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Abstract

In this dissertation, I aim at understanding better technology transfer across organizations and providing a profound knowledge of the contingencies and impediments to technology transfer. Acknowledging the fact that the context in which technology transfer takes place influences the way firms interact and how the technology is transferred, I study this phenomenon in two extreme contexts, i.e. market for technology and market for firms, exploring the factors effective at institutional, dyadic and technological levels. In the first chapter, I focus on technology transfer in market for technology. The effect of the patent system on firms' innovativeness is a highly contested topic in the innovation literature. In order to shed more light on this unresolved debate with a specific focus on policy changes, I study the impact of patent enforcement strength on firms' incentives to patent and engage in market trade. In the second chapter, I study technology transfers in market for firms. Providing a criticism and reconceptualization of firms' efficiency in absorbing external technology, I identify the factors influential at dyadic and technological levels, and test how they relate to the merged entity's efficiency in technology absorption and innovativeness. In the final chapter, the distinction between two types of transactions, i.e. patent sale vs. patent license, are explored in market for technology. With the aim of extending market for technology literature, we study the factors influential in the decision on transfer or retention of ownership rights in technology market transactions.

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Introduction

Technological knowledge is a key firm resource for creating and sustaining competitive advantage and a well-established area of research in strategic management field. Innovation and technological advancement are crucial components of firm success in a knowledge economy. Yet, rapid technological change and environmental uncertainty pose challenges for firms in attaining competitive advantage. To innovate successfully and enhance competitive advantage, firms need to complement internal development of knowledge and technologies with external knowledge sources (Cassiman & Veugelers, 2006). Therefore, firms have begun to rely heavily on external knowledge and technologies to achieve rapid innovation, maintain their technologies at the frontier and get ahead of the product market competition (Arora & Gambardella, 2010; Leone & Reichstein, 2012). Transfer of external technology is seen as a means to broaden firms' knowledge base (Cohen & Levinthal, 1989; Huber, 1991) and improve their combinative capabilities through the synthesis of internal and external technological knowledge (Kogut & Zander, 1992). This synthesis, in turn, enhances the pace of innovation (Kessler & Chakrabarti, 1996).

Cassiman (2009) asserts that 76% of innovative firms undertake some form of external technology transfer. The sources of external technology transfer range from arms-length transactions in technology markets, such as licensing, to more collaborative and equity based arrangements, such as alliances, joint ventures, acquisitions. The context in which the technology transfer takes place influences the way firms interact and how the technology is transferred. Thus, in order to have a holistic view of technology transfer, it is necessary to study different contexts in which technology transfer takes place. Moreover, technology transfer is a complex process (von Hippel, 1994; Grant, 1996) which entails numerous factors impactful at various levels, such as institutional, dyadic, technological. In this dissertation, I study inter-organizational technology transfer in two contexts, namely, market for technology and market for firms, and at three different levels, institutional, dyadic and technological.

In the first chapter, I focus on technology transfers in market for technology. The technology market refers to the trade of technologies in disembodied form (Arora & Gambardella, 2010). Typically, transactions in the technology markets are at arm's length, e.g. intellectual property (IP) sale, licensing, and involve numerous actors, i.e. technology providers, patent pioneers, manufacturing firms, intermediaries, etc. Prior research identifies the determinants of transactions in technology markets under three broad categories, i.e. institutions, firm characteristics and industry structure (Conti, Gambardella & Novelli, 2013). The role of institutions in this context mainly relates to alleviating inefficiencies in market transactions (Arora, 1995; Gans, et.al., 2002, 2008). At the institutional level, IP regime, the strength of patent system in particular, plays an important role in functioning of technology markets (Gans & Stern, 2010). However, the effect of the patent system on firms' innovativeness is a highly contested topic in the innovation literature.

While proponents of a strong patent system contends that it stimulates firm innovation (e.g. Kitch, 1977; Mansfield, 1986; Hall & Ziedonis, 2001), opponents purport that it rather stifles innovation through issues related to anticommons, hold-up, royalty stacking, etc (e.g. Merges & Nelson, 1990; Cockburn, et.al. 2010, Lemley & Shapiro, 2006). In order to shed more light on this unresolved debate with a specific focus on IP policy changes, I study the impact of patent enforcement strength on firms' incentives to patent and engage in market trade. Exploiting a momentous Supreme Court decision in 2006, which has shifted the strength of patent enforcement downward in the US context, I present how the patenting and out-licensing patterns of US firms have changed as opposed to a control group of European firms. I also provide evidence for which types of firms are affected more upon this shift and whether there exists a change in the industry structure.

In the second chapter, I study technology transfers in market for firms. The second chapter relates to the fact that technologies are exchanged also through acquisition of technology-based firms (Agarwal & Helfat, 2009; Ahuja & Katila, 2001). Acquirers pursue technology-based firm acquisitions to tap the innovative potential of target firms through attaining their strategically valuable technological knowledge (Graebner, et.al., 2010). Most theoretical advancements in this context focus on the absorptive capacity (Cohen & Levinthal, 1989, 1990) of the acquirer in leveraging the acquired technological knowledge (e.g. Puranam & Srikanth, 2007). Extending this theory, Zahra & George (2002) introduce efficiency factor as a concept that indicates the extent to which firms generate value from technological knowledge acquisition. In this chapter, I provide a criticism and reconceptualization of efficiency factor, identify its antecedents at dyadic and technological levels, and test how it relates to the merged entity's innovativeness. Taking into account the costs incurred in developing capabilities to absorb acquired technological knowledge, I explore the optimum level of leverage that maximizes the merged entity's innovative performance. In doing so, I compare acquisition deals in highly IP-intensive and below-average IP-intensive industries, and also between- and within-industry acquisition settings.

In the third chapter, with my co-author Alfonso Gambardella, we distinguish between two types of transactions, i.e. patent sale vs. patent license, in market for technology. Although patent sales are high-priced transactions that constitute a sizeable portion of technology transfers in market for technology, the prior literature mainly focuses on licensing agreements in technology transfer. Most of the theoretical and empirical research on this phenomenon investigates the extent and functioning of the technology markets by studying patent licensing (e.g. Arora & Ceccagnoli, 2006; Arora & Fosfuri, 2003; Fosfuri, 2006; Gans & Stern, 2003; Gans, et.al. 2008). We try to extend this line of literature by studying the incentives of the patent owner to sell or license a patented invention and providing a broader view of alternative ways of patent monetization and factors influential in the actual decision. Focusing on the patent owner, trade partner and patent characteristics, we explain what determines the decision to transfer or retention of ownership rights in technology market transactions.

Chapter 1

Shooting Ourselves in the Foot to Kill a Fly?

Weakening of Patent Enforcement Stifles Market for Technology

This study examines the impact of patent enforcement strength on firms' incentives to patent and out-license. In addressing a patent dispute between eBay vs. MercExchange, in 2006, a precedential US Supreme Court decision has altered the strength of patent enforcement for all US patents. Exploiting this shift in patent enforcement strength in the US in comparison to the European context, I show that upon the diminution in patent enforcement strength, US firms have decreased their patenting and out-licensing activities compared to European firms. Moreover, the decline in out-licensing activities is more pronounced for small and medium sized firms. Likewise, upstream technology providers have faced a sharper decline in out-licensing activities compared to downstream manufacturers. Besides, European firms, 'heavily patenting in the US' before the Supreme Court's decision, are affected similar to US firms. I also present that the weakening of patent enforcement strength does not impede entry by specialized technology providers although it adversely impacts royalty rates in licensing agreements. This research aims at contributing new insights to the market for technology literature by depicting how it is impacted by the strength of patent enforcement and discusses possible patent policy implications.

Key words: patent enforcement, licensing, market for technology, difference-in-difference

INTRODUCTION

'*In an effort to make it harder for patent trolls to obtain injunctions yet another bad decision [U.S. Supreme Court's eBay case ruling] has weakened the patent system for everyone. Yet, patent trolls, or non-practicing entities if you prefer, like Acacia Technologies, seem unphased. This shooting ourselves in the foot to kill a fly really has to stop. The fly lives and we have a hole in our foot*.'

'Happy 5th Anniversary: The Impact of eBay v. MercExchange' (2011)
(Gene Quinn, patent attorney and the founder of IPWatchdog.com)

The US patent policy has been subjected to fundamental changes over the last several years and further patent reforms are about to enter the US Congressional calendar. After the enactment of the America Invents Act (AIA) in 2011, the US Congress is willing to resume the patent reform to pass an additional legislation to prevent abusive patent litigation. Supporters of the patent reform assert that it would retrench costly lawsuits, reduce patent abuses, and stimulate innovation. Opponents of the patent reform argue to the contrary that it would depress patent value and stifle innovation. How these ongoing legislative changes have impacted the patent enforcement strength and, in turn, firms' incentives to patent and engage in technology trade is an open question and the main interest of this study.

The impact of patent system on firms' innovativeness is a highly contested topic in the innovation literature. The proponents of a strong patent system contend that it encourages innovation, facilitates market for technology, and enhances vertical specialization and small firm entry (e.g. Arora, Fosfuri & Gambardella, 2001; Arora & Ceccagnoli, 2006; Breschi, Malerba & Orsenigo, 2000; Gans and Stern, 2003; Hall & Ziedonis, 2001). Conversely, the opponents of the strong patent system assert that it stifles innovation through, e.g. restricted access to upstream discoveries especially in industries where technologies advance cumulatively (Merges & Nelson, 1990; Scotchmer, 1991), potential hold-up and royalty stacking problems (Cockburn, MacGarvie & Muller, 2010; Galasso & Schankerman, 2010; Heller & Eisenberg, 1998; Lemley & Shapiro, 2006; Ziedonis, 2004), increased cost of innovation due to escalating defensive patenting and patent portfolio races among firms (Hall & Ziedonis, 2001, Shapiro, 2000), and inflation in patent thickets (Graevenitz, et.al., 2013), patent litigations (Bessen & Meuer, 2005; Galasso & Schankerman, 2010) and patent trolling activities (Bessen, et.al., 2011; Fischer & Henkel, 2012; Reitzig, et.al., 2007).

As Teece (1986) defines, the patent system refers to the environmental factors that govern an innovator's ability to capture the profits generated by an innovation such as the efficacy of legal mechanisms of protection. Gambardella, et. al. (2007) claim that ‘patents are stronger if they are well enforced by the judicial system’. Therefore, in addition to the interplay of policy instruments, such as patent duration, patent scope and inventive step, which constitute the base of patent protection; the strength of patent enforcement is also a crucial dimension of the patent system.

In this context, I try to answer the following research questions: How does the patent enforcement strength affect firms’ patenting decisions? What is the impact of patent enforcement strength on the functioning of market for technology? Which types of firms are more dependent on the strength of patent enforcement to engage in technology trade? There are two main challenges in testing these research questions. First, measuring patent enforcement strength is not straightforward. Second, finding any variation (e.g. quasi-experimental variation) in patent protection within the same patent system is difficult (Williams, forthcoming). This study overcomes these challenges by exploiting a momentous Supreme Court decision in 2006, which has shifted the strength of patent enforcement downward in the US context. In particular, my analyses are based on the US Supreme Court's decision on eBay vs. MercExchange patent dispute case, which marked a turning point in injunctive relief policy. The US Supreme Court upheld the notion that '*an injunction should not be automatically issued based on a finding of patent infringement*'. In effect, this ruling has reduced the probability of securing a permanent injunction for infringed patents. Thus, the patent policy debate has entered a new phase with the Supreme Court's decision on eBay case. Exploiting this precedential court decision as an exogenous shock to the US patent system, I tested the patenting and out-licensing activities of US firms in IP-intensive industries with a difference-in-difference estimation, comparing pre- (2001-2005) and post-eBay case periods (2007-2010), with a control group of European firms (i.e. German and Swiss) which experienced no policy change in patent enforcement during that period.

The results show that in the post-eBay period, US firms have decreased their patenting and out-licensing activities compared to European firms. Although the number of patent applications has decreased regardless of firm size, the decline in out-licensing activities is more pronounced for small and medium sized firms. Moreover, US firms' patent applications and out-licensing activities have diminished in all IP-intensive industries, except medical devices industry. Besides, European firms 'heavily patenting in US' before the Supreme Court's decision are impacted similar to the US firms. In addition, I found that upstream technology providers have encountered a sharper decline in out-licensing activities as opposed to downstream manufacturers. If upstream technology providers are key players in market for technology, owing to the decline in their out-licensing, it is important to understand how a weaker patent enforcement affects their business. In order to understand this, first, I checked the entry rates and found that the weakening of patent enforcement strength does not impede entry by specialized technology providers. This suggests that they might have been diverted to new business models. In other words, while weaker patent enforcement discourages technology markets, it may not discourage entry by upstream technology providers. Second, I conducted an additional analysis to see whether upon the weakening of patent enforcement the new upstream entrants have performed poorer compared to those that entered the market before the Supreme Court's eBay case decision. I observed no significant difference in financial performance of new entrants compared to that of early entrants. Finally, I checked the actual royalty rates in licensing agreements to see whether the downward shift in the patent enforcement strength decreased potential licensors' bargaining power in licensing negotiations. I found that the weakening of patent enforcement adversely impacted the royalty rates in licensing agreements.

This research aims at contributing new insights to the market for technology literature by depicting the relationship between patent enforcement strength and firms' incentives to patent and engage in technology trade. In doing so, it provides a more robust and systematic evidence on a large dataset to address an important and controversial debate in the literature. Moreover, the scholarly debate on the consequences of Supreme Court's eBay case decision has thus far been centered in the patent policy literature and been largely theoretical or based on follow-on plaintiff success rates in patent disputes (e.g. Davis, 2008; Diessel, 2007; Grab, 2006; Tang, 2006). This study also informs the US policy makers by presenting how the downward shift in patent enforcement strength altered firms' incentives to patent and out-license and which type of firms are influenced more severely.

The paper is organized as follows. Next section puts forward the theoretical background on the strength of patent enforcement and its effect on patenting and market for technology. The following section propounds the characteristics of US patent policy up until 2006 and how it has changed since then with the Supreme Court's decision on eBay case. It is followed by presentation of the trends in the aggregate data and the empirical results of the firm/year observations. Final section discusses the implications of the results and concludes with explaining the limitations of the current study and identifies further research avenues.

PATENT PROTECTION AND PATENT ENFORCEMENT

A patent system is composed of three main features: patent duration, patent scope and inventive step (Zaby, 2010). In general, the duration of a patent is defined clearly and objectively. The effective life of a patent is 20 years and nearly uniform worldwide due to the harmonization through the agreement of Trade-Related Aspects of Intellectual Property Rights (TRIPS) since 1994. The other two dimensions of patent protection are rather less straightforward. The patent scope refers to the boundaries of a patent and determines what is protected and what is not. In the European Patent Convention (1973) the patent scope is defined as follows: 'The extent of the patent protection conferred by a European patent or a European patent application shall be determined by the claims' (Art. 69 (61), EPC). Therefore, patent claims define the legal scope of the invention for which protection is being granted (Guellec & van Pottelsberghe, 2006). Finally, the inventive step refers to the extent of novelty requirement and defines how much a new invention needs to differ from prior art to receive patent protection. Scotchmer (2004) asserts that patent scope and inventive step are rather interdependent dimensions and jointly determine the extent of novelty and non-obviousness requirement for a non-infringing patent. As Zaby (2010) puts forward, most of the theoretical arguments on the optimal patent system design is centered on the interplay of these three different dimensions constituting a patent[1]. A combination of these and other factors are also used as dimensions of patent protection such as the codifiability of knowledge, the cost of application and the cost of disclosure (Horstmann et al. 1985). Some scholars use 'patent effectiveness' as a term that combines these factors to denote the strength of patent protection and prefer to exploit it as a summary measure of the strength of patent system due to empirical difficulties in distinguishing among these factors (Arora & Ceccagnoli, 2006).

In addition to the main features constituting a patent, the patent enforcement strength is another important aspect of the patent system. According to World Intellectual Property Organization's (WIPO) Intellectual Property Handbook (Chapter 4, 2004), '*there is no point in establishing a detailed and comprehensive system for protecting intellectual property rights and disseminating information concerning them, if it is not possible for the right-owners to enforce their rights effectively*'. A patent is by definition the right, enforceable in a court, to prevent the manufacture, sale and use of a patented invention (35 U.S. Code § 154). In environments where the patent system is "tight", in other words, the efficacy of legal mechanisms of protection is high, an invention is relatively easy to protect; whereas in "weak" patent systems it is difficult to protect an invention from imitation (Teece, 1986). Thus, in addition to the interplay of policy instruments,

[1] For a detailed literature review on the economic analyses of patent systems, See Encaoua, et. al. (2006) 'Patent systems for encouraging innovation: Lessons from economic analysis', Research Policy, 35, 1423-1440.

such as patent duration, patent scope and inventive step, the strength of patent enforcement is a crucial dimension of the patent system.

The relationship between the strength of patent system on firms' incentives to innovate has long been a scholarly interest (e.g. Arrow, 1962; Hall & Ziedonis, 2001; Kaufer, 1989; Kitch, 1977; Kortum & Lerner 1999; Machlup, 1958; Mansfield, 1986; Nelson, 1959; Nordhaus, 1969; Scherer, 1980). However, the extant literature on the role of the strength of patent system on firms' innovativeness present conflicting views. On the one hand, a significant amount of research has highlighted the benefits of a strong patent system (Arora et al., 2001; Kitch, 1977). This body of literature suggests that a strong patent system may facilitate firms' incentives to innovate and engage in patent trade in the market for technology, encourage further investment in R&D with commercial potential, and mitigate disincentives to disclose and exchange knowledge which might otherwise remain secret (Arora et. al., 2001; Gans & Stern, 2000; Hall & Ziedonis, 2001; Merges & Nelson, 1990, 1994). For instance, Kitch (1977) argues that strong patents are valuable precisely because they can function as broad technological prospects. Firms can, thereby, explore and develop new ideas free from the interference of others. Some survey evidence also suggests that, a strong patent system stimulates innovation (Mansfield, 1986). It is also suggested that, within the context of university research, a strong patent system offers important incentives to move nascent discoveries out of the 'ivory tower' and into commercial practice (Hellman, 2007). On the other hand, opponents of a strong patent system assert that it stifles innovation. For instance, it is argued that the expansion of patent rights results in privatizing the scientific commons and limited scientific progress (Argyres & Liebskind, 1998; Heller & Eisenberg, 1998; Merges & Nelson, 1990; Scotchmer, 1991). Another body of literature warns for accelerated hold-up and royalty stacking problems specifically in information technology industry where patent ownership is highly fragmented and one patent covers a component or feature of a complex product (Cockburn, MacGarvie & Muller, 2010; Lemley & Shapiro, 2006; 2007). Furthermore, strengthening of the patent system is considered as increasing the cost of innovation due to accelerated defensive patenting and patent portfolio races among firms, especially in semiconductors industry (Hall & Ziedonis, 2001, Shapiro, 2000), and the need for navigating through patent thickets (Cockburn, MacGarvie & Muller, 2010; von Graevenitz, et.al., 2013). Reflecting on this debate, some scholars argue that there is lack of empirical evidence on the negative impact of a strong patent system (Denicolo, et.al.,2008). They claim that the potential patent hold-up and royalty stacking problems are rather sporadic than pervasive (Denicolo, et.al.,2008). Although, a recent study by Galasso & Schankerman (2014) shows that removal of patent rights by court invalidation leads to an increase in subsequent patent citations, it examines removal of patent rights in a strong patent system where subsequent patents are still highly enforceable. Therefore, it is not certain how subsequent patenting would be impacted with a decrease in enforcement strength. Conversely, Williams (2013) documents that patents on human genes may not discourage follow-on innovation because patents preserve open access to materials for academic scientists due to information disclosure requirement.

In addition, not all patented inventions are aimed at directly profiting from innovation. Empirical studies on firms' incentives to patent demonstrate that firms do so for many reasons beyond directly profiting from innovation through commercialization and licensing: i.e. to block or 'enclose' rivals (preventing them from pursuing a given line of patented research), signal plans to enter a new technological area or market, facilitate cross-licensing, indicate stock market value, or for defensive reasons, to secure freedom to operate and prevent law suits. (e.g. Cohen et. al., 2000; Hall & Ziedonis, 2001; Harabi, 1994; Kingston, 2001; Levin et al., 1987; Rivette and Kline, 2000a,b). In their seminal work, Cohen, et. al. (2000) also argue that firms' motives to patent vary by industry. In particular, they assert that firms' motives to patent in discrete product industries, such as chemicals, differ from complex product industries, such as telecommunications and semiconductors. While in the chemical industry firms patent more commonly to block competitors from patenting related inventions, firms engaging in production of more complex technologies patent for using in trade negotiations. Hence, a strong patent system is believed to encourage strategic patenting of the firms (Hall & Ziedonis, 2001).

In their survey of manufacturing firms, Cohen et.al (2000) have found that the two main reasons for firms to not to patent inventions are: the amount of information disclosed and the ease of legally inventing around. Therefore, in a "weak" patent system where it is difficult to protect an invention from imitation (Teece, 1986), firms' incentives to patent are expected to be lower. As Aoki & Spiegel (2009) put forward, on the decision to patent, the firm faces the trade-off between applying for a patent, which allows it to sue a rival for patent infringement and disclosing information underlying the invention, which may increase the rival's chances of inventing around. In their model, they capture the patent strength by two factors: the likelihood of a patent will be granted and the likelihood that the patentee will win a patent infringement suit. They have found that if the patent protection is weak, so that a patent is unlikely to be upheld in court, the firm prefers not to file a patent. In line with this reasoning, I argue that to the extent that the patent enforcement strength dominates the risk of invent around due to revealing patent information, it increases the firm's incentive to apply for a patent. Therefore, in case of a downward shift in patent enforcement strength, the risk of information disclosure may dominate and the firm may refrain from filing a patent.

Hypothesis 1: The strength of the patent enforcement is positively associated to the firms' incentives to patent.

Market for technology literature highlights the role of institutional factors in facilitating technology trade. This body of literature contends that the strength of patent system is an essential factor in firms' licensing activities (Arora & Gambardella, 2010; Conti, Gambardella & Novelli, 2013). From the potential licensor's perspective, one concern is the risk of expropriation. When an invention is disclosed to potential licensees so that they can assess its value, the underlying knowledge may leak out (Arrow, 1962). Arora and Fosfuri (2003) discuss that the potential licensor's incentives to out-license are diminished when the patent system is weak and the firm cannot rely on legal rights to protect the use of a technology. Yet, from the potential licensee's perspective, the scope of the invention may be uncertain and there may be concerns about inventing around the invention without infringing it (Gans, et.al, 2002). For instance, Gans, et.al. (2008) show that licensing activities largely take place within a narrow window around the grant of the patent which is argued to reflect the patent system's influence in reducing the uncertainty and asymmetric information regarding the scope of the invention. Thus, market for technology literature underlines the importance of the strength of patent system in preventing knowledge expropriation and reducing the uncertainty regarding the scope of an invention (Arora & Ceccagnoli, 2006; Gans, et.al, 2002; Gans and Stern, 2010). Firms' technology commercialization strategies heavily depend on the level of excludability from imitation (Gans & Stern, 2003). For example, Gans, et.al. (2002) indicate that in the biotech industry, firms are more likely to out-license their technology when the patent system is strong; otherwise, firms are more inclined to commercialize their technology through downstream integration. Similarly, Arora & Ceccagnoli (2006) argue and empirically show that the impact of the strength of patent system on firms' out-licensing activities are stronger when firms do not engage in downstream manufacturing. In addition, Arora & Gambardella (2010) note that when upstream R&D and downstream manufacturing processes are complementary, an increase in patent protection strength may have no effect on firms' licensing activities; whereas, a strong patent system increases propensity to out-license when there exists no complementarity between upstream R&D and downstream manufacturing. They also argue that the licensing propensity of small firms, as opposed to large firms, can be more responsive to the patent system's effectiveness. It is also emphasized that the effectiveness of patent system may vary in different industries. The market is argued to function more efficiently in discrete technology industries, such as chemical and pharmaceutical industries, where the patent system is more effective to protect patent rights (Anand & Khanna, 2000; Cohen, et.al., 2000). Taken together, in a strong patent system, it is expected that the market for technology will operate more efficiently and there will be a high volume of licensing activities.

With regards to the impact of patent enforcement strength on firms' incentives to out-license, it can be said that there are two factors at play. First, to the extent that a strong patent enforcement protects potential licensor from the risk of expropriation, it enhances the firm's incentives to out-license. Prior research has found that firms' reputation for toughness in patent enforcement significantly reduces spillovers (Agarval, et.al., 2009). If the likelihood of winning a patent infringement suit is high due to strong patent enforcement, the potential licensor is expected to have more bargaining power in ex-ante licensing negotiations. As Arora & Ceccagnoli (2006) state, more effective patent protection increases the potential licensor's bargaining power. Hence, the strength of patent enforcement is expected to have a positive impact on firm's incentives to engage in technology trade. Second, to the extent that a weak patent protection discourages firms from filing a patent through a switch from patenting to alternative ways of protection, i.e. secrecy, lead time, complementary assets etc., or an overall decrease in the rate of inventions, this would impact the firms' licensing activities. Since codification is the pre-condition of technology trade (Conti, et.al, 2013) and patents are necessary for licensing (Arora & Ceccagnoli, 2006), a decrease in the number of patent applications resulting from a weaker patent protection is also expected to impede market for technology. Taken these two factors together, the relationship between the strength of patent enforcement and firms' incentives to out-license is expected to be positive.

Hypothesis 2: The strength of the patent enforcement is positively associated to the firms' incentives to out-license.

Besides, not all firms are expected to be influenced similarly by a downward shift in patent enforcement. This is mainly due to the availability of alternative mechanisms of protection, i.e. secrecy, lead time, complementary assets etc., which vary for different types of firms. As Teece (1986) argues, out-licensing is a way of profiting from innovation if there is a strong patent system and the firm lacks complementary assets, such as manufacturing and marketing. Access to complementary assets is typically difficult and costly. A strong patent system is more likely to encourage out-licensing by firms that lack these assets compared to firms that already possess those (Arora & Ceccagnoli, 2006). Therefore, the strength of patent enforcement affects firms' out-licensing activities with respect to the firms' level of dependence on the effectiveness of the legal protection. Particularly, there are two types of firms, which are expected to be more dependent on the strength of patent enforcement. First, small and medium size firms generally lack the necessary financial resources to invest in alternative mechanisms of protection compared to large firms. Due to the smaller scale of their businesses, they have less access to complementary assets. Moreover, to the extent that these firms hold smaller patent portfolios than large firms do, they have less chances of engaging in cross-licensing agreements to gain freedom of operating. Therefore, the licensing propensity of small and medium size firms, as opposed to large firms, may be more responsive to the patent system's effectiveness (Arora & Gambardella, 2010). Second, the strength of patent enforcement is also expected to have a differential impact on the businesses of the upstream technology providers, as opposed to, downstream manufacturers. Stronger patent protection is positively associated with the market entry by specialized design firms (Hall & Ziedonis, 2001). Especially in IP-intensive industries such as semiconductors, biotechnology and electronics, there are a number of firms specialized in chip design, technical advances in life science, and electronic system design which function as technology providers for the downstream manufacturers. These industries are characterized by vertical specialization and division of innovative labor (Arora, et.al., 2001). Upstream technology providers profit from innovation through out-licensing their technologies, instead of downstream integration and product commercialization. As Gans, et.al. (2002) claim, in the biotech industry, firms are more likely to out-license their technology when the patent system is strong; otherwise, firms are more inclined to commercialize their technologies through downstream integration. Due to their business model, upstream technology providers also lack alternative mechanisms of protection from imitation; thus, are more dependent on the strength of patent enforcement in their out-licensing activities, compared to downstream manufacturing firms. Therefore, the strength of patent enforcement is expected to have a higher impact on upstream technology providers than downstream manufacturing firms.

Hypothesis 3: The positive relationship between the strength of patent enforcement and the volume of out-licensing is greater for small and medium size firms compared to large firms.

Hypothesis 4: The positive relationship between the strength of patent enforcement and the volume of out-licensing is greater for upstream technology providers compared to downstream manufacturers.

US PATENT POLICY

Pre-eBay Case Period

Starting from early 1980s, important changes in the US patent rights created a pro-patent shift towards a stronger patent system. Establishment of the Court of Appeals for the Federal Circuit (CAFC) in 1982 to uniform judicial treatment in patent cases was an important step in strengthening the patent protection. CAFC not only consolidated all appeals in patent cases but also appeared as a pro-patent court in handling patent litigations (Cohen, 2005; Hall and Ziedonis, 2001). According to Cohen (2005), the pro-patent shift in US revealed itself mainly in three ways: increase in the plaintiff success rates, expansion in patentable subject matter and extension of eligibility regarding who can patent.

The pro-patent movement in the US has altered the patenting behavior of both firms and universities. The annual rate of patent grants increased substantially after 1980 (Hall & Ziedonis, 2001; Kortum & Lerner, 1999). Patenting by both US and foreign firms in US jumped from 61,819 in 1980 to 169,039 in 2003 (USPTO statistics). This was also reflected in the number of patents per million dollars of R&D, which increased from 0.35 to 0.50 patents per million dollars (Jaffe, 2000). Hicks, et. al. (2001) evidenced that patenting has mostly increased in health and information technology fields.

The increase in patenting has brought along with it a notable increase in patent litigations. The number of patent suits filed has doubled over the decade of the 1990s (Clermont & Eisenberg, 2000). The patent trial rate has also doubled the average of federal civil litigation, patent trials have become especially expensive, and filings have increased rapidly (Bessen & Meuer, 2005). Some attributed this increase in the number of patent litigations to the emergence of new actors in the IP market, such as non-practicing entities (NPEs). These entities, due to their business model, do not engage in the production of the technology underlying their patents, but instead make money from royalty payments they obtain directly from their licensees or indirectly in terms of damage awards (Reitzig, Henkel & Heath, 2007).

The raised concerns about pro-patent shift, i.e. anticommons, patent hold-up, royalty stacking etc., and escalated number of patent litigations, in turn, drew attention of US policy makers. In 2003, US Federal Trade Commission (FTC) reported that the patent system requires an alignment with the antitrust enforcement, which can be achieved with a proper balance between patent exclusivity and competition policy. It is admitted that the ability of patentees to assert their patents against infringers is important to the patent system's role in promoting innovation and facilitating technology transfer. For this purpose, permanent injunctions are put in place to deter infringement and protect the exclusivity. Three characteristics of injunctions are argued to support innovation: (a) its ability to preserve exclusivity that provides the foundation of the patent system's incentives to innovate, (b) credible threat of an injunction deters infringement in the first place, (c) a predictable injunction threat will promote ex ante licensing by the parties. However, an injunction can also cause patent hold-up due to high switching costs which may deter innovation. With the desire to protect patent exclusivity to incentivize innovation while preventing patent trolling activities and potential hold-up problems which may undermine innovation, in 2006, the US Supreme Court unanimously rejected a general rule supporting the grant of a permanent injunction following a finding of patent infringement.

eBay Case and Post-eBay Period

In addressing a patent dispute between eBay and MercExchange, a small Virginia based NPE, regarding the infringement of one of MercExchange's patents related to the fixed-price auction feature that makes up an integral part of eBay's "Buy It Now" section of its website, the US Supreme Court upheld the notion that '*an injunction should not be automatically issued based on a finding of patent infringement*'. The Supreme Court ruled that the traditional "*principles of equity*" should be applied to permanent injunction decisions for disputes arising under the Patent Act. In other words, the court determined that in order to receive a permanent injunction in a patent litigation the victorious plaintiff needs to demonstrate that: (a) it has suffered an irreparable injury; (b) remedies available at law, such as monetary damages, are inadequate to compensate for that injury; (c) considering the balance of hardships between the plaintiff and defendant, a remedy in equity is warranted; and (d) the public interest would not be disserved by a permanent injunction. In effect, this ruling has reduced the probability of securing a permanent injunction for infringed patents. By removal of the presumption of irreparable injury from equitable balancing, it has become harder especially for small firms, and firms which solely focus on monetizing their patents through licensing and litigation, to obtain an injunction. While prior to Supreme Court's decision on eBay case it was unheard of a district court to deny a victorious plaintiff a permanent injunction upon a finding of infringement, after this decision, the denial rates have started to increase. According to Patstat.org, since eBay case (until April 2011), in 43 cases out of 174 a permanent injunction has been denied. The courts have started issuing permanent injunctions in cases where the plaintiff and defendant are direct competitors and denying otherwise.

The changed landscape for patent enforcement with its potential impact on innovation has become a highly disputed topic in patent policy research. Some argue that issuing permanent injunctions only in cases where the plaintiff and the defendant are direct competitors can decrease incentives to innovate by small firms, individual inventors and technology licensing firms (Diessel, 2007; Beckerman-Rodau, 2008). The Supreme Court's decision is considered to favor mainly large firms (Diessel, 2007; Tang, 2006). It is also argued that this ruling reduces the large firms' incentives to engage in ex-ante licensing agreements (Tang, 2006). Thus, the legitimate non-practicing patent holders; i.e. patent pioneers, universities, think tanks, independent inventors, are argued to become easy targets for willful patent infringement (Davis, 2008; Grab 2006). In addition, some scholars question the rationale behind the weakening of patent enforcement, stating that there is lack of evidence that the so-called patent hold-up and royalty stacking problems have had any significant impact on ex-ante R&D investments and innovation (Denicolo, et.al.,2008). They also put forward that Supreme Court's decision on eBay case by limiting the patent holder's ability to stop infringing activity will severely diminish the value of the patents.

The Supreme Court's decision on eBay case was followed by other court rulings and legislative changes (Table-1a) which have decreased potential damages awards by limiting the royalty base to value of the sub-component reading on the infringed patent (Lucent vs. Gateway case, 2009; Laser Dynamics vs. Quanta case, 2012), lowered the bar for invalidating patents on the base of obviousness (KSR vs. Teleflex case, 2007), raised the bar for evidencing willful infringement (Convolve vs. Seagate case, 2007), and introduced inter partes review for invalidating patent claims (America Invents Act, 2011). These subsequent court decisions have added to weakening of patent enforcement and raised further the bar for succeeding in patent assertion (Ludlow, 2014).

Table-1a about here

A Glimpse at the Aggregate Data

In order to see the impact of the US Supreme Court's eBay case decision on firms' incentives to patent and out-license, a cross-country trend analysis is warranted. According to Hypothesis 1 and 2, the downward shift in the strength of patent enforcement upon the Supreme Court's eBay case decision should have decreased the US firms' incentives to patent and out-license compared to European firms. Therefore, it is fruitful to begin the analyses by looking at the aggregate data. Figure-1a shows the first evidence from patent applications across countries. It presents the aggregate number of worldwide patent applications by US and European (German and Swiss) firms in six IP-intensive industries, in pre- and post-eBay case periods[2]. The figure shows that in the post-eBay case period, the US firms decreased their total number of patent applications, while

[2] The data sources are Bureau van Dijk's ORBIS database for US firms and AMADEUS database for German and Swiss firms. These databases provide firm-patent matching information obtained from the PATSTAT database. The patenting information was available for a total number of 161,822 firms in six IP-intensive industries; i.e. chemicals (NAICS 325), machinery (NAICS 333), computer/electronics (NAICS 334), electrical equipment (NAICS 335), medical devices (NAICS 3391), and software (NAICS 5415).

the volume of patent applications by German and Swiss firms remains steady. Out-licensing activities by US firms presents a similar pattern. Figure-2a compares the aggregate volume of out-licensing agreements by US, German and Swiss firms[3]. The figure shows that in the post-eBay case period out-licensing activities of US firms have dropped; whereas, the volume of out-licensing activities by German and Swiss firms remain the same. The aggregate data on worldwide patent applications and out-licensing activities presents the preliminary evidence that upon the diminution in patent enforcement, US firms have decreased their patenting and out-licensing activities compared to European firms which experienced no change in IP policy legislation during that period.

Figure-1a about here

Figure-2a about here

Next, if the Supreme Court's eBay case decision has rendered the US less attractive as a destination country of patenting due to weakened patent enforcement, it should have reflected in a reduction in both domestic patent applications of US firms and European firms' patent applications in the US and an increase in US firms' foreign patent applications. For this purpose, I explored the decomposition of US firms' patent applications (Figure-3a). The figure shows a

[3] The data sources for out-licensing activities are ktMINE database for US firms and FACTIVA database for German and Swiss firms. These databases categorize licensing agreements depending on the motivation of the parties. The sample is composed of all agreements under the technology transfer category.

decline in both ‘domestic’ and ‘foreign’ patent applications of the US firms in the post-eBay period. The decrease in US firms’ domestic patent applications is in line with the expectation that the weakening of patent enforcement rendered the US a less attractive destination of patenting; however, the decline in foreign patent applications of US firms is rather more complex. To the extent that foreign patent applications of US firms is a percentage of domestic applications, i.e. suppose p is the number of US firms’ domestic patent applications and αp is the share of US firms’ foreign patent applications, if the decrease in domestic patent applications is large enough, the overall number of foreign patent applications may drop despite an increase in α. Second, in order to check the foreign firm applications for US patents, I decomposed the European firms’ patent applications (Figure-4a). It is seen that in the post-eBay period, German and Swiss firms have decreased the volume of their patent applications in US, while the total number of patent applications by these European firms remains constant. This further analysis points to the decreased potency the US as a destination country of patenting in the post-eBay period.

Figure-3a about here

Figure-4a about here

EMPIRICAL EVIDENCE

Data and Sample

I tested the hypotheses of this study by comparing the volume of patent filings and out-licensing agreements of US firms in pre- (2001-2005) and post-eBay case period (2007-2010) with those of European firms (i.e. Germany and Switzerland). The selection of firms in two European countries as a control group follows the rationale that there exists a sizeable market for technology in these countries and there is no legal change in their patent systems in the identified period. For the purposes of this study, I gathered an initial sample of 495,716 firms (i.e. full population) in six IP-intensive industries, i.e. chemicals (NAICS 325), machinery (NAICS 333), computer/electronics (NAICS 334), electrical equipment (NAICS 335), medical devices (NAICS 3391) and software (NAICS 5415); in the US, Germany and Switzerland. I obtained the initial sample of US firms from Bureau van Dijk's ORBIS database while I gathered the data on German and Swiss firms from Bureau van Dijk's AMADEUS database for the period 2001-2010 in the specified IP-intensive industries. One advantage of these databases is that they provide a matching of firms with their patenting information obtained from the PATSTAT database. PATSTAT database is widely used for patent characteristics (e.g. Grimpe & Hussinger, 2014; Wagner, Hoisl & Thoma, 2014; Nandkumar & Srikanth, forthcoming). The firm-patent matching information was available for 136,920 firms which, in turn, provided a panel dataset of 976,207 firm/year observations. I complemented this dataset by the licensing agreements of the firms. For that purpose I used ktMINE database for licensing agreements of US firms. One advantage of using this database is that it provides the most comprehensive database on licensing agreements for 15,282 deals in US (Fosfuri, Helmers & Roux, 2014). I supplemented this dataset with licensing agreements of German and Swiss firms which I gathered through company name search and manual match with licensing news in FACTIVA database. I identified a total number of 1,492 licensing agreements for German and Swiss firms between 2001 and 2010.

Measures

Dependent variables

Patent Applications: I measured this construct by the number of patent filings per year by each firm for the period of 2001-2010. I terminated sampling for firm patenting activities by the end of year 2010 for the following reason. In September 16th, 2011, America Invents Act came into effect which brought several changes in the US patent system, including inter partes review for invalidating patent claims. Therefore, I test the patenting behavior of firms during 2001-2010, where there is no change in the legal patent rights (i.e. patent duration, patent scope and inventive step) but rather a shift in patent enforcement strength following the Supreme Court's eBay case decision.

Out-licensing Agreements: I measured this construct by the number of out-licensing agreements per year by each firm in the sample for the period of 2001-2010. Licensing agreements of US firms are gathered from ktMINE database; whereas, licensing agreements of German and Swiss firms are obtained from FACTIVA database. In both databases, licensing agreements are categorized depending on the type of the deal. The sample consists of all the technology transfer agreements available in the databases for US, German and Swiss firms.

Control variables

Operating Revenue: In order to account for the potential confounding effect of firms' financial resources on patenting and out-licensing decisions, I controlled for both firm revenues and profitability. I measured operating revenue by the yearly revenue amount (in thousand $) reported by each firm in the sample. Data on operating revenues was available on ORBIS and AMADEUS databases.

Profit Margin: To control for the firm profitability which may affect firms' investment in R&D and I used profit margin. I measured this construct by the yearly percentage of [(profit before tax/operating revenue)*100] reported by each firm in the sample. Data on profit margin was available on ORBIS and AMADEUS databases.

Cumulative Number of Patent Applications: To account for potential patent portfolio effect, I measured and controlled for the total number of patent applications by each firm up to one year before the focal year of observation.

Firm Age: To control for the potential age effect on firms' patenting and out-licensing activities, I constructed this variable as such: for each firm in the sample, I took the difference of each year observed from the year of incorporation as the age of firms.

Country: I measured the country effect by creating a dummy variable for each country, i.e. US, Germany and Switzerland, that takes the value of 1 if a firm operates in the respective country, 0 otherwise.

Size: Firm size is measured by the categorization provided by ORBIS and AMADEUS databases, which identify firms under four categories: small, medium, large, and very large firms depending on their operating revenues, total assets and number of employees. I created a dummy variable for each category, which gets the value of 1 if a firm is in that category and 0 otherwise. I used this time invariant categorization mainly for the split sample analyses.

Number of Employees: In addition to the categorical variable I used for split sample analyses, I further controlled for the change in the size effect by adding number of employees per year in the analyses.

Industry: I measured industry effect by dummy variables for each industry specified in the analyses, such as chemical, machinery, computer/electronics, electrical equipment, medical devices and software. Each dummy variable gets the value of 1 if the firm operates in that industry, and 0 otherwise.

The *year* dummies are also inserted in the analyses to control for time effects.

Model

In order to compare the patenting and licensing activities of US firms in the pre- and post-eBay case period with those of the European firms, a difference-in-difference method is adopted. One advantage of this estimation is that it removes the biases in post-treatment period comparisons between the treatment and control group that could result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of trends (Wooldridge, 2007). The difference-in-difference estimator tested in STATA 14 is specified below:

$$Y_{it} = \beta_0 + \beta_1 X_i + \beta_2 T_t + \beta_3 X_i{*}T_t + \beta_k(\text{control variables})_{it} + \varepsilon_{it}$$

where X_i is a dummy variable taking the value of 1 if the firm is in US (treated), else 0; T_t is a dummy variable taking the value of 1 in the post-treatment period (2007-2010) and 0 in the pre-treatment period (2001-2005), omitting year 2006 in which the US Supreme Court upheld its decision on eBay v. MercExchange case. The coefficient of β_3 gives the treatment effect, namely, the impact of the court decisions in the post-eBay period on US firms patenting and out-licensing activities. Since the dependent variables are count data with non-negative integers, I applied a log transformation in the fixed-effects (within) regressions in panel data analyses. I preferred fixed-effects (within) OLS regression (i.e. xtreg) because of the short panel (i.e. many individual units and few time periods) characteristic of the dataset. Fixed-effect estimation with nonlinear panel models (e.g. xtpoisson, xtnbreg) is not consistent in short panels due to incidental parameters problem.

RESULTS

Descriptive Statistics

The descriptive statistics of the data are depicted in Table-2a. According to the sampled data, on average firms file 0.5 patent applications per year with a wide range from 0 applications to 2584 applications per year. Whereas, most of the firms in the data do not engage in out-licensing activities at all which results in 0.001 average number of licensing agreements per year. The maximum number of out-licensing agreements made in a year is 17. Firms have 10.8 patents on average in their patent portfolio. On average, the operating revenue of the sample firms is $17.7 million, the number of employees is 48 and the firm age is 16.6. 21.8% of the observations are constituted of US firms, 61.8% of German firms and 16.3% of Swiss firms. While small firms comprise 56.8% of the sample, medium sized firms are 31.4% and large and very large firms add up to 11.7% of the total sample. Software industry has the highest representation in the data with 37.1%, it is followed by machinery industry (22.2%) and computer/electronics industry (15.4%), while chemical industry has the lowest representation by 7.6% of the total observations.

Table-2a about here

Table-3a displays the correlations between variables. It is shown that none of the control variables is highly correlated to the dependent variables. The highest correlation is between small and medium sized firms with -.809. Moreover, German firms are negatively correlated with US firms (-.618) and Swiss firms (-.625). Also, number of employees is positively correlated with the operating revenue (0.702). Lastly, operating revenue is positively correlated to the cumulative number of patent applications (0.536).

Table-3a about here

Regression Results

Table-4a presents the panel data regression results for the difference-in-difference estimations with fixed effects model. In Model-1, the results show that the interaction term is negative and significant ($p<0.01$), which confirms Hypothesis-1, upon the weakening of patent enforcement, in the post-eBay case period the US firms' patent applications have decreased compared to those of European firms. Model-2 presents the results for out-licensing agreements. It shows that the interaction term is negative and significant ($p<0.01$), supporting Hypothesis-2, which asserts that in the post-eBay period the weakening of patent enforcement is negatively associated with out-licensing activities of US firms. Therefore, on average, US firms' patenting and out-licensing activities have declined upon the weakening of patent enforcement.

Table-4a about here

In order to test Hypothesis-3 and make a finer grain analysis of the data and have a better understanding of the factors influencing US firms' patent applications and out-licensing agreements, I reexamined the data through various subsamples. First, the sample is split depending on the firm size to analyze the size effects on firms' patenting and licensing activities. The split sample analyses are depicted in Table-5a. In Model 1-4, the results show that the treatment effect is negative and significant ($p<0.01$) for all firm sizes which suggest that the US firms' patent applications have decreased regardless of firm size in the post-eBay period. In addition, split sample analyses on out-licensing agreements depict a different pattern. As it is seen in Model 5-8, for small and medium sized firms, the volume of out-licensing agreements has dropped in the post-eBay period, the interaction term is negative and significant ($p<0.01$ and $p<0.05$, respectively). However, there is no significant change in the volume of out-licensing agreements for large and very large firms. The results on firm size effects provide support for Hypothesis-3.

Table-5a about here

Second, I checked potential industry level variance in firms' patenting and licensing activities. The split sample analyses are presented in Table-6a. Model 1-6 show the treatment effect is negative and significant ($p<0.01$) for all industries, evidencing that the volume of US firms' patent applications has dropped in all IP-intensive industries. A similar pattern is observed for the volume of US firms' licensing agreements as well. Model 7-12 present that, except than the medical devices industry, the out-licensing activities of US firms have decreased in all IP-intensive industries during the post-eBay period.

Table-6a about here

Third, in order to test Hypothesis-4 and check which type of firms would be affected the most from the weakening of IP enforcement, I identified a subsample of upstream '*technology provider*s' (i.e. fabless semiconductors, system designers and biotech firms)[4]. This group of firms is argued to be severely affected by the Supreme Court's eBay case decision (Davis, 2008; Diessel, 2007; Grab, 2006; Tang, 2006). I tested the impact of the weakening of patent enforcement on the US upstream technology providers in comparison to the US downstream manufacturers. Table-7a shows the analysis results. Model 1 and 2 are comparing the US upstream technology providers

[4] The data sources are GSA-Global Semiconductor Alliance directory for fabless semiconductor firms, Bio-Biotechnology Industry Organization directory for biotech firms and BoogarLists for system design firms in electronics.

with the rest of the US firms, while Model 3 and 4 are comparing the US upstream technology providers with the rest of the US firms within the same 6-digit NAICS industry classification. The treatment effect on technology providers is negative but insignificant for patent applications; while its impact on out-licensing activities is negative and significant ($p<0.01$) in both comparisons. These results indicate that the decrease in patent applications is at the same level for US technology providers and US downstream manufacturers. However, US technology providers face a sharper decline in their out-licensing activities in the post-eBay case period, in support of Hypothesis-4.

Table-7a about here

Fourth, I further analyzed the data to see the impact of the weakening of patent enforcement on European firms which were '*heavily patenting in US*' before the Supreme Court's eBay decision. If the Supreme Court's decision is influencing all US patentees, these firms also should have been affected similar to the US firms. I identified a subsample of European firms which had above average ($n \geq 5$) yearly patent applications in US before the Supreme Court's eBay decision as '*heavily patenting in US*' and compared them to the rest of European firms. Table-8a presents the analysis results. Model 1 shows that European firms 'heavily patenting in US' have decreased their patent applications in US in the post-eBay period. Yet, there is no significant volume difference between 'heavy US patentees' and rest of the European firms in their rest of the world patent applications (Model 2). Furthermore, Model 3 presents that the out-licensing agreements of 'heavy US patentees' had a sharper decline compared to the rest of European firms. These results indicate that European firms ‘heavily patenting in US’ are affected similar to US firms in the post-eBay period.

Table-8a about here

Fifth, I also analyzed the data to see whether the declining patenting and out-licensing activities of US firms made an impact on the industry structure. Prior literature suggests that strengthening of patent protection facilitates vertical specialization and entry by small design firms (Hall & Ziedonis, 2001). Likewise, a downward shift in the patent enforcement strength is expected to decrease entry by specialized small firms. Table-9a shows the comparison of US upstream technology provider firm entry with the rest of US firm entry in pre- and post-eBay case period. The results of Cox proportional hazards model, which takes firm entry as the hazard, indicate that there is no significant difference between US upstream technology provider entry and rest of US firm entry in the pre- and post-eBay case periods. The results imply that the weakening of patent enforcement does not suffocate vertical specialization. An additional analysis is conducted to see whether upon the weakening of patent enforcement these new entrants have performed poorer compared to those that entered the market before the Supreme Court’s eBay case decision. No significant difference is observed in operating revenue or profit margin of new technology providers compared to earlier entrants.

Table-9a about here

Next, to the extent that the downward shift in the patent enforcement strength devalued patents and decreased potential licensors' bargaining power in licensing negotiations, a decline is expected to be observed in royalty rates. In order to test whether there has been a drop in royalty rates[5] (i.e. share of net sales) in actual licensing agreements, I split the US firms' licensing agreements into two depending on being a technology or non-technology related agreement and the royalty rates are compared for pre- and post-eBay periods (Table-10a). The results show that royalty rates in technology licensing agreements have decreased compared to non-technology agreements in the post-eBay period in the US ($p<0.05$).

Table-10a about here

Lastly, in order to analyze whether the decline in the volume of US firms' out-licensing agreements is influenced by the drop in patent applications by these firms, I tested a fixed-effects (within) instrumental variable regression, where the volume of patent applications is instrumented by the exogenous Supreme Court decision (Table-11a). The results of the analysis indicate that there is a positive and significant relationship between the volume of patent applications and the volume of out-licensing agreements ($p<0.01$). I interpreted the results of these analyses and presented possible policy implications in the discussion section.

[5] The data source of royalty rates is ktMINE database, which classifies the royalty rates according to the payment type; e.g. share of net sales, gross sales, net profit, gross profit, per unit, etc. It also provides a classification of agreement type that helps to distinguish technology related agreements, e.g. manufacturing/process intangibles, from non-technology related agreements, e.g. marketing, distribution, franchising, etc.

Table-11a about here

ROBUSTNESS CHECKS

An alternative explanation for the decline in the volume of patent applications and out-licensing agreement in the US can be the economic downturn in 2008. One might think that the economic crisis has mostly affected the US firms and the observed decrease in patenting and out-licensing activities is confounded by the severe macroeconomic conditions. To control for the possible confounding effect of the economic crisis, in all analyses operating revenue and profit margin of firms are inserted. To the extent that the economic crisis impacts firms' financial performance (i.e. operating revenue and profit margin), it is washed out from the firm-year observations. In addition, due to the cross-country nature of the analyses, I checked the timing of the economic crisis' impact on each country through the drop in gross domestic product (GDP). Figure-5a depicts the GDP of the US, Germany and Switzerland for the years 2000-2010. It can be seen that the financial crisis hits all countries in question simultaneously in 2009. Therefore, it is highly unlikely that the results of this study are driven by the differential impact of the financial crisis across countries or a lag in the timing of the effect.

Figure-5a about here

One might also think that to the extent that the firms are operating globally and the patents are applied for international use, a downward shift in patent enforcement strength may not affect US firms' patenting and out-licensing activities. First, in a research setting where cross-country variation in patent enforcement strength is exploited if the inventions are created for a global market, this would make it harder to find significant results due to under-estimation. Yet, this study presents a significant decline in patenting and out-licensing activities of US firms compared to those of German and Swiss firms in the post-eBay period. Second, to account for the potential impact of this possibility, I retested the arguments of this study on a control group of German and Swiss firms which do not have 'heavy patenting activities in US' and I found that the results are qualitatively the same.

Lastly, in order to see whether the difference-in-difference estimation applied in the analyses is capturing the impact of the US Supreme Court's decision or a trend which has begun before the eBay case decision, I employed several placebo difference-in-difference tests. I retested the arguments for placebo shocks in 2004 and 2005 for 1-year and 2-years intervals before and after. The results of these analyses do not show any trend change before the actual court decision in 2006. Therefore, the results of this study are robust under various specifications and cut-off points.

DISCUSSION AND CONCLUSION

In this study, I examine the impact of patent enforcement strength on firms' patenting and out-licensing activities. In doing so, I exploited a recent shift in the US patent policy reflected in an exemplary Supreme Court decision to present how the weakening of patent enforcement affects the volume of patent applications and out-licensing agreements of US firms in the IP-intensive industries.

The results of this study are interpreted as follows. The decrease in patenting and licensing activities of US firms in the post-eBay period points to the fact that, the weakening of patent enforcement triggers a disincentive for firms to file patents and a reluctance to engage in technology trade. In line with the prior literature highlighting the benefits of a strong patent system (Arora et al., 2001; Gans & Stern, 2000; Hall & Ziedonis, 2001; Kitch, 1977; Merges & Nelson, 1990, 1994) in facilitating firms' incentives to innovate and engage in patent trade in the market for technology, the weakening of patent enforcement results in a decreased number of patenting and out-licensing activities on average. The results of this study also imply that the so-called patent hold-up and royalty stacking problems which are argued to stifle follow-on innovation (Cockburn, MacGarvie & Muller, 2010; Lemley & Shapiro, 2006; 2007) are rather sporadic than pervasive (Denicolo, et.al.,2008). The results also point to the fact that the sharp decline in out-licensing activities is affected by two factors: an overall decrease in patent applications and a decrease in the bargaining power of the potential licensors. To the extent that the drop in the volume of patent applications reflect into a lower volume of codified inventions to be out-licensed, it can be said that the weakening of patent enforcement has impacted the volume of out-licensing agreements through its effect on firms' incentives to patent. In addition, the split sample analyses help to improve our understanding of which type of firms are more dependent on the strength of patent enforcement and severely affected by the downward shift. Although the Supreme Court's eBay decision is associated with a decrease in patenting activities for all sizes of firms, the decline in out-licensing agreements is more pronounced for small and medium sized firms. This result suggests that small and medium sized firms, which typically lack alternative mechanisms to protect their inventions from imitation, i.e. co-specialized complementary assets (Teece, 1986), rely more heavily on the strength of the patent enforcement. As the probability of succeeding in patent assertion decreases in the post-eBay period, the risk of expropriation increases for the small and medium sized licensors. The inflated risk of expropriation may pose disincentives for these firms to out-license their inventions (Arora and Fosfuri, 2003). Furthermore, as the strength of patent enforcement has weakened, it may become harder for these firms to negotiate for a license agreement with potential infringers. Due to the decreased bargaining power of the licensor, the potential licensee may refrain from an ex-ante licensing agreement with the hope of challenging the licensor's patents in the court (Davis, 2008; Mulder, 2007; Tang, 2006). However, for large firms the weakening of patent enforcement may not pose a big threat on out-licensing activities, due to the availability of engaging in cross-licensing agreements for large patent portfolios. Cross-licensing agreements are seen as alternative mechanisms to prevent litigations (Ziedonis, 2004) and gain access to complementary patent portfolios.

This study also presents that US firms' patent applications have declined in all IP-intensive industries. Although the earlier research shows that, firms' motives to patent vary by industry (Cohen, et. al., 2000), this research suggests that the diminution in patent enforcement strength impacts all IP-intensive industries similarly. Moreover, the upstream technology providers in these IP-intensive industries appear as the group that is affected the most upon the shift in patent enforcement. Technology providers, due to their business model, vertically specialize and focus on technology licensing rather than downstream product manufacturing. For these firms a strong patent system is essential to vertically disintegrate and operate as technology providers to downstream manufacturers (Arora et al., 2001; Hall and Ziedonis, 2001). Building on the earlier arguments it can be said that due to higher risk of expropriation and lower bargaining power (Arora and Fosfuri, 2003; Davis, 2008; Mulder, 2007; Tang, 2006), out-licensing activities of upstream technology providers are severely impacted in the post-eBay period. However, weakening of patent enforcement strength does not influence industry structure. There is no significant decrease in entry by specialized firms or a difference in financial performance between early and latecomers to the industry. These results may imply an entry by imitation strategy despite a decrease in the volume of out-licensing agreements and royalty rates. This final point requires further analysis on potential sources of revenue generation for technology providers. The results of this study have also some policy implications. The shift patent enforcement strength does not affect all firms with the same intensity. Small and medium sized firms and upstream technology providers appear to be impacted the most. These results point to the importance of taking into account firm size and business model effects in stimulating innovation and addressing problems in the patent system.

This study also has some limitations. First, although this research shows that the weakening of patent enforcement has an adverse impact on both patenting and out-licensing activities of the firms, it does not theorize whether these results imply an overall decrease in incentives to innovate or a shift from patenting to alternative mechanisms of protection; i.e. secrecy, lead time, investment in co-specialized complementary assets etc. Future studies can extend this line of research by testing the impact of patent strength on alternative mechanisms of protection. Second, this study exploits a rich dataset of firm-patent matching per year, yet it lacks patent-license matching information with royalty rates. Further research is needed on patent-license matching information to have a finer grained understanding of how the licensors' bargaining power have decreased upon the diminution in patent enforcement strength reflected in royalty rates. Finally, the analyses are based on changes in the volume of patent applications rather than the quality of the patents applied for after the eBay case. Future studies can test whether the weakening of patent enforcement strength resulted in fewer number of higher quality patents. I hope that this research paves the way to refine future theorizing on these lines of research.

Chapter 2

Optimal Absorptive Capacity in Technology-based Firm Acquisitions: The Impact of Relatedness and Structure

This research examines the determinants of efficiency in absorbing external knowledge, i.e. efficiency factor, in technology-based firm acquisitions, and how it relates to the merged entity's innovative performance. Drivers of efficiency factor are identified as knowledge structure, i.e. technological complexity of target firm's knowledge stock, and knowledge relatedness, i.e. technological distance between acquirer and target firms' knowledge stocks. Testing a sample of between- and within-industry acquisitions undertaken during 2000-2008, for target firms in six U.S. manufacturing industries, it is found that technological distance between the acquirer and target firms' knowledge stocks has a negative impact on efficiency factor; while, technological complexity positively affects the efficiency factor. Moreover, efficiency factor has an inverted U-shaped relationship with the merged entity's innovative performance, suggesting that there is an optimum level of absorption in exploiting external knowledge.

Key words: knowledge transfer, technological complexity, relatedness, acquisitions

INTRODUCTION

In the recent decades, firms have begun to rely more heavily on external knowledge and technologies to achieve rapid innovation, maintain their technologies at the frontier and get ahead of the product market competition (Arora & Gambardella, 2010; Leone & Reichstein, 2012). Acquisition of external technology is seen as a means to broaden the firms' knowledge stock (Cohen & Levinthal, 1989; Huber, 1991) and improve their combinative capabilities through the synthesis of existing and acquired technological knowledge (Kogut & Zander, 1992). Among the possible sources of external technology transfer, acquisition of technology-based firms is considered as one of the prominent firm strategies (Ahuja & Katila, 2001; Bresman, et.al, 1999; Graebner, et.al., 2010; Kale & Puranam, 2004; Leonard-Barton, 1995; McEvily, et.al, 2004). However, in order to innovate, firms need not only to acquire external technological knowledge, but also to leverage it by exploiting and recombining with the existing technological competencies (McEvily, et.al., 2004). This is one of the main challenges of acquiring firms which desire to enhance their innovativeness.

In order to enhance their innovativeness, firms need to recognize the value of external knowledge, assimilate it, and apply to commercial ends. This ability is defined as *absorptive capacity (AC)* (Cohen & Levinthal, 1990), it is positioned as a key concept in firms' innovative processes (Cohen & Levinthal, 1989) and drew considerable scholarly interest in the subsequent 25 years. Extending this concept and reconceptualizing AC as a dynamic capability, Zahra & George (2002) distinguish among four dimensions of AC, i.e. acquisition, assimilation, transformation and exploitation. They argue that AC is composed of two subsets, potential and realized AC, which have complementary roles in extracting value from external knowledge. In particular, potential AC is associated with firms' receptiveness to acquisition and assimilation of external knowledge; whereas, realized AC reflects the firms' capacity to transform and exploit the assimilated knowledge. They argue that firms focusing on potential AC are able to continuously renew their knowledge stock, but they may suffer from the costs of acquisition without gaining the benefits of exploitation (Zahra & George, 2002). Conversely, firms focusing on realized AC may attain short-term benefits through exploitation but fall into a competence trap. Therefore, they propose the term '*efficiency factor*' (η) which denotes the ratio of realized AC to potential AC. The efficiency factor indicates that, due to variations in their capabilities to exploit knowledge, firms differ in value generation from external knowledge acquisition. Since value generation is attained mainly through realized AC (Grant, 1996), they assert that firms that achieve high efficiency factor increase their innovative performance. Adding to this line of literature, in their critical review of Zahra & George's (2002) reconceptualization of AC, Todorova & Durisin (2007) affirm the importance of efficiency in absorbing external knowledge for firm innovativeness and the need for an empirically meaningful definition. They suggest that 'the ratio of the knowledge embodied in successful new processes or products to the knowledge that enters the boundaries of the organization' can be analyzed as an efficiency factor for external knowledge absorption. Moreover, in their comprehensive review of AC, Volberda, et.al. (2010) argue that due to the lack of cost consideration in developing AC in the literature, the issue of whether there is an optimum level of AC does not appear to be raised. They claim that prior literature on AC implicitly assumed that maximum AC is highly desirable, although in the presence of organizational costs of developing and maintaining AC, optimum AC may not be equal to maximum AC. Thus, they call for future research to identify optimum AC and its determinants. In sum, the prior literature on AC highlights the importance of efficiency in absorbing external knowledge and the optimum level of AC on firm's innovative performance. Interestingly, despite more than two decades of presence of the AC concept and a growing body of theoretical advancements in the construct (e.g. Todorova & Durisin, 2007; Volberda, et.al., 2010; Zahra & George, 2002), empirical research on AC largely focused on R&D rates in various industries, managerial antecedents and interorganizational antecedents of AC[6], and overlooked the efficiency factor, its antecedents and how it affects the firm's innovative performance.

Building on Zahra & George's (2002) conceptualization and following Todorova & Durisin's (2007) redefinition, this study focuses on the *efficiency factor* which is defined here as '*the ratio of the external knowledge embodied in innovative output to the external knowledge that enters the boundaries of the firm*', and empirically explores its antecedents and its impact on innovative performance. Efficiency factor presents how much of the external knowledge acquired by the firm is actually exploited to create innovative output. In their seminal piece, Cohen & Levinthal (1990) claim that external knowledge characteristics, such as complexity of the external knowledge and relatedness between the prior knowledge and external knowledge have important implications for the development of AC and, in turn, innovative performance. In line with their specification, antecedents of efficiency factor are identified here as knowledge structure of the target firm; i.e. *technological complexity*, which refers to the density of linkages among the target firm's pre-deal technological assets, and knowledge relatedness; i.e. *technological distance* between the acquirer and target firms' pre-deal knowledge stocks. In addition, this research investigates the impact of efficiency factor on firm's innovative performance and explores the optimal level of AC.

[6]For a bibliometric analysis of AC, see Volberda, et.al. (2010) study which presents the analyses performed by the Centre for Science and Technology Studies, Leyden University, for the period 1992-2005.

This paper aims to make three main contributions to the AC literature. First, this study advances the research on AC by extending the theoretical definition of efficiency factor. Following Todorova & Durisin's (2007) redefinition of the concept developed by Zahra & George (2002), a reconceptualization of efficiency factor is provided. Second, this research theorizes on and presents the first empirical assessment of the antecedents of efficiency factor. Prior empirical research on AC rather focuses on the organizational antecedents of potential AC and realized AC (e.g. Jansen, et.al, 2005), and antecedents of potential AC (e.g. Fosfuri & Tribo, 2008). Third, this study presents how efficiency factor is related to the innovative performance of the firm. Earlier studies on AC concentrates on potential AC's impact on innovative performance (Fosfuri & Tribo, 2008), how potential AC and realized AC affect market performance and financial performance (Brettel, et.al., 2011) and the efficiency factor's impact on financial performance (Therin, 2007). To date, this body of literature remains silent on efficiency factor's impact on innovative performance and the optimum level of AC. Volberda, et.al. (2010) call for future research on evaluation of optimal AC. This study aims at addressing this gap in the literature by empirically testing the optimal AC for firm innovativeness.

THEORY AND HYPOTHESES

Technology-based firm acquisition is the rising trend among established firms in high-tech industries (Agarwal & Helfat, 2009). Acquirers pursue technology-based firm acquisitions to tap the innovative potential of target firms through attaining their strategically valuable technological knowledge (Graebner, et.al., 2010). The ability of the firm to exploit external knowledge is an essential component of innovative capabilities (Chesbrough, 2003; Laursen & Salter, 2006). Firms endowed with higher levels of AC can generate greater value from external knowledge acquisition and increase their innovative performance (Tsai, 2001). Zahra & George (2002) argue that AC is a multidimensional construct. They identify four distinct but complementary processes that compose a firm's AC: acquisition, assimilation, transformation and exploitation of external knowledge. *Acquisition* refers to the firm's ability to identify and acquire externally generated knowledge; yet, *assimilation* refers to the firm's routines and processes that allow it to analyze, process, interpret, and understand external knowledge (Zahra & George, 2002). In their view, these two components of AC constitute potential AC, which helps firms to process and internalize external knowledge and reconfigure the knowledge stock. Potential AC influences innovative performance through the flexibility of resources and capabilities. The other two components of AC are *transformation* and *exploitation* of external knowledge; where the former refers to the ability of the firm to combine existing knowledge stock with the newly assimilated knowledge, while the latter refers to the firm's ability to incorporate acquired and transformed knowledge into its innovative operations. Consisted of these two components, realized AC helps the firm to leverage on the absorbed external knowledge. They argue that realized AC influences innovative performance through creation of new knowledge and development of new products. Without the effective functioning of realized AC, potential AC cannot improve firm's innovative performance. Therefore, they identify the ratio of realized AC to potential AC as the efficiency factor and assert that the firm which achieves or maintains high efficiency factor can increase its innovative performance. This dichotomous view of AC is criticized by Todorova & Durisin (2007), who put forward that assimilation component of potential AC and transformation component of realized AC are not sequential but rather alternative processes of developing cognitive structures which help the firm to combine external knowledge with the existing knowledge stock. Therefore, identification of assimilation and transformation as parallel processes of combining external and existing knowledge renders it impossible to disentangle AC into two distinct subsets. Hence, Todorova & Durisin (2007) assert that the problems with the clear differentiation of the two subsets of AC, cast doubts on their appropriateness in measuring their distinct effects in empirical studies of value creation. Moreover, they claim that ‘the term *potential* refers to the new knowledge that enters the organization and is not yet assimilated or transformed, rather than to the capacity to absorb new knowledge, which is an organizational process’ (Todorova & Durisin, 2007). Nevertheless, they affirm that the efficiency in absorption of external knowledge remains as an essential concept in extracting value from external knowledge acquisition. They reconceptualize this construct as the ratio of the external knowledge embodied in successful new processes and products to the knowledge that enters the firm boundaries. With this broader conceptualization, efficiency factor accounts for the ability of the firm to create value from the acquired external knowledge.

In the theoretical model proposed by Zahra & George (2002), efficiency factor is proposed to be influenced by social integration mechanisms. In order to increase mutual understanding and comprehension of the external knowledge (Garvin, 1993), it needs to be shared among the members of the firm (Spender, 1996). Social integration mechanisms have the role to facilitate the sharing and exploitation of the knowledge. Thus, it is proposed that use of social integration mechanisms reduces the gap between realized AC and potential AC, thereby increasing the efficiency factor (Zahra & George, 2002). However, in this theorizing, it is not clear whether the social integration mechanisms only increase transformation and exploitation of the assimilated knowledge which increases realized AC for a given level of potential AC, or they also influence knowledge assimilation through increasing ‘mutual understanding and comprehension of the external knowledge’ (Garvin, 1993). In the latter case, potential AC is expected to increase as well; thus, the resultant effect of social integration mechanisms on efficiency factor, when it is specified as the ratio of realized AC to potential AC remains ambiguous. Moreover, the focus on organizational mechanisms overlooks the role of the nature of external knowledge and relatedness of the prior knowledge stock with external knowledge as the key determinants of AC in Cohen & Levinthal's (1990) theoretical model. This study reintroduces the structure of the external knowledge and relatedness of the prior knowledge stock with the external knowledge as important factors which not only determine the level of AC but also the efficiency factor in extracting value from external knowledge. Prior literature on AC focuses on the effect of knowledge structure (e.g. Kogut & Zander, 1992; Simonin, 1999; Szulanski, 1996) and knowledge relatedness (e.g. Ahuja & Katila, 2001; Makri, et.al., 2010; Puranam & Srikanth, 2007; Sears & Hoetker, 2014) on assimilation of the external knowledge. Following this line of research, I propose that knowledge structure and knowledge relatedness also have an impact on firm's ability to exploit external knowledge; thereby influence the efficiency in absorption of external knowledge. The proposed model is depicted in Figure-1b.

Figure-1b about here

The first antecedent of efficiency factor is knowledge structure; in particular, complexity of the acquired external knowledge. In their review of AC literature, Lane, et.al. (2006) claim that the focus of earlier research is on two aspects of Cohen & Levinthal's definition; i.e. how the nature of knowledge influences firm's ability to recognize valuable external knowledge and the firm's ability to assimilate that knowledge. They emphasize that, in addition to the lack of empirical evidence, the influence of the knowledge structure on firm's ability to exploit has received relatively little attention, reflecting the underlying assumption that mere acquisition enhances firm's innovative performance. Challenging this assumption, the above proposed model asserts that efficiency in extracting value from acquired external knowledge is influenced by the knowledge structure. Prior literature on AC identifies knowledge characteristics such as complexity, ambiguity (Simonin, 1999) and tacitness (Inkpen & Dinur, 1998; Kogut & Zander, 1992; Ranft & Lord, 1998; Simonin, 1999) as barriers to knowledge transfer and absorption. Cohen & Levinthal (1990) claim that complexity of the external knowledge determines the ease of learning which, in turn, affects the firm's incentives to learn and invest in AC. Knowledge complexity refers to the complementarity of technological assets, e.g. patents, linked to a particular technological knowledge (von Graevenitz, et.al., 2013). In other words, a technology becomes more complex as the density of interdependence among the technological assets increases. In an attempt to better understand the link between knowledge structure and invention, Fleming & Sorenson (2001) develop a theory which regards invention process as a recombinant search over technology landscapes. They suggest that inventors might face a 'complexity catastrophe' when they attempt to combine highly interdependent technologies. Empirical research on knowledge complexity indicates that it has a negative impact on the firm's innovativeness (Simonin, 1999). Cohen & Levinthal (1989) explain this effect as follows: an increase in the knowledge complexity requires higher internal R&D for its absorption; thus, the cost of absorption increases. This means that, for a given level of R&D expenditure, knowledge absorption decreases with knowledge complexity which, in turn, decreases innovative performance.

However, concerning the efficiency in absorbing acquired external knowledge a reverse effect is expected. Earlier work points out that AC of the firm is enhanced by the development of routines that pursue resource recombination and knowledge complexity (Galunic & Rodan, 1998; Van den Bosch, et.al., 1999), which in turn, enables the firm to recognize and assimilate more complex external knowledge. Likewise, as the knowledge becomes more complex, the firm needs to absorb more areas of knowledge content, as well as understand the interlinkages between various content areas (Garud & Nayyar, 1994). For instance, especially in technology fields where technological knowledge is developing cumulatively, later inventions are embracing a higher rate of prior art. Due to this characteristic, as firms continue to innovate, the interdependencies among technological assets increase and render the technology highly complex. Exploitation of this type of technological knowledge requires combination and recombination of a higher rate of prior technological assets. In sum, in technology-based acquisitions, innovations of the newly merged entity are expected to leverage on a larger portion of target firm's knowledge stock as the complexity of that knowledge increases. Thus, the efficiency in absorbing external knowledge, namely efficiency factor, is positively associated with the complexity of the acquired external knowledge.

Hypothesis 1 (H1): Complexity of target firm's knowledge stock is positively related to the merged entity's efficiency in absorbing external knowledge.

Another antecedent of efficiency factor is knowledge relatedness. Eisenhardt & Santos (2002) identify knowledge relatedness as one of the main factors influencing the external knowledge transfer. Relatedness of unifying knowledge stocks of the acquirer and target firms is seen as one of the prominent determinants of firm innovativeness (Ahuja & Katila, 2001; Lane & Lubatkin, 1998; Lubatkin, 1983; Puranam & Srikanth, 2007; Seth, 1990; Singh & Montgomery, 1987).

Relatedness refers to the content of the technological knowledge of the firms (Ahuja & Katila, 2001) and it is expected to have an impact on the ability of the acquirer to exploit the acquired technology depending on its level of AC (Cohen & Levinthal, 1990). The theory on AC asserts that firm's ability to use external technological knowledge is greater if the relatedness is high between external and prior knowledge stocks. In situations where the acquirer and target firms have distant knowledge stocks, integration of the these stocks is likely to be resource consuming or counter to the routines of the acquirer (Haspeslagh & Jemison, 1991; Singh & Zollo, 1997) which hamper the exploitation of the external knowledge. Thus, knowledge utilization is expected to be low in technologically distant firm acquisitions. On the contrary, AC theory argues that in very similar acquisitions little can be added to the innovative performance due to duplicates and redundancies in knowledge (Ahuja & Katila, 2001; Cohen & Levinthal, 1990). Combining very similar technological stocks may produce less novel innovative output (Makri, et.al., 2010). This view is mostly supported by empirical research. For instance, Ahuja & Katila (2001) found an inverted-U shaped relationship between knowledge relatedness and post-acquisition innovative output. Similarly, Cloodt, et.al (2006) found that relatedness between the acquired and acquiring firms' knowledge stocks has an inverted-U shaped relationship with the acquiring firm's innovative performance. However, Makri, et.al, (2010) found no relationship between knowledge relatedness, i.e. technological similarity, and innovative quantity.

Concerning the efficiency in absorbing acquired external knowledge, i.e. efficiency factor, relatedness of the external knowledge is expected to increase its exploitation in subsequent innovations. Acquirers leverage on external knowledge by combining and recombining acquired knowledge with the prior knowledge stock (Kogut & Zander, 1992). Combining and recombining external and prior knowledge requires alignment of two knowledge stocks (Dinur, et.al., 1998). If the acquired external knowledge has a significantly different content than the prior knowledge stock, this may delay its comprehension and absorption by the acquirer (Leonard-Barton, 1995). Conversely, very similar knowledge stocks may have little to add to the knowledge exploitation of the merged entity (Ahuja & Katila, 2001; Cohen & Levinthal, 1990; Makri, et.al., 2010). If the target firm's knowledge stock is very similar to the acquirer's, the acquirer might not leverage on that knowledge due to duplications and redundancies. When two knowledge stocks are very similar, it is expected that no acquisition will take place. Therefore, it is assumed that the acquirer will undertake acquisition of a target firm only when the target firm's knowledge stock is somewhat different than the acquirer's prior knowledge stock. In this case, the hampering effect of very similar knowledge stocks may not be observed while the negative impact of very distant acquisitions may still be notable. These arguments suggest that in technology-based acquisitions knowledge exploitation is enhanced when acquirer and target firms endow similar technological knowledge stocks and hampered as the technological distance between the acquirer and target firms widens. Therefore, it is expected that technological distance between the acquirer and target firms' knowledge stocks is negatively associated with the efficiency in absorbing external knowledge.

Hypothesis 2 (H2): Technological distance between the acquirer and target firms' knowledge stocks is negatively related to the merged entity's efficiency in absorbing external knowledge.

In their seminal paper, Cohen & Levinthal (1990) argue that 'because AC is intangible and its benefits are indirect, one can have little confidence that the appropriate level, to say nothing of the optimal level, of investment in AC is reached'. Although it is hard to determine the optimum level of AC a priori and invest accordingly, theoretical developments in the AC literature highlighted the importance of efficiency in absorbing external knowledge and its impact on firm innovativeness (Todorova & Durisin, 2007; Zahra & George, 2002). In their reconceptualization of AC, Zahra & George (2002) claim that a high efficiency factor, i.e. a high ratio of realized AC to potential AC, is positively associated with future innovative performance. They argue that externally acquired knowledge undergoes multiple processes before the acquirer can successfully exploit it. To enhance acquirer's innovativeness, realized AC would approach potential AC. This view is questioned by other researchers, who argue that firms may not always be better off by fully realizing their potential AC in dynamic environments (Volberda, et.al, 2010). Although realized AC promotes innovation, the resultant products and services may rapidly converge to industry standards and become obsolete relative to current environmental demands (Sorensen & Stuart, 2000). The latter view also found some empirical support, Jansen, et.al. (2005), in line with their findings, claim that organizational units with baseline levels of realized AC and high levels of potential AC will obtain above-normal performance in dynamic markets.

In their review of AC literature, Volberda, et.al. (2010) assert that there is little consideration of the cost of developing AC, changing it, or in some way taking advantage of a firm's AC. However, developing AC is costly and it is overlooked in the prior research. For this reason, the issue of whether there is an optimum level of AC is not questioned in the literature. Maximum AC is implicitly assumed to be desirable, although in the presence of organizational costs of building and maintaining AC, optimum AC may not be equal to maximum AC (Volberda, et.al., 2010). Regarding the efficiency in absorbing external knowledge, optimum AC can be less than maximum AC due to two reasons depending on the relevance of the acquired external knowledge for the subsequent innovative activities of the firm. First, although the acquired knowledge can be totally useful for the acquirer firm's innovative activities, the cost of assimilation and exploitation of all the acquired knowledge stock may exceed the benefits of the innovative activities; i.e. the revenue to be generated by product innovations and/or the cost reduction to be achieved by process innovations. In this case, the acquirer may prefer to exploit a portion of the acquired knowledge stock which results in an optimum AC which less than the maximum level. Second, not all of the acquired knowledge may be useful for the acquirer's innovative activities. Due to information asymmetries and uncertainty regarding the usefulness of the acquired knowledge, the acquirer may only ascertain the true value of the knowledge *ex post* and realize that only some portion of the acquired knowledge is useful for its subsequent innovative activities. Again, in this case, the acquirer may prefer to exploit less than total of the acquired knowledge which induces the optimum AC less than the maximum level. Consistent with these arguments, it is expected that the optimum AC which facilitates innovative performance is less than maximum AC. Therefore, an inverted U-shaped relationship between efficiency factor and innovative performance is expected.

Hypothesis 3 (H3): The merged entity's efficiency in absorbing external knowledge has an inverted U-shaped relationship with innovative performance.

METHODS

Data and Sample

In order to test the hypotheses of this study, I used a sample of technology-based firm acquisitions undertaken for target firms in six U.S. manufacturing industries during the period of 2000-2008. A major strength of using technology-based firm acquisitions as a context is that, with this specification, it is easy to determine the timing and amount of external technological knowledge that enters the firm boundaries and the level of its exploitation in the subsequent innovative activities. The selection of the industries follows the rationale of having a pool of target firms which provide enough variance in IP intensity, as it is announced by a recent report of USPTO (USPTO IP-Report, 2012), to capture the variance in knowledge exploitation in different industries. For this purpose, three industries with the highest IP-intensity; i.e. computer and peripheral equipment (NAICS 3341), communications equipment (NAICS 3342), semiconductor and other electronic components (NAICS 3344); and three less IP-intensive industries; i.e. plastics and rubber products (NAICS 326), motor vehicles, trailers and parts (NAICS 3361-63), nonmetallic mineral products (NAICS 327), are selected where the latter group is characterized by having below-average IP-intensity but still endowing high enough technological knowledge which can be redeployed by the acquirer. I obtained the initial sample of acquisitions from Bureau van Dijk's ZEPHYR database and included all between- and within-industry acquisitions for the period 2000-2012 in the specified IP-intensive and less IP-intensive industries. This resulted in 3,666 acquisition-deals for target firms affiliated primarily to the selected industries[7]. From this population, acquisitions less than 100% equity stake and acquisitions of the remaining stakes are eliminated. To determine the technology-based firm acquisitions, deals with target firms which have at least 5 technological assets, i.e. patents, before the acquisition are identified[8]. This filtering ended up with 520 technology-based firm acquisitions. Data is further constrained to measure the

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[7] Acquirer firms are not constrained by industry affiliation to allow for the analysis of both between- and within-industry acquisitions.

[8]Similar specifications are widely used in technology acquisition literature (e.g. Ahuja & Katila, 2001; Ernst &Vitt, 2000; Granstrand & Sjolander, 1990; Puranam & Srikanth, 2007). For instance Ahuja & Katila (2001) identified technology acquisitions as deals with target firms which have at least one technological input. Similarly, Ceccagnoli & Hicks (2012) determine high-tech target firms with endowment of at least 15 technological inputs.

efficiency factor within four years following the acquisition; therefore, sampling is ended by year 2008. After implementing these filters and constraints, and the deductions due to missing values, the final sample consisted of 356 acquisition-deals.

Measures

Dependent Variable

Innovative Performance: I measured this construct by the number of granted patents for which the application is made by either acquirer or target firm within 4 years following the acquisition deal. This specification follows the rationale of accounting for the overall innovativeness of the merged entity and taking into account the possibility that the merged entity may keep applying patenting under the name of target firm when it is not fully integrated. Data for the number of patent applications are gathered from USPTO database.

Independent Variables

Efficiency Factor: I measured this construct by the share of pre-deal target patents exploited by either acquirer or target firm within 4 years following the acquisition deal. A patent is considered to be exploited if it received a forward citation from acquirer or target firm patents within the specified time period after the deal. In order to account for the overall knowledge exploitation of the merged entity, i.e. not just to account unidirectional knowledge transfer from target firm to the acquirer, both acquirer and target forward citations to the pre-deal target patents are examined. Data for patents and forward citations are gathered from USPTO database. Traditionally, patent forward citations are used as a measure of invention quality (e.g. Trajtenberg, 1990; Valentini, 2012) because they are considered to be a reflection of ‘the ability of a set of patents to support future inventions by creating a ''ripple effect'' to stimulate subsequent patents' (Makri, et.al., 2010). However, there is another body of research which considers citations as an evidence of inter- or intra-firm knowledge transfer (Almeida et al., 2002; Rosenkopf & Almeida, 2003; Song, et.al, 2003). Citations are assumed to be an indicator of successful transfer of knowledge with its tacit and codified components (Almeida et al., 2002; Almeida & Kogut, 1999; Jaffe et al., 1993; Jaffe & Trajtenberg, 1996; Jaffe, Trajtenberg, & Fogarty, 2002; Song et al., 2003). Puranam & Srikanth (2007) use post-acquisition forward citations from acquirer patents' to pre-deal target firm patents as a measure of the leverage of target firm technological knowledge codified in patents and residing in employees. In this study, this measure is advanced by adding target firm's self-citations to the pre-deal patents from post-deal ones to have a more comprehensive account of the innovative activity produced by the merged entity. Forward citations received by target firm patents from acquirer's or target's subsequent patents in the post-acquisition period indicate that these patents are exploited by the merged entity and a new body of technological knowledge is created by combining and advancing the acquired knowledge.

A major concern about the use of patent citations as an indicator of spillovers and knowledge transfer is that citations are argued to be a noisy indicator which can be interpreted in several different ways than actual knowledge flow (Jaffe et al., 1998). In particular, it is asserted that 'where citations are added by the patent examiner, we cannot judge whether or not the applicants were aware of the cited patent' (Criscuoloa & Verspagen, 2008). In this study, the post-deal forward citations measured are either target firm's self-citations or acquirer's citations, which in total can be considered as post-deal self-citations of the merged entity. Thus, the applicant is supposedly aware of the cited patent and these citations are proper indicators of knowledge exploitation.

Technological Distance: Following Jaffe's (1986) measure of technological proximity, I measured this construct by examining the extent to which pre-deal acquirer and target firm patents are in the same patent classes. This measure is aiming at capturing the position of one firm relative to the other in the technology space (Sampson, 2007). The technological distance between two firms is calculated by creating a vector for each firm to measure the distribution of its patents across patent classes, denoted as $F_i=(F_1 \ldots F_n)$, n=1,…,473 (473 is the total number of patent classes in USPTO database) and by calculating the formula below:

$$\text{TECHDIST} = 1 - \frac{F_i F_j'}{\sqrt{(F_i F_i')(F_j F_j')}}$$

where i≠j. This measure is ranging between 0 and 1, higher values are indicating greater technological distance between the acquirer and target firms. For patent classes, the emphasis is given on the primary patent class assigned to the patent by checking the 3-digit patent class code and not digging into sub-classes. This is a common method used in studies that apply Jaffe's formula (e.g. Makri, et.al., 2010; Sampson, 2007). In cases where acquirer firm has no patents to calculate the technological distance, depending on the type of acquisition (i.e. between- or within-industry), the average technological distance of that type of acquisitions is used and to account for any systematic error created in the variable, a control variable (TDDUMMY) is added, which takes value of 1 when the average is inserted and 0 otherwise.

Technological Complexity: Complexity of a technology is assumed to be increasing as the density of interdependence among the technological assets, i.e. patents, increases. Interdependence of the patents is assessed by the citation network among the patents. Clarkson (2005) proposes a density measure of the backward citations among a pool of patents taking into account the fact that younger patents can make more backward citations than the older ones. For the purposes of this study, technological complexity construct is measured by the weighted average citation network density among target firm's patents before acquisition (Clarkson, 2005). Density is measured as such:

$$\Delta_p = \frac{\sum_{n=1}^{g}\sum_{j=1}^{g} X_{nj}}{g(g-1)/2}$$

where Δ_p is the density of citation network, n is the focal patent, g is the total number of patents of the target firm before acquisition, j is the citations to and from patent n. This is a measure between 0 and 1. As the density increases, the complexity of the technology increases as well.

Control Variables

Several control variables are included in the analyses. First, to account for the impact of knowledge stock of the acquirer in exploiting acquired knowledge (Cohen & Levinthal, 1990), *Acquirer's Knowledge Stock* is controlled and measured by the number of pre-deal acquirer firm's patents. Second, the data is further controlled for the *Target Firm's Knowledge Stock* which is measured by the number of pre-deal target firm's patents. Third, empirical studies on patenting quality generally determine the level quality by the number of forward citations received by these patents (e.g. Valentini, 2012); therefore a measure of the *Number of Target Patents Cited Before*

Acquisition is included in the analyses. Fourth, to account for the acknowledgement of target firm's pre-deal knowledge stock by the acquirer, *Number of Target Patents Cited by Acquirer Before Acquisition* is contained in the analyses. Fifth, to control the effect of *Prior Acquisition Experience of Acquirer Firm*, a measure is included for the number of acquisitions undertaken by the acquirer within five years before the focal acquisition. The data for this variable is gathered from ZEPHYR database. Sixth, to control for the external knowledge inflows to the acquirer firm other than the focal acquisition, a measure for *Prior Technology Licensing Experience of Acquirer Firm* is contained in the analyses and it is measured by the number of technology licensing agreements made by the acquirer within five years before the focal acquisition. The data for this variable is gathered from FACTIVA database by searching 'company name' and 'licensing agreement' in press releases for the specified time period. Seventh, to control for the industry-level factors that may affect the knowledge exploitation and innovative performance, such as *Industry Concentration*, Herfindahl-Hirschman Index (HRFNDHL) is included, it is calculated by squaring the market share of each firm in the industry, and then summing the resultant numbers. Eighth, a number of dummy variables are created to specify acquisition characteristics, i.e. within- vs. between-industry, measured by *Within-Industry Acquisitions* (WITHINA), which takes the value of 1 when it is a within-industry acquisition and 0 if it is a between-industry acquisition; likewise, IP-intensive and less IP-intensive industries are differentiated by a dummy measure: *IP-intensive Industries* (IPINT) which takes the value of 1 when the target firm is operating in an IP-intensive industry and 0 otherwise, and *Year* dummies.

Model

Due to the mediation effect theorized in the model, a hierarchical regression is chosen to test the hypotheses. The model consists of two discrete steps where the first step tests the impact of technological complexity and technological distance on the efficiency factor, including the controls, and the second step regression tests the effect of efficiency factor on innovative performance, including technological complexity, technological distance and controls in the regression.

The dependent variable of the first stage regression is the fraction of pre-deal target firm patents exploited after the acquisition and thus, bound between 0 and 1. A quasi-likelihood method is proposed by Papke & Wooldridge (1996) for the estimation of regression models with a fractional dependent variable based on the logistic distribution. The advantages of this regression model is that it can estimate the possible nonlinear relationships better than a linear model with conditional mean or log-odds transformed variables (Conti, 2013). This method is used in many similar studies which estimate fractional dependent variables (e.g. Adegbesan & Higgins, 2010; Conti, 2013; Kleinbaum & Stuart, 2014; York & Lenox, 2013). It is implemented using generalized linear model (GLM) in STATA with a Binomial variance function and a Logit link with robust standard errors (McDowell & Cox, 2004). Using this model, the first two assertions of the study are tested on efficiency factor.

The dependent variable of the second step regression, i.e. innovative performance, is a count variable, the number of granted patents to the merged entity; which is zero inflated; therefore, Negative Binomial model is chosen to account for overdispersion in the count data (Ver Hoef & Boveng, 2007).

To account for possible correlations among the error terms in the hierarchical regression model, a robustness check is provided with path analysis, which is a type of structural equation modeling (SEM) where each variable has only one indicator. Using a maximum likelihood estimator (MLE), this model simultaneously estimates the path coefficients and errors (Fosfuri & Tribo, 2008).

RESULTS

Descriptive Statistics

The descriptive statistics of the data are depicted in Table-1b. According to the sampled data, the innovative performance of the merged entities ranges between 0 and 8380 patent applications within four years after the focal acquisition with the average of 232 patent applications. Furthermore, on average 13.2% of the target firm technological knowledge stock is exploited after the acquisition. Technology leverage goes up to 14.55% for IP-intensive industries; whereas, it drops to 8.76% in less IP-intensive industries. There is substantial variance in the independent variables, i.e. technological distance and technological complexity, and also in control variables such as industry concentration (HRFNDHL), acquirers' prior acquisition experience, size of acquirer's and target's existing technological knowledge stocks, number of target patents cited before acquisition and share of target firm patents cited by the acquirer before acquisition.

Table-1b about here

Table-2b displays the correlations between variables. The independent variables *technological distance* and *technological complexity* are not highly correlated and there are no high correlations observed between the independent variables and *efficiency factor* or *innovative performance*. Two controls are highly correlated with the innovative performance: acquirer's knowledge stock (0.590) and acquirer's licensing experience (0.578). Size of acquirer's knowledge stock is also highly correlated with acquirer's licensing experience (0.852). And lastly, the number of target patents cited before acquisition is highly correlated with the size of target's knowledge stock (0.998).

Table-2b about here

Regression Results

Table-3b presents the regression results for the first stage GLM estimations using Binomial family and Logit link (Papke & Wooldridge, 1996), reported with robust errors, on the total sample. Model 1 depicts the basic model with all controls. The independent variables are added to the basic model one by one. In the basic model (Model 1), the control variables show that the size of the target's knowledge stock has a significant positive effect on the efficiency factor ($p<0.05$), while the number of target firm patents cited before acquisition has a significant negative effect on efficiency factor ($p<0.05$). However, the number of target firm patents that are cited by the acquirer before the focal acquisition significantly increases efficiency factor ($p<0.1$). In order to test Hypothesis 1, knowledge complexity is added to the basic model. As it can be seen in Model 2, knowledge complexity has direct positive effect ($p<0.01$) on efficiency factor. This is the first evidence of the positive relationship between technological complexity and efficiency factor. In Model 3, to test Hypothesis 2, technological distance is added to the regression, and the results indicate that it has a negative and significant effect on efficiency factor ($p<0.01$). Finally, Model 4 depicts the full model with all independent variables. Here, the results show that technological complexity has a positive and significant effect on efficiency factor ($p<0.01$), which confirms H1; whereas, technological distance has a negative and significant impact ($p<0.01$), supporting H2. These results indicate that all proposed direct effects on efficiency factor are confirmed.

Table-3b about here

In the second stage analysis, the effect of efficiency factor on the merged entity's innovative performance is tested. Table-4b depicts the regression results for Negative Binomial estimations. In Model 1, the control variables are inserted in the regression. This analysis indicates that industry concentration, measured by Herfindahl Index, has a significant negative impact on the innovative performance ($p<0.05$); whereas, the size of acquirer's knowledge stock and the number of target firm patents cited by the acquirer have a positive and significant effect on innovative performance ($p<0.05$ and $p<0.1$ respectively). Moreover, acquirer's acquisition experience significantly increases innovative performance ($p<0.01$). Model 2 tests the effect of technological complexity and technological distance on innovative performance. This model shows that the impact of technological complexity on innovative performance is insignificant and technological distance has a negative impact on innovative performance ($p<0.1$). Model 3 tests H3, the curvilinear effect of efficiency factor on innovative performance. The results show that efficiency factor has a positive and significant impact ($p<0.01$) on innovative performance and the squared term is also a negative and significant ($p<0.01$), which indicate that efficiency factor has an inverted U-shaped relationship with innovative performance, confirming H3. The inflection point is provided in Figure-2b. The figure shows that innovative performance is maximized when 55.15% of external knowledge is exploited by the firm. Moreover, the results indicate that the effect of technological distance on innovative performance is fully mediated by efficiency factor; whereas the effect of technological complexity is partially mediated by efficiency factor. Technological complexity has a direct negative impact on innovative performance ($p<0.05$). These outcomes are interpreted in detail in the discussion section.

Table-4b about here

Figure-2b about here

Robustness Check

As a robustness check, path analysis technique is used to estimate the theoretical model. A MLE model is implemented on STATA with *pathreg* comment. The model is composed of two paths: one from technological complexity and technological distance to efficiency factor, including controls, and the other one from efficiency factor to innovative performance, including technological complexity, technological distance and controls. These two paths are simultaneously estimated. The results are similar to the earlier hierarchical regression results (Table-5b). The aforementioned antecedents of efficiency factor; i.e. technological complexity and technological distance, are both significant at 0.01 level. Efficiency factor has a significant inverted U-shaped relationship with innovative performance. Marginal effects of all variables are contained in the analyses.

Table-5b about here

Sensitivity Analyses

In order to make a finer grain analysis of the data and have a better understanding of the factors influencing efficiency factor and innovative performance in firm acquisitions, the data is reexamined through various subsamples. First, to better identify the objective of the acquisitions, in addition to the techniques applied in sampling steps, a subsample of '*technology acquisitions*' is determined through the motives of acquisitions stated at the time of the acquisition in press releases. For this purpose, final sample of 356 acquisition-deals are further searched for their motives in press releases, through FACTIVA database with 'company name' and 'target name' around the deal date. Those announcements which refer to the use of target firm's 'technology', 'patent portfolio' or 'technological/innovative capabilities' are labeled as technology acquisitions. As a result of this search, 223 of the 356 firm acquisitions came out to be technology acquisitions. This specification is considered to bring more precision about the motives of acquisitions. The results of the analyses are provided in Table-6b. The results are qualitatively similar to the total sample with the exception that the effect of technological distance on efficiency factor loses its significance. Technological complexity significantly increases efficiency factor. Also, the inverted U-shaped relationship between efficiency factor and innovative performance is preserved.

Table-6b about here

An additional test is conducted to examine the factors effective on different types of acquisitions, i.e. between- vs. within-industry. By splitting the total sample into two for between- and within-industry acquisitions, 183 between-industry and 173 within-industry acquisitions are identified. Results for these analyses are given in Table-7b. The analyses of within-industry acquisitions show that the results are qualitatively similar to the total sample. The results for between-industry acquisitions are also quite similar to the total sample with the exception that the impact of technological distance on efficiency factor becomes insignificant.

Table-7b about here

A final set of analyses are conducted to account for the differences arising from the characteristics of the target firms' industries. Depending on the characteristics of the industry, total sample is splitted into two for IP-intensive and less IP-intensive industries. This resulted in 271 IP-intensive industry and 85 less IP-intensive industry acquisitions. The results are provided in Table 8. It is shown that in IP-intensive industry acquisitions the results are qualitatively similar to the total sample; whereas, in less IP-intensive industry acquisitions the results are slightly different. While technological complexity significantly increases efficiency factor, the effect of technological distance is negative and insignificant in less IP-intensive industry acquisitions. Conversely, technological distance appears to have a positive and significant impact on innovative performance. Analyses also confirm the inverted U-shaped relationship between efficiency factor and innovative performance.

Table-8b about here

DISCUSSION AND CONCLUSION

This study examines the efficiency factor, its antecedents and how it affects innovative performance in technology-based firm acquisitions. Two main factors are identified to be influential in efficiency factor: technological complexity, which refers to the density of linkages among the target firm's pre-deal technological assets, and knowledge relatedness; i.e. technological distance between the acquirer and target firms' pre-deal knowledge stocks. In addition, this research investigates the impact of efficiency factor on the merged firm's innovative performance and explores the optimal level of AC. The results suggest that technological distance between the acquirer and target firm knowledge stocks negatively impacts efficiency factor; whereas, technological complexity has a positive effect on efficiency factor. Furthermore, efficiency factor has an inverted U-shaped relationship with innovative performance. These results are interpreted as follows. As Cohen & Levinthal (1990) proposed, knowledge complexity determines the ease of learning which, in turn, affects the innovative performance of the firm. The results of this study indicate that knowledge complexity has a positive impact on the efficiency factor as it is hypothesized; confirming the need to embrace a greater portion of the acquired knowledge to innovate when the knowledge structure is composed of highly interlinked technological assets. In addition, knowledge complexity is found to have a direct negative impact on firm's innovativeness which supports the earlier research on knowledge complexity and innovative performance relationship (Simonin, 1999). In the light of these results, it can be said that complexity of the acquired knowledge decreases firm innovativeness by reducing the number of patents filed by the firm; however, it increases the efficiency factor, meaning that, the patents filed by the merged entity includes a higher percentage of acquired knowledge when the technology has a complex structure.

Concerning the relatedness of the prior knowledge stock of the acquirer and the acquired knowledge, it is found that technological distance between the two knowledge stocks is decreasing the efficiency factor; in other words, a lower percentage of acquired knowledge is actually exploited by the merged entity when the acquired knowledge is distant from the prior knowledge stock of the acquirer. However, it has no direct impact on the innovative performance. There are two possible implications of these results. Earlier research on the impact of technological distance on innovative performance has found an inverted U-shaped relationship (Ahuja & Katila, 2001; Cloodt, et.al., 2006). Here it is found that this relationship is instead mediated by the efficiency factor. Prior literature on AC overlooked the mediation effect of efficiency factor on the relationship between technological distance and innovative performance. The second implication is that acquirers are undertaking technology-based firm acquisitions only when the target firm's knowledge stock is distant enough from its prior knowledge stock. Acquirers are well aware of the fact that acquisition of target firms which endow very similar knowledge stocks to its prior knowledge has little to add to the innovative performance. Therefore, in technology-based firm acquisitions, technological distance is negatively associated to efficiency factor.

The relationship between efficiency factor and innovative performance is found to be curvilinear, indicating that efficiency factor enhances innovative performance up to a certain threshold, at which, the cost of developing AC exceeds the benefits of innovative value creation. This result is in line with the previous literature which theorizes that optimum AC can be less than the maximum level, when it comes to maximizing innovative performance (e.g. Volberda, et.al, 2010). Innovative performance is found to be maximized when the efficiency factor is 55%, in other words, when 55% of the acquired technological knowledge is exploited by the firm. This result, though it is based on US patenting data, is similar to the average use of patents (50.5%) by European inventors through internal exploitation for commercial or industrial purposes (Giuri, et.al., 2007). Although it is difficult to disentangle the underlying mechanisms in this empirical setting, two possible explanations are provided. First, the cost of exploiting acquired knowledge may exceed the benefits of the innovative activities, which leads the acquirer to leverage on some portion of the acquired knowledge although it is fully useful for the acquirer's innovative activities. Else, not all of the acquired knowledge stock might be useful for the innovative purposes of the acquirer, which results in less than total exploitation of acquired external knowledge. Data specification of this study does not allow determining which possible explanation is the main driver of the results. Thus, the test of these mechanisms is left for future research.

Sensitivity analyses on various subsamples provide a better understanding of the factors effective in the innovative performance. Considering technological complexity it can be said that, it improves efficiency factor in all subsamples, and it is highly influential on both between- and within-industry acquisitions and also in IP-intensive and less IP-intensive industries. Moreover, it has a direct negative influence on the innovative performance in all subsamples with the exception of less IP-intensive industries where its effect is negative but insignificant. Instead, technological distance is significantly hampering efficiency factor and this effect is mostly observed in within-industry acquisitions and IP-intensive industries. The inverted U-shaped relationship between efficiency factor and innovative performance holds in all subsamples. Differences in the impact of other factors on efficiency factor and innovative performance with regards to acquisition type and industry are venues for future research.

This study also has some limitations. First of all, determining the motives of acquisitions is problematic in technology-based firm acquisitions. In this study, in order to identify the technology-based firm acquisitions, it is assumed that deals with target firms which have at least 5 technological assets before the acquisition are acquired for their technology. Similar specifications are used in other studies on technology acquisitions (e.g. Ahuja & Katila, 2001; Ceccagnoli & Hicks, 2012; Ernst & Vitt, 2000; Granstrand & Sjolander, 1990; Puranam & Srikanth, 2007). However, this specification does not guarantee that these acquisitions are undertaken for their technologies. Therefore, an additional search is executed on acquisition announcements in press releases to understand the intention of the acquirers. Even in this case, it is not certain whether acquirers hesitate to announce that they intent to use target's knowledge stock or they declare the use of target's technology although they do not intent to exploit. Additional research is needed to better specify the motives of acquisitions. Second, this study focuses on six industries, three IP-intensive and three less IP-intensive industries. The proposed model is tested on a specific IP regime, i.e. U.S. context, and the results may differ depending on the strength of the IP regime. Third, level of integration is argued to be an important driver of the knowledge leverage in technology-based firm acquisitions (Birkinshaw, 1999; Puranam, et.al., 2006; Puranam & Srikanth; 2007; Ranft & Lord, 2002); however, due to data unavailability it is not accounted in this research. Future studies can advance this research by adding post-merger integration as another determinant of efficiency factor and innovative performance in technology-based firm acquisitions.

This research also provides implications for managers. Regarding innovative performance in technology-based firm acquisitions which aim at acquisition, assimilation and exploitation of external technology, managers are advised to appreciate factors effective at different levels, assess their external technology access along these factors and make their acquisition decisions accordingly. To enhance the innovative value creation through M&As, managers are advised to target those firms which endow technologically similar, but not very similar, knowledge stocks. The impact of technological complexity is rather ambiguous. Complexity of the external knowledge has two contrasting effects; first, it enhances the exploitation of acquired external knowledge which, in turn, increases innovative performance; second, it decreases the innovative performance by reducing the number of innovative output produced. Therefore, it is not certain which effect will dominate in technology-based firm acquisitions. However, acquisition of target firms endowed with technologically complex knowledge stocks is envisioned to be beneficial in the long-run for the acquirer by enhancing its capacity to learn more complex knowledge.

In conclusion, this study shows that structure and the relatedness of the external knowledge have an influence on innovative performance of the firm which is mediated through efficiency factor in technology-based firm acquisitions. It also shows that there is an optimum level of AC which maximizes innovative performance. This paper advances our knowledge on how acquirer's create innovative value through M&As. Future research can expose how the effects of these factors vary depending on the post-merger integration decision. It is hoped that this research helps to refine future theorizing on this line of literature.

Chapter 3

When to Sell vs. When to Lease? Transfer or Retention of Intellectual Property Ownership in Market for Technology

(Co-authored with Alfonso Gambardella)

The extant literature on market for technology mainly focuses on licensing agreements in technology transfer. Most of the theoretical and empirical research on this phenomenon investigates the size and functioning of the technology markets by studying patent licensing. This paper aims at contributing to the market for technology literature by taking into account patent sale, i.e. transfer of ownership rights, which accounts for a sizeable share of transactions in market for technology. This research tries to shed more light on our knowledge of technology markets by identifying the determinants of the decision to transfer or retain ownership rights in technology transactions. Focusing on the patent owner, trade partner and patent characteristics, we explain the factors influential in the choice between patent sale vs. patent licensing in market transactions.

Key words: patent sale, patent licensing, market for technology, ownership transfer

INTRODUCTION

Sale of intangible assets, especially for financially distressed or bankrupted firms, is seen as a means to appropriate returns from investment in R&D. With the desire to monetize the underlying technology, firms sell their patent portfolios partially or fully to third parties. Well-known examples of this type of transactions include the sale of bankrupt Nortel Network's patent portfolio of over 6,000 patents to a consortium, including Apple, Microsoft, Sony, RIM; for $45 billion in 2011 (Arthur, 2011), bankrupt Eastman Kodak's sale agreement for its digital imaging patents with a consortium of bidders, including Google and Apple, for $525 million in 2012 (Martin, 2012) and financially distressed AOL's deal with Microsoft to sell its patent portfolio for $1.1 billion in 2012 (Jannarone & Ramachandran, 2012). Instead, recently, firms have started to transfer the rights to use of their patent portfolios through sale and/or licensing as alternative options. Examples of these kind of offerings are as follows:

> "Delphi Technologies facilitates streamlined access to Delphi's innovative technologies through *patent sales and licensing*. Delphi has numerous technologies for transportation and non-transportation applications and is continually growing and investing in new intellectual property to enhance its portfolio." (www.delphi.com)

> "HP owns one of the world's largest patent portfolios comprised of more than 37,000 worldwide patents. Currently more than 2000 patents are available for *license or sale*." (www.hp.com)

These examples point to the fact that patent sale and/or licensing agreements are emerging as prominent firm strategies for patent portfolio management. However, the extant literature on market for technology mainly focuses on licensing agreements in technology transfer. Most of the theoretical and empirical research on this phenomenon investigates the extent and functioning of the technology markets by studying patent licensing (e.g. Arora & Ceccagnoli, 2006; Arora & Fosfuri, 2003; Arora & Gambardella, 2010; Fosfuri, 2006; Gans & Stern, 2003; Gans, et.al. 2002)[9]. Although patent sales constitute a non-negligible portion of transactions in the market for technology, i.e. 5.47% of patents are sold while 8% of patents are licensed according to a recent survey (PatVal-II), theoretical and empirical research on this phenomenon is in its infancy. Some of the preliminary studies on patent sale are by Figueroa & Serrano (2010) and Serrano (2010), where the focus is on the dynamics of reassignment and renewal of patents. Scholars also investigate patent sale at auctions (Odasso, Scellato & Ughetto, 2015) and reassignment of patents as collateral (Amable, Chatelain & Ralf, 2010; Fischer & Ringler, 2014). In this paper, we aim at contributing to the market for technology literature by taking into account both patent sale and licensing activities, and empirically testing the research question: "What determines the decision on transfer vs. retention of ownership rights in market for technology?"

Studying the decision to transfer or retain ownership rights in technology markets is important for at least three reasons. First, although patent sale, i.e. reassignment, and patent licensing agreements are high-priced transactions, prior literature has mainly focused on the latter, in particular to the incentives of the potential licensor (e.g. Arora & Fosfuri, 2003; Fosfuri, 2006; Gans & Stern, 2003) to engage in market trade and to a less extent to those of the potential licensee (e.g. Ceccagnoli, et.al, 2010). Our approach is commingling the incentives of the patent owner to

[9] For a detailed review of research on markets for technology, see Conti, R., Gambardella, A. & Novelli, E. 2013. "Research on markets for inventions and implications for R&D allocation strategies". The Academy of Management Annals, 7: 717-774.

sell or license a patented invention to provide a broader view of alternative ways of patent monetization and factors influential in the actual decision. Second, mostly due to the lack of reliable patent-licensee information in license agreements, the literature on the demand side is quite limited and even so previous research on that matter (e.g. Ceccagnoli, et.al, 2010) relies on patent reassignments, which in fact, corresponds to patent sale rather than patent licensing. In this research, we dichotomize these two decisions in order to present a more refined measurement and analysis of their determinants. Third, regarding the intellectual property management, our knowledge of ownership transfer is rather scant, we know little about, conditional on selection to transfer rights to use of a patented invention to a third party, what drives the ownership change. We would like to contribute also to intellectual property management literature by depicting the factors at play in sell vs. license decisions.

The main challenge in testing the decision on transfer vs. retention of ownership rights in technology market transactions is the lack of data availability on assignor-assignee and licensor-licensee characteristics. We overcome this challenge by bringing together various data sources and making use of a recent survey on inventors. The results of our analyses show that conditional on selection to transfer the right to use of a patented invention to a third party, the decision to transfer the ownership rights is minimally affected by the size of the patent owner or the trade partner. Instead, the decision is highly impacted by the commercialization of the patented invention or the desire to commercialize in the future by the patent owner. In this case, the patent owner prefers to transfer the right to use as opposed to transfer of ownership rights. However, patents with co-applicants and patents in larger portfolios are more likely to encounter ownership change. Interestingly, indicators of patent quality, such as number of citations, number of claims, are effective in selection to transfer the right to use of patented inventions to a third party; however, these factors are not influential in the choice between patent sale vs. license. This can be one of the explanations why technology firms like Delphi, HP, etc offer their patents with both monetizing options.

The paper is organized as follows. In the next section, we put forward the theoretical background on patent sale, licensing and monetization. Next, we propound the empirical setting and methods. It is followed by the empirical results of our analyses. In the final section, we discuss the implications of the results and conclude with explaining the limitations of the current study and identifying further research venues.

THEORETICAL BACKGROUND

Transfer of patent ownership rights is a sizeable portion of transactions in the market for technology. Some recent work presents that 13.5% of all granted U.S. patents are reassigned at least once over their validity periods (Serrano, 2010). The main difference between transfer of ownership rights, i.e. patent reassignment[10], and transfer of rights to use, i.e. patent license, is that the former corresponds to the transfer of the owner's right, title and interest in a patent to a third party, the latter rather refers to an owner's permission to use of a patent by a third party without the fear of infringement. Our objective is to understand the factors that are influential in the choice between transfer of ownership rights vs rights to use in technology market transactions.

The extant literature in economics and management fields has examined the determinants of market for technology. *Institutions,* i.e. effectiveness of the patent protection, *firm characteristics*,

[10] Throughout this paper, we use the words 'reassignment' and 'sale' interchangeably due to the fact that both denote a transfer of ownership rights.

e.g. size, complementary assets, market share, and *industry structure*, such as vertical specialization, product market fragmentation, are identified to be influential factors in functioning of technology markets (Conti, Gambardella & Novelli, 2013). The vast majority of these studies focuses on the transfer of rights to use, i.e. patent licensing (e.g. Arora & Ceccagnoli, 2006; Arora & Fosfuri, 2003; Arora & Gambardella, 2010; Fosfuri, 2006; Gans & Stern, 2003; Gans, et.al. 2002). This body of literature shows that small firms are both more likely to license their patents than large firms (Anand & Khanna 2000; Arora & Fosfuri, 2003; Arora, Fosfuri & Gambardella 2001, Fosfuri, 2006, Gambardella, Giuri & Luzzi, 2007). It is also shown that the lack of specialized complementary assets increases a firm's incentives to out-license its technology (Teece, 1986; Arora & Ceccagnoli, 2006).

In contrast to the existence of a large body of literature on patent licensing, the theoretical and empirical literature on ownership transfer, i.e. patent sale, is quite scarce. Lamoreaux & Sokoloff (1997, 1999) are among the first to explore the patent sale to study markets for technology. They provide evidence from the late 19th century on how the expansion of opportunities to patent sale was closely associated with increases in specialization at invention, as well as advances in rates of invention in general. More recent contributions to that literature are the studies by Serrano (2010) and Figueroa & Serrano (2010, 2013). By making use of the patent reassignment database that compiles The United States Patent and Trademark Office (USPTO) registries, Serrano (2010) presents the stylized facts on patent ownership transfer across technology fields, various types of patent owners and patent characteristics. Basically, he shows that the probability of patent reassignment increases with the patent owner being an individual or small firm, patent quality, i.e. number of forward citations, patent generality and patent being traded previously. Conversely, the likelihood of patent reassignment decreases with the age of the patent. He also finds variation in patent transfer across technology fields, while the lowest rate of transfer is observed in mechanical field, the highest rate is in drugs and medical fields. In contrast to the view that large firms have a comparative advantage over small firms in development and commercialization of inventions (Arrow, 1983; Holmstrom, 1989) and so are more likely to acquire traded patents in the technology market, Figueroa & Serrano (2010, 2013) evidence that small firms are more likely to sell their patents but they also acquire more patents than large firms. Moreover, large firms are observed to be more likely to acquire higher quality patents. They also show that patents that are not at the core technology area of the patent owner are more likely to be sold.

Although prior studies on the market for technology are rather silent in explaining the patent owner’s decision on transfer of ownership rights, i.e. patent sale vs. patent licensing, research on both patent licensing and patent sale highlight the importance of size effects in market transactions. Concerning our research interest, we would like to know the impact of patent owner’s size on the decision to transfer or retain ownership rights in technology market transactions. We argue that small firms are more likely to transfer ownership rights; namely, sell their patents as opposed to license, than large firms for two reasons. First, the opportunity cost of selling a patent as opposed to licensing is lower for small firms than large firms. Small firms are typically restricted in their financial resources and lack the manufacturing capabilities to convert their patented inventions into product and process innovations compared to large firms (Teece, 1986). Due to this fact, a small firm’s opportunity cost of monetizing its patent through ownership transfer that, in effect, means giving up on the control rights and future interest in the patent, is less than that of a large firm. Large firms, endowed with more financial and production resources and capabilities typically have more options for the use of a patent, i.e. commercialization, cross-licensing, blocking competitors, etc., have higher opportunity costs incurred in case of an ownership transfer through patent sale as opposed to a transfer of rights to use with a license. Therefore, we expect the probability of ownership transfer to drop with patent owner size. Second, the search cost of finding a trade partner is higher for small firms than that of large firms. Large firms may have dedicated intellectual asset management units, which help them to find and negotiate with multiple trade partners for a patented invention. The possibility of market trade with multiple partners and the ease of finding trade partners may induce large firms to prefer patent licensing to sale. In contrast, small firms may lack the financial resources necessary to search for multiple trade partners. Moreover, small firms lacking financial resources may be more interested in short-term gains from patent trade through patent sale to cover their R&D expenses rapidly. For that reason, we expect the probability of ownership transfer to be higher for small firms as opposed to large firms.

Hypothesis-1*: Conditional on selection to transfer rights to use of a patented invention, the probability of ownership right transfer decreases with the size of patent owner.*

Another important factor identified in the prior literature is the patent owner's possession of specialized complementary assets (Teece, 1986). In his seminal piece, Teece (1986) argues that possession of the co-specialized complementary assets helps firms to profit from innovation through commercialization. Endowment of the complementary assets, e.g. manufacturing, marketing, etc, enables firms to engage in downstream commercialization of their patented technologies. In line with this argument, some research in market for technology literature evidences that firms that lack complementary assets are more likely to license their technologies, in strong patent regimes (Arora and Ceccagnoli, 2006). Therefore, it is intuitive to expect that firms that profit from innovation through commercialization of their patented inventions are overall less likely to sell or license their patents. However, firms may be in possession of only part of the complementary assets needed for the use of the patented invention to its full potential. Especially for general-purpose technologies (Arora & Gambardella, 1994; Gambardella & McGahan, 2010), the patent owner may have complementary assets for the use of the technology only in some sectors and yet lack the complementary assets and capabilities for the commercialization of the technology in other sectors. In this case, firms that already commercialized their technologies can be interested in generating additional revenues through licensing their technology to third parties. To the extent that licensing of the technology do not increase product market competition, i.e. rent dissipation effect (Fosfuri, 2006), the patent owner may be interested in licensing its technology to third parties, i.e. revenue effect. Thus, conditional on selection to transfer the rights to use of a patented invention, we expect the patent owner to be more willing to license as opposed to sell a commercialized invention.

Hypothesis-2*: Conditional on selection to transfer rights to use of a patented invention, the probability of ownership right transfer decreases with commercialization of the patent by the patent owner.*

Another stylized fact in the prior literature about the invention process is the open-innovation paradigm, which considers R&D process as an open-system where firms benefit from a variety of collaborative activities (Chesbrough, 2003, 2006). These collaborative R&D activities mostly result in co-ownership of the patented invention, i.e. co-patenting. Although collaborative R&D activities increase the firms' innovativeness through combination of internal and external knowledge sources (Kogut & Zander, 1993), these collaborations make it harder to appropriate returns from innovation for the parties involved in the process (Chesbrough & Rosenbloom, 2002; Di Minin & Faems, 2013; Henkel, 2006). This can be partially due to the difficulties in exploitation of the ownership rights. Scholars claim that, in the US, transferring ownership rights or engaging in license agreements do not imply consent from the other owners, while in Europe consent from the other owners is the rule (Paradiso & Pietrowski, 2009). Empirical research on co-patenting presents that the firm’s financial performance is negatively affected by the share of the co-patents in its patent portfolio (Hagedoorn, 2003). Likewise, a firm’s market valuation is found to be negatively associated with co-patenting (Belderbos, et al., 2010). A recent study by Belderbos, et.al. (2014) shows that the appropriation challenges are higher when firms co-patent with firms in the same industry. Given the challenges in appropriating returns from co-patented inventions, we expect the probability of ownership transfer, i.e. patent sale, to increase for the co-patented inventions. Since the ownership rights are split among the co-owners of the patent, there may be difficulties in sharing revenues. In this case, conditional on selection to transfer the rights to use to a third party, co-owners may favor patent sale over licensing as it reduces the possible complications in royalty sharing. To the extent that patent sale is perceived as a solution to the challenges associated with co-ownership, we expect the likelihood of patent sale to be higher for the co-patented inventions.

> ***Hypothesis-3****: Conditional on the selection to transfer rights to use of a patented invention, the probability of ownership right transfer increases with co-patenting.*

RESEARCH SETTING AND METHOD

Data and Sample

To test our hypotheses, we used a collection of recent surveys PatVal-EU II, PatVal-US and PatVal-JP, which interviewed inventors of EPO patents with priority dates in 2003-2005 in 20 European countries, US, Japan and Israel. These surveys build on the PatVal-EU survey conducted in 2003-2005. PatVal-EU survey has been used in previous studies on breakthrough inventions (Conti, et.al., 2014), invention processes (Davis, et.al., 2013), knowledge sourcing (Giarratana & Mariani, 2014), and employee entrepreneurship (Gambardella, et.al., 2015). Regarding the PatVal-EU II, PatVal-US and PatVal-JP surveys, in November, 2011, 22,533 responses received which cover inventors in all surveyed countries with a response rate of 20%. These surveys are supplemented by PATSTAT database for patent characteristics, such as number of citations, technological fields, number of claims etc. We complemented this dataset also by Google patents legal events for the patent reassignment information which provides information on changes in the legal status of the patents with legal status codes. We identified legal events with RAP1-RAP4 codes which document changes in applicant/patent owner name (www.epo.org). We further complemented our dataset by creating a patent-licensee match through key word search and manual check of the depicted technology in the patent abstracts with the news reports in FACTIVA database for licensing agreements with the given patent owner name. Finally, for the identified assignees and licensees we gathered financial data from ORBIS database. As a result of this data gathering, we identified 1,640 patent reassignments and 706 licensing agreements with a single trade partner. Then, we deducted those licensing deals which resulted in a patent sale (180 of the agreements) and cross-licensing deals which resulted in a patent sale (22 of the agreements). We dropped the agreements for which we lack information on patent citations and economic value of the patent. Hence, our final dataset is composed of 1,790 patent sale and licensing agreements.

Measures

Dependent Variable

Ownership Transfer: This construct is measured as a binary variable, which gets the value of 1 if the patent owner sells a particular patent, 0 if the patent owner out-licenses the patent. In the survey, the inventor is asked whether the ownership right of the patent was sold to another party not related to the original owner(s) or applicant(s). We have 809 'Yes' responses to that question. Other answers to this question include, 'no' (12,912), 'no, but willing to' (823) or 'I don't know' (2,392). There are also 6,119 no answers to that question. Since the information gathered on patent sale was at the time of the survey, some ownership change in the sample might have occurred after the survey or the inventor is not knowledgeable about the ownership change even at the time of the survey, given the high number of 'I don't know' answers and no answers. To have an up-to-date objective measure of the reassignment of patents, which also takes into account possible ownership changes after the survey, we searched all patents in our survey on Google Patents Legal Events for applicant/owner name changes under the codes RAP1, RAP2, RAP3 and RAP4. This search helped us to identify those patents, which are not mentioned by the inventor as sold, but in fact, transferred to a third party. A total of 831 patents are identified as sold and added to our dataset as an ownership transfer. In order to focus our attention on the dichotomous decision on sale vs licensing, we dropped patents which are first out-licensed or cross-licensed and then finally sold to a third party. With these specifications, we obtained 1,351 patent sale information. Regarding the licensing decision, we have 706 'Yes' answers to the question: Has this patent been licensed by (one of) the patent-holder(s) to an independent party? and ‘only 1’ answer to the question: How many parties (roughly) have obtained a license?. We wanted to restrict our attention to ‘one-to-one’ and ‘unidirectional’ out-licensing agreements to have an exact set of licensor-licensee match. By dropping the out-licensed patents that are sold at a later time and cross-licensing agreements, we ended up having 439 out-licensing agreements in our dataset.

Explanatory Variables

Patent Owner Size: We measured this construct by the number of employees (in thousand) the patent owner had in year 2006. The median number of employees are calculated as 23.36 and the median number is replaced with the missing information on number of employees. To control for the median number whenever it is replaced with a missing value, we created a dummy variable which takes the value of 1 when median number is inserted, 0 else. For the patent owners that are individuals or affiliated to a non-profit organization, we took the number of employees as 0.001 and controlled with a dummy variable which takes the value of 1 when this number is inserted, 0 else.

Trade Partner Size: We measured this construct by the number of employees (in thousand) the assignee or licensee had in year 2006. The median number of employees are calculated as 3.204 for assignees and 3.884 for the licensees, the median numbers are replaced with the missing information on number of employees. To control for the median numbers whenever they are replaced with a missing value, we created a dummy variable which takes the value of 1 when median number is inserted, 0 else.

Commercialization: For the measurement of this construct, we used the inventor response to the following question: ‘Have the applicant(s) or affiliated parties ever used this patented invention commercially, i.e. in a product, service or in a manufacturing process?’. Our dichotomous variable takes the value of 1 if the inventor gives a ‘Yes’ answer, 0 else.

Willing-to-Commercialize: This construct uses the same commercialization question to the inventor and takes the value of 1 if the inventor gives the answer: ‘Not yet, but still investigating the possibility’, 0 else.

Co-patenting: This construct is a binary variable, which takes the value of 1 if the patent has co-applicants, 0 otherwise.

Control Variables

Patent Stock: In order to control for the portfolio size effects, we included the cumulative number of patents granted to the consolidated applicant firm in our analyses. Data is gathered from PATSTAT.

Granted: To see the possible impact of patent grant on the ownership transfer decision, we added a dummy variable that controls whether the focal patent application is granted at the time of the survey and it takes the value of 1 if granted, 0 otherwise.

Citations: 5-year window forward citations of the patents are gathered from PATSTAT and EPASYS databases. We use citation information together with the number of claims as an indicator of the patent quality.

Claims: In addition to the use of 5-year window forward citations as an indicator of patent value, we controlled our analyses for the number of claims listed in the patent at the date of grant. This information is supplemented from PATSTAT and EPASYS databases.

Patent Scope: Our analysis also involve a measure of patent generality, measured by patent scope, the total number of patent classes the focal patent is associated with in EPO's former patent classification system (ECLA).

Patent Economic Value: The economic value of the patent may have an impact on the ownership transfer or retention decision; therefore, it is included in our analyses. Economic value is measured in our survey with a direct question to the inventor. She is asked to rate the economic value of the focal patent in comparison to other patents in her industry or technological field. The responses are recoded in a descending order from 4 to 1, depending on the answers such as: 'top 10%', 'top 25% but not top 10%', 'top 50%, but not top 25%' and 'bottom 50%'.

Patent Family: Some scholars argue that the value of a single patent may be dependent on the overall portfolio to which it belongs (Reitzig, 2003). To account for this possibility, we control our analyses with a measure of the patent family. In our survey, the inventor is asked whether the focal patent is part of a patent family with several fillings at the EPO. We created a dummy variable which takes the value of 1 for the 'Yes' answers, 0 otherwise.

Creative Process: In order to understand whether the patent sale and licensing decisions are impacted by the creative process, we made use of the following survey question: 'which of the following scenarios best describes the creative process that led to your invention?' The answers to this question fall under six categories: 1) targeted achievement of the R&D project, 2) expected by-product of the R&D project, 3) unexpected by-product of the R&D project, 4) directly related to the inventor's normal job, which is not inventing, and then further developed, 5) related to the inventor's normal job, which is not inventing, and then not developed further, 6) pure inspiration/creativity that was not further developed in an R&D project. We created dummy variables for each category of creative process which takes the value of 1 for the corresponding answer regarding the creative process, 0 otherwise.

Intensity of Technology Competition: We also controlled for the possible effect of technology competition on the patent owner's ownership transfer decision. In our survey, the inventors are asked whether they were aware of one or of several other parties competing with the inventor's organization for the patent during the invention process. If the inventor responds as 'Yes' to existence of one or several other parties, they are further asked how aggressively these other parties were competing with the inventor's organization for the patent. A Likert scale is used where 1 denotes not aggressively at all and 5 denotes very aggressively. We used the responses of the inventors to this scale as a measure of intensity of technology competition.

Intensity of Product Market Competition: Product market competition may also have an impact on the patent owner's willingness to engage in technology trade and transfer ownership rights. Therefore, we computed the Herfindahl Hirschman Index (HHI) of the parent company. This market concentration index has takes values between 0 and 1, where higher values denote a higher market concentration and a lower product market competition.

Individual: This dummy variable controls for the individual patent owners and takes the value of 1 if the patent owner is an individual, 0 else.

Non-profit organization: This dummy variable controls for the non-profit organizations as patent owners and takes the value of 1 if the patent owner is a non-profit organization, 0 else.

Industry: We also controlled our analyses for the industry effects. 2-digit SIC codes of the patent owner is used as a dummy in the estimations.

Model

In this study, we are interested in the factors that affect the decision on ownership rights transfer vs. retention in technology markets. Therefore, our dependent variable is a dichotomous variable that takes only two discrete values, i.e. 1 for patent sale, 0 for patent license. This binary characteristic of our dependent variable requires the use of a nonlinear model (e.g. probit, logit) (Hoetker, 2007; Wiersema & Bowen, 2009; Zelner, 2009). We would like to test conditional on the patent owner's selection to transfer the rights to use of a patented invention, either through sale or licensing, as opposed to other uses of the invention such as: solely commercial use, cross-licensing, start-up foundation, how the decision to transfer ownership is affected by the identified factors. For this purpose, we modeled our analyses as in two stages, where the first stage is the selection of the patent owner to transfer the rights to use of a patented invention '*decision-to-sell/license*', and the second stage is the decision to transfer ownership rights or not, i.e. '*ownership transfer'*. The likelihood of ownership rights transfer is estimated, conditional on the invention being selected for sale/license. To account for potential unobserved heterogeneity, which can produce biased standard errors, a sample selection probit model is employed (Boyes, Hoffman, & Low, 1989; Heckman, 1976, 1979; Leiblein, Reuer & Dalsace, 2002; Somaya, 2003).

RESULTS

Descriptive Statistics

The descriptive statistics of the variables in ownership transfer model are depicted in Table-1c. In our dataset, 75% of patents is undergone an ownership right change in market for technology. On average, the patent owners have 33,679 employees as opposed to trade partners, which have 17,140 employees. The patent stock of the parent company to which the inventor's business unit is affiliated ranges between 0 and 13,017 with an average of 1,064. The forward citations received by the patents in a 5-year window has the range of 0-22 with the average of 1.2. Likewise, patent scope ranges between 1 and 15 and the average is 2.7. Maximum number of claims in a patent is observed as 195 with an average of 18.9. At the time of the survey, 29% of the inventions were granted a patent already. 54.5% of the inventions are commercialized and 19.5% is not yet commercialized but still investigating the possibility. 7.6% of the patent owners are individuals, whereas 9.2% are non-profit organizations. Average patent value is 2.4 in a scale from 1 to 4. 42% of the patents belong to a patent family/portfolio. 11.5% of the patents have co-applicants. Mean values of the explanatory and control variables are provided under the respective columns of sold and licensed patents.

Table-1c about here

Table-2c displays the correlations between variables. It is shown that none of the explanatory and control variables is highly correlated to the dependent variable. The highest correlation is between patent stock of the patent owner's parent organization and patent owner size with 0.729.

Also, patent stock of the patent owner's parent organization is positively correlated with the trade partner size (0.401).

Table-2c about here

Analyses

Table-3c presents the results of probit model with sample selection. In the first stage we test the selection of the patent owner to transfer the rights to use of a patented invention '*decision-to-sell/license*', and in the second stage we test the patent owner's decision to transfer ownership rights, i.e. '*ownership transfer'*, conditional on the selection to transfer rights to use. Wald test for independent equations shows that we can reject the null hypothesis ($p<0.01$) that the first and second stage equations are in fact independent. Therefore, it is better to estimate two equations concurrently. In the selection model (Model-1), results show that patent owner size has a negative and significant ($p<0.01$) impact on selection to transfer rights to use. In other words, larger firms are less like to transfer the rights to use of their patents to a third party. Whereas, firms with larger patent stocks are more likely to transfer the use of their patents ($p<0.01$). Regarding the quality of the patents, the results show that patents with more number of forward citations ($p<0.05$) and more number of claims ($p<0.01$) are more likely to be selected for market trade. Patents that are commercialized by the owner ($p<0.01$) or willing to be commercialized ($p<0.01$) are less likely to be selected for sale or out-licensing. However, patents which belong to a patent family (e.g. portfolio) ($p<0.01$) and have multiple applicants (i.e. co-applicants) ($p<0.01$) are more likely to be selected for the transfer of right to use. Finally, market concentration is positively associated (p<0.01) with the selection to transfer rights to use. Put differently, in markets where product competition is lower, the likelihood of technology market transactions are higher.

In the second stage model (Model-2), results point to the fact that conditional on selection to transfer the rights to use, the decision to transfer the ownership rights are negatively impacted by the owner size (p<0.01). This result provides the preliminary evidence in support of Hypothesis-1. Interestingly, the size of the trade partner is not influential in the decision on ownership rights transfer. The decision is rather impacted by the commercialization of the patent or the patent owner's willingness-to-commercialize in the future. The results show that patents that are already commercialized (p<0.01) or planned to be commercialized (p<0.01) are less likely to have an ownership rights change. In other words, patents that are commercialized or planned to be commercialized are out-licensed rather than sold to a third party. These results are in support of Hypothesis-2. The results also show that patents with multiple applicants (i.e. co-applicants) are more likely to be sold than out-licensed (p<0.01). This result is in line with Hypothesis-3. Finally, our two-stage model depicts that patent quality, in terms of citations and claims, and being part of a patent family are factors affecting a patents probability to be selected for technology market transactions, however given the selection, patent quality and portfolio effects are not influential in the decision to sell vs. out-license.

Table-3c about here

With regards to the interpretation of coefficients and magnitude of effect sizes in non-linear models, scholars warn that the effect of a change in one variable depends on the initial probability of the event occurring and on the values of the other variables (Hoetker, 2007). Hence, the marginal effect is not equal to the coefficient of the variable (Wiersema & Bowen, 2009). Instead, the direct relationship between the explanatory variables and the dependent variable is given by the variables' marginal effects, which again vary with the value of the other variables in the model. Therefore, examining the sign and significance of the explanatory variables' marginal effects over all values of variables in the model is warranted. For that reason, we analyzed the marginal effects of our explanatory variables by computing the values of marginal effects using the sample mean of all variables in the second-stage model and then reassessing their significance. The results of the conditional marginal effects analysis is depicted in Table-4c. The first column shows the marginal effect of variables at their mean values for the second stage estimation. The sign and significance of the marginal effects are in line with our earlier analyses. Yet, the marginal effects are quite different from the probit model coefficients. Although owner size is negative and significant ($p<0.01$) in the analysis, the effect size is nearly zero (0.1%). This result points to the fact that the patent owner size is minimally affecting the decision on ownership rights transfer. Moreover, commercialization of the patent and willingness to commercialize in the future highly decrease the probability of patent sale (64.2% and 18.3% respectively). In contrast, patents that have multiple applicants are 17.4% more likely to be sold.

Table-4c about here

For a better assessment of the marginal effects and the confidence intervals, a graphical plot is fruitful (Hoetker, 2007; Wiersema & Bowen, 2009). We plotted conditional marginal effects of the explanatory variables of the ownership transfer estimation with 95% confidence interval (Figure-

1c). The plot depicts the changes in the probability of ownership rights transfer due to a conditional marginal change in our variables. The figure clearly shows that patent commercialization has the highest negative marginal impact on the probability of ownership transfer. It is followed by willingness-to-commercialize which also has a negative impact on ownership transfer. Conversely, existence of co-applicants of a patent increases the likelihood of ownership transfer.

Figure-1c about here

Robustness Checks

We performed several supplementary analyses to check the robustness of our results. First, we retested our probit model with sample selection with alternative measures of patent owner and partner size. Instead of number of employees, we employed the operating revenue of the patent owner and the trade partner as a measure of size. Table-5c presents the results of our analyses with the new size measure. The results of our alternative specification remain qualitatively the same. In the selection model (Model-1) results show that patent owner size has a negatively associated with ($p<0.01$) the selection to transfer rights to use. Likewise, in the second stage model (Model-2), the decision to transfer the ownership rights are negatively impacted by the owner size ($p<0.05$) and not affected by the trade partner size. We have also re-estimated the marginal effects of our new size variables. Although patent owner size variable is significant, the effect size is nearly zero. The partner size is again observed to be insignificant. These results reconfirm our findings regarding the patent owner and partner size effects on decision to transfer ownership rights.

Table-5c about here

Second, we retested the marginal effects of variables in our probit model with sample selection with *mfx* command in STATA in addition to the results of *margins* command we presented previously. The results of the alternative estimation of the marginal effects are in line with our earlier findings (Table-6c). The impact of patent owner and partner size on transfer of ownership decision is nearly zero. Commercialization decreases the likelihood of ownership transfer by 61% and it is followed by the willingness to commercialize which decreases the probability of transfer by 10%. In contrast, co-patenting increases the likelihood of ownership transfer by 14.3%.

Table-6c about here

Lastly, we employed the simulation method suggested by Zelner (2009) for the interpretation of non-linear models. Using the *estsimp* command, we re-estimated a probit model with our second stage equation and simulated the coefficients 1,000 times. The results of this analysis are presented in Table-7c. This analysis shows that patent owner and partner size have no impact on the decision to transfer ownership rights. Commercialization and the willingness to commercialize negatively impact the likelihood of ownership transfer. Yet, the existence of co-applicants increases the probability of ownership transfer.

Table-7c about here

DISCUSSION AND CONCLUSION

In this study, we examine the determinants of the decision to transfer ownership rights in technology market transactions conditional on the patent owner's selection to transfer rights to use. In doing so, we exploit recent surveys conducted on inventors (PatVal-II, PatVal-US, Patval-JP) and supplement this dataset by various data sources for assignee and licensee characteristics. Our selection model results point to the fact that conditional on patent owner's selection to transfer the rights to use of an invention to a third party, the decision to transfer ownership rights is minimally affected by the patent owner size. Moreover, the decision to transfer ownership rights is not impacted by the size of the trade partner. However, the probability of ownership transfer heavily depends on the commercialization of the patent by the patent owner. In this case, the patent owner prefers to retain the ownership rights while transferring the rights to use through a license agreement. The same effect also holds if the patent owner is willing to commercialize the patent in the future. The likelihood of ownership transfer decreases with the patent owner's search for opportunities to commercialize the patented invention. Our results also present that co-patented inventions of joint R&D are more likely to be sold than out-licensed. Interestingly, patent characteristics such as scope, quality, economic value, etc., are associated with the patent's likelihood of being selected for market trade, i.e. decision to transfer rights to use, yet these characteristics do not influence the decision to transfer ownership rights.

We interpret our results as follows. Regarding the patent owner size effect on licensing agreements, prior literature on market for technology presents a negative relationship (Anand & Khanna 2000; Arora & Fosfuri, 2003; Arora, Fosfuri & Gambardella 2001, Fosfuri, 2006, Gambardella, Giuri & Luzzi, 2007). This body of literature is complemented by the recent studies on patent sale, which evidence that small firms are more likely to sell their patents than large firms (Figueroa & Serrano, 2010, 2013; Serrano, 2010). Our selection model on ownership transfer shows that owner size is more impactful on the patent owner's selection to transfer rights to use than the decision to transfer ownership rights. In other words, conditional on selection to transfer the rights to use of a patented invention, the decision to sell or license is minimally affected by the patent owner size. Prior research on that matter does not consider the patent owner's decision as two steps where in the first step the owner decides whether to transfer rights to use and in the second step she decides whether to transfer or retain ownership rights. By specifying our research as a two-stage selection model, we are able to present a finer-grained analysis of the size effect. Our results on size effects also explain why technology firms, like Delphi, HP, are indifferent in their intellectual property strategies between selling and licensing once they select a portfolio of patents to offer in the market for technology.

In addition, profiting from innovation through commercialization (Teece,1986) is the main determinant of the decision on ownership transfer. Intuitively, patent owners that already commercialized their patented inventions or not yet commercialized but searching for opportunities, are less selected to transfer the rights to use, and even less so to transfer the ownership rights. Therefore, as long as the patent owner is also a downstream product manufacturer, ownership transfer through sale is a less preferred option than licensing. This can be explained by the revenue generation through licensing royalties, which can balance the rent dissipation through having a new competitor in the market (Fosfuri, 2006). In case of a patent sale, the owner withdraws from all current and future interest and revenues in exchange of an amount agreed upon with the trade partner. This amount may not compensate fully for the revenue loss when the technology is already commercialized. Moreover, the patent owner that is willing to commercialize its technology in the future may predict the future returns as higher than the current patent sale rate. Thus, the likelihood of ownership transfer declines with the commercialization and willingness to commercialize.

In contrast, co-patented inventions are more likely to be selected for transfer of rights to use and also the transfer of ownership rights. The negative impact of co-patenting on firm performance and market valuation is evidenced in the prior literature (Belderbos, et al., 2010; Hagedoorn, 2003). It is argued that collaborative R&D makes it harder to appropriate returns from innovation for the parties involved in the process (Chesbrough & Rosenbloom, 2002; Di Minin & Faems, 2013; Henkel, 2006). Due to these difficulties in value appropriation, co-patented inventions can be better candidates for sale than license. The transfer of ownership rights can be perceived as an easier way of monetizing the patent.

With this study, we aim at contributing to market for technology literature by examining what determines the decision to transfer or retain ownership rights in market transactions. Benefiting from in depth surveys on inventors and supplementary data sources, we inform this body of literature of the factors effective at different stages of decision making. Moreover, by bringing together information on both patent owner and licensee/assignee characteristics, we provide a broader view of the market transactions. We account for the characteristics of both parties and try to understand which factors are at play in patent sale and patent licensing agreements. We also inform the literature on collaborative R&D and co-patenting by presenting its positive impact on technology markets. Our study provides empirical evidence that co-patented inventions are more likely to be traded in the market for technology. Lastly, we contribute to intellectual property management literature by depicting what the drivers of ownership rights transfer are and how the patent owners choose between sale and license options.

This study also has its own limitations. First, the cross-sectional nature of the survey data makes it difficult to infer causality. Although our study setup controls for the selection bias, we refrain from claiming a causal relationship in our model. Second, we focus our attention on patented inventions. In fact, a major part of inventions are not ever patented or may be traded as know-how transfer rather than a patent sale or license. Future studies can extend this research by taking into account know-how transfer in the technology markets. Third, we based our study on the dichotomous decision on patent sale vs. patent license. However, a patent can be licensed with an option to buy in the future. Future research can enrich this line of literature by examining, license with an option to buy as an alternative to the options we identified in our current study. We hope that this research opens up the way to advance theorizing on this line of research.

Conclusion

In this dissertation, with the aim of understanding better the technology transfer across organizations and the contingencies and impediments to technology transfer, I study this phenomenon in two contexts, i.e. market for technology and market for firms, and at three different levels, institutional, dyadic and technological. Focusing on the functioning of market for technology at the institutional level, in the first chapter, I found that upon the diminution in patent enforcement strength, US firms have decreased their patenting and out-licensing activities compared to European firms. The decline in out-licensing activities is more pronounced for small and medium sized firms. Likewise, upstream technology providers have faced a sharper decline in out-licensing activities compared to downstream manufacturers. I also observed that the weakening of patent enforcement strength does not impede entry by specialized technology providers although it adversely impacts royalty rates in licensing agreements. The main take away of this research is that weakening of patent enforcement strength to alleviate inflated patent trolling activities hampers the patenting and out-licensing activities of US firms in IP-intensive industries. Small and medium sized firms and upstream technology providers are the kind of firms that are affected more severely upon the downward shift in patent enforcement strength. The study aims at contributing new insights to the market for technology literature. Future studies can advance our knowledge on this line of research but testing the quality of the filed and traded patents after the weakening of patent enforcement. The impact of patent enforcement strength on firm innovativeness is left for future research due to data unavailability. Future studies can also show whether the decrease in patenting implies an overall decrease in firm innovation or a shift from patenting to other mechanisms of protection.

In the second chapter, I examined the technology transfers in market for firms. I found that technological distance between the acquirer and target firm knowledge stocks negatively affects efficiency factor whereas, technological complexity has a positive effect on efficiency factor. In addition, I observed that knowledge complexity have a direct negative impact on firm’s innovativeness. These results point to the fact that complexity of the acquired technology decreases firm innovativeness by reducing the number of patents filed; however, it increases the percentage of acquired knowledge leveraged by the merged entity. Yet, efficiency factor has an inverted U-shaped relationship with innovative performance. This result implies that efficiency factor enhances innovative performance up to a certain threshold, at which, the cost of developing AC exceeds the revenues generated through innovative value creation. This study aims at contributing to the literature on technology transfer, absorptive capacity and technology-based firm acquisitions. Further research can advance on this line by taking into account firm integration in explaining how the acquirer transfers the technological knowledge in different levels of integration.

In the third chapter, we study the distinction between patent sale and patent license as two modes of technology transfer in market for technology and focus on the patent owner’s decision on ownership transfer. Patent sale is a considerable portion of the transactions in technology markets, yet we know very little on the determinants of ownership transfer. Our results provide new insights on this line of research by showing that conditional on selection to transfer the right to use of a patented invention to a third party, the decision to transfer the ownership rights is minimally affected by the size of the patent owner or the trade partner. Instead, the decision is highly influenced by patent owner's commercialization of the patented invention or the desire to commercialize in the future. In this case, the patent owner prefers to transfer the right to use as opposed to transfer of ownership rights. Instead, patents with co-applicants and patents in larger portfolios are more prone to ownership change. Moreover, we found that indicators of patent quality, such as number of citations, number of claims, are effective in selection to transfer the right to use of patented inventions to a third party; yet, these factors are not influential in the choice between patent sale vs. license. Future studies can extend this research by examining the impact of relative bargaining power of the patent owner and trade partner with a specific emphasis on patent sale for the advancement of market for technology literature.

References

Adegbesan, J. A. & Higgins, M. J. 2010. The intra-alliance division of value created through collaboration. Strategic Management Journal, 32(2): 187–211.

Agarwal, R. & Helfat, C. E. 2009. Strategic renewal of organizations. Organization Science, 20(2): 281-293.

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

Ahuja, G. & Katila, R. 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. Strategic Management Journal, 22(3): 197–220.

Almeida P, Song J, & Grant RM. 2002. Are firms superior to alliances and markets? An empirical test of crossborder knowledge building. Organization Science, 13(2): 147–161.

Almeida, P, & Kogut, B. 1999. Localization of knowledge and the mobility of engineers in regional networks. Management Science, 45(7): 905–917.

Amable, B., Chatelain, J. B. & Ralf, K. 2010. Patents as collateral. Journal of Economic Dynamics & Control, 34: 1092-1104.

Anand, B. N. & Khanna, T. 2000. The structure of licensing contracts. Review of Industrial Organization, 48: 103-134.

Andersen, B. 2004. If ‘intellectual property rights’ is the answer, what is the question? Revisiting the patent controversies. Economics of Innovation and New Technology, 13:5, 417-442.

Aoki, R. & Spiegel, Y. 2009. Pre-grant patent publication and cumulative innovation. International Journal of Industrial Organization, 27: 333-345.

Argyres, N., & Liebskind, J., 1998. Privatizing the intellectual commons: Universities and the commercialization of biotechnology research. Journal of Economic Behavior and Organization, 35: 427–454.

Arora, A. & Fosfuri, A. 2003. Licensing the market for technology, Journal of Economic Behavior and Organization, 52, 277–295.

Arora, A. & Gambardella, A. 1994. The changing technology of technological change: General and abstract knowledge and the division of innovative labour. Research Policy, 23(5): 523-532.

Arora, A. & Gambardella, A. 2010. Ideas for rent: An overview of markets for technology. Industrial and Corporate Change, 19(3): 775–803.

Arora, A., & Ceccagnoli, M. 2006. Patent protection, complementary assets, and firms' incentives for technology licensing. Management Science, 52(2): 293-308.

Arora, A., Fosfuri, A., & Gambardella, A. 2001. Markets for technology: The economics of innovation and corporate strategy. Cambridge, MA: MIT Press.

Arrow, J. K. 1962. Economics welfare and the allocation of resources for innovation. In R. Nelson (Ed.), The rate and direction of inventive activity (pp.164-181). Princeton, Nj: Princeton University Press.

Arrow, K. 1983. Innovation in large and small firms. In Entrepreneurship, ed. By J. Ronen. Lexington Books, Lexington, MA.

Arthur, C. 2011. Nortel patents sold for $4.5bn. The Guardian, available online at: http://www.theguardian.com/technology/2011/jul/01/nortel-patents-sold-apple-sony-microsoft

Barton, J., 2000. Intellectual property rights. Reforming the patent system. Science, 287: 1933–1934.

Beckerman-Rodau, A. 2007. The Supreme Court Engages in Judicial Activism in Interpreting the Patent Law in eBay, Inc. v. MercExchange, L.L.C.. Suffolk University Law School, Research Paper, available at: http://ssrn.com/abstract=1089537

Belderbos, R., Cassiman, B., Faems, D., Leten, B. & Van Looy, B., 2014. Co-ownership of intelectual property: Exploring the value-appropriation and value-creation implications of co-patenting with different partners. Research Policy, 43: 841-852.

Belderbos, R., Faems, D., Leten, B. & Van Looy, B., 2010. Technological activities and their impact on the financial performance of the firm: Exploitation and exploration within and between firms. Journal of Product Innovation Management, 27: 869–882.

Bessen, J. & Hunt, R.M. 2003. An Empirical Look at Software Patents. Working Paper No. 03-17. Federal Reserve Bank of Philadelphia, Available at http://www.researchon innovation.org/swpat.pdf

Bessen, J. E. & Meuer, M. J. 2005. The Patent Litigation Explosion. Boston University School of Law, Working Paper No. 05-18. Available at SSRN: http://ssrn.com/abstract=831685 or http://dx.doi.org/10.2139/ssrn.831685

Bessen, J. E., Meurer, M. J. & Ford, J. L. 2011. The Private and Social Costs of Patent Trolls Boston Univ. School of Law, Law and Economics Research Paper No. 11-45. Available at SSRN: http://ssrn.com/abstract=1930272 or http://dx.doi.org/10.2139/ssrn.1930272

Bessen, S. & Raskind, L. 1991. An Introduction to the Law and Economics of Intellectual Property. Journal of Economic Perspectives, 5(1), 3–27.

Birkinshaw, J. 1999. Acquiring intellect: Managing the integration of knowledge-intensive acquisitions. Business Horizons, 42(3): 33–40.

Boyes, W.J., Hoffman, D.L. & Low, S. A. 1989. An econometric analysis of the bank credit scoring problem. Journal of Econometrics, 40(1): 3-14.

Breschi, S., Malerba, F., & Orsenigo, L. 2000. Technological regimes and Schumpeterian patterns of innovation. The Economic Journal, 110: 388-410.

Bresman, H., Birkinshaw, J. & Nobel, R. 1999. Knowledge transfer in international acquisitions. Journal of International Business Studies, 30(3): 439-462.

Brettel, M., Greve, G. I. & Flatten, T.C. 2011. Giving up linearity: Absorptive capacity and performance. Journal of Managerial Issues, 23(2): 164-189.

Cassiman, B. 2009. Complementarities in innovation strategies and the link to science'. Barcelona: Opuscle CREI Research Center, Universitat Pompeu Fabra.

Cassiman, B. & Veugelers, R. 2006. In search of complementarity in innovation strategy: Internal R&D and external knowledge acquisition. Management Science, 52: 68-52.

Ceccagnoli, M. & Hicks, D. 2012. Complementary assets and the choice of organizational governance: Empirical evidence from a large sample of U.S. technology-based firms. IEEE Transactions on Engineering Management (forthcoming).

Ceccagnoli, M., Graham, S. J. H., Higgins, M.J. & Lee, J. 2010. Productivity and the role of complementarity assets in firms' demand for technology innovations. Industrial and Corporate Change, 19(3): 839-869.

Chesbrough, H. & Rosenbloom, R., 2002. The role of the business model in capturing value from innovation: Evidence from Xerox Corporation's technology spin-off companies. Industrial and Corporate Change, 11: 529–555.

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

Chesbrough, H., 2003. The era of open innovation. MIT Sloan Management Review, 44: 35–41.

Chesbrough, H., 2006. Open innovation: a new paradigm for understanding industrial innovation. In: Chesbrough, H., Vanhaverbeke, W., West, J. (Eds.), Open Innovation: Researching a New Paradigm. Oxford University Press, Oxford, 1–12.

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

Clermont, K. M. & Eisenberg, T. 2000. Anti-plaintiff bias in the federal appellate courts. Judicature, 84:128-134.

Cloodt M, Hagedoorn J, & Van Kranenburg H. 2006. Mergers and acquisitions: their effect on the innovative performance of companies in high-tech industries. Research Policy, 35: 642–668.

Cockburn, I. M., MacGarvie, M. J. & Müller, E. 2010. Patent thickets, licensing and innovative performance. Industrial and Corporate Change, 19(3): 899-925.

Cohen WM, & Levinthal D. 1989. Innovation and learning: The two faces of R&D. Economic Journal, 99(397): 569–596.

Cohen, W. M. 2005. Patents and appropriation: Concerns and evidence. Journal of Technology Transfer, 30: 57-71.

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). NBER Working Paper 7522, revised, 2004, as mimeo, Duke University.

Cohen, W.M, & Levinthal, D.A. 1990. Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly, 35(1): 128–152.

Conti, R. 2013. Do non-competition agreements lead firms to pursue risky R&D projects? Strategic Management Journal, June 29: DOI: 10.1002/smj.2155

Conti, R., Gambardella, A. & Mariani, M. 2014. Learning to be Edison: Inventors, organizations, and Breakthrough Inventions. Organization Science, 25(3): 833-849.

Conti, R., Gambardella, A. & Novelli, E. 2013. Research on markets for inventions and implications for R&D allocation strategies. The Academy of Management Annals, 7: 717-774.

David, P., 2000. The digital technology boomerang: New intellectual property rights threaten global open science. Stanford Working Paper #00-016.

David, P., 2003. Can ‘open science’ be protected from the evolving regime of IPR protections? Stanford Working Paper #03-011.

Davis, L. N., Davis, J. D. & Hoisl, K. 2013. Leisure time invention. Organization Science, 24(5): 1439-1458.

Davis, R.M. 2008. Failed attempts to dwarf the patent trolls: Permanent injunctions in patent infringement cases under the proposed patent reform act of 2005 and eBay v. MercExchange. Cornell Journal of Law and Public Policy, 17, 431-452.

Denicolo, V., Geradin, D., Layne-Farrar, A. & Padilla, A.J. 2008. Revisiting Injunctive Relief: Interpreting eBay in high-tech industries with non-practicing patent holders. Journal of Competition Law & Economics, 4(3), 571–608.

Di Minin, A. & Faems, D., 2013. Building appropriation advantage: An introduction to the special issue on intellectual property management. California Management Review, 55: 7–14.

Diessel, B.H. 2007. Trolling for Trolls: The Pitfalls of the Emerging Market Competition Requirement for Permanent Injunctions in Patent Cases Post-eBay. Michigan Law Review, 106, 2, 305-345.

Dinur, A., Hamilton, R. & Inkpen, A., 1998. Knowledge transfer in the multinational corporation. Charleston, SC: Academy of International Business, November, 1999.

Eisenhardt, K. M. & Santos, F. M. 2002. Knowledge-based view: A new theory of strategy? In: A. Pettigrew, H. Thomas and R. Whittington (Eds.), Handbook of Strategy and Management, 139–164. London : Sage.

Ernst, H. & Vitt, J. 2000. The influence of corporate acquisitions on the behavior of key inventors. R&D Management 30(2): 105–120.

Etzkowitz, H., 1998. The norms of entrepreneurial science: cognitive effects of the new university-industry linkages. Research Policy, 27, 823–833.

Federal Trade Commission, 2003. To promote innovation: The proper balance of competition and patent law and policy. Available online at: http://www.ftc.gov/sites/default /files/documents/reports/promote-innovation-proper-balance-competition-and-patent-law-and-policy/innovationrpt.pdf

Figueroa, N. & Serrano, C. J. 2010. Firm size, patent fit and technology linkages: The determinants of patent trading flows in the market for technology. Working paper, available at: http://www.webmeets.com/files/papers/SAEE/2010/386/SERRANO_SAE2010.pdf

Figueroa, N. & Serrano, C. J. 2013. Patent trading flows of small and large firms. NBER working paper, available at: http://www.nber.org/papers/w18982

Fischer, T. & Henkel, J. 2012. Patent trolls on markets for technology–An empirical analysis of NPEs' patent acquisitions. Research Policy, Volume 41, Issue 9, 1519–1533.

Fischer, T. & Ringler, P. 2014. What patents are used as collateral? An empirical analysis of patent reassignment data. Journal of Business Venturing, 29: 633-650.

Fleming, L., & Sorenson, O., 2001. Technology as a complex adaptive system: Evidence from patent data. Research Policy, 30: 1019–1039.

Fosfuri, A. & Tribo, J.A. 2008. Exploring the antecedents of potential absorptive capacity and its impact on innovative performance. Omega International Journal of Management Science, 36: 173-187.

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

Fosfuri, A., Helmers, C., Roux, C. 2014. Are joint patents collusive? Evidence from the U.S. and Europe. Working paper. Available at SSRN: http://ssrn.com/abstract=2164222 or http://dx.doi.org/10.2139/ssrn.2164222

Galasso, A. & Schankerman, M. 2010. Patent thickets, courts, and the market for innovation. The RAND Journal of Economics, 41: 472–503.

Galasso, A. & Schankerman, M. 2014. Patents and cumulative innovation: Causal evidence from the courts. NBER Working Paper, No. 20269. June.

Galunic, D. C., & Rodan, S. 1998. Resource recombinations in the firm: Knowledge structures and the potential for schumpeterian innovation. Strategic Management Journal, 19(12): 1193–1201.

Gambardella, A. & McGahan, A. M. 2010. Business-model innovation: General purpose technologies and their implications for industry structure. Long Range Planning, 43(2-3): 262-271.

Gambardella, A., Ganco, M. & Honore, F. 2015. Using what you know: Patented knowledge in incumbent firms and employee entrepreneurship. Organization Science, 26(2): 456-474.

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

Gans, J. & Stern, S. 2010. Is there a market for ideas?, Industrial and Corporate Change, 19, 3, 805-837.

Gans, J. S., & Stern, S. 2003. The product market and the market for ideas: Commercialization strategies for technology entrepreneurs. Research Policy, 32: 333-350.

Gans, J. S., & Stern, S., 2000. Incumbency and R&D incentives: Licensing the gale of creative destruction. Journal of Economics and Management Strategy 9, 485–551.

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

Gans, J., Hsu, D.H. & 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.

Garud R, & Nayyar P.R. 1994. Transformative capacity: Continual structuring by intertemporal technology transfer. Strategic Management Journal, 15(5): 365–385.

Garvin, D. 1993. Building a learning organization. Harvard Business Review, 73(4): 78-91.

Giarratana, M. S. & Mariani, M. 2014. The relationship between knowledge sourcing and fear of imitation. Strategic Management Journal, 35: 1144-1163.

Ginarte, J.C., & Park, W.G., 1997. Determinants of patent rights: A cross-national study. Research Policy, 26: 283–301.

Giuri, P, Brusoni, S, Crespi, G, Francoz, D, Gambardella, A, Garcia-Fontes, W, Geuna, A, Gonzales, R, Harhoff, D, Hoisl, K, Lebas, C, Luzzi, A, Magazzini, L, Mariani, M, Nesta, L, Nomaler, O, Palomeras, N, Patel, P, Romanelli, M, Verspagen, B, 2007. Inventors and invention processes in Europe. Results from the PatVal-EU survey. Research Policy, 36(8): 1107-1127.

Gould, D.M. & Gruben, W.C. 1996. The role of intellectual property rights in economic growth. Journal of Development Economics, 48: 323-350

Grab, L. T. 2006. Equitable Concerns of eBay v. MercExchange: Did the Supreme Court successfully balance patent protection against patent trolls?. North Carolina Journal of Law and Technology, 8, 1, 81-115.

Graebner, M. E., Eisenhardt, K.M., & Roundy, P.T. 2010. Success and failure in technology acquisitions: Lessons for buyers and sellers. Academy of Management Perspectives, August: 73-92.

Grant, R. M. 1996. Toward a knowledge-based theory of the firm. Strategic Management Journal, 17(Winter Special Issue): 109-122.

Grimpe, C. & Hussinger, K. 2014. Resource complementarity and value capture in firm acquisitions: The role of intellectual property rights. Strategic Management Journal, 35: 1762-1780.

Guellec, D. & van Pottelsberghe de la Potterie, B. 2006. The Economics of the European Patent System. Oxford University press, Oxford.

Hagedoorn, J., 2003. Sharing intellectual property rights – An exploratory study of joint patenting amongst companies. Industrial and Corporate Change, 12: 1035–1050.

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

Harabi, N. 1994. Appropriability of Technical Innovations: An Empirical Analysis. Research Policy, 24, 981–992.

Haspeslagh P.C, & Jemison D.B. 1991. Managing acquisitions: Creating value through Corporate Renewal. New York: Free Press.

Heckman, J. 1976. The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. Annals of Economic and Social Measurement, 5(4): 475-792.

Heckman, J. 1979. Sample selection bias as a specification error. Econometrica, 47(1): 153-161.

Heller, M. & Eisenberg, R. 1998. Can patents deter innovation? The anticommons in biomedical research. Science 280, 698–701.

Hellman, T., 2007. Bridging the science to market gap: the role of patents. Journal of Economic Behavior and Organization, 63, 624–647.

Henkel, J., 2006. Selective revealing in open innovation processes: The case of embedded Linux. Research Policy, 35: 953–969.

Hicks, D., Breitzman, T., Olivastro, D., & Hamilton, K. 2001. The changing composition of innovative activity in the US—A portrait based on patent analysis,' Research Policy, 30: 681–704.

Hoetker, G. 2007. The use of logit and probit models in strategic management research: Critical issues. Strategic Management Journal, 28: 331-343.

Holmstrom, B. 1989. Agency costs and innovation. Journal of Economic Behavior and Organization, 12 (3), 305-327.

Horstmann I., MacDonald, G.M., & Slivinsky, A. 1985. Patents as information transfer mechanisms: To patent or (maybe) not to patent. Journal of Political Economy, 93: 837-858.

Huber, G.P. 1991. Organizational learning: The contributing processes and the literatures. Organization Science, 2(1): 88–116.

Inkpen, A. C. & A. Dinur 1998. Knowledge management processes and international joint-ventures. Organization Science, 9(4): 454-468.

Jaffe A, & Trajtenberg M. 1996. Flows of knowledge from universities and federal laboratories. Proceedings of the National Academy of Sciences, 93(23): 12671–12677.

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

Jaffe A, Trajtenberg M, and Fogarty M. 2002. The meaning of patent citations: Report on the NBER/Case-Western reserve survey of patentees. In Patents, Citation and Innovations: A Window on the Knowledge Economy, Jaffe A, Trajtenberg M (Eds.), MIT Press: Cambridge, MA: 379–403.

Jaffe, A. B. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profitsand market value. American Economic Review, 76: 984–1001.

Jaffe, A., 2000. The U.S. patent system in transition: Policy innovation and the innovation process. Research Policy, 29, 531–558.

Jaffe, A.B., Fogarty, M.S., & Banks, B.A., 1998. Evidence from patents and patent citations on the impact of NASA and other federal labs on commercial innovation. Journal of Industrial Economics, 46: 183–205.

Jannarone, J. & Ramachandran, S. 2012. AOL's deal eases pressure. The Wall Street Journal, available online at: http://www.wsj.com/articles/SB10001424052702303815404577333323756192742

Jansen, J. J. P., Van den Bosch, F. A. J. & Volberda. H. W. 2005. Managing potential and realized absorptive capacity: How do organizational antecedents matter? Academy of Management Journal, 48: 999–1015.

Kale P, & Puranam P. 2004. Choosing equity stakes in technology sourcing relationships: An integrative framework. California Management Review, 46(3): 77–99.

Kaufer, E. 1989. The Economics of The Patent System. Chur: Harwood Academic.

Kingston, W. 2001. Innovation Needs Patents Reform. Research Policy, 30, 403–423.

Kitch, E. W., 1977. The nature and function of the patent system. Journal of Law and Economics, 20: 265–290.

Kleinbaum, A.M. & Stuart, T.E. 2014. Inside the black box of the corporate staff: Social networks and the implementation of corporate strategy. Strategic Management Journal, 35(1): 24–47.

Kogut, B. & Zander U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organization Science, 3(3): 383–398.

Kogut, B. & Zander, U. 1993. Knowledge of the firm and the evolutionary theory of the multinational corporation. Journal of International Business Studies, 24 (4): 625-645.

Kortum, S. & Lerner, J. 1999. What is behind the recent surge in patenting?. Research Policy, 28: 1–22.

Krimsky, S., 2003. Science and the Private Interest. Rowman-Littlefield Publishing Co., Lanham.

Lamoreaux, N. & Sokoloff, K. 1997. Inventors, firms and the market for technology: U.S. Manufacturing in the late nineteenth and early twentieth centuries. NBER working paper no. H0098.

Lamoreaux, N. & Sokoloff, K. 1999. Inventive activity and the market for technology in the United States, 1840-1920. NBER working paper no 7107.

Lane PJ, & Lubatkin MH. 1998. Relative absorptive capacity and interorganizational learning. Strategic Management Journal, 19(5): 461–477.

Lane, P. J., B. R. Koka, & S. Pathak. 2006. The reification of absorptive capacity: A critical review and rejuvenation of the construct. Academy of Management Review. 31(4): 833–863.

Lanjouw, J.O. & Lerner, J. 1998. The enforcement of intellectual property rights: A survey of the empirical literature,’ Annales d’Economie et de Statistique, 49/50: 223–246.

Laursen, K. & A. Salter, 2006. Open for innovation: The role of openness in explaining innovation perdormance among U.K. manufacturing firms. Strategic Management Review, 27: 131–150.

Leiblein, M. J., Reuer, J. J. & Dalsace, F. 2002. Do make or buy decisions matter? The influence of organizational governance on technological performance. Strategic Management Journal, 23: 817-833.

Lemley, M. A. & Shapiro, C. 2006. Patent hold-up and royalty stacking. Texas Law Review, 85: 1991-2050.

Lemley, M. A. & Shapiro, C. 2007. Reply: Patent holdup and royalty stacking. Texas Law Review, Vol. 85, 2007; Stanford Law and Economics Olin Working Paper No. 345. Available at SSRN: http://ssrn.com/abstract=1005727

Leonard-Barton D. 1995. Wellsprings of knowledge: Building and sustaining the sources of innovation. Boston, MA: Harvard Business School Press.

Leone, M. I. & Reichstein, T. 2012. Licensing-in fosters rapid invention! The effect of the grant-back clause and technological unfamiliarity. Strategic Management Journal, 33: 965–985.

Lessig, L., 2002. The Future of Ideas: The Fate of the Commons in a Connected World. Random House, New York.

Levin, R.C., Klevorick, A.K., Nelson, R.R. & Winter, S.G. 1987. Appropriating the Returns from Industrial Research and Development. Brookings Papers on Economic Activity, 3, 783–820.

Lubatkin M. 1983. Mergers and the performance of the acquiring firm. Academy of Management Review, 8(2): 218–225.

Ludlow, T. 2014. Sign of the times: Trends in technology IP licensing. Intellectual Asset Management, 66, electronic publication on May, 30th at: http://www.iam-magazine.com/Magazine/Issue/66/Features/Sign-of-the-times-trends-in-technology-IP-licensing

Machlup, F. 1958. An Economic Review of the Patent System: Study of the Subcommittee on Patents, Trademarks and Copyrights of the Committee on the Judiciary, US Senate, 85th Congress, 2nd Session, Study Number 15, Washington: United States Government Printing Office, pp. 1–86.

Makri M, Hitt MA, & Lane PJ. 2010. Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. Strategic Management Journal, 31(6): 602–628.

Mansfield, E. 1986. Patents and Innovation: An Empirical Study. Management Science, 32, 173–181.

Martin, A. 2012. Kodak to sell digital imaging patents for $525 million. The New York Times, available online at: http://www.nytimes.com/2012/12/20/business/kodak-to-sell-patents-for-525-million.html?_r =1

Maskus, K.E. 2000. Globalization and the Economics of Intellectual Property Rights: Dancing the Dual Distortion. Intellectual Property Rights in the Global Economy. Washington, DC: Institute for International Economics.

Mazzoleni, R. & Nelson, R. 1998. The Benefits and Costs of Strong Patent Protection: A Contribution to the Current Debate. Research Policy, 27, 273–284.

McDowell A, & Cox NJ. 2004. Logit transformation. Stata corporation: College station, TX. http://www.stata.com/support/faqs/stat/logit.html

McEvily S.K., Eisenhardt K.M., & Prescott JE. 2004. The global acquisition, leverage, and protection of technological competencies. Strategic Management Journal, 25(8–9): 713–722.

Merges, R. & Nelson, R. R. 1990. On the complex economics of patent scope. Columbia Law Review, 90: 839-916.

Merges, R. & Nelson, R. R. 1994. On limiting or encouraging rivalry in technical progress: The effect of patent scope decisions. Journal of Economic Behavior & Organization, 25: 1–24.

Merges, R., 1999. As many as six impossible patents before breakfast: Property rights for business concepts and patent system reform. Berkeley High Technology Law Journal, 14: 577–615.

Nandkumar, A. & Srikanth, K. forthcoming. Right person in the right place: How the host country IPR influences the distribution of inventors in offshore R&D projects of multinational enterprises. Strategic Management Journal.

Nelson, R.R. 1959. The Simple Economics of Basic Scientific Research. Journal of Political Economy, 67, 297–306.

Nordhaus, W. 1969. Invention Growth and Welfare. MIT Press, Cambridge, MA.

Odasso, C., Scellato, G. & Ughetto, E. 2015. Selling patents at auction: An empirical analysis of patent value. Industrial and Corporate Change, 24(2): 417-438.

Papke, L, & Wooldridge J. 1996. Econometric methods for fractional response variables with an application to401(k) plan participation rates. Journal of Applied Econometrics, 11: 619–632.

Paradiso, R.J. & Pietrowski, E., 2009. Dilemmas of joint patent ownership. New Jersey Law Journal, 197: 912–913.

Park, W. G. 2008. International patent protection: 1960–2005. Research Policy, 37: 761–766.

Puranam, P., & Srikanth, K. 2007. What they know vs. What they do: How acquirers leverage technology acquisition. Strategic Management Journal, April: 805–825.

Quinn, G. 2011. Happy 5th Anniversary: The Impact of eBay v. MercExchange, online article available at: http://www.ipwatchdog.com/2011/05/15/happy-5th-anniversary-ebay-v-mercexchange /id=16894/

Ranft, A., & Lord, M. 1998. Acquiring knowledge-based resources through retention of human capital: Evidence from high-tech acquisitions. Academy of Management Proceedings, August 1, 1998 H1-H7.

Ranft, A., & Lord, M. 2002. Acquiring new technologies and capabilities: A grounded model of acquisition implementation. Organization Science, 13(4): 420–441.

Reitzig, M. 2003. What determines patent value? Insights from the semiconductor industry. Research Policy, 32(1): 13-26.

Reitzig, M., Henkel, J., & Heath, C. 2007. On sharks, trolls, and their patent prey—Unrealistic damage awards and firms' strategies of "being infringed". Research Policy, 36: 134–154.

Rivette, K.G. & Kline, D. 2000a. Discovering New Value In Intellectual Property. Harvard Business Review, January–February, 54–66.

Rivette, K.G. & Kline, D. 2000b. Rembrandts in the Attic. Unlocking the Hidden Value of Patents. Boston, MA: Harvard Business School Press.

Rosenkopf, L. & Almeida P. 2003. Overcoming local search through alliances and mobility. Management Science, 49(6): 751–767.

Sampson, R.C. 2007. R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. Academy of Management Journal, April 1 50(2): 364-386.

Scherer, F.M., 1980. Industrial Market Structure and Economic Performance, 2nd edn. Houghton Mifflin, Boston, MA.

Scotchmer, S. 1991. Standing on the shoulders of giants: Cumulative research and the patent law,' Journal of Economic Perspectives, 5: 29–41.

Scotchmer, S. 2004. Innovation and Incentives. The MIT Press, Cambridge, MA.

Sears, J. & Hoetker, G. 2014. Technological overlap, technological capabilities, and resource recombination in technological acquisitions. Strategic Management Journal, 35: 48-67.

Serrano, C. J. 2010. The dynamics of the transfer and renewal of patents. RAND Journal of Economics, 41(4): 686-708.

Seth A. 1990. Sources of value creation in acquisitions: An empirical investigation. Strategic Management Journal, 11(6): 431–446.

Shapiro, C., 2000. Navigating the patent thicket: Cross licenses, patent pools, and standard setting. in Innovation Policy and the Economy, Vol. 1, A. Jaffe, J. Lerner and S. Stern (eds.), Cambridge, National Bureau of Economic Research and MIT Press.

Simonin, B. l. 1999. Ambiguity and the process of knowledge transfer in strategic alliances. Strategic Management Journal, 20: 595-623.

Singh H, & Montgomery CA. 1987. Corporate acquisition strategies and economic performance. Strategic Management Journal, 8(4): 377–386.

Singh H, & Zollo M. 1997. Knowledge accumulation mechanisms and the evolution of post-acquisition integration strategies. Pennsylvania : Working paper, University of Pennsylvania.

Somaya, D. 2003. Strategic determinants of decisions not to settle patent litigation. Strategic Management Journal, 24: 17-38.

Song J, Almeida P, & Wu G. 2003. Learning-by-hiring: When is mobility more likely to facilitate interfirm knowledge transfer? Management Science, 49(4): 351–365.

Sorensen, J., & Stuart. T. 2000. Aging, obsolescence and organizational innovation. Administrative Science Quarterly, 45: 81-112.

Spender, J.C. 1996. Making knowledge the basis of a dynamic theory of the firm. Strategic Management Journal, 52: 102-122.

Szulanski, G. 1996. Exploring internal stickiness: Impediments to the transfer of best practice within the firm. Strategic Management Journal, Winter Special Issue, 17: 27–43

Tang, Y.H. 2006. The future of patent enforcement after eBay v. MercExchange. Harvard Journal of Law & Technology, 20, 1, 236-252.

Teece, D. J., 1986. Profiting from technological innovation. Research Policy, 15: 285–305.

Therin, F. 2007. Absorptive capacity: An empirical test of Zahra & George's Contribution in Small Business Settings. Gestion, 24(4): 17-30.

Todorova, G., & Durisin, B. 2007. Absorptive capacity: Valuing a reconceptualization. Academy of Management Review, 32(3): 774–786.

Trajtenberg M. 1990. A penny for your quotes: Patent citations and the value of innovations. RAND Journal of Economics, 21: 172–187.

Tsai, W. 2001. Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance. Academy of Management Journal, 44(5): 996-1004

USPTO 2012. Intellectual property and the U.S. economy: Industries in focus. http://www.uspto.gov/news/publications/IP_Report_March_2012.pdf

Valentini, G. 2012. Measuring the effect of M&A on patenting quantity and quality. Strategic Management Journal, 33: 336-346.

Van den Bosch, F. A. J., Volberda, H. W & de Boer. M. 1999. Co-evolution of firm absorptive capacity and knowledge environment: Organizational forms and combinative capabilities. Organization Science, 10(5): 551-68.

Ver Hoef, J M. & Boveng, P. L. 2007. Quasi-poisson vs negative binomial regression: How should we model overdipersed count data? Ecology, 88: 2766–2772.

Volberda H. W., Foss N. J., & Lyles M. A. 2010. Absorbing the notion of absorptive capacity: How to realize its potential in the organization field. Organization Science, 21(4): 931–951.

von Graevenitz, G., Wagner, S. & Harhoff, D. 2013. Incidence and growth of patent thickets: The impact of technological opportunities and complexity. The Journal of Industrial Economics, 3: 521-563.

von Hippel, E. 1994. Sticky information and the locus of problem solving: Implications ofr innovation. Management Science, 40(4): 429-439.

Wagner, S., Hoisl, K. & Thoma, G. 2014. Overcoming localization of knowledge – The role of professional service firms. Strategic Management Journal, 35: 1671-1688.

Wiersema, M. F. & Bowen, H. P. 2009. The use of limited dependent variable techniques in strategic research: Issues and methods. Strategic Management Journal, 30: 679-692.

Williams, H. 2013. Intellectual property rights and innovation: Evidence from the human genome. Journal of Political Economy, 121 (1), 25-37.

Wooldridge, J.M. 2007. What's New in Econometrics? Lecture 10 Difference-in-Differences Estimation, NBER Summer Institute, mimeo.

York, J.G. & Lenox, M.J. 2013. Exploring the sociocultural determinants of de novo versus de alio entry in emerging industries. Strategic Management Journal, November 8: DOI: 10.1002/smj.2187

Zaby, A.K. 2010. The Decision to Patent. Springer Heidelberg.

Zahra, S. A., & George, G. 2002. Absorptive capacity: A review, reconceptualization, and extension. Academy of Management Review. 27: 185–203.

Zelner, B. A. 2009. Using simulation to interpret results from logit, probit, and other nonlinear models. Strategic Management Journal, 30: 1335-1348.

Ziedonis, R. H. 2004. Don’t fence me in: Fragmented markets for technology and the patent acquisition strategies of firms. Management Science, 50(4): 804-820.

Appendix-A

Table-1a Some Key Decisions and Legislative Changes

Case/Legislation	Subject	Effect
eBay v. MercExchange (2006)	Reduced the probability of getting an injunction based on a finding of infringement	Lowers penalty for infringing patents and thus reduces patent values – encourages use of International Trade Commission (ITC) as an alternate forum for a US injunction-like exclusion order and also the use of foreign courts (eg, Germany, where injunctions are still possible)
Sandisk v. STMicroelectronics (in light of MedImmune v. Genentech) (2007)	Lowered the bar significantly on the grounds for filing a declaratory judgment	Firms that receive unsolicited patent licensing opportunities can initiate a declaratory judgment action in the court of their choice rather than waiting to be sued in the court of the patent holder's choice • Makes it more difficult to license patents
KSR v. Teleflex (2007)	Lowered the bar for obviousness	Makes it easier to invalidate patents
Convolve v. Seagate (2007)	Raised the bar for willful infringement; requires a showing of "objective recklessness" on the part of the infringer	Reduces the prospect of high damages for patent infringement

Quanta Computer v. LG (2008)	Patent exhaustion for downstream products	Under the exhaustion doctrine, when authorized sale of a patented article occurs, the patent holder's exclusive rights to control the use and sale of that article are exhausted, and the purchaser is free to use or resell that article without further restraint from patent law • Limits options for licensing
Cornell U v. HP (2009) Lucent v. Gateway (2009)	Virtual elimination of entire market value (EMV) basis for damages	Reduces royalty base to the value of a sub-component, in most cases reducing the potential damages award. Allows EMV as a royalty base only in cases where the patented technology "creates the basis for customer demand"
America Invents Act (AIA) (2011)	*Inter partes* review (for the patentability of one or more claims in a patent)	Expected to have a negative effect on patent values. About 95% of patent claims reaching decision have been cancelled to date.
Uniloc v. Microsoft (2011)	Elimination of 25% rule as an admissible rule of thumb to determine damages	Requires comparable license agreements to determine royalty rates rather than empirical 25% of profits.
Laser Dynamics v. Quanta Computer (2012)	Apportionment; damages based on smallest saleable patent practicing unit	Damage case becomes much more important – damage values drop with shrinking royalty base
Motorola v. Apple (2012)	Sufficiency of damages expert opinions questioned	An example that highlights the risks and uncertainty of damages law for patent cases
Motorola v. Microsoft (2013)	Standards-essential patents (SEPs)	Value of SEPs drops. • Also the European Commission Competition Directorate General has investigated Microsoft/Nokia (2012), Samsung (2013) and Motorola

		Mobility (2013) for anti-competitive uses of SEPs. • The US Federal Trade Commission has conducted similar investigations
Samsung v. Apple (2013)	International Trade Commission (ITC) case looking at SEPs	A presidential veto was used for the first time since 1987 to deny an exclusion order based on the ‘anti-competitive’ use of SEPs
Alice Corp v. CLS Bank (2014)	Software patent eligibility	Value of software patents drops. Merely requiring generic computer implementation fails to transform that abstract idea into a patent-eligible invention.
Proposed Federal Rules of Civil Procedure revisions (Innovation Act, 2013)	Requiring more ‘robust’ pleading and complaints – potentially providing more information on infringement allegations at the outset of a trial.	Depicts the clear trend of continuing to ‘raise the bar’ for patent assertion.

Source: Ludlow (2014) ‘Sign of the times: Trends in technology IP licensing’

Table-2a Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Licensing	976207	.001	.055	0	17
Patent Appl.	976207	.497	12.620	0	2584
Cum. Patent Appl.	976207	10.819	320.610	0	47902
Operating Rev	976207	17716.9	545078.8	-1838875	8.85e+07
N of Employees	976207	48.191	1158.31	0	140700
Profit margin	976207	.160	3.046	-99.51	100
Firm Age	976207	16.589	19.364	0	185
US	976207	.218	.413	0	1
Germany	976207	.618	.486	0	1
Switzerland	976207	.164	.370	0	1
Small	976207	.568	.495	0	1
Medium	976207	.314	.464	0	1
Large	976207	.086	.280	0	1
Very Large	976207	.031	.174	0	1
Chemical	976207	.076	.265	0	1
Machinery	976207	.222	.415	0	1
Computer	976207	.154	.361	0	1
Electric	976207	.056	.231	0	1
Medical	976207	.083	.276	0	1
Software	976207	.371	.483	0	1

Table-3a Correlation Matrix

		1	2	3	4	5	6	7	8	9	10
1	Licensing	1.000									
2	Patent Appl.	0.084*	1.000								
3	Cum. Patent Appl.	0.100*	0.275*	1.000							
4	Operating Rev.	0.077*	0.214*	0.536*	1.000						
5	Number of Emp.	0.074*	0.211*	0.414*	0.702*	1.000					
6	Profit Margin	-0.004*	0.038*	0.040*	0.065*	0.047*	1.000				
7	Firm Age	0.010*	0.116*	0.069*	0.058*	0.059*	0.032*	1.000			
8	US	0.032*	0.231*	0.042*	0.026*	0.021*	-0.023*	0.123*	1.000		
9	Germany	-0.023*	-0.132*	-0.027*	-0.015*	-0.011*	0.037*	-0.046*	-0.618*	1.000	
10	Switzerland	-0.005*	-0.065*	-0.012*	-0.009*	-0.009*	-0.023*	-0.077*	-0.227*	-0.625*	1.000
11	Small	-0.022*	-0.205*	-0.034*	-0.030*	-0.030*	-0.041*	-0.275*	-0.286*	0.106*	0.153*
12	Medium	-0.009*	0.005*	-0.017*	-0.016*	-0.014*	0.004*	0.134*	0.120*	-0.017*	-0.098*
13	Large	0.007*	0.150*	0.004*	-0.001	0.002*	0.047*	0.193*	0.209*	-0.105*	-0.078*
14	Very Large	0.076*	0.383*	0.135*	0.129*	0.120*	0.032*	0.113*	0.211*	-0.113*	-0.069*
15	Chemical	0.043*	0.064*	0.033*	0.027*	0.016*	0.010*	0.109*	0.120*	-0.079*	-0.021*
16	Machinery	-0.009*	0.021*	0.001	-0.001	-0.003*	0.014*	0.186*	0.068*	0.023*	-0.096*
17	Computer	0.004*	0.093*	0.013*	0.010*	0.014*	-0.004*	0.020*	0.167*	-0.103*	-0.039*
18	Electric	-0.003*	0.032*	0.001	-0.001	0.002*	0.004*	0.076*	0.052*	-0.018*	-0.029*
19	Medical	-0.001	0.009*	-0.006*	-0.006*	-0.005*	-0.012*	0.010*	0.010*	0.015*	-0.028*
20	Software	-0.014*	-0.130*	-0.024*	-0.016*	-0.014*	-0.012*	-0.312*	-0.232*	0.062*	0.153*

		11	12	13	14	15	16	17	18	19	20
11	Small	1.000									
12	Medium	-0.809*	1.000								
13	Large	-0.366*	-0.150*	1.000							
14	Very Large	-0.218*	-0.090*	-0.041*	1.000						
15	Chemical	-0.097*	0.022*	0.084*	0.105*	1.000					
16	Machinery	-0.182*	0.153*	0.082*	-0.005*	-0.136*	1.000				
17	Computer	-0.126*	0.075*	0.064*	0.077*	-0.109*	-0.195*	1.000			
18	Electric	-0.082*	0.056*	0.046*	0.022*	-0.064*	-0.113*	-0.091*	1.000		
19	Medical	0.040*	-0.025*	-0.028*	-0.009*	-0.079*	-0.140*	-0.113*	-0.066*	1.000	
20	Software	0.319*	-0.221*	-0.162*	-0.104*	-0.246*	-0.438*	-0.352*	-0.205*	-0.253*	1.000

Table-4a Results of Fixed-effects (within) Estimations for Patenting and Out-licensing Activities

Comparison of US firms with European firms before and after eBay		
	(1)	(2)
VARIABLES	Patent Applications	Out-licensing Agreements
Post-eBay Period*US firm	-0.0339***	-0.000920***
	(0.00108)	(0.000117)
Post-eBay Period	-0.000281	0.000788
	(0.00703)	(0.000762)
Cumulative Patent App	-0.000104***	-6.53e-06***
	(6.09e-06)	(6.61e-07)
Operating Revenue	-3.49e-09***	-8.98e-10***
	(9.14e-10)	(9.91e-11)
Number of Employees	2.43e-06***	3.27e-07***
	(4.23e-07)	(4.59e-08)
Profit Margin	0.00119***	-4.15e-05***
	(8.50e-05)	(9.22e-06)
Firm Age	-0.000936	-0.000107
	(0.000821)	(8.90e-05)
Constant	0.0635***	0.00277***
	(0.00976)	(0.00106)
Year FE	YES	YES
Firm FE	YES	YES
Observations	976,207	976,207
R-squared	0.003	0.000
Number of company_id	136,920	136,920

NOTE: Standard errors in parentheses, DVs log-transformed, country, size and industry dummies inserted. (*** p<0.01, ** p<0.05, * p<0.1)

Table-5a Results of Fixed-effects (within) Estimations for Firm Size Effects on Patenting and Out-licensing Activities

	(1)	(2)	(3)	(4)
	Small	Medium	Large	Very Large
VARIABLES	Patent Applications	Patent Applications	Patent Applications	Patent Applications
Post-eBay Period*US firm	-0.0264***	-0.0150***	-0.0463***	-0.133***
	(0.000984)	(0.00180)	(0.00557)	(0.0140)
Post-eBay Period	-0.00688	-0.00938	0.0234	0.187*
	(0.00470)	(0.0132)	(0.0466)	(0.109)
Cumulative Patent App	-7.92e-05***	-0.00512***	-0.00318***	-6.28e-05***
	(6.65e-06)	(0.000114)	(0.000179)	(1.84e-05)
Operating Revenue	-5.86e-08***	-1.67e-08	-3.44e-09	-5.89e-09**
	(6.07e-09)	(1.46e-08)	(5.12e-09)	(2.58e-09)
Number of Employees	1.02e-05***	4.41e-05***	3.84e-05***	1.74e-06
	(3.29e-06)	(6.21e-06)	(1.06e-05)	(1.15e-06)
Profit Margin	0.000454***	0.00105***	0.000271	0.00209***
	(0.000117)	(0.000202)	(0.000318)	(0.000341)
Firm Age	0.000102	0.000412	-0.00130	-0.0242*
	(0.000549)	(0.00155)	(0.00544)	(0.0127)
Observations	554,750	306,865	83,906	30,686
R-squared	0.003	0.010	0.009	0.013
Number of company_id	84,655	38,510	10,048	3,707
	(5)	(6)	(7)	(8)
	Small	Medium	Large	Very Large
	Out-licensing Agreements	Out-licensing Agreements	Out-licensing Agreements	Out-licensing Agreements
Post-eBay Period*US firm	-0.000320***	-0.000301**	-0.000181	-0.00313
	(8.86e-05)	(0.000120)	(0.000466)	(0.00252)
Post-eBay Period	0.000407	0.000151	-0.00250	0.0222
	(0.000424)	(0.000883)	(0.00390)	(0.0195)
Cumulative Patent App	-2.06e-07	-0.000141***	6.25e-06	-6.15e-06*
	(5.99e-07)	(7.63e-06)	(1.49e-05)	(3.30e-06)
Operating Revenue	0	-6.75e-09***	-2.13e-10	-9.36e-10**
	(5.47e-10)	(9.76e-10)	(4.28e-10)	(4.64e-10)
Number of Employees	4.35e-08	4.83e-06***	1.06e-07	3.83e-07*
	(2.97e-07)	(4.14e-07)	(8.87e-07)	(2.07e-07)
Profit Margin	3.18e-05***	-5.26e-05***	-4.50e-05*	-4.83e-05
	(1.05e-05)	(1.35e-05)	(2.66e-05)	(6.14e-05)
Firm Age	-4.88e-05	-1.34e-05	0.000217	-0.00320
	(4.94e-05)	(0.000103)	(0.000455)	(0.00228)
Observations	554,750	306,865	83,906	30,686
R-squared	0.003	0.010	0.009	0.013
Number of company_id	84,655	38,510	10,048	3,707

NOTE: Standard errors in parentheses, DVs log-transformed, country, industry and year dummies inserted (*** p<0.01, ** p<0.05, * p<0.1)

Table-6a Results of Fixed-effects (within) Estimations for Industry Effects on Patenting and Out-licensing Activities

	Chemical	Machinery	Computer	Electric	Medical D.	Software
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Patent Applications	Patent Applications	Patent Applications	Patent Applications	Patent Applications	Patent Applications
Post-eBay*US firm	-0.0452***	-0.0226***	-0.0511***	-0.0196***	-0.0185***	-0.0346***
	(0.00467)	(0.00222)	(0.00325)	(0.00515)	(0.00380)	(0.00134)
Post-eBay Period	0.0250	0.00473	0.00556	-0.0353	0.0207	-0.00628
	(0.0358)	(0.0162)	(0.0250)	(0.0385)	(0.0242)	(0.00621)
Cumulative Patent App	-8.74e-05***	-0.000254***	-0.000112***	2.44e-05	0.000151**	-0.000501***
	(2.49e-05)	(2.49e-05)	(9.80e-06)	(4.90e-05)	(6.56e-05)	(3.20e-05)
Operating Revenue	-1.58e-08***	1.12e-08***	2.06e-08***	-1.72e-08**	7.47e-08***	1.38e-08***
	(2.01e-09)	(2.38e-09)	(2.57e-09)	(7.91e-09)	(1.68e-08)	(3.33e-09)
Number of Employees	5.25e-06***	2.20e-06*	-4.30e-06***	1.26e-05***	-2.14e-05***	-7.64e-07
	(1.10e-06)	(1.15e-06)	(1.01e-06)	(2.26e-06)	(4.54e-06)	(8.68e-07)
Profit Margin	0.00157***	0.00134***	0.00130***	0.000217	0.000417	0.00126***
	(0.000283)	(0.000239)	(0.000206)	(0.000456)	(0.000312)	(0.000103)
Firm Age	-0.00642	-0.000737	-0.00248	0.00440	-0.00308	-0.000150
	(0.00418)	(0.00190)	(0.00292)	(0.00450)	(0.00283)	(0.000724)
Observations	74,230	216,458	150,385	55,001	80,782	362,585
R-squared	0.011	0.003	0.006	0.002	0.001	0.005
Number of company_id	10,096	28,486	19,971	7,145	10,740	55,789

	Chemical	Machinery	Computer	Electric	Medical D.	Software
	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Out-licensing Agreements	Out-licensing Agreements	Out-licensing Agreements	Out-licensing Agreements	Out-licensing Agreements	Out-licensing Agreements
Post-eBay*US firm	-0.00246**	-0.000377***	-0.00106***	-0.00110***	-0.000368	-0.000491***
	(0.000991)	(0.000114)	(0.000300)	(0.000333)	(0.000380)	(0.000111)
Post-eBay Period	0.0120	0.000316	0.000457	-0.000497	-0.000760	-0.000212
	(0.00759)	(0.000838)	(0.00231)	(0.00249)	(0.00242)	(0.000515)
Cumulative Patent App	5.27e-06	6.04e-06***	-1.02e-05***	-1.33e-07	-2.04e-05***	-7.57e-05***
	(5.29e-06)	(1.28e-06)	(9.06e-07)	(3.17e-06)	(6.57e-06)	(2.66e-06)
Operating Revenue	-2.10e-09***	-4.57e-10***	1.30e-09***	2.15e-10	2.05e-09	-2.87e-09***
	(4.26e-10)	(1.23e-10)	(2.38e-10)	(5.12e-10)	(1.68e-09)	(2.76e-10)
Number of Employees	2.65e-07	3.20e-07***	-2.21e-08	-6.18e-08	-4.64e-07	1.16e-06***
	(2.34e-07)	(5.91e-08)	(9.32e-08)	(1.46e-07)	(4.55e-07)	(7.20e-08)
Profit Margin	-0.000187***	1.35e-05	1.74e-05	7.54e-05**	-9.36e-05***	-4.60e-05***
	(6.00e-05)	(1.23e-05)	(1.91e-05)	(2.95e-05)	(3.13e-05)	(8.54e-06)
Firm Age	-0.00146*	-4.09e-05	-0.000145	0.000106	8.54e-05	2.94e-05
	(0.000886)	(9.79e-05)	(0.000270)	(0.000291)	(0.000283)	(6.01e-05)
Observations	74,230	216,458	150,385	55,001	80,782	362,585
R-squared	0.001	0.001	0.001	0.001	0.001	0.004
Number of company_id	10,096	28,486	19,971	7,145	10,740	55,789

Table-7a Results of Fixed-effects (within) Estimations for Main Effects on Technology Providers' Patenting and Out-licensing Activities

	US Technology Providers v. Rest of US firms		US Technology Providers v. Rest of US firms within industry	
	(1)	(2)	(3)	(4)
VARIABLES	Patent Applications	Out-licensing Agreements	Patent Applications	Out-licensing Agreements
Post-eBay Period*US Technology Provider	-0.00923	-0.00601***	-0.00610	-0.00567***
	(0.0140)	(0.00168)	(0.0145)	(0.00188)
Post-eBay Period	-0.0724***	-0.00164***	-0.0862***	-0.00197***
	(0.00320)	(0.000383)	(0.00387)	(0.000500)
Cumulative Patent App	-0.000104***	-6.15e-06***	-9.01e-05***	-6.68e-06***
	(1.21e-05)	(1.44e-06)	(1.31e-05)	(1.69e-06)
Operating Revenue	-1.39e-10	-1.56e-09***	1.08e-10	-2.09e-09***
	(1.80e-09)	(2.16e-10)	(2.03e-09)	(2.61e-10)
Number of Employees	6.43e-07	7.20e-07***	-1.31e-06	7.93e-07***
	(8.21e-07)	(9.83e-08)	(9.60e-07)	(1.24e-07)
Profit Margin	0.00129***	-4.51e-05*	0.00156***	-4.59e-05
	(0.000199)	(2.38e-05)	(0.000219)	(2.83e-05)
Observations	216,607	216,607	159,530	159,530
R-squared	0.006	0.001	0.007	0.001
Number of company_id	28,148	28,148	21,134	21,134

NOTE: Standard errors in parentheses, DVs log-transformed, year, size and industry dummies inserted. (*** p<0.01, ** p<0.05, * p<0.1)

Table-8a Results of Fixed-effects (within) Estimations for Main Effects on 'Heavy US Patenter' European Firms' Patenting and Out-licensing Activities

Comparison of European Firms 'Heavily Patenting in US' v. Rest of European Firms			
VARIABLES	(1) European Firms' Patent Applications (in US)	(2) European Firms' Patent Applications (rest of the world)	(3) European Firms' Out-licensing Activities (worldwide)
Post-eBay*Heavy US Patenter	-0.361***	0.00462	-0.00296***
	(0.00323)	(0.00577)	(0.000498)
Post-eBay Period	0.000124	0.000565	-2.63e-06
	(0.000355)	(0.000633)	(5.47e-05)
Cumulative N. of US Patent Appl.	-0.000116***	-0.000854***	-5.19e-05***
	(1.89e-05)	(3.37e-05)	(2.91e-06)
Cumulative N. of Patent Appl.	1.21e-05	0.000270***	1.88e-05***
	(1.04e-05)	(1.85e-05)	(1.60e-06)
Operating Revenue	-1.06e-08***	-1.41e-08***	5.93e-10***
	(6.86e-10)	(1.22e-09)	(1.06e-10)
Number of Employees	7.99e-06***	8.88e-06***	-1.35e-06***
	(3.48e-07)	(6.21e-07)	(5.36e-08)
Profit Margin	0.000191***	0.000770***	-1.77e-05**
	(4.52e-05)	(8.06e-05)	(6.96e-06)
Constant	0.00926***	0.00329**	0.000122
	(0.000737)	(0.00131)	(0.000113)
Observations	763,290	763,283	763,290
R-squared	0.023	0.003	0.002
Number of company_id	109,182	109,182	109,182

NOTE: Standard errors in parentheses, DVs log-transformed, year, size and industry dummies inserted. (*** p<0.01, ** p<0.05, * p<0.1)

Table-9a Results of Cox Regression for Entry by US Upstream Technology Providers v. Entry by Rest of US Firms

Comparison of US Upstream Tech Provider Firm Entry v. Rest of US Firm Entry	
	(1)
VARIABLES	Firm Entry
Post-eBay*Hightech Firm	-0.0621
	(0.114)
Post-eBay Period	1.163
	(0)
Hightech Firm	0.313***
	(0.0776)
Small	0.432***
	(0.00861)
Large	-0.385***
	(0.0221)
Very large	-0.0546*
	(0.0293)
chemical	0.0314
	(0.0765)
machinery	-0.299***
	(0.0763)
computer	-0.00218
	(0.0763)
electric	0.0262
	(0.0769)
medical	-0.127*
	(0.0768)
software	0.0618
	(0.0762)
Year FE	YES
Observations	3,033,303
Log likelihood	-1826621.7
LR chi2(11)	8255.17
Prob > chi2	0.0000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-10a Results of Tobit Regression for Royalty Rates of Technology Licenses

VARIABLES	(1) Royalty Rates (Share of Net Sales)
Post-eBay*Technology License	-2.939**
	(1.367)
Post-eBay Period	5.847***
	(1.683)
Technology License	-0.118
	(0.661)
Multi-Exclusive	1.705*
	(0.896)
Exclusive	0.882
	(0.909)
Non-Exclusive	4.865***
	(1.617)
Constant	10.21***
	(1.101)
Observations	3,923

Standard errors in parentheses
Year dummies inserted
*** p<0.01, ** p<0.05, * p<0.1

Table-11a Results of Fixed-effects (within) IV Regression for the Impact of Patenting on Out-licensing

VARIABLES	(1) Out-licensing Agreements
Patent Applications	0.0270***
	(0.00354)
Cumulative Patent App	-3.72e-06***
	(7.84e-07)
Operating Revenue	-8.03e-10***
	(1.03e-10)
Number of Employees	2.62e-07***
	(4.78e-08)
Profit Margin	-7.38e-05***
	(1.04e-05)
Firm Age	1.01e-05
	(1.34e-05)
Constant	-1.31e-05
	(0.000376)
Observations	976,207
R-squared	0.006
Number of company_id	136,920

Standard errors in parentheses
Year dummies are inserted
Patent applications are instrumented by the shock on patent enforcement
*** p<0.01, ** p<0.05, * p<0.1

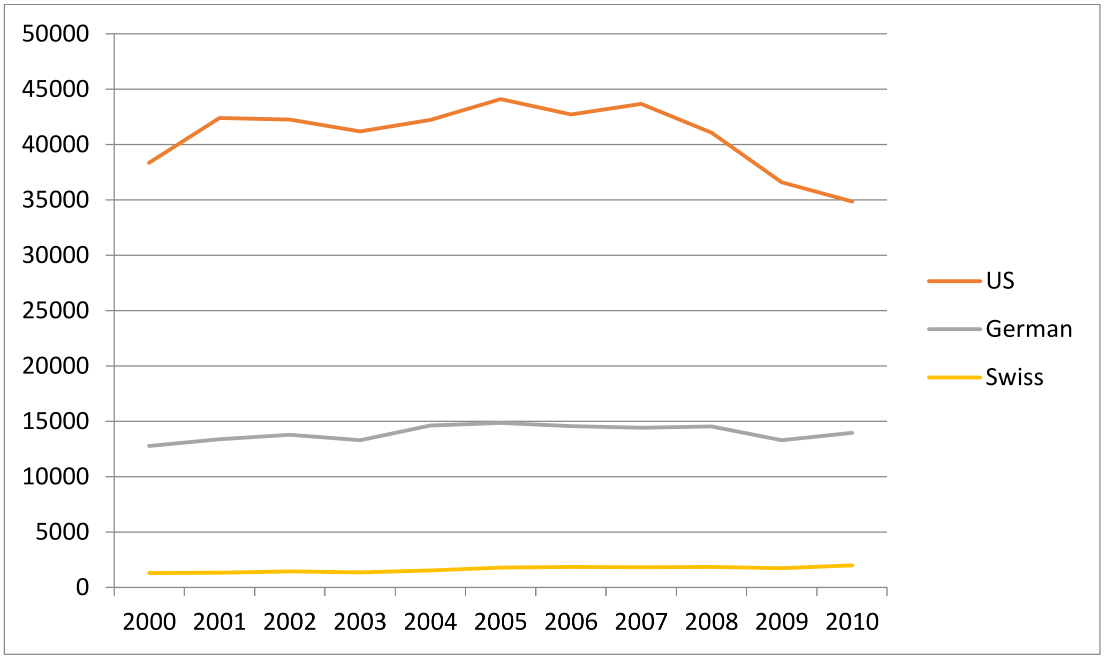

Figure 1a: Worldwide Patent Applications

Figure-2a Worldwide Out-licensing Activities

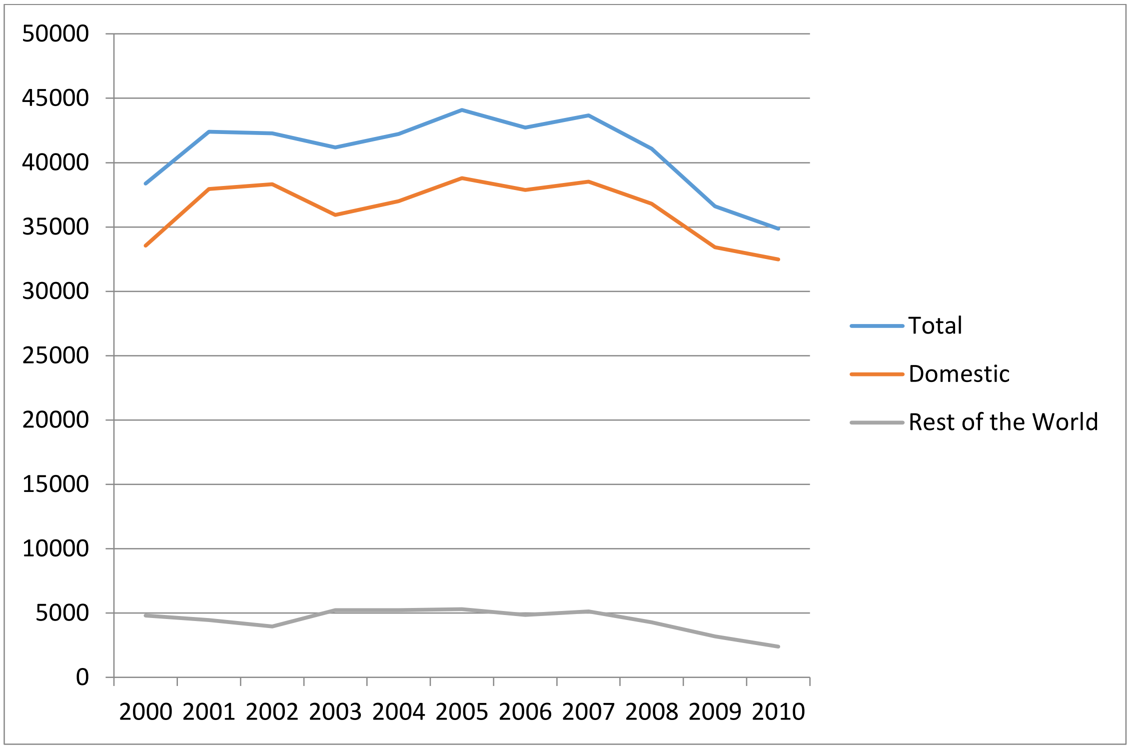

Figure-3a Decomposition of US Firms' Patent Applications

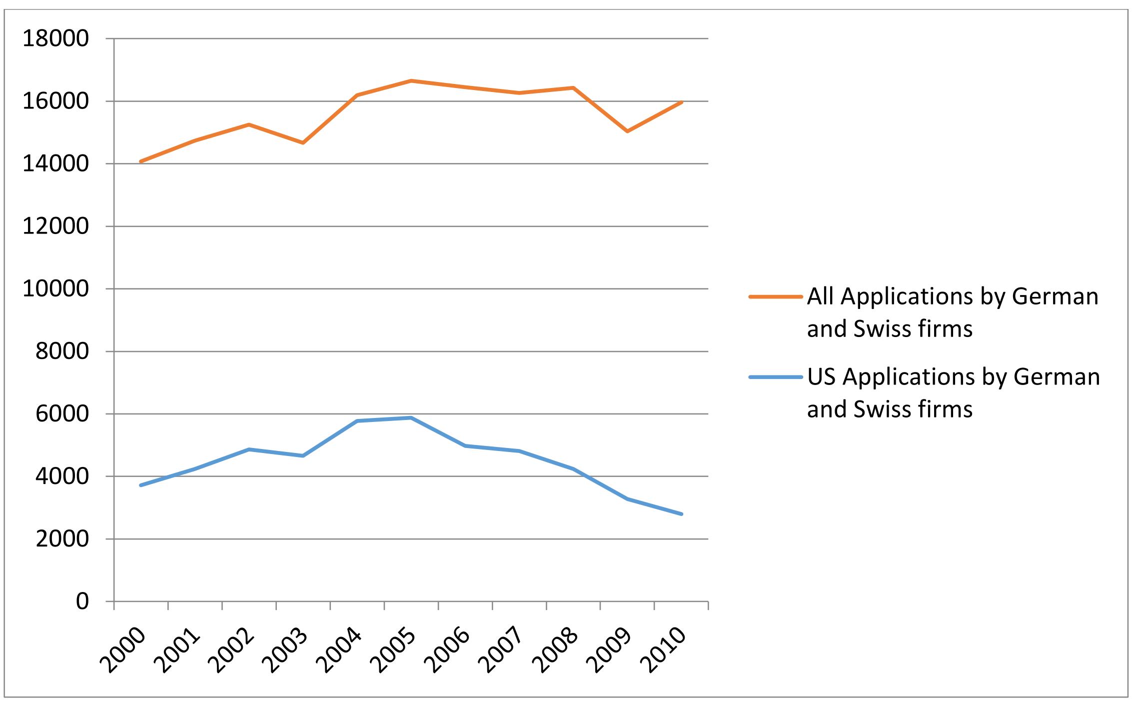

Figure-4a Decomposition of European Firms' Patent Applications

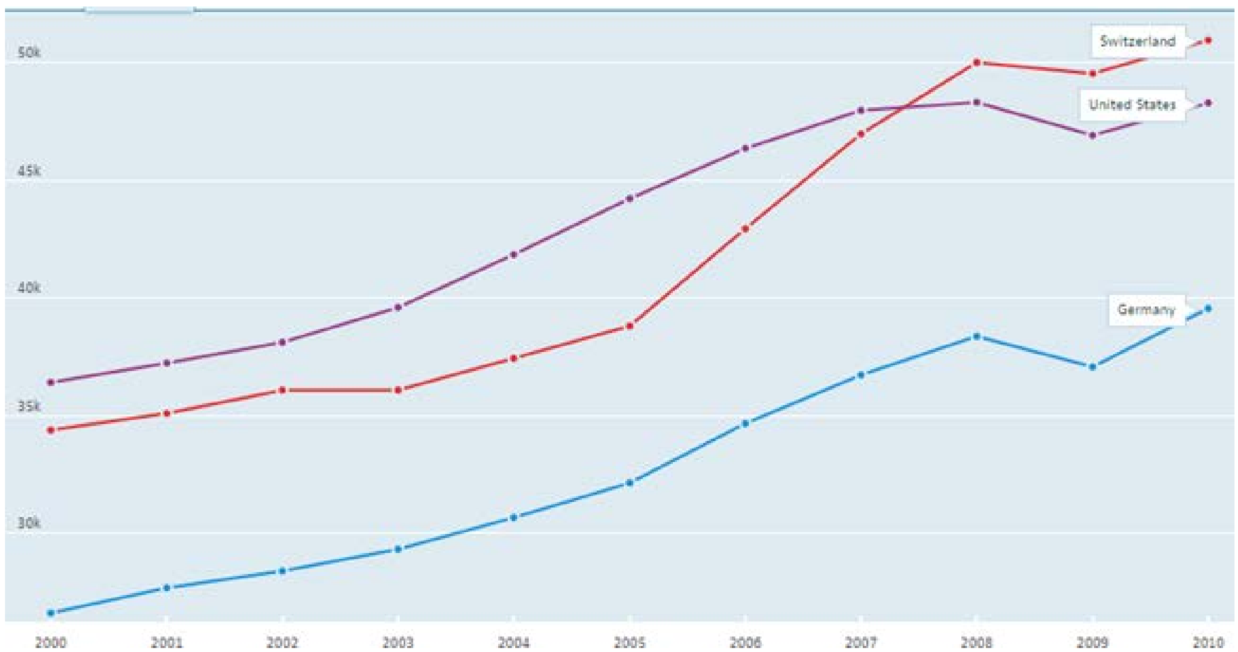

Figure-5a Gross Domestic Product by Country

Appendix-B

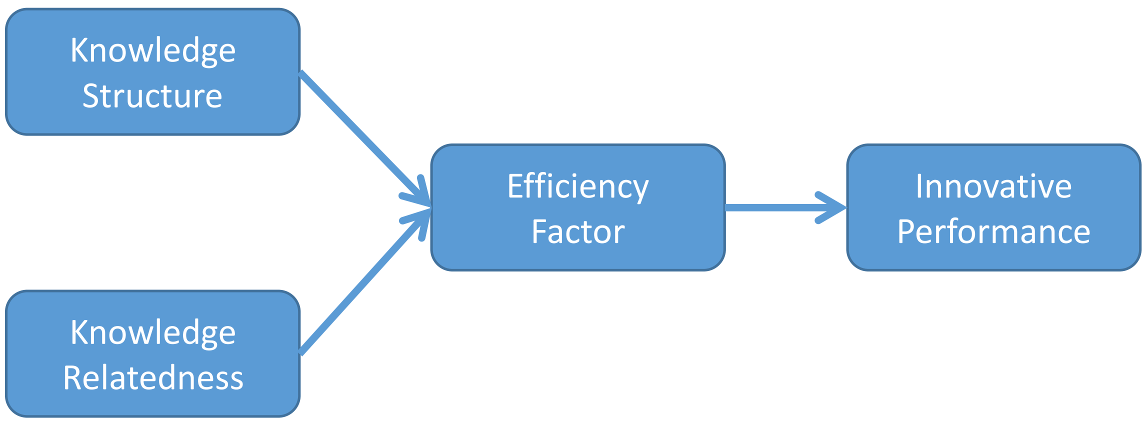

Figure-1b Theoretical Model

Table-1b Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Innovative Performance	356	232.306	784.795	0	8380
Efficiency Factor	356	.132	.227	0	1
Technological Distance	356	.694	.272	0	1
Technological Complexity	356	.059	.087	0	.5368
Herfindahl Index	356	.146	.098	.050	.674
Acquirer's Licensing Experience	356	2.247	7.497	0	55
Target's Knowledge Stock	356	51.051	232.713	5	3591
Acquirer's Knowledge Stock	356	1001.747	3333.827	0	20210
Number of Target Patents Cited	356	42.610	203.744	0	3135
Number of Target Patents Cited by Acquirer	356	.069	.149	0	.875
Acquirer's Acquisition Experience	356	5.230	9.888	0	77
Within-Industry Acquisitions	356	.486	.501	0	1
IP-Intensive Industry	356	.761	.427	0	1

Table-2b Correlations Matrix

		1	2	3	4	5	6	7
1	**Innovative Performance**	1.000						
2	**Efficiency Factor**	0.141*	1.000					
3	**Technological Distance**	-0.025	-0.126*	1.000				
4	**Technological Complexity**	-0.069	0.304*	0.061	1.000			
5	**Herfindahl Index**	-0.031	-0.074	0.026	0.011	1.000		
6	**Acquirer's Licensing Experience**	0.578*	-0.019	-0.041	-0.030	-0.005	1.000	
7	**Target's Knowledge Stock**	0.289*	-0.002	-0.007	-0.100*	0.076	0.166*	1.000
8	**Acquirer's Knowledge Stock**	0.590*	-0.019	-0.005	-0.044	0.029	0.852*	0.196*
9	**Number of Target Patents Cited**	0.302*	-0.003	-0.012	-0.097*	0.076	0.168*	0.998*
10	**Number of Target Patents Cited by Acquirer**	0.310*	0.410*	-0.229*	0.181*	-0.102*	0.134*	0.017
11	**Acquirer's Acquisition Experience**	0.212*	-0.052	0.047	-0.056	0.064	0.341*	0.095*
12	**Within-Industry Acquisitions**	0.105*	-0.015	-0.260*	-0.112*	-0.145*	0.076	-0.015
13	**IP-Intensive Industry**	0.135*	0.110*	-0.154*	0.000	-0.428*	0.147*	-0.061

		8	9	10	11	12	13
8	**Acquirer's Knowledge Stock**	1.000					
9	**Number of Target Patents Cited**	0.191*	1.000				
10	**Number of Target Patents Cited by Acquirer**	0.145*	0.024	1.000			
11	**Acquirer's Acquisition Experience**	0.404*	0.088*	0.049	1.000		
12	**Within-Industry Acquisitions**	0.057	-0.012	0.043	0.058	1.000	
13	**IP-Intensive Industry**	0.126*	-0.060	0.138*	0.071	0.149*	1.000

Table-3b Results for the First Step GLM Estimations

VARIABLES	(1) Efficiency Factor	(2) Efficiency Factor	(3) Efficiency Factor	(4) Efficiency Factor
Technological Distance			-0.918***	-1.117***
			(0.346)	(0.353)
Technological Complexity		6.015***		6.340***
		(1.145)		(1.186)
HRFNDHL	-0.144	-0.068	-0.459	-0.440
	(1.368)	(1.293)	(1.468)	(1.420)
Acquirer’s Licensing Exp	-0.014	-0.017	-0.017	-0.018
	(0.025)	(0.025)	(0.025)	(0.025)
Target’s Knowledge Stock	0.015**	0.017***	0.016**	0.018***
	(0.007)	(0.006)	(0.007)	(0.005)
Acquirer’s Knowledge Stock	-2.12e-05	-1.39e-05	-1.65e-05	-1.00e-05
	(5.56e-05)	(5.70e-05)	(5.42e-05)	(5.46e-05)
Num of Target Patent’s Cited	-0.020**	-0.022***	-0.021**	-0.022***
	(0.010)	(0.008)	(0.010)	(0.007)
Num of Target Patent’s Cited by Acquirer	0.016*	0.013**	0.015*	0.013**
	(0.008)	(0.006)	(0.008)	(0.005)
Acquirer’s Acq. Experience	-0.011	-0.010	-0.007	-0.004
	(0.013)	(0.012)	(0.012)	(0.011)
Within Industry Acquisition	-0.274	-0.035	-0.410*	-0.202
	(0.244)	(0.240)	(0.245)	(0.241)
IP-Intensive Industry	0.450	0.329	0.310	0.169
	(0.287)	(0.270)	(0.289)	(0.261)
TDDUMMY	-1.304***	-1.520***	-1.287***	-1.510***
	(0.476)	(0.414)	(0.484)	(0.421)
Constant	-2.261***	-2.984***	-1.530***	-2.137***
	(0.534)	(0.502)	(0.585)	(0.565)
Observations	356	356	356	356

Robust standard errors in parentheses
Year Dummies are inserted
*** p<0.01, ** p<0.05, * p<0.1

Table-4b Results for the Second Step Negative Binomial Estimations

VARIABLES	(1) INNOVATIVE PERFORMANCE	(2) INNOVATIVE PERFORMANCE	(3) INNOVATIVE PERFORMANCE
Eff.Factor^2			-2.828***
			(0.557)
Eff. Factor			3.188***
			(0.414)
Technological Complexity		-0.158	-1.238**
		(0.530)	(0.501)
Technological Distance		-0.255*	-0.058
		(0.138)	(0.114)
HRFNDHL	-1.244**	-1.348**	-1.186**
	(0.622)	(0.638)	(0.583)
Acquirer's Licensing Exp	0.003	0.003	0.006
	(0.007)	(0.007)	(0.006)
Target's Knowledge Stock	0.006	0.006	-0.001
	(0.004)	(0.004)	(0.003)
Acquirer's Knowledge Stock	4.03e-05**	4.08e-05**	4.71e-05***
	(1.78e-05)	(1.80e-05)	(1.41e-05)
Num of Target Patent's Cited	-0.006	-0.006	0.001
	(0.004)	(0.004)	(0.003)
Num of Target Patent's Cited by Acquirer	0.002*	0.002*	-0.001
	(0.001)	(0.001)	(0.001)
Acquirer's Acq. Experience	0.012***	0.012***	0.011***
	(0.004)	(0.005)	(0.004)
Within Industry Acquisition	0.047	0.011	0.020
	(0.078)	(0.080)	(0.072)
IP-Intensive Industry	0.155	0.115	0.116
	(0.114)	(0.118)	(0.105)
TDDUMMY	-1.548***	-1.548***	-1.330***
	(0.210)	(0.210)	(0.200)
Constant	0.728***	0.957***	0.735***
	(0.207)	(0.243)	(0.221)
lnalpha	-2.151***	-2.184***	-7.158
	(0.401)	(0.409)	(50.83)
Observations	356	356	356

Robust standard errors in parentheses
Year Dummies are inserted
*** p<0.01, ** p<0.05, * p<0.1

Figure-2b Quadratic Model with Inflection Point Noted

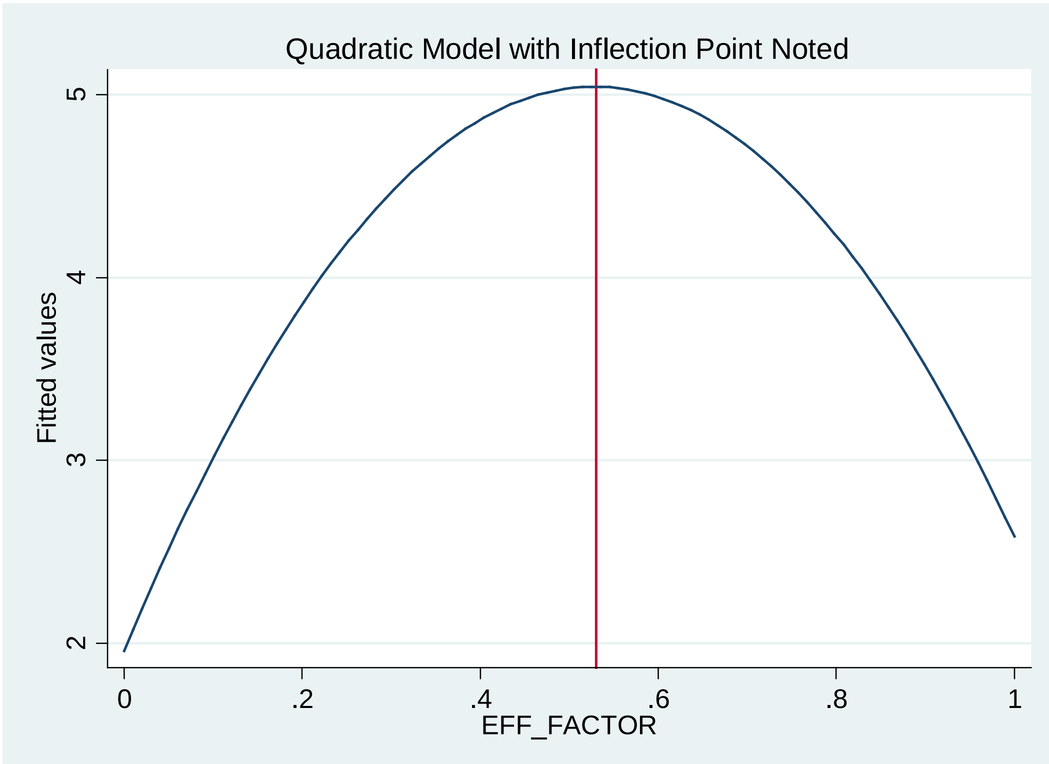

Table-5b Results for the Path Analysis with MLE Estimations

Path Analysis

VARIABLES	(1) Efficiency Factor	Beta	(2) Innovative Performance	Beta
Eff. Factor^2			-8.871***	-.664
			(1.340)	
Eff. Factor			9.894***	.933
			(1.088)	
Technological Distance	-.136***	-.163	-.126	-.014
	(.044)		(.335)	
Technological Complexity	.846***	.325	-2.921***	-.106
	(.131)		(1.049)	
HRFNDHL	-.050	-.021	-1.704*	-.069
	(.130)		(.990)	
Acquirer's Licensing Exp	-.001	-.043	.035	.108
	(.003)		(.023)	
Target's Knowledge Stock	.002**	1.96	.007	.714
	(.001)		(.007)	
Acquirer's Knowledge Stock	-2.68e-06	-.039	.000***	.297
	(6.81e-06)		(.000)	
Num of Target Patent's Cited	-.002**	-2.064	-.008	-.650
	(.001)		(.008)	
Num of Target Patent's Cited by Acquirer	.001***	.216	.001	.016
	(.001)		(.004)	
Acquirer's Acq. Experience	-.000	-.022	.034***	.140
	(.001)		(.010)	
Within-Industry Acquisition	-.032	-.070	.080	.017
	(.024)		(.181)	
IP-Intensive Industry	.019	.037	.375	.067
	(.030)		(.229)	
TDDUMMY	-.116***	-.205	-1.374***	-.229
	(.030)		(.234)	
Constant	.141**		1.668***	
	(.061)		(.469)	
Number of Observations	356		356	
R^2	0.2049		0.5974	
sqrt(1-R^2)	0.8917		0.6345	

Robust standard errors in parentheses
Year Dummies inserted
*** p<0.01, ** p<0.05, * p<0.1

Table-6b Results for the Subset of Technology Acquisitions

Subset-1 Technology Acquisitions			
VARIABLES	(1) Efficiency Factor	(2) Innovative Performance	(3) Innovative Performance
Eff.Factor^2			-3.437***
			(1.255)
Eff. Factor		2.891***	5.588***
		(0.588)	(1.171)
Technological Distance	-0.525	0.590	0.501
	(0.437)	(0.467)	(0.494)
Technological Complexity	5.386***	-5.105***	-4.878***
	(1.459)	(1.183)	(1.211)
HRFNDHL	0.382	-2.191*	-1.971
	(1.487)	(1.243)	(1.288)
Acquirer’s Licensing Experience	-0.011	0.035	0.039
	(0.030)	(0.039)	(0.039)
Target’s Knowledge Stock	0.015**	0.020	0.016
	(0.007)	(0.0243	(0.024)
Acquirer’s Knowledge Stock	-1.64e-05	0.000**	0.000**
	(6.41e-05)	(8.74e-05)	(9.29e-05)
Num of Target Patent’s Cited	-0.024**	-0.027	-0.022
	(0.009)	(0.027)	(0.027)
Num of Target Patent’s Cited by Acquirer	0.098***	0.079***	0.067***
	(0.031)	(0.025)	(0.025)
Acquirer’s Acq. Experience	-0.011	0.060*	0.062*
	(0.015)	(0.035)	(0.036)
Within Industry Acquisition	-0.124	-0.055	-0.140
	(0.317)	(0.245)	(0.258)
IP-Intensive Industry	0.084	0.244	0.203
	(0.340)	(0.362)	(0.374)
TDDUMMY	-1.407**	-3.063***	-3.008***
	(0.604)	(0.395)	(0.379)
Constant	-2.244***	2.868***	2.781***
	(0.699)	(0.885)	(0.910)
lnalpha		0.771***	0.748***
		(0.087)	(0.085)
Observations	223	223	223

Robust standard errors in parentheses
Year Dummies are inserted
*** p<0.01, ** p<0.05, * p<0.1

Table-7b Results for Within- and Between-Industry Acquisitions

	Within-Industry Acquisitions		Between-Industry Acquisitions	
	(1)	(2)	(3)	(4)
VARIABLES	Efficiency Factor	Innovative Performance	Efficiency Factor	Innovative Performance
Eff.Factor^2		-7.975***		-5.624***
		(2.981)		(1.996)
Eff. Factor		8.139***		7.550***
		(1.722)		(1.948)
Technological Distance	-1.376***	0.413	-0.552	-0.493
	(0.477)	(0.519)	(0.616)	(0.658)
Technological Complexity	6.080***	-4.564**	5.579***	-5.923***
	(2.135)	(2.298)	(1.296)	(1.529)
HRFNDHL	0.422	0.422	-0.881	-1.208
	(1.953)	(1.736)	(1.933)	(2.091)
Acquirer's Licensing Exp.	-0.005	-0.053	-0.025	0.040
	(0.031)	(0.067)	(0.042)	(0.053)
Target's Knowledge Stock	0.040**	0.024***	0.011***	0.009
	(0.017)	(0.009)	(0.004)	(0.025)
Acquirer's Knowledge Stock	-3.29e-05	0.000*	2.13e-05	0.000
	(6.87e-05)	(0.000)	(0.000)	(0.000)
Num of Target Patent's Cited	-0.049**	-0.027**	-0.019***	-0.017
	(0.020)	(0.011)	(0.006)	(0.027)
Num of Target Patent's Cited by Acquirer	0.022***	0.004	0.092**	0.117***
	(0.007)	(0.008)	(0.038)	(0.043)
Acquirer's Acq. Experience	-0.003	0.035	-0.018	0.091***
	(0.012)	(0.042)	(0.022)	(0.031)
IP-Intensive Industry	0.338	1.635***	0.008	0.058
	(0.406)	(0.464)	(0.377)	(0.372)
TDDUMMY	-0.600	-1.983***	-2.201***	-2.687***
	(0.466)	(0.506)	(0.700)	(0.421)
Constant	-3.149***	1.406**	-1.887**	2.697**
	(0.854)	(0.622)	(0.737)	(1.177)
lnalpha		0.813***		0.937***
		(0.099)		(0.088)
Observations	173	173	183	183

Robust standard errors in parentheses
Year Dummies inserted
*** p<0.01, ** p<0.05, * p<0.1

Table-8b Results for IP-Intensive and less IP-Intensive Industry Acquisitions

	IP-Intensive Industry		Less IP-Intensive Industry	
VARIABLES	(1) Efficiency Factor	(2) Innovative Performance	(3) Efficiency Factor	(4) Innovative Performance
Eff.Factor^2		-4.968***		-9.919**
		(1.237)		(4.337)
Eff. Factor		7.664***		8.434***
		(1.106)		(2.826)
Technological Distance	-1.199***	0.455	-0.108	1.684**
	(0.407)	(0.458)	(0.807)	(0.830)
Tech. Complexity	6.222***	-6.839***	7.298***	-2.329
	(1.427)	(1.273)	(2.811)	(2.395)
HRFNDHL	-1.608	-2.267	-1.458	-3.785***
	(2.087)	(1.681)	(1.424)	(1.138)
Acquirer's Licensing Exp	-0.015	0.043**	0.234	0.168
	(0.025)	(0.021)	(0.341)	(0.149)
Target's Knowledge Stock	0.027**	0.026**	0.013**	0.025*
	(0.011)	(0.013)	(0.006)	(0.014)
Acquirer's Knowledge Stock	-8.75e-06	0.000**	-0.000	0.001***
	(5.41e-05)	(6.21e-05)	(0.000)	(0.000)
Num of Target Patent's Cited	-0.035**	-0.031**	-0.028***	-0.049**
	(0.014)	(0.014)	(0.011)	(0.020)
Num of Target Patent's Cited by Acquirer	0.022***	0.012**	0.202**	0.341***
	(0.008)	(0.005)	(0.084)	(0.095)
Acquirer's Acq. Experience	0.002	0.072**	-0.073	0.055***
	(0.012)	(0.030)	(0.045)	(0.012)
Within-Industry Acquisition	-0.291	0.224	-0.054	-0.096
	(0.295)	(0.217)	(0.519)	(0.346)
TDDUMMY	-1.449***	-3.366***	-1.243**	-1.155***
	(0.538)	(0.337)	(0.590)	(0.373)
Constant	-1.633***	3.120***	-4.417***	-0.342
	(0.597)	(0.552)	(1.132)	(0.968)
lnalpha		0.913***		0.190
		(0.076)		(0.191)
Observations	271	271	85	85

Robust standard errors in parentheses
Year Dummies inserted
*** p<0.01, ** p<0.05, * p<0.1

Appendix-C

Table-1c Descriptive Statistics for Ownership Transfer Model

Variable	Obs	Mean	Std. Dev.	Min	Max	Patent Sale (Mean)	Patent License (Mean)
Ownership transfer	1790	.755	.430	0	1		
Owner size	1790	33.679	68.804	.001	520.112	38.404	20.459
Partner size	1790	17.140	59.368	0	328.645	20.754	7.052
Patent Stock	1790	1064	2648.386	0	13017	1300.93	416.648
Citations	1790	1.245	2.073	0	22	1.251	1.253
Patent Scope	1790	2.741	1.991	1	15	2.764	2.753
Granted	1790	.294	.456	0	1	.261	.394
Claims	1790	18.922	14.401	0	195	18.604	19.717
Commercialized	1790	.545	.498	0	1	.504	.669
Willing-to-commercialize	1790	.195	.396	0	1	.199	.886
Intensity of tech. comp.	1790	.791	1.538	0	5	.776	.179
Individual	1790	.076	.265	0	1	.042	.886
Non-profit org.	1790	.092	.289	0	1	.049	.165
Patent Value	1790	2.353	1.117	1	4	2.266	.211
Patent Family	1790	.426	.495	0	1	.400.	.526
Co-applicant	1790	.115	.319	0	1	.121	.094

Table-2c Correlation Matrix for Ownership Transfer Model

		1	2	3	4	5	6	7	8
1	Ownership transfer	1.000							
2	Owner size	0.118*	1.000						
3	Partner size	0.104*	0.051*	1.000					
4	Patent Stock	0.148*	0.729*	0.401*	1.000				
5	Citations	0.005	-0.009	0.030	-0.000	1.000			
6	Patent Scope	0.005	-0.006	0.052*	-0.003	0.146*	1000		
7	Granted	-0.134*	0.023*	-0.066*	-0.010	-0.030*	-0.045*	1.000	
8	Claims	-0.027	-0.072*	-0.055*	-0.061*	0.173*	0.105*	-0.105*	1.000
9	Commercialized	-0.151*	-0.037*	-0.083*	-0.057*	-0.019*	-0.056*	0.062*	-0.009
10	Willing-to-commercialize	0.015	0.023*	-0.009	0.015*	0.024*	0.039*	-0.016*	0.037*
11	Intensity of tech. comp.	-0.035	-0.015*	0.088*	-0.026*	0.078*	0.050*	-0.020*	-0.001
12	Individual	-0.218*	-0.133*	-0.066*	-0.111*	-0.056*	-0.031*	-0.027*	-0.027*
13	Non-profit org.	-0.246*	-0.118*	-0.062*	-0.081*	0.001	0.031*	-0.026*	0.076*
14	Patent Value	-0.134*	-0.086*	-0.115*	-0.105*	0.036*	0.022*	0.025*	0.030*
15	Patent Family	-0.113*	-0.014*	-0.013	-0.014*	0.089*	0.059*	-0.020*	0.072*
16	Co-applicant	0.029	-0.028*	0.003	-0.042*	0.030*	0.015*	-0.021*	0.018*

		9	10	11	12	13	14	15	16
9	Commercialized	1.000							
10	Willing-to-commercialize	-0.324*	1.000						
11	Intensity of tech. comp.	0.045*	0.014*	1.000					
12	Individual	-0.026*	0.038*	-0.051*	1.000				
13	Non-profit org.	-0.065*	0.084*	-0.020*	-0.051*	1.000			
14	Patent Value	0.138*	0.036*	0.088*	0.145*	0.040*	1.000		
15	Patent Family	0.185*	0.140*	0.162*	-0.022*	0.004	0.149*	1.000	
16	Co-applicant	-0.034*	0.028*	0.024*	0.124*	0.130*	0.034*	0.017*	1.000

Table-3c Results of Probit Model with Sample Selection for Ownership Transfer

VARIABLES	(1) Selection Model	(2) Ownership Transfer
Partner size		.000
		(.000)
Partner size dummy		-.129***
		(.045)
Owner size	-.001***	-.002***
	(.000)	(.000)
Owner size dummy	.106***	.136***
	(.037)	(.048)
Commercialized	-2.047***	-1.777***
	(.070)	(.083)
Willing-to-commercialize	-.553***	-.507***
	(.091)	(.087)
Co-applicant	.434***	.008***
	(.069)	(.047)
Patent Stock	.000***	.000***
	(.000)	(.000)
Citations	.021**	.017
	(.008)	(.011)
Patent Scope	.000	.001
	(.009)	(.011)
Granted	-.158***	-.293***
	(.036)	(.048)
Claims	.004***	.002
	(.001)	(.002)
Intensity of tech. comp.	-.009	-.016
	(.011)	(.014)
Individual	.115	-.289***
	(.090)	(.101)
Non-profit org.	.711***	-
	(.078)	
Patent Value	.029*	.000
	(.017)	(.020)
Patent Family	.109***	.008
	(.036)	(.047)

Herfindahl	.132***	
	(.049)	
Creative process1	.022	
	(.049)	
Creative process2	-.003	
	(.058)	
Creative process3	.059	
	(.060)	
Creative process4	.111**	
	(.054)	
Creative process6	.053	
	(.060)	
Constant	.566***	.601***
	(.093)	(.102)
Industry Dummies		YES
Number of Obs	8456	
Censored Obs	6666	
Uncensored Obs	1790	
Wald chi2 (25)	7564.67	
Prob>chi2	0.0000	
Log Pseudolikelihood	-4132.214	
Wald test of indep. Equations (rho=0):		
chi2(1)	45.44	
Prob>chi2	0.0000	

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

Table-4c Results of Conditional Marginal Effects Analysis for the Second Stage Variables

VARIABLES	(Delta-method) Ownership Transfer
Owner Size	-.001***
	(.000)
Owner Size dummy	.049***
	(.018)
Partner Size	.000
	(.000)
Partner Size dummy	-.046***
	(.017)
Commercialized	-.642***
	(.028)
Willing-to-commercialize	-.183***
	(.032)
Co-applicant	.174***
	(.029)
Patent Stock	.000***
	(5.92e-06)
Citations	.006
	(.004)
Patent Scope	.000
	(.004)
Granted	-.106***
	(.018)
Claims	.001
	(.001)
Intensity of tech. comp.	-.006
	(.005)
Individual	-.104***
	(.037)
Patent Value	.000
	(.007)
Patent Family	.003
	(.017)
Number of Obs	1790
Model VCE	Robust
Pr(Ownership Transfer=1)	

Figure-1c Plot of Conditional Marginal Effects

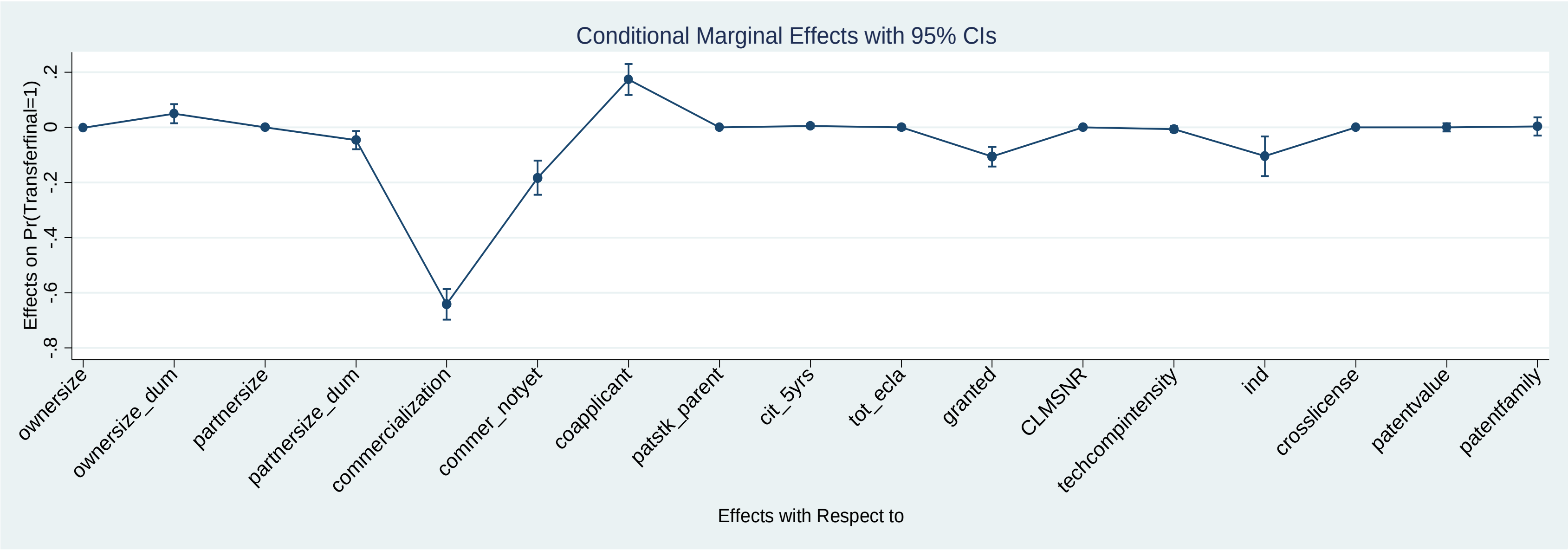

Table-5c Results of Probit Model with Sample Selection for Alternative Patent Owner and Partner Size Specifications

VARIABLES	(1) Selection Model	(2) Ownership Transfer
Partner size		-.000
		(.000)
Partner size dummy		-.129***
		(.048)
Owner size	-.000***	-.000**
	(.000)	(.000)
Owner size dummy	.111***	.134***
	(.037)	(.048)
Commercialized	-2.051***	-1.773***
	(.070)	(.085)
Willing-to-commercialize	-.554***	-.508***
	(.091)	(.087)
Co-applicant	.436***	.482***
	(.069)	(.149)
Patent Stock	.000***	.000***
	(.000)	(.000)
Citations	.022**	.018
	(.008)	(.011)
Patent Scope	.000	.000
	(.009)	(.011)
Granted	-.159***	-.304***
	(.036)	(.048)
Claims	.004***	.002
	(.001)	(.002)
Intensity of tech. comp.	-.008	-.014
	(.011)	(.014)
Individual	.120	-.287***
	(.090)	(.102)
Non-profit org.	.713***	-
	(.079)	
Patent Value	.029*	.002
	(.017)	(.020)
Patent Family	.110***	.005
	(.036)	(.048)
Herfindahl	.128***	
	(.049)	
Creative process1	.022	

	(.049)	
Creative process2	-.003	
	(.058)	
Creative process3	.063	
	(.060)	
Creative process4	.113**	
	(.054)	
Creative process6	.058	
	(.061)	
Constant	.564***	.614***
	(.094)	(.105)
Industry Dummy		YES
Number of Obs	8456	
Censored Obs	6666	
Uncensored Obs	1790	
Wald chi2 (25)	7335.38	
Prob>chi2	0.0000	
Log Pseudolikelihood	-4135.021	
Wald test of indep. Eqns. (rho=0):		
chi2(1)	45.00	
Prob>chi2	0.0000	

Robust Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-6c Results of Alternative Conditional Marginal Effects Analysis for Probit Model with Sample Selection [Pr(Ownership Transfer=1)]

VARIABLES	(Delta-method) Ownership Transfer
Owner Size	-.000***
	(.000)
Owner Size dummy	.034***
	(.013)
Partner Size	.000
	(.000)
Partner Size dummy	-.031**
	(.012)
Commercialized	-.605***
	(.022)
Willing-to-commercialize	-.100***
	(.015)
Co-applicant	.143***
	(.028)
Patent Stock	.000***
	(.000)
Citations	.004
	(.003)
Patent Scope	.000
	(.003)
Granted	-.071***
	(.014)
Claims	.001
	(.000)
Intensity of tech. comp.	-.004
	(.004)
Individual	-.063***
	(.021)
Patent Value	.000
	(.005)
Patent Family	.002
	(.012)
Number of Obs	1790
Model VCE	Robust
Pr(Ownership Transfer=1)	

Table-7c Results of Probit Model with Coefficients Simulated 1,000 Times

VARIABLES	Ownership Transfer
Owner Size	-.000
	(.001)
Owner Size dummy	.380***
	(.074)
Partner Size	.000
	(.001)
Partner Size dummy	-.355***
	(.100)
Patent Stock	.000***
	(.000)
Citations	.004
	(.017)
Patent Scope	-.001
	(.018)
Granted	-.340***
	(.075)
Claims	-.004*
	(.002)
Commercialized	-.400***
	(.091)
Willing-to-commercialize	-.236**
	(.111)
Intensity of tech. comp.	-.023
	(.023)
Individual	-.598***
	(.126)
Patent Value	-.059*
	(.032)
Patent Family	-.227***
	(.072)
Co-applicant	.311***
	(.114)
Constant	1.478***
	(.158)
Num of Obs.	1790
LR chi2(16)	248.35
Prob>chi2	0.0000
Log Likelihood	-872.96101
Pseudo R2	0.1245