Academic R&D and University Patents

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Abstract

Many studies have shown indirect effects of academic research by linking academic research to firm patents. However, since the Bayh-Dole act, universities are allowed to patent inventions that were funded by federal money and to retain the royalties that these patents generate. As a consequence, universities now are interested in protecting their 'profitable' discoveries, just like any commercial firm doing R&D. In this paper, we apply the econometric techniques traditionally used to estimate the patent production function of firms on data for American universities. We find that more money spent on academic research leads to more university patents, with elasticities that are similar to those found for commercial firms.

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1) Introduction

Each year, several billions of US$ are spent on academic research. It is not surprising then that several economists have searched for convincing evidence of the results of these ‘investments’.

Some authors have highlighted the ‘academic’ effects of R&D expenditures: Adams and Griliches (1996-1998) for example, relate the total number of papers and the number of citations of university departments to the amount of research expenditures, in order to find out whether there are decreasing, increasing or constant returns to scale in the production of academic articles.

Others have focused on the effects on the ‘real’ or non-academic world. Such ‘real’ effects of academic research have been revealed by ‘economic-geography’-studies that show how regions with universities differ from regions without universities. The most influential of these is probably Jaffe’s study (1989) showing how academic R&D expenditures increase the number of patents granted to firms. His results have been extended to counts of ‘innovations’ by Acs et al. (1991) and Anselin et al. (1997). In a similar spirit, Beeson and Montgomery (1993) looked at the effect of universities’ R&D expenditures on the local labor-markets and Bania et al (1993) linked university research to the creation of new firms.

As an alternative to this kind of studies that stress the geographic coexistence, some authors have sent questionnaires to firms in which they asked how many of the firms’ innovations could not have been developed, or only with a substantial delay, in the absence of academic research. Mansfield (1995,1998) reports that for a sample of big US firms, about 10% of the firms’ innovations are made possible by academic research. Beise and Stahl (1999) find a similar number using a large number of German firms.

The above studies have in common that, rather than searching for any direct proofs, they try to find spillover effects of academic research. The 1980 Bayh-Dole act, however, allows universities to patent inventions that were funded by federal money and to retain the royalties that these patents generate. Hence, while before the universities had little incentives to pursue the patenting of their research results, they now can establish ownership-rights and generate a new source of income[1]. Hence, universities now should be interested in protecting their ‘profitable’ discoveries (just like any commercial firm doing R&D) which makes it possible to look for direct real effects of academic R&D.

2) The relationship between patents and R&D

Such direct effects can be revealed by estimating the relationship between a university’s R&D expenditures and its number of patents. The same relationship but at the ‘commercial firm’-level has generated an extensive literature. In a survey article about patents, Griliches (1990) notes[2]:

“A major conclusion, emphasized by Pakes and Griliches, is that there is quite a strong relationship between R&D and the number of patents received at the cross-sectional level, across firms and industries… The same relationship, though still statistically significant, is much weaker in the within-firms time series dimension…Nevertheless, the evidence is quite strong that when a firm changes its R&D expenditures, parallel changes occur also in its patent numbers.” And further: “The evidence [of decreasing returns] is suggestive but not conclusive”.

More recent studies (Cincera (1997), Crepon and Duguet (1997a -1997b), with more and more refined econometric methods, tend to confirm the above findings.
In this paper, we will use the same econometric techniques that are used in the literature about firms such that it is possible to compare our estimates for universities with those found for commercial firms[3].

[1] Mowery and Ziedonis (1999) note that before Bayh-Dole, universities could negotiate ‘Institutional Patent Agreements’ with the federal funding agencies.
[2] This survey also looks at the drawbacks of patent-data: not all inventions are patented, patents differ in quality and so on.

3) Research about university patenting

While much has been written on the impact of the 'entrepreneurial' spirit on the academic world (for example, Powell and Owen-Smith (1998) or Argyres and Liebeskind (1998)), large-scale empirical studies on the patenting behavior of universities are rare. We are aware of three studies: first, Henderson et al. (1998) compare the patents granted to US universities between 1965 and 1988 with a random sample of US patents. They found that universities tend to be more interested in drugs and medical technologies and less interested in mechanical technologies. They further showed that until 1982 or 1983 university patents used to receive more citations and citations from more different patent classes. However, for the more recent periods, there does not seem to be a 'quality' difference anymore, between university patents and patents granted to other organizations.

Two other papers look, like us, at the relationship between money and university patents. First, there is work by Foltz et al. (2000) that focuses on the production of agricultural biotechnology patents. Using a cross-section of AUTM patent data, they estimate a negative binomial model of the patent production function of 142 universities, using the number of 'Office of Technology Transfer (OTT)' staff, the number of OTT staff squared, government-funded R&D expenditures, institutionally funded R&D expenditures, industry-funded R&D expenditures and a reputational ranking as dependent variables. Next to the staff and rank variables, only government supported R&D seem to matter.

Second, Payne and Siow (1999) use OLS and TOBIT to estimate the link between federal R&D funds and patents for 58 universities and find a positive relationship.

However, for several reasons their results are difficult to compare with those of the firm-patents literature. First, it is unlikely that the reputation of the university is unrelated to the universities R&D expenditures, which implies that the Foltz et al. (2000) estimate gives only the direct effect of R&D on patents (see Coupé (2000) for the relationship between R&D expenditures and the reputational ratings). Second, there is a clear sample selection: the 142 AUTM universities are mainly the bigger universities as are the 58 universities used by Payne and Siow (1999). We'll use all

[3] Jaffe and Lerner (1999) investigate similar issues for the laboratories of the US Department of Energy.

454 universities for which the NSF recorded positive R&D expenditures in 1990. Third, neither the AUTM patent data nor the data used by Payne and Siow (1999) are counts by year of application (in contrast to the data we will use). Traditionally, one uses counts by year of application as this time-period should be closest to the date of discovery and because the time between the application and the issuing of a patent will differ over patents[4]. With these extensions, we follow the tradition for estimating patent production functions for firms.

In addition, we will control for differences in the quality of university patents by using citation counts. We will also split up the total expenditures and the total patents in six categories that represent specific disciplines (following the methodology of Jaffe (1989)). This will not only allow us to estimate the patent-R&D relationship for different groups of patents but pooling these observations will also make it possible to control for university-specific effects.

4) Data

a) Academic R&D

For R&D expenditures, we use data from the NSF 'Survey of Research Expenditures'[5]. In this survey, "*Item 2 requested total and Federally financed current fund expenditures for separately budgeted R&D by detailed S&E field*". Under "*Current fund separately budgeted research and development (R&D) expenditures* ", the following is understood: " *Separately budgeted research and development (R&D) expenditures include all funds expended for activities specifically organized to produce research outcomes and commissioned by an agency either external to the institution or separately budgeted by a unit of the organization. Included are expenditures for research equipment purchased under research project awards from current fund accounts. Also included are research funds for which an outside organization, educational or other, is a subrecipient. Excluded are training grants, public service grants, demonstration grants, and departmental research expenditures that are not separately budgeted. Also excluded are any R&D expenditures in the fields of education, law, humanities, music, the arts, physical education, library science, as well as other non-science fields. Current funds are expenditures of funds*

[4] Note however, that Payne and Siow (1999) use panel data and IV-estimation.
[5] NSF: National Science Foundation

available for current operations. Such expenditures include all unrestricted gifts and restricted current funds to the extent that such funds were expended for current operating purposes."

These data have been used by all of the above-cited 'economic geography'-studies. None of these explicitly mentioned, however, that, in spite of the fact that the NSF uses the heading 'total R&D expenditures', this is not necessarily equal to the **total** expenditures for research as it only consists of separately budgeted research. To the extent that for example the salary of professors is considered as an instructional cost (the non-separately budgeted research expenditures are indeed counted under this heading by the NSF), it understates the real expenditures[6].

One could argue that smaller universities will have less accurate accounting practices (for example salaries can be considered completely as instruction costs even if the faculty is doing some research) which would bias the results towards decreasing returns to scale. Note that a similar question has been raised with respect to firm-level data: "Small firms are likely to be doing relatively more informal R&D, reporting less of it, and hence providing the appearance of more patents per reported R&D dollar (Griliches, 1990)[7]".

Anyhow, Goldberger et al (1995) write: 'this is a very carefully conducted survey with attention given to the recordkeeping process at the institution to ensure consistency from one year to the next."

[6] A recent NSF (issue brief 99-317) report (foot)notes: 'It does not include departmental research, and thus excludes funds-notably for faculty salaries- in cases where research activities are not separately budgeted'. And further: 'Some of the growth in institutional R&D funds may be due to accounting changes, including both a shift of departmental research to separately budgeted research and increased institutional ability to calculate unreimbursed indirect costs, including mandatory and voluntary cost sharing'.

[7] The firm-data that have been used for the United States (HHG(1984), HGH(1986),…) are from the Bureau of Census- NSF survey of R&D expenditures by manufacturing firms. Our data come from a similar survey set up by the NSF and covering the 'Academic' R&D.

b) University Patents[8]

Patent counts per university are constructed by merging two databases. From the USPTO we obtained a database with patent-numbers and assignee-names of the patents used for the USPTO publication ‘ US Universities and Colleges, Utility Patent Grants, 1969-1998’[9]. These patent-numbers were then selected from a database containing information like citations and patent class, for all US patents issued before 1995. For the university patents, about 95% of the patents are granted within the four years following the application-year[10]. Therefor, we focus on patents applied for in 1990. Similarly, we’ll take the citations to patents applied for in 1990. As this implies that the period over which the patents can receive a citation is fairly small (and truncated), we construct an ‘expected’ number of citations. For this, we take the median number of citations over a period of 5 year, received by patents applied for by the university between 1982 and 1986. Hence, for a university patent applied for in 1986, we consider the citations by US patents applied for in the period 1986-1990 (later years would be incomplete as the patenting process takes 5 years). By taking citation counts rather than patent counts, we control for quality differences between patents[11].

c) Some descriptive statistics.

Table 1: descriptive statistics.

	Mean	Std Dev	Minimum	Maximum	variance to mean
Patents	3.11	9.40	0	103.00	28.38
Citations	3.25	10.85	0	133.00	36.23
Expected citations	4.65	18.62	0	206.00	74.56
Log R&D	8.32	2.50	2.39	14.32	

In 1990, the average university did three patented inventions and its 1990 patents were then cited about 3 times. Not surprisingly, there are substantial differences between universities. The Massachusetts Institute of Technology for example leads

[8] One should also be aware of the fact that some branch campuses have one common ‘assignee’ , f.e. the different universities of the University of California all have ‘the Regents of the University of California’ as assignee.
[9] USPTO: United States Patent and Trademark Office.
[10] Based on university patents applied for in the period 1980-1985: 95% of the patents that are granted within 10 years are granted within 5 years. Griliches (1990) similarly notes that for the applications in 1980, about 97% of those that will eventually be granted a patent, had received a patent by 1984.

both the ranking of the number of patents (103) and the ranking of the number of citations (133). But as one can notice from table 2 several universities did not receive even one patent in 1990.

Table 2: the distribution of the number of patents and citations over universities.

	Patents: #univ	Cites: #univ	Exp. Cites: #univ
0	317	341	357
0<>5	66	47	27
6<>10	35	27	25
11<>15	11	12	5
16<>20	10	9	16
21+	16	19	26

Note that 70% of the universities with positive R&D have zero patents. This might seem a huge number but in the patent literature, this is not that exceptional: for example, Crepon and Duguet's (1997) sample consists of 451 French manufacturing firms of which 73% did not apply for a patent and Licht and Zoz (1998) have a similar percentage in a sample of 1685 German firms.

For each university patent, we also know to which patent class it belongs. Jaffe (1986) divides these classes over five groups, which Jaffe (1989) then links to academic disciplines. Using the most recent classification of Jaffe (which has six classes), we will estimate a cross-section by 'discipline'[12]. Table 3 gives for each discipline the number of patents since 1969, the part of the university patents in the total number of US patents (period 1969-1998), the number of university patents per billion of US$ in 1990 and the average number of citations per patent[13].

[11] See Hall et al. (2000) for a survey about the use of patent citations.
[12] The mapping of Jaffe's classification of patents into NSF disciplines is given in the Appendix.
[13] The second and the third column are based on USPTO (1998) while the last column is computed on the basis of citations by patents awarded up to 1994.

Table 3: the number of patents by disciplinary groups.

Disciplines	#patents 69-98	% of total US patents	Patents per Billion $	#Cit/Pat
Chemical	6817	1.39	372	0.99
Computers & Communications	1639	0.75	217	1.22
Drugs & Medical	9532	5.35	44	0.75
Electrical & Electronic	5094	1.15	138	1.38
Mechanical	1757	0.33	45	1.6
Other	1686	0.31	31	0.87

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One can see that universities hold mainly (also in the absolute) 'Drugs and Medical' patents. Still, the part of universities in the total number of patents is extremely small. The 'Drugs and Medical' patents-group also seems to be one of the more 'expensive' ones: for each billion dollar of separately budgeted R&D, universities are granted about 44 patents. For the same amount of money, they 'buy' 217 'Computer' patents or 372 'Chemical' patents. Finally, 'Mechanical' university patents are the patents that, on average, are most often cited.

5) Econometrics[14].

a) University-level data

To take into account the special nature of patent-data (they are count data), economists tend to use Poisson regressions. In these models, it is assumed that the chance of having Y patents is defined as following

$$P(Y|X)= \exp(-\lambda)*\lambda^{Y} / Y!$$

where $E[Y|X]=Var[Y|X]= \lambda=\exp(\beta X)$, with X containing the explicative variables, in this case, a constant (β_0) and the R&D expenditures (β_1).

The Poisson distribution supposes that the conditional mean and the conditional variance are equal. To relax this assumption, one traditionally uses the negative binomial distribution (Negbin). The most comprehensive specification of such models is the Negbin_k model where the variance is:

[14] R&D expenditures are in 1998 dollars and in logarithms. In our regressions, we'll use Eicker-White standard errors which are heteroskedasticity-consistent.

$Var[Y|X]=E[Y|X]*(1+\alpha*E[Y|X]^{1-k})$

The $Negbin_k$ model includes both the $Negbin_I$ (k=1) model and the $Negbin_{II}$ (k=0) model.

As mentioned above, the Poisson-model assumes equivalence between the conditional mean and the conditional variance. The raw data, however, have a variance-mean ratio of about 28 (88/3.1) which makes it likely that this hypothesis will be violated. To test whether the data are overdispersed, we used a regression-based test, a Wald-test and a LR-test as described in Cameron and Trivedi (1997). The three tests all reject the Poisson-model in favor of both $Negbin_I$ and $Negbin_{II}$. To discriminate between the latter two models, we use the Vuong-test statistic for non-nested models Its value, 1.7, points in the direction of accepting $Negbin_I$ as does the $Negbin_k$ model where k is significantly bigger than 0 but close to 1.

Table 4: Poisson and Negative binomial estimates.

	Poisson	$Negbin_I$	$Negbin_{II}$	$Negbin_k$
β_0	-9.75	-9.17	-10.8	-10.3
	(0.7)	(0.52)	(0.73)	(0.81)
β_1	1.02	0.97	1.1	1.06
	(0.06)	(0.04)	(0.06)	(0.07)
α		5.2	0.87	3
		(1.1)	(0.17)	(0.76)
K				0.72
				(0.14)
Loglik.	-761	-501	-520	-499

ML-estimates with Eicker-White standard errors between brackets. All coefficients statistically significant from zero at the 1%-level.

Next we consider the interpretation of the coefficients. As our R&D variable is in logarithmic form, coefficients give elasticities. Our estimates point in the direction of constant returns to scale: an increase of one percent in R&D expenditures will increase the number of granted patents by one percent.

In table 5, we try to control for quality differences and use the number of times the patents of university X (and applied for in 1990) have been cited rather than a simple patent count. In a third specification, we use the ‘expected’ number of citations (as explained above).

Table 5: citation production functions.

	Citations		Expected Citations	
	Poisson	$Negbin_I$	Poisson	$Negbin_I$
β_0	-9.7	-9.26	-10	-9.8
	(0.95)	(0.67)	(0.81)	(0.7)
β_1	1.02	0.98	1.07	1.06
	(0.08)	(0.06)	(0.07)	(0.05)
α		12.3		26.3
		(2.3)		(6.7)
Loglik.	-1033	-476	-1720	-480

ML-estimates with Eicker-White standard errors between brackets. All coefficients statistically significant from zero at the 1%-level.

Controlling for quality only marginally influences our results. The coefficients of the citation count model are nearly identical to those of the patent count model. The 'expected' citation model has somewhat bigger coefficients though never to such an extent that constant returns to scale can be rejected.

Table 6 compares the observed counts with the predicted counts for the different patent count models. The predicted counts are obtained by using first the independent variable-values for each observation to calculate the probabilities of observing 0,1,… patents and then summing over the individual observations (see Dione and Vanasse (1992)).

Table 6: # of firms with X patents, observed and predicted

	Observed	Poisson	$Negbin_I$	$Negbin_{II}$	$Negbin_k$	Hurdle	ZIP
0	317	270.9	316.1	301.1	314.3	317.0	317.7
1	28	48.9	23.2	43.8	15.9	15.5	16.5
2	10	22.5	15.2	20.5	6.0	11.9	11.1
3	10	15.1	11.7	13.3	2.9	10.0	9.2
4	9	11.9	9.6	9.8	1.5	8.9	8.4
5	9	10.2	8.2	7.6	0.9	8.3	8.0
6	9	8.9	7.0	6.2	0.5	7.9	7.7
7	4	7.9	6.2	5.2	0.3	7.5	7.4
8	10	7.0	5.4	4.4	0.2	7.0	7.0
9	4	6.1	4.8	3.8	0.1	6.5	6.6
10	8	5.4	4.3	3.3	0.1	6.0	6.1

The table illustrates another problem of the Poisson-regression: the excess-zero problem. Line 2 of the above table shows that while we observed 317 universities that had no patent, the Poisson-model only predicts 271 zero observations. One can see that allowing for overdispersion through $Negbin_I$ or $Negbin_k$ already solves the problem. We also experimented with the Hurdle model and the Zero-inflated model (ZIP - see Crepon and Duguet (1997) and Licht and Zoz (1998) for applications on firm-data) which lead to similar conclusions.

We further ran some other regression as robustness checks. Using a weighted function of lagged values (25% of the 1989 R&D, 50 % of the 1988 R&D, 25% of the 1987 R&D) like in Adams and Griliches (1996) or using the sum of the R&D in the previous five year did not change our results. We also tried to see whether there is a significant difference between public and private universities. No significant difference could be found (in 1990, public universities have, on average, less patents but also less R&D expenditures).

b) Discipline-level data

We now focus on the disciplinary level and estimate patent production functions and citation production functions for six disciplines.

Table 7a: Poisson and $Negbin_k$: Chemical, Computers and Drugs patents.

	Chemical		Computers		Drugs	
	Poisson	$Negbin_k$	Poisson	$Negbin_k$	Poisson	$Negbin_k$
β_0	-8.1	-8.2	-5.9	-6.7	-9.7	-9.6
	(0.56)	(0.56)	(0.74)	(1.05)	(0.83)	(0.8)
β_1	1.04	1.05	0.7	0.81	0.98	0.98
	(0.06)	(0.06)	(0.09)	(0.14)	(0.07)	(0.07)
α		1.15		2.9		2.05
		(0.36)		(0.9)		(0.56)
k		0.86		0.45		0.87
		(0.15)		(1.2)		(0.12)
Loglik.	-323	-291	-184	-135	-378	-300
#obs.	354	354	239	239	406	406
#obs>0	110	110	44	44	99	99

ML-estimates with Eicker-White standard errors between brackets. All coefficients statistically significant from zero at the 1%-level.

Table 7b: Poisson and Negbin$_k$: Electrical, Mechanical and Other patents.

	Electrical		Mechanical		Other	
	Poisson	Negbin$_k$	Poisson	Negbin$_k$	Poisson	Negbin$_k$
β_0	-7.1	-7.4	-8.3	-8.4	-6.6	-6.7
	(0.84)	(0.61)	(1.2)	(1.32)	(0.57)	(0.58)
β_1	0.84	0.87	0.85	0.86	0.64	0.64
	(0.09)	(0.07)	(0.13)	(0.14)	(0.06)	(0.06)
α		1.88		1.4		0.76
		(0.53)		(0.26)		(0.32)
K		0.26*		0.83		0.88
		(0.18)		(0.38)		(0.31)
Loglik.	-327	-246	-166	-144	-193	-83.5
#obs.	330	330	260	260	385	385
#obs>0	81	81	46	46	58	58

ML-estimates with Eicker-White standard errors between brackets. All coefficients statistically significant from zero at the 1%-level, except *.

For Chemical and Drugs patents, we find elasticities that are close to what we found on the university level: an increase of one percent in the funds for these disciplines increases patents by one percent. For four out of six disciplines, we find elasticities that are smaller than those we estimated for the university level. But only for the 'Other' category, we can reject the constant returns to scale hypothesis: a one percent increase in funds will increase patents by 0.6 percent.

Next, we estimate the citation-production function on the disciplinary level.

Table 8a: Poisson and Negbin$_k$: Chemical, Computers and Drugs patent citations.

	Chemical		Computers		Drugs	
	Poisson	Negbin$_k$	Poisson	Negbin$_k$	Poisson	Negbin$_k$
β_0	-8.7	-8.7	-6	-5.5	-8	-7.2
	(1)	(0.99)	(0.83)	(0.69)	(0.93)	(1.5)
β_1	1.10	1.10	0.74	0.68	0.81	0.74
	(0.11)	(0.11)	(0.11)	(0.08)	(0.08)	(0.13)
α		5.3		8.5		8*
		(1.1)		(2.8)		(4.3)
K		0.89				1.46
		(0.12)				(0.44)
Loglik.	-419	-259	-251	-127	-433	-257
#obs.	354	354	239	239	406	406
#obs>0	74	74	31	31	72	72

ML-estimates with Eicker-White standard errors between brackets. All coefficients statistically significant from zero at the 1%-level.

Table 8b: Poisson and $Negbin_k$: Electrical, Mechanical and Other patent citations.

	Electrical		Mechanical		Other	
	Poisson	$Negbin_k$	Poisson	$Negbin_k$	Poisson	$Negbin_k$
β_0	-7.6	-7.9	-10.4	-10.8	-6.7	-6.3
	(1.06)	(0.9)	(1.9)	(1.89)	(0.81)	(0.58)
β_1	0.92	0.95	1.11	1.14	0.63	0.59
	(0.11)	(0.1)	(0.2)	(0.19)	(0.08)	(0.06)
α		7.22		7.3		2.3
		(1.42)		(1.9)		(1)
K		0.68		0.5		1.31
		(0.12)		(0.19)		(0.48)
Loglik.	-454	-232	-280	-135	-205	-143
#obs.	330	330	260	260	385	385
#obs>0	58	58	31	31	33	33

ML-estimates with Eicker-White standard errors between brackets. All coefficients statistically significant from zero at the 1%-level.

In addition to the ‘Other’ category, we now also find decreasing returns to scale in the ‘Drugs’ category and the ‘Computers’ category. The coefficients of the other disciplines, however, are bigger in the citation-regression than in the patent-regression. Note that Adams and Griliches (1996) found constant returns to scale on the university level but decreasing returns on the disciplinary level for the production of scientific articles. One can explain this phenomenon either by a misclassification of the R&D expenditures, or by spillovers between the different parts of a university.

Next we pool the six disciplines, using those 106 universities that have expenditures in each of the categories and received at least one patent. The advantage of this is that it allows us to use fixed university effects: if big spenders tend to have a Technology Transfer Office and this office is effective in turning inventions into patents, then we’ll get a positively biased coefficient on the R&D variable. Including university dummies, however, would capture such an effect. At the same time, we get rid of the effects of differences in accounting practices.

Table 9: the results of the pooled Poisson regression: patent counts.

	Patent Counts				
	Poisson				Negative Binomial
β_0	-4.2 (0.46)	-	-	-	-
β_1	0.52 (0.05)	0.7 (0.06)	0.28 (0.04)	0.28 (0.05)	0.3 (0.11)
DiscDum	NO	YES	NO	YES	YES
UniDum	NO	NO	YES	YES	YES
Loglik	-1413	-1185	-1035	-867	-860
#obs	636	636	636	636	636

ML-estimates with Eicker-White standard errors between brackets. All coefficients statistically significant from zero at the 1%-level.

Table 10: the results of the pooled Poisson regression: citation counts.

	Citation Counts				
	Poisson				Negative Binomial
β_0	-3.3 (0.48)	-	-	-	-
β_1	0.44 (0.05)	0.68 (0.08)	0.21 (0.048)	0.34 (0.08)	0.37 (0.08)
DiscDum	NO	YES	NO	YES	YES
UniDum	NO	NO	YES	YES	YES
Loglik	-1819	-1553	-1264	-867	-860
#obs	558	558	558	636	636

ML-estimates with Eicker-White standard errors between brackets. All coefficients statistically significant from zero at the 1%-level.

The pooling of the disciplines clearly points towards decreasing returns to scale. Controlling for disciplinary differences does increase the elasticity somewhat but constant returns still can be rejected. The dummies of the individual disciplines further show that, for a given amount of money, 'Chemistry' is the most productive discipline, with about 2 times the number of patents of the "Electrical" category and of the "Computer Sciences" category. Then follow "Drugs" (4 times), "Mechanical" (6 times) and "Other" (7.5 times).

Allowing for university effects has the opposite effect: it decreases the sensitivity to R&D to 0.3. Note further that the university-effects cover a wide range: the university with the highest effect (MIT) produces 60 times more patents, with the same amount of money, than the one with lowest effect.

Combining the university and the disciplinary effects finally shows that a one percent rise in expenditures leads to 0.3 percent more patents. Using citations rather than patents leads to similar results: a one percent rise in expenditures leads to a 0.34 percent increase in the number of citations.

6) Some ideas for future research

Empirical studies about university patenting in Europe seem to be nonexistent[15]. Janssens (1996), however, studies extensively the laws governing employee and university inventions in several European countries. She finds that in Germany, Finland, Sweden and Denmark, the inventions of university scientists are considered to be the property of the scientist, while in the Netherlands, Italy, Portugal, Austria, France, Spain, the UK and Greece, the property rights reside by the university. Hence, simple counts of the patents owned by European universities will be of great interest and could shed some light about the effects of ownership on the propensity to patent (though it will be difficult to discover patents with university origins when the assignee is not the university).

Further, for the US, both data on patents and data on academic R&D are available since the beginning of the seventies. This makes it possible to test the robustness of the cross-sectional results by using panel-techniques. The time-dimension will also allow us to find out whether the introduction of the Bayh-Dole Act really mattered. Similarly, combining the above data with data on the foundation-dates of the "Technology Transfer Offices" should enable us to make inferences about the usefulness of such institutions. Indeed, one would expect that once a university creates such an office, it gets more patents per US-dollar of research expenditures.

Even more interesting might be a replication of the Jaffe (1989) study. Indeed, he used data for the seventies, hence a period in which universities only rarely protected their findings by taking patents. It's natural to suppose that some of these unprotected findings will have been patented by nearby-situated firms, thus provoking spillovers. Hence, it would be interesting to know whether the introduction of Bayh-Dole did not reduce such spillovers.

[15] She also gives, for some universities, indications for the number of patents. Meyer-Krahmer and Schmoch(1998) count, for 1993, 1033 applications for patents by German professors (not universities!). BMBF(1998) includes a graph that shows that the patent-applications of German universities increased from about 400 in 1973 to about 1600 in 1997.

7) Conclusions

This paper has highlighted the 'direct real effects' of academic research: academic R&D expenditures do not only influence the number of patents that are granted to nearby firms (like Jaffe (1989)), they also significantly influence the number of patents granted to the university itself. In addition, we found some indications for constant returns to scale at the institutional level. However, once controlling for fixed effects, we find, just like the traditional firm-studies, much smaller coefficients indicating decreasing returns to scale. Moreover, our fixed effects coefficient fall into the 0.25 - 0.6 range that Cincera (1997) finds when looking at a number of firm-level studies[16].

Research by Henderson et al. (1998) has already shown that university-patents do not differ (anymore) from firm-patents in terms of quality. Hence, one can conclude quite safely that, these days, universities resemble firms in several aspects.

[16] Note this does not necessarily imply that for the same amount of money, they will have the same number of patents.

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Appendix: Jaffe’s patent classification and the NSF disciplines.

- Chemical: Chemistry and Chemical Engineering.
- Computers and Communications: Computer Science
- Drugs and Medical: Biology, Medicine, Agricultural Sciences and Other Life Sciences.
- Electrical & Electronic: Electrical Engineering, Astronomy and Physics
- Mechanical: Mechanical Engineering, Civil Engineering, Materials Engineering, Aerospace Engineering, Other Engineering and Other Physical Sciences.
- Other: Atmospheric Sciences, Earth Sciences, Oceanography, Other Geosciences, Mathematics and Statistics, Psychology, Economics, Political Science, Sociology, Other Social Sciences and Interdisciplinary or Other Sciences.