Paper to be presented at the

DRUID Society Conference 2014, CBS, Copenhagen, June 16-18

Academic knowledge as a driver for technological innovation? Comparing universities, small and large firms in knowledge production and dissemination

Friedrich Dornbusch
Fraunhofer Institute for Systems and Innovation Research
Competence Center Policy and Regions
friedrich.dornbusch@isi.fraunhofer.de

Peter Neuhäusler
Fraunhofer Institute for Systems and Innovation Research ISI
Competence Center Policy and Regions
peter.neuhaeusler@isi.fraunhofer.de

Abstract

It is generally claimed that universities provide the scientific basis for future technological progress. Still, empirical evidence of the impact of direct links between universities and firms remains weak and is often at least inconsistent. This paper aims at contributing to the literature by analyzing how direct academic involvement affects the output of inventive activities of research teams in different organizational backgrounds. By applying a unique dataset of German academic and corporate patents, we find that boundary-spanning knowledge production with academic inventors raises the innovative performance of SMEs and MNEs. Furthermore, geographical proximity between team members is generally shown to be valuable for team performance in terms of the influence on future technological developments. At the same time, the results indicate that academic involvement helps inventor teams to profit from spatially distant knowledge sources.

Jelcodes:O31,-

Academic knowledge as a driver for technological innovation? Comparing universities, small and large firms in knowledge production and dissemination

Abstract: It is generally claimed that universities provide the scientific basis for future technological progress. Still, empirical evidence of the impact of direct links between universities and firms remains weak and is often at least inconsistent. This paper aims at contributing to the literature by analyzing how direct academic involvement affects the output of inventive activities of research teams in different organizational backgrounds. By applying a unique dataset of German academic and corporate patents, we find that boundary-spanning knowledge production with academic inventors raises the innovative performance of SMEs and MNEs. Furthermore, geographical proximity between team members is generally shown to be valuable for team performance in terms of the influence on future technological developments. At the same time, the results indicate that academic involvement helps inventor teams to profit from spatially distant knowledge sources.

1 Introduction

The literature on knowledge based economic development has made essential contributions in proving that basic science fosters technological progress (Adams 1990; Jaffe 1989). A new generation of studies on networks and open science additionally reveals an increasing importance of sourcing knowledge from external organizations in general and from universities in particular (Powell, Grodal 2005; Cohen et al. 2002). However, further understanding the links between university and industry has significant implications for public policy and the rationales beyond funding basic research in universities as well as firms. In this context, knowledge creation and innovation are increasingly seen as a socially embedded process, which is highly dependent on inter-organizational and social networks. Particularly in collaborations between universities and industry, the often tacit nature of advanced scientific and technological knowledge makes relationship-based interactions highly relevant. R&D collaborations based on relationships are the preferred ways of exchange, enabling regular face-to-face contacts, reciprocal and bi-directional knowledge exchanges as well as the circulation of ideas between theory and practice (Perkmann, Walsh 2007; Perkmann, Walsh 2009). In sum, boarder-crossing team work and inter-organizational collaboration activities can be seen as one of the most important mechanisms of knowledge flows from university to industry. This finds further support in the fact that potential tensions and cultural barriers between university and industry - due to different institutional norms governing public and private knowledge - can be overcome in trust-based interactions where corporate and academic researchers act as boundary spanners (Bruneel et al. 2010).

However, although there is a huge body of literature on the ties between universities and firms, few studies aimed at understanding the performance effect of direct industry-science links, especially on the invention or project level (Cassiman et al. 2008). Empirical evidence on the impact of academic involvement in corporate inventive performance remains weak (Ahrweiler et al. 2011). Quantitative studies, often based on single sectors, use indirect ways to measure the impact of academic research on industrial innovation, e.g. spillover studies using a knowledge production function (Jaffe et al. 1993). Others employ patent citations to non-patent literature (NPL) as a proxy for science linkages (Fleming, Sorenson 2004; Harhoff et al. 2003; Narin et al. 1997) and provide interesting, but at least partly inconclusive results (Cassiman et al. 2008). NPL-citations, however, are a fragile measure for links to science. This is due to the fact that NPL-citations remain indirect, i.e. the real link and the true contribution of science cannot be observed, since searching and using codified scientific knowledge is fundamentally different from relationship-based links. It is particularly the person-to-person interaction that matters in the transfer of highly advanced technological knowledge. Empirical approaches, using direct links to measure the influence of academic involvement, however, are to our knowledge still missing.

Furthermore, existing literature has proven the spatially bounded nature of knowledge in general, and from universities in particular (Ponds et al. 2007; Singh 2008). As face-to-face contacts are an important condition for the generation and exchange of non-standardized and complex knowledge, they are particularly applicable when advanced technical and scientific knowledge is involved in interactions (van Oort et al. 2008). Relations between university and industry are therefore claimed to benefit from spatial proximity, since these often involve complex upstream basic research and require reciprocal learning processes (D'Este, Iammarino 2010). If sufficient cognitive and organizational proximity between the partners prevail, spatial and social proximity make local collaborations more likely (Boschma 2005). Nevertheless, this does not necessarily mean that spatially bounded academic knowledge has greatest impact on inventions. Academics and innovative firms usually search and exchange knowledge on an international scale (Hewitt-Dundas 2013; Manniche 2012) and distant knowledge is often superior to that available locally (Laursen et al. 2011). Furthermore, non-proximate actors are often equally, if not better, able to transfer and absorb complex knowledge even across spatial boundaries, given an adequate network structure is in place (Huggins et al. 2008). Thus, the question whether spatial proximity favors the innovative performance of inventor teams is far from being resolved.

We focus on these fronts firstly by introducing the *technological impulse* on future technological progress as a new measure for the innovative performance of a team. It builds on the frequently used technological impact (as measured by forward citations), but enables us to further differentiate by accounting for the originality of an invention, i.e. the amount of existing knowledge that an invention builds upon, indicated by backward citations. Secondly, employing a unique dataset, containing all German patents with academic involvement between 2000 and 2005, enables us to observe direct science-industry links. Complementing this with patents involving only inventors from SMEs or MNEs, we are able to test the university-industry linked patents against two control groups. The inventor and ownership information on patents serves as a proxy for different compositions of inventor teams and their institutional-organizational backgrounds, i.e. if the research team is composed of corporate inventors only or a mixture of academic and corporate inventors (Bercovitz, Feldman 2011; von Proff, Dettmann 2012).

Another often ignored aspect in the discussion on quality and technological impact of patented inventions is the organizational framework in which inventions emerge (Cassiman et al. 2008). Though both, academic and industrial researchers are interested in gathering new knowledge, the type and the ways to learn, operate and generate knowledge are fundamentally different. Academic environments focusing on basic knowledge are mainly interested in pushing frontiers of research, understanding particular fundamental phenomena and to disseminate the gained analytical knowledge in often exclusive globally configured epistemic communities (Manniche 2012; Stephan 2012). Industrial researchers are more interested in applied research and their motivation to collaborate with academic researchers is access to basic research results in order to advance their explorative capabilities and research productivity. Nevertheless, this depends on firms’ existing abilities to a) participate in science, technology and innovation based modes of learning (Jensen et al. 2007) and b) to transfer basic research into a sequence of technological applications (Cohen et al. 2002; Fleming, Sorenson 2004; Trajtenberg et al. 1997). While particularly large R&D intensive firms with large R&D departments (MNEs) are able to integrate, assimilate and exploit science based knowledge, in the sense of advanced innovations (Tödtling et al. 2009), small and medium sized firms (SMEs) are often, due to resource constraints, restricted to applied and exploitative problem-solving activities. Their innovation behavior is mainly characterized by doing, using and interaction modes of learning, leading to incremental innovations through novel combinations of existing knowledge (Jensen et al. 2007; Laursen, Salter 2004; Santoro, Chakrabarti 2002). Therefore, we will additionally account for this basic picture in that inventions emerging in heterogeneous organizational and institutional frameworks are influenced by the researchers working environments.

In sum, this paper aims to answer the following questions:

How does direct involvement of academic inventors affect the impulse that inventions exert on technological progress – in the light of heterogeneous organizational backgrounds?

How does spatial proximity influence the impulse that inventions exert on technological progress – in the light of heterogeneous organizational backgrounds?

The remainder of this paper is structured as follows. In the theoretical section, we will lay out the theoretical framework and develop the hypotheses which are tested in the empirical section. Section three composes theoretical backup for the technological impulse, describes the data and the empirical strategy. Section four presents and discusses the results of our analyses. Section five concludes this paper.

2 Theory and hypotheses: Collaboration, distance and the role of universities and firms for innovation

2.1 Collaborating with Science as a Trigger for Technological Evolution

The introduction revealed a rather basic picture on the role that heterogeneous institutional and organizational backgrounds play for innovative behavior. The question that emerges from these considerations is how boundary-spanning interactions between academic and corporate inventors influence the innovative performance compared to pure SME, MNE or university teams. The basic assumption hereby is that scientific basic knowledge enhances the inventor teams' research performance, its problem-solving abilities and the likelihood to contribute to technological progress.

Two broad directions in which scientific knowledge helps industrial engineers to trigger technological, more radical advancements can be identified. Firstly, radical advances occur due to "presumptive anomalies" (Constant 1980). Assumptions from engineers and researchers derived from scientific knowledge indicate that either the existing conventional technology will fail to function properly or that a radically different technology will do a better job. This is where scientific knowledge provides engineers with a kind of map that helps them to systematically structure the search for technological knowledge (Fleming, Sorenson 2004). Secondly, engineers become aware of actual functional failures, occurring when a technology is subject to increasing demand or is applied in new situations and search actively for radical solutions (Vincenti 1990). In particular the latter points to the value of networks and bi-directional knowledge exchanges between academic and industrial researchers (Perkmann, Walsh 2009). On the one hand corporations, having a sense for system failures and the need for new and radical solutions, and on the other hand academics, providing advanced technological knowledge, drive the circulation of knowledge between applied and basic contexts. Confirming this, academic patents assigned to corporations are more frequently opposed, suggesting that they are more likely to capture applied inventions with a higher market potential (Czarnitzki et al. 2009). Therefore, particularly, inventions that emerge in collaboration between both spheres might exert a strong impulse on future technological paths.

At the same time, at the firm-level, heterogeneous capacities to deal with scientific knowledge are likely to prevail. Firstly, idiosyncratic firm-level competencies influence a firm's ability to pursue particular technology paths. Secondly, firms must invest in scientific knowledge to develop their "capacity to absorb" knowledge and exploit opportunities emerging from the state-of-the-art elsewhere (Cohen, Levinthal 1990). Therefore, the capabilities to deal with scientific knowledge and to build cognitive proximity to academia are diverse, in particular for SMEs. While the majority of SMEs is, as discussed above, engaged in incremental and less science-based interactions, some are assumed to build heavily on academics as partners, particularly in science-based industries. Some SMEs, specialized on R&D activities, are highly innovative and most of the people employed are skilled workers with a background in academic research. Their primary purpose and business model is to translate basic research into applicable contexts. Those firms often are spin-offs from universities and large firms (Cohen et al. 2002) or other knowledge intensive business services (Laursen, Salter 2004). Thus, we assume that those SMEs that engage in direct collaboration with universities develop a particularly strong effect on future technological paths.

H1a: Inventions that emerge from mixed inventor teams with heterogeneous organizational backgrounds are likely to exert a stronger impulse on technological paths than other inventions. This effect is likely to be particularly strong for SMEs.

Research in purely academic research teams is very likely to be complex and original - in the sense that it basically aims at pushing the frontiers of research - and is conducted under intense competition (Stephan 2012). Striving for scientific reputation provides strong incentives for academics to be inventive. Nevertheless, the primary goal of scientists is not to apply knowledge to technological components, but to publish and to discuss their ideas within academic communities. Purely academic and basic research is probably neither directly inspired by application-based technological problems, nor it is directed towards their solution. University inventions capture more basic research, since they focus on solving scientific questions while industry R&D is directed at commercial success (Trajtenberg et al. 1997). Thus, inventions out of purely academic environments might lack direct short- and mid-term technological connectivity.

H1b: Research conducted in purely academic inventor teams is likely to be "original", i.e. building on a small stock of prior knowledge, while at the same time it is less likely to be easily applicable to future technological paths.

2.2 Distance in collaborations and different organizational backgrounds

The degree to which inventor teams combine new knowledge from new locations and domains plays an important role in shaping the success in technological innovation (Laursen 2012). Yet, from an individual's perspective, cognitive limitations make it impossible for single researchers and engineers to know and to evaluate every technological opportunity in relation to other options. Thus, searching along established paths, networks, routines and heuristics is easier and therefore mostly conducted in familiar and proximate neighborhoods (Malerba, Orsenigo 1993). Nevertheless, this may lead to sub-optimal solutions as superior knowledge from non-local and cognitively more distant contexts is over-looked (Brökel, Binder 2007; Fleming, Sorenson 2004; Rosenkopf, Nerkar 2001). Two distance dimensions appear to be relevant within this context. Firstly, inventions combining larger shares of knowledge from distant knowledge domains have been shown to exert a stronger technological impact (Fleming, Sorenson 2004; Rosenkopf, Nerkar 2001). Thus, a higher technological distance is likely to enhance the generated technological impulse.

H2a: A higher technological distance between the inventor teams' knowledge domain and the knowledge source is likely to have a positive influence on the technological impulse emanating from an invention.

Secondly, individual's bounded rationality is also likely to affect the spatial distance over which researchers span their networks, search and exchange knowledge. The basic argument here is that individuals do not perform exhaustive search processes across an entire search space, but prefer - if other distant solutions are not known - the spatially and socially most proximate and cognitively satisfying solutions. Thus, applying heuristics in search processes directs the focus of individuals towards their existing social networks which are – favored by spatial proximity and face-to-face interactions – often spatially biased (Brökel, Binder 2007). In line with this, previous empirical studies have revealed that knowledge is spatially bounded and inventions mostly emerge from regional partnerships (Ponds et al. 2007; Singh 2008). Therefore, the simple message is: Geography matters, but, does geography also influence the quality and performance of collaborative activities?

The literature on collaborative teams has highlighted teamwork as an important element of leveraging creativity, expertise and diversity of the teams' knowledge base. Thus, it can enlarge the stock of information that is applied to the innovation process (Dahlin et al. 2005; Giuri et al. 2010). Nevertheless, teams are confronted with coordination and communication problems that can hinder the success of a research project. The more complex, ambitious and innovative the project, the more this is the case. In this context, face-to-face meetings can serve as social tools which reassure common agreements, solve conflicts and define further milestones (Torre 2008). Face-to-face contacts enable the exchange of non-verbal information, which is required to obtain the complete picture of other researchers' social as well as competence profiles. Even more importantly, they increase the likelihood of intense and intact relationships between team members, which are strong drivers for successful collaborations (Agrawal et al. 2006; von Proff, Dettmann 2012). In sum, successful collaborative relationships must find a way to develop social, organizational and cognitive features that enable them to reach their project goal. In this context, face-to-face contacts and spatial proximity can facilitate the emergence of those relationship features (Boschma 2005). Thus, we assume that more complex and ambitious research projects rely more on frequent face-to-face encounters and the teams' innovative performance is more sensitive to spatial distance.

H2b: A higher spatial distance between inventor teams is likely to have a negative influence on the technological impulse emanating from an invention.

Contrary to H2b, collaborations over distance can increase the opportunity to investigate more distant – and potentially useful – possibilities (Laursen 2012). As discussed above, knowledge networks and exchange are spatially biased and the knowledge landscape is likely to be shaped by industry and region-specific institutional structures. Thus, knowledge, being in large parts implicit and context-dependent, is not equally distributed over space. Searching for non-local knowledge can add to innovation activities and help to avoid regional lock-in. Following Boschma (2005), the role of geographic proximity as a facilitator of knowledge interaction can be substituted by other relationship features, namely cognitive, social, organizational, institutional proximity. The need for geographical proximity is weakened when strong coordination mechanisms are implemented and partners share cognitive experiences (Torre 2008). The implications are twofold:

Firstly, institutional and organizational proximity created in subsidiaries and contractually bound partners enables firms to access specific knowledge and personnel, making spatial proximity between partners less important (von Proff, Dettmann 2012). Due to resource constraints, in small businesses only few people are familiar with the tasks in R&D and knowledge management. They lack the resource-based backup of colleagues and are likely to be more oriented towards their local environment if this provides sufficient opportunities for local interactions. Thus, firms with more R&D personnel are more likely to benefit from geographically dispersed inventor teams and organizational backgrounds.

Secondly, the direct involvement of academics as team members might serve as an entrance card into nationally and globally configured often exclusive and academic "epistemic communities", where learning takes place by searching and researching, both being intentional and directed. The knowledge resulting from this analytical knowledge processing is to a large extent codified and can be transferred across space. Nevertheless, particularly cognitive proximity and an adequate organizational framework are indispensible for individuals to achieve correct interpretations of codified knowledge and to obtain access to the usually stored knowledge (Manniche 2012). It is therefore likely that research teams that involve academics as team members have a higher likelihood to increase their performance by tapping into these mostly non-local networks.

In sum, we assume that the organizational background of inventor teams provides heterogeneous opportunities for dealing with and efficiently integrating spatially distant knowledge sources into the innovation process.

H2c: The influence of spatial distance on the technological impulse emanating from an invention is highly dependent on the institutional and organizational background of inventor teams.

3 Empirical strategy

3.1 Patent citations as a measure of technological impulse: Two sides of the same coin

Building on previous studies dealing with the technological impact of an invention (Carpenter et al. 1981; Fleming, Sorenson 2004; Harhoff et al. 2003; Trajtenberg 1990) we use citations related to patents as indicators for innovation performance (Cassiman et al. 2008). Citations, provided either by the patent applicant or the patent examiner[1], are listed on a patent document and reflect references made to prior art, most commonly to other patents but also to scientific literature. These citations can be counted from a forward looking as well as a backward looking perspective. The forward looking indicator is the number of citations a patent receives from subsequent patent filings, which are commonly referred to as patent forward citations. The basic assumption is that the number of forward citations measures the degree to which a patent contributes to further developing advanced technology. Thus, it can be seen as an indicator of basicness, novelty or technological significance of a patent in terms of spill-over effects (Carpenter et al. 1981; Trajtenberg 1990). The backward looking indicator is patent backward citations. Patent backward citations refer to previous patents and are mostly used as an indicator of technological breadth and can give hints on the scope of a patent (e.g. Harhoff et al. 2003). Yet, it can also be interpreted as a measure of "originality": Patents with a large number of backward citations can be assumed to build on a larger given pool of already existing knowledge, whereas patents with only few backward citations have a small existing knowledge stock to build upon (Rosenkopf, Nerkar 2001). Thus, it is quite intuitive to state that a small number of references made to previous patents imply that the commercially used knowledge stock which can be built upon is rather limited.

Based on these remarks, we combine the forward and backward looking perspective as two sides of the same coin. This enables us to construct a general measure for the originality of knowledge generation modes on the one hand and the technological significance of a patent for the development of future advanced technologies on the other. By relating the amount of knowledge a patent builds upon to the knowledge a patent creates, so to say, the *technological impulse* of a patent (from its originality to its significance for future technologies) can be identified. With the help of this indicator, we are able to measure the technological impulse of academic patents and compare it to the technological impulse emanating from inventions filed by MNEs and SMEs. The exact calculation of the indicator is described in section 3.2.

3.2 Dataset and variables

In this section, we will give an overview of the creation of our dataset, introduce the variables and discuss their operationalization.

Dataset creation

In order to conduct our analyses, a patent level dataset based on the "EPO Worldwide Patent Statistical Database" (PATSTAT) in its April 2012 version, which provides information about published patents collected from 83 patent authorities worldwide, was constructed. It is comprised of all academic pa-

---

1 We are aware of the fact that the motives for citing previous patents might differ between patent applicants and patent examiners. However, for our analysis, it is not necessary to directly link the senders and recipients of knowledge flows. We use patent citations to characterize the knowledge stock comprised in an invention and thus a differentiation between applicant and examiner citations is not necessary, as both indicate a given "stock" of prior art.

tents as well as non-academic SME and MNE patent filings from German applicants at the EPO between 2000 and 2005. It thus covers all patents that are produced within or in cooperation with universities and not only the ones that are filed by universities. In order to identify academic patents, the method described in Dornbusch et al. (2013) was applied. The basic principle is an algorithm that matches author names from scientific publications with inventor names derived from patent filings. Estimates show that the search algorithm correctly identifies academic patents with a high precision of over 93 percent.

Overall, we collected information on a total of 6,193 German academic patents filed at the EPO between the priority years 2000 and 2005. All non-academic SME filings (N=21.694) and a randomly drawn sample of 35,000 non-academic MNE filings were added to this dataset. In order to create comparable groups and to avoid a possible sample selection bias, a Propensity Score Matching (PSM) was applied (Heinrich et al. 2010).[2] In doing so, statistically comparable twins with regard to technology fields and priority years were extracted. Consequently, we attained a balanced sample of 4,217 observations for each of the three groups, which leaves us with a final sample of 12,651 patents in total.[3]

Variables and operationalization

In order to operationalize the technological impulse (*TechImp*), which will form the explained part in our following regression models, we added the relevant citation related indicators from the PATSTAT database, i.e. the number of patent forward citations - in a 4-year citation window in order to leave all the patents the same amount of time to be cited - and the number of patent backward citations stated on the patent application. As for the modeling of the technological impulse we generated two dependent variables (dVs):

The first is the ratio of the number of forward citations a patent receives from subsequent patents to the number of backward citations to previous patents that are stated on a patent filing. This variable is supposed to capture the relation between an organizations' innovation behavior in that it generates technological knowledge with a certain degree of novelty and its reliance on already existing knowledge. However, the caveat of this variable, although it is a handy indicator, is that it is not able to differentiate between patents that have a low number of backward citations as well as a low number of forward citations on the one hand and a high number of backward citations as well as a high number of forward citations on the other.

We thus generated a second variable with four categories, relocating a patent into a matrix along the two dimensions: quantity of backward citations given and the quantity of forward citations received. In order to differentiate between high and low, we used the median of the respective variables. In the

---

2 We apply a nearest neighbor matching without replacement and employ a calliper, serving as a tolerance level of the maximum propensity score distance of two matched observations. This calliper reduces the risk of bad matches and is calculated as the standard deviation of the estimated propensity score multiplied by 0.25 (Rosenbaum, Rubin 1985).

3 Tests comparing the PSM-created against a randomly drawn sample showed that field and period specific distribution differences are significantly reduced.

case of forward citations the median is 1, meaning that all citations with one or fewer citations belong to the "low number of forward citations" category and vice versa. For the backward citations, the median lies at 5, so all patents with five or less backward citations belong to the "low number of backward citations" category and vice versa.

In order to make the handling easier and to improve readability, we decided to give each group a distinct name:

- The first category of “Mavericks” (coded "0") has a low number of forward and a low number of backward citations. Inventions are based on a small stock of existing knowledge, but also have a weak connectivity to future technological paths. "Mavericks" are weakly connected into both directions.
- The second category of “Pioneers” (coded "1) is characterized by a high number of forward and a low number of backward citations. It relies on a small stock of existing knowledge, yet has a strong significance for the following technological trajectory. It opens or at least contributes to the opening of a new technological path.
- The third category labeled “Adopters” (coded "2") has low number of forward and a high number of backward citations. This indicates a strong reliance on existing knowledge, but only a weak impact on future paths.
- The fourth category of “Enablers” (coded "3") has a high number of both, forward and backward citations. Enablers thus rely on a large stock of existing knowledge, but are also able to generate impact on future technological paths.

In order to test our hypotheses, we use three sets of explanatory variables:

1. Organizational background and university-industry collaboration (ORG): To differentiate between organizational backgrounds, a manually created classification of the patent applicants was employed.[4] Corresponding to the German SME definition, applicants with more than 500 employees (Günterberg, Kayser 2004) and more than three patent filings in a three-year time window between the priority years 1996 and 2008 were classified as MNEs. The remaining applicants with more than three patent filings in the given time window and less than 500 employees were classified as SMEs.

In sum, our dataset differentiates between five different organizational backgrounds (see Table 1): Patents emerging from purely corporate backgrounds are either defined as *purely MNE* (case 1) or *purely SME* (case 2). Furthermore, we define patents that are filed with academic participation by MNEs as *mixed MNE* (case 3.1) or as *mixed SME* (case 3.2). Finally, *purely academic* patents are those filed by UNI (case 3.3). Note that other applicants of academic patents (private applicants and other PROs) are collapsed in a fourth category. This differentiation is used to test the organizational backgrounds’ influence on the technological impulse.

4 The name and legal status of an applicant (e.g. Inc., AG, GmbH, S.R.L, etc.) as well as the difference between the name of the applicant and the name of the inventor show if the applicant is a company (compare also Frietsch et al. (2011)).

Table 1 Sample description

Case 1: Non-academic patents filed by MNEs	Case 2: Non-academic patents filed by SMEs	Case 3: Academic patents		
		Case 3.1: filed by MNEs	Case 3.2: filed by SMEs	Case 3.3: filed by the university itself (UNI)

Source: Own compilation

2. Geographical distance (GD): Furthermore, we added a variable representing the average geographical distance between the inventors named on a patent filing. The distances were calculated based on the coordinates[5] belonging to each of the postal codes of the inventors' home addresses.

3. Technological distance (TD): Finally, in order to indicate the technological distance of a patent application, we included the share of backward citations to patents in foreign technology fields to the sum of foreign and home-field citations.[6] In order to do so, we included a differentiation indicating whether a citation listed on a patent document referred to a patent outside the technology field of the original patent within the 34 WIPO classes (Schmoch 2008), which are based on the International Patent Classification (IPC) (foreign-field citation).

As for the control variables, we include the number of IPC-classes that are stated on a patent application to control for technological breadth as well as the number of inventors listed on a patent application to control for a possible effect of team size on the technological impulse of a patent application. As discussed above, references to non-patent literature are frequently used to indicate the closeness to science. We leave them out in the construction of our dependent variable, but control for their influence. Furthermore, we add the family size of a patent application, i.e. the number of distinct patent offices where a patent has been filed. It indicates the breadth of international market coverage, which is also associated with rather high patenting costs and might thus also influence the technological impulse variable. Finally, we add dummy variables for the time periods (2000-2005) to control for period-specific effects as well as field dummies alongside the 34 WIPO classes. A summary of the variables used for our regression models can be found in Table 2.

---

5 The coordinates were retrieved from http://opengeodb.org/wiki/OpenGeoDB.

6 A patent can be classified into two or more technological fields and be double-counted. We thus use the sum of foreign-field and home-field citations as the denominator for the construction of the variable in order to make sure it runs from 0 to 1.

Table 2 Overview of the variables and summary statistics

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Technological impulse					
Ratio: forward citations/backward citations	12,190	0.43	1.13	0	33
Forward/Backward Index	12,651	1.36	1.18	0	3
low forward/low backward	3,508			0	0
high forward/low backward	1,928			1	1
low forward/high backward	3,301			2	2
high forward/high backward	2,873			3	3
Organizational type	12,651	1.00	0.82	0	2
Purely MNE (MNE filing)	4,217			1	1
Purely SME (SME filing)	4,217			2	2
Academic Patent	4,217			0	0
Mixed MNE	2,045			0	1
Mixed SME	933			0	1
Purely academic (UNI)	415			0	1
Mixed OTHER	625			0	1
Distance Variables					
Technological distance	12,190	0.42	0.19	0	1
Geographical distance	9,421	81.11	108.11	0	727
Control Variables					
Number of inventors	12,651	3.24	2.20	1	50
Number if IPC-classes	12,651	2.06	1.22	1	12
Family size	12,651	6.42	4.66	1	40
Number of NPL-citations	12,651	4.98	14.08	0	462

Source: EPO – PATSTAT, own calculations

3.3 Econometric modeling

In order to test our hypotheses, we set up a formal model estimating the technological impulse of a patent by means of regression techniques. In a first step, we isolate the effect of the basic organizational background on the technological impulse and test if the operationalization of *TechImp* fits the basic picture derived from the literature. Our basic model can (in a simplified form) be described as follows:

$$TechImp_i = \alpha_{1i}ORGbasic_i + \alpha_{2i}IPC_i + \alpha_{3i}INV_i + \alpha_{4i}FAM_i + \alpha_{5i}NPL_i + x_i{}'\beta_i + \varepsilon_i \qquad (1)$$
$$\text{with } i=1,...n$$

where $TechImp_i$ denotes the technological impulse of patent i, $ORGbasic_i$ differentiates the basic organizational backgrounds (*purely MNE*, *purely SME*, *academic)*, respectively, IPC_i is the number of IPC classes of patent i and INV_i is the number of inventors listed on the respective patent application. FAM_i denotes the patent's family size and NPL_i the number of NPL-citations. $x_i{}'$ is a vector of field and period specific control variables and ε_i idiosyncratic errors.

Based on this basic approach, we subsequently add three explanatory parameters to the regression in order to test our hypotheses. The extended model is described as follows:

$$TechImp_i = \alpha_{1i}ORGext_i+\alpha_{2i}IPC_i+\alpha_{3i}INV_i+\alpha_{4i}FAM_i+\alpha_{5i}NPL_i+\alpha_{6i}GD_i+\alpha_{7i}TD_i+x_i{'}\beta_i+ \varepsilon_i \quad (2)$$
$$\text{with } i=1,...n$$

where $ORGext_i$ now denotes the organizational backgrounds of the inventor team of patent i, but is extended and differentiates the academic patents alongside the cases 3.1-3.3 (*mixed MNE; mixed SME; purely academic*) in Table 1. This extension allows us to test if organizational border-crossing (directly measured by inventor team composition) influences the technological impulse emanating from an invention (H1a & H1b). GD_i denotes the geographical distance (H2b & H2c) and TD_i the technological distance (H2a).

As stated above, we employ two different dependent variables measuring the technological impulse that is generated by an invention. The first one, i.e. the ratio of forward to backward citations, is a continuous variable. As its numerator has an excessive number of zeros, this variable is left-censored. In this case an OLS model might result in inconsistent parameter estimates. The Tobit-model is designed to estimate linear relationships between variables when there is either left- or right-censoring in the dependent variable (Wooldridge 2002). In order to further differentiate and obtain additional information from our explanatory variables we complement our analyses with a Multinomial-Logit-Model (MLM) on the categorical dV. We choose the "mavericks"-category as the base category. In order to ease interpretation and comparison of the coefficients, we calculate average marginal effects (Williams 2011). Non-constancy in the residual variance of the variables is controlled by employing robust standard errors in all our models (White 1980).

4 Results and discussion

4.1 Descriptive analyses

This section provides first insights on how far the explained variables resemble the basic picture of learning and innovation shaped by different organizational backgrounds. Table 3 provides an overview of the differences in the average forward and backward citation rates between academic, MNE and SME filings. Academic patents on average receive 0.61 more citations from subsequent patents than SMEs. MNEs are located in the middle with a value of 2.33. The two-sided t-tests in the lower part of the table show that these differences are significant over all categories. Also in accordance with existing literature, academic patents refer to about 1.3 previous patents less than MNEs. Here, SMEs are located in the middle with a value of 8.76. Yet, the difference between academic patents and SME filings is not significant. All in all, this results in a ratio of forward to backward citations of 0.53 for academic patents, 0.39 for MNE filings and 0.36 for SME filings. The differences between academic patents and SME and MNE filings are highly significant for this indicator, which forms the core dependent variable for our models measuring the technological impulse.

Table 3 Forward and backward citations across types of organizations (SME, MNE, UNI)

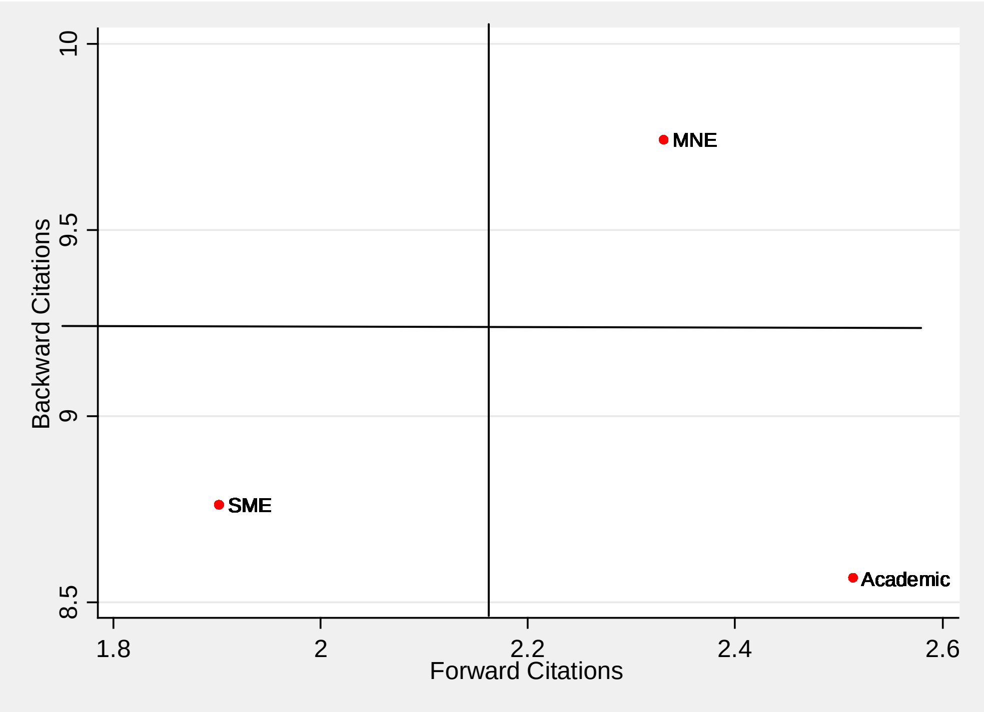
Mean values			
	Academic	**MNE**	**SME**
Number of forward citations	2.51	2.33	1.90
Number of backward citations	8.57	9.74	8.76
Ratio: forward citations/backward citations	0.53	0.39	0.36
T-Tests			
	Academic vs. MNE	**Academic vs. SME**	**SME vs. MNE**
Number of forward citations	-1.914*	-6.864***	-5.040***
Number of backward citations	4.341***	0.724	-3.691***
Ratio: forward citations/backward citations	-5.591***	-6.172***	-1.068

Source: EPO-PATSTAT, own calculations

Note: Significances levels: ***p<0.01, **p<0.05, *p<0.1

Complementing on these findings, Figure 1 shows the average number of forward citations by backward citations over the different types of organizations. Academic patents are located in the lower right-hand corner of the graph, indicating a high number of forward citations and a comparably lower number of backward citations on average. In sum, the graph closely resembles the basic picture of learning as discussed in the introduction, implying that the technological impulse differs between academic and industry patents.

Figure 1 Average number of forward citations by backward citations over type of organization (SME, MNE, UNI)



Source: EPO – PATSTAT, own calculations

4.2 Multivariate analyses

In this section, we will present and discuss the results of our multivariate models. First, we focus on the basic model (M1 & M2 in Table 4) with the set of dummy variables indicating the organizational type of a patent application (UNI, MNE, SME). The primary aim here is to further confirm the basic picture on the roles played by different organizational backgrounds. This is followed by a test of our hypotheses on collaborations between university and industrial research teams (H1a& H1b; M3 & M4 in Table 4) as well as on the role of distance for the innovative performance of an inventor team and their application in different organizational backgrounds (H2a-H2c; M5 – M10 in Table 4 & Table 5). The interpretation of the coefficients always starts with the Tobit-model and then goes into more detail by taking the more differentiated MLM into account. Yet, before interpreting our explanatory variables, we will briefly turn to the effects of the control variables.

Control variables

As the coefficient in M1 shows, the number of inventors has a significantly positive effect on the technological impulse of a patent application on average. This is resembled in M2, where the "pioneering" and the "enabling"-categories are positively affected by the size of an inventor team. As for the number of IPC-classes, however, we only find a weakly significant positive coefficient, implying that the technological breadth of a patent filing in terms of IPC-classes only marginally affects its technological impulse on average. Yet, the family size of a patent application, indicating the breadth in terms of market coverage, has a significantly positive effect on the technological impulse. Interestingly, the number of NPL-citations listed on a patent application has a significantly negative coefficient. A closer look at M2 reveals that the coefficient is only negative in the case of the inventions that build on a small stock of knowledge, while those building on a larger stock of knowledge are positively affected.

Academic vs. corporate backgrounds: A basic differentiation

Turning our attention to the basic organizational variables, it can be observed that the technological impulse is lower for SME filings compared to MNE filings. It can also be found that SME filings significantly more often fall into the category of “Mavericks" and "Adopters" than filings by MNEs. Inventions created in pure SME teams are also less likely to act as "Enablers". Pure SME-backgrounds thus are less likely to provide the organizational and institutional framework under which inventor teams generate high quality inventions (in the sense of future technological connectivity), regardless of whether they draw on a large or small stock of existing knowledge. MNEs fall in the middle between SME filings and academic patents (M1). MNE patents are less likely to belong to the “Mavericks”-category, while they have the highest probability to act as “Enablers”. In sum, this indicates that MNEs are more likely to combine the search and absorption of existing knowledge while at the same time they translate this into future technological paths.

With regard to academic patents, a positive effect on *TechImp* is observed in M1, implying a higher technological impulse of academic patents than MNE patents on average. Most notably, the probability that an invention belongs to the “pioneering”-category is highest for academic patents. However, we also find a highly significant positive effect for the “Mavericks”-category. This indicates the existence of two contrary types of inventions emerging from an academic background: The first one has a strong connection to future technologies, whereas the second one shows a low connectivity. Yet, both are relying on a small stock of existing knowledge. We can state that direct academic involvement in inventor teams makes inventions more original, in that they generally build on a small stock of existing knowledge. “Adopting” or “enabling” inventions, however, are less often created within academic backgrounds.

One interesting side-result is notable here. As described above, NPL citations show a counter-rotating effect to that of direct and personal academic involvement in inventor teams. This only partially supports the findings by Fleming and Sorenson (2004), who found that scientific knowledge derived from NPL (basically scientific publications) provides inventors with maps which lead them to promising new knowledge combinations. Our results add a new dimension to their findings. It seems that codified scientific knowledge mainly helps to structure knowledge searches if a large amount of existing knowledge is at hand (“adopting” as well as “enabling” inventions). They can thus help to make search processes more efficient. However, if the existing knowledge base is small, NPL citations can negatively influence the connectivity to future technological paths (“pioneers”). This might indicate that scientific publications as knowledge sources do not serve as a good starting point for finding innovative solutions unless they are not embedded into a broader (technical/applied) knowledge context.

In sum, the results of M1 and M2 confirm our assumption of the role the different organizational backgrounds play in the process of knowledge production and dissemination. SMEs are less likely to generate inventions with a strong technological impulse and are more likely to adopt current technological trends. They engage in more incremental and less original innovations. MNEs on average fulfill their role as “enablers”. They manage a larger spectrum of activities ranging from exploitative and incremental modes of innovation to more explorative ones. Thus, they are more likely to integrate existing knowledge and connect this to future technological paths. An academic background, however, provides the institutional frame in which the strongest technological impulse is generated. This highlights the importance of academic scientists and their research as a seedbed for new technological paths. Yet, we also find that academic involvement leads to patents with a low connectivity into both directions. A further differentiation of academic patents, which will be provided from M3 onwards, therefore yields the potential to gain a better understanding of the ongoing processes by considering mixed organizational and institutional backgrounds.

University-Industry collaboration

The previous results on the role of academic patents left us with the somewhat ambiguous finding that academic involvement might either lead to weakly connected “mavericks” or to “pioneering” patents with a strong connection to future technological paths. M3 and M4 provide the results for the differentiation of academic patents by their different backgrounds. In line with H1a, M3 shows that collaborations between firm and academic inventors (mixed MNE & mixed SME) indeed raise the likelihood that the patent filing exerts an impulse on future technological paths. M4 shows that this is particularly driven by positive effects in the “pioneering” inventions category.

Also in line with H1a, the coefficient for mixed SME-teams in M3 is higher than that of mixed MNE-teams. Thus, the influence of academic involvement indeed is stronger than in the case of MNEs. Mixed SME patents have a high probability to be “pioneering”, whereas, as shown above, SME-filings without academic involvement on average fall more often into the “adopters” or “mavericks” categories. This confirms our assumption that SMEs that collaborate with universities are specialized in doing so. It is likely that these are often spin-offs, either from universities or MNEs, as e.g. potentially VCs-funded and outsourced R&D-Ventures.

Interestingly, purely academic patents (UNI) are strongly significant for the “mavericks”-category, but we do not find a significant effect for the “pioneering”-category. This supports hypothesis H1b, which states that inventions that emerge in purely academic inventor teams have a higher likelihood of being more original, but they also lack the connectivity to future technological developments.

In sum, our results generally confirm the picture drawn in the theoretical section. Combining the perspectives from academic and industrial backgrounds in inventor teams provides the largest potential to contribute to new technological paths. The output from collaborative work between industrial and academic inventor teams shapes future technologies, while connecting existing knowledge and future paths is likely to take place against MNE-backgrounds. SMEs play a very special role. The ones that include academic inventors into their research teams often act as pioneers in establishing new pathways for technological developments. For purely academic inventor teams, however, we find that the impact of their patented inventive activities lacks the usefulness of those done in collaboration with industry. Yet, this explains the observed diverging effect of academic patents in the previous section and has severe policy implications, which will be discussed in the conclusion.

Technological distance

Introducing the technological distance variable in M5 and M6 only slightly changes the coefficients of the organizational variables in M4. While the technological distance is not significant in M5, it shows significant effects in M6. Searching in foreign technology fields raises the likelihood of belonging to the “adopters” and “enablers” categories. If inventions rely on small amounts of existing knowledge (“mavericks” and “pioneers”), searching in foreign technology fields reduces the likelihood of belonging to either one of both categories.

In sum, we have to reject H2a. A broad strategy to search for technological knowledge does not positively affect the technological impulse. If an invention is more original in nature, it rather reverts to (a smaller amount of) existing knowledge from its own technology field.

Table 4 Multivariate results I: University – Industry collaboration and technological distance

	BASIC					University-Industry Collaboration					Technological Distance				
	M1	M2				M3	M4				M5	M6			
	TOBIT	Mfx: ∂TechImp / ∂X (4CAT)				TOBIT	Mfx: ∂TechImp / ∂X (4CAT)				TOBIT	Mfx: ∂TechImp / ∂X (4CAT)			
dV =	TechImp	Maverick ∂y/∂x (Kat0)	Pioneer ∂y/∂x (Kat1)	Adopter ∂y/∂x (Kat2)	Enabler ∂y/∂x (Kat3)	TechImp	Maverick ∂y/∂x (Kat0)	Pioneer ∂y/∂x (Kat1)	Adopter ∂y/∂x (Kat2)	Enabler ∂y/∂x (Kat3)		Maverick ∂y/∂x (Kat0)	Pioneer ∂y/∂x (Kat1)	Adopter ∂y/∂x (Kat2)	Enabler ∂y/∂x (Kat3)
Purely: SME	-0.0756**	0.0201**	-0.0031	0.0223**	-0.0393***	-0.0774**	0.0210**	-0.0031	0.0222**	-0.0401***	-0.0774**	0.0214**	-0.0043	0.0235**	-0.0406***
Academic patent (all)	0.1465***	0.0403***	0.0343***	-0.0332***	-0.0414***										
Mixed: MNE/Acad						0.1741***	0.0233*	0.0298***	-0.0339***	-0.0192*	0.1741***	0.0219*	0.0274***	-0.0318***	-0.0175
Mixed: SME/Acad						0.2283***	0.0154	0.0547***	-0.0213	-0.0488***	0.2283***	0.0076	0.0570***	-0.0171	-0.0475***
Purely: Academic/UNI						0.1175	0.0633***	0.0317	-0.0331	-0.0619***	0.1174	0.0467*	0.031	-0.0233	-0.0544***
Mixed: OTHER/Acad						-0.0382	0.1184***	0.0305*	-0.0480***	-0.1009***	-0.0382	0.1126***	0.0257	-0.0401**	-0.0982***
Techological_dist											0.0014	-0.1172***	-0.0622***	0.0832***	0.0962***
Number of inventors	0.0876***	-0.0101***	0.0068***	-0.0072***	0.0105***	0.0862***	-0.0087***	0.0066***	-0.0078***	0.0099***	0.0862***	-0.0078***	0.0064***	-0.0085***	0.0098***
Number if IPC-classes	0.0540*	0.0034	0.007	-0.0077	-0.0027	0.0570**	0.0024	0.0065	-0.0074	-0.0015	0.0570**	0.0008	0.0059	-0.0064	-0.0003
Family size	0.0295***	-0.0189***	0.0009	0.0071***	0.0109***	0.0286***	-0.0185***	0.001	0.0071***	0.0103***	0.0286***	-0.0182***	0.001	0.0068***	0.0104***
Number of NPL-citations	-0.0034***	-0.0148***	-0.0042***	0.0097***	0.0093***	-0.0033***	-0.0155***	-0.0041***	0.0101***	0.0096***	-0.0033***	-0.0167***	-0.0046***	0.0110***	0.0103***
Constant	-0.9551***					-0.9469***					-0.9473***				
Field Dummies	YES														
Time Dummies	YES														
N	12190	12651				12008	12452				12008	12008			
Pseudo R²	0.024	0.072				0.024	0.074				0.024	0.075			
F/Wald Chi²	6.187	1527.05				5.734	1537.9				5.622	1509.26			
aic	32217.69	31768.37				31764.229	31235.872				31766.228	30178.207			
bic	32565.88	32795.85				32133.895	32328.028				32143.288	31287.206			
Prob > F/Prob > chi2	0.000	0.000				0.000	0.000				0.000	0.000			

Source: EPO – PATSTAT, own calculations

Significance Level: ***p<0.01, **p<0.05, *p<0.1, robust standard errors

Note: MNE filing serves as a base outcome for the variables SME filing and academic patent as well as the mixed types in the extended ORG variable. N is lower in the ratio calculation since there are patents with no backward citations for which no ratio could be calculated.

Different organizational backgrounds and the specific role of geographical distance

When including the average geographical distance among inventor teams into our regressions, the overall picture stays largely consistent with the previous models described above. However, two differences can be observed. First, pure SME-filings lose significance in the Tobit-model as well as in the "mavericks"-category and second, purely academic filings now show a weakly significant coefficient for the "pioneering"-category, slightly softening our findings regarding H1b.

Regarding the influence of distance, both regressions (M7 & M8) show no significant effects. Yet, the sensitivity of inventor teams is likely to be dependent on the resource-infrastructure and the institutional configuration derived from their organizational background. Therefore, we assumed a causal relation between both explanatory variables and included an interaction term (ORG*GD) in both regressions. The Tobit-model (M9) as well as the MLM (M10) provide significant effects for the interaction terms as well as the main factors. Thus, as hypothesized in H3c, we can basically state that there is a significant moderating effect from ORG on GD.[7]

The marginal effects provide us with two basic findings. Firstly, after including the interaction term, the geographical distance between the members of an inventor team (M9) exerts a significantly negative effect on *TechImp* as well as for "pioneering"-patents in the MLM (M10), which confirms H2b. Geographical distance as a barrier to face-to-face contacts generally has a negative influence on the output of collaborative activities. Therefore, geography matters not only for the formation of networks. Geographical proximity also increases the innovative performance of inventor teams, as measured by the technological impulse. This underlines the assumption that collaborative work which is conducted under spatial proximity is more likely to produce "high quality output", particularly in ambitious research projects leading to rather radical and new solutions.

---

7 For further interpretation, we solely refer to the marginal effects, as the effects derived from an interaction term cannot be interpreted in isolation from the main factors. The STATA margins command provides the first order derivatives of the regression equation and takes the causality between ORG and GD into account (Williams 2011).

Table 5 Multivariate results II: Geographic distance and its dependency on the organizational background

	Geographical Distance					Interaction term: Organizational background & Geographical distance									
	M7	M8				M9		M10							
	TOBIT	Mfx: ∂TechImp / ∂X (4CAT)				Mfx / TOBIT	TOBIT	Mfx: ∂TechImp / ∂X (4CAT)				MLM (4CAT)			
dV =	TechImp	Maverick ∂y/∂x (Kat0)	Pioneer ∂y/∂x (Kat1)	Adopter ∂y/∂x (Kat2)	Enabler ∂y/∂x (Kat3)	TechImp	TechImp	Maverick ∂y/∂x (Kat0)	Pioneer ∂y/∂x (Kat1)	Adopter ∂y/∂x (Kat2)	Enabler ∂y/∂x (Kat3)		Pioneer (Kat1)	Adopter (Kat2)	Enabler (Kat3)
Purely: SME	-0.0675	0.0195	-0.004	0.0226*	-0.0381***	-0.0514	-0.1096*	0.0169	-0.0014	0.0229*	-0.0384***	Maverick: Outcome 0 = Base category	-0.1575	-0.0597	-0.2945***
Mixed: MNE/Acad	0.1931***	0.0239*	0.0328***	-0.0379***	-0.0187	0.1951***	0.0964	0.0191	0.0312***	-0.0333**	-0.0169		-0.0428	-0.1518	-0.1196
Mixed: SME/Acad	0.2560***	0.0124	0.0618***	-0.0153	-0.0589***	0.2709***	0.2005	0.0153	0.0630***	-0.0162	-0.0622***		0.0947	-0.2355	-0.5119***
Purely: Academic/UNI	0.1527	0.0484*	0.0377*	-0.0189	-0.0672***	0.1546	0.0067	0.0489*	0.0368*	-0.0204	-0.0653***		-0.2046	-0.3749*	-0.4521**
Mixed: OTHER/Acad	-0.018	0.1176***	0.0370*	-0.0522**	-0.1024***	-0.0009	-0.065	0.1153***	0.0403**	-0.0528***	-0.1028***		-0.2241	-0.6528***	-0.7977***
Geographical_dist	-0.0256	-0.0002	-0.0027	0.0029	0.0000	-0.0381**	-0.1024***	0.0023	-0.0069*	0.0038	0.0009		-0.1924**	-0.0197	-0.0307
SME X geo_dist						β(SME*GD)	0.0723	β(SME*GD)					0.1174	0.0938	0.0902
A_MNE X geo_dist						β(A_MNE*GD)	0.1226**	β(MNE*GD)					0.2387**	-0.0846	-0.0395
A_SME X geo_dist						β(A_SME*GD)	0.0876	β(A_SME*GD)					0.3000**	0.1101	0.1986*
UNI X geo_dist						β(UNI*GD)	0.1838**	β(A_UNI*GD)					0.3564**	0.1235	-0.0346
A_OTHER X geo_dist						β(A_OT*GD)	0.0796	β(A_OTHER*GD)					0.1821	0.0265	-0.1363
Techological_dist	0.0114	-0.1183***	-0.0609**	0.0743***	0.1050***	0.0112	0.0112	-0.1189***	-0.0600**	0.0728***	0.1062***		0.0074	0.7474***	0.9208***
Number of inventors	0.0866***	-0.004	0.0054***	-0.0095***	0.0082***	0.0866***	0.0866***	-0.0041*	0.0055***	-0.0094***	0.0081***		0.0498***	-0.0227	0.0479***
Number if IPC-classes	0.0355	0.0025	0.0032	-0.0051	-0.0005	0.0349	0.0349	0.0022	0.0029	-0.0048	-0.0004		0.0116	-0.0276	-0.011
Family size	0.0279***	-0.0156***	0.0006	0.0049***	0.0101***	0.0281***	0.0281***	-0.0157***	0.0007	0.0049***	0.0101***		0.0560***	0.0765***	0.1013***
Number of NPL-citations	-0.0037***	-0.0153***	-0.0047***	0.0098***	0.0103***	-0.0037***	-0.0037***	-0.0153***	-0.0047***	0.0098***	0.0103***		0.0201	0.0963***	0.1032***
Constant	-1.0400***						-0.9973***						-1.5617***	-1.2930***	-1.9510***
Field Dummies	YES														
Time Dummies	YES														
N	8892	8892				8892		8892							
Pseudo R²	0.021	0.075				0.021		0.076							
F/Wald Chi²	4.294	1122				4.028		1122							
aic	25002.062	22623.376				25005.699		22625.051							
bic	25370.893	23708.591				25409.995		23816.659							
Prob > F/Prob > chi2	0.000	0.000				0.000		0.000							

Source: EPO – PATSTAT, own calculations

Significance Level: ***p<0.01, **p<0.05, *p<0.1, robust standard errors

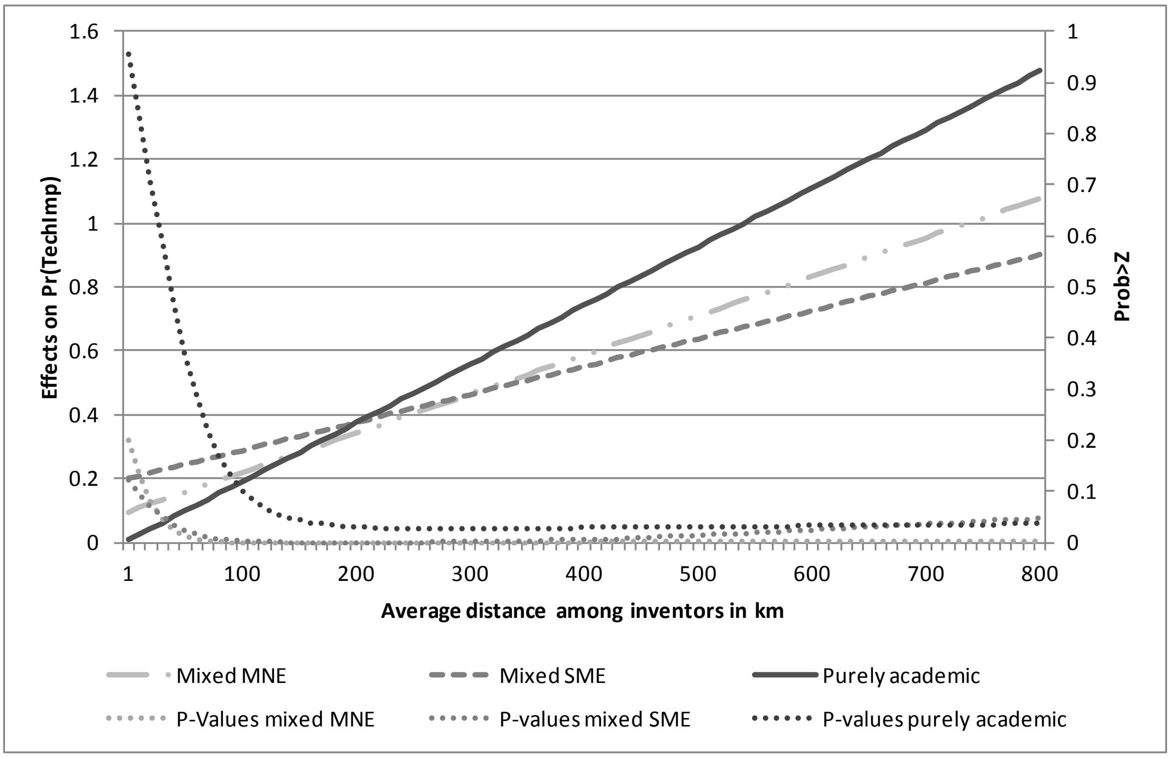
Note: MNE filing serves as a base outcome for the variables SME filing and academic patent as well as the mixed types in the extended ORG variable. N is lower in the ratio calculation since there are patents with no backward citations for which no ratio could be calculated. N is further reduced because distance is only calculated for patents on which at least two inventors are listed.

Secondly, the influence of spatial distance depends on the organizational background of the inventor team (H2c). In order to attain the full picture, however, we calculated the marginal effect for each team background at representative values of distance. Figure 2 shows how responsive the distance is to the moderating effect of a team's organizational embedding. Only significant slopes are displayed. For the sake of simplicity, we focus on the ratio of forward over backward citations.[8] In sum, for projects that emerged with academic participation, distance has a positive effect on the technological impulse. Thus, under certain conditions, distance between the members of a research team can also increase their innovative performance. This is contingent on the involvement of academics in the team and might be due to two interrelated reasons. Firstly, academic inventors are highly mobile, even compared to other highly skilled workers (Maier et al. 2007). Secondly, recent research has shown that social and cognitive proximity helps to substitute the need for spatial proximity in later knowledge exchanges (Boschma 2005). Academics maintain former local relationships to academia and industry, which provide the personalized infrastructure for interregional knowledge transfer. They provide an antenna function and serve inventor teams as bridging agents into distant knowledge sources providing access to often exclusive and (mostly) non-local epistemic communities. Thus, academic involvement in the team seems to extend the search scope and screening capability.

For mixed academic-corporate teams, Figure 2 shows that MNEs profit more from collaborations with academics over distance than SMEs. Again, it seems reasonable to assume that they simply have more resources available to co-ordinate networks into distant knowledge domains. Mixed SMEs which have the largest effect in shorter distances might represent a “spin-off”-effect, in that those which often stay in proximity to their parent organization are active in interactions with local scientists (Helm, Mauroner 2007). Purely academic inventor teams are by nature cognitively and socially better embedded into epistemic communities. Thus, it is not surprising that they seem to gain the largest profits from distant collaborations. This at first comes into play from a certain threshold onwards (ca. 110km). This is reasonable since purely academic inventor teams tend to collaborate more over shorter distances than mixed teams (von Proff, Dettmann 2012), but if distant inventors are involved, these come from another university, which is usually not in the direct neighborhood.

8 We performed analogous analyzes for the "pioneering" category with very similar results.

Figure 2 Predicted marginal effects of cross-institutional and purely academic teams on the technological impulse at values of geographical distance



Source: EPO – PATSTAT, own calculations
Note: Only significant slopes are displayed

5 Summary and conclusions

This paper aimed at analyzing how direct academic involvement in inventor teams affects the impulse that inventions exert on technological paths and how distance in a spatial as well as technological sense influences the outcome of inventive activities. Our results firstly confirm the expected clear-cut picture that has been derived from the literature review. Our citation-based indicator clearly reflects the different modes of learning and capabilities in technological innovation of the three institutional domains: SMEs, MNEs and universities. While SMEs are more likely to adapt to current technological trends, we find that MNEs manage a larger spectrum of activities, ranging from the exploitation of existing knowledge to connecting this to future technological paths. Inventions with an academic background are more likely to influence future technologies, while relying on a small stock of existing knowledge. We thus empirically observe the expected division of labor in technological innovation.

Our second finding differentiates the role that academic backgrounds have in determining the influence of inventive activities on future technological paths. Our results suggest that inventions from cross-institutional backgrounds in mixed inventor teams provide the largest potential to contribute to new technological paths. This highlights and adds empirical evidence to the importance of university-industry collaboration for putting the innovative potential of science into force. Particularly the innovativeness of SMEs is positively affected by collaborations with academic inventors. This indicates the importance of spin-offs and small R&D-intensive firms as actors in knowledge transfer from universities, especially for the valorization of radical inventions. Thus, our results also add empirical evidence to the role of innovative SMEs as drivers for technological innovation. Overall, we can conclude - and confirm the simulation-based findings by Ahrweiler et al. (2011) - that co-operating universities raise the knowledge and competence levels among firms in technology generation. From a policy perspective, this strengthens the arguments for improving and supporting university-industry interactions as well as spin-off formation.

However, the effectiveness of such interventions will depend on how these interaction patterns are implemented and managed (Perkmann, Walsh 2007). In this vein, the results at least question the importance of university patenting for technology transfer. In Germany, the legal regime was changed from professor's privilege to institutional IP ownership in 2002. This was accompanied by several funding initiatives, following the 1980 US role model - the "Bayh-Dole Act" -, aiming at increasing the patenting and exploitation activities of universities. Here our results indicate that increasing universities' filing activities should be considered with caution, since the largest share of purely academic patents seems to lack connectivity to both future technological developments as well as current technologies, at least in the short-term.

This gives further reason to concern that an increasing focus on commercialization may induce researchers to shift resources towards disclosing and patenting of lower quality inventions. However, we should keep in mind that our observation period as well as the operationalization of our variables might play a role. Firstly, one should remember that forward citations are counted within a time-window of four years. Thus, these inventions might gain importance in the long-term. Secondly, evidence from the US shows that the quality of inventions did decline after 1980 due to the entry of universities with little patenting experience, not to a general decline in quality of inventions patented by all universities (Mowery, Sampat 2004). This might imply that German universities should improve their competencies in technology management, the patenting process and their intellectual property portfolio. Another implication from a university and policy perspective is that technology transfer offices and funding programs should take the inter-organizational and inter-personal boundary-spanning networks between academics and firms into account and focus on supporting bottom-up-driven networking activities.

The third main finding highlights the importance of geographical proximity for the output generated by inventor teams. Our results contribute to the ongoing discussion on the role of spatial proximity in that it matters not only for the formation of collaborations, but also for the success of collaborative activities. Teamwork that is conducted under spatial proximity is likely to produce a higher quality output in terms of technological impulse. At the same time, tapping into distant knowledge sources is beneficial if it is accompanied by academic inventors. Thus, we provide new evidence by showing that the effect of involving academics raises the spatial search scope of an inventor team and increases the technological impulse that is emanating from its inventions. The findings show that intra-corporate networks and communities of practice profit from localized interaction in pursuing existing technological paths, but tapping in geographically distant knowledge is significantly enhanced by academic involvement. This highlights the role of academic inventors as bridging agents and carriers of inter-regional knowledge transfers. As members of epistemic communities, they are able to connect often locally-oriented inventor teams to inter-regional knowledge streams and to facilitate access to distant knowledge.

References

Adams, J.D., 1990. Fundamental Stocks of Knowledge and Productivity Growth. Journal of Political Economy 98, 673.

Agrawal, A.; Cockburn, I.; McHale, J., 2006. Gone but not forgotten: Knowledge flows, labor mobility, and enduring social relationships. Journal of Economic Geography 6, 571-91.

Ahrweiler, P.; Pyka, A.; Gilbert, N., 2011. A new model for university-industry links in knowledge-based economies. Journal of Product Innovation Management 28, 218-35.

Bercovitz, J.; Feldman, M., 2011. The mechanisms of collaboration in inventive teams: Composition, social networks, and geography. Research Policy 40, 81-93.

Boschma, R.A., 2005. Proximity and innovation: A critical assessment. Regional Studies 39, 61-74.

Brökel, T.; Binder, M., 2007. The regional dimension of knowledge transfers - A behavioral approach. Industry and Innovation 14, 151-75.

Bruneel, J.; D'Este, P.; Salter, A., 2010. Investigating the factors that diminish the barriers to university-industry collaboration. Research Policy 39, 858-68.

Carpenter, M.P.; Narin, F.; Woolf, P., 1981. Citation rates to technologically important patents. World Patent Information 3, 160-63.

Cassiman, B.; Veugelers, R.; Zuniga, P., 2008. In search of performance effects of (in)direct industry science links. Industrial and Corporate Change 17, 611-46.

Cohen, W.M.; Levinthal, D.A., 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. Administrative Science Quarterly 35, 128.

Cohen, W.M.; Nelson, R.R.; Walsh, J.P., 2002. Links and impacts: The influence of public research on industrial R&D. Management Science 48, 1-23.

Constant, E.W., 1980. The Origins of the Turbojet Revolution. John Hopkins University Press, Baltimore, MD.

Czarnitzki, D.; Glänzel, W.; Hussinger, K., 2009. Heterogeneity of patenting activity and its implications for scientific research. Research Policy 38, 26-34.

D'Este, P.; Iammarino, S., 2010. The spatial profile of university-business research partnerships. Papers in Regional Science 89, 335-50.

Dahlin, K.B.; Weingart, L.R.; Hinds, P.J., 2005. Team diversity and information use. Academy of Management Journal 48, 1107-23.

Dornbusch, F.; Schmoch, U.; Schulze, N.; Bethke, N., 2013. Identification of university-based patents: A new large-scale approach. Research Evaluation 22, 52-63.

Fleming, L.; Sorenson, O., 2004. Science as a map in technological search. Strategic Management Journal 25, 909-28.

Frietsch, R.; Neuhäusler, P.; Rothengatter, O., 2011. SME Patenting - An Empirical Analysis in Nine Countries. Presentation at the Atlanta Conference on Science and Innovation Policy, October 2011.

Giuri, P.; Ploner, M.; Rullani, F.; Torrisi, S., 2010. Skills, division of labor and performance in collective inventions: Evidence from open source software. International Journal of Industrial Organization 28, 54-68.

Günterberg, B.; Kayser, G. (2004): SMEs in Germany - Facts and Figures 2004, IfM-Materialien, Bonn: Institut für Mittelstandsforschung (IfM).

Harhoff, D.; Scherer, F.M.; Vopel, K., 2003. Citations, Family Size, Opposition and the Value of Patent Rights. Research Policy 32, 1343-63.

Heinrich, C.; Maffioli, A.; Vázquez, G. (2010): A Primer for Applying Propensity-Score Matching, SPD Working Papers.

Helm, R.; Mauroner, O., 2007. Success of research-based spin-offs. State-of-the-art and guidelines for further research. RMS 1, 237-70.

Hewitt-Dundas, N., 2013. The role of proximity in university-business cooperation for innovation. Journal of Technology Transfer 38, 93-115.

Huggins, R.; Johnston, A.; Steffenson, R., 2008. Universities, knowledge networks and regional policy. Cambridge Journal of Regions, Economy and Society 1, 321-40.

Jaffe, A.B., 1989. Real effects of academic research. American Economic Review 79, 957-70.

Jaffe, A.B.; Trajtenberg, M.; Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Quarterly Journal of Economics 108, 577-98.

Jensen, M.B.; Johnson, B.; Lorenz, E.; Lundvall, B.A., 2007. Forms of knowledge and modes of innovation. Research Policy 36, 680-93.

Laursen, K., 2012. Keep searching and you'll find: What do we know about variety creation through firms' search activities for innovation? Industrial and Corporate Change 21, 1181-220.

Laursen, K.; Reichstein, T.; Salter, A., 2011. Exploring the effect of geographical proximity and university quality on university-industry collaboration in the United Kingdom. Regional Studies 45, 507-23.

Laursen, K.; Salter, A., 2004. Searching high and low: What types of firms use universities as a source of innovation? Research Policy 33, 1201-15.

Maier, G.; Kurka, B.; Trippl, M., 2007. Knowledge Spillover Agents and Regional Development - Spatial Distribution and Mobility of Star Scientists. Working Paper Number 17/2007.

Malerba, F.; Orsenigo, L., 1993. Technological regimes and firm behavior. Industrial and Corporate Change 2, 45-71.

Manniche, J., 2012. Combinatorial Knowledge Dynamics: On the Usefulness of the Differentiated Knowledge Bases Model. European Planning Studies 20, 1823-41.

Mowery, D.C.; Sampat, B.N., 2004. The Bayh-Dole Act of 1980 and university-industry technology transfer: A model for other OECD governments? Journal of Technology Transfer 30, 115-27.

Narin, F.; Hamilton, K.S.; Olivastro, D., 1997. The increasing linkage between U.S. technology and public science. Research Policy 26, 317-30.

Perkmann, M.; Walsh, K., 2007. University-industry relationships and open innovation: Towards a research agenda. International Journal of Management Reviews 9, 259-80.

Perkmann, M.; Walsh, K., 2009. The two faces of collaboration: Impacts of university-industry relations on public research. Industrial and Corporate Change 18, 1033-65.

Ponds, R.; van Oort, F.; Frenken, K., 2007. The geographical and institutional proximity of research collaboration. Papers in Regional Science 86, 423-43.

Rosenbaum, P.R./Rubin, D.B. 1985. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. The American Statistician 39, 33-38.

Rosenkopf, L.; Nerkar, A., 2001. Beyond Local Search: Boundary-Spanning, Exploration and Impact in the Optical Disc Industry. Strategic Management Journal 22, 287-306.

Powell, W.; Grodal, S., 2005. Networks of innovators, in: Fagerberg, J., Mowery, D.C., Nelson, R.R. (Eds.), The Oxford Handbook of Innovation, 56-85.

Santoro, M.D.; Chakrabarti, A.K., 2002. Firm size and technology centrality in industry-university interactions. Research Policy 31, 1163-80.

Schmoch, U., 2008. Concept of a Technology Classification for Country Comparisons. Final Report to the World Intellectual Property Office (WIPO). Fraunhofer ISI, Karlsruhe.

Singh, J., 2008. Distributed R&D, cross-regional knowledge integration and quality of innovative output. Research Policy 37, 77-96.

Stephan, P., 2012. Economics of Science. Harvard University Press.

Tödtling, F.; Lehner, P.; Kaufmann, A., 2009. Do different types of innovation rely on specific kinds of knowledge interactions? Technovation 29, 59-71.

Torre, A., 2008. On the role played by temporary geographical proximity in knowledge transmission. Regional Studies 42, 869-89.

Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovation. Rand Journal of Economics 21, 172-87.

Trajtenberg, M.; Henderson, R.; Jaffe, A., 1997. University versus corporate patents: A window on the basicness of invention. Economics of Innovation and New Technology 5, 19-50.

van Oort, F.G.; Burger, M.; Raspe, O., 2008. Inter-firm relations and economic clustering in the Dutch Randstad region. The Economics of Regional Clusters 145-65.

Vincenti, W.G., 1990. What Engineers Know and How They Know It: Analytical Studies from Aeronautical History. John Hopkins University Press, Baltimore.

von Proff, S., Dettmann, A., 2013. Inventor collaboration over distance: a comparison of academic and corporate patents. Scientometrics 94, 1217-38.

White, H., 1980. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. Econometrica 48, 817-38.

Williams, R., 2011. Using the Margins Command to Estimate and Interpret Adjusted Predictions and Marginal Effects - CHI11 Stata Conference. Stata Users Group.

Wooldridge, J.M., 2002. Introductory Econometrics - A modern approach. South-Western Educational Publishing, 2nd edition.