MARKETS FOR TECHNOLOGY AND THE IMPORTANCE OF FIRM-SPECIFIC SEARCH FOR INNOVATION PERFORMANCE

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ABSTRACT

Firms rely increasingly on external knowledge, e.g. from universities, to improve their innovation performance. Existing research models the acquisition of knowledge either as a firm-specific search or a purchase on markets for technology. The former implies that a firm chooses and develops relationships with knowledge sources while the latter suggests a transaction governed by markets. We argue that both mechanisms increase a firm's innovation performance but that they are interrelated. While on the firm level firm-specific search and acquisitions on markets for technology complement each other, the costs of firm-specific search are only justified in underdeveloped markets. Otherwise, market transactions provide higher efficiency and flexibility. This negative cross-level interaction effect is stronger the more knowledge in an industry is covered by markets for technology. We test and support these hypotheses for a sample of 2131 German firms.

Keywords: knowledge search, markets for technology, innovation performance

INTRODUCTION

The question of how firms acquire resources that will consequently constitute sustained competitive advantage is central to research and practice of strategic management (Barney, 1986, 1991; Amit and Schoemaker, 1993). Many modern firms achieve competitive advantage by offering unique products based on unique knowledge the firm possesses. This allows them to charge higher prices than their competitors. However, the necessary R&D investments for developing unique knowledge are high and firms are increasingly incorporating external knowledge, e.g. from universities or suppliers, to improve their own innovation performance (Chesbrough, 2003a). Interestingly enough, though, strategy research has developed two largely disconnected streams on how firms can acquire external knowledge. One stream considers the acquisition of knowledge as a firm-specific search in which firms pick and choose particular knowledge sources and develop relationships with them (Laursen and Salter, 2006; Leiponen and Helfat, 2010). The second stream of literature perceives knowledge acquisition as a transaction on markets for technology on which disembodied knowledge is traded at a certain price (Gans, Hsu, and Stern, 2008; Arora and Gambardella, 2010; Arora and Nandkumar, 2012). For most firms, however, firm-specific search and markets for technology do not exist in isolation since these may be two channels for finding solutions to similar problems. In this paper, we seek to develop theory that captures simultaneously the firm level and the market level of knowledge acquisition. We review both theoretical mechanisms and develop hypotheses on cross-level interactions and their effect on innovation performance. In this sense, we model a firm’s search for knowledge in a context in which markets for technology exist and predict varying performance effects.

We base our argumentation on a model in which every knowledge acquisition process has to identify promising knowledge sources, evaluate their knowledge and facilitate the transfer of knowledge. In the case of firm-specific search the individual firm has full control over all of these stages. It can decide how broadly it wants to search and how deeply it wants to engage with particular knowledge sources (Katila and Ahuja, 2002; Laursen and Salter, 2006). This allows the searching firm to develop targeted search strategies (Koehler, Sofka, and Grimpe, 2012) and acquire knowledge that is not equally available to competitors (Dyer and Hatch, 2006). Then again, the focal firm has to cover all costs for the search. These costs can be so substantial that they outweigh the benefits that the searching firm can derive from it (Laursen and Salter, 2006). Given that many of the investments for developing channels with particular knowledge sources are specific to this knowledge source, e.g. the co-location of laboratories with a selected university, the firm's search becomes path-dependent and loses flexibility because a change in search would be costly.

Markets for technology, though, separate the knowledge producer from its knowledge, i.e. the knowledge becomes disembodied so that it can be traded (Arora and Gambardella, 2010; Conti, Gambardella, and Novelli, 2013). Knowledge acquisition in that sense becomes a transaction. On an efficient and safe market for technology buyers and sellers can reveal their knowledge and price preferences (Gans and Stern, 2010). Hence, the costs for matching supply and demand as well as for determining the value and price of the knowledge are born at the market level. There are, however, limits to the type of knowledge that can be traded on markets for technologies. The knowledge needs to be codified and can be separated from its producer. Moreover, strong intellectual property rights (IPR) need to be in place (Gans *et al.*, 2008). Otherwise, knowledge producers will not offer their knowledge because of the inherent appropriability hazard (Oxley, 1997): Knowledge suppliers need to provide information about the knowledge for evaluation by potential buyers but once they have obtained this information they may no longer want to pay for it.

We extend existing literature from both streams of research which state that firm-specific search and markets for technology will increase firm performance respectively. Based on a comparison of knowledge acquisition through firm-specific search and markets for technology, we suggest their firm-level interaction effect on innovation performance to be positive: firms can focus scarce resources on firm-specific search that targets particular knowledge sources with a high potential for providing unique knowledge while other, more codified and ready-to-use types of external knowledge may be better – and presumably also more cheaply – acquired on markets for technology. More importantly however, we hypothesize that the cross-level interaction between them is negative. We base this hypothesis on the rationale that with increasing size of the market for technology in an industry the cost advantages and the flexibility from market transactions outweigh the advantages from specific relations developed with particular knowledge sources in firm-specific search. Put differently, we argue that firm-specific search is most valuable to firms if the markets for technology in their industry are underdeveloped.

We refine this line of argumentation by relating the size of the market for technology with overall knowledge production in an industry. The market coverage of knowledge in an industry would only be complete if all knowledge was offered for sale. In reality, industries differ in the way in which these conditions are fulfilled. Knowledge producers in an industry may have strong incentives for not offering their knowledge for sale to industry competitors to protect its value as a strategic asset (Arora and Nandkumar, 2012). Hence, we conclude that the substitution effect between firm-specific search and markets for technology is higher when the market coverage of knowledge in the industry is increasingly complete. We test and support these hypotheses for 2131 firm-year observations from Germany between 2001 and 2009. The data provide us with the unique opportunity to capture the firm-specific search as well as the demand side of the market for technology, i.e. the licensing expenditures in 20 different industries, over time.

These findings have immediate relevance for academic research and management practice. From an academic perspective our study has two primary implications. First, we eliminate a source of bias in studies that have investigated a firm's search for external knowledge while neglecting interactions with the market for technology (e.g. Laursen and Salter, 2006, Leiponen and Helfat, 2010). Our findings allow the distinction between general industry effects, e.g. technological opportunity or IPR regimes, and the specific influence of the market for technology. In this sense, there is a much more clearly defined route for developing new theory on firm-specific search that takes into account alternative forms of knowledge acquisition. Secondly, we introduce, to the best of our knowledge, a new direction in the theory stream of markets for technology. Several studies have highlighted that markets for technologies are underdeveloped or inefficient (Gans *et al.*, 2008; Gans and Stern, 2010) but so far mitigating mechanisms at the firm level have been absent from theoretical development. We show that the firm and market level interact. Firm-specific search is especially valuable if markets for technology are underdeveloped. This provides a promising route for further studies on markets for technology which allow firms to adjust firm-level strategies to counterbalance weaknesses of market institutions in knowledge acquisition.

These academic implications have direct implications for management practice as well as policy making. First, we provide much more precise insights into how firms can benefit from "open innovation" trends (Huston and Sakkab, 2006). Our findings suggest that firms should rely on market mechanisms for acquiring external knowledge as far as possible. If markets for technology are small, though, the value of developing firm-specific search strategies increases. Moreover, our findings can also inform policy making. Several factors underlying the efficiency and coverage of markets for technology are subject to rules and regulations set by government, e.g. on IPR regulation. Our findings indicate that changes to these rules have repercussions for firms that have developed firm-specific search strategies. A comprehensive impact analysis on policy changes will need to take into account that such firms would lose competitive advantage originating from specific knowledge ties if the efficiency of the markets for technology is strengthened.

The remainder of this paper is organized as follows. The following section outlines our theoretical background and establishes at set of hypotheses. Data, measures and the empirical model are described in section 3 while section 4 presents the results. They are discussed in section 5, leading to conclusions, limitations, and implications for further research in section 6.

THEORY AND HYPOTHESES

At the heart of our study is a unified understanding of how firms acquire and exploit external knowledge, i.e. through a firm-specific search effort and/or an exchange on markets for technology. We theorize on the benefits that firms can generate from receiving external knowledge or buying it on markets for technology, i.e. we focus on the demand side. Our goal is to link the two theoretical streams of firm-specific search for knowledge as well as markets for technology and explore their interactive effects on firm’s innovation performance. We start out by defining central constructs and highlighting basic mechanisms.

The dependent variable in our theoretical model is innovation performance. We adopt the strategy definition of innovation performance, i.e. the value a firm can capture from its innovations, and not a technological one, i.e. simply the presence of an invention (Nerkar and Shane, 2007). Further, we define the firm-specific search for external knowledge as all activities at the firm level directed at identifying promising knowledge sources outside of the firm boundaries, such as universities or suppliers, and transferring knowledge from these sources (Laursen and Salter, 2006, Grimpe and Sofka, 2009). Search at the firm-level implies that firms engage with a variety of partners and tailor the knowledge identification and transfer to the particular norms and conventions of various knowledge sources (Laursen, 2012). Markets for technology, though, organize the transfer of knowledge at a price and in disembodied form (Conti *et al.*, 2013). In principle, the market for technology should be separate from the acquisition of equipment or hiring new employees and the acquired knowledge should be ready to be used by the buyer.

The overall positive effect of external knowledge on firm's internal innovation activities is already well understood. The innovation performance of firms depends increasingly on knowledge that is produced outside of the firm boundaries, e.g. by universities, suppliers or customers (Chesbrough, 2003b; Cohen and Levinthal, 1989). Two primary mechanisms have been identified for these positive performance effects of external knowledge. First, external knowledge especially from academic research can guide firm R&D activities towards promising outcomes. As a result, the firm's internal time and resource requirements are comparatively lower (Fleming and Sorenson, 2004; Leone and Reichstein, 2012). Second, successful innovations are typically not the outcome of an isolated piece of knowledge but the result of combinations of knowledge. A firm that is limited to its internal knowledge stock can reach the limits of possible re-combinations. Integrating external with internal knowledge has therefore significant potential to increase the degree of novelty of a firm's knowledge and consequently its innovations (Rosenkopf and Nerkar, 2001; Cassiman and Veugelers, 2006). Firms are more likely to have unique offerings on the product market based on novel knowledge and can charge comparatively higher prices in an at least temporary quasi monopolistic situation. As a result, innovation performance will be higher. In sum, firms have strong incentives to acquire external knowledge.

We will argue that these positive effects of external knowledge differ depending on whether the knowledge acquisition originates from a firm-specific search or is governed by markets for technology. The general acquisition process of external knowledge – both at the firm and market level – has three primary steps. First, promising knowledge sources need to be identified for supplying knowledge. Second, the knowledge needs to be screened and evaluated. Third, the most promising knowledge has to be transferred from the knowledge source to the focal firm. All of these steps can be accomplished at the firm or the market level. We will integrate both levels in a single theoretical model by discussing the underlying mechanisms separately first before including interactions at the firm and market level.

Firm-specific knowledge search

Search for external knowledge at the firm-level has received much attention in recent academic discussion especially under the heading of "open innovation" (for a recent review see Laursen, 2012). These theoretical models typically assume that firms search by defining initially a scope of technologies (Katila and Ahuja, 2002) or breadth of knowledge sources (Laursen and Salter, 2006). The external knowledge identified needs to be screened for value to the particular company. Screening knowledge is costly since the information processing capacities of a firm are limited (Koput, 1997). The costs for screening external knowledge can be so high that they outweigh the benefits that a firm can derive from utilizing the knowledge itself (Laursen and Salter, 2006). A result of this screening is that firms decide to intensify their search in some technologies or with some knowledge sources and neglect others. The intensification of a firm's search is typically referred to as its depth (Katila and Ahuja, 2002; Laursen and Salter, 2006). Firms incur additional costs when increasing the depth of their search for knowledge. These costs stem from developing stable channels with promising knowledge sources, e.g. leading universities or clients, which benefit from a shared language or geographical co-location. As a consequence, firms are heterogeneous in their search for external knowledge (Koehler *et al.*, 2012). On the one hand, this allows them to develop firm-specific relationships with external knowledge sources that are not available to their competitors or not to the same degree (Dyer and Hatch, 2006). On the other hand, the search process itself is costly and creates path dependency because many of the costs incurred are specific to the knowledge source. The latter factor limits the flexibility of a firm's search for knowledge. For example, a firm scientist who has worked intensively with university scientists for understanding the discovery of pharmaceutical molecules can transfer hardly any of the developed skills to working with leading clients in health services if these become a promising source of knowledge.

On balance, most empirical studies find that firms that search for external knowledge increase their innovation performance (Leiponen and Helfat, 2010; Grimpe and Sofka, 2009; Koehler *et al.*, 2012). However, the search costs can be so substantial for the firms that they outweigh the advantages when firms search excessively broadly and deeply (Laursen and Salter, 2006).

Markets for technology

The knowledge acquisition process for firms buying external knowledge on markets for technology[1] is fundamentally different (for a recent review see Conti *et al.*, 2013). Suppliers and buyers of knowledge are only connected through a market on which knowledge can be sold and bought. Efficient markets allow for allocative efficiency (Arora and Gambardella, 2010). Markets allow producers of knowledge to sell the knowledge itself, typically through licensing, instead of developing complementary assets, e.g. in distribution, manufacturing or servicing, for commercializing it on the product market (Lamoreaux and Sokoloff, 2001; Gans and Stern, 2003). Conversely, firms that possess complementary assets do not need to invest into the development of new technologies because they can simply buy them on markets for technology (Arora and Nandkumar, 2012).

The acquisition of knowledge on markets for technology is transactional in nature and not based on the particular relationship between a knowledge source and a recipient. At the market level, it is important that enough potential buyers and suppliers are present for the market to match them efficiently ("thickness of the market") (Gans and Stern, 2010). The knowledge exchange does not depend upon the presence of a specific dyad of knowledge buyer and supplier. The value of the knowledge is also only indirectly determined by individual market participants. On perfectly efficient markets for technology, potential buyers and suppliers can reveal their preference prices

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[1] Other studies have used the term "markets for ideas" (Gans and Stern, 2003, 2010) for the market-based exchange of knowledge. There exists no theoretical discrepancy with the term "markets for technology" within the framework of our study and it provides a closer link with recent strategic management literature (Arora and Nandkumar, 2012). It is important to note that this conceptualization is not limited to the exchange of technological knowledge and does not include buying and selling of high-tech equipment because this would be governed by product markets (Conti *et al.*, 2013).

for a particular technology and the market mechanism determines the equilibrium price at which both buyers and suppliers cannot find a better offer. Even if markets for technology are not fully efficient, they can significantly reduce the search costs between buyers and suppliers of knowledge by providing services such as brokerage, auctioning or online presentation (Yanagisawa and Guellec, 2009; Dushnitsky and Klueter, 2011). Finally, the market exchange "disembodies" the knowledge, i.e. it becomes separated from the equipment or scientists of the knowledge producer (Conti *et al.*, 2013). For this purpose the knowledge has to be codified comprehensively. This feature allows the buyer to use the knowledge without further interaction with its producer.[2] Then again, it limits the pool of knowledge that can be traded on a market to knowledge that it typically fully developed and ready to use.

In sum, the costs that an individual firm has to bear for identifying knowledge sources, evaluating available knowledge and transferring it on a market for technology are low. Arora and Nandkumar (2012) caution that the value of the acquired knowledge is also lower to the firm because the uniqueness of the knowledge is reduced. The same knowledge is in principle also available to other firms in the industry. Table 1 summarizes the comparison between firm-specific search and markets for technology along major dimensions.

[Table 1 about here]

Based on the comparison laid out in Table 1 we conclude that it is unlikely that knowledge acquired through firm-specific search and knowledge acquired on markets for technology are

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[2] We acknowledge that research has found that firms increase the benefits that they can generate from licensed technologies when they involve the individual that invented (Agrawal, 2006). For the purpose of our argumentation it is important to note that this involvement is not a necessary condition to benefit from the acquired knowledge.

direct substitutes. Instead, a firm can be expected to be better off if it combines both modes for acquiring external knowledge. An optimal strategy for acquiring external knowledge would be focussing scarce resources on firm-specific search targeting particular knowledge sources with a high potential for providing unique knowledge even when it is early in its development and hard to codify. Other types of external knowledge should be better acquired on markets for technology. Hence, we conclude that a combination of firm-specific search and acquiring knowledge on markets for technology outperforms approaches which focus exclusively on one or the other. We propose:

Hypothesis 1: Firm innovation performance is higher for firms which combine firm-specific search for external knowledge with acquisitions on markets for technology, i.e. there is a positive interaction effect.

Table 1 makes it also clear that many of the advantages of acquiring knowledge on markets for technology, e.g. flexibility and availability, are determined by factors at the market-level, especially the size of the market. In the following, we will thus argue that a cross-level interaction effect exists between the performance effect of firm-specific search and the size of the market for technology.

The size of the market for technology is determined by the nature of the knowledge that is tradable and the institutional rules, especially on intellectual property rights (IPR) that govern potential market transactions. First, knowledge traded on markets needs to be codified. In principle, all knowledge would be codifiable, however the costs can become exceedingly high (Conti *et al.*, 2013). If these costs are too high, the knowledge will not be codified and therefore not offered on a market for technology. Second, appropriability regimes are determined by legal and technological conditions in an industry (Teece, 1986). With increasing appropriability hazards, fewer knowledge producers will be willing to offer knowledge on markets for technology (Gans *et al.*, 2008). Arundel et al. (1998) estimate that roughly a third of all inventions is patented. They find that this patent propensity ranges from 15 percent in iron and steel production to 74 percent in pharmaceuticals. Hence, there is a remarkable share of knowledge production that does not qualify for patenting based on the formal criteria of the patent office or the expected benefits of the inventors. The low levels of patented knowledge combined with strong inter-industry differences can be interpreted as an indication that substantial parts of knowledge production in almost all industries do not fulfil the requirements for codification and legal protection that would qualify it for trading on markets for technology. Finally, the design of markets for technology affects their efficiency (Gans and Stern, 2010). Only thick markets with enough potential buyers and suppliers that allow uncongested and safe transactions attract market participants.

In that sense, firms facing comparatively small markets for technology, have no viable alternative to firm-specific search for external knowledge. However, the comparative disadvantages of firm-specific search become apparent with increasing size of the market for technology. Firm-specific search reduces the flexibility of the firm's knowledge search and increases the risk that it will miss out on important trends outside of its historic focus. In sharp contrast, knowledge acquisitions on markets for technology are transactional in nature. A large market for technology thus provides the focal firm with a high degree of flexibility. It can draw from a potentially large pool of available external knowledge that is instantaneously accessible and usable. Hence, the firm is less exposed to a lock-in situation from its knowledge acquisition in the past since it did not have to make relationship-specific investments with particular knowledge sources.

On balance, firm-specific search for knowledge enables firms to access a rich pool of external knowledge from selected sources at substantial costs. Markets for technology enable a firm to acquire knowledge at presumably lower costs and with much more flexibility for changing the direction of a firm's knowledge acquisition. We argue that with increasing size of the market for technology the downside of not developing deep relationships with particular knowledge sources will be outweighed by the breadth and availability of knowledge on markets for technology. If this is the case, the positive effect on innovation performance from firm-specific search for external knowledge will be lower with increasing size of the market for technology in the firm's industry. We propose:

Hypothesis 2: The effect of firm-specific search on innovation performance is negatively moderated by the size of the market for technology, i.e. the interaction term is negative.

Finally, we argue that the effect outlined in Hypothesis 2 is stronger the more knowledge in an industry is traded on markets compared to the amount of knowledge that is produced. This implies that the market for technology can cover the knowledge supply in an industry to varying degrees. We will argue that given certain technological and institutional constraints on the size of the market for technology, markets for technology can differ in how completely they cover the knowledge in an industry.

Arora and Nandkumar, 2012 show that a firm's own technological capabilities become less valuable in competition the more technology is available on markets. This implies that competitors in an industry have incentives not to offer knowledge on the market that they have produced themselves. These incentives exist independent of technological or institutional limitations for the size of the market for technology. Given these incentive structures, the market for technology is likely to be incomplete, i.e. it covers only a fraction of the knowledge that is relevant for the industry. It is important to note that the advantages of transactions on markets for technology laid out in Table 1 accrue only to the fraction of the relevant knowledge in an industry which is covered by the market. With increasing gaps in the coverage of the market for technology in an industry the advantages of firm-specific search increase because the firm can direct its search efforts to areas that are not offered on markets. Put differently, the advantages of using the market for technology instead of firm-specific search for acquiring knowledge put forward in Hypothesis 2 are higher if the market for technology is both large and complete in coverage of relevant knowledge in the industry. In the latter situation the advantages of markets for technology with regards to low transaction costs and knowledge that is broadly accessible reach their maximum. Hence, our last hypothesis reads:

Hypothesis 3: The effect of firm-specific search on innovation performance is negatively moderated by the size of the market for technology in the industry and this negative moderation effect is stronger the more complete the coverage of the market for technology is of the knowledge produced in the industry.

DATA AND METHODS

Data

Our empirical analysis relies on data from the “Mannheim Innovation Panel” (MIP) which is the German contribution to the Community Innovation Survey (CIS) of the European Union. The methodology and questionnaire used follow CIS standards and the Oslo manual of the OECD

(OECD, 2005). CIS surveys target decision makers for a firm's innovation activities such as CEOs, heads of innovation management units or R&D departments. Respondents provide direct, importance-weighted measures for a number of questions on innovation inputs, processes and outputs (Criscuolo, Haskel, and Slaughter, 2005). Several recent contributions in the strategy and innovation literature have relied on data provided by CIS surveys (e.g., Laursen and Salter, 2006; Grimpe and Kaiser, 2010; Leiponen and Helfat, 2011a).

CIS surveys have been applied in European Union member and associated states for more than a decade. They are subject to extensive pre-testing and piloting in various countries, industries and firms with regards to interpretability, reliability and validity (Laursen and Salter, 2006). Moreover, the questionnaire contains detailed definitions and examples to increase response accuracy. A comprehensive non-response analysis shows no evidence for any systematic distortions between responding and non-responding firms (Rammer *et al.*, 2005).

Nevertheless, not all variables of interest are available on an annual basis and not all firms answer the questionnaire regularly. Therefore we use data from the surveys conducted in 2001, 2005 and 2009, which contain our variables of interest, and pool them since the number of firms answering in at least two consecutive years is rather low, leading to a highly unbalanced panel. The questionnaires refer to the three-year period prior to the survey year. In order to allow for a time lag between the dependent and explanatory variables and hence to provide clarity in interpretation by eliminating potential simultaneity issues, we draw the dependent variable on innovation performance from the survey conducted two years later, i.e. in 2003, 2007 and 2011, respectively. We complement this dataset with patent statistics derived from the European Patent Office (EPO). After dropping observations with item non-response, we end up with a final sample of 2131 firm-year observations which are based on 1886 unique firms.

Variables

Dependent variable.

Extant literature features a variety of constructs used to measure innovation performance (for an overview see OECD, 2005). These include innovation inputs such as R&D expenditures and a broad range of output measures, e.g. patents, new processes and products. Our research follows the latter approach. Since the existence of a novel product is hardly a good predictor for the economic performance of an innovation we refer to the market acceptance that turns a novelty into a successful product innovation. Consequently, we follow other CIS-based literature and take the sales achieved with newly introduced product innovations normalized by the firm's total sales as our measure for innovation performance in $t+2$ (e.g., Laursen and Salter, 2006; Leiponen and Helfat, 2011a). CIS surveys draw a distinction between sales with products new to the firm and products new to the market, the latter indicating a higher degree of novelty. We use the sales with firm novelties which include market novelties and are thus the more comprehensive construct. Moreover, correlation between the two figures is quite high (0.54) and for more than 36 percent of firms in the sample the sales with firm novelties equal those with market novelties.

Focus variables.

Our first main explanatory variable is the extent of external knowledge sourcing. Knowledge flows are intangible by nature and hence difficult to capture. For this reason and in line with other recent research on external knowledge sourcing (e.g., Laursen and Salter, 2006; Leiponen and Helfat, 2010), we follow a different approach by focusing on the knowledge sources that firms report to have used.[3] In the survey, respondents are provided with a list of knowledge sources and asked to rate their importance for the firm's innovation activities on a four-point scale from zero (not important at all/not used) to three (very important). The potential sources include suppliers, customers, competitors, universities, research institutes, conferences (including professional exchanges and journal publications) and trade fairs. We adopt the approach suggested by Leiponen and Helfat (2011b) and generate a variable for the extent of external knowledge sourcing based on a two-step procedure. First, for each of the knowledge sources we create a binary variable that takes a value of one if the firm has given a response of either two (important) or three (very important). A response of zero (not important at all/not used) or one (some importance) leads to a value of zero in the binary variable. Using binary variables avoids potential measurement error resulting from the use of Likert scales (Cohen and Malerba, 2001). Second, we created a summary variable of the binary values to depict the extent of external knowledge sourcing. The variable consequently varies between zero and seven.

The second explanatory variable measures the firm's expenditure for licensing. In the questionnaire, firms are asked to provide information on several types of innovation expenditure, including inlicensing. The variable enters the regressions normalized by the firm's total sales.

The third explanatory variable is the size of the market for technology. Prior literature has focussed on narrow sets of high-tech industries (Gans *et al.*, 2008) or relied on university patents

[3] Other studies have relied on patent statistics (e.g., Rosenkopf and Nerkar, 2001), which however only reflect particular knowledge flows and sources. Moreover, patenting activity is concentrated, with dominant shares in relatively few sectors (e.g., pharmaceuticals) (e.g., Arundel and Kabla, 1998). Significant portions of all inventions are not patented because of cost and disclosure considerations or because they do not qualify for patent protection (e.g., Griliches, 1979; Encaoua, Guellec, and Martinez, 2006). In sum, the knowledge a firm may potentially search for is likely much more diverse than the patented sub-domain.

as a measure of technology supply on markets for technology (Arora and Nandkumar, 2012) which captures only a fraction of the actual market for technology that firms can make use of. Instead, we rely on a demand side measure that we expect to more appropriately reflect the availability of knowledge on markets for technology. The Mannheim Innovation Panel is a representative dataset based on stratified random sampling of the complete population of German firms. This is due to the fact that it provides the official reporting of the innovation activities of German firms to the German Ministry of Education and Research. Hence, projected figures on innovation expenditures can be calculated for the population of German firms. We use these figures on the firm's expenditures for licensing which are calculated on the NACE two-digit industry level as our measure of the size of the market for technology. The figures capture the aggregate demand for licensed technology by German firms which we suggest to be a useful indicator of market size. The two-digit level industry classification allows us to identify relevant markets that are neither too narrow nor too coarse. We obtain 20 different markets for technology per observation period in which, for example, automobile manufacturers are in the same industry group as suppliers of automotive parts. Hence, we are able to distinguish between the technology that the firm has bought and the size of the market for technology from which it has bought. This allows us to separate firm and market-level effects.

The fourth main explanatory variable is the completeness of the coverage of the market for technology. Again, we make use of the projected expenditure figures for the population of German firms and divide the industry licensing expenditures by the sum of industry expenditures for internal as well as external, i.e. commissioned, R&D. The idea of this measure is to capture the knowledge used in an industry by in-licensing in relation to the knowledge produced in-house or by exclusive R&D contractors. Holding industry R&D expenditure constant, the higher the amount of in-licensing, the better the market for technology covers the knowledge on which innovation is based in an industry. We acknowledge that this measure cannot capture supply for the market for technology from other industries. There is, to the best of our knowledge, no such measure available and knowledge production through R&D within the industry can serve as a meaningful proxy variable. Our measure would be a conservative measure for industries in which substantial supply of knowledge stems from other industries and this induces a downward bias in our estimations, i.e. we would be less likely to find support for hypothesis 3.

Control variables.

Several other factors have been identified in the literature as influencing a firm's innovation performance (for an extensive review see Ahuja, Lampert, and Tandon, 2008). In that sense, we include the firm's R&D intensity, defined as the share of a firm's internal R&D expenditures over sales. To account for differences in firms' past R&D activities we calculate the patent stock for each firm on all patents filed at the European Patent Office from 1978 to *t*-2 of the survey year using the perpetual inventory method with a constant knowledge depreciation rate of 15 percent as is standard in the literature (e.g., Hall, Jaffe, and Trajtenberg, 2005). Since it is highly skewed, the variable enters the regressions in logarithm. Moreover, we include the firm's size by the number of employees (in log), whether it is part of a company group (dummy) and whether it also engages in process innovation. All of these factors have been found to influence a firm's knowledge production function (Koehler *et al.*, 2012; Leiponen and Byma, 2009; Reichstein and Salter, 2006). We control for different degrees of internationalization through the share of exports over total sales because internationalization and innovation activities are related (Cassiman and Golovko, 2011). To control for regional differences, we include a dummy variable indicating whether a firm is located in East Germany. Finally, we include industry dummies at the grouped NACE two-digit level (high-tech, medium-tech, and low-tech manufacturing, and technology-oriented, knowledge-intensive, and distributive services) to control for any remaining industry effect as well as survey year dummies.

Model

Our estimation follows a production function approach which has frequently been used before in studies on the relationship between search and innovation output (e.g., Laursen and Salter, 2006; Leiponen and Helfat, 2010). All firms in the sample have either successfully innovated or attempted but failed to innovate. Because the dependent variable (share of sales with newly introduced product innovations) is censored between zero and one, we need to apply a tobit model that takes account of this (Wooldridge, 2007). Even though the number of firms that answered in more than one survey is rather low (out of 2131 firm-year observations only 245 firms answered more than once) we choose to adjust the standard errors to account for differences in within and between firm variations.

Our model specifications include the extent of external knowledge sourcing, the firm's inlicensing expenditures over sales and the size of the market for technology by industry as direct effects (baseline expectation) and subsequently an interaction term each between the extent of external knowledge sourcing and firm inlicensing as well as the size of the market for technology (hypothesis 1 and 2). To test hypothesis 3, we use a sample split along the median value of the completeness of coverage variable. Since tobit models are non-linear models, the correct interpretation of interaction effects requires the calculation of their marginal effects. We follow the procedure suggested by Wiersema and Bowen (2009) and report marginal effects in order to test the hypotheses.

In addition to our main models, we run a series of consistency check estimations to eliminate alternative explanations and to demonstrate the robustness of results with regard to estimation techniques employed. First, we include a variable measuring the effectiveness of the patent appropriability regime on the industry level that follows McGahan and Silverman (2006). Using projected data from the Mannheim Innovation Panel, this measure builds on the importance of patents as a means to protect a firm's inventions. It is defined as the number of firms in a NACE two-digit industry that assessed patents to be highly important to protect their competitive advantage divided by the total number of innovating firms in the industry. This measure is only available for the 2001 and 2005 survey years which consequently reduces the number of observations available for analysis. The intention to include this measure is to separate the size of the market for technology from the strength of the IPR regime and thereby eliminate an alternative explanation for the empirical results.

Another issue to consider is our combination of firm-level and industry-level data which suggests the data to be clustered, i.e. firms are clustered within industries. It turns out that the variance in the outcome variable explained on the industry level is rather low: the intra-class correlation is 10.3 percent. Nevertheless, we use two different approaches that account for the hierarchical structure of our data. First, we estimate a heteroscedasticity-robust tobit model in which the variance of the random variable differs by industry to avoid an underestimation of the variance and to provide a more conservative estimate of the standard error (Wooldridge, 2007). Thus we include the industry dummies in a heteroscedastic regression where we consider the variance σ_i^2 of observation *i* to be of the form $\sigma_i = \sigma \exp(z_i' a)$. *z* represents the vector of variables in the heteroscedasticity term while *a* denotes the vector of additional coefficients to be estimated. This correction allows the estimation of heteroscedasticity-consistent coefficients. We choose the more parsimonious tobit model for reporting results in the main estimations. Second, we estimate a random intercept model in which the intercept is allowed to vary by industry. Since our regressions include variables measured on the industry level as well (i.e., so-called level-2 covariates), the model accounts for variation in the intercepts (Aguinis, Gottfredson, and Culpepper, 2013).

RESULTS

Table 2 provides summary statistics for the full sample. The average share of sales with newly introduced product innovations is 20 percent. Firms list on average three external sources of knowledge to be important. Regarding firms' participation in the market for technology it turns out that firms in each of the 20 industries spent in aggregate 130 mn Euro in the year prior to the survey year on the in-licensing of technology. This figure corresponds to about 10 percent of the total internal and external R&D expenditures in the respective industries. The vast majority of funds available for innovative activity is therefore not spent on licensing but on own or commissioned technology development.

[Table 2 about here]

Table 3 shows the pairwise correlation coefficients as well as the variance inflation factors and condition number. We do not find an indication of collinearity problems in our data by any conventionally applied standard (e.g., Belsley, Kuh, and Welsh, 1980).

[Table 3 about here]

Table 4 shows the results of the main tobit regression models. We estimate five models in different specifications. All of them include our set of control variables which turn out to be consistent across the specifications. Model 1 shows the results of a controls-only specification. Here we find the R&D intensity, export intensity and firm size to be positively associated with innovation performance. Moreover, firm age turns out to be negatively related to innovation performance. These findings are in line with prior studies in the field that use a similar production function approach (e.g., Laursen and Salter, 2006; Grimpe and Kaiser, 2010). There is no effect of the patent stock, whether the firm is a process innovator, located in East Germany, or part of a group of firms.

Model 2 includes our main explanatory variables. We find a positive and significant effect of the extent of firm-specific external knowledge sourcing and of the firm's inlicensing expenditure on innovation performance. Moreover, we find a positive and significant relationship between the size of the market for technology and innovation performance. Model 2 also includes the variable capturing the completeness of the market for technology which is subsequently used for the sample split along its median. Even though the coefficient suggests a positive relationship with innovation performance, the effect is marginally insignificant. In Model 3 we include the interaction terms between the extent of external knowledge sourcing and firms' inlicensing as well as the size of the market for technology. The first effect turns out to be positive and significant, lending support to hypothesis 1. The marginal effect – i.e. the secondary moderating effect (Wiersema and Bowen, 2009) – equals 0.68 and is significant at the 5 percent level.[4] The second interaction effect is negative and significant, which supports hypothesis 2. The marginal effect equals -0.06 and is significant at the 5 percent level. Apparently, there is a complementary

[4] Wiersema and Bowen (2009) suggest plotting the secondary moderating effect to determine whether it is significant for all observations in the sample. The graph can be found in Figure 1 in the appendix.

relationship between search and firms' inlicensing but a substitute relationship between search and the size of the market for technology. Model 4 and 5 are based on the two different samples of firms confronted with a high (low) coverage of knowledge through the market for technology. As expected, we find a positive and significant effect of the first interaction term and a negative and significant effect of the second interaction term in case of high coverage but we do not find significant effects in case of low coverage. The marginal effects in the former model are 0.61, significant at the 10 percent level, and -0.05, also significant at the 10 percent level; the marginal effects are insignificant in the models for low coverage. These findings confirm our third hypothesis that search and firms' inlicensing are complements and search and the market for technology are substitutes particularly if the coverage of relevant knowledge through the market for technology is sufficiently high.

[Table 4 about here]

Models 6 to 8 in Table 5 test for the robustness of our results. Model 6 includes the industry patent appropriability regime variable in order to control for industry differences in IPR regimes that the other model variables might have confounded with the size of the market for technology. As expected, the strength of the IPR regime is positively associated with innovation performance. Apparently, industries in which firms can rely on patents to protect their innovative assets perform better in their innovation activities. More importantly, the inclusion of the variable does not alter our main model results. Models 7 and 8 take the hierarchical structure of our data into account by estimating a heteroscedasticity-robust tobit and a random intercept model. Again, we find our results to be supported.

[Table 5 about here]

DISCUSSION

The acquisition of external knowledge and its combination with knowledge produced in-house are crucial components for improving firm's innovation performance (e.g., Laursen and Salter, 2006; Grimpe and Kaiser, 2010). By focusing on firm-specific search on the one hand and knowledge acquisition on markets for technology on the other, our research sheds new light on two prominent channels of external knowledge acquisition. As expected, we find them to have a separate, positive effect on firms' innovation performance. However, prior literature has largely treated them in isolation, ignoring that firms may consider firm-specific search and knowledge acquisition on markets for technology as interrelated channels to find solutions to similar problems. Our results show that, on the firm-level, both firm-specific search and acquisitions on markets for technology complement each other. However, the cross-level interaction effect between firm-specific search and acquisitions on markets for technology turns out to be negative, i.e. the benefits of firm-specific search for innovation performance decrease in the size of markets for technology. We find this effect to be particularly pronounced in industries in which the market for technology covers a high share of the overall knowledge produced. In this regard, our research contributes to the literature in at least three ways.

First, extant strategy research has developed two largely disconnected streams on how firms can acquire external knowledge (Laursen and Salter, 2006; Leiponen and Helfat, 2010; Gans *et al.*, 2008; Arora and Gambardella, 2010; Arora and Nandkumar, 2012). Moreover, these two streams are based on two different levels of analysis, i.e. the firm level versus the market level. Our paper integrates these two streams to derive an analytical framework that considers both the benefits and costs of either knowledge acquisition channel. In that sense, we integrate the firm and market level in order to advance our understanding of firms' knowledge acquisition processes.

The cross-level interaction effect between firm-specific search and the size of the market for technology in fact indicates a strong interrelationship between the two levels of analysis that prior literature has so far paid little attention to. Firm-specific search is most valuable to firms if the markets for technology in their industry are underdeveloped and vice versa. This opens a new route for further studies on markets for technology which allow firms to adjust firm-level strategies and to balance the weaknesses of market institutions in knowledge acquisition. Hence, our research informs and extends the literature on both firm-specific search and markets for technology by putting emphasis on the respective other channel and the resulting interaction.

Second, we relate the theoretical discussion on markets for technology to the overall knowledge production within an industry. Although prior research acknowledges that not all relevant knowledge may be traded on markets (Gans *et al.*, 2008; Arora and Gambardella, 2010), the relative importance that markets for technology have for firms' innovation processes has received surprisingly little attention. For this reason, we refine our argumentation by shedding light on the actual degree to which markets for technology cover the overall knowledge produced in an industry. Gans and Stern (2010) argue that the market coverage of knowledge in an industry would only be complete if all knowledge could be codified, protected by strong IPR regulation and governed on markets with many buyers and sellers which could trade safely and free of congestions. Higher coverage suggests markets for technology to play a more important role in firms' external knowledge acquisition which, as a consequence, has implications for the substitution effect between firm-specific search and knowledge available on markets for technology.

Third, our research employs novel measures on the demand side of markets for technology. Based on a representative survey of the innovation activities of German firms, we are able to provide an approximation of the actual amount spent on markets for technology. In that sense, our research extends existing supply side measures, as for example the supply of university patents in a particular field of technology (Arora and Nandkumar, 2012), which may only cover a certain and highly specific fraction of the actual market. Moreover, our research is not limited to a particular industry but maps the market for technology in 20 different industries. We are able to distinguish between general industry effects, e.g. technological opportunity or IPR regimes, and the specific influence of the market for technology.

These academic implications translate into several implications for management practice and policy making. First, our research informs decision makers in R&D on how to better benefit from an "open innovation" strategy (Huston and Sakkab, 2006). Our findings advocate the use of market transactions as far as possible in order to benefit from efficiency and flexibility advantages that these transactions incur. In turn, firm-specific search, a complex and costly strategy, should be intensified in case of small and underdeveloped markets for technology. Such a state of development also raises implications for policy making since markets for technology are subject to rules and regulations set by government, for example on IPR regulation. Making market transactions more efficient in this regard may benefit the innovation performance of firms in an entire economy. Nevertheless, it should not be overlooked that higher effectiveness of markets may relatively devalue complex firm-specific search strategies that firms may have considerably invested in.

LIMITATIONS

While our research makes several contributions to two important streams of literature, we need to acknowledge several limitations that translate into considerable opportunities for further research. First of all, the structure of our data does not allow us to follow firms' investments into search and markets for technology over time. Although we are able to measure inputs and outputs of the firm's knowledge production at different points in time, the number of firms in our sample that we do observe over time is comparatively low. It would thus be desirable to generate more longitudinal datasets that would provide an eye on firm's decision making on external knowledge acquisition over time and the implications for innovation performance.

Second, while our measure of the market for technology provides an estimate of the realized demand of firms for technological knowledge, we do not know whether the supply side could actually have been larger. Firms that lack financial resources might actually be excluded from using the market for technology, and such financial restrictions could be more pronounced in certain industries or in certain firm size cohorts. Hence, while we assume our measure to appropriately reflect the actual size of the market, it may be biased due to other, unobserved factors.

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TABLES

Table 1: Comparison of knowledge acquisition through firm-specific search and markets for technology

Dimension	Firm-specific search	Market for technology
Type of knowledge that can be acquired	All technology development stages; codified or tacit	Only codifiable knowledge which is ready to use
Scope of available external knowledge	Limited by firm's search capacity	Limited by supply of technology
Uniqueness of acquired knowledge	Potentially high	Low; knowledge is in principle also available to competitors
Transfer of knowledge	Typically requires relation-specific investment with knowledge source	Transaction
Costs for identification of knowledge sources	High and firm-specific	Low and at least partially born by knowledge suppliers
Flexibility for entering new search directions	Low; limited by relation-specific investments with existing knowledge sources	High
Opportunity for comparing alternative technological solutions	Low; limited by relation-specific investments with existing knowledge sources	High; limited by supply side of market

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Share of sales w/ new products (t+2)	0.20	0.24	0	1
Extent external knowledge sourcing	3.09	1.62	0	7
Inlicensing expenditures per sales (share)	0.00	0.01	0	0.24
Industry licensing exp. (bn EUR)	0.13	0.15	0.00	0.95
Industry licensing exp. as share of R&D exp.	0.10	0.11	0.01	0.75
R&D intensity	0.04	0.09	0	0.97
Patent stock (log)	0.33	0.83	0	8.20
Firm age (log)	2.97	0.93	0	5.26
No of employees (log)	4.15	1.67	0	12.39
Export intensity	0.21	0.26	0	1
Process innovator (d)	0.56	0.50	0	1
East Germany (d)	0.35	0.48	0	1
Part of group (d)	0.35	0.48	0	1
Low-tech manufacturing (d)	0.35	0.48	0	1
Medium-tech manufacturing (d)	0.22	0.42	0	1
High-tech manufacturing (d)	0.11	0.31	0	1
Distributive services (d)	0.09	0.28	0	1
Knowledge-intensive services (d)	0.08	0.27	0	1
Technology-oriented services (d)	0.15	0.36	0	1
Survey year 2001	0.31	0.46	0	1
Survey year 2005	0.32	0.47	0	1
Survey year 2009	0.37	0.48	0	1

n=2131

Table 3: Correlation coefficients

	Explanatory variables	1	2	3	4	5	6	7	8	9	10	11	12
1	Extent external knowledge sourcing	1.00											
2	Inlicensing expenditures per sales (share)	0.04	1.00										
3	Industry licensing exp. (bn EUR)	0.02	0.02	1.00									
4	Industry licensing exp. as share of R&D exp.	-0.12	0.03	0.01	1.00								
5	R&D intensity	0.12	0.08	0.04	-0.14	1.00							
6	Patent stock (log)	0.18	-0.02	0.05	-0.15	0.06	1.00						
7	Firm age (log)	0.02	-0.07	-0.07	0.07	-0.18	0.22	1.00					
8	No of employees (log)	0.16	-0.10	0.12	-0.06	-0.13	0.46	0.29	1.00				
9	Export intensity	0.14	-0.01	0.08	-0.21	0.08	0.42	0.15	0.36	1.00			
10	Process innovator (d)	0.09	0.02	0.04	-0.01	-0.01	0.09	0.00	0.19	0.05	1.00		
11	East Germany (d)	0.05	0.01	-0.05	-0.02	0.14	-0.18	-0.35	-0.23	-0.23	0.00	1.00	
12	Part of group (d)	0.09	-0.01	0.08	-0.02	-0.08	0.30	0.09	0.50	0.26	0.11	-0.16	1.00
	Variance inflation factor	1.10	1.04	1.28	1.97	1.23	1.47	1.30	1.89	1.52	1.05	1.23	1.38
	Condition number	18.75											

n=2131

Table 4: Tobit results for the share of sales with new products

	Model 1 Full sample	Model 2 Full sample	Model 3 Full sample	Model 4 High mft cov.	Model 5 Low mft cov.
R&D intensity (ratio)	0.80***	0.76***	0.75***	0.71***	0.73***
	(0.10)	(0.09)	(0.09)	(0.14)	(0.12)
Patent stock (log)	0.01	0.01	0.01	0.02	0
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Company age in years (log)	-0.04***	-0.04***	-0.04***	-0.03***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
No of employees (log)	0.02***	0.01**	0.01**	0.01*	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Export intensity (ratio)	0.14***	0.14***	0.14***	0.19***	0.10**
	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)
Process innovator (d)	0.01	0.01	0.01	0.02	-0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
East Germany (d)	0.00	-0.01	-0.01	0.01	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Part of group (d)	-0.01	-0.02	-0.02	0	-0.03
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Industry dummies	incl.	incl.	incl.	incl.	incl.
Survey year dummies	incl.	incl.	incl.	incl.	incl.
Extent of external knowledge sourcing (index)		0.02***	0.03***	0.03***	0.03***
		(0.00)	(0.01)	(0.01)	(0.01)
Inlicensing expenditures per sales (share)		1.52**	-1.19	-1.33	1.41
		(0.61)	(1.36)	(1.45)	(4.95)
Industry licensing exp. (bn EUR)		0.13***	0.35***	0.31**	0.29
		(0.05)	(0.10)	(0.12)	(0.19)
Industry licensing exp. as share of R&D exp.		0.11	0.1	0.20**	1.33*
		(0.07)	(0.07)	(0.08)	(0.79)
Extent ext. know. sourcing * inlicensing			0.86**	0.86**	0.41
			(0.38)	(0.43)	(1.19)
Extent ext. know. sourcing * industry licensing			-0.07***	-0.07**	-0.06
			(0.03)	(0.03)	(0.04)
Constant	0.15***	0.09**	0.06*	-0.04	0.11*
	(0.03)	(0.04)	(0.04)	(0.05)	(0.07)
Pseudo R2	0.23	0.26	0.26	0.28	0.21
N	2131	2131	2131	1014	1117
F-statistic	22.04	20.83	19.79	12.43	7.75
P-value	0.00	0.00	0.00	0.00	0.00

Coefficients are shown; standard errors in parentheses; (d) dummy variable; * p<0.10, ** p<0.05, *** p<0.01
Industry dummies are jointly significant in each model; survey year dummies are not significant.

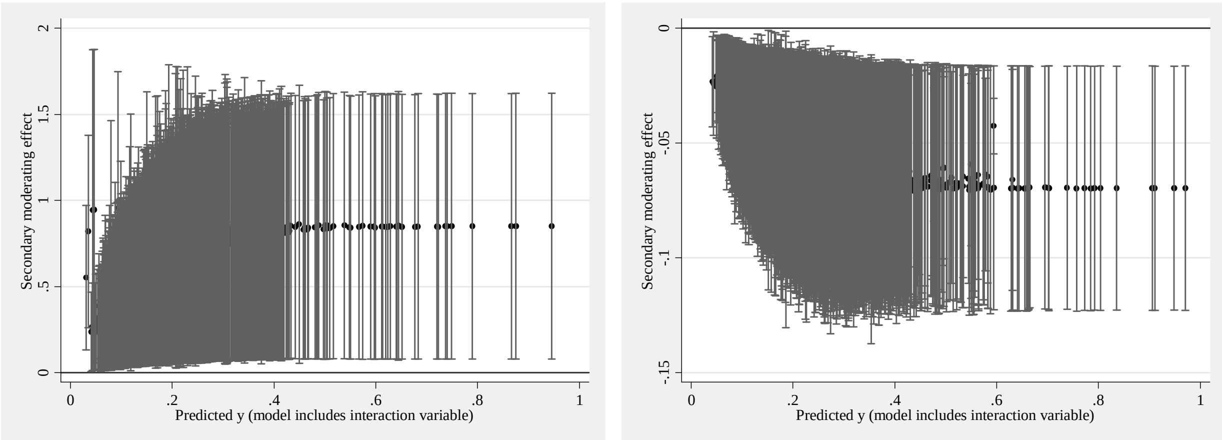
Table 5: Tobit results for the share of sales with new products (consistency checks)

	Model 6 Reduced sample	Model 7 Heteroscedastic tobit [a)]	Model 8 Random intercept model [b)]
R&D intensity (ratio)	0.82***	0.72***	0.63***
	(0.14)	(0.08)	(0.06)
Patent stock (log)	-0.01	0.00	0.00
	(0.01)	(0.01)	(0.01)
Company age in years (log)	-0.03***	-0.04***	-0.03***
	(0.01)	(0.01)	(0.01)
No of employees (log)	0.02***	0.01***	0.01
	(0.01)	(0.00)	(0.00)
Export intensity (ratio)	0.19***	0.12***	0.09***
	(0.04)	(0.03)	(0.02)
Process innovator (d)	-0.01	0.00	0.01
	(0.02)	(0.01)	(0.01)
East Germany (d)	-0.01	0.00	0.01
	(0.02)	(0.01)	(0.01)
Part of group (d)	-0.02	-0.02	-0.01
	(0.02)	(0.01)	(0.01)
Industry dummies	included	included	not included
Survey year dummies	included	included	included
Extent of external knowledge sourcing (index)	0.03***	0.03***	0.02***
	(0.01)	(0.00)	(0.00)
Inlicensing expenditures per sales (share)	-2.32	-1.45	-1.24
	(2.19)	(1.51)	(1.14)
Industry licensing exp. (bn EUR)	0.32**	0.34***	0.18**
	(0.14)	(0.10)	(0.08)
Industry licensing exp. as share of R&D exp.	0.34**	0.14*	-0.05
	(0.16)	(0.08)	(0.06)
Extent ext. know. sourcing * inlicensing	1.16*	0.90**	0.80**
	(0.70)	(0.44)	(0.33)
Extent ext. know. sourcing * industry licensing	-0.09**	-0.07**	-0.04*
	(0.04)	(0.03)	(0.02)
Industry patenting importance (share)	0.43**		
	(0.18)		
Constant	-0.11*	0.02	0.16***
	(0.06)	(0.03)	(0.03)
Pseudo R2	0.23	0.26	
N	1335	2131	2131
F-statistic / Wald Chi2	12.64	20.33	413.2
P-value	0.00	0.00	0.00

Coefficients are shown; standard errors in parentheses; (d) dummy variable; * p<0.10, ** p<0.05, *** p<0.01
[a)] Industry dummies included in heteroscedasticity term; [b)] The intercept varies across 19 industries

APPENDIX

Figure 1: Secondary moderating effects



Note: Graphs show the secondary moderating effects (Wiersema and Bowen, 2009) at each observation in the full sample for the interaction of external knowledge search and firm inlicensing (left figure) and for the interaction of external knowledge search and industry licensing (right figure). The graphs also indicate the 95 percent confidence interval for each moderating effect. In both panels, the confidence interval does not intersect with the horizontal axis, indicating that the moderating effect is in fact significantly different from zero. Calculating the moderating effects in the split samples show consistent results: the moderating effect is positive (negative) and significant for the interaction between external knowledge search and firm inlicensing (the interaction between external knowledge search and industry licensing) in the high coverage sample and insignificant in the low coverage sample.