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Universities as local knowledge hubs under different technology regimes ? New evidence from academic patenting

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Abstract

Universities often are claimed to act as local knowledge factories. Although this function is largely analyzed in previous research, there still is a knowledge gap regarding the role of a technological match between the profiles of interaction partners in university-industry interactions. In addition, the effects of different knowledge dynamics in technological regimes remain under-researched.

In this paper, we thus draw special attention to the question how geographical distance and the specific role of a technological fit between the knowledge provided by the university and the technological needs of the local industry affects interactions between universities and firms. Thereby, we differentiate between six technological regimes constituted by different knowledge dynamics.

Our analyses are based on a unique dataset containing all German universities? academic patenting and publication activities. Being further enriched by secondary data, this enables us to show that the technological fit between a university and its surrounding region (in terms of local industry needs) indeed has a significant influence on a universities innovation related research interactions, especially with small firms. We further show that this effect additionally depends on the underlying knowledge base in heterogeneous technological regimes.

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Universities as local knowledge hubs under different technology regimes – New evidence from academic patenting

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Abstract: It is often claimed that universities act as local knowledge factories. Although this function is largely analyzed in previous research, there still is a knowledge gap regarding the role of a technological match between the profiles of partners in university-industry interactions. In addition, the effects of different knowledge dynamics in technological regimes remain under-researched.

In this paper, we thus draw special attention to the question how geographical distance and the specific role of a technological fit between the knowledge provided by the university and the technological needs of the local industry affects interactions between universities and firms. Thereby, we differentiate between six technological regimes constituted by different knowledge dynamics.

Our analyses are based on a unique dataset containing all German universities' academic patenting and publication activities. As these are further enriched by secondary data, they enable us to show that the technological fit between a university and its surrounding region (in terms of local industry needs) indeed has a significant influence on a university's innovation-related research interactions, especially with small firms. We further show that this effect additionally depends on the underlying knowledge base in heterogeneous technological regimes.

I. Introduction

Universities are generally speaking expected to act, beside their primary task of research and teaching, as local knowledge factories. Thereby, local knowledge and technology transfer from universities is found to be affected by several factors, among them geographical distances, type of research, kinds of universities (e.g. Drucker/Goldstein 2007; Uyarra 2010; Youtie/Shapira 2008) as well as the attributes of its surrounding region (Smith/Bagchi-Sen 2012). Thus, a match between the knowledge provided by the university and regional conditions in terms of local actors' willingness and ability to interact is needed to generate regional impact (Bercovitz/Feldmann 2006; Malmberg/Power 2005). Therefore, simply assuming a positive effect from universities on their local environment would disregard the basic incentive structures in academic research. This makes it important to account for different types of knowledge production (Rutten/Boekma 2009) and for the relationship between firm behavior, in terms of basic strategies and organization and technological regimes, in terms of opportunity, appropriability and the complexity of the knowledge bases in technological regimes (Malerba/Orsenigo 1993).

The academic system is rooted in Mertonian norms of science (Merton 1957) and usually generates knowledge within and for academic communities. This is why the basic type of knowledge production (mode 1) (Gibbons et al. 1994) in universities refers mainly to the dissemination of basic and science-based knowledge and its absorption strongly depends on the ability of other actors to assimilate and interpret it. This has strong implications for universities' outgoing linkages with firms. It can help to improve a firm's basic understanding of particular phenomena and thus enhance its awareness of new research and technological opportunities. However, interactions containing this kind of mode 1 or "know-why" knowledge (Jensen et al. 2007) require long-term resource investments in pre-market R&D and the employment of researchers with networks in academic communities. These are particularly important for companies which intend to overcome knowledge exchange problems with the scientific system (Bercovitz/Feldman 2007; De Faria et al. 2010; Tödtling et al. 2009). The exchange of this knowledge usually entails large shares of codified information and takes place within epistemic communities that are not necessarily bound to the local level (Manniche 2012).

A smaller share of academic knowledge is produced in an interactive, multidisciplinary and application oriented way requiring face-to-face contacts with practitioners (Gibbons et al. 1994; Rutten/Boekma 2009). It contributes to a firm's exploitation abilities and problem-solving capabilities (Bishop et al. 2011; Cohen et al. 2002). This mode 2 type of knowledge production refers more to "know-how" knowledge (Jensen et al. 2007) and is often derived via social networks which play an important role for iterative exchange processes. These patterns in knowledge interaction are assumed to be strongly bound to the co-location of actors (Rutten/Boekma 2009) and takes place within communities of practice (Manniche 2012).

In sum, knowledge interactions from universities crossing organizational boarders to industry depend on the type of knowledge as well as the characteristics of the participating counterpart, in terms of ability to deal with different types of academic knowledge production. As previous case study-based research shows, industries and technological sectors consist of different combinations of knowledge bases (Asheim 2007; Manniche 2012) highlighting a differentiated perspective on academic contribution to local industries knowledge pools. In this sense, this paper wants to add insights into the patterns of interactions between universities and firms and how the role of universities as providers of locally applicable knowledge differs under different technology regimes.

⇨ *Thus, the main questions to which this paper wants to contribute are:*

a. *how the similarity between a university's scientific profile and the local environment's technological profile influences its knowledge interaction with small and large firms.*

b. how this differs between various technology regimes.

Our empirical analyzes rely on a unique dataset containing academic patents that are either filed by universities, by small firms or by large corporations and is further enriched by secondary data to examine the influences of regional environment and organizational characteristics of universities. Inventions with academic participation and turning them into patented- as well as marketable innovations involves a complex daisy chain set of relationships including academic scientists and in many cases company researchers (Feller, Feldman 2009; Von Proff, Dettmann 2012). Knowledge interactions serve the integration of complementary and additional knowledge during the innovation process while academics are often only one source of knowledge (Manniche 2012). While a minority of academic patents is assigned by the universities themselves, the larger share is derived from collaborations with firms and assigned by firms (Geuna/Rossi 2011; Schmoch 2007). Thus, the basic proposition of this paper is that the key for cross-organizational interactions between universities and firms are personal networks and relationships between members of inventor teams. The emergence and maintenance of those is influenced by and embedded in institutional and organizational backgrounds, shaping the composition of the underlying inventor networks (Von Proff, Dettmann 2012). Therefore, we take patterns of ownership in academic patenting as a proxy for different organizational and institutional backgrounds of inventor teams. In order to show how these shape cross-organizational interactions we differentiate between inventor teams embedded in purely academic backgrounds, those being cross-organizational reflecting boarder-crossing interactions between universities and small firms and finally those crossing organizational boarders between universities and large firms.

The reminder of the paper is structured as follows. The second section provides the theoretical background which is used to develop the paper's hypotheses. The third section describes the dataset while the fourth section describes the results of multivariate regressions for different technological sectors, the fifth section contains the summary and discussion and section six the conclusion.

II. Theory

The main aspects of an organization's interaction with its surroundings seem to be, firstly, the opportunities based on resources that are available to an organization to trigger knowledge interaction, secondly, the social capital of an organization and thirdly, the opportunities provided by the local environment in which an organization is embedded (Malmberg/Power 2005).

II.1 Knowledge bases and technological regimes

As already stressed in the introduction, it is important to keep in mind that sectors rest on a mix of different knowledge bases shaping the patterns of knowledge interactions in innovative projects (Manniche 2012). Thus, knowledge should not be treated as a coherent whole. Learning processes and the ways how firms interact with universities are likely to be different, depending on the dominant type of knowledge base in different sectors. We refer to the synthetic and analytical knowledge base (Asheim et al. 2007), because both consider knowledge interactions with universities as conceptual elements.

The *synthetic* knowledge base is mainly characterized by incremental innovations through novel combinations of existing knowledge. This is often instrumental, context specific, and practice related, that is to say aimed at solving specific problems arising in interactions with clients and suppliers (Manniche 2012). The dominant forms of learning are learning by doing, using and interacting (Jensen et al. 2007). Learning takes place as an interactive, recursive trial and error process, including constant feedback-loops (Moodysson et al. 2008) and, in the context of markets and networks, often involving customers, suppliers as well as institutions conducting applied research. Synthetic knowledge is practice-related and largely tacit. Know-how is the most important knowledge and face-to-face interactions foster knowledge exchanges (Asheim et al. 2007). Here, scientists interested in design, development and industrial exploitation of technological artifacts, act as mediators between the two spheres of academic basic science and industrial development. Close collaboration and regular interaction facilitate learning across organizational boarders and contribute to the formation of “communities of practice” between university and industry (Perkmann/Walsh 2009). Mutual cognitive understanding and social proximity become crucial, since networks between company researchers and university scientists are exclusive and created over time (Breschi/Lissoni 2001; Mattes 2012). Thus, spatial proximity alone does not trigger knowledge flows between academics and local engineers. Knowledge is rather circulated in individual social networks that are often biased towards the local environment (Breschi/Lissoni 2009; Ostergaard 2009). These typical characteristics of engineering related sectors at best describe circumstances that allow for the mode 2 type of academic knowledge production (Gibbons et al. 1994; Mattes 2012), enhancing the probability that universities contribute to local knowledge production.

In contrast, *analytical* knowledge mainly aims at understanding basic principles and mechanisms. Innovations are radical and generate new knowledge. Analytical knowledge generation constitutes the core attributes of universities, research institutions and R&D departments of companies (Manniche 2012; Moodysson et al. 2008). The innovation process is a more formalized one, characterized by know-why knowledge. It is based on activities where scientific understanding is important and learning takes place by searching and researching, both being intentional and directed. The knowledge resulting from analytical knowledge processing is to a large extent codified and can be transferred across space. But still, a certain amount of tacit knowledge as well as shared concepts are needed to interpret, understand and work with codified knowledge. Typical case-study examples named in the literature are genetics, biotech, life science, pharmaceuticals and some segments of information and communication technology (e.g. Manniche 2012). Here, 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. Thus, both dimensions are crucial for cross-organizational knowledge interactions, while social and geographical attributes facilitate the transfer of knowledge (Mattes 2012). In doing so, epistemic communities are the dominant frameworks for learning by searching and researching in these sectors (Manniche 2012) and scientists' knowledge dissemination is likely to take place within exclusive, academic and global networks constituted by mode 1 type of knowledge production, making local communities less important.

In sum, patterns of boundary-spanning interactions presumably depend on the combination of knowledge bases underlying a technological regime. To our knowledge, no previous quantitative approach has tried to model patterns of university-industry interaction in the light of different knowledge bases in technological regimes. Therefore, as we are conducting an explorative approach, we highlight the importance of a differentiated perspective, but abstain from developing concrete hypotheses. We study six different sectors, which can be assumed to be shaped by different knowledge dynamics. In sum, the studies cited above show that engineering (electrical and mechanical) related sectors are predominantly based on synthetic knowledge. For life sciences and chemicals we find case-study based evidence that they are dominated by analytical knowledge. For measurement and controls as well as information and communication technologies (ICT) the picture is less clear and we consider both as being more heterogeneous than the four other sectors.

II.2 Technological fit and proximity

Boschma (2005) introduces five proximity dimensions that facilitate knowledge interactions. Following this idea, different dimensions substitute for other missing features in relationships between actors, i.e. the need for geographical proximity turn out to be relative to the existence of cognitive, social, organizational, cultural or institutional proximity.

Especially the *social* and *geographical proximity dimensions* foster and facilitate the creation of other types of proximity (Mattes 2012). Both are related, since the main advantages of close spatial proximity are seen in (1) the reduction of communication costs, (2) a higher probability of meetings and (3) a higher probability that social relationships will evolve. All three aspects can open new arrays of social networking and can provide new opportunities for knowledge exchange (Agrawal et al. 2006). Face-to-face contacts act as a communication tool and are generally viewed as instruments that build up trust, facilitate screening, socializing and provide incentives for the inclusion of new relationships (Asheim et al. 2007; Zeller 2002). Thus, enhanced opportunities for social interaction in close proximity, increases the probability of establishing social networks (Singh 2005; Sorenson et al. 2006) and search processes of firms and individuals are often biased towards their local environment as well as well-known and familiar technologies in that search processes take place along established trajectories created by past experience, routines, and heuristics (Dosi 1982; Malerba/Orsenigo 1993). Individuals searching under bounded rationality often chose the first seemingly appropriate (often second best) solution, leading to a spatial bias in networking and knowledge exchange (Brökel/Binder 2007). Consequently, a proportionally higher share of information, experiences and knowledge are gathered from local sources and social networks and have a higher propensity to be built up locally. This becomes evident in communities of practice, where informal relationships and networks are important channels for job changes and knowledge exchange (Breschi/Lissoni 2009; Malmberg/Power 2005). Consequently, co-location of economic actors often resides in the context-specificity of knowledge (Gertler 2003). Institutional factors like habits, routines, practices and laws often shape territory and industry-specific structures in which individuals are embedded (Asheim/Coenen 2005) creating *institutional proximity* as a normative dimension that regulates interactions between actors in shared local environments (Boschma 2005; Mattes 2012).

We are not able to measure the different kinds of proximity in our empirical approach, except for geographical proximity (see below). However, cultural differences between academia and industry require inter-organizational trust and long-term systems of informal reciprocity are considered as important parts of university-industry networks (Bruneel et al. 2010). Individuals act as bridging agents between the two spheres (Lam 2007) while the establishment of knowledge exchange relationships and open science channels is in most cases based on existing social relationships and informal networks. Thus, the various kinds of proximity between academia and economy are more likely to develop if both deal with similar issues at the same location. Therefore, we consider the technological fit between a university and its economic environment important for the development of interaction between the two spheres. However, we expect a strong difference between large and small firms in the relevance of this technological fit.

The institutional and organizational proximity created in subsidiaries and with contractually bound partners enables firms to access specific knowledge and personnel, making spatial proximity between partners less important (Von Proff, Dettmann 2012). Thus, large firms are able to maintain inter-regional partnerships and look for horizontal co-operation with companies and research institutions outside their region, while they build vertical networks to smaller businesses within the region (Torre 2008). Hence,

H1a: *Large firms' knowledge interactions with universities are not or only slightly sensitive to the technological fit between university and its economic environment.*

Due to resource constraints, small businesses are more likely to interact within existing clusters (Torre 2008). They are often missing the opportunities of large firms with big R&D departments and only few people are familiar with tasks in R&D and knowledge management (Tödtling et al. 2009). They miss 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, spatial proximity and local opportunities for knowledge sharing are more likely to become a determining factor.

H1b: *Small businesses' knowledge interactions with universities are sensitive and positively affected by the technological fit between the university and its economic environment.*

II.3 Geographic proximity

As discussed above, other kinds of proximity can substitute for geographical proximity and various kinds of proximity interact. The need for geographical proximity is rather weak when strong coordination mechanisms are implemented and partners share cognitive experiences (Torre 2008).

Nevertheless, face-to-face meetings are found to remain important to reassure common agreements among the partners, to discuss unsolved problems, to solve conflicts and to define further milestones. Resource endowments, particularly in R&D personnel, are seen as the most important factor to mediate geographical distance (Asheim/Coenen 2005). In most studies, limiting effects of physical proximity tend to refer to small and medium-sized enterprises. Companies with low or very application-oriented R&D-capacities are found to be rather sensitive to geographical proximity in interactions with universities. This seems to apply less for large companies and suggests that large companies are less likely to be subject to the limitation of geographical distances and simply have more resources available to meet their needs for physical proximity (Torre 2008). The bigger the firm, the more easily it adjusts its localizations to the temporal nature of the need for proximity.

H2a: *Inventor teams of patents filed by large firms are likely to span over larger distances than those of other organizations.*

For purely academic inventor teams von Proff and Dettmann show that these are more sensitive to distance than corporate teams, because focusing on basic research shapes the characteristics of inventing teams(Von Proff, Dettmann 2012). Complexity and uncertainty in basic research require the establishment of particularly strong social and communicative processes. Additionally, personal and carrier-related issues drive academics' membership in research groups. Thus, in a purely academic environment research teams show strong social cohesion and form group structures that last longer than those of teams that were just formed to provide a specific solution to a certain predefined task. In order to maintain this particularly strong social cohesion in the long-run, these teams require intense interactions and face-to-face contacts that are difficult to substitute.

H2b: *Inventor teams of patents filed by universities are likely to span shorter distances than those of other organizations.*

Additionally, following these remarks we expect that inventor teams with a background of a small firm bridge larger distances than those of universities, but shorter distances than inventor teams with a background of a large firm. Thus, they have an in-between position between both other categories.

Table 1 sums up the derived hypotheses and shows the expected directions of the effects by putting the outcome categories in relation to each other.

Table 1: Summary of hypotheses

dV	***H1: Similarity***			***H2: Distance***		
	Hypothesis	Expected effect	Category relation	Hypothesis	Expected effect	Category relation
UNI	*No hypothesis derived*			*H2b*	*(--)*	*UNI<SME&MNE*
SME	*H1b*	*(++)*	*SME>MNE*		*(-/+)*	*UNI<SME>MNE*
MNE	*H1a*	*(O)*	*MNE<SME*	*H2a*	*(++)*	*MNE>SME&UNI*

Sources: Own compilation

III Data

III.1 Data sources

Up to now, a major problem with regard to identifying and thus conducting analyses regarding the phenomenon of academic patenting was that a solid and comprehensive large scale approach to identify academic patents has been missing. It should be noted, that if research is financed fully or partly by external contractors like private companies, it remains possible for parties to negotiate the allocation of patent rights (Geuna/Rossi 2011). Particularly the patents invented partially or in total by university employees, but then filed by extra-university entities as part of contractual agreements represent the blind spot in analyses dealing with the issue of academic patenting. In order to identify the full range of academic patents, this paper draws on a recently developed approach to identify academic patenting activities (for details see Dornbusch et al. (2013). The basic principle is an algorithm that matches author names from scientific publications with inventor names derived from patent filings. The patent data were extracted from the "EPO Worldwide Patent Statistical Database" (PATSTAT), which provides information about published patents collected from 81 patent authorities worldwide. All patent filings at the DPMA (Deutsches Patent und Markenamt) were included. For the publications Scopus, provided by Elsevier, was chosen. It encompasses information on articles of about 18,500 peer-reviewed journals and further 1,000 titles from trade publications, book series and conference proceedings. The dataset was on both sides restricted to authors from German organizations and to inventors residing in Germany, in order to account for the inventor principle (Hinze/Schmoch 2004),. This enables us to differentiate between academic patents applied for by the universities themselves (university-owned) and those filed by other organizations like enterprises. Taken together, both groups are referred to as academic patents (Lissoni et al. 2008; Meyer 2003).

Two steps are employed during the matching. The first includes the construction of appropriate databases including the cleaning, harmonizing and complementing of missing data. The second involves the matching of names of inventors and authors complemented by further filtering criteria[1] to increase the matching accuracy. When dealing with a trade-off between high recall and precision priority is put on precision. Thus, the rate of incorrect assignments was kept as low as possible. Estimates show that the assigned patents are correctly identified in more than 93 percent of the cases[2]. As a consequence the dataset contains only approximately 60 percent of all academic patents – meaning patents that the algorithm should identify. Hence, we miss quite a number of academic patents, but those identified are characterized by high precision allowing representative analyzes of structures in academic patenting (see also Dornbusch et al. 2013).

The analyses refer to academic patents filed at the DPMA with priority year 2007 including all patents with either a university or a firm as the applicant. The differentiation of academic patent filings by the type of filing entity was made by the following distinction, 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. Applicants with more than three patent filings in a three year time window between priority years 1996 and 2008 and more than 500 employees were classified as MNEs, others as SMEs, corresponding to the German SME definition (Günterberg/Kayser 2004). Data on employees were taken from Hoppenstedt and complemented with information from internet searches where necessary.

Since one aim of this study is to consider different knowledge dynamics in different sectors it was important to coherently assign scientific articles to patent technology codes. The WIPO34 technology fields (Schmoch 2008) were aggregated into seven technology groups for which all existing Web of Science journal codes could be assigned without any overlap. Scientists and patent attorneys active in research on both patent analysis as well as bibliometric indicators at

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1 These criteria were: 1. Location of the authors' employer and the inventors' residence by postal codes. 2. 2-years-publication period to each priority year of patent filings, considering a time-lag of one year that is needed for the review of scientific publications. 3. Assignment of the scientific subject (of the publishing journal) to the technological area of the patent.

2 Due to recent improvements of the matching approach an even higher precision rate is likely. One of the improvements was the integration of NUTS3-codes and a distance matrix enabling us to use a more precise location criterion.

the Fraunhofer ISI validated the classification.[3] In the end seven technological sectors and associated scientific disciplines were obtained: electrical engineering, IT and ICT, measurement and controls, life sciences, chemicals, mechanical engineering, environmental sciences.

Additional data regarding regional and university characteristics are gathered from Eurostat and from the EUMIDA dataset, which was established within the European Union project "*Feasibility Study for Creating a European University Data Collection*".[4]

III.2 Dependent variable and regression

The categorical dependent variable (dV) is defined as UNI if an academic patent was filed by a university[5], as SME if a small or medium sized enterprise filed the patent, or as MNE if a large and multinational enterprise filed the patent.

Several multinomial logit regression models with robust standard errors using this variable (dV) are employed in order to test the hypotheses developed in the previous section. The reference category is universities. To ease interpretations and to make the retrieved coefficients comparable in terms of probabilities, we calculated marginal effects at the means of the independent vars. In doing so, the logits are turned into probabilities enabling an interpretation in terms of probability that a one unit change in the predictors alters the dependent variable (see Williams (2011) for a detailed discussion). The regressions are run for each of the above-named technology-science fields separately. Due to low numbers, we had to exclude environmental sciences.

III.3 Independent variables

<u>Proximity measures</u>

Two explanatory variables measure types of proximity, a physical distance and a cognitive proximity:

- DIST: The first variable represents the average geographical distance between the inventors on a patent. The distances were calculated based on the coordinates[6] belonging to each of the postal codes of German inventors' home addresses.

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3 We are particularly grateful to Professor Ulrich Schmoch. Without his expert knowledge and helpful advice these analyses would not have been possible.

4 http://datahub.io/dataset/eumida

5 A reverse-check of university-owned patents indeed revealed that only few patents are co-invented with firms. From a randomly drawn sample of 55 patents only three involved inventors from large firms. Two patents involved inventors from small firms. Two inventors could not be uniquely identified.

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

- SIM: The technological fit between a university's scientific and its local environment's profile is calculated as the cosine similarity between the specialization of a university's scientific and a region's technological specialization.
  As a measure for specialization we employ the Revealed Symmetric Comparative Advantage (RSCA) as defined by (Laursen 1998). Where the Revealed Comparative Advantage (RCA)

$$RCA_{ij} = \frac{Xij / \sum_i Xij}{\sum_j Xij / \sum_i \sum_j Xij} \qquad \text{(I)}$$

  is standardized and made symmetric

$$RSCA = (RCA - 1)/(RCA + 1) \qquad \text{(II)}$$

  The RSCA is calculated for both, the scientific output (publications[7]) and economic innovation activity (patents) and is used to calculate the cosine similarity which measures the cosine of the angle between two vectors of an inner product space:

$$similarity = \cos(\theta) = \frac{A \bullet B}{\| A \| \| B \|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} (A_i)^2} \times \sqrt{\sum_{i=1}^{n} (B_i)^2}} \qquad \text{(III)}$$

  The vectors A and B are defined by the specialization of A = each university in a scientific field and B the adhering NUTS2 regions specialization in the belonging technology. Thus, a value between 0 and 1 indicates the similarity between a university's scientific and local environment's technological activities, where 1 means high and 0 no similarity.

University characteristics

In addition, we account for general university characteristics in order to model the overall mission-orientation of a university. We operationalize the orientation towards basic science in sense of mode 1 type of knowledge production with two indicators:

- SR: On the basis of the journal-specific expected citation the indicator Scientific Regard (SR) was calculated. It indicates whether a publication of an entity is cited above or be-

7 We used a classification of all publishing German institutions in WoS which was implemented by the "Institut für Wissenschafts- und Technikforschung (IWT) - University of Bielefeld". We acknowledge and are thankful for the valuable work which has been supported and funded by the German Ministry for Education and Research under the research project "Kompetenzzentrum Bibliometrie" (Förderkennzeichen 01PQ08004D).

low average compared to the other documents in the same journal.[8] A positive SR shows above-average citation rates, negative values indicate below-average citation rates and 0 means equivalent to the average.

- RES: The research intensity of a university is measured by the number of PhD students and postdocs (ISCED6) per students (ISCED5). This is the most commonly used proxy of research intensity as it provides an indication of the effort spent on research compared to that on teaching (Seeber et al. 2012; Van Vught 2009).

The universities' orientation towards more applied research is also proxied by two indicators:

- IND: The share of industrial R&D of total third party funding a university receives.
- PAT: Average number of patents a university contributed to from 2005 till 2007 in the specific sector.

Further control variables

The control variables include publications per scientist measuring publication intensity (PUB) and academic staff (STAFF) measuring the size of the university. Furthermore, for each patent a dummy is determined, which is 1 if non-patent literature (NPL) is cited in the patent and 0 otherwise. It is included as a proxy for a patent's closeness to science (Deng et al. 1999). We further control for the characteristics of the regional environment by share of SMEs (%REG), GDP per capita (GDP) and population in a region (POP) as indicators of wealth and agglomeration effects in the university's home region.

Table2: Summary of variables

Variable		Definition
uni/sme/mne	categorical	Indicates if a university is applicant of a patent (dependent variable)
SIM	metric	Cosine similarity between a university's scientific and the local technological profile
DIST	metric	Average distance amomg inventor teams in kilometres
SR	metric	Scientific reputation of a university measured by journal-specific expected citation rates
RES	metric	Research intensity of a university measured no. of PhDs / students
IND	metric	Universities share of industrial R&D by total third party funding
PAT	metric	Avg. no. of patents with university contribution between 2005 and 2007
NPL	dummy	Indicates if a patent cites non patent literature as a proxy for science closeness
PUB	metric	Publications per scientist
STAFF	metric	No. of academic staff employed
%SME	metric	Share of SMEs in the university's region
GDP	metric	GPD/capita in the university's region
POP	metric	Total population in the university's region

Source: Own compilation

8 The calculation of the SR is represented in the following formula: $SR_k = 100 \tanh \ln (OBS_k/EXP_k)$; OBS_k refers to the actual observed citation frequency of publications of an entity k. EXP_k is the expected citation rate resulting from the average citation frequency of the journals where the authors of this entity published their papers.

III.2 Summary statistics

The sample contains 1061 patents accounting for 1201 cases. 140 patents appear twice, since either inventors from two universities are involved or two different applicants appear as the owner of the patent. Since patents are often classified in different IPC classes some appear in more than one field. The summary statistics show that the sectors electrical engineering, ICT and mechanical engineering are characterized by high shares of large firms' filings. While university-owned patents are around 20-25 percent, those of small firms are under 15 percent. Particularly, in ICT this share is low (ca. 8 percent), indicating a generally stronger share of collaborations with larger firms.

Table 3: Summary statistics

Variable	Electrical engieneering					ICT					Measurement and controls				
	Freq.	%				Freq.	%				Freq.	%			
uni	40	22,6				46	20,91				76	31,67			
sme	24	13,56				17	7,73				54	22,5			
mne	113	63,84				157	71,36				110	45,83			
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
SIM	177	0,93	0,10	0,56	1,00	220	0,95	0,08	0,57	1,00	240	0,95	0,09	0,62	1,00
DIST[1]	163	0,88	1,18	0,00	7,29	200	0,62	0,85	0,00	3,82	212	0,73	0,85	0,00	4,36
SR	177	11,40	9,58	-20,03	27,12	220	12,85	8,52	-20,03	27,12	240	10,82	9,22	-20,03	25,98
RES	177	0,05	0,03	0,00	0,15	220	0,05	0,03	0,00	0,15	240	0,06	0,03	0,02	0,34
IND	177	0,03	0,02	0,01	0,10	220	0,03	0,02	0,01	0,07	240	0,03	0,02	0,01	0,09
PAT	177	15,76	13,98	0,33	40,67	220	30,81	25,96	0,33	63,67	240	12,34	9,98	0,33	32,33
NPL	177	0,29	0,45	0	1	220	0,36	0,48	0	1	240	0,45	0,50	0	1
PUB	177	0,35	0,08	0,07	0,90	220	0,37	0,09	0,10	0,90	240	0,39	0,28	0,10	2,69
STAFF[2]	177	2,84	1,27	0,30	5,35	220	3,37	1,26	0,30	5,35	240	2,71	1,26	0,19	5,35
%SME	177	73,81	4,03	67,56	95,75	220	73,01	1,49	67,56	78,07	240	73,66	3,89	67,56	95,07
GDP[1]	177	331,75	68,73	212,00	475,00	220	359,66	66,39	206,00	475,00	240	315,03	69,69	206,00	475,00
POP[3]	177	2641,69	1234,79	515,90	4387,90	220	3313,63	1206,10	663,50	5212,70	240	2715,36	1193,71	663,50	5212,70

Variable	Life Sciences					Chemicals					Mechanical engineering				
	Freq.	%				Freq.	%				Freq.	%			
uni	164	40,39				112	41,03				62	24,41			
sme	81	19,95				54	19,78				38	14,96			
mne	161	39,66				107	39,19				154	60,63			
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
SIM	406	0,96	0,06	0,73	1,00	273	0,94	0,08	0,61	1,00	254	0,94	0,06	0,67	1,00
DIST[1]	349	0,84	1,07	0,00	4,91	261	1,12	1,30	0,00	7,29	234	0,74	0,85	0,00	4,24
SR	406	10,17	9,12	-33,80	25,98	273	7,90	10,49	-33,80	27,12	254	7,33	11,72	-20,03	45,39
RES	406	0,07	0,04	0,02	0,48	273	0,07	0,03	0,00	0,19	254	0,06	0,04	0,02	0,48
IND	406	0,03	0,02	0,01	0,09	273	0,03	0,02	0,01	0,09	254	0,04	0,02	0,01	0,07
PAT	406	19,46	14,21	0,33	50,33	273	10,54	8,00	0,33	32,33	254	16,21	11,12	0,33	30,67
NPL	406	0,60	0,49	0	1	273	0,65	0,48	0	1	254	0,19	0,39	0	1
PUB	406	0,40	0,28	0,21	2,69	273	0,36	0,19	0,13	2,69	254	0,35	0,10	0,08	0,90
STAFF[2]	406	2,70	1,20	0,03	5,35	273	2,28	1,18	0,03	5,35	254	2,44	1,20	0,31	5,35
%SME	406	73,40	2,82	67,56	95,07	273	73,88	4,08	67,56	95,07	254	73,50	3,83	67,56	95,07
GDP[1]	406	306,40	68,04	206,00	475,00	273	287,35	65,82	206,00	475,00	254	319,33	70,74	212,00	475,00
POP[3]	406	2730,17	1234,95	663,50	5212,70	273	2553,88	1193,66	1039,90	5212,70	254	2899,41	1222,19	663,50	5212,70

[1]per 100; [2]per 1.000; [3]per 10.000

Source: Own calculations

The highest shares of university ownership appear in life sciences and chemicals. Both are usually seen as being close to science and having a high share of analytical knowledge. This assumption is further supported by the high share of NPL citations with more than 60 percent of the patents citing these. A surprisingly high share of university-owned patents in measurement indicates a comparatively strong purely academic inventive activity. Furthermore, 45 percent of patents with NPL citations seem to indicate a relatively strong science link. Both indicators support Paula Stephan's (2012) consideration of measurement as being a sector where academic input at the frontier of research is getting increasingly important. Additional anecdotal evidence indicates that, since working with laboratory equipment is commonplace and essential for academics, they often have to invent new tools and improve existing equipment for their research leading to more university patent applications. In the three sectors life sciences, chemicals and measurement the shares of SMEs are comparably high (around 20 percent), reflecting a relatively stronger importance of academic knowledge for SMEs in these sectors.

Mechanical and electrical engineering show rather low shares of NPL references. This was expected and underlines their application-oriented research with strong shares of a synthetic knowledge base. This might also explain why the total number of SMEs appearing as applicants in these sectors is rather low compared to other sectors. For SMEs collaborating with universities in applied sectors is less interesting and affordable than in more science-based sectors.

IV Results and discussion

As discussed above, we conducted the regression analysis for six technological sectors separately to account for different knowledge dynamics in heterogeneous technology regimes. Table 4 provides a summary of the regression results. To ease interpretation, only significant effects and the direction of influence are displayed and discussed (the complete regression results are presented in Table A.1 in the appendix). Furthermore, only marginal effects are presented for each category in order to allow for comparisons among the three dependent variables.

IV.1 Technological fit between a university and its economic surroundings

Our findings corroborate the assumption that the technological fit between a university and its economic surrounding matters for knowledge interactions.

In line with Hypothesis H1b, in two cases, electrical and mechanical engineering, SMEs are more often applicants of academic patents if the technological fit between universities and their local environment is high. Hence, for SMEs the technological fit between a university and its surroundings seems to matter, but only in engineering-related sectors. The coefficients (see table A.1) in both sectors are particularly strong and significantly raise the probability by 103 respectively 113 percent that SMEs appear as applicants in academic patenting.

Table 4: Summary of marginal effects in the six sector-specific regressions

Electrical engineering												
d(V) = UNI / SME / LME	Proximity		University characteristics				Controls					
(MfX / (dy/dx) atmeans)	SIM	DIST	SR	RES	IND	PAT	NPL	PUB	STAFF	%REG	GDP	POP
d(**UNI**)/d(X)		- **	+ ***	+ *			+ ***			- **	- ***	+ *
d(**SME**)/d(X)	+ **				+ *		+ **			- ***	- ***	
d(**MNE**)/d(X)	- ***	+ **	- ***				- ***			+ ***	+ ***	
Information and communication technologies												
d(V) = UNI / SME / LME	Proximity		University characteristics				Controls					
(MfX / (dy/dx) atmeans)	SIM	DIST	SR	RES	IND	PAT	NPL	PUB	STAFF	%REG	GDP	POP
d(**UNI**)/d(X)		- ***	+ ***						- *			
d(**SME**)/d(X)		+ **									- **	+ *
d(**MNE**)/d(X)			- *						+ **		+ **	- **
Measurement and controls												
d(V) = UNI / SME / LME	Proximity		University characteristics				Controls					
(MfX / (dy/dx) atmeans)	SIM	DIST	SR	RES	IND	PAT	NPL	PUB	STAFF	%REG	GDP	POP
d(**UNI**)/d(X)	+ **	- ***					+ **				- **	
d(**SME**)/d(X)	- *						+ **					
d(**MNE**)/d(X)		+ ***				+ **	- ***				+ ***	- *
Life Sciences												
d(V) = UNI / SME / LME	Proximity		University characteristics				Controls					
(MfX / (dy/dx) atmeans)	SIM	DIST	SR	RES	IND	PAT	NPL	PUB	STAFF	%REG	GDP	POP
d(**UNI**)/d(X)		- ***	+ *		- *	- ***	+ ***				- ***	- ***
d(**SME**)/d(X)							- *			- **		+ *
d(**MNE**)/d(X)		+ ***			+ **	+ ***					+ **	+ **
Chemicals												
d(V) = UNI / SME / LME	Proximity		University characteristics				Controls					
(MfX / (dy/dx) atmeans)	SIM	DIST	SR	RES	IND	PAT	NPL	PUB	STAFF	%REG	GDP	POP
d(**UNI**)/d(X)		- ***		- ***		- *	+ ***		+ *		- ***	
d(**SME**)/d(X)				+ ***		+ *	- *					
d(**MNE**)/d(X)	- *	+ ***					- *			+ *	+ ***	
Mechanical engineering												
d(V) = UNI / SME / LME	Proximity		University characteristics				Controls					
(MfX / (dy/dx) atmeans)	SIM	DIST	SR	RES	IND	PAT	NPL	PUB	STAFF	%REG	GDP	POP
d(**UNI**)/d(X)		- ***					+ **		+ **	+ **	- ***	
d(**SME**)/d(X)	+ **										- **	
d(**MNE**)/d(X)		+ ***					- **				+ ***	

Source: Own calculations

However, for measurement and controls we find the opposite: In contrast to Hypothesis H1b, the technological fit decreases the probability that SMEs and enhances the probability that universities file academic patents. This seems to indicate some kind of ingoing effect for universities and academic scientists which are embedded in a complementary local environment with knowledge assets that contribute to academic research. This might be rooted in the original tasks of academics, as their daily work often requires the usage of laboratory and measurement equipment. Thus, being embedded in a complementary milieu provides new incentives to improve their own equipment and tools. It might also be a trigger to conduct more application-oriented research.

Furthermore, the findings are in line with Hypothesis H1a, assuming that large firms are less sensitive to the technological fit between universities and their surroundings. Significant negative effects are found for chemicals and electrical engineering. For electrical engineering a very high marginal effect is found (compare table A.1). This means that especially in electrical engineering universities with fitting surroundings tend to conduct a comparably small share of their patent-relevant research for large firms. Fitting surroundings lead universities, especially in electrical engineering and chemicals, to conduct more research as a leading partner and/or as a partner of SMEs.

For life sciences and ICT we find no such effect. From a technological perspective our results show that those regimes, which tend to be dominated by a synthetic knowledge base, are more likely to be affected by a technological fit between the university and its region. As suggested in the theoretical section, our results further corroborate that in engineering-related sectors universities are most likely to contribute to industry by means of mode 2 type of knowledge production. In life sciences, chemicals and ICT similarity has a limited influence on patterns of knowledge interaction. A potential explanation, finding further support from previous research, is that here interactions contain a high share of codified knowledge, making local communities and technological fit less important for university-industry interaction. In sum, the effect of the technological fit between universities and their surroundings seems to be strong in sectors with a strong synthetic knowledge base, while they are weak or non-existing in sectors with a strong analytical knowledge base.

IV.2 Geographic proximity

Hypotheses *H2a* and *H2b* are confirmed by the results in table 4. All six regressions clearly show that inventor teams with a shorter average distance show a higher probability of the university filing the patent. This confirms previous results by Von Proff and Dettmann (2012). However, it contrasts findings that research networks (measured by publications) span over larger distances than innovation networks (measured by patents) (Ponds 2009; Sorenson/Singh 2007). But we have to keep in mind that we compare patents that are invented by university researchers only with patents that are invented by university researchers in collaboration with firms. The former seems to involve, on average, more local interaction than the latter.

Furthermore, the analyses clearly show that inventor networks that span over larger distances are more likely to come along with MNEs, that are equipped with sufficient R&D resources to manage and co-ordinate these networks.

As expected, we do not find significant marginal effects for SMEs, meaning that the relevance of geographic proximity for SMEs is between those for large firms and pure academic patenting. The only significant effect for SMEs is found in ICT – which is positive. Due to the particularly low numbers in this category (see table 3), the findings have to be carefully interpreted, but indicate that SMEs in ICT are able to establish and maintain inventor teams over larger distances. The coefficients for SMEs and MNEs derived from the full mlogit models help to gain further insights. They show for both firm categories that inventor teams in corporate environments bridge larger distances compared to those in purely academic ones (see table A.1 with universities as base category). In sum, inventor teams with shorter distances emerge in academic backgrounds, while those in firms, especially large firms, span over larger distances. Indeed, large firms' capacities seem to enable them to source knowledge over larger distances and to integrate it into their invention process. In the case of geographic distance we do not find different effects for technologies that are based on synthetic knowledge compared to those based on analytic knowledge.

IV.3 Control variables

Some control variables show clear significant effects that merit some short discussions. First, the effects of NPL citations are significantly positive in five of six sectors for universities and significantly negative in four of six sectors for large firms. Hence, university-owned patents have a strong science link, while patents owned by large firms, even if they involve university scientists, refer less to scientific publications.

Regarding scientific reputation we find the interesting result that in electrical engineering, ICT, and life sciences, universities with a high scientific reputation are more likely to be the owner of patents in which they are involved. This indicates that academic environments with an orientation towards scientific excellence and reputation are likely to also raise the emergence of patents filed by universities. In line with previous studies, we find that excellence in research comes together with higher patenting activities (Larsen 2011). Thus, our findings partially support that raising the amount of university-owned patents is most likely to be achieved by supporting an excellence-oriented research environment in IP relevant research disciplines.

Additional effects emerge in chemicals where research intensity raises the probability that SMEs file an academic patent while universities are negatively influenced. Resources invested in research-relevant personnel seem to increase the likelihood that SMEs collaborate with the university. For application-orientation hardly any conclusive evidence is found. Only in life sciences we find that an application-oriented university mission raises the probability that large firms collaborate with universities. Previous patent activities of universities increase the probability of cooperation with firms in a number of sectors. Among the regional control variables only GDP shows a clear picture. Universities in regions with a high GDP seem to be much more able to be involved in patents filed by large firms, probably because these firms are located in such regions.

V Summary and conclusions

Summing up the findings, we obtain clear evidence for the fact that the technological fit between a university's scientific and its local environment's profile matters for interactions between universities and industry. This further confirms and highlights the importance of complementarities between university type and profile and the industry's requirements, needs and abilities to absorb the knowledge offered by the local university. In particular, interactions between universities and small firms are more likely to emerge with a rising technological fit, if the technological regimes they are embedded in rest mainly on a synthetic knowledge base. We find that universities sharing complementary knowledge production with local industry are much more likely to act as local knowledge factories and to contribute to local knowledge anchoring via mode 2 types of knowledge production in collaboration with SMEs. But we also find remarkably clear evidence that this effect can not be observed for technology regimes resting mainly on analytical knowledge, where mode 1 types of academic knowledge production play a dominant role. Hence, we do not find indications that complementarities between universities' knowledge production and local knowledge demand are important for the local absorption of academic knowledge, neither for small nor for large firms, in these technologies.

Large firms are largely unaffected by the technological fit between the universities' academic and the region's innovation activities, electrical engineering and chemicals constituting interesting substitution effects. In line with the finding that large firms' inventor networks spread over larger distances, this indicates that large firms tend to acquire the knowledge they need independently from its geographical location. Contrarily, purely academic inventor teams seem to be more affected by internal mechanisms, as cohesion processes in close geographical proximity and team dynamics are influenced by a university's orientation towards basic science.

To our knowledge, this is the first quantitative study that tries to model the match between a university's scientific and its region's technological profile. Thereby, a new indicator has been developed and its usefulness for other studies has been proven. Future studies with times series data and more fine-grained assignment of scientific and technological classification could help to test the robustness of our results and to gather more detailed insights into the knowledge dynamics in interactions between academics and local company researchers. Nevertheless, our results provide a first insight into the role played by universities in different technological regimes.

Thus, this paper proves the value of sector-specific analyses for scientific purposes as well as adequate policy advice. Different technology regimes resting on different combinations of knowledge bases indeed show different patterns of interaction. Mode 2 knowledge produced in direct application contexts and technologically fitting environments is disseminated as part of the generation process and subsequently contributes to the local knowledge pool of SMEs. Local knowledge anchoring in mode 1 types of knowledge production seems to be more challenging as its exchange takes place in globally configured epistemic communities that are often only attainable by a small number of eligible professionals.

Thus, the function of universities as local knowledge hubs in analytical knowledge bases depends on the existence of communities between academics and firm R&D units that are capable of absorbing, translating and making this knowledge available to other actors in the region. This is likely to depend on both the technological fit and on the absorptive capacity of firms in the universities' local environment. Here, only firms that provide sufficient R&D resources are able to collaborate with universities in mode 1 interactions. These do not depend on a specific local context, but form national or global knowledge networks. In regions with high absorptive capacity trickling-down effects from mode 1 knowledge are more likely to take place, independent from the geographic location of the knowledge producing university. Thus, future research should also consider the absorptive capacity that is located in a region in order to test whether regions with higher absorptive capacity are more likely to participate from mode 1 knowledge. From a policy perspective, the importance of networks and networking between university and local "high-end" (Rutten/Boekma 2009) users should be highlighted. Two elements in this context are in need of further clarification: Firstly, policy funding programs and their effectiveness in supporting the emergence of long-term networks between adequate partners. Secondly, the role that publicly funded intermediaries like transfer offices and exploitation agencies can and should play.

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Annex I

Table A.1: Full regressions for six sectors (part I)

	Electrical engineering					Information and communication technologies					Measurement and controls				
	m-logit (UNI = Baseoutcome)		d(V) = UNI / SME / MNE (MfX / (dy/dx) atmeans)			m-logit (UNI = Baseoutcome)		d(V) = UNI / SME / MNE (MfX / (dy/dx) atmeans)			m-logit (UNI = Baseoutcome)		d(V) = UNI / SME / MNE (MfX / (dy/dx) atmeans)		
	SME	MNE	d(UNI)/d(X)	d(SME)/d(X)	d(MNE)/d(X)	SME	MNE	d(UNI)/d(X)	d(SME)/d(X)	d(MNE)/d(X)	SME	MNE	d(UNI)/d(X)	d(SME)/d(X)	d(MNE)/d(X)
Sim field	8.755 **	-5.295 **	0.456	1.030 **	-1.486 ***	-3.370	-1.866	0.226	-0.129	-0.098	-8.117 ***	-7.030 **	1.618 **	-0.664 *	-0.954
s.e.	4.313	2.625	0.309	0.436	0.533	3.635	3.082	0.335	0.241	0.447	3.129	3.268	0.653	0.355	0.615
Avg. Distance	0.241	0.683 **	-0.074 **	-0.027	0.101 **	1.467 ***	0.968 ***	-0.114 ***	0.046 **	0.068	0.567 *	1.035 ***	-0.195 ***	-0.007	0.202 ***
s.e.	0.319	0.288	0.034	0.025	0.048	0.382	0.364	0.043	0.019	0.047	0.316	0.307	0.060	0.038	0.059
SR	-0.075	-0.160 ***	0.018 ***	0.005	-0.022 ***	-0.088 *	-0.095 ***	0.011 ***	0.000	-0.010 *	-0.014	-0.006	0.002	-0.002	0.000
s.e.	0.058	0.052	0.006	0.003	0.007	0.046	0.029	0.004	0.003	0.005	0.027	0.031	0.006	0.004	0.007
Research_int	-19.606	-21.870 *	2.517 *	-0.073	-2.443	-13.436	-25.393 *	2.746	0.610	-3.356	-10.086	-8.211	1.932	-0.876	-1.055
s.e.	13.760	12.717	1.526	0.944	1.852	17.630	15.268	1.824	1.192	2.352	8.249	6.840	1.412	1.171	1.452
Ind_RD (%)	60.920	-24.917	1.919	6.379 *	-8.298	-17.890	0.908	0.090	-1.359	1.269	14.640	17.555	-3.654	0.721	2.933
s.e.	48.872	29.584	3.275	3.763	5.090	22.682	17.843	1.947	1.461	2.599	16.301	14.100	2.740	2.584	3.309
No.pat/field (3y_avg	0.067	-0.006	0.000	0.006	-0.005	0.034	0.010	-0.001	0.002	-0.001	-0.016	0.067 *	-0.009	-0.009	0.018 **
s.e.	0.058	0.054	0.006	0.003	0.007	0.039	0.029	0.003	0.002	0.004	0.044	0.036	0.007	0.006	0.008
NPL_cit (0/1)	-0.794	-2.828 ***	0.306 ***	0.126 **	-0.431 ***	-0.618	-0.581	0.066	-0.009	-0.057	0.190	-1.404 ***	0.199 **	0.169 **	-0.368 ***
s.e.	0.681	0.610	0.083	0.060	0.097	0.709	0.469	0.052	0.046	0.070	0.479	0.414	0.083	0.071	0.094
Publ_int (pub/cap)	-2.017	-5.264	0.575	0.192	-0.767	3.813	0.792	-0.120	0.228	-0.108	-0.228	0.477	-0.056	-0.085	0.141
s.e.	3.417	4.363	0.490	0.293	0.692	3.294	2.780	0.301	0.223	0.411	0.803	0.771	0.154	0.112	0.163
Size (total staff)	0.765	1.097	-0.124	-0.013	0.137	0.344	1.062 **	-0.113 *	-0.041	0.154 **	-0.440	0.014	0.028	-0.075	0.046
s.e.	0.834	0.703	0.084	0.068	0.115	0.638	0.455	0.058	0.042	0.071	0.422	0.365	0.076	0.058	0.076
Reg_SME (%)	-0.378	0.221 ***	-0.019 **	-0.044 ***	0.063 ***	-0.182	-0.227	0.025	0.001	-0.026	-0.042	-0.005	0.004	-0.007	0.003
s.e.	0.264	0.070	0.008	0.015	0.016	0.177	0.152	0.018	0.011	0.023	0.054	0.066	0.012	0.008	0.015
GDP/cap	-0.005	0.035 ***	-0.004 ***	-0.003 ***	0.006 ***	-0.010	0.009	-0.001	-0.001 **	0.002 **	0.010 *	0.015 ***	-0.003 ***	0.000	0.003 ***
s.e.	0.012	0.008	0.001	0.001	0.001	0.008	0.006	0.001	0.001	0.001	0.006	0.005	0.001	0.001	0.001
Pop (totals)	-0.008	-0.008 **	0.001 *	0.000	-0.001	0.003	-0.004	0.000	0.000 *	-0.001 **	0.002	-0.003	0.000	0.001	-0.001 *
s.e.	0.005	0.004	0.001	0.000	0.001	0.004	0.002	0.000	0.000	0.000	0.002	0.002	0.000	0.000	0.000
Obs.		163					200					212			
P		0.000 ***					0.000 ***					0.000 ***			
p-R²		0.353 ***					0.290 ***					0.229 ***			

Source: Own calculations

Table A.1: Full regressions for six sectors (part II)

	Life Sciences					Chemicals					Mechanical engineering				
	m-logit (UNI = Baseoutcome)		d(V) = UNI / SME / MNE (MfX / (dy/dx) atmeans)			m-logit (UNI = Baseoutcome)		d(V) = UNI / SME / MNE (MfX / (dy/dx) atmeans)			m-logit (UNI = Baseoutcome)		d(V) = UNI / SME / MNE (MfX / (dy/dx) atmeans)		
	SME	MNE	d(UNI)/d(X)	d(SME)/d(X)	d(MNE)/d(X)	SME	MNE	d(UNI)/d(X)	d(SME)/d(X)	d(MNE)/d(X)	SME	MNE	d(UNI)/d(X)	d(SME)/d(X)	d(MNE)/d(X)
Sim field	-0.054	0.420	-0.063	-0.042	0.104	-1.674	-4.819 *	0.914	0.118	-1.032 *	12.315 **	3.921	-0.828	1.125 **	-0.297
s.e.	3.402	2.706	0.613	0.482	0.571	3.198	2.925	0.631	0.435	0.625	5.081	3.666	0.544	0.534	0.708
Avg. Distance	0.515 ***	0.723 ***	-0.158 ***	0.026	0.132 ***	0.393 **	0.624 ***	-0.132 ***	0.012	0.120 ***	1.389 ***	1.560 ***	-0.235 ***	0.021	0.214 ***
s.e.	0.196	0.199	0.043	0.023	0.038	0.185	0.168	0.037	0.022	0.033	0.538	0.512	0.060	0.030	0.060
SR	-0.037	-0.034	0.008 *	-0.003	-0.005	-0.005	0.010	-0.001	-0.002	0.003	0.024	0.031	-0.005	0.000	0.005
s.e.	0.028	0.025	0.005	0.004	0.006	0.023	0.020	0.004	0.003	0.004	0.034	0.028	0.004	0.003	0.005
Research_int	-1.429	-4.842	0.891	0.152	-1.043	20.431 ***	8.290	-2.923 **	2.525 ***	0.399	-4.905	0.236	0.102	-0.618	0.517
s.e.	5.643	4.876	1.024	0.858	1.105	6.874	6.261	1.348	0.916	1.333	10.400	3.792	0.601	1.203	1.135
Ind_RD (%)	4.994	25.061 **	-4.416 *	-1.172	5.588 **	-14.039	-16.393	3.753	-0.895	-2.857	15.724	-9.038	0.724	2.766	-3.491
s.e.	10.690	11.653	2.330	1.583	2.560	14.890	13.005	2.883	1.953	2.685	42.744	23.413	3.452	4.866	5.561
No.pat/field (3y_avg	0.044 **	0.089 ***	-0.018 ***	0.000	0.018 ***	0.058 **	0.031	-0.009 *	0.007 *	0.003	0.023	-0.016	0.001	0.004	-0.006
s.e.	0.021	0.017	0.004	0.003	0.004	0.029	0.025	0.005	0.004	0.005	0.038	0.030	0.004	0.004	0.006
NPL_cit (0/1)	-0.975 ***	-0.756 **	0.200 ***	-0.096 *	-0.104	-1.162 ***	-0.972 **	0.248 ***	-0.104 *	-0.143 *	-0.685	-1.306 ***	0.184 **	0.040	-0.224 **
s.e.	0.355	0.307	0.066	0.051	0.066	0.424	0.378	0.082	0.055	0.079	0.615	0.479	0.073	0.067	0.094
Publ_int (pub/cap)	-0.003	-0.807	0.129	0.063	-0.192	1.798	0.876	-0.281	0.211	0.070	1.780	2.429	-0.356	-0.014	0.370
s.e.	0.620	0.844	0.158	0.099	0.190	1.247	1.266	0.286	0.130	0.239	3.374	2.280	0.355	0.352	0.442
Size (total staff)	-0.336	-0.200	0.059	-0.038	-0.021	-0.538	-0.502 *	0.123 *	-0.044	-0.079	-0.567	-0.872 **	0.126 **	0.014	-0.139
s.e.	0.235	0.224	0.048	0.033	0.048	0.343	0.293	0.064	0.047	0.062	0.685	0.353	0.053	0.081	0.089
Reg_SME (%)	-0.173 *	-0.010	0.016	-0.027 **	0.011	-0.017	0.062	-0.009	-0.008	0.016 *	-0.091	-0.092 **	0.014 **	-0.002	-0.012
s.e.	0.089	0.044	0.011	0.014	0.011	0.090	0.039	0.011	0.013	0.010	0.071	0.046	0.006	0.008	0.010
GDP/cap	0.005	0.012 ***	-0.002 ***	0.000	0.002 ***	0.008 *	0.017 ***	-0.003 ***	0.000	0.003 ***	0.001	0.021 ***	-0.003 ***	-0.002 **	0.005 ***
s.e.	0.004	0.003	0.001	0.001	0.001	0.005	0.004	0.001	0.001	0.001	0.009	0.007	0.001	0.001	0.001
Pop (totals)	0.005 ***	0.005 ***	-0.001 ***	0.000 *	0.001 **	-0.001	0.001	0.000	0.000	0.000	0.001	-0.002	0.000	0.000	0.000
s.e.	0.002	0.002	0.000	0.000	0.000	0.002	0.002	0.000	0.000	0.000	0.005	0.004	0.001	0.001	0.001
Obs.		349					261					234			
P		0.000 ***					0.000 ***					0.000 ***			
p-R²		0.195 ***					0.179 ***					0.219 ***			

Source: Own calculations