KATHOLIEKE UNIVERSITEIT
LEUVEN

Faculty of Economics and Applied Economics

An empirical assessment of co-activity among German professors

Dirk Czarnitzki, Wolfgang Glänzel and Katrin Hussinger

DEPARTMENT OF MANAGERIAL ECONOMICS, STRATEGY AND INNOVATION (MSI)

MSI 0608

An Empirical Assessment of Co-Activity among German Professors[1]

Dirk Czarnitzki[a,b,c], Wolfgang Glänzel[a,b,d], Katrin Hussinger[b,c]

[a]*Steunpunt O&O Statistieken, K. U. Leuven, Leuven (Belgium)*
[b]*K. U. Leuven, Dept.of Managerial Economics, Strategy and Innovation, Leuven (Belgium)*
[c]*Centre for European Economic Research (ZEW), Mannheim (Germany)*
[d]*Hungarian Academy of Sciences, Institute for Science Policy Research, Budapest (Hungary)*

October 2006

Abstract

The growing importance of technology relevant non-publication output of university research has come into the focus of policy-makers' interest. A fierce debate arose on possible negative consequences of the increasing commercialization of science, as it may come along with a reduction in research performance. This paper investigates the relationship between publishing as a measure of scientific output and patenting for German professors active in a range of science fields. We combine bibliometric/technometric indicators and econometric techniques to show that patenting positively correlates with, first, the publication output and, second, with publication quality of patenting researchers.

Keywords: academic inventors; patents; publications

JEL: O31, O32, O34

---

[1] Email correspondence: dirk.czarnitzki@econ.kuleuven.be, wolfgang.glanzel@econ.kuleuven.be, katrin.hussinger@econ.kuleuven.be.
We thank the participants of the 9th International Conference on Science and Technology Indicators for helpful comments. Further, Katrin Hussinger gratefully acknowledges financial support under the grant KUL – OT/04/07A.

1 Introduction

The growing importance of technology relevant non-publication output of university research and of co-operation between universities and industry has come into the focus of policy-makers' interest in recent years. In the context of a growing number of scientific researchers active in commercializing their discoveries, some fear that patenting might significantly reduce scientific output in the economy, which could have, in turn, detrimental implications for long-term growth, competitiveness and employment. Productivity in science can measured in terms of publication output and research quality of scientists engaging in commercialization activities. This paper combines bibliometric/technometric indicators and econometric techniques to investigate the correlation between patenting and publication output and quality for a large data set of professors active in a number of research fields in Germany.

The commercialization of science is supposed to have a number of positive implications such as the realization of complementarities between applied and basic research (Azoulay et al., 2006), the generation of new research ideas through industry-university collaboration (Rosenberg, 1998), and the overcoming of "underfunding" of basic research through the private sector (Agrawal and Henderson, 2002). However, the surge in academic patenting raised a controversy on the potential effects for the future of scientific research. Does the increased patenting activity of scientific researchers reflect that the traditional motivations for researchers, which are seen in the intrinsic satisfaction of problem solving (Stern, 2004), the search for fame and status (Merton, 1973), and the interest in winning the game (Stephan and Levin, 1992), changed towards an incentive structure aiming at personal wealth? And what are the consequences for the production of science? Does patenting crowd out scientific publications? And is there an impact on research quality?

A complete crowding out of publication outcome is considered as unlikely because academic scientists heavily depend on their scientific reputation (Azoulay et al., 2006, Thursby et al., 2005, Scotchmer, 2004). Academic prestige serves as a positive signal in the post-discovery period, as well as for the search of industrial collaboration partners and financiers or the attraction of new scientific personal. Earlier studies accordingly found no empirical evidence for a negative impact of patenting activities on publication output (Agrawal and Henderson, 2002, Markiewitz and DiMinin, 2005, Stephan et al., 2006, van Looy et al. 2006). Also the additional time spent on transferring scientific discoveries into marketable inventions and possible interdictions to communicate research outcomes due to contractor's requirements (Thursby and Thursby, 2005) does not significantly affect publication outcome (Azoulay et al., 2006). Patents are found to be by-products of scientific work rather than substitutes (Murray, 2002).

A perhaps more serious concern than a possible crowding out of scientific output is that the quality of research might suffer from the business activities of researchers. Inventions demanded by the market are typically rather applied and do not necessarily touch academic research frontiers. Recent studies, however, argue that contacts to scientists in the business sector are rather enrichment for university researchers (Agrawal and Henderson, 2002, for MIT scientists, Breschi et al., 2006, for academic inventors in Italy) and that industry-science collaboration even triggers new basic research (Rosenberg, 1998, for the US chemistry). The result that research does not decline in quality if scientists engage in commercialization of their discoveries is also supported by Azoulay et al. (2006) within a large sample of academic life scientists. Azoulay et al. (2006) and van Looy et al. (2006) attempt to further analyze the effect of co-activity on the content of publication output. For their large sample of US scientists, Azoulay et al. (2006) cannot rule out a shift towards research questions that are of commercial interest. Van Looy et al. (2006) conclude that patenting researchers at the Catholic University of Leuven publish in rather basic research-orientated journals compared to their non-patenting colleagues.

Our analysis is based on a newly created large sample of professors active in various science fields in Germany. We establish a link between the individual scientists and their patenting and publication records. This yields a sample of more than 3.500 patenting professors holding more than 10.000 patents and having more than 40.000

publications in several fields of science and technology covering the years 1998 to 2002. Our study combines regression analysis and bibliometric/technometric indicators to investigate the incidence of patenting and publishing of scientists. We answer the question whether patenting has a negative impact on publication output and whether there is an effect on research quality.

The remainder of the paper is organized as follows: the following section illustrates some methodological issues; section 3 introduces our data set and presents some descriptive statistics; section 4 shows the regression results and the last section concludes.

2 Methodology

There are some methodological issues worth to be mentioned. First, we discuss the advantage of a scientist-based assessment of co-activity versus a publication-based approach. Second, we describe the advantage of our methodological set-up that combines bibliometric/technometric indicators with multivariate regression analysis.

2.1 Publication-based versus scientist-based

In the field of bibliometrics/technometrics, the analysis of patenting and scientific publishing by scientists has long become standard. Most articles focus on citation-based measures to explore the closeness of science and technology. Both non-patent references (NPRs) in patents (e.g., Narin and Noma, 1985) and patent references in scientific publications (e.g., Hicks, 2000, Glänzel and Meyer, 2004) are used as measures of ‘science-intensity’ of technology and of other aspects of science-technology relationship. The general message of the bibliometric/technometric literature is that science and technology are getting increasingly closer over time. The strength of links established through citations is, however, somewhat limited.[2]

[2] This is, among other factors, a consequence of the citation behaviour of authors, inventors and patent examiners as well as of the different functions citations have in scientific papers and in patents. Meyer (2000) argues that citation linkages hardly present a direct link between cited paper and citing patent. Agrawal and Henderson (2002) critically discuss the use of patent based measures to evaluate public funding of university departments.

Much stronger – and maybe even more meaningful – links are established through co-active knowledge production expressed by inventor-author relations as introduced by Meyer (2006). Based on a sample of scientists active in nano-science and nano-technology, Meyer (2006) analyzes their publishing and patenting activities, which he refers to as co-activity. His main interest is on the question whether co-active researchers outperform their colleagues, who concentrate on the science sector only. Based on a bibliometric analysis, Meyer concludes that co-active scientists indeed outperform others in terms of their publication and citation record. Meyer (2006), however, concedes that co-active scientists do not have the lead in the top-performance class.

2.2 Combining bibliometric/technometric indicators and regression analysis

The empirical analysis makes use of both, advances in bibliometric/technometric indicators and in multivariate regression analysis. In order to measure patenting activity we use a simple count of publications per researcher per year. The number of citations received during a sufficiently large period gives insight into the reception of the published results by the scientific community. Although citations may not unambiguously represent an indication of research quality, Holmes and Oppenheim (2001) have shown that citation measures significantly correlate with other quality measures. Therefore, we use citation count as a simple *proxy for research quality*. This measure is, however, too simple from a bibliometric/technometric point of view as it depends on too many factors not directly linked to quality issues. Therefore, we rely on the mean observed citation rate, the relative citation rate and the normalized mean citation rate – all based on three-year citation windows – as more sophisticated quality indicators.

- The *Mean Observed Citation Rate* (MOCR) is defined as the ratio of citation count to publication count. It reflects the factual citation impact of a scientist's publication output independently of its size. Nonetheless, this measure is still influenced by subject characteristics, and is therefore – without further normalization – not appropriate for cross-field comparisons and multidisciplinary application (Glänzel and Moed, 2002) such as the patenting activity of German professors in this study.

- The *mean expected citation rate* (MECR) is needed to calculate the relative citation rate and therefore used as an auxiliary measure but not as individual variable in this study. MECR of a single paper is defined as the average citation rate of all papers published in the same journal in the same year. A three-year citation window to the source year is used. For a set of papers assigned to a particular scientist, the indicator is the average of the individual expected citation rates over the whole set.
- The *Relative Citation Rate* (RCR) is defined as the ratio of the Mean Observed Citation Rate to the Mean Expected Citation Rate per publication: RCR = MOCR/MECR. This indicator measures whether the publications of a particular scientist attract more or less citations than expected on the basis of the impact measures, i.e., the average citation rates of the journals in which they appeared. Since the citation rates of the papers are gauged against the standards set by the specific journals, it is largely insensitive to the big differences between the citation practices of the different science fields and subfields. An RCR that equals zero corresponds to uncitedness, RCR < 1 means lower-than-average, RCR > 1 higher-than-average citation rate, RCR = 1 if the set of papers in question attracts just the number of citations expected on the basis of the average citation rate of the publishing journals. RCR has been introduced by Schubert et al. (1983), and largely been applied to comparative macro and meso studies since.
- The *Normalised Mean Citation Rate* (NMCR) is defined analogously to the RCR as the ratio of the Mean Observed Citation to the weighted average of the mean citation rates of subfields. In contrast to the RCR, NMCR gauges citation rates of the papers against the standards set by the specific subfields. Its neutral value is 1 and NMCR >(<) 1 indicates higher(lower)-than-average citation rate than expected on the basis of the average citation rate of the subfield. NMCR has been introduced by Braun and Glänzel (1990) in the context of national publication strategy.

Those indicators are used as endogenous variables in our regression analysis. We specify the relationship between publishing activities pub_{it} and patent activities pat_{it}

and further control variables for a sample of n individuals i that are observed over a period of t years as:

$$pub_{it} = \beta\, pat_{i,t-1} + f(control\ variables_{it}) + \varepsilon_{it} \tag{1}$$

β denotes the effects of patenting on publication activities, f a function of control variables, and ε_{it} the error term of the model that accounts for all random effects not captured by the regressors. We include that patent variable as a one-year lag. As we intend to analyze whether commercialization activity is negatively correlated with scientific output, it is desirable to contrast publication and patent activity that took place at the same time, that is, the time window when the scientist was most probably using his or her time for both activities in parallel. We observe the application date in the patent database, and thus we can assume that the researcher had worked on the underlying technology closely before filing the patent application. For the publications, however, we do not observe journal submission date but only publication year. The submission must necessarily have taken place a certain time before publication. In absence of a better guess, we model that the researchers submitted their papers about one year before the publication of the article in a journal. By using a "publication in period *t*" to "patent application in *t*-1" relationship as in eq. (1), we attempt to approximate a time window where the scientist worked on both the publications that appeared in year *t* and patents filed in *t*-1, such that the actual research for publishing and patenting took possibly place in year *t*-2. Of course, we are aware that publication lags may vary in time, but currently we do not have any better information at hand, which would improve the selection of a more appropriate time window.

Regression analysis may have several advantages over merely qualitative and descriptive approaches that are predominant in the bibliometric literature:

- *Avoidance of information losses*: The distribution of patents held by scientific researchers is typically very skew ranging from scientists with a zero patent outcome to academic researchers with a large patent portfolio. In purely descriptive assessments, such information is often compressed for presentation purpose, for example by using classes of patenting activity that range e.g. from "not patenting scientists" to "scientists with one or more patents but less than twenty" to "highly active patentees". Regression analysis does not require such a classification of patent activities. For the estimation of models such as eq. (1), the patent variable can enter as continuous variable so that the full range of the distribution is taken into account for the estimation of β which reflects the interdependence between publications and patents. Thus, regression techniques avoid information loss due to grouping of continuous variables into discrete numbers.

- *Accounting for other effects that may influence publication activity:* While it is basically possible to account for multivariate relationships in descriptive analyses, it is often too cumbersome to describe the data in several dimensions at the same time. In a regression analysis framework, other factors possibly influencing publication activity can be easily taken into account as covariates in the regression equation. In this paper, we account for time and gender effects. It may be that our dependent variable changes over time due to other reasons than patenting. A series of annual dummy variables controls for factors that may affect the average values of the dependent variable over time. A dummy variable indicating female scientist allows for variations due to gender effects.

- *Accounting for periods without publication activity*: Typically scholars compare publications and patents of scientists in a given time period. However, there may be many periods where professors either do not publish or do not patent. In descriptive studies where the data is often grouped, such zero outcomes are often neglected. This may result in a bias of the estimated relationship. In the worst case, professors may not publish as they used all their time to patent in a given period. As we employ data reflecting the population of patents filed by the professors in the sample and the population of their publications, we know that they did either not patent or publish in a year for which we did not find a record in either database. Thus, we can code the value of the variable with zero for those cases. As a result, we get a panel database where the full history of patenting and publishing can be traced over time for each professor.

- *Accounting for individual fixed effects*: Possibly the most important advantage of regression analysis we suggest in this paper is the possibility to control for unobserved heterogeneity among scientists in the sense that there are star scientists that have a higher publication output than others every year and such individuals that almost never publish. Due to our panel data structure, we can make use of the time-series history of publishing for each individual over time by including individual-specific average publication activity. Such unobserved individual-specific effects are taken into account by introducing an own intercept for every individual into eq. (1):

  $$pub_{it} = \beta\ pat_{i,t-1} + f(control\ variables_{it}) + \alpha_i + \varepsilon_{it} \qquad (2)$$

  α_i, the individual-specific effect, denotes the unobserved ability of a scientist that might be caused by unobserved factors such as a better education, higher IQ, higher academic ambitions, family status etc. While descriptive studies hardly make use of such advantages stemming from the combination of cross-sectional and time-series data, the regression model presented in eq. (2) will disentangle the influence of patenting and unobserved specific skills of each researcher causing heterogeneity in average publication activity over the cross-section of scientists in the sample.

Of course, a number of advantages do not come without cost. In contrast to descriptive analyzes, we assume a specific functional form relationship between the dependent variable and its covariates. Furthermore, certain statistical assumptions on the random error term are necessary. Among others, in many regression models it is assumed that ε_{it} are normally distributed.

3 Data and Descriptive Statistics

Our analysis is based on a newly created data set that contains patent applications and publication records of professors active in Germany. The starting point is the database of the German Patent and Trademark Office (DPMA) which contains all patents filed with the DPMA and the European Patent Office (EPO) where the applicant requests patent protection in Germany from 1980 onwards. We identified all inventors by using the persons' title "Prof. Dr." and variations of that. We checked whether the names of those people appeared in the patent database without the title but with the same address in order to verify that the title field is always filled in the data. The verification of a sample of persons had shown that we can identify university professors (or professors at other higher education facilities such as polytechnical colleges) by their title with high precision. It basically never happens that inventor names appear sometimes with "Prof. Dr." (or similar title) and sometimes without on other patents. Thus, we can safely argue that this procedure delivers a listing of patents where professors are recorded as inventors. In total, we found 42,065 inventor records with professors. As there are sometimes multiple professors listed as inventors on one patent, the number of different patents with professors amounts to 36,223.

As the inventors had to be linked to publication data, we first had to identify a list of unique inventors from the identified patents, that is, we had to create a key that identifies the same person on multiple patents. This was conducted by both computer assisted text field searches and manual checks. First, we used a text field search engine on names and city of residence of the inventors (by putting a high weight on name similarity). The potential matches of identical person records on different patents were manually checked afterwards. If the text fields of last name and first name or initials and city were sufficiently similar we assigned "hits". In case the city was different, we cross-referenced with other information if the person is identical, that is, field of research, distance among cities and distinctness of names. This approach allows tracing professors who move during the observed period. Of course, there were occurrences where it was not possible to code records as identical persons. If very common names like "Müller" or "Schmidt" appeared with common first names and large or different cities we preferred to drop such inventors from the lists. In total, we discarded 6.758 patents out of 36.223 patents, where we were not able to create a unique person ID. The remaining 29.465 patents turn out to contain 6.324 different professors.

The professors who were listed as inventors on the patents were traced in the Web of Science® database of Thomson–Scientific (Philadelphia, PA, USA). We used a similar search algorithm as described above, but the fact that the patent data contain the place of residence of the inventors while the bibliographic database records the authors' institutional address made additional manual cross-referencing necessary. The high amount of required manual checking of records forced us to restrict our further analysis on the linked data to a five-year period from 1998-2002, leaving us with 10.699 different patents with 3.812 different identified professors as inventors. In total, we matched 44.509 publications to the inventors for the observed five year period.

A first look at the patenting patterns of professors shows a significant increase of patents filed over time. Figure 1 depicts the surge in patent applications by professors and the development of the total patent applications over time. The total number of patent applications increased by 137% over the period 1987-2002 with a temporary maximum in 1999.

Figure 1: Growth of Total Number of Patents Applications and the Number of Patent Applications by Professors Located in Germany; 3-year moving averages (number of patents in 1987=1)

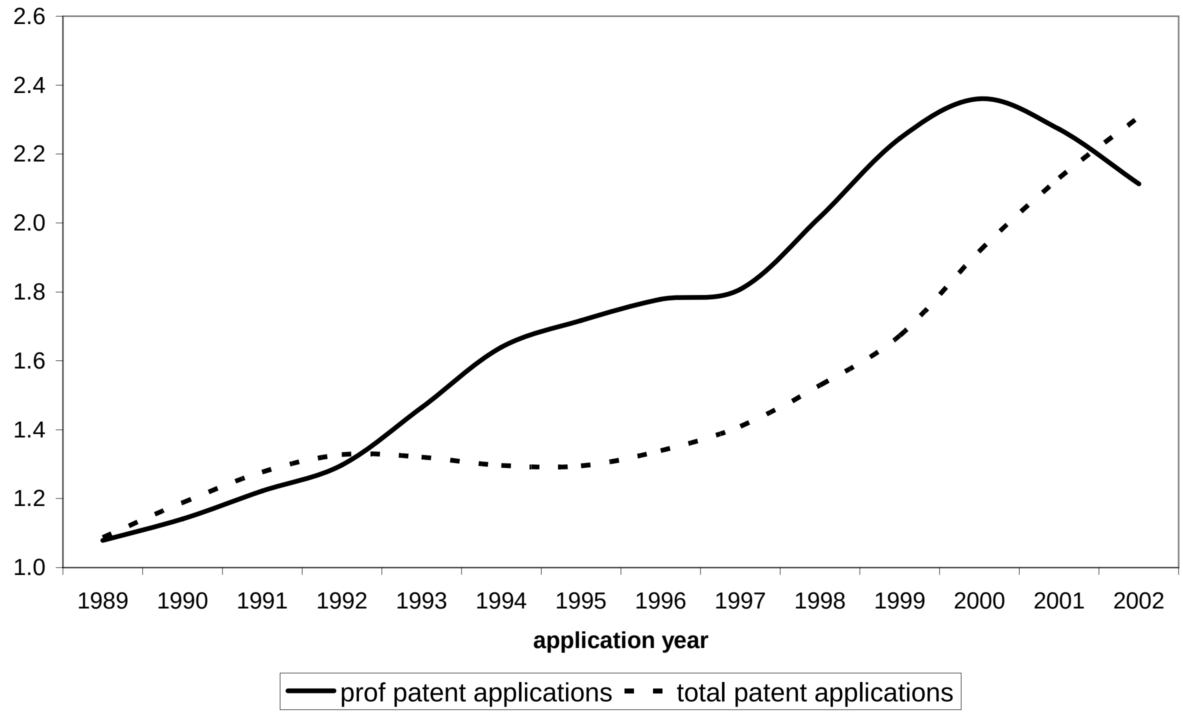
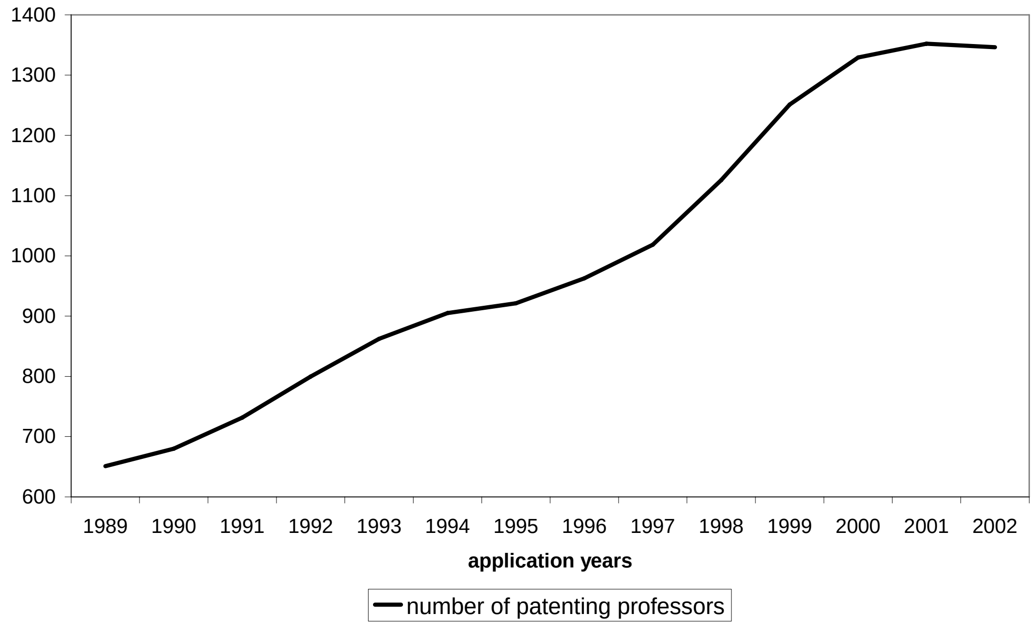


Figure 2 shows that also the number of patenting professors in Germany increased significantly over the same time period. The total increase amounts to 123%. A surge in patenting professors and scientists' patent applications at the end of the 1990s becomes apparent. This might be due to the abolishment of the "Hochschullehrerprivileg" in 2002. According to this law, professors were the only occupational group in Germany that had the right to use their scientific results for private commercialization even if the underlying research was financed by the university. The increase in patenting scientists and in patent applications might have been initiated by anticipation of the change in law.

Figure 2: 3-Year Moving Averages of the Number of Patenting Professors Located in Germany



On average, each professor in our sample applied for 3.4 patents in the period 1998-2002. As expected, the patent distribution shows a considerable skewness. The mean professors applied for 2 patents and the most active professor applied for 106 patents in the same time window.

Focusing on the publication activities of professors the distribution of activity in our sample looks similarly skew. Whereas the average professor published 14 scientific articles in the observation period, the median professors had only three publications and the most active person had 309 articles. 40% of the professors had no publication in journals covered in the Web of Science during 1998-2002.

The main fields of publication activity are chemistry and physics. More than 20% of the total publications are attributable to either one of these fields. More than 10% of the publications contribute to clinical and experimental medicine and the bioscience sector.

A look at the gender distribution of the professors shows that 97% of the patentees are male. Only 2% of patents correspond to female scientists.[3]

4 Regression Analysis

This section presents the empirical findings from regression analysis. In a first assessment, we ignore individual-specific differences in publication productivity and estimate eq (1). The first column of Table 1 presents the results for the correlation between patenting and publication output; the further columns present the estimation results for the correlation between patenting and research performance, measured as citation count, MOCR, RCR and NMRC. To account for the censoring of the endogenous variable a tobit model is estimated.[4] Our specification controls for the gender of the scientists and for time effects. Table 1 shows that there is positive, highly statistically significant correlation between publishing and patenting and also that there is a positive, highly statistically significant effect between publishing and the "quality" of research measured by citation impact. The latter effect is robust if bibliometric/technometric indicators are used as endogenous variables rather than a simple citation count showing that patenting correlates with publication activities if the citations are normalized by the number of publications (MOCR), and if the expected publication rate (RCR) and science subfield heterogeneity (NMCR) is accounted for.

Since all estimated coefficients β are positive and statistically different from zero across all estimated models, we can conclude that patenting does neither reduce scientific output nor its citation impact.

A further interesting result from our analysis is that the few female patenting scientists are more productive in terms of publishing than their male colleagues and

[3] 1% of the inventors could not be classified with respect to gender because their patent records contained either initials only or we were not able to determine whether the first name refers to a male or female person, especially in cases of foreign names.

[4] Unlike linear regression models such as ordinary least squares estimation, tobit models account for censored distributions, that is, the dependent variable includes many zeros. As a more detailed technical explanation of the estimaters used is beyond the scope of this paper, we refer the reader to further literature. Tobit models are standard econometric techniques outlined in standard textbooks such as Greene (2003) or Verbeek (2000), among many others.

that they also produce higher publication quality in terms of citation-based measures and weighted citation-based measures, all else constant. There is weak evidence for time effects.

Table 2 shows the results from a panel tobit regression as shown in eq (2). This specification explicitly accounts for unobserved individual-specific heterogeneity in research productivity.[5] Note that the gender dummy is now included in the individual-specific effect along with other unobservable factors as education, ability, and family status and the like. The positive correlation between patenting and publications outcome and quality is still highly significant for all specifications. The estimated variance of α_i shows that there are statistically significant individual-specific effects. The coefficient ρ in Table 2 indicates how much of the total variance of the estimation is due to the variation over the cross-section, that is, to what extent unobserved individual-specific effects explain the variation of the dependent variable in the total sample. The coefficient is the percent contribution to total variance. If $\rho = 0$, the estimates of eqs. (1) and (2) would have been identical. As becomes clear, it is very important to account for such effects whenever possible, as a part of such effects may otherwise misleadingly be attributed to other characteristics such as patenting. This can be seen in the fact that the estimation of eq. (1) reports higher coefficient values for β than that of eq. (2). If we would not have accounted for unobserved individual skills, α_i, the effect of patenting would have been overstated.

[5] These regressions amount to the estimation of so-called „random effects tobit models". See Wooldrige (2002) for further details on the estimator.

Table 1: Effects of Patenting on Research Performance: Results from Pooled Tobit Regression

	Publication outcome	**Citation impact**			
Endogenous variable	**# publications**	**# citations**	**MOCR**	**RCR**	**NMCR**
	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)
# patent applications [β coefficient as in eq. (1)]	0.53***	4.23***	0.31***	0.03***	0.07***
	(0.05)	(0.44)	(0.05)	(0.01)	(0.01)
female	1.17**	15.50***	2.21***	0.16**	0.35***
	(0.53)	(5.17)	(0.54)	(0.07)	(0.11)
y1	0.86***	4.62*	0.45*	0.03	0.13**
	(0.27)	(2.64)	(0.27)	(0.03)	(0.05)
y2	0.56**	2.36	0.17	0.01	0.07
	(0.27)	(2.64)	(0.28)	(0.03)	(0.05)
y3	0.38	1.13	-0.03	0.00	0.02
	(0.27)	(2.65)	(0.28)	(0.03)	(0.05)
y4	0.26	4.49*	0.37	0.00	0.08
	(0.27)	(2.64)	(0.28)	(0.03)	(0.05)
constant	-2.12***	-38.75***	-3.19***	-0.46***	-0.55***
	(0.20)	(1.98)	(0.21)	(0.03)	(0.04)
# observations			15,675		
# professors			3,135		
Censored obs. (i.e. dependent variable = 0)			8,140		
χ^2 test on joint significance of coefficients	101.69***	65.03***	69.85***	27.60***	57.87***

Notes: *** (**,*) refers to a significance level of 1% (5, 10%).

Table 2: Effects of Patenting on Research Performance: Results from Random Effects Panel Tobit Regression

	Publication outcome	Citation impact			
Endogenous variable	**# publications**	**# citations**	**MOCR**	**RCR**	**NMCR**
	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)
# patent applications [β coefficient as in eq. (2)]	0.05*** (0.02)	0.87*** (0.21)	0.08** (0.03)	0.01*** (0.01)	0.02** (0.01)
y1	0.74*** (0.10)	3.09*** (1.13)	0.39** (0.18)	0.03 (0.03)	0.13*** (0.04)
y2	0.58*** (0.10)	1.93* (1.14)	0.13 (0.18)	0.00 (0.03)	0.07* (0.04)
y3	0.46*** (0.10)	1.44*** (1.14)	-0.05 (0.18)	0.00 (0.03)	0.02 (0.04)
y4	0.32*** (0.10)	3.51*** (1.14)	0.40** (0.18)	0.00 (0.03)	0.09** (0.04)
constant	1.03*** (0.10)	11.61*** (0.95)	0.53*** (0.15)	-0.46*** (0.02)	-0.53*** (0.03)
Var(α_i)	8.11*** (0.08)	71.90*** (0.91)	0.69*** (0.10)	0.61*** (0.01)	1.51*** (0.02)
ρ (= contribution of panel variance component, α_i, to total variance)	0.87*** (0.00)	0.82*** (0.00)	0.59*** (0.01)	0.30*** 0.01	0.64*** (0.01)
# observations			15,675		
# professors			3,135		
Censored obs. (i.e. dependent variable = 0)			8,140		
χ^2 test on joint significance of coefficients	68.40***	28.81***	15.32***	7.43***	20.10***

Notes: *** (**,*) refers to a significance level of 1% (5, 10%).

5 Conclusions

In the context of an ongoing debate on patenting activities of university scientists our analysis of a large sample of professors active in Germany provides empirical evidence on whether the commercialization of discoveries by academic inventors has negative implications on their publication activities.

The present paper features a number of novel aspects when compared to the existing literature. With regard to science policy, we find the important result that patenting is not negatively correlated with scientific output for a large sample of German professors. Although this result has been found in previous literature, this study is the first that confirms such findings for the German academic landscape. Thus, recent policy efforts to make universities more “entrepreneurial” do not seem to harm the production of science at a first glance, at least when patenting is under consideration - neither in terms of amount nor in quality of publications as measured through several bibliometric citation indices. Instead of supporting the fear that the commercialization of inventions reduces research efforts, we find that professors rather appear to be knowledge integrators.

Besides policy implications, we also advance the methodology in this field of the literature. While economic literature typically only counts publications or weights those with citations, we employ more sophisticated bibliometric indicators that adjust for journal quality and idiosyncrasies of the different science fields. In turn, we also suggest borrowing from econometrics in the field of bibliometrics. While dominated by descriptive research, we suggest making use of multivariate regression methods that account for several data peculiarities as outlined in section 3. Most important is possibly the construction of panel data sets allowing to trace individual scientist over time, and thus enabling the analyst to control for unobserved individual-specific attributes, such as education, intellectual brilliance, and other factors that may affect the variables of interest.

The policy implications should, of course, be interpreted carefully. Patenting is only one aspect of an entrepreneurial university. Further, our present study is only a first step in this line of research. While we find that patenting is generally positively correlated with publication activity, it would be desirable to conduct more research on the heterogeneity of patents. There may be large differences between patents that are based on basic research and which are owned by the university compared to patents owned by corporations stemming from contract research that the scientists engaged in. Further database developments will allow such analyzes in the future.

References

Agrawal, A., Henderson, R. (2002), Putting patents in context: Exploring knowledge transfer from MIT, *Management Science* 48(1), 44-60.

Azoulay, P. Ding, W. Stuart, T. (2006), *The impact of academic patenting on the rate, quality and direction of (public) research*, NBER working paper 11917, Cambridge, MA.

Braun, T., Glänzel, W. (1990), United Germany: The new scientific superpower? *Scientometrics* 19(22), 513.521.

Breschi, S., Lissoni, F., Montobbio F. (2006), The scientific productivity of acvademic inventors: New evidence from Italian data, *Economics of Innovation and New Technology*, forthcoming.

Glänzel, W., Meyer, M. (2004), Patents cited in the scientific literature: An exploratory study of 'reverse' citation relations in the Triple Helix, *Scientometrics* 58(2), 415-428.

Glänzel, W., Moed, H.F. (2002), Journal impact measures in bibliometric research, *Scientometrics* 53(2), 171-193.

Greene, W.H. (2003), *Econometric analysis*, 5th ed., Prentice-Hall: Upper Saddle River.

Hicks, D. (2000), 360 Degree linkage analysis, *Research Evaluation* 9(2), 133-143.

Holmes A., Oppenheim C. (2001), Use of citation analysis to predict the outcome of the 2001 research assessment exercise for unit of assessment (UoA) 61: library and information management, *Information Research* 6(2).

Markiewicz, K.R., DiMinin, A. (2005), *Commercializing the laboratory: faculty patenting and the open science environment*, Working Paper, University of California.

Merton, R.K. (1973), The normative structure of science, In: R.K. Merton (Ed), *The sociology of science: theoretical and empirical investigations*, Chicago, IL: The University of Chicago Press.

Meyer, M. (2000), Does science push technology? Patents citing scientific literature, *Research Policy* 29(3), 409-434.

Meyer, M., (2006), Knowledge integrators or weak links? An exploratory comparison of patenting researchers with their non-inventing peers in nano-science and technology. In: P. Ingwersen and B. Larsen (eds.), *Proceedings of ISSI 2005 – the 10th International Conference of the International Society for Scientometrics and Informetrics*, Stockholm, Sweden, July 24-28, 2005, Karolinska University Press, 34-44.

Murray, F. (2002), Innovation as co-evolution of scientific and technological networks: Exploring tissue engineering, *Research Policy* 31(8-9), 1389-1403.

Narin, F., Noma E. (1985), Is technology becoming science? *Scientometrics* 7(3-6), 369-381.

Noyons, E.C.M., Van Raan, A.F.J., Grupp, H., Schmoch, U. (1994), Exploring the science and technology interface – inventor author relations in laser medicine research, *Research Policy* 23, 443-457.

Rosenberg, N. (1998), Chemical engineering as a general purpose technology. In: E. Helpman (Ed), *General Purpose Technologies and Economic Growth*, Cambridge: MIT Press, 167-92.

Schubert, A., Glänzel, W., Braun, T. (1983), Relative Citation Rate: A new indicator for measuring the impact of publication. In: Tomov D., Dimitrova, L. (Eds), *Proceedings of the 1st National Conference with International Participation on Scientometrics and Linguistic of the Scientific Text*, Varna, 80-81.

Scotchmer, S. (2004), *Innovation and incentives*, Cambridge, MA: MIT Press.

Stephan, P., Gurmu, S., Sumell, A.J., Black, G. (2006), Who's patenting in the university? *Economics of Innovation and New Technology*, forthcoming.

Stephan, P., Levin, S. (1992), *Striking the mother lode in science: The importance of age, place and time*, Oxford University Press: New York, NY.

Stern, S. (2004), Do scientists pay to be scientists? *Management Science*, 50(6), 835-853.

Thursby, J.G., Thursby, M.C. (2002). Who is selling the ivory tower? Sources of growth in university licensing." *Management Science* 48 (1), 90-104.

Thursby, M.C., Thursby, J.G., Mukherjee S. (2005). Are there real effects of licensing on academic research? A life cycle view, NBER Working Paper 11497, Cambridge, MA.

Van Looy, B., Callaert, J., Debackere K. (2006), Publication and patent behaviour of academic researchers: Conflicting, reinforcing or merely co-existing? *Research Policy* 35, 596-609.

Verbeek, M. (2000), *A* guide *to modern econometrics*, Chichester: John Wiley & Sons.

Wooldridge, J.M. (2002), *Econometric analysis of cross-section and panel data*, Cambridge: MIT Press.