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Knowledge Protection and Input Complexity Arising from Open Innovation

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Abstract

Controlling unique knowledge is of increasing importance to firms. Therefore, firms use knowledge protection mechanisms to prevent competitors from imitating their knowledge. We study the effects of the complexity of knowledge inputs that arises from open innovation on the importance of two widely used protection mechanisms: patents and trademarks. We argue that this complexity makes the threat of imitation less predictable, and thus makes knowledge protection more important. By analyzing survey data of 938 German firms, we find that patents are more important for firms in industries with higher knowledge input complexity. Furthermore, we show that the dynamics and not the level of knowledge input complexity positively affect the importance of trademarks.

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ABSTRACT

Controlling unique knowledge is of increasing importance to firms. Therefore, firms use knowledge protection mechanisms to prevent competitors from imitating their knowledge. We study the effects of the complexity of knowledge inputs that arises from open innovation on the importance of two widely used protection mechanisms: patents and trademarks. We argue that this complexity makes the threat of imitation less predictable, and thus makes knowledge protection more important. By analyzing survey data of 938 German firms, we find that patents are more important for firms in industries with higher knowledge input complexity. Furthermore, we show that the dynamics and not the level of knowledge input complexity positively affect the importance of trademarks.

Keywords: Appropriability Strategy, Complexity, Imitation, Open Innovation, Patents, Trademarks

INTRODUCTION

Firm performance depends increasingly on a firm's control over unique knowledge (Spender and Grant, 1996). This fact challenges management to prevent its knowledge from imitation by competitors because the knowledge would lose its value as a competitive resource (Teece, 1986; Ceccagnoli, 2009). Consequently a firm's ability to predict the abilities of potential imitators as well as the likelihood of successful imitation are an important factor in determining knowledge protection strategies (Zhao, 2006). Most existing studies reduce this predictability of imitation to technological opportunities as well as the presence and strength of intellectual property rights regimes (Teece, 1986; Ginarte and Park, 1997). We argue that the complexity of knowledge inputs in an industry is an important and so far largely ignored determinant for the predictability of imitation in an industry. We suggest that with increasing complexity of knowledge inputs in an industry the importance of knowledge protection at the firm-level increases because firms can no longer foresee ways in which potential imitators will copy their knowledge. More precisely, we distinguish between the importance of patents and trademarks for knowledge protection. The former provide protection for technologies while the latter protects co-specialized assets of technologies such as brands. We predict that trademarks will be more important protection mechanisms if the complexity of knowledge inputs in an industry changes dynamically because patent protection is not flexible enough under such conditions.

We place our study in a context in which firms increasingly rely on knowledge, information, and technologies developed outside of their boundaries (Chesbrough, 2003b). This open innovation trend is evidenced by academic research (Cassiman and Veugelers, 2006; Laursen and Salter, 2006; Leiponen and Helfat, 2011) as well as management practice (Huston and Sakkab, 2006). An often times neglected consequence of this open innovation trend is that it enables imitation. Potential imitators have a broader set of external knowledge to draw from and can combine it flexibly. Köhler, Sofka and Grimpe (2012) present empirical evidence for the link between a firm's external knowledge and an increase in imitation. We theorize that the open innovation trend makes imitation in an industry less predictable for innovative firms. Open innovation induces complexity in the sense that it makes the technologies and innovations emerging from the interactions of the knowledge inputs in an industry more uncertain and unpredictable. As a consequence, we hypothesize that the importance of patents and trademarks for knowledge protection will increase with the complexity of knowledge inputs in an industry and that the latter will be more important than the former, the more dynamic the change in complexity is.

We test our hypotheses using survey data on the innovation activities of 938 German firms between 2001 and 2005. Our findings indicate that patents (but not trademarks) are more important for firms that operate in industries with high knowledge input complexity, i.e. an industry characterized by a high number of external knowledge sources which could potentially be used and combined for imitation. Furthermore, the change in complexity over time increases the importance of trademarks, suggesting that change forces trade-offs in knowledge protection strategies.

Our results have immediate relevance for two primary research streams in the sense that that they allow the prediction of firm behavior in complex environments (Brown and Eisenhardt, 1997). Firstly, this study goes beyond the usual (and important) thesis that the tightness of the appropriability regime sets firms' appropriability agendas (Levin, Klevorick et al., 1987; Cohen, Nelson and Walsh, 2000). We contribute to the appropriability literature by showing how the complexity of knowledge inputs in an industry affects the importance of two widely used protection mechanisms: patents and trademarks. Studies which would ignore the influence of complexity in knowledge inputs would suffer from biases or misinterpret industry differences as related to IPR regimes. What is more, we show that not only the level of complexity is of importance and should be taken into account, but the dynamics of complexity as well. The notion that both effects are present and, as in our case, have distinct firm responses, is of importance to future studies addressing complexity. Dynamically changing complexity in knowledge inputs favors trademark protection over patent protection. Hence, we provide an additional dimension to how firms adapt differently under varying conditions of complexity (Brown and Eisenhardt, 1997). Secondly, we contribute to the relatively young literature on open innovation. Few studies have explicitly linked the openness of innovation to the strategy of appropriating the returns of innovation or the predictability of imitation, yet those that do focus on the relationship between appropriability strategy and the openness of one firm (e.g. Laursen and Salter, forthcoming). Our study links the opportunities originating from open innovation practices to its challenges, i.e. enabling imitation. In this regard, it adds a cautionary notion to a stream of management research which seems to suggest that more open innovation is always better for innovative firms.

The remainder of the article is organized as follows: We review theory and develop hypotheses in the following section. Afterwards we introduce the empirical study and present its results. The final sections discuss our findings and draw conclusions also with regards to future research.

THEORETICAL BACKGROUND AND HYPOTHESES

The goal of our theoretical reasoning is to explain differences in the knowledge protection behavior of firms. We will argue that the complexity of knowledge inputs in a firm's industry allows predictions on its knowledge protection. We define knowledge protection as firm level mechanisms for preventing the imitation of a firm's knowledge by competitors (e.g. de Faria and Sofka, 2010).

Managers have strong incentives to prevent knowledge outflows to competitors because unique knowledge is key to recovering investments into knowledge creation through R&D. In this regard, the rational for preventing imitation is similar to other resource-based theories of firm strategy (Spender and Grant, 1996). Firms can charge higher prices if they can establish an at least temporary monopoly situation based on innovative products (or services), resulting in superior firm performance ((Liebeskind, 1996)). Once competitors can imitate the underlying knowledge and offer competitive products, this performance advantage disappears. Knowledge has characteristics of public goods and is therefore especially vulnerable to imitation (Arrow, 1962). Knowledge protection is therefore a central topic for managers and strategy scholars (Teece, 1998) (Ceccagnoli, 2009).

We focus on knowledge protection through patents and trademarks as two primary forms of knowledge protection (Cohen et al., 2000; Arora, Ceccagnoli and Cohen, 2008; Sandner and Block, 2011). The theoretical mechanisms between both forms of knowledge protection differ significantly which provides an opportunity to create precise theoretical predications on how they relate to the complexity of the complexity of knowledge inputs in a firm's industry. We will review both mechanisms briefly.

Knowledge protection through patents and trademarks have in common that they provide legal protection from imitation. Firms have to apply for protection at a government agency and once the protection is granted they can sue imitators for infringement in court (Encaoua, Guellec and Martinez, 2006; McGahan and Silverman, 2006). Patents protect technological inventions which can be codified in a patent application. The patent office determines whether an invention has the necessary degree of novelty to qualify for patent protection (Encaoua et al., 2006). The application process can take several years and often times requires substantial financial resources, legal expertise and counselling (Ahuja, Coff and Lee, 2005; Harhoff, Hoisl, Reichl and van Pottelsberghe de la Potterie, 2009). Once a patent is granted, imitators would be force to find an alternative technological solution if they want to compete with the focal firm (Mansfield, Schwartz and Wagner, 1981).

Trademarks do not protect technologies but words or graphics which are non-generic and distinguishable from existing trademarks (Sandner and Block, 2011). The use of trademarks is not limited to innovations. The rationale behind knowledge protection through registered trademarks stems from the opportunity to establish brand awareness among clients (Yoo, Donthu and Lee, 2000). Trademarks offer differential distinctiveness (Ramello and Silva, 2006). Imitators may be able to copy a technology but they cannot use the firm's trademark. If a firm can associate its innovative products with its trademark protected brand it can charge comparatively higher prices (Simon and Sullivan, 1993). Within such a setting, brands can serve as co-specialized assets which allow firms to reap benefits from innovative products even if they were not the first to invent the technology (Teece, 1986). In sum, patents protect technologies from imitation; trademarks protect brands which can be co-specialized assets for technologies. We will return to this distinction when developing our hypotheses.

Knowledge input complexity

Knowledge is arguably the most important input for firm innovation. Traditionally, a firm's knowledge was produced within its own R&D department and therefore under its direct control (Chesbrough, 2003b). Within this traditional view, both innovation and imitation originates from internal R&D. This feature makes imitation somewhat predictable. Mansfield et al. (1981) show for example that imitation is nearly as expensive and time consuming as innovation activities. We will argue that the emergence of external knowledge as an important element of knowledge acquisition outside of firm's boundaries makes knowledge inputs in an industry more complex and less predictable. We will theorize that this knowledge input complexity affects firm decisions on knowledge protection. We define knowledge input complexity as the complexity that arises from the availability of external knowledge from multiple sources which can potentially be flexibly combined.

Systems are complex when they are composed of many interacting elements that interact in uncertain and unpredictable ways (Simon, 1962; Anderson, 1999). Analogously, innovations become more complex when they are developed based on knowledge from different sources (Dougherty and Dunne, 2011). A central topic in the literature on complexity and complex systems is "emergence". Emergence is the notion that, at any level of analysis, order emerges from individual interaction on a lower aggregation level in complex systems (Anderson, 1999; Dougherty and Dunne, 2011). This order can take a variety of formats, such as social structures and regulatory regimes, but also the form of knowledge, which is most applicable to our case of complexity. Applied to technology and innovation management, emergence in complex systems is disconcerting in the sense that what precise technology or innovation actually emerges from the complex system cannot be controlled or predicted. (Dougherty and Dunne, 2011).

A growing literature on open innovation –with many articles addressing the openness of innovation avant la lettre- suggests that firms increasingly make use of externally developed knowledge in innovation processes (Chesbrough, 2003a; Dahlander and Gann, 2010). This stream of research has spawned a large number of studies to the various means to obtain external knowledge and to the specific sources of external knowledge, with many studies being a combination between these two topics. Examples of the methods to attract external knowledge range from receiving spillovers by observation (Leonard-Barton, 1995), hiring of people (Creplet, Dupouet et al., 2001), plain market transactions of technologies (Atuahene-Gima, 1992), various forms of collaboration in R&D (Shan, Walker and Kogut, 1994; Grant and Baden Fuller, 2004; Bell, den Ouden and Ziggers, 2006), outsourcing of R&D (Martinez-Noya, Garcia-Canal and Guillen, 2013), and venturing (Dushnitsky and Lenox, 2005), to acquisitions of complete subsidiaries or firms (Karim and Mitchell, 2000, 2004). Among the sources of external knowledge that have been studied are: customers or users (von Hippel, 1978, 1986; Nambisan, 2002), suppliers (Clark, 1989), competitors (Oxley and Sampson, 2004; Cassiman, Di Guardo and Valentini, 2009), public research organizations and universities (Veugelers and Cassiman, 2005; Bierly, Damanpour and Santoro, 2009), and consultants (Creplet et al., 2001). Combinations of knowledge acquisition methods and knowledge sources have been studied in various specific settings, such as foreign direct investment (Penner-Hahn, 1998), networks of innovation (Powell, Koput and Smith-Doerr, 1996; Tsai, 2001; König, Battiston, Napoletano and Schweitzer, 2011), and ecosystems (Adner and Kapoor, 2010).

The literature has also shown that firms are heterogeneous in the knowledge sources that they use and combine. This is largely due to the fact that search is costly in terms of time and resources (Dosi, 1988). By selecting the right depth and breadth in knowledge search, firms can increase their innovation performance (Katila and Ahuja, 2002). Moreover, firms need to select the right sources of knowledge (Andrews and Delahaye, 2000). Consequently, firms are heterogeneous in the way in which they access and combine external knowledge from different sources and large parts of these differences can be explained through technological opportunities and institutional settings at the industry level, such as efficient markets for technology (Gans, Hsu and Stern, 2008; Grimpe and Sofka, 2009; Köhler et al., 2012). Under such conditions imitation can occur by using multiple knowledge sources and combining their knowledge flexibly. Consequently, an innovative firm would find it harder to predict potential pathways for imitation.

We conclude that industries in which external knowledge is available from an increasing number of sources experience higher levels of knowledge input complexity. Under such conditions, we suspect the risk of being imitated is less predictable for firms in these industries. This increased risk alleviates their need for knowledge protection. Consequently, we predict that the importance of knowledge protection through patents and trademarks will increase with the complexity of knowledge inputs in a firm's industry. We hypothesize:

Hypothesis 1: Knowledge input complexity in an industry positively affects the importance of knowledge protection through patents for firms in that industry.

Hypothesis 2: Knowledge input complexity in an industry positively affects the importance of knowledge protection through trademarks for firms in that industry.

However, the predictability of imitation in an industry may not just be dependent on the level of knowledge input intensity but also on its dynamics. Many existing studies suggest that the availability of external knowledge has changed significantly in recent years (Lane and Lubatkin, 1998; Chesbrough, 2003b; Spithoven, Clarysse and Knockaert, 2011). Hence, there is a dynamic component in knowledge inflow complexity apart from its level.

First of all, comparing the two knowledge protection mechanisms we previously discussed, protection through patents will be the most elaborate and time consuming mechanism. Using trademarks and brands, however, allows for a speedier reaction to the changing environment: Technological relationships do not have to be codified and tested for compliance with mandatory standards for novelty of the patent office.

Secondly, the dynamics in complexity can best be described with what Teece called a pre-paradigmatic stage (1986). In the pre-paradigmatic stage in this sense, no consensus has been reached with respect to how complex the innovation inputs in an industry are. In the pre-paradigmatic stage, because of its volatility, it does not make much sense to invest in *specialized* complementary assets, with a unilateral dependence between the asset and the innovation (Teece, 1986). However, *generic* complementary assets, that do not need to be tailored to the specific innovation, can help in appropriating the returns from that and upcoming innovations. Since trademarks are used to tell products and services from a particular source apart from others, their degree of co-specialization as a complementary asset can be adjusted. Combining these two mechanisms, we expect that a change in innovation input complexity in an industry has a more profound positive effect on the importance of trademarks for firms in that industry compared with knowledge protection through patents.

Hypothesis 3: Knowledge input complexity dynamics in an industry positively affect the importance of knowledge protection through trademarks for firms in that industry stronger than the importance of knowledge protection through patents.

DATA AND METHODS

We test our hypotheses using data from the German Innovation Survey 'Mannheim Innovation Panel' of 2001 and 2005. This survey is the German version of the European Union's Community Innovation Survey (CIS). We complement this data with data from the European Patent Office (EPO) and Creditreform, the leading German rating agency.

Our main data source, the CIS survey, provides data on the innovation activities of firms from both manufacturing and service sectors. The survey sample is stratified by region (East and West Germany), industry, and firm size. Therefore, this sample is representative for Germany as a whole.

The survey is directed at decision makers on innovation activities within firms, such as CEOs and the heads of R&D or innovation management departments. Through the use of questions that follow the OECD standard that is outlined in the Oslo manual (OECD and Eurostat, 2005), they are asked if and how their firms were able to generate and protect innovations. CIS surveys are extensively pre-tested and piloted in various EU member states, industries, and firms with regard to interpretability, reliability and validity (Laursen and Salter, 2006). Not surprisingly, CIS data have been used in recent publications in highly ranked management journals (e.g. Laursen and Salter (2006) with UK data; Grimpe and Kaiser (2010) with German data, and Leiponen and Helfat (2010, 2011) with Finnish data).

Survey approaches are well-established in tracing knowledge protection (e.g. Harabi, 1995; Cohen et al., 2000), and knowledge search at the firm level (e.g. Laursen and Salter, 2006; Leiponen and Helfat, 2010, 2011).We merge the survey data with patent statistics from EPO. Creditreform is our source of data on the competition intensity (concentration) in product markets at the industry level. This database, which is the basis for the German entries in the Amadeus database by Bureau van Dijk, is frequently used for the population of German firms. Industries are measured using the classification of economic activities in the European Community (NACE). The final sample is representative for Germany, covering 42 industries at the two-digit level. The dataset consists of 938 firm observations from 2005. We use the information from the survey wave of 2001 to calculate knowledge input complexity and its dynamics (see information below).

Variables

Dependent variables

We use two dependent variables that measure the importance of appropriability mechanisms. Two survey questions in the CIS ask the respondents directly to assess the importance of patents and trademarks as a knowledge protection instrument in their innovation activities in the previous three years. The respondents use a four point Likert-based scale (3='highly important' to 0='not relevant at all') for their assessment.

Using survey questions has three primary advantages over counts of patents or trademarks. First, the distribution of valuable patents is highly skewed. Only a fraction of patents is highly valuable and patent counts may be misleading and result in estimation biases (Arora et al., 2008). Secondly, firms apply for legal knowledge protection for a variety of reasons such as signaling to partners and investors (Ndofor and Levitas, 2004). The survey question is much more precise in capturing the particular importance for knowledge protection as predicted in our theoretical model. Finally, relating patents and trademarks to their importance for knowledge protection allows a comparison between both. This could not be guaranteed using count variables since both differ in how costly they are to apply for (Harhoff et al., 2009). In sum, the survey questions provide useful and appropriate measurement. We conduct additional consistency checks to assure validity.

Independent variables

Systems are complex when they are composed of many interacting elements that interact in complex ways (Simon, 1962; Rivkin, 2001). Analogously, we deem industries as more complex with regard to knowledge inputs when they are composed of knowledge from various sources that are considered to be highly important to the innovating firm (Dougherty and Dunne, 2011). Knowledge input complexity in an industry is measured by summing up the share of firms in an industry that denote specific knowledge sources of high importance. Specifically, we use a question in the CIS that asks the respondents asked about the importance of six categories of knowledge sources: suppliers, customers, competitors, consultants, universities, and research institutes. The respondent answers range from 3, indicating 'highly important', to 0, indicating 'not relevant at all'. Per knowledge source, we calculate the share of firms scoring the maximum of 3. Finally, we sum up these numbers for all six categories per industry. To rule out and avoid issues that arise from simultaneity, we use data from the 2001 survey to calculate this measure. Replacing the variable with 2005 data leads to identical findings.

An important advantage of using CIS data originates from the representative nature of the sample for the population of German firms. It allows us to project all information to the industry level of the population. Hence, our insights are not limited to the sample. We are, to the best of our knowledge, not aware of a similar opportunity to capture the extent of open innovation in an industry for a comparable number of industries in a representative way. What is more, the survey question itself is validated and has been used repeatedly in top management journal publication to capture firm's search for external knowledge (Laursen and Salter, 2006; Leiponen and Helfat, 2010, 2011).

For the dynamics of innovation input complexity, we calculate the innovation input complexity of 2001 and 2005 using the method described above. Because we are interested in the dynamics and not just the increase of decrease of complexity, we subtract the 2001 value from the 2005 value, and take the square root of its squared term.

Control variables

We control for several other factors. First, the importance of patents and to a lesser extent the importance of trademarks might very well be dependent upon the number of patents a firm has. We add the firms' stock of patents at EPO (per employee) to the analyses. We use a measure of patent stock that is depreciated with a yearly rate of 15 percent, as applied in various scientific publications (Aerts and Schmidt, 2008). Second, we insert the firm's internal R&D expenditures (as a share of sales) in the model, to control for the firm's knowledge generation and its absorptive capacity (Cohen and Levinthal, 1990). Third, we control for effects arising from competitive intensity within the focal firm's product market by adding the Herfindahl-Hirschman concentration index at the industry level. We calculate this index based on employment numbers provided by leading German credit rating agency, Creditreform (sales numbers reduce the number of observations but are almost perfectly correlated with employment numbers). Fourth, we control for the firms' degree of internationalization through the export share of their sales. Internationalization activities and innovation have been found to be closely related (Golovko and Valentini, 2011). Fifth, we add a knowledge intensity measure, summing of the importance of all knowledge inflows on a firm level, as analogous to Cassiman and Veugelers (2002). Hence, we can differentiate between open innovation at the firm and industry level.

Moreover, we control for possible structural differences among the firms in our sample. We include the age of the company (number of years since founding in logs) and company size (number of employees in logs) for resource availability. A firm can also be structurally different because it belongs to a multinational group, as it enables it to benefit from knowledge spillovers, internal access to finance or other synergies. Therefore, we include a dummy variable for whether the firm is part of a foreign multinational corporation.

Knowledge protection and knowledge inflows have been found to depend upon industry characteristics such as the appropriability regime and the nature of technological opportunities (Teece, 1986; Grimpe and Sofka, 2009). We include five industry dummy variables according to OECD classifications (see Appendix A for an overview): medium high-tech manufacturing, high-tech manufacturing, distributive services, knowledge-intensive services and technological services. The comparison group is low-tech manufacturing.

Analysis

Since a part of our data has been collected using a single survey instrument we need to deal with the potential threats that common method bias and single respondent bias pose to the validity of our conclusions. Several remedies exist (Podsakoff, MacKenzie, Lee and Podsakoff, 2003). In addition to the precautions taken by the institution responsible for designing and collecting the data (see OECD and Eurostat, 2005 for further details), we take some additional measures. First of all, we have complemented our survey data with other, archival data. Secondly, by using Harman's one factor test we check how much of the variance in our data can be explained by one factor (16.5%). The combination of these measures assures us that the abovementioned biases do not significantly affect our results.

To match our ordinal dependent variables (importance of patents and importance of trademarks are ordered response constructs), we use an ordered probit approach (Greene, 2003). As a robustness test, we test the appropriateness across equations with a seemingly unrelated regression. Finally, we run robustness test to rule out that a latent appropriability mechanism variable might drive our results. Given that the dependent variables in these robustness tests have the same ordered structure as our original variable, we again use an ordered probit approach.

RESULTS

The descriptive statistics of our variables and their correlations are displayed in Table I. The average importance of patenting and trademarks is low, with values below 1. Yet, their relatively high standard deviations indicate a high variance in these dependent variables. The correlation between these variables is positive and significant, which is not surprising since both variables aim at protecting innovations against imitation and can be used as complements (Cohen et al., 2000).

We inspect the data for the presence of multicollinearity. The mean variance inflation factor is 1.44, the highest individual variance inflation factor 2.17. Hence, there is no indication that multicollinearity would influence our estimation results.

INSERT TABLE I ABOUT HERE

Table II shows the results of our ordered probit analyses. In Model 1 we examine the effects of complexity of knowledge inputs in an industry on the importance of patents. The model is significant ($p<0.00$). The results show that higher complexity of knowledge inputs in 2001 is associated with higher importance of patents, which supports our first hypothesis. Since we use ordered probit analysis, we can interpret the sign and significance of the coefficients but not the coefficients per se. Therefore, we calculate the magnitude of this effect and find that, with all other variables kept at their mean, one standard deviation increase of knowledge input complexity is associated with a 4% higher probability that the firm will rank patents as “highly important”, the highest value of the variable. The dynamics of the knowledge input complexity has a positive, but not significant effect on the importance of patents. All other variables in the model have predictable effects.

INSERT TABLE II ABOUT HERE

Model 2 in Table II is used to examine the results on the importance of trademarks. Again, the model is significant ($p<0.00$). Complexity of knowledge inputs in 2001 has a positive, yet insignificant effect on the importance of trademarks. Per hypothesis 2, we would have expected a positive significant effect. Our hypothesis is thus not supported. For the dynamics of complexity, however, the effect is positive and significant. Again, we assess the magnitude of effect and find that a one standard deviation increase in complexity dynamics leads to a 6% higher likelihood that trademarks are highly important for firms.

Finally, the dynamic of complexity of knowledge inputs in the industry affects the importance of trademarks positively and significantly but not for patents. We test whether the coefficients are significantly different between patents and trademarks. This test is supported ($p<0.05$). Hence, we can conclude that hypothesis 3 is supported and that dynamic changes in the complexity of knowledge inputs in an industry are more important for knowledge protection through trademarks than through patents.

We do not develop hypotheses for the control variables and most of their effects are as expected, with a notable exception in the internationalization variables. Being part of a foreign MNC is associated with a *lower* importance of trademarks. Furthermore, the positive and significant effect of the share of exports that is present in model for the importance of patents is not present in the model for the importance of trademarks.

Robustness checks

To check the robustness of our results, we perform some additional analyses. First, we estimate both equations simultaneously applying seemingly unrelated estimation techniques. This takes into account that the importance of both patents and trademarks for knowledge protection is driven by a joint unobserved variable. There is some indication for this since the residuals of both equations are positively (0.24) and significantly correlated ($p<0.001$). The precision of estimations can be increased by modeling the correlation between both error terms. However, the effects of our independent variables are the same in sign and significance when estimated simultaneously.

Secondly, we run additional models with the knowledge input complexity variable based on data from 2005, the same year as the responses of the surveys and thus our DVs are collected. The effects of the variable are identical in sign and significance to those of the 2001 variable. To rule out reverse causality or mere correlation, we prefer to use the 2001 variable in our main models.

Thirdly, we explore whether the concentration of knowledge input complexity (i.e. whether the extensive use of few sources versus the more equally distributed use of more sources) might be a driving factor of the importance of patents and trademarks. We calculate this measure by calculating the Herfindahl-Hirschman index of knowledge input complexity. We report the results as Models 3 and 4 in Appendix B. We do not find significant results for this measure and the significance and sign of our independent variables do not change. Moreover, adding the concentration variable does not significantly improve our models.

Fourthly, we test whether our two primary independent variables, the complexity of knowledge inputs in an industry and its dynamic, have additional interactive effects. This would suggest that the effects of dynamic changes depend on the level of complexity. This is not the case.

Furthermore, to rule out that our results are driven by a latent appropriability mechanism variable, we run analyses with other well-known knowledge protection mechanisms: secrecy, copyrights, the complexity of designs, and the lead time of the innovation. These results are reported as Models 5 to 8 in appendix B. We do not find significant effects of our independent variables on these knowledge protection mechanisms, ruling out the latent factor explanation.

DISCUSSION AND CONCLUSION

Our results support our hypothesis that patents are more important to firms when they face higher knowledge input complexity that arises from open innovation in its industry. Yet, the importance of trademarks is not affected by the level of complexity, which leaves our second hypothesis unsupported. However, we do find that the dynamics of this complexity in an industry positively affect the importance of trademarks for firms in its industry.

These findings advance our understanding of appropriability strategies of firms. Earlier research has already shown that firms choose their knowledge protection mechanisms according to the tightness or weakness of the appropriability regime they operate in (Teece, 1986; Levin et al., 1987; Cohen et al., 2000). Our findings go beyond this relationship, by showing that the complexity of knowledge inputs is also an important factor in the importance of patents for firms. Not only do this findings help in better understanding or explaining appropriability strategies, it also provides a possible explanation for changes in firm behavior with respect to appropriability in the absence of changes in the IPR regime. With the increasing use of knowledge developed by external sources (Chesbrough, 2003b) and thus an increasing knowledge input complexity in industries, we can predict an increase in the importance of patents as a knowledge protection mechanism based on our results. Extrapolating this finding leads to the hypothesis that firms patent more in industries with higher knowledge input complexity.

Furthermore, our results suggest that in industries where the openness of innovation is changing, trademarks become more important. This finding combined with the mechanism that we describe suggests that trademarks can offer flexible and effective protection in environments with changing knowledge input complexity. Apparently, it takes longer for patents to be effective protection mechanisms.

Our findings also contribute to the literature on complexity. Our results illustrate the difference between the effects that the level of knowledge input complexity has as opposed to a change in that level. This illustrates the difference between adaptation of firms in a complex environment versus adaptation in environments with changing complexity (Eisenhardt and Tabrizi, 1995; Brown and Eisenhardt, 1997). Furthermore, we consider our study benefitting from an empirical setting where we can estimate complexity of knowledge inputs at the industry level as a unique opportunity to complement to complexity studies using simulation models (e.g. Rivkin, 2001).

Finally, our study contributes to the literature on open innovation. Specifically, our findings further refine the “paradox of openness”, where the creation of knowledge requires openness, but the appropriation of the economic rents requires protection (Laursen and Salter, forthcoming). Our study suggests that the opportunities originating from more open innovation in an industry also make the threat of being imitated less predictable, and thus make knowledge protection mechanisms more important to firms in these industries. This finding can be interpreted as a caveat to an emerging literature that seems to suggest that opening up innovation processes for externally developed knowledge is always good for innovative firms.

Our findings have direct implications for managers and policy makers. First, we identify conditions under which trademarks are more important knowledge protection instruments than patents. Firms operating in industries in which patent propensity is high and the dominant form of knowledge protection, e.g. pharmaceuticals (Arundel and Kabla, 1998) may lack the experience and expertise for using trademarks for establishing brands. Yet, brands are built over time (Urde, 1999). Thus, it may pay off for firms to invest in company brands and trademarks *before* an era of change so that they are better protected *during* that change.

Similarly, policy makers have emphasized the need for collaborative research and put incentives in place for firms to participate (Cohen, Nelson and Walsh, 2002). Such policies increase the prevalence of open innovation and make imitation less predictable for innovative firms. A comprehensive policy design would therefore include not only incentives for firms to participate in open innovation but also for developing and refining knowledge protection capabilities. Our results suggest that firms could use support in protecting knowledge through trademarks especially when the complexity of knowledge inputs in an industry is changing, e.g. through policy initiatives strengthening open innovation in the industry. Under stable conditions of knowledge input complexity, though, policy support for developing patenting capabilities and expertise would be advisable.

Limitations and suggestions for further research

One characteristic of our study which is both a strength and a weakness originates from the diversity of industries that we examine. Although this enables us to generalize our findings, our approach lacks the refinement that is necessary to exactly pinpoint the mechanisms that take place in specific industries. A combined qualitative and quantitative approach focused on one or a few industries could further explore the mechanisms that we describe in this study.

With regard to complexity, we only take one specific type of complexity into account: the complexity that arises from using knowledge from multiple sources. We do not study the complexity of these knowledge components (Sorenson, Rivkin and Fleming, 2006), processes (Vaccaro, Brusoni and Veloso, 2011), nor the complexity of the resulting products (Gann and Salter, 2000). Therefore, we stress that our findings are specific for complexity at the level that we study. At other levels, such as at the knowledge or product level, complexity can even be a protection mechanism in itself (Reed and Defillippi, 1990; Sorenson et al., 2006). While intriguing, it was outside the scope of our research to study the interplay of complexity on different levels and its effect on appropriability strategies.

The difference in effects that we find for the level of knowledge input complexity (higher importance of patents) and its dynamics (higher importance of patents) is perhaps the most promising avenue for further research. What will happen, for example, with the importance and use of trademarks when the dynamics of complexity change from high to zero (resulting in a constant, but higher than before complexity)? Unfortunately, our research setting did not enable us to explore such sequential effects.

Conclusion

We study the effect of knowledge input complexity on the importance of two important but distinct knowledge protection mechanisms: patents and trademarks. Our results indicate that the importance of patents is affected by the level of knowledge input complexity, whereas the dynamics of that complexity affect the importance of trademarks. Our findings make important contributions to the appropriability literature and to the literature on open innovation.

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Table I: Variable descriptives and correlations

Variable	*Mean*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*
1. Importance of patents	0.88	1.28	1.00															
2. Importance of trademarks	0.59	1.10	0.35	1.00														
3. Knowl. Input Complexity 2001	80.94	15.88	0.29	0.06	1.00													
4. KI Complexity dynamics	14.66	6.12	-0.01	0.09	-0.27	1.00												
5. Internal R&D as share of sales	0.04	0.09	0.23	0.09	0.11	0.19	1.00											
6. Intensity of knowl. inflows	11.28	4.41	0.20	0.12	0.11	-0.01	0.08	1.00										
7. Patentstock per employee	0.01	0.06	0.29	0.08	0.11	0.00	0.24	0.07	1.00									
8. No of employees (log)	4.14	1.66	0.36	0.25	0.12	-0.12	-0.16	0.19	0.00	1.00								
9. Share exports of sales (ratio)	0.21	0.26	0.44	0.17	0.28	-0.04	0.11	0.13	0.24	0.33	1.00							
10. Foreign MNC (d)	0.09	0.28	0.15	0.01	0.12	-0.05	-0.02	0.07	0.11	0.23	0.20	1.00						
11. Company age (years, logs)	2.67	0.81	0.04	-0.01	-0.03	-0.08	-0.13	0.03	-0.09	0.28	0.06	0.04	1.00					
12. Competition HHI	9.71	46.00	0.01	0.03	-0.16	0.19	-0.02	-0.00	-0.02	0.11	0.01	0.02	0.03	1.00				
13. Medium high-tech manuf. (d)	0.20	0.40	0.27	0.11	0.55	-0.15	0.07	0.06	0.07	0.18	0.36	0.10	0.00	0.01	1.00			
14. High-tech manuf. (d)	0.11	0.31	0.20	0.10	0.15	0.21	0.17	0.13	0.13	0.01	0.14	0.06	-0.00	-0.01	-0.18	1.00		
15. Distributive services (d)	0.09	0.28	-0.18	-0.09	-0.35	-0.13	-0.12	-0.14	-0.07	-0.08	-0.18	-0.04	0.06	-0.06	-0.16	-0.11	1.00	
16. Knowledge-intens. services (d)	0.07	0.25	-0.16	-0.05	-0.11	0.28	-0.06	0.04	-0.06	-0.04	-0.21	-0.02	0.14	0.01	-0.14	-0.10	-0.08	1.00
17. Technological services (d)	0.15	0.36	-0.11	-0.09	-0.06	0.27	0.20	0.02	-0.02	-0.24	-0.19	-0.11	-0.16	-0.07	-0.21	-0.15	-0.13	-0.11

(d) Binary coded variables, coded 1 if condition is fulfilled and 0 otherwise

All correlations > 0.08 significant at p<0.01

Table II: Results of ordered probit analyses

Variable	*Imp. Patents (1)*	*Imp. Trademarks (2)*
Main		
Knowledge input complexity level 2001	0.01**	0.00
	(0.00)	(0.00)
Dynamics of KI complexity 2005-2001	0.01	0.03***
	(0.01)	(0.01)
Controls		
Internal R&D as share of sales	3.21***	1.25**
	(0.54)	(0.50)
Intensity of knowl. inflows	0.02**	0.02
	(0.01)	(0.01)
Patentstock per empl. prev. year(ratio)	9.34***	0.92
	(1.55)	(0.76)
No of employees (log)	0.30***	0.22***
	(0.03)	(0.03)
Share exports of sales (ratio)	0.79***	0.10
	(0.20)	(0.20)
Foreign MNC (d)	0.02	-0.33**
	(0.16)	(0.16)
Company age (years, logs)	0.02	-0.10*
	(0.06)	(0.06)
Competition Herfindahl-Hirschman index	0.00	0.00
	(0.00)	(0.00)
Medium high-tech manuf. (d)	0.17	0.18
	(0.15)	(0.16)
High-tech manuf. (d)	0.25	0.12
	(0.17)	(0.17)
Distributive services (d)	-0.49*	-0.31
	(0.25)	(0.21)
Knowledge-intensive services (d)	-0.96***	-0.39*
	(0.31)	(0.23)
Technological services (d)	-0.16	-0.44**
	(0.17)	(0.17)
Pseudo R^2	0.24	0.08
N	938	938
LR χ^2 (15)	415.26	114.02
P-value	0.00	0.00

(d) Binary coded variables, coded 1 if condition is fulfilled and 0 otherwise
* $p<0.10$, ** $p<0.05$, *** $p<0.01$
Unstandardized coefficients, standard deviations in parentheses.

Appendix A: Industry breakdown

Industry	*NACE Code*	*Industry Group*
Mining and quarrying	10 – 14	Low-tech manufacturing
Food and tobacco	15 – 16	Low-tech manufacturing
Textiles and leather	17 – 19	Low-tech manufacturing
Wood / paper / publishing	20 – 22	Low-tech manufacturing
Chemicals / petroleum	23 – 24	Medium high-tech manufacturing
Plastic / rubber	25	Low-tech manufacturing
Glass / ceramics	26	Low-tech manufacturing
Metal	27 – 28	Low-tech manufacturing
Manufacture of machinery and equipment	29	Medium high-tech manufacturing
Manufacture of electrical machinery	30 – 32	High-tech manufacturing
Medical, precision and optical instruments	33	High-tech manufacturing
Manufacture of motor vehicles	34 – 35	Medium high-tech manufacturing
Manufacture of furniture, jewelry, sports equipment and toys	36 – 37	Low-tech manufacturing
Electricity, gas and water supply	40 – 41	Low-tech manufacturing
Construction	45	Low-tech manufacturing
Retail and motor trade	50, 52	Distributive services
Wholesale trade	51	Distributive services
Transportation and communication	60 – 63, 64.1	Distributive services
Financial intermediation	65 – 67	Knowledge-intensive services
Real estate activities and renting	70 – 71	Distributive services
ICT services	72, 64.2	Technological services
Technical services	73, 74.2, 74.3	Technological services
Consulting	74.1, 74.4	Knowledge-intensive services
Other business-oriented services	74.5 – 74.8, 90	Distributive services

Appendix B: Robustness tests

Variable	*Imp. Patents (3)*	*Imp. Trademarks (4)*	*Imp. Copyrights (5)*	*Imp. Secrecy (6)*	*Imp. Complex Designs (7)*	*Imp. Lead Time (8)*
Main						
Knowledge input complexity 2001	0.01**	-0.00	0.01	0.00	-0.00	-0.00
2001	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Dynamics of KI complexity 2005-	0.01	0.03***	-0.01	0.01	-0.01	0.01
2001	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Alternative						
Concentration of complexity	1.00	-1.21				
	(1.34)	(1.34)				
Controls						
Internal R&D as share of sales	3.19***	1.25**	0.68	2.85***	1.47***	2.17***
	(0.54)	(0.50)	(0.64)	(0.59)	(0.49)	(0.52)
Intensity of knowl. inflows	0.02**	0.01	0.03*	0.06***	0.03**	0.02**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Patentstock per empl. prev.	9.32***	0.91	0.67	1.51	-0.10	1.78*
	(1.55)	(0.76)	(1.00)	(0.95)	(0.85)	(0.97)
No of employees (log)	0.29***	0.22***	0.23***	0.11***	0.06*	0.14***
	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.03)
Share exports of sales (ratio)	0.78***	0.12	0.23	0.61***	0.48**	0.58***
	(0.20)	(0.20)	(0.28)	(0.19)	(0.21)	(0.19)
Foreign MNC (d)	0.03	-0.34**	-0.12	0.04	-0.26	-0.48***
	(0.16)	(0.16)	(0.21)	(0.15)	(0.17)	(0.16)
Company age (years, logs)	0.02	-0.10*	-0.01	-0.11**	-0.16**	-0.09
	(0.06)	(0.06)	(0.08)	(0.05)	(0.06)	(0.05)
Competition HHI	-0.00	-0.00	-0.02**	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Medium high-tech manuf. (d)	0.14	0.21	0.03	0.42***	0.20	0.22
	(0.16)	(0.16)	(0.22)	(0.14)	(0.16)	(0.14)
High-tech manuf. (d)	0.23	0.14	0.33	0.49***	0.50***	0.52***
	(0.17)	(0.17)	(0.22)	(0.16)	(0.17)	(0.17)
Distributive services (d)	-0.47*	-0.32	-0.41	-0.25	-0.04	-0.42**
	(0.25)	(0.21)	(0.39)	(0.19)	(0.20)	(0.18)
Knowledge-intensive services (d)	-0.92***	-0.43*	0.49	-0.04	0.05	-0.27
	(0.32)	(0.23)	(0.31)	(0.20)	(0.23)	(0.20)
Technological services (d)	-0.14	-0.45***	0.27	0.09	0.18	-0.01
	(0.17)	(0.17)	(0.22)	(0.15)	(0.16))	(0.14)
Pseudo R^2	0.24	0.08	0.10	0.13	0.05	0.09
N	938	938	938	938	938	938
LR χ^2 (15)			67.78	240.66	67.98	166.77
LR χ^2 (16)	415.81	114.84				
P-value	0.00	0.00	0.00	0.00	0.00	0.00

(d) Binary coded variables, coded 1 if condition is fulfilled
* p<0.10, ** p<0.05, *** p<0.01