How can firms extend their limits to processing diversified knowledge?

The effects of foreign direct investment and R&D cooperation

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Abstract

Recent research suggests that the positive effect of knowledge diversification on the value of corporate knowledge is limited. This study uses an information processing perspective to explore the highest value that firms can draw from knowledge diversification and to argue that foreign direct investment and R&D cooperation help develop this value. Regressions on a sample of 21.434 patents of German manufacturing firms show that technologically diversified knowledge has an inverted U-shaped influence on the value of technological knowledge. The findings also suggest that foreign direct investment increases the value generated by geographically diversified knowledge, and that R&D cooperation increases the value generated by technologically diversified knowledge.

Keywords

Knowledge, patent citations, FDI, cooperation

INTRODUCTION

Technological knowledge is an essential asset for manufacturing firms. There are two opposing views regarding the effect of diversified knowledge. On the one hand, low diversification of knowledge leads to scale economies in R&D, and specialization increases a firm's ability to solve in-depth problems (Christensen & Montgomery, 1981; Kim, Lim, & Park, 2009). On the other hand, specialization may lead to being "locked-into" old knowledge (Narula, 2002; Redding, 2002). To avoid this technological cul-de-sac, knowledge diversification is necessary for further innovations (Feldman & Audretsch, 1999; Garcia-Vega, 2006; Nesta & Saviotti, 2005). We propose in this paper that firms benefit from knowledge diversification, however, as soon as the information to be processed becomes too complex, knowledge diversification has a negative effect. The studies of Leten, Belderbos, & Van Looy (2007) as well as Kotabe et al. (2007) reveal such an inverted U-shape of knowledge diversification. We further examine how the optimal level of knowledge diversification can be extended by increasing the firm's information processing capacity. We investigate foreign direct investment (FDI) as a mechanism to augment a firm's information processing capacity concerning geographically distant knowledge and R&D cooperation to increase a firm's capacity to process technologically distant knowledge.

Jaffe, Trajtenberg, & Henderson (1993) and Jaffe & Trajtenberg (1999) show that firms tend to use technologically proximate knowledge when creating new knowledge. Furthermore, they reveal that patents more likely cite patents from the same country, thus knowledge tends to remain localized. They constitute these findings by endogenous economic growth models such as Romer (1990) and Grossman & Helpman (1991), which state that knowledge is distributed in an economy, but it does not diffuse across economies. In the literature of international business, Kim, Hwang, & Burgers (1993) and Qian (1997) reveal that geographical diversification in the sense of internationalization has a positive effect, whereas Hitt, Hoskisson, & Kim (1997) as well as Chang & Wang (2007) find an inverted U-shaped effect. Kotabe et al. (2007) consider the limit of geographical diversification of knowledge and find an inverted U-shaped relationship between international knowledge transfer and innovative performance. They apply a resource-based view and explain the positive effect of geographical diversification of knowledge at low levels of knowledge transfer by a firm's competitive advantage through strategic assets and capabilities. Kotabe et al. (2007) justify the negative effect after the turning point by a bundle of theories. Models from the literatures on knowledge, social network, and complexity argue that integrating transferred knowledge at high levels of diversification require a complex and costly integration.

Regarding technological diversity of knowledge, Nesta & Saviotti (2005), Garcia-Vega (2006), and Rosenkopf & Nerkar (2001) find a positive effect on innovative performance. Rosenkopf & Nerkar (2001) apply the resource-based view (Wernerfelt, 1984) and emphasize the usefulness of technologically distant knowledge as knowledge exploration, which spans organizational and technological boundaries and enables a stronger impact on subsequent technological evolution than technologically proximate knowledge. Leten, Belderbos, & Van Looy (2007) identify the limit of technological knowledge diversification and reveal an inverted U-shape. They argue that technological diversification offers opportunities for technology fusion and cross-fertilization. However, at high levels of technological diversification, costs of coordinating and integrating diversified knowledge exceed the benefits. A non-linear influence of geographically and technologically diversified knowledge has been described, however, no fully consistent theory is given as an explanation. Furthermore, appropriate mechanisms by which firms can expand the maximum extent of knowledge diversification have not been considered yet.

Due to constraints to processing highly diversified knowledge, firms search for mechanisms to extend the optimal level of knowledge diversification. We investigate mechanisms at the intra- and the inter-firm level. At the intra-firm level, firms may acquire other firms (Carayannopoulos & Auster, 2010) or build up foreign subsidiaries close to the knowledge gap of their interest (Branstetter, 2006). In the long run, it is more effective for large firms to position a subsidiary in a foreign country to benefit from its knowledge (Kimura, 1989; Frost, 2001). Therefore, we concentrate on FDI as a mechanism to increase the information processing capacity at the intra-firm level. Firms profit from an improved access to geographically distant knowledge by FDI. Foreign subsidiaries benefit from the access to local information channels and exploit local firms in host countries (Branstetter, 2006), as they use regional knowledge significantly more intensively than domestic firms do (Almeida, 1996). The positive effect of processing geographically distant knowledge through FDI can be viewed analogous to absorbing this knowledge; foreign subsidiaries increase a firm’s information processing capacity. At the inter-firm level, companies may collaborate in R&D (Wang & Zajac, 2007) to increase the relevant information processing capacity. R&D partnership is the most cost-efficient and time-saving mode of learning (Kumar & Nti, 1998). We define collaborative R&D projects as any kind of R&D partnership between companies that result in a joint patent. R&D cooperation provides an access to technical skills and technological capabilities of cooperating partners (Mariti & Smiley, 1983; Mody, 1993; Scott, 2003; Shan, 1990). These advantages of R&D collaborations support a firm in processing technologically distant knowledge. Dunlap-Hinkler, Kotabe, & Mudambi (2010) investigate the effect of FDI as well as cooperation on the likelihood of an innovation to be breakthrough. They found that a firm’s breakthrough capabilities are positively influenced by FDI as well as cooperation.

We build a theoretical framework using information theory to predict a non-linear relationship of geographically as well as technologically distant knowledge on the value of a firm’s technological knowledge. We investigate whether the optimal level of knowledge diversification may be extended by increasing a firm’s information processing capacity through FDI or R&D cooperation. Our sample includes patent citations of the 102 largest listed manufacturing firms in Germany. We chose manufacturing companies as they are responsible for the major share of R&D in Germany (Lang, 2009).

We proceed as follows. In the next section we derive our hypotheses. In the third section, we present the data and measurements and explain the empirical methods used to test the hypotheses. The fourth section presents the results of the influences of technologically and geographically distant knowledge on the value of technological knowledge of a firm. Moreover, we investigate the moderating effects of FDI and R&D cooperation on these relationships. In the last section, we discuss our findings, conclude the study with research and management implications, and shed light on its limitations.

HYPOTHESES DEVELOPMENT

The value of technological knowledge relates to its information content. In Shannon's (1948) information theory, entropy quantifies the information content of a message. According to Galbraith's (1977) information processing theory, organizations have the ability to process a certain amount of information. Information processing in organizations is generally defined as including the gathering of data, the transformation of data into information, and the communication and storage of information in the organization (Galbraith, 1973). Thus information must effect a change in knowledge. An organization is efficient in the perspective of Galbraith (1977) when the required amount of information processing is equal to the information processing capacity. At low levels of knowledge diversification, firms can directly benefit from diversified knowledge, as it holds a higher information content than narrow knowledge. At high levels of knowledge diversification, their capacity to process information reaches a limit, as processing the diversified knowledge becomes too complex. High levels of knowledge diversification deal with knowledge that is heterogeneous and probably even unique. Processing this kind of knowledge is additionally a non-routine process, which makes information processing even more difficult. Based on this argument, we predict that knowledge diversification has an inverted U-shaped influence on the value of technological knowledge. In an MNC it can be assumed that a relatively high amount of diversified knowledge has to be processed. According to Galbraith's (1977) information processing theory an MNC may either reduce its need for information processing or increase the capacity to process information. As an MNC may create a competitive advantage via a high knowledge diversification rather than limiting its demand on new information and stagnating, it should use external effects supporting the MNC to process a high amount of diversified knowledge.

We distinguish between geographically and technologically diversified knowledge. Geographically distant knowledge evolves in countries that show a weak interchange of information. Firms in distinct countries may have used different approaches and reached different solutions for the same problem.

Therefore, it can be beneficial for a firm to combine these results to a new solution, even though the knowledge is allocated in the same technological area. New knowledge from a geographical distance produces a positive effect on the value of technological knowledge of a firm as long as the content of information and thus the number of countries from which information is drawn does not become excessive. Otherwise, processing geographically distant information reaches a limit and turns into a negative effect on the value of technological knowledge as information processing gets too complex. This prediction corresponds to Kotabe et al. (2007) who find that international knowledge has an inverted U-shaped effect on innovative performance.

H1a: The geographical diversity of knowledge has an inverted U-shaped influence on the value of technological knowledge.

As new ideas typically arise by combining previous ideas, firms also benefit from technologically distant knowledge. The positive effect of knowledge diversification will continue as long as the firm has sufficient information processing capacity. The effect will turn negative when the diversity of knowledge becomes confusing and makes the combination of ideas more difficult. In analogy to geographical diversity, we expect that technological diversified knowledge has an inverted U-shaped effect on the value of technological knowledge as found by Leten, Belderbos, & Van Looy (2007).

H1b: The technological diversity of knowledge has an inverted U-shaped influence on the value of technological knowledge.

To cope with rising information processing requirements, organizations may employ mechanisms to increase their information processing capacity (Galbraith, 1977). They can augment their information processing capacity concerning geographically distant knowledge by FDI, since foreign subsidiaries are familiar with local knowledge. An internal entity as a subsidiary creates a more reliable access to local knowledge than an external agent intermediating for the MNC on the foreign market. Chung & Yealpe (2008) and Phene & Almeida (2008) show that FDI increases a firm’s ability to absorb knowledge which develops in a foreign country. It seems likely that also processing this knowledge can be done more efficiently by the assistance of foreign subsidiaries.

H2: Foreign direct investment positively moderates the relationship between geographically distant knowledge and the value of technological knowledge.

To extend the optimal level of technologically distant knowledge, firms may enter R&D cooperation. R&D partnerships can be seen as a complementary strategy to in-house R&D, as it makes the cooperating partners' resources available to the firm (Mowery, Oxley, & Silverman 1996; Zahra & George, 2002). They increase the information processing capacity regarding technologically distant knowledge when the partner possesses additional abilities and knowledge to process information more efficiently. Collaborating firms seem to be more successful in absorbing technologically distant and unique knowledge than firms doing research in solo (Cassiman & Veugelers, 2002; Chung & Yealpe, 2008; de Jong & Freel, 2010). We also expect a positive effect of R&D cooperation on processing technologically distant knowledge.

H3: R&D collaborations positively moderate the relationship between technologically distant knowledge and the value of technological knowledge.

EMPIRICAL METHODS

Data

The sampling process started with the 102 quoted manufacturing firms that are recorded in the *Welt 500* list of the largest German companies in the year 1990. Patent data of these firms were collected from the *OECD/EPO patent citation database*, which features all European patents as well as their cited patents. The citation data are complemented from 2000 on backwards until 1990. Citations of earlier patents are used to track knowledge flows (Rosenkopf & Almeida, 2003). It needs to be mentioned that not all citations reflect knowledge flows, as some citations are made to distinguish the invention from similar ones or to avoid litigation. A further limitation of patent data is that firms undertake research that is not granted in patents (Desrochers, 1998). Nevertheless, patent citations allow for observing technological knowledge flows in a larger sample than any other known method.

Applicant information for the cited patents is not provided by the *OECD/EPO patent citation database*. The data were collected by the cited patents' number from the German patent office database *DEPATISNET*, which includes worldwide patents. The data were then matched back to the sample group. 77 of the 102 manufacturing firms held 25.492 patents in the observation period, citing in total 107.640 prior patents. 43 of the companies held patents in cooperation with other firms, two of them have patents which resulted from R&D collaborations only. Based on scientometrics where research collaboration is measured by co-authorship (Katz & Martin, 1997), we use co-applicants to identify cooperative research between firms. The applicant firms' names were harmonized, e.g. the German automotive company *Bayerische Motoren Werke Aktiengesellschaft* appears also as *BMW AG*, *Bayerische Motorenwerke AG*, or *Bayerische Motorenwerke Aktiengesellschaft*. Patents with more than one applicant firm and with at least two inventors working for different firms were classified as cooperative. As some of the patents have more than one of the sample group's companies as applicants, these patents were counted multiple times. The final sample of patents that are to reflect R&D collaboration consists of 1.391 observations. These 1.391 focal patents cite 6.171 previous patents.

During the period of observation, German accounting standards required listed firms to display their (foreign) subsidiaries in the annual reports. We collected data on firm FDI from annual reports as well as from *Hoppenstedt Aktienführer* (a periodical collection of financial data on German listed firms), *Thomson Reuters Datastream*, and *Bureau van Dijk*'s databases *Amadeus* and *Dafne* for the years 1990-2000. We excluded firms that patented in one year during the observation period. The final sample of patents that refer to FDI comprises 21.434 observations of 68 firms. As some firms do not have patents in each year, the panel has gaps and is unbalanced.

Measures

Dependent variable

To assess the importance of geographically and technologically diversified knowledge, we examine its effect on the *value of technological knowledge*. The simple number of patents a firm holds does not give information about the importance and thus value of a patent (Griliches, Pakes, & Hall, 1987). Therefore we measure the *value of technological knowledge* by the number of forward citations of the focal patent (Harhoff et al., 1999; Trajtenberg, 1990). Citations may be used to capture knowledge flows (e.g., Jaffe, Forgarty, & Banks, 1998; Mudambi & Navarra, 2004) but also to measure the value of a patent (e.g., Hall, Jaffe, & Trajtenberg, 2005; Narin, Noma, & Perry, 1998). Forward citations are citations received by the focal patent from subsequently issued patents. In contrast to scientific publications inventors have no incentive to cite other patents unnecessarily, as it may reduce their claims to novelty of the invention. Thus a high number of received citations indicate a patent of relatively high value, as forward citations show that the information in the focal patent has served as a basis for a future invention. A high value indicates that the focal patent is subject to a great level of competition (Lanjouw & Schankerman, 2001) and thus could add to the competitive advantage of a firm. As the patents in our sample have different levels of maturity and the citation frequency of young patents should be lower, we only observe the three years after a patent's grant, as the citation frequency to German-invented patents is highest in these years (Jaffe & Trajtenberg, 1999).

Independent variables

We capture the *geographical diversity* of knowledge by the number of countries from which the cited patents' firms originate. As all firms are German, a patent that cites only patents of German firms has a *geographical diversity* of 0. In opposite, a patent with a geographical diversity of 1 builds just on foreign knowledge. Data of the cited patents were collected from *DEPATISNET*. The sample's patents cite in total patents from applicants coming from 49 different countries worldwide. Most of the cited patents' applicants are from Germany, the United States and Japan. We follow Lerner's (1994) approach to measure a patent's *technological diversity*. However, instead of capturing the focal patent's scope, we measure *technological diversity* by the technological diversity of its knowledge sources. *Technological diversity* is the number of different three-digit international patent classifications (IPCs) codes of the cited patents according to their application document. On the one hand, we contemplate an increase of information processing through *FDI*. *FDI* is the number of countries in which a firm maintains foreign subsidiaries. Information about the firms' foreign subsidiaries was collected from their annual reports and *Hoppenstedt Aktienführer*. The firms of the focal patents have in total subsidiaries in 100 different countries. However, 50% of all foreign subsidiaries of the patents' firms are in the top ten countries. On the other hand, information capacity may be increased by collaborating in R&D. Patents with more than one applicant and more than one inventor are considered as an outcome of R&D collaboration. We count the number of collaborating partners to measure *cooperation*.

Control variables

As patent-level controls, we use the number of patents, the number of inventors, and the exploitative character of a patent. The number of patents indicates the absorptive capacity of a firm and should have a positive impact on its innovation performance and on the value of its technological knowledge (Escribano, Fosfuri, & Tribo 2009). We divide the number of patents a firm produced per year by the total number of patents of that firm. We logarithmize this ratio as the value of technological knowledge of a company does not increase proportionally with the number of patents (variable name *logpatent*). We measure the number of inventors as a proxy of the resources which were invested in a research project. The more people assigned, the higher are the costs of a project. A high number of inventors in a project should lead to a valuable result in a successful company (Gittelman & Kogut, 2003). We logarithmize this variable, as the value of technological knowledge in a firm increases less than proportionally as the number of inventors rises (*loginventor*).

We follow March's (1991) concept of knowledge exploration and exploitation and create a binary variable to distinguish these two methods of knowledge creation. A dummy variable indicates whether the patent cites patents of the focal firm, hence exploits knowledge (*exploitation* = 1), or explores knowledge by citing patents of other firms only (*exploitation* = 0). For collaborative R&D projects, we assign patents to explorative collaborations if there are no citations of patents of the focal company or its cooperation partners. We attribute those patents to exploitative collaborations in which at least one of the applicant firms of the cited patents is identical to a firm on the focal patent.

We use age and size as firm-level controls. Older firms tend to have accumulated experience and knowledge in different technological fields. However, they often do not create new knowledge, and therefore their innovations have less impact than those of younger firms. Older firms tend to create less valuable knowledge as they are less flexible and more risk-averse than young firms since they have inertial structures and routines and managers tend to be less entrepreneurial (Sorenson & Stuart, 2000). We measure the age of the firm by the number of years since establishment and logarithmize it as technological knowledge of a company does not increase proportionally with rising age (*logage*). Large firms seem to create less new knowledge than small firms (Acs & Audretsch, 1991). As large firms are mostly diversified they do not profit from additional diversification as much as small firms do. However, large firms tend to have a larger knowledge base compared to small firms. In addition, large firms have more financial and technological resources to invest in R&D than small firms and thus may diversify risk of unpredictable R&D outcomes. Therefore we expect a positive influence of firm size on the value of its technological knowledge. We use the total number of employees to operationalize firm size and, due to the distribution in the sample, logarithmize the variable (*logsize*).

The dependent variable consists of non-negative integers, thus we need to use a count data model. Poisson regression could be a suitable technique. However, as there is an overdispersion of the dependent variable, viz. the variance is substantially larger than the mean, we use negative binomial regressions; they are widely used in patent literature. There might be unobserved heterogeneity among firms which causes error terms at the firm level to be correlated over time, which leads to inconsistent estimates. To control for these correlations, we follow Hausman, Hall, & Griliches (1984) who recommend a conditional fixed-effects negative binomial model. Allison & Waterman (2002) reveal that the conditional fixed effects negative binomial model is not a true fixed effects model as it does not control for all predictors, therefore we follow Hilbe (2008) and use a random-effects negative binomial model instead which includes time dummies and clusters by firms.

RESULTS

Table 1 reveals the descriptive statistics. The focal patents received 0 to 25 citations, have foreign subsidiaries in 12 countries on average and cooperate with up to 4 partners in one research project. The variables show weak pairwise correlations. The variance inflation factors (VIF) of all variables are low, indicating little problems of multicollinearity.

Insert Table 1 about here

Table 2 presents the regressions. Model 1 is the base model. Model 2 tests the linear term of *geographical diversity*. It is significant and positive. We include the squared term of *geographical diversity* in Model 3. Opposed to the prediction of *Hypothesis 1a*, it is not significant. The linear term of *geographical diversity* also turns to be insignificant. This finding contradicts *Hypothesis 1a,* which expects an inverted U-shaped effect of *geographical diversity* on the *value of technological knowledge*.

Insert Table 2 about here

We test the linear term of *technological diversity* in Model 4. It has a significantly positive influence on the *value of technological knowledge*. We add the squared term of *technological diversity* in Model 5. The squared term is negative and significant as expected while the linear term remains positive and significant. This finding gives support to *Hypothesis 1b* that the benefit of *technologically diversified* knowledge is limited due to information processing restrictions and has an inverted U-shaped influence on the *value of technological knowledge*.

We create the interaction term of *FDI* and *geographical diversity* in Model 6. It is significantly positive, thus *FDI* appears to increase the capacity of information processing of *geographically distant* knowledge and has a significant impact on the *value of technological knowledge* as predicted in *Hypothesis 2*. We add the interaction term of *cooperation* and *technological diversity* in Model 7. As Model 5 shows that technological diversity is U-shaped, we also include the squared term of technological diversity. The interaction of *cooperation* and the U-shaped *technological diversity* is significantly positive. As stated in *Hypothesis 3*, *cooperation* seems to increase the capacity of information processing concerning *technologically distant* knowledge.

Model 8, the full model, contains the linear and squared terms of *technological diversity* and the linear term of *geographical diversity* as well as the interaction terms of *FDI* and *cooperation*. We observe a stable inverted U-shaped influence of *technological diversity* and a linear positive effect of *geographical diversity*. All interaction terms are stable suggesting that *FDI* increases the capacity of information processing concerning *geographically distant* knowledge whilst *cooperation* increases the capacity of information processing concerning *technologically distant* knowledge.

The patent-level control variables *logpatent, loginventor*, and *exploitation* are significantly positive as expected. The firm-level control variables *logsize* and *logage* have the expected signs, however, their influence on the *value of technological knowledge* is not significant. All Wald Chi square tests are significant, indicating that the parameters associated with the explanatory variables are not zero and the variables should be included in the model (Greene, 2008).

DISCUSSION

The paper seeks to clarify whether the value effect of knowledge diversification reaches a limit of information processing capacity and how the optimal level of technologically and geographically diversified knowledge may be extended by FDI and R&D cooperation. We predicted an inverted U-shape of geographically distant knowledge as Kotabe et al. (2007), however, find that geographically distant knowledge has a linear positive effect. A reason for this finding might be that internationalizing firms tend to choose foreign locations along a chain of rising psychic distance (Johanson & Vahlne, 1977; Johanson & Vahlne, 2009; O'Grady & Lane, 1996) and therefore geographical diversification remains relatively low. We find an inverted U-shaped effect of technologically distant knowledge. At low levels of technological diversity, additional technological diversification has a positive effect on the value of technological knowledge. However, with increasing diversity, the limit of information processing capacity seems to be reached and more diversified knowledge leads to confusion rather than to more valuable knowledge.

We investigate whether FDI and cooperation extend the optimal level of knowledge diversification. Establishing foreign subsidiaries in a variety of countries increases a firm's ability to process geographically distant knowledge. In an experimental regression we tested the moderating effect of FDI on the relationship between technologically distant knowledge and the value of technological knowledge and found it to be insignificant. This finding is in line with Chung & Yeaple (2008) who reveal that firms are not motivated to diversify technologically when investigating abroad. However, they are interested in similar R&D efforts to share fixed R&D costs. R&D cooperation augments the capacity of a firm to process technologically distant knowledge. In an experimental regression we tested the interaction term of R&D cooperation and geographically distant knowledge and found it to be significant. Our findings are stable in the full model. Geographically distant knowledge as well as low and moderate levels of technologically distant knowledge have a positive effect on the value of technological knowledge. To avoid a diminishing effect of diversification on the value of technological knowledge, FDI and R&D cooperation may be used to extend the optimal level of knowledge diversification.

The paper applies information theory to justify the effect of technologically and geographically distant knowledge as well as the effect of FDI and R&D cooperation to extend the optimal level of knowledge diversification. Prior studies, e.g. Feldman & Audretsch (1999), Garcia-Vega (2006), and Nesta &

Saviotti (2005), examine a linear positive influence of diversification. We enrich our study by including the squared terms of technologically and geographically distant knowledge as in Kotabe et al. (2007) and Leten, Belderbos, & Van Looy (2007). However, these studies justify their finding of an inverted U-shaped effect of diversification with arguments from different theories. The information theory, which is applied in this paper, provides an explanation for both the inverted U-shape of diversification and the extension of the optimal diversification of knowledge by FDI and R&D cooperation.

As the influence of technological diversity has an inverted U-shape managers should gain knowledge from different technological areas, however, they should not seek knowledge from an excessive number of diverse technological areas. Managers may establish foreign subsidiaries to support processing of geographically distant knowledge. We recommend managers to use R&D cooperation to extend the optimal level of technologically distant knowledge. Specifically, we advise them to choose partners with a diversified technological background.

As firms doing research in solo reach their limits at some point, they may get new knowledge through R&D collaborations. Research funding institutions should encourage firms to find a collaboration partner with a diversified technological background and support this cooperation financially. R&D cooperation are an important driver for creating new knowledge, which strengthen a firm’s competitive advantages and thereby also a country’s superiority.

Our theoretical model misses out on calculating the maximum level of knowledge diversification and is not precise enough to predict the enhancing effects of FDI and R&D cooperation for individual firms. Our implications for research and management are further limited by the sample used in this study. We use patent citations to measure knowledge transfers. However, not all citations represent knowledge spillovers, as some are added by the patent examiner. Moreover, not all inventions are patented. As managers are highly involved in the decision process of initiating foreign subsidiaries and R&D cooperation, the manager’s openness toward new knowledge should be considered. Future research may investigate the issues that remained unattended by this study.

REFERENCES

Acs, Z.J., & Audretsch, D.B. 1991. Innovation and size at firm level. ***Southern Economic Journal***, 57(3): 739-744.

Allison, P.D., & Waterman, R.P. 2002. Fixed-effects negative binomial regression models. ***Sociological Methodology***, 32(1): 247-265.

Almeida, P. 1996. Knowledge sourcing by foreign multinationals: Patent citations analysis in the U.S. semiconductor industry. ***Strategic Management Journal***, 17: 155-165.

Branstetter, L. 2006. Is foreign direct investment a channel of knowledge spillovers? Evidence from Japan`s FDI in the United States. ***Journal of International Economics***, 68(2): 325-344.

Carayannopoulos, S., & Auster, E.R. 2010. External knowledge sourcing in biotechnology through acquisition versus alliance: A KBV approach. ***Research Policy***, 39(2): 254-267.

Cassiman, B., & Veugelers, R. 2002. R&D cooperation and spillovers: Some empirical evidence from Belgium. ***The American Economic Review***, 92(4): 1169-1184.

Chang, S-C., & Wang, C-F. 2007. The effect of product diversification strategies on the relationship between international diversification and firm performance. ***Journal of World Business***, 42(1): 61-79.

Christensen, H.L., & Montgomery, C.A. 1981. Corporate economic performance: Diversification strategy versus market structure. ***Strategic Management Journal***, 2(4): 327-43.

Chung, W., & Yeaple, S. 2008. International knowledge sourcing: Evidence from U.S. firms expanding abroad. ***Strategic Management Journal***, 29(11): 1207-1224.

de Jong, J.P.J., & Freel, M. 2010. Absorptive capacity and the reach of collaboration in high technology small firms. ***Research Policy***, 39(1): 47-54.

Desrochers, P. 1998. On the abuse of patents as economic indicators. ***The Quarterly Journal of Austrian Economics***, 1(4): 51-74.

Dunlap-Hinkler, D., Kotabe, M., & Mudambi, R. 2010. A story of breakthrough versus incremental innovation: Corporate entrepreneurship in the global pharmaceutical industry. ***Strategic Entrepreneurship Journal***, 4(2): 106-127.

Escribano, A., Fosfuri, A., & Tribo, J.A. 2009. Managing external knowledge flows: The moderating role of absorptive capacity. ***Research Policy***, 38(1): 96-105.

Feldman, M.P., & Audretsch, D.B. 1999. Innovation in cities: Science-based diversity, specialization and localized competition. ***European Economic Review***, 43(2): 409-429.

Frost, T.S. 2001. The geographic sources of foreign subsidiaries` innovations. ***Strategic Management Journal***, 22(2): 101-123.

Galbraith, J.R. 1973. ***Designing complex organizations.*** Reading et al.: Addison Wesley Publishing Company.

Galbraith, J.R. 1977. ***Organization design.*** Reading et al.: Addison Wesley Publishing Company.

Garcia-Vega, M. 2006. Does technological diversification promote innovation? An empirical analysis for European firms. ***Research Policy***, 35(2): 230-246.

Gittelman, M., & Kogut, B. 2003. Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns. ***Management Science***, 49(4): 366-382.

Griliches, Z., Pakes, A., & Hall, B.H. 1987. The value of patents as indicators of inventive activity. In: ***Economic policies and technological performance***, Dasgupta, P., & Stoneman, P. (eds.) Cambridge: Cambridge University Press.

Grossman, G.M., & Helpman, E. 1991. Quality ladders in the theory of growth. ***The Review of Economic Studies***, 58(1): 43-61.

Greene, W. 2008. ***Econometric Analysis***. New Jersey: Prentince Hall International.

Hall, B.H., Jaffe, A., & Trajtenberg, M. 2005. Market value and patent citations. ***The RAND Journal of Economics***, 36(1): 16-38.

Harhoff, D., Narin, F., Scherer, F.M., & Vopel, K. 1999. Citation frequency and the value of patented inventions. ***The review of Economics and Statistics***, 81(3): 511-515.

Hausman, J.,Hall, B.H., & Griliches, Z. 1984. Econometric models for count data with an application to the patents-R&D relationship. ***Econometrica***, 52(4): 909-938.

Hilbe, J.M. 2008. ***Negative binomial regression.*** Cambridge: Cambridge University Press.

Hitt, M.A., Hoskisson, R.E, Kim, H. 1997. International diversification: Effects of innovation and firm performance in product-diversified firms. ***Academy of Management Journal***, 40(4): 767-798.

Jaffe, A.B., Fogarty, M.S., & Banks, B.A. 1998. Evidence from patents and patent citations on the impact of NASA and other federal labs on commercial innovation. ***The Journal of Industrial Economics***, 46(2): 183-205.

Jaffe, A.B., Trajtenberg, M., & Henderson R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. ***The Quarterly Journal of Economics***, 63(3): 577-598.

Jaffe, A.B., & Trajtenberg, M. 1999. International knowledge flows: Evidence from patent citations. ***Economics of Innovation and New Technology***, 8(1): 105-136.

Johanson, J., & Vahlne, J.-E. 1977. The internationalization process of the firm. A model of knowledge development and increasing foreign market commitments. ***Journal of International Business Studies***, 8(1): 23-32.

Johanson, J., & Vahlne, J.-E. 2009. The Uppsala internationalization process model revisited: From liability of foreignness to liability of outsidership. ***Journal of International Business Studies***, 40(9): 1411-1431.

Katz, J.S., & Martin, B.R. 1997. What is research collaboration?. ***Research Policy***, 26(1): 1-18.

Kim, H., Lim, H., & Park, Y. 2009. How should firms carry out technological diversification to improve their performance? An analysis of patenting of Korean firms. ***Economics of Innovation and New Technology***, 18(8): 757-770.

Kim**,** W.C., Hwang**,** P., & Burgers W. 1993 Multinationals' diversification and the risk-return trade-off. ***Strategic Management Journal***, 14(4): 275-286.

Kimura, Y. 1989. Firm-specific strategic advantages and foreign direct investment behavior of firms: The case of Japanese semiconductor firms. ***Journal of International Business Studies***, 20(2): 296-314.

Kotabe, M., Dunlap-Hinkler, D., Parente, R., & Mishra, H.A. 2007. Determinants of cross-national knowledge transfer and its effect on firm innovation. ***Journal of International Business Studies***, 38(2): 259-282.

Kumar, R., & Nti, K.O. 1998. Differential learning and interaction in alliance dynamics: A process and outcome discrepancy model. ***Organization Science***, 9(3): 356-367.

Lang, G. 2009. Measuring the returns of R&D – An empirical study of the German manufacturing sector over 45 years. ***Research Policy***, 38(9): 1438-1445.

Lanjouw, J.O., & Schankerman, M. 2001. Characteristics of patent litigation: A window on competition. ***The RAND Journal of Economics***, 32(1): 129-151.

Leten, B., Belderbos, R., &Van Looy, B. 2007. Technological diversification, coherence, and performance of firms. ***The Journal of Product Innovation Management***, 24: 567-579.

Lerner, J. 1994. The importance of patent scope: An empirical analysis. ***The RAND Journal of Economics***, 25(2): 319-333.

March, J.G. 1991. Exploration and exploitation in organizational learning. ***Organization Science***, 2(1): 71-87.

Mariti, P., & Smiley, R.H. 1983. Co-operative agreements and the organization of industry. ***Journal of Industrial Economics***, 31(4): 437-451.

Mody, A. 1993. Learning through alliances. ***Journal of Economic Behavior and Organization***, 20(2): 151-170.

Mowery, D.C., Oxley, J.E., & Siverman, B.S. 1996. Strategic alliances and interfirm knowledge transfer. ***Strategic Management Journal***, 17: 77-91.

Mudambi, R., & Navarra, P. 2004. Is knowledge power? Knowledge flows, subsidiary power and rent-seeking within MNCs. ***Journal of International Business Studies***, 35(5): 395-406.

Narin, F., Noma, E., & Perry, R. 1998. Patents as indicators of corporate technological strength. ***Research Policy***, 16(2-4): 143-155.

Narula, R. 2002. Innovation systems and 'inertia' in R&D location: Norwegian firms and the role of systematic lock-in. ***Research Policy***, 31(5): 795-816.

Nesta, L., & Saviotti, P.P. 2005. Coherence of the knowledge base and the firm's innovative performance: Evidence from the U.S. pharmaceutical industry. ***The Journal of Industrial Economics***, 53(1): 123-142.

O´Grady, S., & Lane, H.W. 1996. The psychic distance paradox. ***Journal of International Business Studies***, 27(2): 309-333.

Phene, A., & Almeida, P. 2008. Innovation in multinational subsidiaries: The role of knowledge assimilation and subsidiary capabilities. ***Journal of International Business Studies,*** 39(5): 901-919.

Qian, G. 1997. Assessing product-market diversification of US firms. ***Management International Review***, 37(2): 127-149.

Redding, S. 2002. Path dependence, endogenous innovation and growth. ***International Economic Review***, 43(4): 1215-1249.

Romer, P.M. 1990. Endogenous technological change. ***Journal of Political Economy***, 98(5): 71-102.

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

Scott, J.T. 2003. Absorptive capacity and the efficiency of research partnerships. ***Technology Analysis & Strategic Management***, 15(2): 247-253.

Shan, W. 1990. An empirical analysis of organizational strategies by entrepreneurial high-technology firms. ***Strategic Management Journal***, 11(2): 129-139.

Shannon, C.E. 1948. A mathematical theory of communication. ***Bell System Technical Journal***, 27: 379-423, 623-656.

Sorenson, J.B., & Stuart, T.E. 2000. Aging, obsolescence and organizational innovation. ***Administrative Science Quarterly***, 45(1): 81-112.

Trajtenberg, M. 1990. A penny for your quotes: Patent citations and the value of innovation. ***The RAND Journal of Economics***, 21(1): 172-187.

Wang, L., & Zajac, E.J. 2007. Alliance or acquisition? A dyadic perspective on interfirm resource combinations. ***Strategic Management Journal***, 28(13): 1291-1317.

Wernerfelt, B. 1984. A resource-based view of the firm. ***Strategic Management Journal***, 5(2): 171-180.

Zahra, S. A., & George, G. 2002. Absorptive capacity: A review, reconceptualization, and extension. ***Academy of Management Review***, 27(2): 185-203.

TABLE 1

Descriptive statistics

	Variable	Obs	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	VIF
	value of knowledge	21434	.53	1.09	0	25										
1	*geo diversity*	21434	1.71	.94	0	10	1.00									1.16
2	*tech diversity*	21434	2.34	1.14	0	10	0.36	1.00								1.16
3	*FDI*	21434	12.82	7.95	0	63	-0.04	-0.03	1.00							1.10
4	*cooperation*	21434	.11	.43	0	4	-0.06	-0.03	-0.00	1.00						1.06
5	*logpatent**	21434	.15	.09	.01	.8	0.01	0.02	-0.04	0.02	1.00					1.05
6	*loginventor**	21434	2.89	1.84	1	21	0.01	-0.05	0.09	-0.02	-0.06	1.00				1.05
7	*exploitation*	21434	.42	.49	0	1	0.05	0.01	0.04	-0.06	-0.03	0.15	1.00			1.04
8	*logage**	21434	120.39	31.15	17	252	-0.02	-0.07	0.03	-0.23	-0.13	0.13	0.10	1.00		1.11
9	*logsize**	21434	66350.19	109105.6	298	466938	-0.08	-0.07	0.28	0.03	0.14	0.04	0.05	0.06	1.00	1.14

*mean, standard deviation, minimum and maximum refer to the non log. variable

TABLE 2

Random-effects negative binomial regressions of the influence factors on the value of technological knowledge

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
cooperation X tech diversity							0.063**	0.067**
							(0.029)	(0.029)
FDI X geo diversity						0.60E-4***		0.59E-4***
						(0.20E-4)		(0.20E-4)
tech diversity²					-0.015**		-0.014*	-0.012*
					(0.007)		(0.007)	(0.007)
tech diversity				0.060***	0.135***		0.129***	0.107***
				(0.012)	(0.037)		(0.037)	(0.038)
geo diversity²			0.001					
			(0.006)					
geo diversity		0.048***	0.040			0.047***		0.033***
		(0.010)	(0.031)			(0.010)		(0.038)
FDI	0.33E-4	0.34E-4	0.34E-4	0.35E-4	0.35E-4	0.24E-4	0.35E-4	0.25E-4
	(0.33E-4)	(0.33E-4)	(0.33E-4)	(0.34E-4)	(0.34E-4)	(0.34E-4)	(0.33E-4)	(0.34E-4)
cooperation	0.169***	0.176***	0.176***	0.180***	0.182***	0.175***	0.188***	0.189***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
logpatent	0.063**	0.060**	0.060**	0.060**	0.059**	0.062**	0.058**	0.059**
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
loginventor	0.219***	0.221***	0.221***	0.217***	0.217***	0.222***	0.217***	0.220***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.024)
exploitation	0.105***	0.100***	0.100***	0.098***	0.095***	0.100***	0.095***	0.094***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
logage	-0.126	-0.119	-0.119	-0.121	-0.118	-0.118	-0.121	-0.117
	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)
logsize	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.004
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Wald Chi²	191.12***	213.09***	214.08***	216.37***	220.27***	235.95***	227.98***	248.10***
Groups	68	68	68	68	68	68	68	68
Observations	21434	21434	21434	21434	21434	21434	21434	21434

Estimation with time dummies, standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%