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Fields of Knowledge, Types of Higher Education Institutions, and Innovative Start-Ups—An Empirical Investigation

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Abstract

We investigate the role played by different fields of academic knowledge and various types of higher education institutions in the emergence of innovative start-ups in a region. We show that education and research in the applied and natural sciences have the strongest effect on the emergence of new businesses in innovative industries. Distinguishing between different indicators for these types of knowledge, the strongest effects are found for the number of professors, followed by the number of students and the amount of external funds attracted. This discovery clearly indicates that it is more the size of the regional knowledge stock than the number of students that is most important for the emergence of innovative stat-ups.

Keywords: New business formation, innovative start-ups, universities, regional knowledge

JEL-classification: L26, L60, L80, O18, R12, R30

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1. Introduction[1]

There is very little doubt that higher education institutions (HEIs) and the knowledge they embody are an important source of new businesses, particularly innovative start-ups. According to the knowledge spillover theory of entrepreneurship (Acs et al. 2009; Acs, Audretsch and Lehmann 2013), new businesses in general, and highly innovative start-ups in particular, are manifestations of knowledge spillover from extant knowledge sources. Hence, the number and type of new businesses should be influenced considerably by the size and characteristics of the respective knowledge base. In particular, the generation of new knowledge via research and development (R&D) activity should be essential to the emergence of innovative start-ups. Since HEIs play an important role in gathering, generating, and distributing knowledge, they can be expected to have a significant effect in this respect. The regional dimension in terms of geographic proximity is important in the process of entrepreneurial knowledge spillover for at least two reasons. First, new knowledge does not flow freely across space but tends to be regionally bounded (Anselin, Varga and Acs 1997; Asheim and Gertler 2006; Boschma 2005). Second, founders have a pronounced tendency to locate their firm in close spatial proximity to their former workplace or near where they reside (Figueiredo, Guimaraes and Woodward 2002; Dahl and Sorenson 2009). Hence, innovative entrepreneurship tends to be a "regional event" (Feldman 2001; Sternberg 2009), meaning that the regional knowledge stock, the regional workforce, and the regional conditions for entrepreneurship are important factors in the emergence of innovative new businesses.

Indeed, many studies find a significantly positive correlation between regional HEIs and the number of innovative startups;[2] however, only little is known about the importance of different fields of academic

[1] We are indebted to Giudo Buenstorf for helpful comments on an earlier version of this paper.

[2] See, for example, Acosta, Coronado and Flores (2011); Audretsch, Lehmann and Warning (2004); Audretsch and Lehmann (2005); Bade and Nerlinger (2000); Baptista and Mendonca (2011); Baptista, Lima and Mendonca (2011); Bonaccorsi et al. (2013); Fritsch and Aamoucke (2013); Harhoff (1999) and Hülsbeck and Pickavé (2014).

knowledge or different types of HEIs. Nor do we know what type of activity, that is, research or education, that has the strongest impact. Based on a rich data set, this paper investigates the role played by different knowledge fields, types of HEIs, and activities in the emergence of innovative start-ups in German regions, with the expectation that not all knowledge fields, types of HEIs, or fields of activity will be equally important.

Section 2 provides an overview of previous research in this area. We then characterize the different fields of knowledge with regard to their assumed relevance for innovative entrepreneurship and describe the types of German HEIs (Section 3). Section 4 introduces the hypotheses; Section 5 describes data and variables. Based on an outline of our empirical approach (Section 6) we present the results (Section 7) and discuss the conclusions (Section 8).

2. Theoretical Framework

2.1 Knowledge Spillovers and Innovative Start-Ups

The knowledge spillover theory of entrepreneurship (Acs et al. 2009; Acs, Audretsch and Lehmann 2013) is based on the assumption that starting an innovative venture requires knowledge. Since a large part of the necessary knowledge resides in universities, non-university public research organizations, and incumbent firms, this approach views innovative start-ups as a form of knowledge spillover, that is, the knowledge of these institutions spills over into the newly founded business. A key assumption of the theory is that the knowledge commercialized by the innovative start-up would not otherwise be exploited. For example, incumbent firms may be unaware of the economic value of the knowledge or they may be unwilling to exploit it because they fear cannibalization of their established product portfolio. Universities and other research institutes either may have no incentive for commercializing their knowledge or not permitted to due to their status as nonprofit organizations. Hence, if someone with an idea about how to turn knowledge into a new product finds it impossible to realize this idea in his or her incumbent organization, then starting an own business may be the only feasible option for putting the idea into practice, especially since, due to the uncertainty of their economic value, new ideas in themselves cannot be traded on the open market.

2.2 Characteristics of Different Scientific Fields

Scientific fields vary considerably with regard to the type of knowledge they generate and its potential for commercialization. It is now common practice to classify knowledge as either codified or tacit. Codified knowledge is easily transmitted across space; tacit knowledge is bound to people and can be transmitted only by direct personal face-to-face contact (Kogut and Zander 1992; Gertler 2003). Thus, spatial proximity to a knowledge source is important for the transmission of tacit knowledge, but far less so for codified knowledge.

Classifying knowledge as either tacit or codified, however, is not always an easy task. According to Stephan (1996) and Asheim and Gertler (2006), knowledge generated by the natural sciences is generally codified knowledge due to this discipline’s strict adherence to standard scientific methods, which enables the knowledge to be accessed via, for example, reading scientific publications. Moreover, knowledge in natural sciences tends to be analytic (Asheim and Gertler 2006) and abstract and thus potentially applicable in diverse contexts. In contrast, knowledge generated by the social sciences tends to be more tacit due to the lower degree of formalization in this field, and the same is true of certain applied sciences, such as engineering, that are more problem oriented than natural science and in which experience plays an important role. Asheim and Gertler (2006) characterize such problem-oriented, experience-based knowledge as “synthetic.”[3]

A third type of knowledge base identified by Asheim et al. (2007) is “symbolic knowledge,” which plays a significant role in fields such as

[3] According to Asheim and Gertler (2006, 295), synthetic knowledge “is created less in a deductive process or through abstraction than through an inductive process of testing, experimentation, computer-based simulation or practical work.” It is much more context specific than analytic knowledge.

cultural production, design, and marketing. Symbolic knowledge manifests as the creation of meaning, aesthetic qualities, and affect. The main sources of symbolic knowledge are creative processes, experimentation, and learning-by-doing. Like synthetic knowledge, symbolic knowledge is largely tacit and often context specific. Thus, spatial proximity will be more relevant for cooperation and spillovers in fields where knowledge is synthetic or symbolic than when it is of an analytic nature.

There is good reason to expect that knowledge generated by different scientific fields will not all be equally suited for commercialization by an innovative start-up. For example, applied research may be much easier to commercialize than knowledge generated from basic research in the natural sciences (e.g., chemistry, physics, and biology) because it is often geared toward solving concrete problems. And, most likely, it will be far easier to transition a technological invention from the natural or applied sciences into a marketable product than it will be to do so with the discoveries of the social sciences, for example, a new interpretation of an ancient philosopher or a further refinement of accounting methods.

3. Previous Research and Open Questions

There are very few empirical studies into how knowledge from different scientific fields influences the emergence of innovative start-ups. There is, however, a fair amount of work that investigates how research conducted in different scientific fields impacts industrial R&D. The majority of these studies suggest that applied sciences are the most important fields in this regard and that their impact clearly exceeds that of the natural sciences (Nelson 1986; Klevorick et at. 1995; Cohen, Nelson and Walsh 2002). However, it is plausible that basic natural sciences have a substantial indirect impact given that they provide the input for the more applied sciences and that quite often those who work in applied sciences have had previous training in basic natural sciences. In support of this idea, work that limits itself to studying HEI activity in the natural and the applied sciences finds a positive relationship between this activity and the opening of new innovative businesses in the respective region (e.g., Acosta, Coronado and Flores 2011; Woodward, Figueiredo and Guimaraes 2006; Zucker, Darby and Brewer 1998).[4] With regard to the relevant type of activity, Accosta, Coronado and Flores (2011) identify a relationship when looking at the number of graduates, but not for the number of university patents or number of publications. Woodward, Figueiredo and Guimaraes (2006) only use R&D expenditure of HEIs engaged in significant research activity. Zucker, Darby and Brewer (1998) find that the number of regional start-ups in biotechnology can be explained by the number of highly productive star scientists and by the number of faculty that have obtained federal support for their research.[5] The authors suggest that the star scientists play a considerable role as founders of these new firms.

We are aware of only three studies that consider a broader spectrum of academic disciplines when assessing their impact on the emergence of innovative start-ups. The first of these, that by Audretsch, Lehmann and Warning (2004), analyzes the regional distribution of 281 publicly listed firms in German high-technology and knowledge-intensive industries. According to this analysis, knowledge spillovers from universities had a strong effect on the location decisions of these firms, which decisions were based not only on the output of universities but also on the nature of this output. The second study, Audretsch and Lehmann (2005), finds that if the number of publications is taken as a measure of a university's research output, it is only the number of publications generated by the natural sciences, not by the social sciences, that is statistically related to the number of innovative start-ups in the region. If the number of students and graduates is used as an output indicator, then both fields of knowledge appear to have a positive effect on the location decisions of innovative start-ups. The age of a university, which may be viewed as an indication of reputation, is not statistically significant.

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[4] The study by Acosta, Coronado and Flores (2011) is limited to HEI activity in "science and technology," but how this field is defined in detail is unclear. Woodward, Figueiredo and Guimaraes (2006) analyze engineering, physical sciences, geosciences, mathematics and computer sciences, life sciences (including agricultural, biological, medical, and other life sciences), and science and engineering technologies. The study by Zucker, Darby and Brewer (1998) is limited to biotechnology.

[5] Remarkably, the number of co-authors of the star scientists has no statistically significant positive effect.

The third study (Baptista and Mendonça 2010) uses longitudinal data for firms, universities, and human capital in the regions of Portugal. The authors distinguish between two groups of disciplines: one group includes the basic sciences and engineering, the other is comprised of the social sciences. Three indicators for the presence of universities are included in the empirical models: the number of universities in the region, the number of students, and the number of graduates. Baptista and Mendonça (2010) find a positive and statistically significant effect for all three indicators. The number of students and graduates in basic and applied sciences has a significant positive effect on the number of new businesses in innovative manufacturing industries and knowledge-intensive services, whereas the effect of students and graduates in social sciences is limited to having a positive effect only on new business creation in knowledge-intensive services.

To summarize this rather sparse evidence, there is some indication that university activity in the fields of natural and applied sciences is somewhat more important for regional new business formation than activity in the social sciences.

Previous work on how different academic disciplines influence the emergence of innovative new business leaves many questions unanswered. The three studies that account for different fields of academic knowledge (Baptista and Mendonca 2010; Audretsch, Lehmann and Warning 2004; Audretsch and Lehmann 2005) distinguish between only two research fields[6] and disregard others. Moreover, these studies have limited information about HEI activity in these fields. A further limitation of the work by Audretsch, Lehmann and Warning (2004) and Audretsch and Lehmann (2005) is that the authors analyze only a selection of German universities, notably ignoring universities of applied sciences (*Fachhochschulen*), art schools, and universities of public

[6] Baptista and Mendonca (2010) merge engineering and basic sciences into one field and consider the social sciences as their second field. Audretsch, Lehmann and Warning (2004) and Audretsch and Lehmann (2005) distinguish between natural sciences and the social sciences.

administration.[7] Another limitation of these works is their restricted focus on firms that are publicly listed on the German stock market. Clearly, these firms are not representative of the total population of innovative start-ups but are instead firms for which financiers had positive expectations with regard to growth and profitability. Hence, the relative importance of various disciplines to the emergence of innovative business remains an open question. Moreover, nothing is known about the possible impact of other types of HEIs, such as medical schools, universities of applied sciences, art schools, or schools of public administration.

Another as yet unanswered question concerns the channels by which the knowledge that resides in HEIs spills over to new businesses. Who is it that transforms the academic knowledge into innovative start-ups? How many of these innovative new firms are started by former students? How many by faculty and former researchers? While Zucker, Daby and Brewer (1998) suggest that star scientists play an important role as founders of new firms in the U.S. biotech-industry, Asterbro, Bazzazian and Braguinsky (2012) argue that the majority of founders should be former students simply because there are more of them (compared to faculty or researchers). Moreover, researchers with tenure may be unlikely to give up their secure job for something as risky as starting a firm. This may be particularly true of professors in German public universities who are civil servants and thus considerably restricted in regard to engaging in private-sector activity.

4. Research Design and Hypotheses

4.1 Classification of HEIs and Fields of Scientific Knowledge

Nearly all HEIs in Germany are public. The higher education system consists of regular universities and universities of applied sciences (*Fachhochschulen*), and the two are different in many respects, including purpose, scope and size, teaching, and research (Warning 2007). The

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[7] Baptista and Mendonca (2010) provide no information about different types of HEIs in their data.

universities of applied sciences are mainly intended to provide undergraduate education with a focus on transferring theoretical concepts and scientific methods into practical application; these universities do not grant Ph.Ds. Courses are more structured than in regular universities and classes are smaller. Professors at the universities of applied sciences have much higher teaching loads than those at the regular universities and little or no support in terms of finance or personnel for conducting research. On average, universities of applied sciences are much smaller in terms of personnel and students than regular universities.

The regular universities usually cover a broad range of academic disciplines. They include medical schools (*Universitätskliniken*), schools of public administration (*Verwaltungshochschulen*), and arts colleges (*Kunsthochschulen*), all of which are significantly different in regard to both their research as well as their educational profiles. A special feature of the medical schools is that they have hospitals. Due to their distinct characteristics, we count the medial schools as a separate university although nearly all of them are part of a university. The main mission of the universities of public administration is to educate civil servants for higher positions in public service with a clear focus on law and management. Art colleges engage in very little research at all, according to the conventional understanding of the term, and are characterized by quite special forms of education. The more symbolic type of knowledge that these institutions generate and possess, however, could be important for the emergence of innovative new businesses.

Germany is also home to a number of independent non-university research institutes, including those of the Max Planck Society, the Fraunhofer Society, the Helmholtz Association, and the Gottfried Wilhelm Leibniz Scientific Community. Although these institutes have in common that they are predominantly nongovernmental and nonprofit associations funded by the federal and state governments, they differ with regard to the type of research in which they engage. For example, the institutes of the Max Planck Society conduct predominantly basic research in different fields such as applied sciences, natural sciences, social sciences, and the arts and humanities, whereas the institutes of the Fraunhofer Society specialize in applied sciences research in collaboration with various industrial sectors. The Helmholtz Association of German Research Centers and the Gottfried Wilhelm Leibniz Scientific Community are networks of national laboratories and institutes that perform research in applied sciences as well as in basic natural sciences. These non-university research institutes are famous for the quality and prominence of their work. For instance, the Max Planck Institutes, which are regarded as the foremost basic research organization in Germany and Europe, have received no fewer than 17 Nobel prizes over the last 65 years.

All indicators for HEIs distinguish between five categories of academic knowledge: natural sciences, applied sciences, medical science, administrative and political sciences, and other disciplines. This typology is designed to account for the unique aspects of each field and for the common assignment of academic disciplines to specific departments or schools. Note that the non-university research institutes are assigned to these fields, too.[8] Natural sciences include fields that seek to discover the rules that govern the natural world, for example, physics, chemistry, biology, mathematics, and the like. Applied sciences cover technical fields that focus on developing more practical applications from existing scientific knowledge, for example, architecture, engineering, and spatial planning. Medical science is largely based on natural sciences with a focus on concrete problem solving. Administration and political sciences include those fields concerned with the organization of society, such as economics, law, management, political sciences, public administration, and sociology. “Other disciplines” cover a broad range of nontechnical academic fields, such as linguistics, history, arts, and theology, the research results of which are rarely commercialized by private-sector innovators. Table A1 in the Appendix contains a list of the disciplines included in each category. With regard to the type of HEI, we distinguish

[8] The non-university research institutes that may be relevant for medical science focus on natural sciences such as pharmacy and biology. Hence, we assign these institutes to the natural sciences and not to medicine.

between regular universities, universities of applied sciences, medical schools, schools of public administration, and arts colleges.

4.2 Expectations

Given the limited knowledge about the relationship between academic disciplines, type of HEI, and innovative start-ups, our investigation is explorative in nature. Our basic hypothesis is that the knowledge generated by different disciplines will not all equally create opportunities for innovative start-ups; moreover, when such knowledge does have such potential, we hypothesize that its realization will take different forms. It also seems reasonable to expect that knowledge spillovers in each scientific field predominantly foster a certain kind of start-up. Accordingly, research and education in basic and applied sciences (including medical science) should be particularly conducive to new business formation in high-tech manufacturing, while the activities of other disciplines may primarily generate start-ups in technology-oriented services.

We expect that regional knowledge in natural, applied, and medical science will have a positive effect on the emergence of innovative start-ups. Since applied and medical science often generate technical knowledge from practical problem solving, this knowledge should be easier to commercialize than knowledge generated by the natural sciences. Hence, the relationship between knowledge in the applied and medical sciences and start-ups should be stronger than for knowledge in the natural sciences. Knowledge from administrative, political, and other sciences such as sociology, psychology, law, and management has only limited potential for commercialization. Thus, we expect that HEI activity in such fields will have a weak effect, if any, on the emergence of innovative start-ups.

Because the regular universities and medical schools conduct much more research than the universities of applied sciences, we expect that they have a stronger impact on the emergence of innovative new businesses. Similarly, because arts schools and universities of public administration have hardly any focus on technology, their effect should be relatively weak. Another reason for expecting that universities of public administration will have no pronounced effect on the emergence of innovative start-ups is that their mission is to train personnel for the public sector, which, almost by definition, should attract individuals with a low propensity to start an own business.

HEIs' knowledge resides in their scientific staff, particularly the professors, who are key to organizing research and applying for research funds. Hence, the number of professors can be viewed as a key indicator for the knowledge stock. Another measure for the amount and quality of research is the amount of external research funds obtained. Because external funds are nearly always allocated via some kind of competitive procedure, they can be regarded as an indication of research quality. When funding is granted by private firms, it is usually for collaborative and contract research and, therefore, indicates knowledge transfer to the private sector for purposes of commercialization. A considerable part of HEIs' knowledge is transferred to students via teaching activities. Later in life, these students may attempt to commercialize this knowledge by founding an own business. Since professors in German public universities are civil servants who are subject to considerable restriction in regard to engaging in private-sector activity, their propensity for starting an own firm can be assumed to be much lower than that of former students. Moreover, sheer numbers alone make it more likely that more new businesses are set up by students, as opposed to professors or other researchers (Astebro, Bazzazian and Braguinsky 2012). For these reasons, it is plausible to expect a closer statistical relationship between the number of students and graduates and the number of innovative new businesses than between the number of professors and research staff and the number of new businesses.

5. Data, Variables, and Descriptive Statistics

5.1 Data

Our data on start-ups are from the Founder Panel of the Center for European Economic Research (ZEW-Mannheim) and include nearly every independent firm founded during the period 1995–2008. These data are based on information from the largest German credit rating agency (Creditreform). This agency covers all private sectors in Germany and identifies innovative new businesses based on their affiliation with certain industries. We use the common way of classifying industries based on their presumed innovativeness and distinguish between (1) high-technology manufacturing industries that devote more than 8.5 percent of their input to R&D, (2) technologically advanced manufacturing industries with an R&D intensity between 3.5 and 8.5 percent, and (3) technology-oriented services (Grupp and Legler 2000; OECD 2005; Gehrke et al. 2010). Technology-oriented services comprise a subgroup of knowledge-intensive services and include industries that are particularly related to innovation activity such as architectural and engineering activities, technical consultancy, and technical testing and analysis. In addition, we run all models for those industries not classified as innovative or knowledge intensive. A main problem of this classification system is that industry affiliation is a fuzzy criterion because there are innovative and not so innovative firms in all industries. Given the limited availability of data on innovation, however, this is often the only feasible way to identify new businesses as being innovative.[9]

Most of the information on the independent variables comes from one of two sources. Data on regional private-sector employment and R&D employment are from the German Employment Statistics, which covers all employees subject to compulsory social insurance contributions (Spengler 2008). The second data source is the University Statistics of the German Federal Statistical Office, which provides detailed information about every university in Germany (Statistisches Bundesamt various volumes). Data

[9] See Fritsch (2011) for the classification of German industries as “innovative,” “technologically advanced,” or “technology-intensive services.”

on unemployment are from the German Employment Agency (Bundesagentur für Arbeit). The spatial framework of the analysis is based on the 439 German districts (Kreise). To attain functional regions, we merged those districts that only encompass cities (kreisfreie Stadt) with the surrounding territorial districts, resulting in 325 regions (Federal Office for Building and Regional Planning 2003).

No detailed regional data are available for the extra-university public research institutions. However, we know how many of such institutes there are in each region.[10] Information about the number of patents is from the Patent Statistics. Patents are assigned to the region where the inventor has his or her residence.[11]

5.2 Variables

As dependent variables, we use the number of start-ups in high-technology manufacturing industries, in technologically advanced manufacturing industries, in technology-oriented services, and in those industries that are not classified as innovative or knowledge intensive. In our baseline model we include the size of the regional workforce, which represents the pool of potential entrepreneurs and also reflects economies of size and agglomeration effects. The regional workforce is divided into the number of private-sector R&D employees, the number of employed persons excluding R&D employees, and the number of persons registered as being unemployed. The number of R&D employees is an important part of a region's knowledge pool. Since the number of R&D employees is highly correlated with the number of people with a tertiary degree, we do not include an indicator for the share of the workforce holding a tertiary degree. We expect a positive effect on the emergence of innovative start-ups from the number of employed people, particularly the number of R&D

[10] We account for all institutes of the four large public research organizations in Germany, i.e., the Fraunhofer, the Helmholtz, the Leibnitz, and the Max Planck Society. Data were collected from various sources, chiefly from publications of these organizations and the Federal Ministry of Education and Research. Since a number of these institutes have several locations, the publicly available information about their budgets and number of personnel cannot be meaningfully assigned to regions.

[11] If a patent has more than one inventor, the count is divided by the number of inventors and each inventor is assigned his or her share of that patent.

employees, but the impact of the number of unemployed people is a priori unclear. On the one hand, innovative start-ups, of course, can be set up by the unemployed. On the other hand, unemployed people have a relatively low propensity for starting their own business (Fritsch and Falck 2007), and this may be particularly true when it comes to innovative ventures that primarily represent opportunity, rather than necessity, entrepreneurship and require a relatively high level of qualification. Moreover, a high number of unemployed people in a region can be viewed as an indication of bad economic conditions and, therefore, indicate poor prospects for success, which may prevent potential founders from setting up a firm in the region (Carree 2002; Sutaria and Hicks 2004).

If public and private research in a region is conducive to the emergence of innovative start-ups, we may expect a concentration of this kind of new business in larger cities and agglomerations because both public research institutes as well as private-sector R&D tend to be concentrated in such high-density areas. Other reasons for expecting a relatively high number of innovative start-ups in larger cities include agglomeration economies, such as large and diversified input markets and rich opportunities for direct face-to-face contact, which can be assumed conducive to the transfer of knowledge. We do not include a measure for population density in our standard models because of its close statistical relationship with other variables that would lead to severe multicollinearity problems. Due to its close correlation with many other factors that may be the “true” determinants of innovative start-ups, including population density could obscure the effects that these other factors have on the emergence of innovative start-ups. However, in order to analyze the influence of agglomeration effects, we run our models for groups of regions having various population densities.

As indicators for HEI activity we use the number of professors, the number of students, and the number of Ph.D. graduates, as well as the amount of external funds.[12] These variables reflect different aspects of the

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[12] Alternative indicators of HEI activity, such as the number of graduates, amount of regular funds, etc. (see Fritsch and Aamoucke 2013), are highly correlated with the

HEI’s size. The number of students and Ph.D. graduates indicates a contribution to the workforce’s education (i.e., its qualifications), particularly the number of potential founders with an academic background. The number of professors and amount of external funding obtained primarily signify the knowledge stock and the volume of research being conducted. Tables A2–A5 present descriptive statistics and correlations for the variables included in the analyses.

6. Empirical Approach

Due to the count character of the independent variable—the number of start-ups—we employ a negative binomial estimation technique. Because we find a relatively high share of observations with no regional start-up in high-technology manufacturing in a year (27.78 percent), we could be facing the “too many zero values” problem. A possible solution to this problem is to apply the zero-inflated version of the negative binomial method, which includes only a selection of “true” zero values in the estimation. Under this method, regions in which the event of interest (i.e., formation of an innovative start-up) is never expected to occur are excluded from the estimation. The zero-inflated negative binomial method requires an assumption for identifying and selecting the “true” zero values. Since our data show that all regions in Germany have at least one start-up in high-technology industries from time to time, all the zero values in our data have to be regarded as “true” and thus the zero-inflated negative binomial estimation method is inappropriate. For the technologically advanced start-ups, the share of observations without a new business in a year is 13.54 percent and for technology-intensive services it is 0.07 percent, suggesting that there is no “too many zero values” problem.

We have a time series of yearly observations for a period of 14 years and thus can employ panel estimation techniques. Since many of the potential explanatory variables (e.g., number of universities in the

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indicators reported here and do not provide additional insight. We do not report results for such alternative indicators due to space limitations. Note that the data do not provide information about the number of PhD students but only about those who have actually earned a PhD.

region) show little or no variation over time, a fixed effects estimator that would account for unobserved regional characteristics is not appropriate because a considerable part of the influence of such variables is captured by the fixed effects. We thus use a random effects estimator. Since the standard statistical software packages do not provide spatial lag and spatial error corrections for negative binomial panel models, we include dummy variables for the German Federal States (Laender) in order to control for effects of the wider regional environment. Moreover, the number of R&D employees in adjacent regions is included as a control for interregional spillovers. Since the German Federal States are an important policy-making level, this variable may also indicate the effect of policy measures at this level. Year dummies are included as controls for time-specific effects. All independent variables are lagged by one year.

A severe problem of the empirical analysis is the high correlation among most of the indicators for the universities (see Table A4 in the Appendix). To a considerable extent, these pronounced correlations are caused by a variation of these variables with size due to complementarity, for example, having a large number of students means a larger teaching staff and more resources. We deal with this problem as follows. In a first step, we estimate a baseline model without the indicators for universities and non-university public research institutes. In a second step, we add the indicators for public research one at a time. Our measure for the impact of these indicators is change in the AIC (Akaike information criterion) compared to the baseline model. The AIC is a measure of a statistical model's relative goodness of fit that accounts for the number of independent variables included in the model (Akaike 1974; Greene 2008). A decrease in the AIC value due to the inclusion of an additional variable indicates a better fit of the model in terms of reducing the remaining "unexplained" variance. An increase in the remaining variance leads to a higher AIC value. In a final step, we perform factor analyses in order to aggregate the information about HEIs and add the resulting factor to the variables of the baseline model. Since the dependent as well as the independent variables are logged, the values of the estimated coefficients can be interpreted as elasticities that indicate the relative importance of the respective effect.

7. Results

7.1 Results for the Baseline Model

In our baseline model we find positive and statistically significant effects for the number of regional employees, excluding R&D employees, as well as for the employment share in the respective industries for the number of start-ups in all four industry groups (Table 1). In line with our expectations, the coefficient for the number of R&D employees has the highest value for new businesses in high-technology manufacturing industries followed by those in technologically advanced manufacturing and in technology-oriented services; it is not statistically significant for start-ups in non-innovative industries. The fact that the number of unemployed people has an effect only on start-ups in non-innovative industries clearly indicates that new businesses set up by unemployed people tend to occur in these industries. The share of employees in establishments with fewer than 50 employees also has a statistically significant positive effect except for start-ups in technologically advanced manufacturing. This positive effect may indicate that founders of new businesses were previously employed in small firms or that the presence of industries with low minimum efficient size is conducive to start-ups (Fritsch and Falck 2007).

The number of patents per 1,000 employees has a positive effect on start-ups in high-technology manufacturing and technology-oriented services but it is not statistically significant for start-ups in technologically advanced manufacturing (Table 2). The relationship between number of patents and number of start-ups in non-innovative industries is statistically significant but with a negative sign. This clearly indicates the importance of regional knowledge for the formation of innovative new businesses. We find no significantly positive effect for the number of R&D employees in surrounding regions, suggesting that interregional spillovers from R&D employment are irrelevant for the emergence of new businesses, even in

Table 1: Baseline model for explaining number of start-ups in different groups of industries

	High-technology manufacturing	*Technologically advanced manufacturing*	*Technology-oriented services*	*Non-innovative industries*
Number of employed persons, excluding R&D employees	.0347*** (3.26)	.0311*** (3.56)	.0304*** (7.12)	.5467*** (19.76)
Number of R&D employees	.00002*** (4.11)	7.97e-06*** (2.45)	3.54e-06** (1.92)	6.89e-07 (0.88)
Number of unemployed	.0110 (0.55)	.0095 (0.59)	.0042 (1.00)	.0067*** (7.14)
Share of employees in high-technology manufacturing industries	.0971*** (7.02)	–	–	–
Share of employees in technologically advanced manufacturing industries	–	.0199** (2.09)	–	–
Share of employees in technology-oriented service industries	–	–	.0198*** (2.76)	–
Share of employees in non-innovative industries	–	–	–	.0724*** (2.50)
Share of employees in establishments with fewer than 50 employees	.2427** (1.99)	.0625 (1.57)	.2322*** (2.92)	.2665*** (11.05)
Number of R&D employees in adjacent regions	.0194 (0.84)	-.0102 (0.56)	-.0214*** (3.69)	-.0040* (1.64)
Number of patents per 1,000 employees	51.3587*** (3.38)	-.3425 (0.03)	17.5053*** (3.34)	-2.4442*** (0.94)
Constant	.7197*** (10.26)	1.3684*** (13.82)	2.6735*** (29.67)	-1.4930*** (39.38)
Wald chi2	573.25***	479.07***	899.48***	2756.17***
Dummies for Federal States	Yes***	Yes***	Yes***	Yes***
Dummies for years	Yes***	Yes***	Yes***	Yes***
Number of observations (number of zeros)	4,550 (1,264)	4,550 (616)	4,550 (3)	4,550 (0)
Log likelihood	-8,489.2698	-10,252.936	-16,669.051	-20695.383
AIC	17,042.54	20,563.87	33,402.1	41,455.08
Pseudo R2	.6342	.5545	.7431	.6518
McFadden's R2	.105	.106	.109	.178

Notes: The dependent variable is the number of start-ups per year in the respective group of industries. Negative binomial panel regression with random effects. Z-values in parentheses. All independent variables except dummies are entered with their logarithmic values (ln). ***: statistically significant at the 1% level; **: statistically significant at the 5% level; *: statistically significant at the 10% level.

our rather narrowly defined regions. Including measures for the concentration of the regional industry structure (i.e., spatial clustering) does not lead to any plausible or statistically significant results.

7.2 How Does the Impact of HEIs Differ Across Various Scientific Fields and Types of HEI?

We include the number of professors in different scientific fields in the baseline model and compute the changes in the AIC value.[13] We find the highest increase in explained variance for the number of professors in applied sciences followed by the number of professors in natural sciences and in medical science (Table 2). The effect of the number of professors in administration and political sciences is considerably less pronounced, and professors in "other" scientific fields, such as linguistics, arts, and theology, appear to have the weakest effect on the number of start-ups. It is possible that the results for the applied sciences underestimate the impact of the natural sciences because the basic training in natural sciences that students in applied science receive is assigned to the applied sciences in these estimates (Nelson 1986; Klevorick et at. 1995; Cohen, Nelson and Walsh 2002). For this reason we include both natural and applied sciences together and find the strongest increase in explained variance as indicated by reduction of the AIC value. This finding indicates that applied and natural sciences are the most influential fields for stimulating innovative start-ups.

To compare the effect of different types of HEIs on the explained variance we include the indicators for regular universities and universities of applied sciences with regard to natural sciences and applied sciences separately (Table 2). Moreover, we test the effect of the type of institution (including art colleges and universities of public administration) taking all scientific fields together. With regard to the number of professors in the natural sciences we find the highest increase in explained variance, as indicated by reduction of the AIC values, for the number of professors in

[13] Professors in arts colleges and in universities of public administration are omitted here because of the special character of these types of institutions.

Table 2: Change in the AIC value compared to the baseline model due to the inclusion of the number of professors in different disciplines and types of HEIs

	High-technology manufacturing	*Technologically advanced manufacturing*	*Technology-oriented services*	*Non-innovative industries*
All professors	-36.99 .0742 (6.22)***	-36.31 .0607 (6.28)***	-19.2 .0240 (4.59)***	358.87 -.0050 (1.10)
Scientific field[a]				
- Natural sciences	-111.97 .2835 (2.70)***	-135.11 .2992 (3.51)***	-124.95 .2312 (5.34)***	435.05 -.0536 (1.51)
- Applied sciences	-163.11 .7482 (4.32)***	-154.43 .4486 (3.18)***	-146.92 .2955 (3.95)***	440.02 -.1262 (2.04)**
- Medical science	-105.17 .7572 (3.40)***	-134.73 .6832 (2.50)***	-28.91 .0723 (.098)*	445.03 -.0040 (.59)
- Natural and applied sciences	-179.31 .9575 (3.23)***	-168.12 .6081 (2.52)***	-163.45 .6010 (4.76)***	441.20 -.2060 (1.72)*
- Medical science	-105.17 .7572 (3.40)***	-134.73 .6832 (2.50)***	-28.91 .0723 (.098)*	445.03 -.0040 (.59)
- Administrative and political sciences	-63.80 .0982 (1.06)	-70.11 .2246 (4.79)***	-124.75 .2511 (4.09)***	108.23 .0097 (.200)
- Others	-3.38 .0153 (.93)	-4.43 .0188 (1.49)	-11.30 .0222 (3.64)***	93.84 -.0047 (-.740)
Natural sciences[a]				
- Regular universities	-82.42 .2481 (3.68)***	-110.24 .1711 (5.30)***	-100.88 .0099 (1.07)	436.23 .0860 (1.06)
- Universities of applied sciences	-46.79 .0909 (1.66)*	-93.47 .0850 (2.11)**	-88.05 .0248 (1.22)	430.03 .0017 (.140)
Applied sciences[a]				
- Regular universities	-149.64 .4232 (2.81)***	-144.38 .5928 (4.59)***	-113.95 .1532 (1.35)	447.71 -.0370 (2.05)**
- Universities of applied sciences	-151.12 .4772 (4.32)***	-148.37 .5165 (4.44)***	-124.26 .3094 (3.49)***	446.92 -.1139 (1.53)
Type of HEI				
- Regular universities	-104.79 .8589 (3.56)***	-137.00 .7739 (4.96)***	-25.33 .0494 (.53)	437.00 -.0418 (2.81)***
- Universities of applied sciences	-84.75 .9419 (4.20)***	-137.30 .9475 (3.77)***	-31.45 .1123 (2.06)**	443.41 -.0444 (.97)
- Medical schools	-105.17 .7572 (3.40)***	-134.73 .6832 (2.50)***	-28.91 .0723 (.098)*	445.03 -.0040 (.59)
- Arts colleges	-10.10 .0045 (2.16)**	-15.73 .0056 (3.75)***	-8.53 .0012 (1.49)	87.55 -.0007 (1.09)
- Universities of public administration	-7.29 .0017 (0.65)	-7.13 .0047 (2.34)**	-30.79 .0206 (1.93)**	73.38 .0026 (3.88)***

Notes: Number of professors entered with the logarithmic value (ln). First row: Change in the AIC value due to the inclusion of the variable. Second row: Estimated coefficient and z-value in parentheses. ***: statistically significant at the 10% level; **: statistically significant at the 5% level; *: statistically significant at the 1% level. a: Professors of regular universities (including medical schools) and universities of applied sciences only.

regular universities followed by the number of professors in universities of applied sciences (Table 2). In the applied sciences, professors in both types of institutions produce about the same improvements of the AIC (with a slightly smaller impact of the professors at the regular universities). Taking all scientific fields together results in mixed findings. The effects of regular universities and medical schools are stronger than those of the universities of applied sciences with regard to entries in high-technology manufacturing, but this difference is negligible for start-ups in the other three categories (Table 2). This result may be due to the fact that universities of applied sciences have much higher shares of professors in the applied sciences than do other types of HEIs. Not surprisingly, the effect of the arts colleges and of universities of public administration is considerably weaker than the effect of all other types of HEIs.

7.3 How Does the Impact of HEIs Differ Across Transmission Channel?

We next analyze different transmission channels of knowledge spillovers. We compare the effects of the number of professors with those of the number of students, the number of Ph.D. graduates, and the amount of external funding obtained. These indicators represent two types of transmission channels for knowledge spillovers: (1) the number of students, Ph.D. graduates, and professors indicate the role of these groups as potential founders of innovative new businesses and (2) the extent of research activities and the knowledge stock is represented by the number of professors, the number of Ph.D. students and the amount of external funding obtained. We compare these two types of transmission channels by scientific field as well as by type of HEI.[14]

A key result of these analyses is that in all the scientific fields, the number of professors shows the highest decrease in the AIC value, indicating better model fit (Tables 3 and 4). This finding is valid for all

[14] We omit arts colleges and universities of public administration because of the special character of these types of institutions and because of their rather weak effect, as discussed in the previous section.

Table 3: Change in the AIC value compared to the baseline model due to the inclusion of diverse indicators of HEIs in natural sciences and engineering

	High-technology manufacturing	*Technologically advanced manufacturing*	*Technology-oriented services*	*Non-innovative industries*
Natural sciences				
Number of professors	-111.97	-135.11	-124.95	435.05
	.2835 (2.70)***	.2992 (3.51)***	.2312 (5.34)***	-.0536 (1.51)
Number of students	-90.34	-123,54	-106.21	437.11
	.1365 (3.46)***	.1154 (3.70)***	.0859 (5.47)***	-.0054 (0.46)
Number of Ph.D.	-74.02	-100.05	-121.14	437.01
graduates	.0609 (4.10)***	.0462 (3.83)***	.0310 (4.98)***	-.0030 (0.55)
Amount of external	-74.15	-111.03	-83.97	437.27
funds	.0194 (3.00)***	.0098 (1.97)**	.0071 (2.84)***	.0004 (0.23)
Applied sciences				
Number of professors	-163.11	-154.43	-146.92	440.02
	.7482 (4.32)***	.4486 (3.18)***	.2955 (3.95)***	-.1262 (2.04)**
Number of students	-158.00	-111.69	-137.40	436.57
	.2957 (3.68)***	.1653 (2.51)***	.1140 (3.32)***	-.0754 (2.76)***
Number of Ph.D.	-118.13	-68.71	-115.40	443.69
graduates	.0460 (2.56)***	.0441 (3.02)***	.0175 (2.33)**	-.0038 (0.68)
Amount of external	-118.64	-90.45	-110.67	444.12
funds	.0181 (2.65)***	.0111 (2.06)**	.0054 (2.03)**	.0003 (0.17)
Natural and applied sciences				
Number of professors	-179.31	-168.12	-163.45	441.20
	.9575 (3.23)***	.6081 (2.52)***	.6010 (4.76)***	-.2060 (1.72)*
Number of students	-164.38	-132.90	-143.38	441.89
	.3114 (2.67)***	.2620 (2.77)***	.1936 (3.91)***	-.0639 (1.50)
Number of Ph.D.	-118.24	-120.47	-118.30	442.11
graduates	.1575 (3.27)***	.1562 (4.01)***	.0185 (0.97)	.0158 (1.43)
Amount of external	-118.94	-101.77	-118.81	443.77
funds	.0847 (3.37)***	.0498 (2.47)***	.0118 (1.20)	-.0028 (0.61)
Medical science				
Number of professors	-105.17	-134.73	-28.91	445.03
	.7572 (3.40)***	.6832 (2.50)***	.0723 (.098)*	-.0040 (.59)
Number of students	-101.00	-131.95	-20.47	445.21
	.0231 (2.73)***	.3744 (1.88)*	.05923 (2.22)**	.0008 (.41)
Number of Ph.D.	-103.33	-131.60	-22.84	444.76
graduates	.0437 (3.13)***	.3841 (1.78)*	.0454 (2.71)***	-.0037 (.79)
Amount of external	-47.98	-130.44	-11.15	424.20
funds	.0157 (2.15)**	.1592 (1.41)	-.0003 (.11)	-.0080 (.00)

Notes: Variables entered with their logarithmic values (ln). First row: Change in the AIC value due to the inclusion of the variable. Second row: Estimated coefficient and z-value in parentheses. ***: statistically significant at the 1% level; **: statistically significant at the 5% level; *: statistically significant at the 10% level.

Table 4: Change in the AIC value compared to the baseline model due to the inclusion of diverse indicators of HEIs in regular universities, universities of applied sciences, and medical schools

	High-technology manufacturing	*Technologically advanced manufacturing*	*Technology-oriented services*	*Non-innovative industries*
Regular universities				
Number of professors	-104.79	-137.00	-25.33	437.00
	.8589 (3.56)***	.7739 (4.96)***	.0494 (.53)	-.0418 (2.81)***
Number of students	-99.15	-124.25	-13.78	448.62
	.5717 (3.90)***	.5983 (4.99)***	.0014 (0.30)	-.0298 (3.40)***
Number of Ph.D.	-95.34	-120.82	-11.93	449.65
graduates	.0612 (3.76)***	.0661 (5.01)***	.0038 (0.628)	-.0386 (3.29)***
Amount of external	-85.36	-105.63	-9.81	446.15
funds	.0317 (3.51)***	.0353 (4.75)***	.0001 (0.23)	-.0288 (3.69)***
Universities of applied sciences				
Number of professors	-84.75	-137.30	-31.45	443.41
	.9419 (4.20)***	.9475 (3.77)***	.1123 (2.06)**	-.0444 (.97)
Number of students	-75.65	-111.60	-29.75	436.45
	.5955 (3.65)***	.4429 (3.82)***	.0990 (1.60)	-.1425 (2.81)***
Amount of external	-72.81	-102.73	-29.76	442.56
funds	.0269 (3.25)***	.0148 (2.37)**	.0051 (1.60)	-.0030 (1.34)
Medical schools				
Number of professors	-105.17	-134.73	-28.91	445.03
	.7572 (3.40)***	.6832 (2.50)***	.0723 (.098)*	-.0040 (.59)
Number of students	-101.00	-131.95	-20.47	445.21
	.0231 (2.73)***	.3744 (1.88)*	.05923 (2.22)**	.0008 (.41)
Number of Ph.D.	-103.33	-131.60	-22.84	444.76
graduates	.0437 (3.13)***	.3841 (1.78)*	.0454 (2.71)***	-.0037 (.79)
Amount of external	-47.98	-130.44	-11.15	424.20
funds	.0157 (2.15)**	.1592 (1.41)	-.0003 (.11)	-.0080 (.00)

Notes: First row: Change in the AIC value due to the inclusion of the variable. Second row: Estimated coefficient and z-value in parentheses. ***: statistically significant at the 1% level; **: statistically significant at the 5% level; *: statistically significant at the 10% level. Universities of applied sciences are not entitled to grant Ph.D. degrees.

types of innovative start-up as well as for all types of HEI. The better fit of models with the number of professors compared to models with the number of students and Ph.D. graduates seems contrary to the idea that students and Ph.D. graduates are the main channels through which knowledge is transformed into new innovative businesses. This result is interesting because—as mentioned earlier—due to the institutional framework in Germany, it is unlikely that professors will found an own business. Hence, it is not so much professors as founders themselves, but more their role as knowledge sources, researchers, and fundraisers that has such an impact on the emergence of innovative businesses.

Surprisingly, however, the amount of external funding obtained leads to the lowest decrease in the AIC value in most of the models, possibly indicating that the translation of knowledge into entrepreneurship via the education of students is quantitatively more important than via research.

7.4 Aggregation of Indicators for Regional Public Research

To aggregate the information provided by the indicators for HEIs we conducted factor analyses. These factor analyses showed that different types of HEI activity, such as education and research, could not be meaningfully separated into different factors. Hence, we generated only one factor to represent regional HEIs, which is based on the number of professors, the number of students, the number of graduates, the number of Ph.D. graduates, and the amount of external funding obtained (see Table A6 in the Appendix). In the baseline model, we include, for each scientific field, a factor for the activity of all HEIs within the region and a factor for HEI activity in adjacent regions. These factors are not logged because negative values would result in missing values of the logs.

The results of the baseline model with the aggregate indicators for public research are set out in Table 5. We find that aggregate indicators for applied sciences are highly significant with the expected sign in the models for start-ups in high-technology manufacturing, technologically advanced manufacturing, and technology-oriented services. For natural sciences, the aggregate indicators are significant with the expected sign for both types of manufacturing start-ups. Aggregate indicators for adjacent regions are not significant for any of the scientific fields. A main difference between these results and those of the baseline model without aggregate indicators for public research (Table 2) is that the number of regional private-sector R&D employees loses considerable statistical significance, thus raising questions as to the relationship between and relative importance of private and public R&D. Since the relationship between public and private R&D is complex and because of the considerable correlation between the indicators for the two types of

Table 5: Baseline model with aggregate indicators for higher education institutions

	High-technology manufacturing	*Technologically advanced manufacturing*	*Technology-oriented services*	*Non-innovative industries*
Number of employed persons, excluding R&D employees	.0228** (2.28)	.0290*** (3.64)	.0287*** (6.91)	.5522*** (19.09)
Number of R&D employees	8.16e-06*** (2.40)	1.82e-06 (0.64)	2.97e-06* (1.82)	2.85e-07 (0.36)
Number of unemployed	-.0215 (1.12)	-.0250* (1.67)	-.0159** (2.23)	.0041*** (2.64)
Share of employees in high-technology manufacturing industries	1057*** (7.43)	-	-	-
Share of employees in technologically advanced manufacturing industries	-	.0348*** (3.30)	-	-
Share of employees in technology-oriented service industries	-	-	.0287*** (4.99)	-
Share of employees in non-innovative industries	-	-	-	.0814*** (2.80)
Share of employees in establishments with fewer than 50 employees	.2993** (2.33)	-.1328 (1.62)	.1594*** (4.19)	.2559*** (9.83)
Number of R&D employees in adjacent regions	.0500** (2.28)	.0175 (1.03)	.0007 (..08)	-.0009 (0.35)
Number of patents per 1,000 employees	46.832*** (3.15)	-2.726 (.27)	10.586** (2.41)	-2.249 (.85)
Aggregate indicator for HEIs in:				
- Natural sciences	.0922 (.90)	.0862*** (1.10)	-.0524 (1.22)	.0102 (.55)
- Applied sciences	.2901*** (2.47)	.3072*** (3.47)	.1100** (2.18)	.0194 (.89)
- Medical science	.0369 (1.01)	.0542* (1.87)	.0169 (1.04)	-.0038 (.51)
- Administration and political sciences	-.0389 (.93)	.0079 (.23)	.0046 (.29)	.0131 (1.53)
- Other disciplines	-.0199 (.39)	.0168 (0.33)	-.0236 (1.07)	-.0075 (.65)
Aggregate indicator for HEIs (adjacent regions) in				
- Natural sciences	.1075 (1.00)	-.0366 (.44)	.0104 (.49)	-.0037 (1.31)
- Applied sciences	.0188 (.91)	.0164 (1.03)	-.0238 (1.16)	-.0001 (.02)
- Medicine	-.0750 (1.04)	.0026 (0.05)	-.0206*** (3.76)	-.0080*** (3.09)
- Administration and political sciences	-.0296 (.33)	.0607 (.89)	.0024 (.39)	.0120 (1.39)
- Other disciplines	.0662 (1.34)	.0438 (1.18)	-.0309 (1.13)	.0050 (.35)
Constant	.3367 * (1.86)	1.338*** (9.28)	2.604*** (25.31)	-1.756*** (5.77)
AIC change	-102.91	-96.82	-39.97	18.34

Notes: The dependent variable is the number of start-ups per year in the respective group of industries. Negative binomial panel regression with random effects. Z-values in parentheses. ***: statistically significant at the 1% level; **: statistically significant at the 5% level; *: statistically significant at the 10% level.

activity, it is problematic to conclude from these results that public R&D is more important for innovative start-ups than private-sector R&D. Presumably, the main source of this correlation is that there are pronounced spatially concentrated knowledge spillovers between public and private R&D (Fritsch and Slavtchev 2007). Such spatially bounded knowledge spillovers are one reason for the co-location of public- and private-sector R&D facilities. Moreover, both types of R&D prefer the same type of location, mainly larger cities. Hence, public institutions of education and research may provide important inputs for private-sector R&D, and R&D in both sectors may be interrelated, particularly at the regional level.

7.5 The Impact of Non-University Research Institutes

Since our information on non-university public research institutes is limited to the type and number of such institutes, we include in the baseline model the number of each type of institute in the region and in adjacent regions and compute the change in the AIC value (Table 6). We find that the number of non-university research institutes in natural and applied sciences together shows the highest decrease of the AIC value. This finding is valid for all types of innovative start-ups. If we consider each scientific field separately, the number of non-university institutes in applied sciences induces the highest decrease in the AIC value followed by the institutes working in the natural sciences.

When we add the number of institutes differentiated by scientific field simultaneously to the baseline model (Table 7), we find that the number of non-university research institutes in the region is highly significant with the expected sign and that this effect is stronger for the institutes working in applied sciences than it is for those working in natural sciences and other disciplines. Again, the number of regional private-sector R&D employees loses statistical significance compared to the baseline model (Table 2), probably for the reasons discussed above.

Table 6: Change in the AIC value compared to the baseline model due to the inclusion of the number of non-university research institutes altogether and according to discipline

	High-technology manufacturing	*Technologically advanced manufacturing*	*Technology-oriented services*	*Non-innovative industries*
Number of all non-university research institutes (ln)	-135.90 .2907 (4.16)***	-79.10 .2235 (3.26)***	-68.60 .1752 (2.75)***	96.34 .0003 (0.994)
Scientific fields				
- Natural sciences	-137.63 .4275 (4.23)***	-71.44 .0525 (5.18)***	-65.19 .0378 (4.89)***	430.90 -.0008 (0.993)
- Applied sciences	-156.24 .8488 (3.69)***	-91.30 .1775 (4.81)***	-83.71 .1565 (4.83)***	429.56 .0557 (0.244)
- Natural and applied sciences	-170.11 .9019 (5.21)***	-117.97 .3494 (6.17)***	-108.02 .3442 (6.95)***	431.88 -.0079 (0.939)
- Administration and political sciences	-62.33 .2100 (4.12)***	-53.20 .0127 (4.88)***	-17.92 .0056 (3.12)***	10.43 .0444 (0.173)
- Other disciplines	-2.09 .0744 (2.17)**	-13.10 .0075 (2.22)**	-9.55 .0116 (4.25)***	-0.75 -.0015 (0.951)

Notes: First row: Change in the AIC value due to the inclusion of the variable. Second row: Estimated coefficient and z-value in parentheses. ***: statistically significant at the 10% level; **: statistically significant at the 5% level; *: statistically significant at the 1% level.

Measures for the number on non-university research institutes in adjacent regions are not statistically significant with the expected signs for the majority of the models. Also of interest is that the number of non-university public research institutes has a considerably stronger effect than the aggregate indicators for the regional HEIs. The relatively high coefficients for the number of non-university public research institutions in the region may reflect, at least to some degree, the concentration of this type of public research in high-density areas, which are also where most of the innovative start-ups occur, and therefore could be an overestimation of their effect.

Table 7: Baseline model with number of non-university research institutes according to discipline

	High-technology manufacturing	*Technologically advanced manufacturing*	*Technology-oriented services*	*Non-innovative industries*
Number of employed persons, excluding R&D employees	.0351*** (3.66)	.0259*** (3.74)	.0310*** (8.08)	.5532*** (18.75)
Number of R&D employees	-1.73e-06 (.65)	-3.13e-06 (1.50)	-3.59e-07 (.28)	-9.82e-08 (.12)
Number of unemployed	-.0055 (.35)	-.0221*** (4.63)	-.0140*** (2.53)	.0052*** (3.72)
Share of employees in high-technology manufacturing industries	.0585*** (3.18)	-	-	-
Share of employees in technologically advanced manufacturing industries	-	.0342*** (3.54)	-	-
Share of employees in technology-oriented service industries	-	-	.0177*** (2.56)	-
Share of employees in non-innovative industries	-	-	-	.0775*** (2.57)
Share of employees in establishments with fewer than 50 employees	.5561*** (3.57)	-.2848*** (3.49)	.1817*** (4.86)	.1453*** (6.06)
Number of R&D employees in adjacent regions	.01808 (1.10)	.0131 (1.39)	-.0054 (.89)	-.0036 (1.34)
Number of patents per 1,000 employees	27.0327* (1.81)	21.343** (2.05)	11.782** (2.29)	-9.827*** (3.65)
Number of non-university research institutes in				
- Natural sciences	.5058*** (4.47)	.3083*** (2.93)	.2704*** (3.11)	-.1579 (1.34)
- Applied sciences	.6400*** (2.50)	.8732*** (3.71)	.7053*** (3.52)	.1390 (1.56)
- Administrative and political sciences	.0058* (1.86)	.0115*** (4.08)	.0285 (0.14)	-.0372 (.20)
- Other disciplines	.2061 (.48)	-.3625 (.97)	.4505 (1.44)	.0696 (.25)
Number of non-university research institutes in adjacent regions in				
- Natural sciences	-.0274 (.29)	.1043 (1.29)	.3295* (1.86)	-.0711 (1.32)
- Applied sciences	.0259 (.34)	.0428 (.74)	-.1064 (1.61)	.0392 (.94)
- Administration and political sciences	.1412 (1.54)	.1168 (1.41)	.1409 (1.38)	.3242*** (5.97)
- Other disciplines	.0358 (.46)	-.1060* (1.83)	.0497 (.75)	.0432 (1.04)
Constant	.2704 (1.21)	1.299 (8.11)	2.5736*** (22.77)	-1.829*** (5.82)
AIC change	-104.62	-153.81	-34.00	396:32

Notes: Z-values in parentheses. ***: statistically significant at the 1% level; **: statistically significant at the 5% level; *: statistically significant at the 10% level.

7.6 Extensions and Robustness Checks

We performed a number of robustness checks in order to test the stability of the results.[15] First, we ran the models with fixed effects. As expected, a fixed effects panel estimator does not provide meaningful results. In these models, many of the indicators for public research are not statistically significant, which is obviously due to low levels of variation over time. Second, we ran the regressions for only those regions that have at least one such institute (about 62 percent of all regions). Considerable differences from the estimates of the models for all regions could indicate that the coefficients for the number of institutes mainly reflect the presence of at least one such institute. We find, however, that the results are similar. Excluding regions with a relatively high number of HEIs and extra-university public research institutes, such as Berlin and Munich, did not produce any significantly different results. Third, the models were run separately for East and West Germany, and again there was not much difference in the results, indicating that the commercialization of knowledge through the formation of innovative new businesses follows the same pattern in both parts of the country.

Finally, in order to further analyze the influence of agglomeration effects, based on population density, we sorted the regions into three groups of equal size and ran the regressions separately for regions with relatively low, medium, and high levels of population density. We found that the coefficient for the aggregate effect of HEIs is highest in regions with low population density, somewhat lower in regions with medium density, and relatively low in high-density areas. These results suggest that HEIs may have a particularly pronounced effect in low-density regions and that their effect in high-density areas is somewhat obscured by other factors, making it difficult to identify their precise role with this type of analysis. We also find that the number of non-university public research institutes has a statistically significant effect only in regions with relatively high population density. One main reason for this result may be the high concentration of these institutions in agglomerations and their virtual

[15] The results are available from the authors upon request.

absence from rural areas. Another reason could be the relatively high correlation between the aggregate indicator for HEIs and the number of non-university research institutes.

8. Summary and Conclusions

Knowledge embodied in HEIs may have the potential to be commercially exploited in the form of innovative start-ups. However, this effect may vary based on the type of knowledge and the type of HEI. In this paper, we analyzed the impact of three properties of HEIs on the formation of new businesses in innovative industries. We first looked at the impact of five different types of scientific field: applied sciences, natural sciences, medical science, administration and political sciences, and “other” disciplines. Second, we analyzed the effect of five types of HEIs: regular universities, universities of applied sciences, medical schools, arts colleges, and universities of public administration. Third, we investigated the importance of two transmission channels for knowledge spillover: (1) the number of students, Ph.D. graduates, and professors as potential founders of innovative new businesses and (2) the extent of research activities and the knowledge stock as represented by the number of professors, the number of Ph.D. students and the amount of external funding obtained.

We found, first, that different scientific fields have different impact on innovative start-ups. The results suggest that the applied sciences (including medical science) are more influential for fostering innovative start-ups than are basic natural sciences. The effect of administration and political sciences is weak. No statistically significant effect could be found for other disciplines. Second, the type of HEI plays an important role, with regular universities and medical schools having the strongest effects, presumably due to their relatively high research intensity. Third, the number of professors as sources of knowledge exhibits the strongest statistical relationship with regional levels of innovative start-ups. Fourth, we find no indication of knowledge spillover from adjacent regions. This suggests that the process of transforming knowledge into innovative new businesses is highly localized. All in all, these results suggest that investing in institutions of education and research in applied sciences is an effective way of fostering innovative start-ups in a region.

However, despite these findings of a correlation between type of HEI and number of regional start-ups, we have not identified the underlying causal relationships. What is particularly unclear is how the knowledge embodied in HEIs is transferred into new business formation in the region. It is plausible that some of the regional new businesses are set up by graduates or employees of the local HEIs. However, some of the regional founders may have received their education outside the region and a number of students or employees of local HEIs may set up their firms elsewhere. Studies have shown that the vast majority of academic founders first work as dependent employees before starting their own firm (Mueller 2010; Stuetzer, Goethner and Cantner 2012).[16] A number of these individuals are spatially mobile during their career and so are at least partly motivated by the availability of attractive jobs (Chen and Rosenthal 2008; Dahl and Sorenson 2010). Since founders have a strong tendency to locate their businesses close to their place of residence (Figueiredo, Guimaraes and Woodward 2002; Stam 2007; Dahl and Sorenson 2009), the geographical labor market mobility of potential founders as well as the attractiveness of the region for entrepreneurially-minded people are important factors.[17] Hence, the knowledge of local HEIs is not only important as input for potential founders, but may also contribute to a positive development of regional incumbent firms that provide jobs for potential entrepreneurs from outside the region. Moreover, universities can have other “atmospheric” effects on the regional “climate” that may attract potential founders. Our results clearly confirm that the emergence of innovative new businesses is a regional phenomenon

[16] The average age of an innovative founder in Germany is 41 years (Metzger et al. 2010). Assuming that an average founder has finished his or her university education by age 25, this means that he or she has worked as a dependent employee for around 15 years before starting an own firm.

[17] The importance of spatial mobility is illustrated in a study by Roberts and Eesley (2011) that attempts to assess the employment effects of new businesses set up by alumni of the Massachusetts Institute of Technology. The study finds that less than one-third of the jobs created by these firms are located in Massachusetts and that a considerable number of jobs are in California and Texas.

(Feldman 2001; Sternberg 2009). However, the channels by which regional factors such as the presence of HEIs stimulate the founding of these innovative businesses is still not clear.

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Appendix

Table A1: Classification of scientific fields

Natural sciences	*Administration and political sciences*
Anthropology	Economics
Astronomy	Law
Biology	Management
Chemistry	Political science
Geosciences	Public administration
Informatics	Sociology
Mathematics	
Meteorology	
Mineralogy	
Oceanography	
Pharmacy	
Physics	
Applied sciences	*Others*
Architecture	Arts
Biotechnology	Cultural studies
Cybernetics	History
Engineering	Information science
Geodetics	Journalism
Machinery construction	Linguistics
Mechatronics	Pedagogics
Mining and metallurgy	Philosophy
Nuclear technology	Psychology
Optics	Sports
	Theology
Medical science	

Table A2: Descriptive statistics for the relevant variables in the baseline model

	Mean	*Minimum*	*Maximum*	*Standard deviation*
Number of start-ups in high-technology manufacturing industries[a]	3	0	58	4.820
Number of start-ups in technologically advanced manufacturing industries[a]	5	0	85	7.070
Number of start-ups in technology-intensive service industries[a]	50	0	1,386	95.300
Number of start-ups in non-innovative industries[a]	700	75	13,904	1,065
Number of start-ups in all private industries[a]	758	78	14,992	1,165
Number of employed persons, excluding R&D employees[b]	63,110	7,090	982,295	91,112
Number of unemployed persons[c]	12,652	1,323	310,661	18,839
Number of R&D employees[b]	2,331	60	62,469	5,315
Number of R&D employees in neighboring regions[b]	12,205	126	245,205	18,882
Share of employees in high-technology manufacturing industries[b]	0.010	0	.221	0.024
Share of employees in technologically advanced manufacturing industries[b]	0.037	0	.692	0.069
Share of employees in technology-oriented service industries[b]	0.035	0	.200	0.048
Share of employees in non-innovative industries[b]	0.915	0.245	1	0.120
Number of patents per 1,000 employees[d]	1.937	0.009	16.724	1.572
Share of employees in establishments with fewer than 50 employees[b]	0.51	0.13	0.77	0.09

Notes: a) Source: ZEW Foundation Panel; b) Source: Social Insurance Statistics; c) Source: Federal Employment Agency; d) Source: Patent statistics; e) Source: German University Statistics.

Table A3: Descriptive statistics for the relevant variables of HEIs

	Mean	*Minimum*	*Maximum*	*Standard deviation*
Natural sciences				
- Number of professors	1.320218	0	82	6.506272
- Number of students	1353.984	0	24401	2659.79
- Number of Ph.D. graduates	29.26937	0	817	71.68415
- Amount of external funds	3451.53	0	109987.8	8831.571
Applied sciences				
- Number of professors	.7736077	0	75	4.912762
- Number of students	1343.584	0	21466	2738.16
- Number of Ph.D. graduates	9.385896	0	404	33.61594
- Amount of external funds	2973.573	0	122169.7	10233.03
Medicine				
- Number of professors	.656746	0	40	3.83082
- Number of students	163.6647	0	7731	879.7673
- Number of Ph.D. graduates	12.60516	0	732	73.026
- Amount of external funds	19412.65	0	136175.9	19278.56
Administration and political sciences				
- Number of professors	.9651937	0	61	4.767339
- Number of students	2519.538	0	43420	4687.858
- Number of Ph.D. graduates	13.57173	0	460	33.69664
- Amount of external funds	716.3656	0	24561.71	1915.59
Regular universities				
- Number of professors	11.98232	0	275	35.77968
- Number of students	13408.23	0	113324	16084.97
- Number of Ph.D. graduates	231.1457	0	2306	330.0776
- Amount of external funds	22962.71	0	295084.1	33811.26
Universities of applied sciences				
- Number of professors	.4657738	0	48	2.853504
- Number of students	2475.597	0	34090	3374.908
- Number of Ph.D. graduates	.0018601	0	1	.043097
- Amount of external funds	787.3216	0	22586	1543.922
Arts colleges				
- Number of professors	4.641115	0	144	16.66046
- Number of students	740.7387	0	6144	896.122
- Number of Ph.D. graduates	.2648084	0	11	1.036632
- Amount of external funds	266.2809	0	3648	496.6135
Universities of public administration				
- Number of professors	.0098901	0	2	.1191785
- Number of students	526.8571	0	4824	652.2212
- Number of Ph.D. graduates	0	0	0	0
- Amount of external funds	32.19854	0	5295.849	329.7506

Table A4: Correlations between the variables in the baseline model

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Number of start-ups in high-technology industries	1.00												
2	Number of start-ups in technologically advanced industries	**.755**	1.00											
3	Number of start-ups in technology-intensive service industries	**.786**	**.834**	1.00										
4	Number of employed persons, excluding R&D employees	**.160**	**.174**	**.179**	1.00									
5	Number of R&D employees	**.645**	**.693**	**.807**	**.286**	1.00								
6	Number of unemployed persons	**.119**	**.053**	**.127**	**.392**	**.174**	1.00							
7	Share of employees in high-technology manufacturing industries	**.108**	-.013	*.032*	**-.295**	**-.055**	**.063**	1.00						
8	Share of employees in technologically advanced manufacturing industries	**.088**	*-.034*	.009	**-.292**	**-.065**	**.053**	**.917**	1.00					
9	Share of employees in technology-oriented service industries	**.096**	-.025	*.030*	**-.308**	**-.065**	**.069**	**.947**	**.908**	1.00				
10	Share of employees in establishment with fewer than 50 employees	**-.088**	**-.182**	**-.106**	**.180**	**-.094**	**.625**	**.266**	**.245**	**.287**	1.00			
11	Number of R&D employees in neighboring regions	**.112**	**.111**	**.133**	**.595**	**.257**	**.672**	**-.184**	**-.187**	**-.204**	**.358**	1.00		
12	Number of patents per 1,000 employees	**.160**	**.084**	**.109**	**.274**	**.133**	**.163**	**.190**	**.193**	**.175**	**.209**	**.149**	1.00	
13	Aggregate indicator of HEIs in the region	**.413**	**.421**	**.448**	**.305**	**.465**	**.303**	**-.039**	**-.073**	*-.033*	**-.042**	**.323**	*.033*	1.00
14	Number of non-university public research institutes in the region	**.594**	**.596**	**.744**	**.073**	**.596**	**.097**	.022	-.023	*.036*	**-.109**	**.071**	.011	**.488**

Notes: Coefficients statistically significant at the 1% level in bold and significant at the 5% level in italic.

Table A5: Correlations between different indicators for universities and other pubic research institutes in the region

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 prof	1.00																						
2 stud	**.9543**	1.00																					
3 Ph.D.	**.8794**	**.8496**	1.00																				
4 exfund	**.8704**	**.8330**	**.8878**	1.00																			
5 prof_ns	**.9618**	**.9217**	**.8750**	**.8728**	1.00																		
6 stud_ns	**.9084**	**.9615**	**.8412**	**.8476**	**.9401**	1.00																	
7 Ph.D._ns	**.8775**	**.8615**	**.9590**	**.8774**	**.9108**	**.8939**	1.00																
8 exfund_ns	**.7996**	**.7890**	**.8043**	**.9221**	**.8592**	**.8332**	**.8695**	1.00															
9 prof_as	**.8396**	**.7815**	**.6290**	**.7427**	**.8173**	**.7724**	**.7066**	**.6702**	1.00														
10 stud_as	**.8008**	**.7944**	**.5970**	**.7591**	**.7988**	**.7955**	**.6952**	**.6604**	**.9380**	1.00													
11 Ph.D._as	**.1187**	**.1095**	**.3917**	**.1177**	**.1336**	**.1391**	**.1611**	**.1239**	**.3067**	**.2075**	1.00												
12 exfund_as	**.4936**	**.4688**	**.3526**	**.6768**	**.5319**	**.5286**	**.4936**	**.5542**	**.6847**	**.7804**	**.2356**	1.00											
13 prof_ap	**.9353**	**.9172**	**.7756**	**.7603**	**.8931**	**.8755**	**.8144**	**.7410**	**.7979**	**.7603**	**.1026**	**.4443**	1.00										
14 stud_ap	**.8781**	**.9616**	**.7277**	**.7147**	**.8616**	**.9255**	**.8020**	**.7327**	**.7445**	**.7430**	**.1029**	**.4169**	**.9203**	1.00									
15 Ph.D._ap	**.8497**	**.8684**	**.8450**	**.7480**	**.8547**	**.8531**	**.8795**	**.7855**	**.6248**	**.5917**	**.1097**	**.3082**	**.8544**	**.8550**	1.00								
16 exfund_ap	**.7148**	**.7133**	**.6380**	**.8146**	**.7100**	**.7228**	**.7105**	**.8138**	**.6634**	**.6364**	**.2143**	**.5426**	**.7393**	**.7023**	**.6877**	1.00							
17 prof_u	**.9539**	**.9022**	**.8874**	**.8033**	**.8750**	**.7700**	**.8029**	**.6966**	**.8154**	**.7272**	**.2865**	**.2667**	**.8259**	**.7328**	**.7919**	**.5885**	1.00						
18 stud_u	**.8670**	**.9665**	**.8372**	**.7615**	**.7860**	**.8766**	**.7493**	**.6367**	**.6974**	**.7289**	**.3665**	**.2619**	**.7789**	**.8547**	**.7384**	**.5814**	**.8946**	1.00					
19 Ph.D._u	**.8394**	**.8145**	**.9495**	**.9324**	**.7432**	**.7094**	**.8622**	**.7366**	**.7157**	**.7376**	**.5455**	**.4316**	**.7050**	**.5903**	**.7206**	**.6574**	**.8589**	**.8330**	1.00				
20 exfund_u	**.6391**	**.5999**	**.7393**	**.9192**	**.4885**	**.4909**	**.6022**	**.5701**	**.5611**	**.6162**	**.5594**	**.5124**	**.4723**	**.3377**	**.4247**	**.5719**	**.6531**	**.6414**	**.8472**	1.00			
21 prof_fh	**.8719**	**.8247**	**.6622**	**.7013**	**.7639**	**.7301**	**.6474**	**.5996**	**.8262**	**.7604**	**.1735**	**.4499**	**.8387**	**.7457**	**.6569**	**.6205**	**.7174**	**.7303**	**.6548**	**.6776**	1.00		
22 stud_fh	**.8504**	**.8565**	**.6449**	**.6984**	**.7287**	**.7395**	**.6289**	**.5753**	**.7483**	**.7344**	**.1367**	**.4304**	**.8215**	**.7773**	**.6697**	**.5974**	**.6970**	**.7630**	**.6479**	**.6670**	**.9505**	1.00	
23 Ph.D._fh	**.0908**	**.0686**	*.0797*	**.1542**	**.0854**	**.0665**	**.1008**	**.1625**	**.1179**	**.0851**	.0174	**.0745**	**.0801**	**.0618**	**.0679**	**.0938**	**.1362**	**.0911**	**.1393**	**.1622**	**.0851**	**.0622**	1.00
24 exfund_fh	**.5426**	**.5555**	**.4460**	**.5632**	**.4447**	**.4878**	**.4113**	**.4105**	**.4564**	**.4617**	**.1241**	**.3491**	**.4752**	**.4600**	**.4310**	**.4635**	**.3743**	**.4514**	**.4216**	**.5685**	**.6110**	**.6256**	**.0671**

Notes: Coefficients statistically significant at the 1% level in bold and significant at the 5% level in italic. Prof) number of professor; stud) number of students; Ph.D.) number of Ph.D. graduates; exfund) amount of external funds; ns) natural sciences; as) applied sciences; ss) administration and political sciences; u) regular universities; fh) universities of applied sciences.

Table A6: Factor representing regional HEIs according to the scientific field—factor loadings and unique variances after varimax rotation

Variable	*Natural sciences*		*Applied sciences*		*Social sciences*		*Others*	
	Factor loading	*Unique-ness*	*Factor loading*	*Unique-ness*	*Factor loading*	*Unique-ness*	*Factor loading*	*Unique-ness*
	Same region							
Number of professors	.9272	.1403	.8547	.2695	.8418	.2913	.8482	.2806
Number of students	.8884	.2107	.9553	.0873	.9328	.1299	.9381	.1200
Number of graduates	.9276	.1395	.9636	.0715	.9479	.1014	.9557	.0866
Number of Ph.D. students	.8777	.2297	.6226	.6124	.7906	.3749	.8281	.3143
Amount of external funds (1,000 €)	.7868	.3809	.8108	.3425	.8356	.3018	.9076	.1763
Variance	3.8989		3.6169		3.8006		4.0222	
Cronbach's alpha	.9339		.9014		.9122		.9268	
	Adjacent regions							
Number of professors	.9957	.0086	.9982	.0037	.9942	.0115	.9754	.0487
Number of students	.9933	.0133	.9910	.0180	.9985	.0030	.9786	.0424
Number of graduates	.9924	.0152	.9908	.0183	.9984	.0033	.9627	.0733
Number of Ph.D. students	.9823	.0351	.8085	.3464	.9984	.0033	.8000	.3601
Amount of external funds (1,000 €)	.6896	.5245	.7010	.5086	.6833	.5332	.8487	.2796
Variance	4.4034		4.1050		4.4458		4.1959	
Cronbach's alpha	.9256		.9160		.9234		.9459	

Note: All variables are logged.