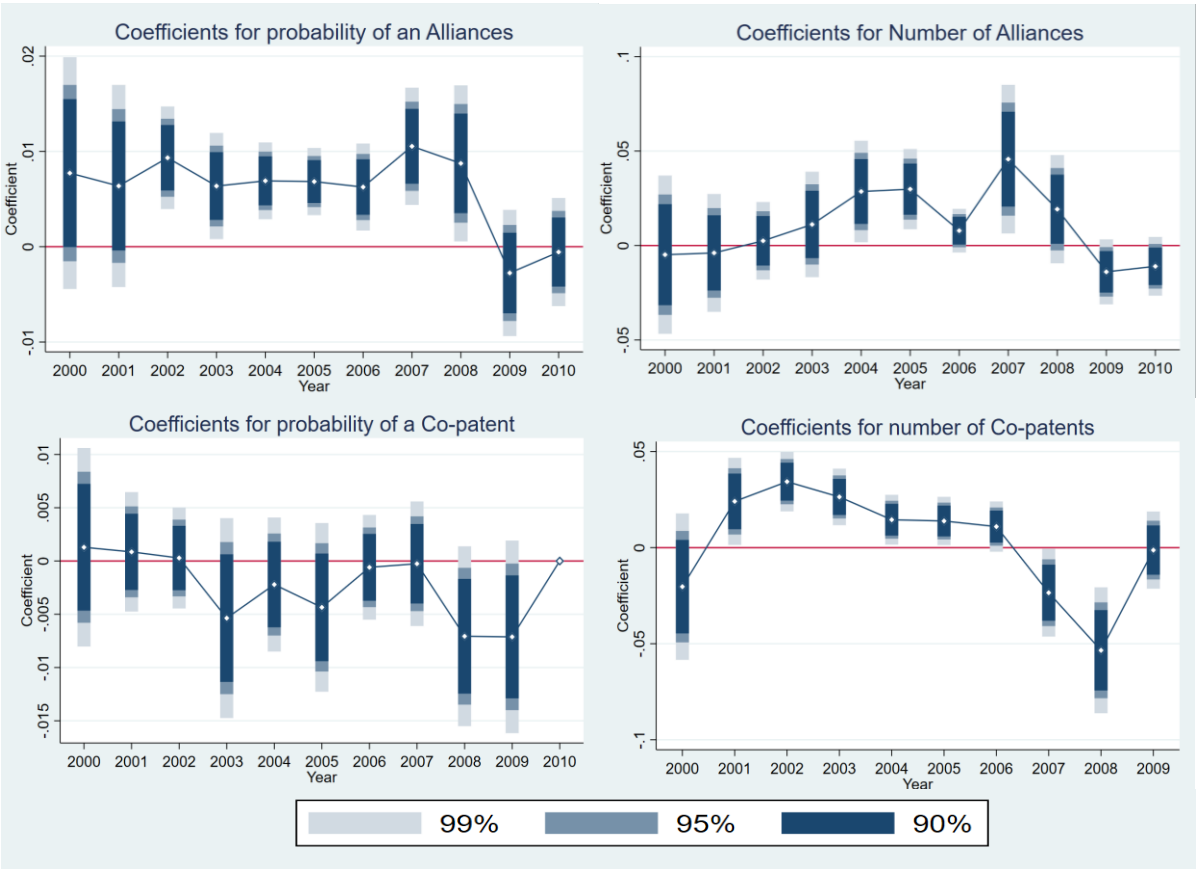


Figure 2: The effect of firm's litigiousness on its collaborative activities over the years.



3.9 Chapter 3 Appendix A

Table A.1: Main results of FE LPM models for the effect of litigiousness on the probability of having at least one (specific type of) alliance and the moderation of knowledge basicness.

VARIABLES	(1) Alliance Probability	(2) Symmetric Alliance Probability	(3) Asymmetric Alliance Probability	(4) Alliances with New Partners Probability	(5) Alliances with Old Partners Probability	(6) Alliance Probability
Litigiousness	0.007***	-0.001	0.004***	0.005***	0.002**	0.007***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
After 2005 × Litigiousness	-0.003***	0.001	-0.005***	-0.004***	-0.001*	-0.003***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Firm with Basic Knowledge × After 2005 × Litigiousness						0.007*
						(0.004)
Firm with Basic Knowledge × Litigiousness						0.000
						(0.005)
Firm with Basic Knowledge × After 2005						0.012
						(0.024)
Patent Stock (log(x+1))	-0.002	0.003	-0.003	-0.010**	-0.001*	-0.003
	(0.003)	(0.002)	(0.002)	(0.004)	(0.001)	(0.004)
ROA	0.001	0.001	-0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Growth Opportunities	0.000	0.000*	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D adjusted by Lagged TA (log(x+1))	0.017	0.003	0.007	-0.005	0.004	0.014
	(0.016)	(0.007)	(0.012)	(0.018)	(0.005)	(0.018)
Sales (log(x+1))	0.000	-0.000	-0.001	-0.000	-0.001	0.001
	(0.004)	(0.002)	(0.003)	(0.005)	(0.001)	(0.005)
Employees (log(x+1))	-0.003	-0.001	0.005	-0.005	0.006	-0.005
	(0.014)	(0.006)	(0.008)	(0.018)	(0.004)	(0.014)
Cash (log(x+1))	-0.000	-0.001	-0.000	0.001	-0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.002)	(0.000)	(0.002)
Firm age (log(x+1))	0.002	-0.014	-0.006	0.007	0.002	0.005
	(0.020)	(0.011)	(0.013)	(0.024)	(0.007)	(0.021)
Lerner Index	-0.000	0.000	0.000*	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.044	0.051*	0.042	0.088	0.006	0.036
	(0.055)	(0.030)	(0.038)	(0.065)	(0.020)	(0.059)
Observations	17,227	17,227	17,227	17,227	17,227	15,033
R-squared	0.012	0.004	0.009	0.011	0.004	0.013
Number of firms	2,566	2,566	2,566	2,566	2,566	2,121
Year FE	YES	YES	YES	YES	YES	YES

Note: Estimates based on the firm-level analyses over 10 years under the specifications of a fixed-effect LPM. Robust standard errors clustered at firm-level are in brackets. ***1% significance, **5% significance, *10% significance.

Table A.2: Main results of FE Poisson models for the effect of litigiousness on the number of (specific type of) alliance and the moderation of knowledge basicness.

VARIABLES	(1) Alliances	(2) Symmetric Alliances	(3) Asymmetric Alliances	(4) Alliances with New Partners	(5) Alliances with Old Partners	(6) Alliances
Litigiousness	0.012***	-0.013	0.015***	0.006	0.019	0.012***
	(0.004)	(0.014)	(0.005)	(0.005)	(0.021)	(0.003)
After 2005 × Litigiousness	-0.006**	0.013	-0.022***	-0.002	-0.012	-0.008**
	(0.003)	(0.020)	(0.007)	(0.004)	(0.015)	(0.004)
Firm with Basic Knowledge × After 2005 × Litigiousness						0.045***
						(0.008)
Firm with Basic Knowledge × Litigiousness						-0.013
						(0.014)
Firm with Basic Knowledge × After 2005						0.217
						(0.180)
Patent Stock (log(x+1))	-0.096	0.411**	-0.291	-0.092	-0.540	-0.075
	(0.123)	(0.179)	(0.177)	(0.148)	(0.362)	(0.133)
ROA	0.001	0.326	-0.066	0.003	0.619	0.000
	(0.003)	(0.318)	(0.048)	(0.004)	(0.451)	(0.003)
Growth Opportunities	-0.004	-0.018	0.029	-0.050	-0.291	-0.009
	(0.027)	(0.039)	(0.051)	(0.032)	(0.277)	(0.027)
R&D adjusted by Lagged TA (log(x+1))	0.151	0.127	-0.027	0.074	-0.026	0.155
	(0.315)	(0.705)	(0.448)	(0.335)	(1.629)	(0.333)
Sales (log(x+1))	-0.050	-0.058	-0.070	-0.013	-0.262	-0.045
	(0.091)	(0.171)	(0.138)	(0.084)	(0.373)	(0.094)
Employees (log(x+1))	0.086	0.003	0.064	0.101	1.607**	-0.089
	(0.321)	(0.420)	(0.461)	(0.242)	(0.707)	(0.364)
Cash (log(x+1))	0.016	-0.109	-0.002	0.018	-0.156	0.056
	(0.050)	(0.093)	(0.091)	(0.046)	(0.205)	(0.055)
Firm age (log(x+1))	-0.348	-0.828	0.027	-0.849**	-0.657	-0.276
	(0.363)	(0.883)	(0.704)	(0.381)	(1.734)	(0.343)
Lerner Index	-0.000***	0.003	0.003**	-0.000	0.002	-0.000***
	(0.000)	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)
Observations	3,806	1,415	1,722	4,759	369	3,481
Number of firms	446	158	201	555	40	405
Year FE	YES	YES	YES	YES	YES	YES

Note: Estimates based on the firm-level analyses over 10 years under the specifications of a fixed-effect Poisson models. Robust standard errors clustered at firm-level are in brackets. ***1% significance, **5% significance, *10% significance.

Table A.3: Results of the effect of litigiousness on firm's co-patenting activities.

VARIABLES	(1) Probability of at least one co-patent	(2) Number of co-patents	(3) Probability of a co-patent with a new collaborator	(4) Probability of a co-patent with an old collaborator	(5) Number of co-patents with a new collaborator	(6) Number of co-patents with an old collaborator	(7) Probability of at least one co-patent	(8) Number of co-patents
Litigiousness	-0.001	-0.005**	0.002*	0.001	-0.003	-0.001	-0.001	-0.004*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.005)	(0.002)	(0.002)
After 2005 × Litigiousness	0.000	-0.019***	-0.002**	0.000	-0.012	-0.008*	-0.000	-0.019***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.008)	(0.004)	(0.001)	(0.003)
Firm with Basic Knowledge × After 2005 × Litigiousness							0.024***	0.039
							(0.003)	(0.024)
Firm with Basic Knowledge × Litigiousness							-0.009	-0.057**
							(0.007)	(0.024)
Firm with Basic Knowledge × After 2005							-0.024	-0.092
							(0.017)	(0.276)
Patent Stock (log(x+1))	0.000	-0.673***	0.000	-0.001	0.055	-0.216	0.001	-0.696***
	(0.002)	(0.115)	(0.001)	(0.001)	(0.312)	(0.337)	(0.002)	(0.119)
ROA	-0.000	-0.440*	-0.000	-0.000	-0.961*	0.049	-0.000	-0.425*
	(0.000)	(0.243)	(0.000)	(0.000)	(0.518)	(0.585)	(0.000)	(0.242)
Growth Opportunities	-0.000	0.032	-0.000	-0.000	-0.246	-0.070	-0.000*	0.033
	(0.000)	(0.094)	(0.000)	(0.000)	(0.254)	(0.127)	(0.000)	(0.094)
R&D adjusted by Lagged TA (log(x+1))	-0.006	-2.558***	-0.000	-0.005	0.450	-2.658*	-0.006	-2.548***
	(0.006)	(0.873)	(0.004)	(0.004)	(1.393)	(1.516)	(0.006)	(0.879)
Sales (log(x+1))	0.006**	1.125***	0.004**	0.004	1.082***	0.538	0.006**	1.101***
	(0.003)	(0.144)	(0.001)	(0.002)	(0.322)	(0.328)	(0.003)	(0.147)
Employees (log(x+1))	0.011	-0.411*	0.009	0.002	-0.370	0.262	0.013	-0.378*
	(0.009)	(0.214)	(0.006)	(0.007)	(0.554)	(0.537)	(0.009)	(0.215)
Cash (log(x+1))	-0.000	0.397***	-0.000	0.001	0.256*	0.186	-0.000	0.389***
	(0.001)	(0.057)	(0.001)	(0.001)	(0.142)	(0.201)	(0.001)	(0.058)
Firm age (log(x+1))	0.001	-0.122	0.006	0.012	-0.559	0.022	-0.005	-0.174
	(0.015)	(0.470)	(0.012)	(0.011)	(1.331)	(1.291)	(0.016)	(0.477)
Lerner Index	-0.000	-0.021	-0.000	-0.000	-0.015	0.059	-0.000	-0.020
	(0.000)	(0.022)	(0.000)	(0.000)	(0.032)	(0.047)	(0.000)	(0.020)
Constant	-0.018		-0.028	-0.038			-0.005	
	(0.041)		(0.033)	(0.032)			(0.043)	
Observations	17,227	1,540	17,227	17,227	1,214	782	15,033	1,520
Number of firms	2,566	162	2,566	2,566	125	83	2,121	159
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Estimates based on the firm-level analyses over 10 years under the specifications of a fixed-effect Poisson models. We use LPM in models 1, 3, 4, and 7. Poisson models are employed in the other models. Robust standard errors clustered at firm-level are in brackets. ***1% significance, **5% significance, *10% significance.

BIBLIOGRAPHY

Abadie, A., Athey, S., Imbens, G.W. and Wooldridge, J., 2017. When should you adjust standard errors for clustering? (No. w24003). ***National Bureau of Economic Research***.

Agarwal, R., Ganco, M. and Ziedonis, R.H., 2009. Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. ***Strategic Management Journal***, *30*(13): 1349-1374.

Aghion, P. & Howitt, P. (1992). ***A Model of Growth through***.

Agrawal, A. & Henderson, R., 2002. Putting patents in context: Exploring knowledge transfer from MIT. ***Management Science***, 48(1): 44-60.

Agrawal, A., Cockburn, I. & McHale, J., 2006, Gone but not forgotten: knowledge flows, labor mobility enduring social relationships. ***Journal of Economic Geography***. 6(5): 571-591

Ahmadpoor, M. and Jones, B.F., 2017. The dual frontier: Patented inventions and prior scientific advance. ***Science***, 357(6351): 583-587.

Ahuja, G., 2007. ***When Atlas shrugged: Preemption, complexity and division of labor in a theory of appropriability***. Working paper, University of Michigan Business School, Ann Arbor, 1001: 48109-1234.

Ahuja, G., Lampert, C. M. & Novelli, E., 2013. The second face of appropriability: Generative appropriability and its determinants. ***Academy of Management Review***, 38(2): 248-269.

Alexy, O., George, G., & Salter, A. J. 2013. Cui bono? The selective revealing of knowledge and its implications for innovative activity. ***Academy of management review***, *38*(2), 270-291.

Alexy, O. & Reitzig, M., 2013. Private–collective innovation, competition, and firms' counterintuitive appropriation strategies. ***Research Policy***, 42(4): 895-913.

Alexy, O., West, J., Klapper, H. & Reitzig, M., 2018. Surrendering control to gain advantage: Reconciling openness and the resource-based view of the firm. ***Strategic Management Journal***, 39(6): 1704-1727.

Allison, J. R., Lemley, M. A., Moore, K. A. & Trunkey, R. D., 2004. Valuable patents. ***Georgetown Law Journal***, 92, 435.

Almeida, P. & Kogut, B., 1999. Localization of Knowledge and the Mobility of Engineers in Regional Networks. ***Management Science*** 45(7): 905-917.

Anand, B. N. & Khanna, T. (2000). The structure of licensing contracts. ***The Journal of Industrial Economics***, 48(1): 103-135.

Arora, A. & Gambardella, A., 2010. Ideas for rent: an overview of markets for technology. ***Industrial and corporate change***, 19(3): 775-803.

Arora, A., & Gambardella, A. 1994. Evaluating technological information and utilizing it: Scientific knowledge, technological capability, and external linkages in biotechnology. ***Journal of Economic Behavior & Organization***, 24(1), 91-114.

Arora, A., 1995. Licensing tacit knowledge: intellectual property rights and the market for know-how. ***Economics of innovation and New Technology,*** 4(1): 41-60.

Arora, A. & Ceccagnoli, M., 2006. Profiting from licensing: The role of patent protection and commercialization capabilities. ***Management Science,*** 52(2): 293-308.

Arora, A., Belenzon, S. and Sheer, L., 2019. *Why do firms invest in research?* NBER Working Paper No., 23187.

Arora, A., Fosfuri, A. & Gambardella, A., 2004. ***Markets for technology: The Economics Of Innovation and Corporate Strategy***. Cambridge, MA: MIT press.

Arts, S., Cassiman, B. & Gomez, J. C., 2018. Text matching to measure patent similarity. Strategic Management Journal, 39(1): 62-84.

Ayvazyan, A. & Matr, S., 2019. How Outbound Open Innovation Strategies affect the Subsequent Innovation Process in the Technology Field: Evidence from IBM's Patent Pledge. Working paper.

Bachmann, A., 1998. Profiles of corporate technological capabilities—A comparison of large British and German pharmaceutical companies. ***Technovation***, 18(10): 593-656.

Barney, J., 1991. Firm resources and competitive advantage. ***Journal of Management,*** 17(1): 99-120.

Belenzon, S. 2012. Cumulative innovation and market value: Evidence from patent citations. ***The Economic Journal***, 122(559), 265-285.

Bertrand, M., Duflo, E. and Mullainathan, S., 2004. How much should we trust difference-in-differences estimates? ***The Quarterly journal of economics***, 119(1): 249-275.

Bessen, J., 2009. Estimates of patent rents from firm market value. ***Research Policy***, 38: 1604-1616.

Bessen, J.E., Bessen, J. and Meurer, M.J., 2008. Patent failure: How judges, bureaucrats, and lawyers put innovators at risk. ***Princeton University Press***.

Boudreau, K., 2010. Open platform strategies and innovation: Granting access vs. devolving control. ***Management Science,*** 56(10): 1849-1872.

Bryan, K.A., Ozcan, Y. and Sampat, B., 2020. In-text patent citations: A user's guide. ***Research Policy***, *49*(4): 103946.

Caballero, R.J. & Jaffe, A.B., 1993. How high are the giants' shoulders: An empirical assessment of knowledge spillovers and creative destruction in a model of economic growth. ***NBER macroeconomics annual***, 8: 15-74.

Cassiman, B. & Valentini, G., 2016. Open innovation: Are inbound and outbound knowledge flows really complementary? ***Strategic Management Journal,*** 37(6): 1034-1046.

Cassiman, B., Veugelers, R. & Arts, S., 2018. Mind the gap: Capturing value from basic research through combining mobile inventors and partnerships. ***Research Policy***, 47(9): 1811-1824.

Cesaroni, F., 2004. Technological outsourcing and product diversification: do markets for technology affect firms' strategies? ***Research Policy,*** 33(10): 1547-1564.

Chesbrough, H., 2003, ***Open innovation: The new imperative for creating and profiting from technology***, Harvard, MA: Harvard Business Press.

Chesbrough, H., 2003. The logic of open innovation: managing intellectual property. ***California Management Review,*** 45 (3): 33-58.

Chesbrough, H., 2006a. ***Open innovation: The new imperative for creating and profiting from technology***. Harvard, MA: Harvard Business Press.

Chesbrough, H., 2006b. ***Open Business Models: How to Thrive in the New Innovation Landscape***, Harvard, MA: Harvard Business Press.

Chesbrough, H., Crowther, A. K., 2006. Beyond high-tech: early adopters of open innovation in other industries. ***R&D Management***, 36(3): 229-236.

Chien, C. V. and Lemley, M. A., 2012. Patent holdup, the itc, and the public interest. ***Cornell Law Review.***

Clarkson, G., 2005. Patent informatics for patent thicket detection: a network analytic approach for measuring the density of patent space. ***Academy of Management***, Honolulu.

Cohen, J. E. & Lemley, M. A., 2001. Patent scope and innovation in the software industry. ***California Law Review***, 89: 1.

Cohen, L.H., Gurun, U. and Kominers S. D., 2014. *Patent Trolls: Evidence from Targeted Firms*. NBER Working Paper No., 20322.

Cohen, W.M. and Levinthal, D.A., 1989. Innovation and learning: the two faces of R & D. ***The economic journal***, 99(397): 569-596.

Cohen, W.M. and Levinthal, D.A., 1990. Absorptive capacity: A new perspective on learning and innovation. ***Administrative science quarterly***, 35(1): 128-152.

Cohen, W.M., Levin, R.C. and Mowery, D.C., 1987. Firm size and R&D intensity: A re-examination (No. w2205). ***National Bureau of Economic Research***.

Cohen, W.M., Nelson, R. R. & Walsh, J. P., 2000. ***Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not),*** Working Paper, no. W7552, National Bureau of Economic Research, Cambridge, MA.

Collis, D.J. & Montgomery, C.A., 1998. ***Corporate strategy: A resource-based view.*** Boston: McGraw-Hill/Irwin.

Contreras, J. L., 2015. Patent pledges. ***Arizona State Law Journal,*** 47(3): 543–557.

Corredoira, R. & Rosenkopf, L., 2010. Should auld acquaintance be Forgot? The reverse transfer of knowledge through mobility ties. ***Strategic Management Journal*** 31: 159-181.

Dahlander, L. & Gann, D., 2007. ***Appropriability, proximity, routines and innovation: How open is open innovation***. Paper presented at DRUID summer conference (Vol. 34).

Dahlander, L. & Gann, D., 2010. How open is innovation? ***Research policy,*** 39(6): 699-709.

Danneels, E., 2007. The process of technological competence leveraging. ***Strategic Management Journal,*** 28(5): 511-533.

Deeds, D.L. and Hill, C.W., 1999. An examination of opportunistic action within research alliances: Evidence from the biotechnology industry. ***Journal of Business Venturing***, 14(2): 141-163.

Denrell, J. & March, J. G., 2001. Adaptation as information restriction: The hot stove effect. ***Organization Science,*** 12(5): 523-538.

Diestre, L., and Rajagopalan, N., 2012. Are all 'sharks' dangerous? new biotechnology ventures and partner selection in R&D alliances. ***Strategic Management Journal***, 33(10): 1115-1134.

Duguet, E. & MacGarvie, M., 2005. How well do patent citations measure flows of technology? Evidence from French innovation surveys. ***Economics of Innovation and New Technology***, 14(5): 375-393.

Dushnitsky, G. and Lenox, M.J., 2005. When do firms undertake R&D by investing in new ventures?. ***Strategic Management Journal***, 26(10): 947-965.

Eggers, JP, & Kaul, A., 2018. Motivation and ability? A behavioral perspective on the pursuit of radical invention in multi-technology incumbents. ***Academy of Management Journal,*** 61(1): 67-93.

Fosfuri, A., 2004. Determinants of international activity: Evidence from the chemical processing industry. ***Research Policy***, 33(10): 1599-1614

Fosfuri, A. & Ronde, T., 2004. High-Tech Clusters, Technology Spillovers, and Trade Secret Laws, ***International Journal of Industrial Organization***, 22: 45-65.

Fosfuri A., 2006. The licensing dilemma: understanding the determinants of the rate of technology licensing. ***Strategic Management Journal***, 27(12): 1141-1158.

Fosfuri, A., Giarratana, M.S. & Luzzi, A., 2008. The penguin has entered the building: The commercialization of open source software products. ***Organization Science,*** 19(2): 292-305.

Galasso, A. & Schankerman, M., 2015. Patents and cumulative innovation: Causal evidence from the courts. ***The Quarterly Journal of Economics***, 130(1): 317-369.

Gambardella, A., Giuri, P. & Luzzi, A., 2007. The market for patents in Europe. ***Research Policy,*** 36(8): 1163-1183.

Ganco, M., Ziedonis, R.H. & Agarwal, R., 2015. More stars stay, but the brightest ones still leave: Job hopping in the shadow of patent enforcement. ***Strategic Management Journal***, 36(5): 659-685.

Gans, J.S. & Stern, S., 2003. The product market and the market for "ideas": commercialization strategies for technology entrepreneurs. ***Research policy***, 32(2): 333-350.

Gans, J.S., Hsu, D.H. and Stern, S., 2008. The impact of uncertain intellectual property rights on the market for ideas: Evidence from patent grant delays. ***Management Science***, 54(5): 982-997.

Gans, J.S. & Hsu, D., Stern, S., 2002. When does start-up innovation spur the gale of creative destruction? ***RAND Journal of Economics,*** 33 (4): 571-586.

Gatignon, H., Tushman, M.L., Smith, W. & Anderson, P., 2002. A structural approach to assessing innovation: Construct development of innovation locus, type, and characteristics. ***Management science,*** 48(9): 1103-1122.

Gay, C. & Le Bas, C., 2005. Uses without too many abuses of patent citations or the simple economics of patent citations as a measure of value and flows of knowledge. ***Economics of Innovation and New Technology***, 14(5): 333-338.

Ge, C., Huang, K.W. & Png, I.P., 2016. Engineer/scientist careers: Patents, online profiles, and misclassification bias. ***Strategic Management Journal***, 37(1): 232-253.

Goettsch, K.D., 2003. Recent Development: SCO Group v. IBM: The Future of Open-Source Software, **University of Illinois Journal on Law, Technology and Policy**, p.581.

Green, J. R. & Scotchmer, S., 1995. On the division of profit in sequential innovation. ***The RAND Journal of Economics***, 26(1): 20-33.

Grindley, P.C. & Teece, D.J., 1997. Managing intellectual capital: licensing and cross-licensing in semiconductors and electronics. California Management Review, 39(2): 8-41.

Guarino, A. & Tedeschi, P., 2006. ***Endogenous Knowledge Spillovers and Labor Mobility in Industrial Clusters***, Working Paper No., 20060507, Università degli Studi di Milano-Bicocca.

Hagedoorn, J., 2003. Sharing intellectual property rights—an exploratory study of joint patenting amongst companies. ***Industrial and Corporate Change***, *12*(5): 1035-1050.

Hall, B.H. & Ziedonis, R.H., 2001. The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979-1995. ***RAND Journal of Economics***, 32(1): 101-128.

Hausknecht, J.P. & Trevor, C.O., 2011. Collective turnover at the group, unit, and organizational levels: Evidence, issues, and implications. ***Journal of Management***, 37(1): 352-388.

Hegde, D., 2014. Tacit knowledge and the structure of license contracts: Evidence from the biomedical industry. ***Journal of Economics & Management Strategy***, 23(3): 568-600.

Henderson, R. and Clark, K.B., 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. ***Administrative science quarterly***, 35(1): 9-30.

Henkel, J., 2006. Selective revealing in open innovation processes: The case of embedded Linux. ***Research policy,*** 35(7): 953-969.

Henkel, J., Schöberl, S. and Alexy, O., 2014. The emergence of openness: How and why firms adopt selective revealing in open innovation. ***Research Policy***, *43*(5): 879-890.

Hoisl, K., 2007. Tracing Mobile Inventors -The Causality between Inventor Mobility and Inventor Productivity. ***Research Policy***, 36: 619-636.

Hoisl, K., 2009. Does Mobility Increase the Productivity of Inventors? ***Journal of Technology Transfer***, 34(2): 212-225

Holte, R. T., 2015. The misinterpretation of eBay v. Mercexchange and why: An analysis of the case history, precedent, and parties. ***Chapman Law Review***.

Huber, G.P., 1991. Organizational learning: The contributing processes and the literatures. ***Organization Science***, 2(1): 88-115.

Jaffe, A.B. and Lerner, J., 2011. ***Innovation and its discontents: How our broken patent system is endangering innovation and progress, and what to do about it***. Princeton University Press.

Jaffe, A.B., Trajtenberg, M. & Fogarty, M.S., 2000. Knowledge spillovers and patent citations: Evidence from a survey of inventors. American Economic Review, 90(2), pp.215-218.

Jaffe, A.B., Trajtenberg, M. and Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. ***The Quarterly Journal of Economics***, 108(3): 577-598.

Jugend, D., Jabbour, C. J. C., Scaliza, J. A. A., Rocha, R. S., Junior, J. A. G., Latan, H. & Salgado, M. H., 2018. Relationships among open innovation, innovative performance, government support and firm size: Comparing Brazilian firms embracing different levels of radicalism in innovation. ***Technovation.*** 74-75:54-65.

Katila, R., Rosenberger, J., and Eisenhardt, K. M., 2008. Swimming with sharks: Technology ventures, defense mechanisms, and corporate relationships. ***Administrative Science Quarterly***, 53: 295–332.

Katz, M. L. & Shapiro, C., 1986. Technology adoption in the presence of network externalities. ***Journal of Political Economy,*** 94(4): 822-841.

Kim, J. & Marschke, G., 2005. Labor Mobility of Scientists, Technological Diffusion, and the Firm's Patenting Decision, ***RAND Journal of Economics,*** 36: 298-317.

Lane, P.J. and Lubatkin, M., 1998. Relative absorptive capacity and interorganizational learning. ***Strategic Management Journal***, 19(5), pp.461-477.

Lang, L.H. and Stulz, R.M., 1994. Tobin's q, corporate diversification, and firm performance. ***Journal of political economy***, *102*(6): 1248-1280.

Lee, J.S., Park, J.H. & Bae, Z.T., 2017. The effects of licensing-in on innovative performance in different technological regimes. Research Policy, 46(2): 485-496.

Lemley, M.A. and Shapiro, C., 2005. Probabilistic patents. ***Journal of Economic Perspectives***, 19(2): 75-98.

Lerner, A., 1934. The concept of monopoly and the measurement of monopoly power. ***Review of Economic Studies***, 1(157): 75.

Levin, R.C., Klevorick, A.K., Nelson, R.R., Winter, S.G., Gilbert, R. and Griliches, Z., 1987. Appropriating the returns from industrial research and development. ***Brookings papers on economic activity***, 1987(3): 783-831.

Levinthal, D. A., 1997. Adaptation on rugged landscapes. ***Management science,*** 43(7): 934-950.

Levinthal, D.A. and March, J.G., 1993. The myopia of learning. ***Strategic management journal***, 14(2): 95-112.

Levitt, B. and March, J.G., 1988. Organizational learning. ***Annual review of sociology***, 14(1): 319-338.

Lewis, T. R. & Yao, D., 2001. ***Innovation, knowledge flow, and worker mobility.*** Unpublished manuscript, Warrington School of Business, University of Florida. Florida.

Lichtenthaler, U. & Ernst, H., 2007. External technology commercialization in large firms: results of a quantitative benchmarking study. ***R&D Management***, 37(5): 383-397.

Ludlow, T., 2014. Sign of the Times: Trends in Technology IP Licensing. ***Intellectual Asset Management***, 66:31-38.

Malerba, F., 2002. Sectoral systems of innovation and production. Research policy, 31(2): 247-264.

Marco, A. C., Sarnoff, J. D. & deGrazia, C., 2016. ***Patent claims and patent scope*** (USPTO Economic Working Paper NO.16001). Hoover Institution Working Group on Intellectual Property, Innovation, and Prosperity Stanford University

Marco, A.C., Myers, A., Graham, S.J., D'Agostino, P. and Apple, K., 2015. The USPTO patent assignment dataset: Descriptions and analysis.

Marco, A.C., Tesfayesus, A. and Toole, A.A., 2017. *Patent Litigation Data from U.S. District Court Electronic Records* (1963-2015).

Maurseth, P. & Svensson, R., 2015. ***Tacit knowledge and the dynamics of inventor activity***. Unpublished working paper, Norwegian Business School.

Mawdsley, J. K. & Somaya, D., 2016. Employee mobility and organizational outcomes: An integrative conceptual framework and research agenda. ***Journal of Management***, 42(1): 85-113.

Mayle, D., 2006. ***Managing innovation and change***. [Ed.], London: Sage.

Melero, E., Palomeras, N. & Wehrheim, D. The Effect of Patent Protection on Inventor Mobility (December 20, 2017). Forthcoming, ***Management Science***. Available at SSRN: https://ssrn.com/abstract=2961312 or http://dx.doi.org/10.2139/ssrn.2961312

Mezzanotti, F. and Simcoe, T., 2019. Patent policy and American innovation after eBay: An empirical examination. ***Research Policy***, 48(5):1271-1281.

Mezzanotti, F., 2019. *Roadblock to innovation: The role of patent litigation in corporate R&D*. Working Paper.

Mitchell, W., 1989. Whether and when? Probability and timing of incumbents' entry into emerging industrial subfields. ***Administrative Science Quarterly***, 34:208-230.

Moen, J., 2005. Is mobility of technical personnel a source of R&D spillovers? ***Journal of Labor Economics,*** 23(1): 81-114.

Mundlak, Y., 1978. On the pooling of time series and cross section data. ***Econometrica: journal of the Econometric Society***, 1: 69-85.

Murray, F., Aghion, P., Dewatripont, M., Kolev, J. & Stern, S., 2016. Of mice and academics: Examining the effect of openness on innovation. ***American Economic Journal: Economic Policy***, 8(1): 212-52.

Nagaoka, S., 2002. ***Impacts of intellectual property rights protection on international licensing: Evidence from the licensing contracts of Japanese industry*** Working paper 02–04, Institute of Innovation research, Hitotsubashi University.

Nagaoka, S. & Kwon, H. U., 2006. The incidence of cross-licensing: A theory and new evidence on the firm and contract level determinants. ***Research Policy,*** 35(9): 1347-1361.

Nordhaus, W.D., 1969. Invention, growth and welfare: a theoretical treatment of technological change (No. HD45 N65).

Novelli, E., 2015. An examination of the antecedents and implications of patent scope. ***Research Policy***, 44(2): 493-507.

Oxley, J.E., 1997. Appropriability hazards and governance in strategic alliances: A transaction cost approach. ***The Journal of Law, Economics, and Organization***, 13(2), pp.387-409.

Palomeras, N. & Melero, E., 2010. Markets for inventors: learning-by-hiring as a driver of mobility. ***Management Science,*** 56: 881-895.

Parker, G. & Van Alstyne, M., 2017. Innovation, openness, and platform control. ***Management Science.*** 41(1): 255-266

Polanyi, M., 1958. ***Personal knowledge: towards a post-critical philosophy***. Abingdon, UK: Psychology Press.

Raymond, E. 1999. The cathedral and the bazaar. ***Knowledge, Technology & Policy***, 12(3), 23-49.

Rosenkopf, L. & Almeida, P., 2003. Overcoming local search through alliances and mobility. ***Management Science***, 49(6): 751-766.

Rosenkopf, L. & Nerkar, A., 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. ***Strategic Management Journal***, 22(4): 287-306.

Rothaermel FT, and Boeker W., 2008. Old technology meets new technology: complementarities, similarities, and alliance formation. ***Strategic Management Journal***., 29(1): 47–77.

Scherer, F.M., 1972. Nordhaus' theory of optimal patent life: A geometric reinterpretation. ***The American Economic Review***, 62(3): 422-427.

Schilling, M. A. & Phelps, C. C., 2007. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. ***Management science,*** 53(7): 1113-1126.

Schroll, A. & Mild, A., 2011. Open innovation modes and the role of internal R&D: An empirical study on open innovation adoption in Europe. ***European Journal of Innovation Management***, 14(4): 475-495.

Schumpeter, J.A. and Fels, R., 1939. Business cycles: a theoretical, historical, and statistical analysis of the capitalist process. New York: McGraw-Hill, (2): 1958-65.

Scotchmer, S., 1991. Standing on the shoulders of giants: cumulative research and the patent law. Journal of Economic Perspectives, 5(1): 29-41.

Scotchmer, S., 2004. ***Innovation and incentives***. Cambridge, MA: MIT press.

Seaman, C. B., 2016. Permanent injunctions in patent litigation after eBay: An empirical study. ***Washington and Lee University School of Law***.

Shapiro, C., 2010. Injunctions, hold-up, and patent royalties. ***American Law and Economics Review***.

Shijaku, E., Larraza-Kintana, M. and Urtasun-Alonso, A., 2016. Organizational dynamic embeddedness and external shocks: The impact of financial and recession crises in strategic networks of the global pharmaceutical industry. ***Complexity***, 21(S1): 602-621.

Singh, J. & Fleming, L., 2010. Lone inventors as sources of breakthroughs: Myth or reality?. ***Management Science***, 56(1): 41-56.

Singh, J., 2005. Collaborative networks as determinants of knowledge diffusion patterns. ***Management science,*** 51(5): 756-770.

Singh, J. & Agrawal, A., 2011. Recruiting for ideas: How firms exploit the prior inventions of new hires. ***Management Science***, 57(1): 129-150.

Smith, P.J., 2001. How do foreign patent rights affect U.S. exports, affiliate sales, and licenses?, ***Journal of International Economics,*** 55(2): 411-439

Song, J., Almeida, P. & Wu, G., 2003. Learning-by-hiring: when is mobility more likely to facilitate interfirm knowledge transfer?. ***Management Science,*** 49: 351-365.

Sosa, M. L., 2009. Application-Specific R&D Capabilities and the Advantage of Incumbents: Evidence from the Anticancer Drug Market. ***Management Science*** 55(8): 1409-1422.

Spence, M., 1984. Cost reduction, competition, and industry performance. ***Econometrica: Journal of the Econometric Society***, 101-121.

Swink, M., 2003, Completing projects on-time: How project acceleration affects new product development, ***Journal of Engineering and Technology Management,*** 20(4): 319-344

Tang, Y.H., 2006. The Future of Patent Enforcement After eBay v. MercExchange. ***Harv. JL and Tech.,*** 20: 235.

Teece, D. J., Pisano, G. & Shuen, A., 1997. Dynamic capabilities and strategic management. ***Strategic management journal,*** 18(7): 509-533.

Teece, D.J., 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. ***Research policy***, 15(6): 285-305.

Tranekjer, T. L. & Knudsen, M. P., 2012. The (unknown) providers to other firms' new product development: what's in it for them?. ***Journal of Product Innovation Management***, 29(6): 986-999.

Tripsas, M. & Gavetti, G. (2000). Capabilities, cognition, and inertia: Evidence from digital imaging. ***Strategic management journal***, *21*(10-11), 1147-1161.

Veugelers, R. & Cassiman, B., 1999. Make and buy in innovation strategies: evidence from Belgian manufacturing firms. ***Research policy,*** 28(1): 63-80.

Veugelers, R., 1997. Internal R & D expenditures and external technology sourcing. ***Research Policy***, 26(3): 303-315.

Von Hippel, E., 1998. Economics of product development by users: The impact of “sticky” local information. ***Management science,*** 44(5): 629-644.

Von Hippel, E., 2005. ***Democratizing Innovation***. Cambridge, MA: MIT press.

Von Hippel, E. & Von Krogh, G, 2003. Open source software and the “private-collective” innovation model: Issues for organization science. ***Organization science***, 14(2): 209-223.

Weigelt, C., 2009. The impact of outsourcing new technologies on integrative capabilities and performance. ***Strategic Management Journal***, 30(6): 595-616.

Wen, W., M. Ceccagnoli, & C. Forman., 2016. Opening up intellectual property strategy: implications for open source software entry by start-up firms. ***Management Science***, 62 (9): 2668–2691.

West, J., 2003. How open is open enough?: Melding proprietary and open source platform strategies. ***Research policy,*** 32(7): 1259-1285.

West, J. & Gallagher, S., 2006. Challenges of open innovation: the paradox of firm investment in open-source software. ***R&D Management***, 36(3): 319-331.

West, J. & O'mahony, S. (2008). The role of participation architecture in growing sponsored open source communities. ***Industry and Innovation,*** 15(2): 145-168.

West, J., Salter, A., Vanhaverbeke, W. & Chesbrough, H., 2014. Open innovation: The next decade. ***Research Policy,*** 43(5): 805-811.

Williamson, O.E., 1979. Transactions-Cost Economics: The Governance of Contractual Relations. ***Journal of Law and Economics***, 22(2): 233–62.

Yamaguchi, K., 1991. Applied social research methods series, ***Event history analysis***. Thousand Oaks, CA: Sage.

Ziedonis, R. H., 2004. Don't fence me in: Fragmented markets for technology and the patent acquisition strategies of firms. ***Management science,*** 50(6): 804-820.

Zucker, L.G., Darby, M.R. & Armstrong, J.S., 2002. Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. ***Management Science***, 48(1): 138-153.