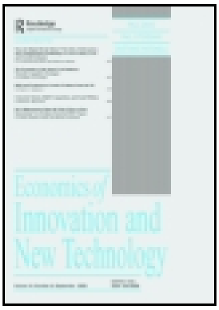

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Research grants, sources of ideas and the effects on academic research

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Based on a sample of research units in science and engineering at German universities, this study reports survey evidence on the relationship between research grants and research content. Research units that receive funds from industry are more likely to source ideas from the private sector. The higher the share of industry funding in a unit's total budget, the more likely it is that large firms influence the research agenda. Public research grants, on the other hand, are associated with a higher importance of conferences and scientific sources. What is more, the different sources of ideas impact scientific output. Research units that source research ideas from small- and medium-sized firms patent more, but are not more successful than others in terms of the impact of their inventions on future patents. If, on the other hand, research units source ideas from large firms, we find them to publish less and with lower impact on future scientific work.

Keywords: university research; scientific productivity; research funding; academic patents; technology transfer

JEL Classification: C23; I23; O31; O34; O38

1. Introduction

Since the early 1980s, there has been an academic and policy debate about the role and the consequences of university–industry interactions. The interest in these issues has triggered a substantial body of conceptual and empirical studies. This previous work identified and studied numerous forms of interactions that occur between academia and industry. Most of these studies take the perspective of the firm and point out channels through which the private sector sources know-how from science and benefits from it (Nelson 1986; Mansfield 1995, 1998; Narin, Hamilton, and Olivastro 1997; Jaffe 1989; Hall, Link, and Scott 2000; Salter and Martin 2001; Agrawal and Henderson 2002). The common underlying idea in this stream of research is that university research creates and expands the pool of ideas from which private sector firms draw when searching for solutions and new technological challenges (Sorenson and Fleming 2004).

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Few studies, however, have taken the perspective that academic researchers may actively source ideas from industry which shape their research agendas. Continuous and even occasional close interactions, for instance, in the form of joint research, contract research and consulting, likely have a lasting impact on both parties involved. Recent empirical studies argued for a direct relationship between research grants and research outcome (Blumenthal et al. 1997; Geuna 1997; Manjarrés-Henríquez et al. 2009; Banal-Estanol, Jofre-Bonet, and Meissner 2010; Hottenrott and Thorwarth 2011; Lawson 2012). Some of this previous research suggested that the share of industry funding negatively affects publication output in subsequent periods. However, whether this observation was due to time constraints of the researchers involved in industry-funded projects, non-disclosure clauses, or due to the project's impact on research content that lead to research agendas of less scientific relevance, remained unexplored.

The current study aims to fill this gap in the literature using data from university research units in Germany to study the relationship between research funding, sources of ideas and research performance. The acquisition of new ideas for research has been identified as one of the main motives for joint research (Lee 2000) and such ideas sourced from industry may expand the researcher's traditional research agenda (Rosenberg 1998), benefitting their overall scientific performance. However, it has also been argued that these ideas may be more applied in nature, resulting in less fundamental research (Cohen et al. 1998). In the following analysis, we investigate if and how research funding, in particular 'external research income', relates to the channels through which university researchers source ideas. In doing so, we distinguish between traditional scientific sources, institutional (university) sources and business sources. Furthermore, we study the influence that these different sources of ideas have on research performance in terms of publications in scientific journals and patents. That is, we investigate whether research funding is indeed associated with sources of ideas that could affect research agendas and hence research output. Thereby, our analysis aims in particular to identify whether 'idea sourcing' from industry indeed affects scientific research outcomes.

Results from the estimation of simultaneous equation models support this hypothesis. First, we find that the higher the share of a research unit's funding from industry, the higher the likelihood that the unit sources ideas from industry partners, especially from large firms. Second, taking into account unobserved heterogeneity in the researchers' *ex ante* capabilities, we estimate count data Poisson models that show that different idea sources affect *ex post* research performance. In particular, research units sourcing ideas from large firms show lower publication rates and receive fewer citations per publication in the seven years following the survey. We do not find such a negative effect on publications for researchers sourcing ideas from small- and medium-sized firms (SMEs). On the contrary, we even observe a positive effect on the number of patents on which the professor was listed as inventor where ideas are sourced from SMEs while ideas from large firms result in fewer patents. Grants from public institutions, however, are associated with the utilization of traditional scientific sources and institutional sources of ideas. Traditional scientific sources are positively related to publications in subsequent years. These insights extend previous work on the relationship between research funding and research performance by suggesting that output effects may be mediated by the sources of ideas scientists consult.

The following section summarizes relevant thoughts from the literature and presents our hypotheses regarding the role of research grants in stimulating research ideas and on how sources of ideas may impact research performance. Section 3 describes the data and Section 4 sets out the econometric framework and presents the results. Section 5 concludes.

2. Research grants, sources of ideas and research output

While there is some evidence on the role of different sources of ideas for the productivity of industrial research and development (R&D) (Allen 1965; Klevorick et al. 1995; Salter and Gann 2003), for university researchers, the most relevant sources of inspiration have been assumed to be found in their scientific environment. Factors such as peers and scientific publications provide inspiration for scientific research and may affect a researcher's future research efforts. Researchers that source ideas from their peers and scientific sources are better connected to the state-of-the-art and could be expected to be more productive. Therefore, public grants that are usually awarded to the most able researchers could be associated with ideas sourced from peers and scientific sources. Indeed previous research has found public grants to positively affect research productivity (Carayol and Matt 2006; Hottenrott and Thorwarth 2011; Jacob and Lefgren 2011).

Yet, in light of a changing university landscape and an increasingly blurred border between industrial research and applied university research (Mowery 1998; Auranen and Nieminen 2010), it seems obvious to assume that university research is influenced by a whole range of idea providers, also arising outside the university and scientific community.

This paper looks at ideas sourced from industry through various channels including contract research, consulting as well as joint or collaborative research. Previous research mostly takes the perspective of the firms involved in such university–industry interactions. Survey-based evidence by Cohen, Nelson, and Walsh (2002), for instance, shows that aside from published research articles and reports, key channels through which university research impacts firm R&D include conferences and meetings, formal and informal collaborations, contract research and consulting. Additionally, previous research found that private sector firms that source ideas from academia derive large benefits for their technological innovations, for instance, by utilizing specialized knowledge and equipment (Nelson 1986; Jaffe 1989; Mansfield 1995, 1998; Narin, Hamilton, and Olivastro 1997; Hall, Link, and Scott 2000; Salter and Martin 2001). It is, therefore, not surprising that firms increasingly seek direct contact with university researchers. Sponsoring research may constitute such a direct means of gaining access to scientific knowledge. Furthermore, research funding may lead to continuous industry–science relations by making researchers more willing to collaborate and hence increase transfer of technological knowledge from science to industry which fosters and accelerates industrial innovations (Bogler 1994). The increasing share of research grants stemming from the private sector in many OECD countries provides support for this reasoning (see OECD 2009 for details).

From the scientists' perspective, industry grants also provide an attractive source of funds supplementing 'core funding' and other public research funding. As well as monetary benefits, industry can also provide ideas for further research. Earlier survey studies that asked researchers about their motivations to work with industries or the benefits of working with industries, such as Lee (2000), stress that acquiring ideas for research is one of the main motives for joint research (see also Slaughter and Rhoades 2004). Likewise Mansfield (1995) concludes from his survey that a substantial number of research projects at universities were initiated through consulting activities with firms. He shows that publicly-sponsored research projects are also often influenced by problems from industry encountered in consulting.

Much existing research has, however, focused on the negative aspect of industry involvement, arguing that funding influences the behavior of researchers in terms of selection of research topics, methodology and finally research orientation, skewing research towards a more applied approach (Slaughter and Leslie 1997; Cohen et al. 1998; Benner and Sandström 2000). Gulbrandsen and Smeby (2005) observe that university researchers in Norway who attracted industry funding are more likely to describe their research as 'applied' compared to researchers without industry funding. Blumenthal et al. (1997) and Glenna et al. (2011) find similar results for biotechnology scientists in the USA. All these papers regard a change in research orientation as a threat to basic scientific research. They implicitly assume that contact with industry gives rise to a change in research orientation, resulting in a decrease in scientific output and an increase in commercial output. Other research mostly assessed quantitatively whether research outcome is directly affected by research sponsorship (Blumenthal et al. 1997; Manjarrés-Henríquez et al. 2009; Banal-Estanol, Jofre-Bonet, and Meissner 2010; Hottenrott and Thorwarth 2011; Lawson 2012) and the results suggest that industry funding may negatively affect scientific performance in terms of publications, but may also inspire patent productivity.[1] However, these previous analyses did not shed light on the underlying mechanisms driving these results. Although sometimes implicitly assumed, no previous study explicitly investigates whether funding affects research agendas by providing research ideas and if the sources that inspire university research may explain the observed phenomena. Ideas from industry sources could be more applied in nature and of lower relevance for scientific discourse than ideas coming from academic peers who are usually involved in the distribution of publicly funded research grants.

2.1. Research grants and idea sourcing

So far no empirical study has analyzed whether industry funds (or public grants) have a direct impact on idea sourcing. A sponsor may become a 'source of ideas' through various mechanisms. Funding relationships may either come in exchange for taking on ideas from the sponsor, usually for a joint project, or ideas simply spill over during a funded research project or consulting work. Such ideas may influence future research either with, but also without the explicit intention of doing so.

Independently of the design of the negotiated agreement, sponsoring relationships generally involve mutual personal contacts between university researchers and the sponsoring firm which facilitate the exchange of ideas. It can thus be expected that researchers receiving a higher share of their budget from industry are also more likely to acquire ideas for research from industry. Public grants, on the other hand, are expected to focus on advancing public knowledge, but usually do not involve personal contacts with the sponsoring agency. We would, therefore, expect a stronger correlation between public grants and traditional scientific sources of ideas.

The effect of industry funding on sources of ideas may, however, differ by the type of company involved. For example, Cohen, Nelson, and Walsh (2002) find that the effect of public research on firm R&D is disproportionately greater for larger firms compared to medium-sized firms. In a similar respect, we hypothesize that larger firms may have a stronger influence on the ideas of partnering university researchers. First, this may simply be explained by the larger amount of funding that is provided by larger firms. Azagra-Caro (2007), for instance, shows that researchers who collaborate with firms mainly do so with large firms. Lee (2000) finds that benefits of industry sponsored projects in terms of funding for graduate students and lab equipment are larger if they involve large firms, as they offer more research support benefits than SMEs. Consequently, one can also argue that larger financial benefits result in a larger influence on the research conducted at the funded research unit. Secondly, large firms may have more capacity to engage their own researchers in joint research projects as well as in the supervision of contract research and in the exchange of results, which may contribute to ideas spilling over to university researchers.

2.2. Idea sourcing and scientific publications

For ideas stemming from a researcher's intuitional environment, scientific gatherings and conferences as well as from wider scientific sources, including books and journals, one would expect a positive effect on the researchers own publication success. Being inspired by the current state-of-the-art and involvement in personal exchanges with peers may contribute to scientific output both in terms of quantity as well as quality.

However, a critical question remains whether the impact of ideas sourced from industry is positive or negative. As already mentioned above, previous literature does not univocally suggest a certain direction. One stream of literature suggests that the impact may be negative if traditional scientific sources of ideas are fully or only partially substituted with ideas from industry, resulting in research agendas further away from basic scientific interests (Cohen et al. 1998). In other words, ideas sourced from industry may shift research agendas from topics of scientific interest to a selection of research projects on the basis of their perceived value in the private sector and not solely on the basis of scientific progress. As argued by Trajtenberg, Henderson, and Jaffe (1997) industry R&D is directed at commercial success, while university research focuses on solving fundamental scientific questions. Thus, research that addresses market demands may not necessarily be close to the academic research frontier which may manifest itself in fewer citations per publication.

This argument assumes that – at least to some degree – sourcing ideas from industry induces a 'skewing problem' which diverts university research in directions of lower academic value, particularly at the cost of more basic research. If such a skewing problem exists, an increased influence of industry on research agendas may have negative effects on whether research is published in scientific journals and, hence, potential long-term consequences for future development of science. Further, long-run effects from industry-inspired research projects may arise if the impact on the research agenda is permanent and not a temporary phenomenon. These concerns rest, however, on the presumption that there is indeed a trade-off between research that is being disclosed in publications and more applied work that is of interest for industry (Rosenberg and Nelson 1994).

This assumption has been challenged, however, as it can be argued that research may be positively influenced by the sourcing of new ideas from industry that expand traditional research agendas (Rosenberg 1998). Some theoretical articles argue that industry can provide ideas for basic research in the sense that applied problems nurture ideas for basic research (Thursby, Thursby, and Gupta-Mukherjee 2007; Banal-Estanol and Macho-Stadler 2010). This is in line with the notion of the 'Pasteur's quadrant' where problems encountered in applied research can also benefit basic research efforts (Stokes 1997). Likewise Siegel, Waldman, and Link (2003) state that '[s]ome scientists explicitly mentioned that these interactions improved the quantity and quality of their basic research'. Thus, industry as a source of ideas may also provide a new and fresh perspective and thus improve academic research performance resulting in more and better publications.

2.3. Idea sourcing and academic patenting

The focus of our discussion has so far been on publication outcomes but in disciplines like science and engineering, research outcomes may not only be measured in terms of scientific publications. Academic patenting has been increasing in recent decades (Henderson, Jaffe, and Trajtenberg 1998; Mowery and Ziedonis 2002; Geuna and Nesta 2006; Verspagen 2006), not least due to the fact that universities have actively encouraged patenting and – like publications in scientific journals – patent applications disclose scientific knowledge and thus contribute to technological advancement. University researchers may, therefore, engage in patenting and publishing or focus on either activity depending on their position in the academic life-cycle (Carayol 2007; Stephan et al. 2007). Previous research has largely assumed that patenting itself is an indicator of applied research and several papers have looked at the effect of patenting on basic research efforts or vice versa. Researchers that draw the majority of their research ideas from their scientific environment may be considered those pursuing more basic research. Thursby and Thursby (2002) discuss that academics interested in pursuing basic research may ascribe little importance to patenting activity even if they realize the commercial potential of their work and thus patent less. On the other hand, as already discussed above, basic and applied research can be considered complementary and ideas gained through basic research may also result in patents (Murray 2002; Thursby, Thursby, and Gupta-Mukherjee 2007). Thursby and Thursby (2011) examine the different hypotheses regarding patenting and academics' research profiles and find that patenting and basic research activity are positively correlated. Indeed several papers confirm that researchers with an excellent publication record are also most likely to patent and commercialize their research (Zucker, Darby, and Brewer 1998; Azoulay, Ding, and Stuart 2007; Murray and Stern 2007; Stephan et al. 2007). Czarnitzki, Glänzel, and Hussinger (2009) qualify these findings in the German context and find a positive correlation only for university-owned patents, while patents owned by industry are negatively correlated with publication and citation numbers.

With regard to ideas sourced from industry, as, for instance, reported in Lee (2000), joint patenting also represents an important motivation for industry–science relationships. Contact with pro-commercialization partners may moreover positively affect a researcher's attitude towards patenting as well as her ability to recognize commercial opportunities (Owen-Smith and Powell 2001; Stuart and Ding 2006). Ideas from industry may thus result in industry-inspired research that is more applied and of higher relevance for industry and thus be more likely to produce patentable inventions.

2.4. *Idea sourcing and firm size*

Existing work does not clarify the direction of the idea-sourcing effect on scientific output, suggesting it depends on the characteristics of the source. In particular, differences may exist between ideas coming from large firms and ideas coming from small firms. Previous research found that larger firms and start-ups have a higher probability of benefiting from academic research (Cohen, Nelson, and Walsh 2002; Mohnen and Hoareau 2003; Arundel and Geuna 2004). SME firms may be more likely than larger firms to substitute internal R&D with university research, especially in highly specialized technologies. This implies that smaller firms may benefit relatively more from rather basic research that complements their own application-oriented R&D. This may be particular relevant for firms whose R&D employees lack specific skills or resources to conduct basic research in-house or smaller firms that want to reduce the risk and costs related to it. Moreover, a qualitative study by Bjerregaard (2009) on university–industry collaborations of nine Danish universities and 19 SMEs suggests that collaboration strategies of SMEs differ from those of large firms in terms of the time-horizon of expected results. In particular, he finds that while some collaborations followed a short-term strategy aimed at achieving immediate R&D results, SME partners relied upon a long-term strategy. These long-term strategies by SMEs that do not push for immediate marketable results may, therefore, induce ideas with little or no skewing of the overall research output, as they may be more in line with the ex ante research orientation of the researcher. Finally, the contractual design of the collaboration may differ between large firms and SMEs, translating into different effects of joint research on academics' research output. Rappert, Webster, and Charles (1999) report that interactions between universities and SMEs usually tend to be informal. Large firms, on the contrary, are more likely to use institutional collaborations. Similarly, recent research by Bodas Freitas, Geuna, and Rossi (2013) stresses that firms that use personal contacts as opposed to institutional collaborations are generally smaller. These different forms of engagement may result in different effects on publication output with collaborations with SMEs being more favorable towards scientific research.

Perkmann, King, and Pavelin (2011) find support for this idea showing that departments with more excellent researchers in terms of research quality in physical and engineering sciences receive more income from SMEs, indicating that excellence and collaboration with SMEs is positively correlated. Also Lawson (2013), looking at the effect of funding coming from large firms and SMEs on patenting and patent ownership in the UK, finds that researchers receiving funding from SMEs are more likely to file patents with their university. This may indicate a positive relationship between SMEs as sources of ideas and research productivity in terms of both publications and patents.

3. Data

The empirical analysis of this paper is based on a unique data set that was assembled using different data sources. The core data were collected through a survey of research units at German higher education institutions in the fields of science and engineering.[2] The Centre for European Economic Research (ZEW, Mannheim) conducted the survey in 2000 at 3507 research units and the sampling method involved stratification by regions. The original sample included public research institutions[3] as well as universities, technical universities (TUs) and universities of applied sciences (UAS) (*Fachhochschulen*). For the purpose of this study, we exclude respondents from public research institutions and focus on faculties at institutes of higher education, i.e. institutions that are also involved in teaching activities.[4] The questionnaire was addressed to the heads of the research units, who are usually full professors with budget and personnel responsibility.[5] The overall response rate to the survey was 24.4%. These survey data have been complemented with publication and patent information of the head of the research unit covering a period before (1994–1999) and after the survey (2000–2007). Publications and patents were carefully and manually matched to the surveyed professors. To assure that publications and patents were correctly assigned, we collected information on each person's career path through their faculty websites and information provided by the German National Library. After the elimination of incomplete records, the final sample used for our analysis contains 663 professor-research unit observations from 46 different higher education institutions of which 57% are Universities (Uni), 24% are TUs and 19% are UAS.[6]

3.1. Sources of ideas

To measure the importance of different 'sources of ideas', the questionnaire asked about the relevance of a set of sources for shaping the units' research agenda in the three years preceding the survey. Respondents ranked their answer from 'no relevance' to 'high relevance' on a four-point Likert-scale. The majority of professors use several sources, yet we want to concentrate on the most relevant sources. In order to obtain a binary indicator of whether a particular source had been a strong stimulus for research at the research unit, we recode these variables such that a dummy takes the value 1 only if the source was ranked

Table 1. 'Source of ideas' stimulating research agendas.

Source type	Not relevant	Little relevant	Relevant	Highly relevant
Small- or medium-sized firms (less than 250 empl.)	27.90	21.72	28.21	22.17
Large firms (250 empl. or more)	22.02	17.35	31.22	29.41
Universities	12.22	12.07	29.11	46.61
Public research centers	24.43	19.61	29.11	26.85
Technology transfer offices (TTOs)	50.53	31.67	13.73	4.07
Consultants	80.84	15.08	3.47	0.60
Exhibitions and fairs	42.38	33.79	17.04	6.79
Patents	57.62	24.28	14.48	3.62
Academic journals	13.73	9.35	24.74	52.19
Conferences, meetings	9.35	7.54	24.43	58.67
Internet, media, other data bases	17.95	16.14	32.58	33.33

Notes: In percent based on 663 observations. Category 'others' not displayed in the table. If professors specified 'others', we assigned these answers to one of the categories. If that was not possible, the observation was dropped from the sample.

to be of 'high relevance'. Table 1 shows descriptive statistics for these variables. The least relevant sources for research are consultants and patents. The most important sources are conferences, academic journals and the university environment.

We conducted a factor analysis, using the maximum-likelihood factor method, to group the 11 sources into a number of (unobserved) aggregate factors. The analysis suggested three groups that can be labeled 'Scientific Sources', 'Institutional Sources', and 'Industry Sources' (see Table A1 for details on the factor loadings). Scientific sources include academic journals, conferences and meetings, as well as internet, media and public databases. The second category comprises universities and public research centers as sources of research ideas. The third group includes large firms, SMEs, TTOs, exhibitions, and trade fairs. 'Consultants' and 'patents' as sources of ideas did not load highly on any of the factors, especially in the factor analysis of the binary indicator. For the purpose of our analysis, we, therefore, decided to consider them as separate categories.

Taking into account that multiple answers were possible, we find that 67.6% and 52.8% of professors named scientific sources and institutional sources as being of high relevance, respectively. 42.1% regarded industry sources of high importance for shaping their research agenda (Table 2). Approx. 85% of professors indicated at least one source as particularly important and about 54% named more than two sources. Of these, 43% considered scientific and institutional, but not industry as important whereas it was the opposite for only 9%. About one-third of professors in the sample considered both traditional scientific and institutional sources as well as industry as highly relevant.

3.2. Research funding

The survey further provides information on the amount and composition of funding in 1999, including 'third-party funding' received in addition to the research units' core funding. In the final sample, 63% of professors stated that they had received funding from industry and 81% had acquired public research grants in addition to their core funding. The amount of industry funding (INDFUND) and its share over the total budget (INDSHARE) at the level of the research unit differ between institution types and research fields (Table A2). On average, this share was 8.7% amounting to approx. 113,000 Euros. The share of research

Table 2. Summary statistics (663 obs.).

Variable		Mean	Std. Dev.	Min	Max
Aggregate sources of ideas (binary)					
Scientific sources	SCIENCE	0.676	0.468	0	1
Industry sources	INDUSTRY	0.421	0.494	0	1
Institutional sources	INSTITUTIONS	0.528	0.500	0	1
Funding:					
Amount ind. funding (T €)	INDFUND	113.48	273.743	0	2539.556
Share of ind. funding in % of total budget	INDSHARE	8.715	13.440	0	100
Amount gov. grants (T €)	GOVFUND	158.064	439.851	0	7008.703
Share of gov. grants in % of total budget	GOVSHARE	22.584	20.042	0	100
Controls:					
Institution size (total # students)	STUDENTS	18,219.70	11,819.43	1451	59,599
Number of people in lab (full time equivalent)	LABSIZE	22.234	31.12	1.2	300
Number of years since PhD	EXPERIENCE	21.872	8.68	1	43
Contact to TTO dummy	TTO	0.738	0.440	0	1
% Technical employees	TECHS	10.203	13.773	0	80
% Employees PhD	SENIORSTAFF	72.259	16.988	3.333	100
University	UNI	0.573	0.495	0	1
Technical university	TU	0.237	0.425	0	1
University of applied sciences	UAS	0.190	0.393	0	1
Female professor dummy	FEMALE	0.032	0.175	0	1

Note: Six scientific field dummies not presented (Table A2).

grants received from public sources (GOVSHARE) is comparable between universities and TUs, but is considerably lower at UAS.[7] On average, research units received 22.6% of their total budget from public research grants, which corresponds to 159,000 Euros.

3.3. *Professor, research unit and university characteristics*

We include a control for institution size in our analysis in order to capture effects of better networking opportunities and scale effects in research that may affect both sources of ideas as well as research productivity. Size is measured in number of students and the average university (or TU or UAS) had 18,220 registered students (STUDENTS) in the survey year.

Additionally, we control for research unit size by counting the number of staff per research unit (LABSIZE), which is 22 on average (median 13). The share of team members with a non-scientific but technical background (TECHS) is 10.2% on average. A higher share of non-academic personnel may increase scientific productivity by reducing professors' administrative burden and by providing research assistance in carrying out routinized experiments.

We further consider the share of senior scientists, which includes researchers with at least a PhD degree (SENIORSTAFF) and is expected to reflect scientific capability and research capacity of the research unit.

Although professors are rather homogenous in their career position as they are all head of a research unit, we still want to control for some life cycle effects (Carayol 2007; Stephan et al. 2007; Thursby, Thursby, and Gupta-Mukherjee 2007). Information on the year in which professors received their PhDs was gathered from the German National Library.[8] The average number of years in academe (EXPERIENCE), i.e. years since completion of PhD, is 22 years (also median of 22). The number of female professors is small with only 21 of the 633 professors in our sample. However, we still want to control for gender differences as recent research found men and women to differ in their collaborator choice strategies (Bozeman and Gaughan 2011), which may also affect idea sourcing.

We further know from the survey whether a professor had contact with his institution's TTO. As it is conceivable that such contacts may impact both stronger technology transfer awareness and reduce the administrative burden of managing industry contacts and other external relations, it may also have effects on patenting and publishing activities. Table 2 provides summary statistics for the main variables of interest.

3.4. Patent and publication data

We supplemented the survey data with information on the patent and publication output of the head of the research unit. Patent and publication records of the responding professor are assumed to proxy the research output of his research unit.[9] Patent information was drawn from the database of the German Patent and Trademark Office (DPMA) in December 2009. We searched for all patents, which listed professors in our sample as inventors and performed extensive manual checks. We further retrieved 'forward citations' to these patents, that is, the number of citations received by each patent after filing. Forward citations have been shown to be a suitable measure for quality, importance or significance of a patented invention and have been used in several previous studies (Henderson, Jaffe, and Trajtenberg 1998; Hall, Jaffe, and Trajtenberg 2001; Czarnitzki, Hussinger, and Schneider 2009).

The publication records of professors were collected via the ISI Web of Science® database of Thomson-Scientific (Philadelphia, PA) in December 2009. The database covers all publication types within a comprehensive collection of academic journals. We searched for publications (articles, notes, reviews and letters) of professors in our sample through the *ISI Web of Knowledge*® platform by name. Subsequently, we manually filtered the results on the basis of affiliations, addresses and research fields. In order to assign publications correctly to professors, we further collected information on their career paths in order to relate publication records to professors even if the affiliation stated on the publication did not correspond to the professor's current affiliation. As for patents, we collected the number of citations for each publication. Despite some limitations (Van Dalen and Klamer 2005), several authors have shown, that citation counts are an adequate indicator to evaluate the quality of research output (Garfield and Welljams-Dorof 1992; Baird and Oppenheim 1994).

All patents, publications and citations were collected from the professor's first publication entry until the end of 2007. For our main analysis, we limit the time horizon to the period 1994–2007. This corresponds to an 'activity window' of six years before (1994–1999) and eight years after the survey (2000–2007). Table 3 provides descriptive statistics for all outcome variables split into the two activity windows.

As is common for scientific output, a relatively small number of professors are responsible for the majority of publications and patents (Stern and Jensen 1983). Of these, 11% did not publish in relevant field journals as included in the ISI database and 44% had not applied for any patent, while 10% of professors published nearly 42% of the total number of 32,971 publications. The same is true for citations: there are very few highly cited

Table 3. Scientific output (663 obs.).

		Mean	Std. Dev.	Min	Max
Scientific output 1994–1999:					
Publications	$PUB_{1994-1999}$	11.329	20.573	0	243
Average citations per publication	$CITperPUB_{1994-1999}$	11.586	20.201	0	210.96
Patents	$PAT_{1994-1999}$	1.388	3.447	0	32
Average citations per patent	$CITPAT_{1994-1999}$	3.918	17.436	0	219.50
Scientific output 2000–2007:					
Publications	$PUB_{2000-2007}$	18.79	30.659	0	211
Average citations per publication	$CITperPUB_{2000-2007}$	5.493	7.324	0	42.45
Patents	$PAT_{2000-2007}$	1.371	3.475	0	36
Average citations per patent	$CITperPAT_{2000-2007}$	0.209	0.843	0	14.75

professors and 10% of publications received no citation at all. On the other hand, there are professors with more than 10,000 total citations or more than 200 citations per paper. For patent applications and citations, we see a similar picture. Ten percent of professors account for about a quarter of the 3010 patent applications. The fact that not all patent applications are successful has to be taken into account when looking at the mean of patent forward citations, which indicates that two-thirds of patent applications did not receive any citations (see Table A3 for publication and patenting numbers by research field.)

4. Methodology and results

The empirical analysis takes place in two parts. First, we study the effects of research grants on sources of ideas. In doing so, we want to shed light on the correlations between grants from private and public sector sources and the different sources of ideas as outlined in the beginning of the previous section. We hypothesize, as described in Section 2, that grants and contracts affect the relevance of different sources of ideas controlling for university and research unit characteristics (STUDENTS, LABSIZE, EXPERIENCE, TECHS, SENIORSTAFF, $PUB_{1995-1999}$, $PAT_{1995-1999}$ and FEMALE).

The second part of the analysis aims at shedding light on how these different sources of ideas affect research productivity. As potential effects are unlikely to show up immediately, we observe the scientific output up to eight years after the survey. We thus expect journal publications and patent applications in the post-survey period 2000–2007 to be a function of sources of ideas that shaped the research agenda in 1999 (SCIENCE, INSTITUTIONS, INDUSTRY) and past publication and patenting efforts ($PUB_{1995-1999}$, $PAT_{1995-1999}$), as past performance is likely to affect future performance due to a 'cumulative advantage'.

Additionally, lab size (LABSIZE), experience (EXPERIENCE), and the skill composition at the lab in terms of the percentage of technical employees (TECHS) and senior researchers (SENIORSTAFF) may affect scientific productivity. Further, we consider attributes such as the research field, the type of institution and gender as control variables in the econometric models to be estimated.

Finally, as publication or patent output may not only be affected in terms of quantity, but also quality, we estimate the effects of idea sourcing on average citations per publication and patent (CITperPUB, CITperPAT). In these models, it is crucial to control for the ex ante research quality with which researchers enter our sample. Hence, as we explain in more detail in Section 4.2.2, we control for quality-weighted heterogeneity in pre-sample research performance when estimating these models.

4.1. Research funding and sourcing ideas

4.1.1. Econometric set-up

We estimate n-equation multivariate probit models ($h = 5$ and 8, respectively) that can be written as

$$y_m^* = x_m\beta_m + \varepsilon_m, \quad m = 1, \ldots, h, \tag{1}$$

$$y_m = D(y_m^* > 0), \quad m = 1, \ldots, h, \tag{2}$$

$$\epsilon = (\varepsilon_1, \ldots \varepsilon_h)' \sim N(0, \Sigma), \tag{3}$$

where m represents the different sources of ideas. The variance–covariance matrix Σ has values of 1 on the diagonal due to normalization and correlations $\rho_{jk} = \rho_{kj}$ as off-diagonal elements. The log-likelihood function is then given by

$$\ln L = (\beta_1, \ldots, \beta_h), \Sigma; y|x = \sum\nolimits_{i=1}^{N} \ln \Phi_h((q_{i,1}x_{i,1}\beta_1, \ldots, q_{i,h,}x_{i,h}\beta_h,); \Omega), \tag{4}$$

where $q_{i,m} = 2y_{i,m} - 1$.

The matrix Ω has values of 1 on the diagonal and $\omega_{j,k} = \omega_{k,j} = q_{i,j}q_{i,k}\rho_{i,k}$ for $j \neq k$ and $j, k = (1, \ldots, h)$ as off-diagonal elements Φ_h denotes the joint normal distribution of order h. The expression for the log-likelihood function thus involves an h-dimensional integral that does not have a closed form. It can be evaluated numerically through simulation. We employ maximum simulated likelihood method using the GHK simulator (Geweke 1989; Keane 1994; Hajivassiliou and McFadden 1998). For a detailed description of simulation methods, we also refer to Train (2009). We use the user-written command *cmp* in Stata to estimate the multivariate probit models (see Roodman 2009).[10]

4.1.2. Results

We estimate two specifications of our main model of which the results are presented in Tables 4 and 5, respectively.[11] As can be seen in Table 4, the share of funding stemming from the private sector (INDSHARE) is significantly positive only in the INDUSTRY-equation, pointing to a positive relationship between funding from industry and sourcing research ideas from industry partners that stimulate research at the unit. Grants from the public sector, on the other hand, are associated with ideas stimulated by traditional scientific sources and scientific institutions. The equation for consultants did not yield any informative insights and will be henceforth omitted from the next specification presented in Table 5.

In the model presented in Table 5, we distinguish industry sources by firm size, i.e. large firms and SMEs to gain insights into which factor(s) inside the industry group drives the result.[12] Other potential sources that were categorized as industry sources before were TTOs, as intermediaries between universities and industry partners, and exhibitions and trade fairs. The latter two were subsumed in the group labeled R_INDUSTRY as presented in column 5 of Table 5. The results show that the positive relationship between industry funding and idea stimulus is driven by larger firms rather than SMEs confirming Lee (2000). However, we also see that public grants can be associated with ideas from large firms, to a much smaller extent however. This effect may be rooted in public grants for university–industry collaborations. The results further suggest that research units with a higher share of industry funding are less likely to source ideas from their institutional surrounding.

The control variables show a diverse picture across the different sources of ideas. In both models, pre-sample publication performance is positively associated with sourcing ideas

Table 4. Simultaneous probit regression results (marginal effects) on ‘sources of ideas’ (663 obs.).

	SCIENCE	INSTITUTIONS	INDUSTRY	PATENTS	CONSULTANTS
INDSHARE	0.0001 (0.0009)	−0.0022 (0.0014)	0.0106*** (0.0018)	0.0001 (0.0001)	0.0000 (0.0000)
GOVSHARE	0.0014*** (0.0004)	0.0050*** (0.0005)	0.0005 (0.0009)	−0.0002 (0.0002)	0.0000 (0.0001)
STUDENTS	0.3624 (0.3081)	0.4186 (0.3792)	0.1194 (0.4202)	−0.0330 (0.0255)	0.0005 (0.0026)
$STUDENTS^2$	−0.0192 (0.0152)	−0.0190 (0.0181)	−0.0081 (0.0222)	0.0024** (0.0012)	0.0000 (0.0001)
LABSIZE	0.0739** (0.0263)	0.0043 (0.0091)	0.1040*** (0.0321)	−0.0015 (0.0061)	0.0004 (0.0015)
$LABSIZE^2$	0.0000 (0.0000)	0.0000*** (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
EXPERIENCE	−0.0021 (0.0169)	0.0040 (0.0042)	−0.0065 (0.0087)	0.0024* (0.0014)	−0.0005 (0.0013)
$EXPERIENCE^2$	−0.0001 (0.0003)	−0.0002** (0.0001)	0.0000 (0.0002)	0.0000 (0.0000)	0.0000 (0.0000)
TECHS	−0.0008 (0.0022)	0.0031*** (0.0003)	−0.0007 (0.0025)	0.0006*** (0.0002)	0.0000 (0.0001)
SENIORSTAFF	−0.0012 (0.0012)	0.0023*** (0.0003)	−0.0044*** (0.0009)	0.0002*** (0.0001)	0.0000 (0.0001)
$PUB_{1995\text{-}1999}$	0.0005 (0.0015)	0.0017*** (0.0004)	−0.0025** (0.0011)	0.0000 (0.0001)	0.0000 (0.0000)
$PAT_{1995\text{-}1999}$	−0.0018 (0.0027)	−0.0155*** (0.0039)	0.0083 (0.0100)	0.0031*** (0.0003)	−0.0003 (0.0008)
FEMALE	0.0176 (0.0520)	0.1821*** (0.0369)	−0.0409 (0.1430)	0.0146 (0.0110)	–
Log-likelihood			−1178.97		
Joint sign. field dummies χ^2 (6)			2.75		
Joint sign. inst. type dummies χ^2 (2)			12.55***		

Notes: All models contain a constant, seven field and three institution type dummies. Standard errors in parentheses are robust and clustered by institution type.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

Table 5. Simultaneous probit regression results (marginal effects) on 'sources of ideas' with industry sources divided by firm size (663 obs.).

	SCIENCE	INSTITUTIONS	LARGE FIRMS	SMEs	R_INDUSTRY	PATENTS
INDSHARE	0.0000 (0.0011)	−0.0024** (0.0012)	0.0071*** (0.0027)	0.0025 (0.0023)	0.0003 (0.0004)	0.0000 (0.0001)
GOVSHARE	0.0010*** (0.0003)	0.0047*** (0.0006)	0.0004*** (0.0001)	−0.0004 (0.0006)	0.0002 (0.0006)	−0.0001 (0.0002)
STUDENTS	0.3530 (0.3422)	0.5173 (0.3854)	−0.4053 (0.3122)	0.2652 (0.3392)	−0.3601*** (0.1211)	−0.0389** (0.0176)
$STUDENTS^2$	−0.0187 (0.0171)	−0.0241 (0.0183)	0.0172 (0.0161)	−0.0145 (0.0181)	0.0181*** (0.0062)	0.0025** (0.0010)
LABSIZE	0.0544 (0.0406)	0.0292 (0.0405)	0.1387 (0.0963)	0.0122 (0.1037)	0.0123 (0.0263)	−0.0241*** (0.0059)
$LABSIZE^2$	0.0095 (0.0114)	0.0019 (0.0086)	−0.0054 (0.0222)	0.0074 (0.0154)	0.0013 (0.0045)	0.0045*** (0.0006)
EXPERIENCE	−0.0039 (0.0173)	0.0017 (0.0040)	−0.0061 (0.0082)	0.0023 (0.0168)	0.0012 (0.0032)	0.0017** (0.0008)
TECHS	0.0004 (0.0025)	0.0037*** (0.0003)	0.0006 (0.0013)	−0.0006 (0.0019)	−0.0004 (0.0004)	0.0005 (0.0001)
SENIORSTAFF	−0.0016 (0.0014)	0.0018*** (0.0005)	−0.0040*** (0.0011)	−0.0020 (0.0027)	0.0001 (0.0006)	0.0003 (0.0001)
$PUB_{1995\text{-}1999}$	0.0004 (0.0015)	0.0017*** (0.0002)	−0.0021** (0.0010)	−0.0012* (0.0007)	−0.0002 (0.0002)	−0.0001*** (0.0001)
$PAT_{1995\text{-}1999}$	−0.0030 (0.0023)	−0.0152*** (0.0039)	0.0052 (0.0077)	0.0082 (0.0070)	0.0001 (0.0014)	0.0029*** (0.0007)
FEMALE	0.0213 (0.0521)	0.1839*** (0.0353)	0.0088 (0.0857)	−0.0754 (0.1000)	0.0131 (0.0187)	0.0231* (0.0120)
Log-likelihood			−1505.08			
Joint sign. field dummies χ^2 (6)			0.12			
Joint sign. inst. type dummies χ^2 (2)			858.34***			

Notes: All models contain a constant, seven field and three institution type dummies. Standard errors in parentheses are robust and clustered by institution type.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

from an institutional environment, which may be explained by presentations of research results at seminars and conferences that stimulate new ideas, especially for actively publishing professors. Not surprisingly, patenting professors are more likely to source ideas from patent applications than the non- or the occasional patenting faculty. Female professors also tend to source ideas from their institutional surrounding and the share of technical staff is positively correlated with sourcing ideas from patents and institutions. The share of senior staff at the research unit is negatively related to large firms as source of ideas which may be explained by the outflow of graduated research to industry especially of those units actively involved with firms. Industry also turned out to be a particularly interesting source of ideas for professors that published less in the past. The effect, however, is more pronounced for large firms as compared to SMEs.

4.2. *Sources of ideas and research productivity*

4.2.1. Econometric set-up

The previous analysis suggested that industry funding impacts a research unit's sources of ideas. In the following analysis, we test if – controlling for unobserved heterogeneity between professors – different sources of ideas translate into differences in research performance in subsequent years, a phenomenon that has been attributed directly to funding in the previous literature (Blumenthal et al. 1997; Geuna 1997; Manjarrés-Henríquez et al. 2009; Banal-Estanol, Jofre-Bonet, and Meissner 2010; Hottenrott and Thorwarth 2011). This previous work, however, did not allow concluding whether this effect was due to time constraints of researchers involved in industry funded projects, non-disclosure clauses, or due to an impact on the research content that leads to research agendas that are more aligned with industry interests rather than with scientific relevance. Thus, the following analysis is aimed at disentangling these effects by looking at the effect stemming from the 'idea-sourcing' argument.

For this purpose, we estimate count data models for investigating the relationship between sources of ideas and research output. The number of publications and patent applications are by nature positive, integer values and also characterized by many zeros, as not all of the professors in our sample publish and/or patent. The same is true for the number of citations. The estimation equation is assumed to be of an exponential functional form and can be written as

$$\lambda_{it} = E[Y_{i,2000-2007}|Z_{i,1999}, X_{it}, c_i] = \exp(\alpha Z_{i1999} + \beta X'_{it} + c_i), \tag{5}$$

where Y_i is the count variable and stands either for publication counts (PUB), patent applications (PAT), or citations per item (CITperPUB, CITperPAT) by scientist i during the time span 2000–2007. The outcome variables are assumed to be Poisson-distributed with $\lambda_{\mathrm{it}} > 0$. $\mathrm{Z}_{\mathrm{i},1999}$ denotes the set of sources of ideas as outlined before. X_{it} represents the set of control variables and α and β are the parameters to be estimated. c_i is the individual specific unobserved effect, such as individual skills of each scientist or their attitude toward publishing or patenting.

A key assumption of the Poisson model is the equality of the conditional mean and the conditional variance, which is typically violated in applications leading to overdispersion. The use of negative binomial regression models may be a solution as it allows for overdispersion.

However, although the negative binomial model relaxes this assumption of equidispersion, it is only consistent and efficient if the functional form and distributional assumption of the variance term are correctly specified. The Poisson model, on the other hand, is consistent under the assumption that the mean is correctly specified even if overdispersion is present. In case the assumption of equidispersion is violated, and hence the obtained standard errors are too small, this can be corrected by using fully robust standard errors (see Wooldridge 2002).

4.2.2. Unobserved heterogeneity in researchers' capabilities

A drawback of cross-sectional survey data is that one cannot control for unobserved heterogeneity between the subjects of interests. In our case, such unobserved effects could be specific skills of each professor that are positively correlated with the right-hand side variables such as the sources of ideas and a potential endogeneity problem arises. For instance, not all scientists may have the necessary absorptive capacities to source ideas from firms or scientific institutions other than their own. Moreover, firms may screen university researchers and contact those who they perceive to meet certain quality or other criteria.

If unobserved subject-specific heterogeneity is present, the estimated coefficient of the sources of ideas variables would be upwards biased. However, given that we do have time-series information of the dependent variables, that is patents and publications and their citations, we can cope with this challenge. For the advantageous case in which time-series for the outcome variables exist, Blundell, Griffith, and van Reenen (1995) and Blundell, Griffith, and Windmeijer (2002) suggest a solution which they call 'feedback model'. The model is based on the argument that the main source of unobserved heterogeneity lies in the different values of the dependent variable Y_i with which observation units (professors in our case) enter the sample. Following Blundell, Griffith, and van Reenen (1995) and Blundell, Griffith, and Windmeijer (2002) we can, therefore, account for unobserved time-invariant professor heterogeneity by using pre-sample information of publications and patents. Blundell, Griffith, and Windmeijer (2002) show in Monte Carlo simulations that the estimator is consistent in the presence of unobserved heterogeneity and pre-determined regressors, as is the case in our estimation. This approach thus helps to address the problem of endogeneity that arises from correlated individual effects and through feedback from the dependent variable. In particular, the model approximates the unobserved heterogeneity by including the log of the Y_i from a pre-sample period average (ln[PUB_MEAN], ln[PAT_MEAN] and ln[CITperPUB_MEAN, ln[CITperPAT_MEAN) into a pooled cross-sectional model. In case Y_i is zero in the pre-sample period, e.g. a professor had no publications, a dummy is used to capture the 'quasi-missing' value in log Y_i in the pre-sample period (d[PUB_MEAN = 0], d[PAT_MEAN = 0] and d[CITperPUB_MEAN = 0], d[CITperPAT = 0]). We constructed the pre-sample mean by using observation values of the respective Y for the years 1994–1999.

4.2.3. Results

The results are presented in Table 6. Model 1 shows the results for the number of publications and model 2 shows the results for the average number of citations per publication. Models 3 and 4 distinguish between large firms, SMEs and other industry sources. As expected, scientific sources inspire research and lead to higher productivity both in terms of quantity and quality. Institutional sources, however, are not significant. Model 1 shows that research impulses from industry are associated with lower publication counts, but not with fewer citations per publication. Interestingly, when distinguishing between large firms and SMEs, it turns out that impulses from large firms reduce publication output both in terms of

Table 6. Estimation results Poisson models with fixed effects on publication output (663 obs.).

	Model 1	Model 2	Model 3	Model 4
Variable	PUB	CITperPUB	PUB	CITperPUB
SCIENCE	0.075* (0.045)	0.094* (0.057)	0.081** (0.042)	0.095 (0.062)
INSTITUTIONS	−0.002 (0.058)	0.012 (0.063)	−0.025 (0.063)	0.007 (0.064)
INDUSTRY	−0.052*** (0.007)	−0.063 (0.044)		
LARGE FIRMS			−0.088*** (0.022)	−0.141** (0.066)
SMEs			−0.024 (0.051)	0.013 (0.048)
PATENTS	0.022 (0.055)	−0.007 (0.040)	−0.024 (0.051)	−0.013 (0.029)
CONSULTANTS/ INDUSTRY_R	−0.166*** (0.028)	0.064** (0.030)	0.092** (0.044)	0.072* (0.032)
STUDENTS	2.572 (1.702)	−2.214 (1.599)	2.999 (1.835)	−1.859 (1.882)
STUDENTS^2	−0.124 (0.086)	0.126 (0.081)	−0.149 (0.093)	0.106 (0.097)
LABSIZE	0.395 (0.301)	0.007 (0.321)	0.417 (0.315)	0.025 (0.358)
LABSIZE^2	−0.070 (0.052)	−0.009 (0.056)	−0.075 (0.055)	−0.010 (0.062)
EXPERIENCE	−0.062*** (0.030)	−0.007 (0.030)	−0.062** (0.031)	−0.012 (0.032)
EXPERIENCE^2	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.000 (0.001)
TTO	0.165 (0.140)	0.144** (0.056)	0.102 (0.165)	0.097* (0.050)
TECHS	0.005 (0.004)	0.000 (0.003)	0.005 (0.004)	0.000 (0.003)
SENIORSTAFF	0.001 (0.001)	−0.006*** (0.001)	0.000 (0.001)	−0.006*** (0.002)
ln[PUB_MEAN]/ ln[CITperPUB_MEAN]	0.630*** (0.009)	0.291*** (0.025)	0.640*** (0.009)	0.293*** (0.026)
ln[PAT_MEAN]/ ln[CITperPAT_MEAN]	0.062*** (0.004)	−0.037*** (0.008)	0.078*** (0.004)	−0.040** (0.017)
Log-likelihood	−4963.27	−2139.29	−4949.40	−2115.97
Joint sign. inst. dum. χ^2 (2)	62.09***	4.59*	59.72***	5.66*
Joint sign. field dum. χ^2 (6)	12.11***	0.08	11.26***	0.03
Joint sign. county dum. χ^2 (15)	7.91**	19.54***	6.97**	35.86***

Notes: Robust standard errors in parentheses are clustered by institution type. All models contain a constant, field, county and institution type dummies. Pre-sample dummies d[X_MEAN] for observations with zero means are not presented. Dependent variables refer to the post-sample period 2000-2007.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

quantity (model 3) and quality (model 4) confirming the 'skewing argument'. Noteworthy, the latter effect on quality is larger than the effect on quantity. SMEs as sources of ideas have no significant impact on publication output. TTOs, exhibitions and trade fairs as summarized in INDUSTRY_R in models 3 and 4, on the other hand, have a positive effect on the number of publications and, although slightly weaker, on the number of citations per publication confirming arguments of complementarities between science and industry (Rosenberg 1998).

The high significance of the pre-sample means of publications (ln[PUB_MEAN]/ln [CITperPUB_MEAN]) and patents (ln[PAT_MEAN]/ln[CITperPAT_MEAN]) underpins the importance of controlling for unobserved heterogeneity. Interestingly, both publication and patent histories are associated with more future publications. As for the effect on the number of citations per publication, it is only previous citations to publications that count, not citations to patents. For control variables, we find the expected signs. Older professors seem to publish less, but do not receive fewer (nor more) citations per publication.

The results of the Poisson models on patent output are reported in Table 7. As already seen for publications, we find a negative effect of industry as idea stimulus on the number of patents. This is contrary to findings of papers that use industry funding directly as a regressor for patenting output (Hottenrott and Thorwarth 2011; Lawson 2012). Model 3,

Table 7. Estimation results Poisson models with fixed effects on patent output (663 obs.).

	Model 1	Model 2	Model 3	Model 4
Variable	PAT	CITperPAT	PAT	CITperPAT
SCIENCE	−0.025 (0.111)	−0.333*** (0.051)	−0.023 (0.138)	−0.336*** (0.021)
INSTITUTIONS	0.001 (0.020)	−0.215*** (0.055)	−0.020 (0.021)	−0.246** (0.097)
INDUSTRY	−0.202* (0.113)	−0.057 (0.138)		
LARGE FIRMS			−0.163** (0.068)	0.013 (0.158)
SMEs			0.083*** (0.023)	−0.081 (0.078)
PATENTS	0.323*** (0.024)	0.564*** (0.072)	0.294*** (0.037)	0.502*** (0.028)
CONSULTANTS/ INDUSTRY_R	−0.164 (0.259)	−0.363 (0.422)	−0.061 (0.173)	0.027 (0.154)
STUDENTS	2.420** (1.127)	13.336* (7.778)	2.024* (1.062)	13.654 (8.515)
STUDENTS^2	−0.128* (0.071)	−0.711* (0.387)	−0.111* (0.068)	−0.728* (0.431)
LABSIZE	0.635*** (0.230)	1.781*** (0.208)	0.590* (0.312)	1.765*** (0.225)
LABSIZE^2	−0.143** (0.063)	−0.238*** (0.026)	−0.135* (0.070)	−0.236*** (0.048)
EXPERIENCE	−0.021 (0.024)	0.092 (0.064)	−0.027** (0.012)	0.108* (0.065)
EXPERIENCE^2	0.000 (0.001)	−0.002* (0.001)	0.000 (0.000)	−0.003** (0.001)
TTO	−0.041 (0.441)	0.380 (0.387)	−0.059 (0.459)	0.397 (0.338)
TECHS	−0.001 (0.006)	0.020*** (0.005)	−0.002 (0.004)	0.020*** (0.005)
SENIORSTAFF	0.007*** (0.001)	−0.028** (0.012)	0.008*** (0.002)	−0.028*** (0.010)
ln[PUB_MEAN]/ ln[CITperPUB_MEAN]	0.014 (0.117)	0.233*** (0.082)	0.022 (0.095)	0.224** (0.097)
ln[PAT_MEAN]/ ln[CITperPAT_MEAN]	0.464*** (0.076)	−0.019 (0.104)	0.467*** (0.063)	−0.008 (0.095)
Log-likelihood	−1079.65	−295.00	−1081.95	−296.37
Joint sign. inst. dum. χ^2 (2)	87.23***	4.3	98.66***	4.2
Joint sign. field dum. χ^2 (6)	1.96	290.00***	2.28	400.00***
Joint sign. county dum. χ^2 (15)	12.55***	411.12***	8.30**	476.39***

Notes: Robust standard errors in parentheses are clustered by institution type. All models contain a constant, field, county and institution type dummies. Pre-sample dummies d[X_MEAN] for observations with zero means are not presented. Dependent variables refer to the post-sample period 2000–2007.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

however, reveals a more nuanced picture. Large firms stimulate research agendas that lead to fewer patents, but SMEs to more while the quality of the patents, as measured by the average number of citations, is not affected. The impact of large firms is in absolute terms larger than the one of SMEs, however, only in terms of patent quantity, not quality. This may point towards differences in the nature of the research commissioned by large firms compared to those with SMEs. Cohen, Nelson, and Walsh (2002), for example, report that large US firms regard 'contributing to project completion' as a more important benefit of collaborating with universities, than 'suggesting new projects'. This indicates that large firms may collaborate on projects which are no longer in a research stage that results in a patent (application), but are already in the development phase. Likewise, Perkmann and Walsh (2009) find that in more applied projects, academics contributed to projects that were already ongoing within the partner firms. Two-thirds of the projects they study involved large firms, supporting the notion that large firms may involve universities at later stages of the R&D process, i.e. post-patenting phase.

As could be expected, sourcing ideas from patents leads to more and more highly cited patents in the future. Interestingly, scientific and institutional sources of ideas do not affect the number of patents, but do affect the technological relevance of patents negatively. This points to the fact that these patents are less relevant to industrial applications. Surprisingly, contact with the university's TTO does not affect patent quantity and quality significantly. Another interesting result is the positive significance of the pre-sample publication history on patent quality. Past patent activity, on the other hand, affects patent quantity, but not quality.

5. Conclusion and discussion

Using data from research units at 46 universities in Germany, the presented analysis strongly supports the perspective that funding does influence the sources of ideas for academic research. In particular, industry sponsoring is associated with a higher impact of industry-influenced ideas on research agendas. More precisely, it is associated with a greater the role of large firms in the idea generation process. The higher the share of industry funding in the overall budget, the more likely the research units were to report that large firms, but not SMEs, had influenced their research agendas. Grants from public institutions, however, positively correlate with utilization of traditional scientific sources and institutional sources of ideas. Further, controlling for unobserved heterogeneity as reflected in pre-sample publication and patenting of the individual researcher, our results suggest that sourcing ideas from large firms is associated with lower publication and patent output in subsequent years. Ideas from SMEs on the contrary appear to stimulate patenting without reducing incentives to publish. These insights add to previous research on the relationship between research funding and research productivity. The results suggest that for the case of the mainly engineering faculty in our sample, the effect of funding on research outcomes may be moderated by the fact that funding relationships, particularly those with industry, stimulate and impact research ideas within the university. This impact may extend beyond the sponsored research project leading to a more general effect on research unit's research orientation.

Azoulay, Ding, and Stuart (2009) point to intra-person economies of scope that emerge when a scientist is involved in both the development of academic and commercial research outcomes that may also be realized when sourcing ideas not only from science but also from industry. Indeed, we find that other sources that were categorized as 'industrial sources' such as exhibitions, trade fairs and TTOs to have a positive impact on publication output. The involvement of a TTO may reduce the individual researcher's burden and hence leave more time for other research projects (Hellman 2007) or may filter ideas with industrial relevance that are also valuable for the scientific community.

While we cannot unequivocally state that these associations are causal, our analysis is the first to study the impact of grants on idea-sourcing and its consequences for research productivity. We strongly encourage further research as funding environments continue to shift. OECD data show the share of industry sponsorship is generally rising. Our study focused on research units in Germany, where the share of industry-funded public research increased most significantly over the past decades and amounted to about 25% in 2007 (OECD 2009). The empirical evidence from Germany suggests that the shift may not be without consequences for the development of science in the long term. However, more research is clearly needed to increase our understanding of how country-level and institution-level characteristics influence the relationship between sponsorship and research content, and finally research productivity.

Policymakers and scholars in the field of the economics of science face the challenge to assess the nature of ideas that spill over through sponsoring contracts with industry and whether the 'idea-sourcing' effect can be distinguished from non-disclosure or delay of publication effect. Such an assessment will be necessary in order to judge whether sponsorship from industry is influential enough to threaten the development of science or whether a potential reduction in the number of publications is the price for increased industry–science collaboration that fosters academic inventorship, patentable discoveries and creates benefits that materialize in the private sector.

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Notes

1. See Hottenrott and Thorwarth (2011) for an earlier study on the direct effects of research funding on research productivity for the sample of research units used in the following analysis.
2. These include physics, mathematics and computer science, chemistry and pharmaceuticals, biology and life sciences, electrical and mechanical engineering, and other engineering and related fields such as geosciences.
3. These include institutes of the Max-Planck-Society, the Helmholtz-Association, Fraunhofer Society and the Leibniz Association.
4. Researchers at public research institutions in Germany usually do not have any teaching obligations and the organizational structure of research units differs substantially from those at teaching institutions.
5. Usually a research unit has only one professor. Larger universities, however, may also have several professors at one department. In any case, only one is the head of the research unit.
6. For each of the 16 German States (*Länder*), the sample contains at least one observation.
7. It should be noted that the sum of INDFUND and GOVFUND is 'total third-party funding' and not the total budget. Adding this to the 'core' institutional funding (COREFUND) yields the units' overall funding: TOTALFUND = INDFUND + GOVFUND + COREFUND.
8. In Germany, all dissertations are recorded in the German National Library (Deutsche Nationalbibliothek). For a few professors, who according to their CVs either obtained their doctoral degree abroad or do not have a PhD, we used the year of their first publication as a proxy for the beginning of their academic career. If professors with very common names like 'Müller' or 'Fischer' and also common first names appeared in our data set, we preferred to drop these from our data set since publication and/or patent data could not be uniquely identified.
9. Even though we do know the number of employees in each research unit and have some details on their qualifications, we do not have further details (e.g. name) of the individual team members. Thus, we cannot collect publication and patent information at the team member level and instead use the publications (and patents) of the head of the research unit. This is justified on the basis that in science and engineering at German institutions, it is common practice to include the 'head' on every publication authored by unit members.
10. The simulation method requires drawing random variables from an upper-truncated normal distribution. We employ draws based on Halton sequences as they are more effective for simulated MSL estimation than pseudo-random draws (Train 2009).
11. It should be noted that we also estimated ordered Probit models on the original categories of the dependent variables. The results confirmed the findings of the binary models. Furthermore, we estimated the models using not the budget share (INDSHARE, GOVSHARE), but the logged amounts (INDFUND, GOVFUND). As the results were very similar, we refrain from presented these in detail.
12. The correlation coefficients between the equations in the MV-probit are displayed in Table A4. Significant correlations between several of the equations support estimation of a simultaneous equation model.

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Appendix

Table A1. Rotated factor loadings and unique variances.

	Ordered variables				Binary variables			
Factors	Factor 1	Factor 2	Factor 3	Uniqueness	Factor 1	Factor 2	Factor 3	Uniqueness
Small- or medium-sized firms (less than 250 empl.)	−0.004	**0.682**	−0.011	0.5353	−0.099	**0.548**	−0.067	0.6853
Large firms (250 empl. or more)	0.127	**0.537**	−0.037	0.6938	0.048	**0.326**	−0.066	0.8874
Universities	**0.593**	0.043	**0.456**	0.4386	**0.441**	0.007	**0.537**	0.5169
Public research centers	**0.424**	0.100	**0.429**	0.6266	0.229	−0.010	**0.495**	0.7029
TTOs	0.114	**0.524**	**0.229**	0.6599	−0.019	**0.397**	0.158	0.8167
Consultants	0.057	**0.379**	0.178	0.8212	0.066	**0.129**	−0.038	0.9776
Exhibitions and fairs	0.189	**0.637**	0.104	0.5473	0.097	**0.543**	0.051	0.3135
Patents	0.240	**0.421**	−0.021	0.765	0.064	**0.242**	0.012	0.9372
Academic journals	**0.900**	0.038	−0.025	0.1888	**0.788**	−0.038	0.109	0.3656
Conferences, meetings	**0.840**	0.079	0.112	0.2757	**0.825**	0.024	0.072	0.6935
Internet, media, other data bases	**0.630**	0.223	0.190	0.5174	**0.432**	0.190	0.261	0.7087

Note: Loadings with absolute value > 0.3 in bold.

Table A2. Competitive funding by research field.

Field	Freq.	%	% Public grants of total budget	% Industry grants of total budget
Physics	106	15.99	32.643	4.241
Mathematics and Computer Science	104	15.69	17.582	6.322
Chemistry	94	14.18	22.335	6.123
Biology	55	8.30	25.713	7.385
Electrical engineering	98	14.78	15.214	11.822
Mechanical engineering	107	16.14	22.062	14.152
Other engineering	99	14.93	23.425	10.265
	663	100.00		

Table A3. Scientific productivity by research field (663 obs.).

	PUB	CITperPUB	PAT	CITperPAT
Field	Publications 1994–1999		Patents 1994–1999	
Physics	22.47	21.74	1.11	2.97
Mathematics and computer science	3.97	6.57	0.21	0.56
Chemistry	27.53	16.07	1.80	5.47
Biology	11.52	21.83	0.91	3.67
Electrical engineering	3.93	5.62	2.27	7.28
Mechanical engineering	3.46	4.99	1.84	5.65
Other engineering	6.94	7.97	1.57	1.70
	Publications 2000–2007		Patents 2000–2007	
Physics	33.29	9.45	0.91	0.20
Mathematics and computer science	6.50	3.61	0.25	0.02
Chemistry	39.06	8.40	1.52	0.13
Biology	19.45	9.26	1.14	0.15
Electrical engineering	11.58	3.00	1.90	0.45
Mechanical engineering	6.54	2.31	1.91	0.26
Other engineering	15.33	3.78	1.79	0.20

Table A4. Correlation coefficients between equations in MV-probit (Table 5).

	Coef.	Rob. S.E.	Z	$P > \|z\|$	[95% Conf. interval]	
/atanhrho_12	0.578	0.037	15.540	0.000	0.505	0.651
/atanhrho_13	0.206	0.012	17.570	0.000	0.183	0.229
/atanhrho_14	0.107	0.038	2.820	0.005	0.033	0.181
/atanhrho_15	0.306	0.183	1.680	0.094	−0.052	0.665
/atanhrho_16	0.266	0.090	2.950	0.003	0.089	0.442
/atanhrho_23	0.167	0.068	2.450	0.014	0.033	0.300
/atanhrho_24	0.096	0.060	1.600	0.109	−0.021	0.213
/atanhrho_25	0.311	0.208	1.500	0.134	−0.096	0.718
/atanhrho_26	0.393	0.165	2.390	0.017	0.070	0.716
/atanhrho_34	0.258	0.123	2.110	0.035	0.018	0.499
/atanhrho_35	0.038	0.033	1.140	0.253	−0.027	0.104
/atanhrho_36	0.187	0.161	1.170	0.244	−0.128	0.503
/atanhrho_45	0.502	0.044	11.330	0.000	0.415	0.589
/atanhrho_46	0.600	0.096	6.280	0.000	0.413	0.788
/atanhrho_56	0.381	0.296	1.280	0.199	−0.200	0.962