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Universities and Regional Innovation Output:

A Detailed Empirical Study of 19 Technologies in Germany

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Abstract

Universities are seen as important drivers of the regional economy and as important contributors to the innovativeness of regions. Their impact on the regional innovation activity is well documented. However, most of the studies in this field analyse either one specific technological field or all innovation activities together. This paper provides a separate examination of 19 technologies in Germany. We study whether the spatial distribution of the patent activities in these 19 technologies is influenced by the number of graduates, the budget of faculties and the amount of research grants at universities. Furthermore, it is studied which kinds of subjects are relevant for which technologies. A spatial econometric approach is taken and various control variables, such as technology-specific employment, business R&D activities, population and so on, are considered. We find quite different relationships for the various technologies.

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I. Introduction

The impact of universities and public research activities on the innovation output of nearby firms has been repeatedly shown in the literature (e.g. Jaffe, 1989; Acs et al., 1992, 2002; Feldman, 1994; Anselin et al., 1997; Blind and Grupp, 1999, Autant-Bernard, 2001, Graf and Henning 2006, D'Este and Iammarino 2010 among others). Therefore, it is a well documented fact that universities and public research support firms through direct and indirect trajectories in their innovation activities. The strength of this impact, however, depends on a broad range on factors.

Recent policy discussion has moved a step further. It is discussed whether the impact of public research activities and university education should depend on the economic activities that are present in a region (see BMBF 2009). Is it successful and efficient to support research and education in a region independent of the industrial structure present? Should university education and public research be adapted to the regional industrial structure?

To answer these questions, insights are necessary that are not given so far in the literature. On the one hand, we have to know about the structure of the impact of universities and public research on regional development. Is this impact multiplicative or additive? In other words, do universities and research institutes have a direct, independent impact on regional innovativeness through generating innovations and people who will find a way commercialising them? Or do universities and research institutes only have an indirect impact through supporting firms in their innovation activity, implying a regional impact only if such firms are present in the region? These two kinds of effects can be studied empirically by using different regression equations. So far, in empirical studies the choice of the functional form of the impact is rather based on statistical characteristics of the used data and ignores this question.

On the other hand, we have to know more about the connections between the fields of public research and education and the different industries. Different subjects contribute in different ways to innovation processes and different industries depend in different ways on public research and education. The impact of education and research in different subjects on regional innovativeness has not been examined so far.

This paper takes a step in both these directions. It analyses the patent activities in Germany and their dependence on local universities. First, we use a flexible functional form as proposed by Brenner and Broekel (2011) for the empirical analysis. Therefore, we allow for additive and multiplicative effects and test statistically which kind of effect better fits the empirical data. Second, we analyse 19 technological fields separately. Third, university education and public research at universities are also distinguished into several scientific fields. This allows us to test the fit between scientific and technological fields and to study whether this matters. Finally, we differentiate between university education, university research and applied university research.

In addition, we study which population in a region does best describe the number of potential innovators. We examine three different specifications: all inhabitants, all employees in industries relevant for the studied technology and R&D employment in the relevant industries. The literature suggests that the R&D employment should be most adequate (Brenner and Broekel 2011). However, innovators might recruit from all these populations.

The paper proceeds as follows. In Section II the existing theories and the available empirical knowledge is presented. Based on the theoretical background we describe the empirical method in Section III. This contains the description of the statistical model as well as the statistical approach and the empirical data. In Section IV results of the statistical analysis are presented and discussed. Section V concludes.

II. Theoretical background

This paper is based on the ideas developed by Brenner and Broekel (2011). They argue that three mechanisms should be distinguished in a discussion or analysis of regional innovation systems. First, there are *innovation attractors* in a region that attract innovation activities to the region. Second, there are *innovation generators*, meaning people creating innovations within the region. Third, there are *innovation facilitators* making innovation generators more or less efficient and productive in their innovation activities. According to Brenner and Broekel (2011) the first mechanisms has to be studied separately from the latter two mechanisms. Therefore, we focus on the latter two mechanisms.

Universities are well-known for their impact on regional innovation output. Nevertheless, some details of the mechanisms and connections between university activities and innovation activities remain unclear. Universities might be involved in all three kinds of mechanisms described above: They might attract innovators to the region, they might contain innovators, and they might facilitate innovators.

Let us first reflect on what is known about the effects of universities from the literature in Subsection II.1. followed by the presentation of the concept developed by Brenner and Broekel (2011) in Subsection II.2. From this we deduce some hypotheses in Subsection II.3.

II.1 Knowledge on the impact of public research and university education on innovation activities

Universities and research institutes have always been seen as key elements of regional innovations systems in the respective literature as they produce and thus spread knowledge. Hence, they promote the innovativeness of nearby firms. There are several explications for the positive influence of universities and public research on regional development. Knowledge spillover and knowledge flows are generated through various mechanisms such as cooperation, graduates and students, internships, movement of employees and informal contacts between employees (Fritsch et al. 2008). In addition, universities offer support for business foundations, consultancy and use of laboratory equipment and they are important sources for spin-offs (ISI, 2000). Fritsch et al. (2008) distinguish between direct and indirect knowledge transfer, where for example research cooperation count for the former and graduates for the latter.

Most of the literature on the effects of research activities concentrates on the US, but there are some examples from European countries (e.g. Jaffe, 1989; Acs et al., 1992, 2002; Feldman, 1994; Anselin et al., 1997; Blind and Grupp, 1999, Autant-Bernard, 2001, Fritsch et al. 2008). Among other empirical studies, Cohen et al. (2002) report that the impact of university research on firms is substantial compared to other influences. Fritsch et al. (2008) highlight the importance of knowledge produced in universities. Their study focuses on research cooperation, but graduates are stated as equally important. With only some exceptions, most of these empirical works found a decline of knowledge flows from public research with growing geographical distance (e.g. Fischer and Varga 2003, Varga 2000, Fritsch et al. 2008). Most of these studies allude to the fact that not only distance influences the impact on firms' innovative behaviour, but also a bunch of other aspects depending on industry branch, size of firm etc.

The importance of graduates is discussed in several ways. A highly skilled workforce is important for the innovativeness of firms as new knowledge is brought into firms. They also enhance firms' capacity to absorb new knowledge which is an important prerequisite for R&D and thus innovations. The employment pools in the region are specialized and nearby firms are able to source the labour force from these highly qualified workers. As university research is often conducted by diploma and doctoral work, the regional labour market and the research focus of universities is often strongly connected (Cohen and Levinthal 1990, Blind and Grupp 1999, Bräuninger et al. 2008, Fritsch et al. 2008, Fritsch and Slavtchev 2007 among others). On the other hand, graduates from university are among the most mobile groups and thus the existence of a university does not automatically lead to a pool of highly qualified graduates that stays in a region. Regional development is only likely to be enhanced by graduates if there are corresponding jobs in the regional economy. Otherwise, graduates tend to leave the region in favour for a job (see, Mohr 2002, Leßmann and Wehrt 2005, Fritsch et al. 2008).

Thus, the main questions in this respect are how this influence of public research and education on firms´ innovativeness is measured, which role is played by the spatial scale and the economic environment for the sourcing of knowledge (see Anselin et al. 2000, Arundel and Geuna, 2004; Fritsch and Slavtchev 2007 among others).

The geographical distance to public research becomes important because of the tacitness of knowledge. People and institutions are still less mobile then capital (see, Blind and Grupp, 1999). As long as the transmission of knowledge is not possible through codified transmission channels, frequent personal contacts, personal mobility and interaction are important. But also if codification is possible, there is a time span during which the ongoing knowledge is not published yet and therefore face-to-face contacts are of major importance. Thus, geographic distance plays an important role, especially for on-going research with a high proportion of applied research (see, Anselin et al. 2000, Del Barrio-Castro and García-Quevedo, 2005). However, the importance of geographical proximity may decline with the relevance of tacit knowledge. The term distance may also hold for cultural and linguistic proximity, which play a role for personal contacts (see, Arundel and Geuna, 2004). It seems that especially larger manufacturing firms conducting their own R&D are more often recipients and profiteers of knowledge emitted by universities and public research. There is also a higher importance for industries in the applied science fields (e.g. Lööf and Broström, 2008; Cohen et. al. 2002).

Hence, the simple presence of a university does not lead to a high regional innovativeness. An industrial structure that is capable to absorb the transmitted knowledge and that relies on university deliveries is essential for the regional effect of universities (Fritsch and Slavtchev 2007).

II.2 Theoretical concept

Brenner and Broekel (2011) depicted the innovation process in an abstract form as shown in Figure 1. They argue that a region's characteristics, denoted as innovation attractors, attract more or less innovation generators to a region. However, all kinds of characteristics and factors might have an innovation attracting role, even the innovation generators themselves when they attract further innovation generators to the region. Hence, feedback loops exist in the development. All these kinds of interactions in a region in combination with historical events shape the structure and content of the spatial unit. This historical process has self-reinforcing characteristics and involves social, economic, and institutional developments. It determines the number of innovation generators in a region.

Brenner and Broekel (2011) state, that this interactive process is too complex for a representation in a simple mathematical model. Thus, we refrain from studying this process. Instead, we consider the number of innovation generators as given in this paper. We analyse the process of innovation generation that is depicted in Figure 1 as the arrow leading to innovation output.

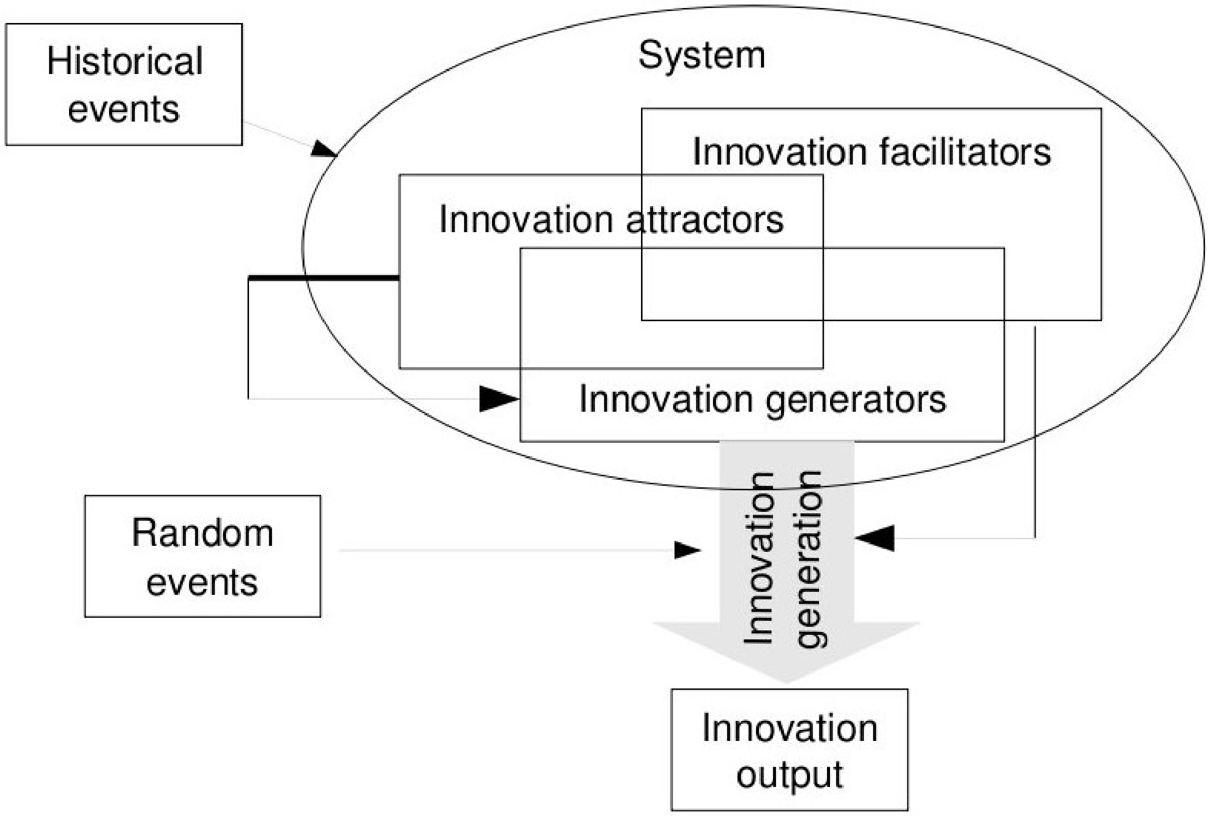

***Figure 1**: Interactions that cause the innovation output of a spatial unit.*

According to Brenner and Broekel (2011), R&D employees in firms are the dominant innovation generators. Other innovation generators might be found in form of other employees in firms, in public research institutes and in universities. There are also some private inventors. A region contains a limited number of such actors that are able to generate innovations. All people that might produce innovation are called innovation generators. One of the tasks of this paper is to identify an adequate empirical variable that reflects the number of innovation generators in a region. The arguments of Brenner and Broekel (2011) suggest that either the R&D employment in firms or a combination of various sources, such as R&D employment, total employment, public research, universities and the number of inhabitants should be adequate.

Innovation generators depend on the regional circumstances in their innovation activities. For example, the presence of a university – that might function as a cooperation partner in research projects – can make innovation generation more or less effective. Many other local factors might also influence the innovation activities of innovation generators in a region. These kind of local factors are called innovation facilitators by Brenner and Broekel (2011). In this paper we will examine especially whether university research spending and graduates represent such innovation facilitators.

Brenner and Broekel (2011) furthermore state that some factors are at the same time innovation facilitators, innovation generators and innovation attractors. Universities are such a factor. As stated above, whether they are innovation attractors is difficult to study. Hence, we focus here on the question of whether universities are rather innovation generators or innovation facilitators or both at the same time.

II.3 Hypotheses

Three questions will be addressed in the empirical analysis. Before the empirical analysis is conducted, we will deduce for each of these questions a hypothesis on the basis of the literature.

The first question is about the main sources of innovation generators. In the context of the model above, Brenner and Broekel (2011) argue that R&D workers in firms should be the dominant group of innovation generators. Other employees in firms, employees in public research institutes and universities and some private persons should also contribute.

Hypothesis 1:
a) A number of populations, such as employees in firms, R&D employees and universities, are sources of innovation generators in a region. The total number of inhabitants might also contribute.
b) The dominant source of innovation generators are the R&D employees in firms.

Second, we will examine the question whether universities play a role for the innovation output generated in regions. The literature, which is reported above, clearly shows that universities are important players. However, not all research fields and education subjects play a similar role. Furthermore, the importance of universities depends on the industry that is studied. Hence, we can state:

Hypothesis 2:
a) Universities in a region significantly influence the innovation output that is generated in this region.

b) However, differences are found between industries, research fields and education subjects.

Third, we address the question of whether universities are rather innovation generators or innovation facilitators. The literature mainly studies the impact that public research and university education has on the innovation performance of firms. Fritsch et al. (2008) show that third-party funds are of major importance. Hence, the innovation facilitating function is strongly proved in the literature. Little is said about the contribution of universities directly to the generation of innovations. Only few patents are applied for by universities. However, often patents are the joint work of firms and university, but the firm applies for the patent. In addition, universities often deliver their innovative results to firms before these are developed into a patent. From the literature it seems as if such direct involvement in the patent generation plays a less important role. While there is some literature that shows the importance of university graduates, public research seems to be more important for the regional innovation output. This is confirmed by the fact that university graduates are quite mobile, while benefiting from university research requires often some proximity. Hence, we state:

Hypothesis 3:

a) Universities are more important as innovation facilitators than as innovation generators.

b) The research, and especially applied research, done in universities is more important for the regional innovation output than the students educated there.

III. Empirical method and data

In the following section we describe the mathematical model we use for our analysis (Subsection III.1) as well as the empirical approach (Subsection III.2). Finally, we present and discuss the empirical data in Subsection III.3.

III.1 Mathematical model

Our aim is to analyse to what extent universities function as innovation generators and/or innovation facilitators. Hence, we need a model describing the innovation output in a region as a function of the presence of innovation generators and innovation facilitators. We start with the model set up by Brenner and Broekel (2011):

$$E\left(I_s\right)=\sum_i \eta_i\left(c_i,F_s\right) \tag{1}$$

$E(I_s)$ denotes the expected number of innovations in region s and G_s the number of innovation generators in this region. $\eta_i(c_i,F_s)$ indicates the productivity of innovation generator i dependent on her characteristics c_i and the regional innovation facilitators F_s. We simplify Equation (1) for the empirical approach used here: we assume that the impact of the innovation facilitators is the same on all innovation generators in a region. Hence we can write

$$E\left(I_s\right)=\sum_i \left[\eta_{c,i}\left(c_i\right)\cdot\eta_F\left(F_s\right)\right] \tag{2}$$

Furthermore, we are not able to distinguish the characteristics of each innovation generator. There is evidence that the likelihood of a R&D worker in a firm to generate an innovation differs from the likelihood of a student just graduated from university to generate an innovation. These two kinds of innovation generators can easily be differentiated in an empirical approach. Two different R&D workers, instead, cannot be distinguished in an analysis on the regional level.

Hence, we assume that there are different kinds k of innovation generators. The number of innovation generators of type k in region s is denoted by $g_{k,s}$. It is presumed that the characteristics of innovation generators of the same kind are the same. Hence, their innovation output is given by $\eta_k * \eta_F(F_s)$. We obtain:

$$E\left(I_s\right)=\sum_{k=1}^{n} \left[\eta_k\cdot g_{k,s}\cdot\eta_F\left(F_s\right)\right] \tag{3}$$

where n denotes the number of different kinds of innovation generators. Equation (3) can be transformed into

$$E\left(I_s\right)=\left[\sum_{k=1}^{n}\left(\eta_k\cdot g_{k,s}\right)\right]\cdot\eta_F\left(F_s\right) . \tag{4}$$

In a next step, we have to examine the term $\eta_F(F_s)$. In order to be able to estimate this part with the help of a regression, we have to determine the functional form of this term. Let us discuss its meaning. The first part of the right-hand side of Equation (4) shows the number of potential innovation generators within a region. Therefore, the second part can be interpreted as the probability of each of these potential innovation generators to produce an innovation. We use the standard logistic specification for this probability given by

$$\eta_F\left(F_s\right)=\frac{1}{1+\exp\left[c-\sum_f\left(a_f\cdot v_{f,s}\right)\right]} \tag{5}$$

where c is a constant, f is the index for each innovation facilitator and $v_{f,s}$ is the value of the innovation facilitator *f* in region *s*. The logistic functional form is a general approach for probabilities in statistical approaches, especially in decision making (Cramer 2003).

Hence, we are finally able to write that the expected number of innovations in region *s* is given by

$$E\left(I_s\right)=\frac{\left[\sum_k \left(\eta_k \cdot g_{k,s}\right)\right]}{1+\exp\left[c-\sum_f \left(a_f \cdot v_{f,s}\right)\right]} . \tag{6}$$

III.2 Empirical approach

Above we have deduced the mathematical model (Equation (6)) based on theoretical considerations. We use this equation as basis to conduct a regression. However, innovation numbers are not normally distributed. They can be expected to be binomially or poisson distributed. Hence, we have to use a respective regression approach.

However, the standard negative binomial distribution – the one mostly used in such a case – contains two parameters. One reflects the probability of events and is estimated dependent on the independent variables. The other reflects the number of counter-events that occur before we see the measured number of events (dependent variable). This second parameter is usually fixed or estimated as a parameter. In our approach, we intend to describe both parameters, the probability and the number of potential events, as functions of the independent variables. On the basis of the theoretical considerations above we derive Equation (6): the number of potential innovations given by the upper term on the right-hand side and the probability that these potential innovations become real given by the lower term on the right-hand side.

Therefore, we model the binomial distribution[1] in an explicit way and define the total number of potential innovations as

$$Pot\left(I\right)=c_{pot}+\sum_k \left(\eta_k \cdot g_{k,s}\right) . \tag{7}$$

The value of η_k determines to what extent each kind of population *k* contributes to the potential number of innovations. Furthermore, we included a constant in order to obtain a standard

[1] For small event probabilities the number of counter-events (r=n-k in the binomial distribution) and of potential events (n) are nearly the same. Hence, using a binomial or negative binomial distribution leads to nearly the same results. However, our theoretical approach leads to a substantial definition of the number of potential events. Therefore, we use the binomial distribution instead of the, within econometric approaches, more common negative binomial distribution.

regression equation. A value of c_{pot} above zero would imply that there are additional innovation generators that are not reflected by our independent variables.
Explicitly we consider the following populations:

- [Empl] Employment in the relevant industries in the region
- [RandD] R&D employees in the relevant industries in the region
- [Inhab] Inhabitants in the region
- [Uni-Research-*fac*] Budget in each relevant *faculty* at the universities in the region, as a proxy for the number of researchers active in this field
- [Uni-Applied-*fac*] Third-party funds in each relevant *faculty* at the universities in the region, as a proxy for the number of researchers active in applied research in this field
- [Uni-Grad-*subj*] Number of graduates (technical, diploma, bachelor and master) in each relevant *subject* at the universities in the region

The lower term on the right-hand side of Equation (7) determines the probability for the realisation of a potential innovation. This probability depends in a logistic form on various regional characteristics (Equation (5)). In our empirical study we consider the following characteristics:

- [Highschool] Share of school leavers in the region with a high-school degree
- [GDP] GDP per inhabitant in the region
- [Dens] Population density in the region
- [Unempl] Unemployment rate in the region (this variable also reflects east-west differences in Germany, it is highly correlated with an potential East-West dummy so that we do not include such a dummy)
- [Uni-Budget-*fac*] Budget in each relevant *faculty* at the universities per inhabitant in the region
- [Uni-3Funds-*fac*] Third-party funds in each relevant *faculty* at the universities per inhabitant in the region
- [Uni-Stud-*subj*] Number of graduates (technical, diploma, bachelor and master) in each relevant *subject* at the universities per inhabitant in the region, as a dummy for the share of highly educated people

The first four variables represent factors that are repeatedly found in the literature to influence the innovation activities in regions. However, the literature does not distinguish whether these factors function as innovation attractors or as innovation facilitators.

The latter three variables represent the activity at universities in the region. These variables are considered for several faculties and subjects. Hence, we do not only have three variables that represent university activities, but 15 to 20 variables in most cases. Furthermore, the variables that represent university activities are included in the description of the potential innovations and the description of the probability of these potential innovations to become real. All these variables are highly correlated – there are high correlations between the presence of the various subjects in Germany as well as the number of graduates, budget and third-party funds are highly correlated – so they cannot be included in the model at the same time. Hence, we proceed in several steps:

1. We conduct separate regression for each of these variables, including only one of them each time. This step provides information about which kind of university activities might have an impact.
2. We identify the variable that leads to the best fit (highest likelihood) in order to find the kind of university activity that has the strongest connection to regional innovativeness. This also provides information about whether university activities rather increase the number of potential innovations or the probability of their realisation.
3. We examine whether adding other university variables to the model with the best fit improves the fit significantly. This answers whether several mechanisms or subjects are involved jointly.

One problem that we face is that we are, obviously, not able to include all local factors that might influence the likelihood of innovations in the set of independent variables. Hence, the regressions have to run either with fixed or with random effects. The use of fixed effects requires sufficient variation in the independent variables over time. This is not the case in our data set. Many independent variables, such as GDP and population density, change very little over time. Furthermore, the data for the universities does either change little over time, such as the number of graduates, or has high fluctuation due to budgetary roles, such as the third-party funds. Hence, we ignore time completely and pool the data for the years of observation (1999-2009). As a consequence, an approach based on fixed effects cannot be used and we use random effects instead. The regressions are conducted numerically[2].

III.3 Empirical data

Aware of the strengths and weaknesses of the information provided by patents (see Feldman and Florida, 1994; Malerba and Orsenigo, 1996; Deyle and Grupp, 2005), we will use them as dependent variables in this study. The analysis builds on data extracted from the European Patent

2 The regression is programmed and conducted in C++. The likelihood is maximised with the help of an optimisation algorithm that mixes an evolutionary strategy with a gradient approach.

Organisation's (EPO) Worldwide Statistical Patent Database version September 2009, the so-called 'PATSTAT September 2009' database.

For the purpose of this paper we selected all patents in the Patstat database that are filed between 1999 and 2009 for which at least one applicant was located in Germany. To this end all patent inventors with addresses in Germany[3] have been assigned to German regions. The unit of analysis is the labour market area, called 'Arbeitsmarktregion', of which there are 270 in Germany (according to the definition of the German Labour Office). We use inventor's addresses, as usual in the literature, because the headquarters of large firms tend to be located far away from the place where the innovation took place (Paci and Usai 2000). If several inventors are involved in one patent, we nevertheless count for each inventor from Germany one innovation event. This approach guarantees that our dependent variable is a count variable, while the standard approach, distributing events among the involved inventors, leads to real value that neither is a natural number nor is a real variable that is able to take all real values. The latter approach leads to statistical problems.

In the next step, we assigned all patents to different technological fields. This involved the identification of the International Patent Classification (IPC) for the relevant patents. Based on these IPCs, we matched the patents to 19 technological fields (see Table A.1 for a list of these fields) with the help of a concordance developed by U. Schmoch and colleagues (the concordance is a current version of the concordance published in Schmoch et al. (2003) and was obtained directly from U. Schmoch).

We use three kinds of independent variables (see Table 1). First, there are a number of control variables that are included in the analysis. These variables are frequently found to have an influence on the innovation output in a region. We use the GDP per capita [GDP], the share of school leavers that have a high-school degree [Highschool], the unemployment rate in the region [Unempl] and the population density [Dens] as control variables. All data is obtained for 2000 from INKAR 2002 database. These variables enter the regression equation as potential innovation facilitators.

Second, we include a number of variables that represent potential innovation generators. According to Hypothesis 1, the main innovation generators are R&D employees in firms [RandD]. The data on R&D employees is taken from the employment panel of the German Institute for Employment Research (Institut für Arbeitsmarkt- und Berufsforschung). We follow Bade (1987) and

[3] We assigned all inventors with a postal code and city name that match list of German municipalities.

define R&D employees as the occupational groups of engineers, chemists and natural scientists.[4] The data on R&D employees is organized by occupational groups as well as industries (WZ03). Based on the work of Schmoch et.al. (2003) industry classes (WZ03) are assigned to patent classes (Table A.1 in the appendix).

Furthermore, all employees in firms [Empl] contribute to innovation activities. Data on the total number of employees is also taken from the employment panel of the German Institute for Employment Research. Again, industries are included according to their assignment to technology classes (see Table A.1). In order to reflect private persons generating innovations, we include the total number of inhabitants [Inhab] as a potential source of innovation generators. The data is obtained from INKAR 2002.

Third, we apply variables that are related to university activities: number of graduates, budgets of faculties and third-party funds in faculties. All these variables are obtained from the German Statistical Office for the years 1999 to 2009 and aggregated for the whole period of time. For each technology studied we employ data for a number of different subjects and faculties. Hence, we have to decide which subjects and faculties play a role for each technology. This is done differently for the subjects and the faculties.

In the case of subjects we use the German Socio-economic panel (SOEP). This panel includes information about the university degrees and the industry classification of the current occupation. From this we obtain the share of employees in each industry that have studied a specific subject. We use all subjects that are studied by at least 5% of the graduated employees in each industry. The total number of people in the SOEP data base and especially the number of people with a university grade is not sufficiently large. Hence, the correspondence is calculated on a 2-digit level. We are not able to assign subjects in this way to some of the industries. Transferring information from the faculty assignment and adding plausible subjects we deal with those cases. The resulting assignments are presented in Table A.1 in the appendix.

In the case of faculties and the variables related to budget and third-party funds, we use a different approach. In the case of graduates, we assume that their main impact is obtained by the work done in firms after finishing their studies. Hence, we assigned subjects according to later occupations. In the case of budget and research funds, we assume that the impact on regional innovativeness results mainly from research activities that lead directly to innovations or support

[4] Bade (1987) defines R&D workers as employees belonging to the occupational groups 032, 60, 61 or 883 of the German occupation classification (IAB, 2005)

innovation activities in firms. Hence, we used the Patstat database (see above) to assign faculties to technologies. We identified all German inventors with a title for a professor in this database. If possible, we identified for these professors the faculty that they are affiliated to. From this we obtain the contribution shares for each faculty and technology. Interestingly, six faculties dominate professor related patenting activities: physics, chemistry, biology, medicine, machine building and electrical engineering. Most of the other faculties rarely even reach a share of 2%. We consider for each technology all faculties that contribute at least 3%. The assigned faculties are listed in Table A.1 in the appendix.

IV. Empirical results and discussion

In the following section we test the three hypotheses stated above. As this paper is work in progress, not all 19 technologies are analysed so far. Hence, we present the results for the technologies studied until now.

IV.1 Innovation generators (Hypothesis 1)

First we address the question which variables do best represent the number of innovation generators in a region. Four sources of innovation generators are tested in our regression models: R&D employees [RandD], total employment [Empl], inhabitants [Inhab], and universities (including different subjects/faculties and the three alternative variables [Uni-Research-*fac*], [Uni-Applied-*fac*] and [Uni-Grad-*subj*]). Table 1 lists the results for the best fitting model of those that includes at least one of the variables [Uni-Research-*fac*], [Uni-Applied-*fac*] and [Uni-Grad-*subj*].

Table 1: Estimated coefficients (η_k) for the variables that describe potential innovation generators (p-values in parentheses, significance level: ***=0.001, **=0.01, *=0.05; average number of potential innovation generators predicted by each variable is given in squared brackets)

No.	Technological Field	[RandD]	[Empl]	[Inhab]	[Uni-...-...]	Best fitting Uni-variable
1	Electrical machinery, apparatus, energy	0.0269398 (0.094) [96]	0 (1) [0]	0.0000879 (0.000 ***) [241]	1.09417 (0.001 ***) [28]	Uni-Grad-Eng
2	Electronic components	0 (1) [0]	0.78023 (0.245) [2455]	0.00349 (0.000 ***) [9561]	0,159401 (0.001 ***) [3105]	Uni-Research-Chem
3	Telecommunications	0 (1) [0]	14.0085 (0.239) [22015]	0.0606758 (0.000 ***) [166612]	128.724 (0.015 *) [21143]	Uni-Grad-EcEng
4	Audio-visual electronics	0 (1) [0]	167.039 (0.196) [166935]	0.338067 (0.000 ***) [928312]	75.2375 (0.000 ***) [362765]	Uni-Applied-Elec
5	Computers, office machinery					

6	Measurement, control					
7	Medical equipment					
8	Optics					
9	Basic chemicals, paints, soaps, petroleum products	0.11529 (0.559) [163]	0.0474654 (0.002 **) [1107]	0.00068993 (0.000 ***) [1895]	0.037146 (0.001 ***) [724]	Uni-Research-Chem
10	Polymers, rubber, man-made fibres	35.3059 (0.000 ***) [10101]	0 (1) [0]	0.0357397 (0.000 ***) [98139]	-	-
11	Non-polymer materials					
12	Pharmaceuticals	0.000622175 (0.909) [1]	0 (1) [0]	0.167927 (0.000 ***) [461117]	-	-
13	Energy machinery	0 (1) [0]	0 (1) [0]	0.000551706 (0000 ***) [1515]	0.0121286 (0.000 ***) [418]	Uni-Research-Mach
14	General machinery	0.0257278 (0.441) [20]	0 (1) [0]	0.00022917 (0.000 ***) [629]	0.262878 (0.000 ***) [111]	Uni-Grad-Mach
15	Machine-tools					
16	Special machinery					
17	Transport					
18	Metal products					
19	Textiles, wearing, leather, wood, paper, domestic appliances, furniture, food					
Number of significant impacts		**1**	**1**	**9**	**7**	

Our results confirm Hypothesis 1 only partly. Hypothesis 1a states that there are a number of regional factors that provide innovation generators. This is confirmed. All factors studied are, at least, validated to play a significant role in providing innovation generators for one technology. Thus, for most technologies various sources of innovation generators exist.

Hypothesis 1b states that R&D employees in firms play a dominant role as innovation generators. This is not confirmed. Without exception, the variable [Inhab] always has the smallest p-value, is always significant and predicts the highest average number of innovation generators. Hence, the dominant source of innovation generators seems to be the total population in the region; or at least something that is well represented by the total population. There are several possible explanations for this finding. First, most patents might, indeed, originate from 'normal' inhabitants in the region. As we know that most patents are applied by firms, this interpretation is not likely. Second, the industry employment included for each technology does not fit perfectly. This implies that patent activities from other industries are not directly included in the regression equation. As a consequence a significant part of the impact of other, not considered industries will be represented by the variable [Inhab]. Third, there are other sources of innovations such as e.g. research institutes that are at least partly reflected by the number of inhabitants. It is likely that the finding is caused by a mixture of the second and third explanation.

Considering the coefficients that are estimated for the various sources of innovation generators (see Table 1), we clearly find that 'normal' inhabitants have the lowest likelihood generating innovations compared to all other significant sources. The likelihood of employees in the relevant industries is between 70 and 500 times as high as those of 'normal' inhabitants. R&D employees show a probability that is 100 to 1,000 times the value for 'normal' inhabitants. Graduates from universities are even 1,000 to 15,000 times as likely as 'normal' inhabitants to generate innovations. However, in the case of graduates we have to interpret this result with care because the number of graduates might stand for the whole activity of the faculty or even the whole university (see the discussion in Section IV.2).

Although the estimated likelihoods for (R&D) employees in the considered industries to be innovation generators are comparably high, this involvement is not significant for most industries. In addition, we can deduce from Table 1 that R&D employees and employees predict the same part of innovation activity. Therefore, one of them is dispensable in each regression. The insignificant results for employment might have two reasons. First, employment might not be as important as we assumed in Hypothesis 1. Second, the matching used between patent classes and industries might not be adequate. The latter reason would also explain the high contribution of 'normal' inhabitants. Since no other matching between patent classes and industries is available in the literature, we are not able to test this explanation.

IV.2 Impact of public research institutes and universities (Hypothesis 2)

The main aim of this paper is to get more insights about the impact of universities on the innovation activities in regions. Whether they rather function as innovation generators or as innovation facilitators is examined in the next subsection. Here we focus on the question whether there is an impact at all and which faculty/subject is relevant for the innovativeness of each technology. To this end, Table 2 lists for all technologies and all measurements of university activity the faculties/subjects that are found in a regression, without any other university variable, to contribute significantly as innovation generators or facilitators. Since we run a lot of similar regressions – each including one university variable – we use the Šidàk correction (Abdi 2007). All university variables with a p-value below 0.05 after this correction are presented in Table 2.

The results lead to a number of insights. First, for nearly all technologies studied we find significant impacts of universities on local patent activity. Hence, our study confirms Hypothesis 2a for nearly all technologies.

Table 2: University variables for which we find significant impact on regional patent activity (variable that leads to the best fit is given in bold letters).

No.	Technological Field	Uni-Research-...	Uni-Applied-...	Uni-Grad-...	Uni-Budget-...	Uni-3Funds-...	Uni-Stud-...
1	Electrical machinery, apparatus, energy	-	Mach	**Eng** Mach	Mach	Mach	Eng Mach
2	Electronic components	Chem	Chem	-	Phys **Chem** Med	Phys Chem Bio	-
3	Telecommunications	Phys Mach	Phys Chem Mach Elec	EcEng Eng Mach	Phys **Mach** Elec	Mach Elec	EcEng Eng Mach
4	Audio-visual electronics	Phys Mach Elec	Phys Mach Elec	EcEng Eng Mach Elec	Phys Mach Elec	Phys Mach **Elec**	EcEng Eng Mach Elec
5	Computers, office machinery						
6	Measurement, control						
7	Medical equipment						
8	Optics						
9	Basic chemicals, paints, soaps, petroleum products	Phys Chem Bio	Chem Bio	-	**Phys** Chem Bio	Phys Chem Bio	-
10	Polymers, rubber, man-made fibres	-	-	-	-	-	-
11	Non-polymer materials						
12	Pharmaceuticals	-	-	-	Phys Chem **Phar** Bio Med	Phys Chem Phar Bio Med	Math Inf Chem Phar
13	Energy machinery	**Mach**	Elec	-	-	Chem	EcEng
14	General machinery	Phys Chem Mach	Mach	Mach	Phys Chem Mach	Phys Chem Mach	**Mach**
15	Machine-tools						
16	Special machinery						
17	Transport						
18	Metal products						
19	Textiles, wearing, leather, wood, paper, domestic appliances, furniture, food						

Second, we find that for most technologies a number of faculties/subjects have a significant impact on regional patent activity. Different kinds of measurement of university activities lead to quite similar results. The diverse measurements for the same faculty/subject are highly correlated and therefore predict the same part of patent activity. In addition, various faculties and subjects are sometimes strongly correlated. Hence, each of the university variables reflects to some extent the total university activity. Including more than two university variables in the regression improved for none of the technologies the empirical fit significantly.

Hence, we find that university activities matter in most technologies. Usually, there are a number of faculties/subjects playing a role, so we might interpret the impact found as the impact of the whole university or, at least, a number of faculties. Some faculties/subjects matter (slightly) more than others as well as some kinds of activities matter (slightly) more than others.

Third, if we consider the university variable that leads to the best fit, we find for different technologies various faculties/subjects that seem to be of importance. Thus, Hypothesis 2b is confirmed. There seem to be also various mechanisms, although faculty budgets as innovation facilitators are found more frequently (4 out of 8 cases). Hence, our study does not confirm the findings by Fritsch et al. (2008) that third-party funds matter most. If at all, there is some higher relevance of the faculty budgets.

IV.3 Public activities as innovation generators or innovation facilitators (Hypothesis 3)

Our regression model contains two parts (Equations (6) and (7)). One describes the potential innovation generators, so it captures the innovation generating function of the independent variables. The other describes the innovation probability, capturing the innovation facilitation function of the independent variables. The university variables are included in each of the two equations.

We start with the inclusion of a university variable in one of the two equations. If, at least, one university variable shows significance, we include two variables; testing the inclusion of all combinations of two variables that have been found significant in the first step. If this leads to a significant improvement (likelihood ratio test), we test the inclusion of three variables in the same way. We stop if further inclusions do not lead to a significant improvement of the fit. For none of the technologies we ended up including more than two university variables (see Table A.3 in the Appendix). In Table 3 we present the results for the included university variables for each technology.

Table 3: Results for university variables within the best fitting model for each technology (p-values in parentheses, significance level: ***=0.001, **=0.01, *=0.05)

		University variable as innovation generator		**University variable as innovation facilitator**	
No.	**Technological Field**	**Name**	**Estimate**	**Name**	**Estimate**
1	Electrical machinery, apparat-us, energy	Uni-Grad-Eng	1.02*** (0.001)	Uni-3Funds-Mach	2.01** (0.002)
2	Electronic components	-	-	Uni-Budget-Chem	3.26*** (0.000)

3	Telecommunications	Uni-Grad-EcEng	128* (0.015)	Uni-Budget-Mach	1.39*** (0.001)
4	Audio-visual electronics	-	-	Uni-3Funds-Phys Uni-3Funds-Elec	7.09*** (0.000) 9.45*** (0.000)
5	Computers, office machinery				
6	Measurement, control				
7	Medical equipment				
8	Optics				
9	Basic chemicals, paints, soaps, petroleum products	-	-	Uni-Budget-Phys	2.30*** (0.000)
10	Polymers, rubber, man-made fibres	-	-	-	-
11	Non-polymer materials				
12	Pharmaceuticals				
13	Energy machinery				
14	General machinery				
15	Machine-tools				
16	Special machinery				
17	Transport				
18	Metal products				
19	Textiles, wearing, leather, wood, paper, domestic appliances, furniture, food				

Table 3 clearly confirms Hypothesis 3a: There are many more significant results for the university as innovation facilitator than for the university as innovation generator. This means that universities rather support regional firms and other actors in their innovation activity than being active in innovation generation themselves. At least, this holds for the innovation activity that leads to patents. As a consequence, universities increase the innovation output of a region only if there are innovation activities in this region that they can support. Therefore, it seems to be important for the universities' impact on innovations that a corresponding economic surrounding is given.

Our results also confirm Hypothesis 3b: Most of the effects that we find originate from the budget or third-party funds of faculties (see Table 3). Hence, the research done at universities seems to be more important for the regional innovation output than the education of students. However, the results contain the interesting fact that the research related variables ([Uni-Budget-...] and [Uni-3Funds-...]) are always found to be innovation facilitators, while the education related variables ([Uni-Grad-...]) are always found to be innovation generators. This might be interpreted as follows. Research done at universities helps firms in their innovation activities, while graduates from universities try to stay in the region and are then active in innovation generation themselves. It implies that educating people at universities might have an impact on the innovation output independent from the economic activity, while research at universities requires a fitting economic surrounding to become effective. The former, however, is only found to have a significant impact in some technologies, while the latter seems to work in nearly all technologies.

Finally, we find that for each technology different faculties/subjects matter. There are a few faculties/subjects that dominate, such as physics, chemistry, general engineering, machine building, electrical engineering and economic engineering. Nevertheless, the most important faculty/subject varies with the technology that is studied. Hence, it is important for the effects of universities on the regional innovation output that the faculties at the universities match the industries and technologies present in the region.

V. Conclusions

The aim of this paper is to analyse the impact of universities on the innovation output of regions. The literature provides strong evidence for such an impact. However, details of this impact are less studied. This paper focuses on two detail issues: first, the question of which research and education subjects are especially relevant and second whether and universities contribute to innovation generation themselves independent of the regional economic activity or facilitate the innovation generation by other actors.

We find that universities mainly function as innovation facilitators. Thus, the main effect of these institutions on regional innovation output is supporting private actors in their innovation generation. This implies that an active economic surrounding is necessary for universities to have their full impact on regional innovation output.

Furthermore, the subjects that play a role for innovativeness differ between technologies. The results show that relationships can be established. In combination with the above result, his is an important finding for policy making. It shows that the establishment of universities do not automatically lead to more innovative activity. It is necessary that the scientific focus of universities match the regional economic structure.

This paper presents a first approach to find out the mechanisms and subjects that are relevant for the relationship between universities and regional innovation activities. More research should be done to obtain detailed insights on these relationships. These insights can then be used to improve university systems.

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Appendix

Table A.1: Overview of technological fields and the related IPC codes, NACE codes, faculties and subjects (for some technologies and identification of the related subjects according to the above defined method was not possible because of too few data, so that we defined the subjects ourselves; these subjects are presented cursively).

No.	Technological Field	IPC codes	NACE codes (WZ03)	Related faculties	Related subjects
1	Electrical machinery, apparatus, energy	B60M, B61L, F21H, F21K, F21L, F21M, F21P, F21Q, F21S, F21V, G08B, G08G, G10K, G21C, G21D, H01H, H01K, H01M, H01R, H01T, H02B, H02H, H02K, H02M, H02N, H02P, H05C, H99Z	31.1 – 31.6	Inf; Phys; Chem; Phar; Bio; Med; Mach; Elec	Econ; EcEng; Eng; Mach; Elec
2	Electronic components	B81B, B81C, G11C, H01C, H01F, H01G, H01J, H01L	32.1	Phys; Chem; Phar; Bio; Med; Mach; Elec	EcEng; Eng; Mach; Elec
3	Telecommunications	G09B, G09C, H01P, H01Q, H01S, H02J, H03B, H03C, H03D, H03F, H03G, H03H, H03M, H04B, H04J, H04K, H04L, H04M, H04Q, H05K, H04W	32.2	Phys; Chem; Bio; Med; Mach; Elec	EcEng; Eng; Mach; Elec
4	Audio-visual electronics	G03H, H03J, H04H, H04N, H04R, H04S	32.3	Phys; Chem; Phar; Bio; Med; Mach; Elec	EcEng; Eng; Mach; Elec
5	Computers, office machinery	B41J, B41K, B43M, G02F, G03G, G05F, G06C, G06D, G06E, G06F, G06G, G06J, G06K, G06M, G06N, G06T, G07B, G07C, G07D, G07F, G07G, G09D, G09G, G10L, G11B, H03K, H03L, G06Q	30	Math; Inf; Phys; Chem; Bio; Med; Mach; Elec	*Math; Inf; Phys; Mach; Elec*
6	Measurement, control	F15C, G01B, G01C, G01D, G01F, G01H, G01J, G01K, G01L, G01M, G01N, G01R, G01S, G01V, G01W, G04B, G04C, G04D, G04F, G04G, G05B, G08C, G12B, G99Z	33.2, 33.3, 33.5	Phys; Chem; Phar; Bio; Med; Mach; Elec	*EcEng; Phys; Med; Mach; Elec*
7	Medical equipment	A61B, A61C, A61D, A61F, A61G, A61H, A61J, A61L, A61M, A61N, A62B, B01L, B04B, C12M, G01T, G21G, G21K, H05G	33.1	Phys; Chem; Phar; Bio; Med; Mach; Elec	*EcEng; Phys; Phar; Med; Mach*
8	Optics	G02B, G02C, G03B, G03D, G03F, G09F	33.4	Phys; Chem; Phar; Bio; Med; Mach; Elec	*EcEng; Phys; Mach; Elec*
9	Basic chemicals, paints, soaps, petroleum products	B01J, B09B, B09C, B27K, C01B, C01C, C01D, C02F, C07B, C07C, C07F, C07G, C09B, C09C, C09D, C09F, C09K, C10B, C10C, C10G, C10H, C10J, C10K, C10L, C11D, C12S, D06L, F17C, F17D, F25J, G21F, A01N, C05B, C05C, C05D, C05F, C05G, A62D, C06B, C06C, C06D, C08H, C09G, C09H, C09J, C10M, C11B, C11C, C14C, D01C, F42B, F42C, F42D, G03C, G21J, A01P, C99Z	24.1 (not 24.16, 24.17), 24.2, 24.3, 24.5, 24.6, 23	Phys; Chem; Phar; Bio; Med; Mach; Elec	Math; Inf; Chem; Phar; Mach
10	Polymers, rubber, man-made fibres	A45C, B29B, B29C, B29D, B60C, B65D, B67D, C08B, C08C, C08F, C08G, C08J, C08K, C08L, D01F, E02B, F16L, H02G	25, 24.7, 24.16, 24.17	Phys; Chem; Phar; Bio; Med; Mach; Elec	Math; Inf; Chem; Phar; Mach
11	Non-polymer materials	B21C, B21G, B22D, B22F, B24D, B28B, B28C, B32B, C01F, C01G, C03B, C03C, C04B, C21B, C21C, C21D, C22B, C22C, C22F, C23C, C23D, C23F, C23G, C25B, C25C, C25D, C25F, C30B, C25B, D07B, E03F, E04B, E04C, E04D, E04F, E04H, F27D, G21B, H01B	26, 27	Phys; Chem; Phar; Bio; Med; Mach; Elec	*Germ; EcEng; Phys; Chem; Eng; Mach*
12	Pharmaceuticals	A61K, A61P, C07D, C07H, C07J, C07K, C12N, C12P, C12Q, C40B, A61Q	24.4	Phys; Chem; Phar; Bio; Med; Mach; Elec	Math; Inf; Chem; Phar; Mach
13	Energy machinery	B23F, F01B, F01C, F01D, F03B, F03C, F03D, F03G, F04B, F04C, F04D, F15B, F16C, F16D, F16F, F16H,	29.1	Psych; Phys; Chem; Bio;	Econ; EcEng; Mach; Elec

		F16K, F16M, F23R		Med; Mach; Elec	
14	General machinery	A62C, B01D, B04C, B05B, B61B, B65G, B66B, B66C, B66D, B66F, C10F, C12L, F16G, F22D, F23B, F23C, F23D, F23G, F23H, F23J, F23K, F23L, F23M, F24F, F24H, F25B, F27B, F28B, F28C, F28D, F28F, F28G, G01G, H05F	29.2	Inf; Phys; Chem; Phar; Bio; Med; Mach; Elec	Econ; EcEng; Mach; Elec
15	Machine-tools	B21D, B21F, B21H, B21J, B23B, B23C, B23D, B23G, B23H, B23K, B23P, B23Q, B24B, B24C, B25D, B25J, B26F, B27B, B27C, B27F, B27J, B28D, B30B, E21C, B99Z	29.4	Phys; Chem; Phar; Bio; Med; Min; Mach; Elec	Econ; EcEng; Mach; Elec
16	Special machinery	A01B, A01C, A01D, A01F, A01G, A01J, A01K, A01M, A21C, A22B, A22C, A23N, A24C, A41H, A42C, A43D, B01F, B02B, B02C, B03B, B03C, B03D, B05C, B05D, B06B, B07B, B07C, B08B, B21B, B22C, B26D, B27L, B31B, B31C, B31D, B31F, B41B, B41C, B41D, B41F, B41G, B41L, B41N, B42B, B42C, B44B, B65B, B65C, B65H, B67B, B67C, B68F, C13C, C13D, C13G, C13H, C14B, D01B, D01D, D01G, D01H, D02G, D02H, D02J, D03C, D03D, D03J, D04B, D04C, D05B, D05C, D06B, D06G, D06H, D21B, D21D, D21F, D21G, E01C, E02D, E02F, E21B, E21D, E21F, F04F, F16N, F26B, H05H, F41A, F41B, F41C, F41F, F41G, F41H, F41J	29.5, 29.3, 29.6	Phys; Chem; Phar; Bio; Med; Mach; Elec	Econ; EcEng; Mach; Elec
17	Transport	B60B, B60D, B60G, B60H, B60J, B60K, B60L, B60N, B60P, B60Q, B60R, B60S, B60T, B62D, E01H, F01L, F01M, F01N, F01P, F02B, F02D, F02F, F02G, F02M, F02N, F02P, F16J, G01P, G05D, G05G, B60F, B60V, B61C, B61D, B61F, B61G, B61H, B61J, B61K, B62C, B62H, B62J, B62K, B62L, B62M, B63B, B63C, B63H, B63J, B64B, B64C, B64D, B64F, B64G, E01B, F02C, F02K, F03H, B63G, B60W, F99Z	34, 35	Phys; Chem; Phar; Bio; Med; Mach; Elec	Econ; EcEng; Eng; Mach; Elec
18	Metal products	A01L, A44B, A47H, A47K, B21K, B21L, B25B, B25C, B25F, B25G, B25H, B26B, B27G, B44C, B65F, B82B, E01D, E01F, E02C, E03B, E03C, E03D, E05B, E05C, E05D, E05F, E05G, E06B, F01K, F15D, F16B, F16P, F16S, F16T, F17B, F22B, F22G, F24J, G21H, E99Z	28	Phys; Chem; Phar; Bio; Med; Min; Mach; Elec	Econ; EcEng; Mach; Elec
19	Textiles, wearing, leather, wood, paper, domestic appliances, furniture, food	A21B, A41B, A41C, A41D, A41F, A41G, A42B, A43B, A43C, A44C, A45B, A45D, A45F, A46B, A46D, A47B, A47C, A47D, A47F, A47G, A47J, A47L, A63B, A63C, A63D, A63F, A63G, A63H, A63J, A63K, B01B, B27D, B27H, B27M, B27N, B41M, B42D, B42F, B43K, B43L, B44D, B44F, B62B, B68B, B68C, B68G, C06F, D04D, D04G, D04H, D06C, D06F, D06J, D06M, D06N, D06P, D06Q, D21C, D21H, D21J, E04G, E06C, F23N, F23Q, F24B, F24C, F24D, F25C, F25D, G10B, G10C, G10D, G10F, G10G, G10H, H05B, A01H, A21D, A23B, A23C, A23D, A23F, A23G, A23J, A23K, A23L, A23P, A24B, A24D, A24F, C12C, C12F, C12G, C12H, C12J, C13F, C13J, C13K, A99Z	15 – 22, 29.7, 36	Phys; Chem; Bio; Med; Mach; Elec	Germ; Econ; EcEng; Inf; Mach

Table A.2: Subjects distinguished in the analysis

Shortcut	**Subject**
Germ	German
Econ	Economics and business administration
EcEng	Economic engineering
Math	Mathematics
Inf	Informatics
Phys	Physics
Chem	Chemistry
Phar	Pharmacy

Bio	Biology
Med	Medical science
Eng	Engineering
Min	Mining
Mach	Machine building and process engineering
Elec	Electrical engineering
Traf	Traffic engineering

Table A.3: Complete regression results for the best model (p-values in parentheses)

	Technology						
Variables	**1**	**2**	**3**	**4**	**9**	**10**	
Constant 1	0 (1)	0 (1)	0 (1)	0.0000149 (0.961)	0 (1)	0 (1)	
Inhab	0.0000849*** (0.000)	0.00369*** (0.000)	0.0607*** (0.000)	0.338*** (0.000)	0.000736*** (0.000)	0.0357*** (0.000)	
Empl	0 (1)	0.748 (0.185)	14.0 (0.239)	167 (0.249)	0.0615** (0.003)	0 (1)	
RandD	0.0251 (0.086)	0 (1)	0 (1)	0 (1)	0 (1)	35.3* (0.010)	
Uni-Grad-Eng	1.02*** (0.001)						
Uni-Grad-EcEng			128* (0.015)				
Constant 2	-3.45*** (0.000)	-9.87*** (0.000)	-9.72*** (0.000)	-14.1*** (0.000)	-6.87*** (0.000)	-8.81*** (0.000)	
Dens	0.000216 (0.104)	0 (1)	0.000301* (0.044)	0.000133 (0.454)	0.000568** (0.002)	0.000485*** (0.000)	
GDP	0.0636*** (0.000)	0.108*** (0.000)	0.0589*** (0.000)	0.0642*** (0.000)	0.0897*** (0.000)	0.0600*** (0.000)	
Unempl	-0.0963*** (0.000)	-0.0176* (0.017)	-0.110*** (0.000)	-0.0919*** (0.000)	0 (1)	-0.0876*** (0.000)	
Highschool	0.0242* (0.015)	0.0199 (0.330)	0.00431 (0.646)	0.0236 (0.064)	0.0200 (0.097)	0.0282*** (0.000)	
Uni-Budget-Phys					2.70*** (0.000)		
Uni-Budget-Chem		3.26*** (0.000)					
Uni-Budget-Mach			1.39*** (0.001)				
Uni-3Funds-Phys				7.09*** (0.000)			
Uni-3Funds-Mach	2.01** (0.002)						
Uni-3Funds-Elec				9.45*** (0.000)			
Random effects	0.943*** (0.000)	1.18*** (0.000)		1.03*** (0.000)	1.12*** (0.000)	0.866*** (0.000)	
AIC	2226.82	1911.16		1277.77	2692.07	2634.66	
McFadden adj. pseudo R^2	0.147	0.100		0.151	0.112	0.107	