Science is Golden:
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 isn't 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].

2) 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[3].

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[1] Mowery and Ziedonis (1999) note that before Bayh-Dole, universities could negotiate ‘Institutional Patent Agreements’ with the federal funding agencies.

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

[3] Note however, that Payne and Siow (1999) use panel data and IV-estimation.

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. 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 universities for which the NSF recorded positive R&D expenditures. 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. With these extensions, we follow the tradition for estimating patent production functions for firms.

Patent counts have the disadvantage that they just take into account the quantity of patents while neglecting that patents can differ dramatically in quality. Therefor, we will also check the robustness of our results by replacing patent counts by citation counts.

We will further try to control for university specific effects in two ways. First, we will 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. Second, we will exploit the panel properties of our data.

The last part of the paper looks at the effectiveness of Technology transfer Offices (TTO). Several studies (Siegel et al. (2000), Thursby and Thursby (2000)) have looked at these offices that are set up by universities to foster the links with industry. Using foundation dates, we look whether universities get more patents per dollar spent on R&D, once they have established a TTO.

4) Data

a) Academic R&D

For R&D expenditures, we use WEBCASPAR-data of the NSF, which are based on its 'Survey of Research Expenditures'.

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 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[4].

[4] 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

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)[5]".

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."

University Patents

Patent data per university come from different sources. From the USPTO we obtained a database with patent-numbers and assignee-names of the patents used for the publication ' US Universities and Colleges, Utility Patent Grants, 1969-1998'. This allowed us to create patent counts by university and year of application for the period 1969-1998. About 95% of the university patents are granted within four years following the application-year[6]. Therefor we use these data up to 1994. Next, we selected these patent-numbers from a database containing information like citations and patent class, for all US patents issued between 1977 and 1994[7]. Therefor we'll use citation counts up to 1990. By taking citation counts rather than patent counts, we try to control for quality differences between patents: the more a patent has been cited by other patents, the higher its quality is supposed to be[8].

institutional ability to calculate unreimbursed indirect costs, including mandatory and voluntary cost sharing'.

[5] The firm-data that have been used for the US (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.

[6] 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.

[7] Provided to us by Adam Jaffe.

[8] See Hall et al. (2000) for a survey about the use of patent citations.

Cross-sections[9]

In our regressions, we will use lagged explicative variables to prevent reversed causality. Therefor, we look at the patents in 1994 for those 537 universities that had positive R&D expenditures in 1993. Table 1 gives some descriptive statistics.

Table 1: descriptive statistics

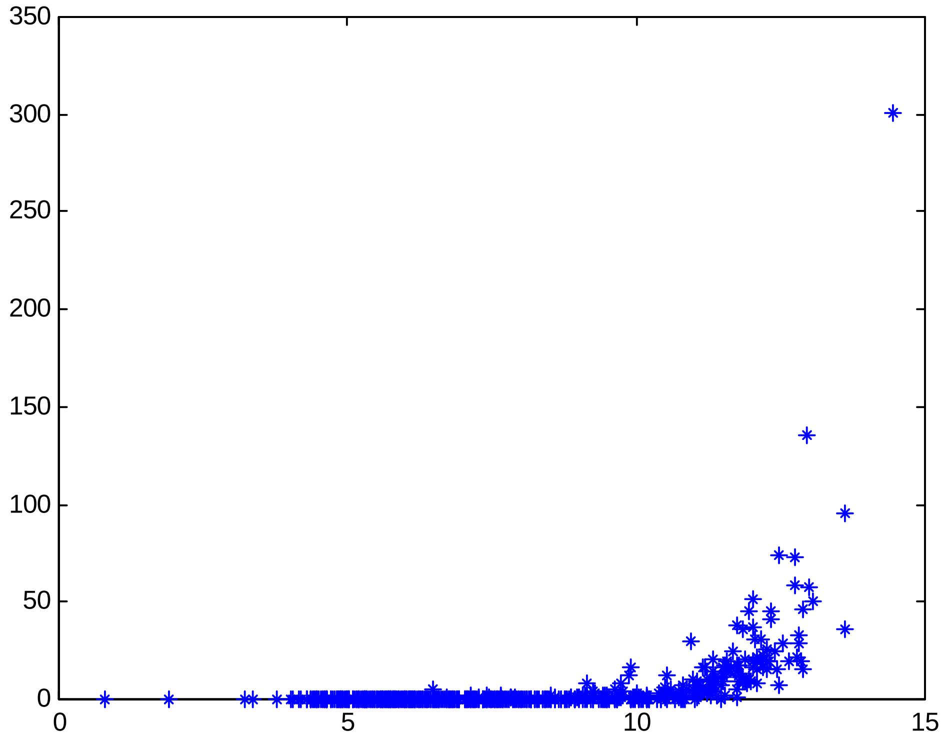
	Patents	Ln(R&D)		Patents: #univ
Mean	4.69	8.05	0	373
Median	0	7.58	0<>5	73
Std	17.4	2.53	6<>10	24
Minimum	0	0.79	11<>15	16
Maximum	301	14.4	16<>20	20
Variance to Mean	65	0.8	21+	31

Logarithms of R&D in 1000 US $.

In 1994, the average university did 4.69 patented inventions with about 31 million $ of R&D expenditures. Not surprisingly, there are substantial differences between universities. The University of California received 301 patents and MIT got 135 patents. But as one can notice from Table 1, 69% of the universities with positive R&D did not receive even one patent in 1994. 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.

[9] R&D expenditures are in 1998 dollars and in logarithms. In our regressions, we'll use Eicker-White standard errors which are heteroskedasticity-consistent, and that are in most cases more conservative than either the Newton or the BHHH standard errors.

Fig 1 plots the number of patents against the log of the R&D expenditures.



When estimating the relationship between the R&D expenditures, one has to take into account the fact that patent data are discrete counts that are never negative. Therefor, we use Poisson regressions rather than OLS regressions. We assume that the (conditional) probability of having Y patents is Poisson distributed

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

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

The β's are then estimated by maximizing the Loglikelihood:

$$L= \sum -\exp(X\beta) + y*X\beta-\log(y!)$$

Table 2: Poisson and Negative binomial estimates.

	Poisson	Poisson	Poisson 3yrs	Poisson 5yrs
Constant	-10.4	-10.27	-9.94	-11.55
	(0.51)	(1)	(1)	(1.15)
R&D	1.11	1.1	1.07	1.07
	(0.043)	(0.088)	(0.089)	(0.089)
Rsq[10]	0.87	0.83	0.81	0.82
Loglik.	-951	-832	-827	-820
#obs.	537	511	418	415

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

As our R&D variable is in logarithmic form, coefficients give elasticities. First, not surprisingly, universities do react to money just like 'real' firms. The estimates in column 1 even point in the direction of increasing returns to scale: an increase of one percent in R&D expenditures will increase the number of granted patents by more than 1 percent. However, in that regression we included the branch-campus universities that use a common assignee name, with as prime example the University of California. Because, we are more interested in the economies of scale at the level of the universities, we exclude from column 2 onwards, the 26 common-assignee universities. While the point estimate remains very similar, it is not significantly different from one anymore, thus indicating constant returns to scale.

Next we experiment with longer R&D lags. In column 4, we use a weighted sum of three years (0.25*t-1, 0.5*t-2,0.25*t-3) like Adams and Grilliches (1996-1998), in column 5 we take an unweighted sum of 5 years (t-1 until t-5). Both slightly reduce the point estimate but confirm the constant returns to scale[11].

[10] The measure of goodness of fit we use is proposed by Cameron and Windmeijer (1993) and gives the improvement (in loglikelihood) over a model with only the constant term relative to a model that perfectly predicts the dependent variable.

[11] Allowing for different coefficients for different lags resulted in nonsensical coefficents.

Table 3: Public versus private universities and enrollment.

	Poisson		Poisson
Constant	-9.68	Constant	-10.61
	(1.43)		(1.17)
R&D	1.06	R&D	1.11
	(0.13)		(0.11)
Public dummy	-0.84	Enrollment	0.03
	(1.62)		(0.1)
β_1*Public dummy	0.047		
	(0.14)		
Rsq	0.84	Rsq	0.83
Loglik.	-815	Loglik.	-742
#obs.	511	#obs.	482

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

We also ran a regression in which we allowed coefficients to vary between private and public universities. We didn't find, however, any indication that private universities are better in turning dollars into patents.

Studies on firms often include sales as measure of size. Adding the enrollment to the above equations, however, does not change our findings.

Table 4: Including the number of faculty.

	Poisson IV		Poisson staff	Poisson staff	Poisson staff
β_0	-12.2	β_0	-10.06	-10.88	-15.2
	(2.46)		(1.36)	(1.15)	(2.1)
β_{1IV}	1.64	β_1(staff)	1.82	1.22	1.11
	(0.29)		(0.2)	(0.12)	(0.12)
		β_2(R&D/staff)	--	1.07	0.97
				(0.11)	(0.12)
		β_3(average salary)		--	1.35
					(0.5)
Rsq	0.34	Rsq	0.47	0.84	0.85
Loglik.	-2115	Loglik.	-1956	-709	-672
#obs.	411	#obs.	560	466	466

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

A an extra assurance against reversed causality, we use the (market value at the beginning of the year of the) lagged endowment of the university as an instrumental variable for the lagged R&D. This results in a considerable increase in the point estimate, and even allows us to reject the constant returns to scale. Finally, we use another, albeit crude, measure of research-intensity: the number of faculty. This measure shows clear increasing returns to scale, doubling the number of staff almost increases the number of patents by 200%. When we include both measures of research intensity, the number of staff and the amount of R&D per staff, we find constant returns to scale for both. Including also the average salary (which should partially overlap the R&D expenditures), gives similar results and further shows that better paying universities are able to attract the more productive scholars.

All in all, our basic Poisson regressions show a quite consistent picture: the academic R&D production has constant returns to scale with some indications of increasing returns to scale.

Negative binomial distribution

However, the Poisson distribution has some shortcomings. First, it supposes that the conditional mean and the conditional variance are equal. The raw data, however, have a variance-mean ratio that is considerably higher than 1 which makes it likely that this hypothesis will be violated. And overdispersion-tests (see Cameron and Trivedi (1997)) indeed reject the mean-variance hypothesis of the Poisson-model.

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 increases with the mean:

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

The Negbin_k model includes the Poisson model (α=0) the Negbin_I (α<>0, k=1) model and the Negbin_{II} (α<>0, k=0) model.

Note that the Negbin II model can be derived from both a random effects model (where the random effect is gamma distributed with mean 1 and variance α) and a contagion model.

As the Negbin distribution has thicker tails, it also helps in alleviating the excess-zero problem. Table 5 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 5: # of firms with X patents, observed and predicted

	Observed	Poisson	$Negbin_{II}$	$Negbin_{I}$	$Negbin_{k}$	Hurdle
0	369	327.0	349.8	367.8	365.5	369.3
1	25	48.2	44.7	21.5	15.2	18.8
2	19	21.4	20.2	13.7	5.4	11.3
3	6	13.4	12.9	10.4	2.6	8.7
4	8	9.7	9.4	8.6	1.4	7.2
5	8	7.8	7.4	7.3	0.8	6.3
6	2	6.7	6.0	6.4	0.5	5.8
7	6	6.0	5.1	5.7	0.3	5.4
8	4	5.5	4.4	5.1	0.2	5.2
9	8	5.1	3.8	4.6	0.1	5.0
10	2	4.7	3.4	4.2	0.1	4.8

Line 2 of the above table shows that while we observed 369 universities that had no patent, the Poisson-model only predicts 327 zero observations. The Negbin models do clearly better: Negbin II predicts 350 observations and Negbin I only misses by one observation.

Table 6: Poisson and Negative binomial estimates.

	$Negbin_{II}$	$Negbin_{I}$	$Negbin_{k}$		Hurdle
β_0	-10.7	-9.1	-10.6	β_0 (y|y>0)	-7.9
	(0.77)	(0.69)	(0.6)		(0.34)
β_1	1.14	1.00	1.13	β_1 (y|y>0)	0.91
	(0.07)	(0.06)	(0.05)		(0.03)
α	0.77	5.97	2.8	β_0 (y|y=0)	-9.9
	(0.18)	(1.22)	(0.61)		(0.81)
K			0.66	β_1 (y|y=0)	0.96
			(0.085)		(0.08)
Loglik.	-556	-538	-531	Loglik.	-762
#obs	511	511	511	#obs	511

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

To discriminate between the latter two models, we use the Vuong-test statistic for non-nested models. Its value, 1.3, is insufficient to make a decisive claim, though it points in the direction of favoring $Negbin_I$. Note that while both model do reject the mean variance equivalence hypothesis of the poisson distribution (α significantly different from zero), they do not alter our basic conclusions (β_1 close to one).

One can see that allowing for overdispersion through $Negbin_I$ or $Negbin_k$ already solves the excess-zeros problem. However, alternatively one can estimate a Hurdle model (see Licht and Zoz (1998) for applications on firm-data). This model supposes that there are two processes at work: a first that determines whether to patent or not and a second that determines how many patents you will be granted once you have decided to take patents. When allowing for different Poisson distributions for both processes, we find some evidence for decreasing returns to scale once one produces patents. However, a Voung test clearly rejects the Poisson-Poisson Hurdle model in favor of the Negbin_I model.

Running the expanded regressions using the Negbin_I specification rather than Poisson generally confirmed our previous findings. The exceptions were the IV estimate that declined to 1.17 and was not significantly different from one anymore and the specification were the average salary was included which showed an increase in the coefficient of the average salary and a decrease in the coefficient of the R&D per staff.

Citations

So far we neglected that all patents are not necessarily equal. It has been documented (see f.e. Sherer (2000)) that the revenues of a patent (both for firms and universities) are highly skewed, the bulk of the revenues are generated by a limited number of patents. While we do not have information on the value generated by each of our university patents, we know how many times a patent has been cited by subsequent patents. Hence, citation counts can be used as a proxy for quality weighted patent counts.

Table 7: descriptive citation statistics

	Patents	Citations		Patents: #univ	Cites: #univ
Mean	2.46	2.7	0	312	331
Median	0	0	0<>5	59	41
Std	7.5	9.7	6<>10	31	26
Minimum	0	0	11<>15	8	10
Maximum	103	133	16<>20	8	7
Variance to Mean	23	34	21+	12	15

Table 7 gives the descriptive statistics for the 1990 patents and the citations to these patents by patents that have been granted before 1995. As one can notice, the citation counts aren even more skewed. Of course, the value of some patents might be discovered more slowly than the value of other patents. To get a better idea on this time-lag effect, we computed the correlation between the number of citations granted within the first five year after the application year and the number of citations within the first fifteen years, using the 1977 patents. This correlation is 0.75 so the 5 year citations seem to be a reasonable quality indicator.

Table 8: citation production functions

	Poisson Patent	Poisson Cites	Negbin_{I} Patents	Negbin_{I} Cites
β_0	-9.98	-10.35	-9.01	-9.39
	(1.09)	(1.5)	(0.7)	(0.96)
β_1	1.045	1.085	0.96	1.00
	(0.1)	(0.13)	(0.06)	(0.086)
α			5.36	12.2
			(1.28)	(2.5)
Loglik.	-657	-882	-433	-411
#obs.	430	430	430	430
#obs>0	118	99	118	99

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

Table 8 shows slightly higher point estimates for the citation production function than for the patent production function. While a doubling of R&D leads to a 104.5% (96%) increase in patents, it leads to a 108.5% (100%) increase in citations. Experimenting with different specification like above (different coefficients for public and private universities, several lags of R&D, including enrollment etc) confirmed the results we found using the ’94 patents.

Hence, our conclusion that at the university level, there are constant returns to scale, with some indications for increasing returns, seem fairly robust. Note that in a the patent literature for firms one also tends to find, in the cross-sectional dimension, coefficients that are close to one (see f.e. Pakes and Griliches (1980), or Griliches (1990)), though often with more difficulties to reject decreasing returns to scale.

Disciplinary Differences.

For each university patent that has been granted before 1995, 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 4 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].

Table 9: 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.

Table 10 gives the Poisson and the Negbin$_I$ estimates for the 6 disciplines. Note that from here on we use data on patents applied for in 1990 rather than 1994, as data are only available for patents granted up to 1994.

[12] The mapping of Jaffe's classification of patents into NSF disciplines is given in the Appendix.

Table 10a: Poisson and Negbin_I: Chemical, Computers and Drugs patents.

	Aggregate		Chemical		Computers		Drugs	
	Poisson	Negbin_I	Poisson	Negbin_I	Poisson	Negbin_I	Poisson	Negbin_I
β_0	-9.98	-9.01	-8.17	-7.98	-5.91	-5.28	-8.96	-8.67
	(1.09)	(0.7)	(0.65)	(0.72)	(0.74)	(0.64)	(0.81)	(0.86)
β_1	1.045	0.96	1.03	1.01	0.69	0.62	0.91	0.88
	(0.1)	(0.06)	(0.07)	(0.08)	(0.1)	(0.08)	(0.07)	(0.075)
α		5.36		1.43		3.26		2.29
		(1.28)		(0.4)		(1.55)		(0.71)
Loglik.	-657	-433	-278	-246	-149	-105	-330	-261
#obs.	430	430	326	326	205	205	387	387
#obs>0	118	118	83	83	27	27	80	80

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

Table 10b: Poisson and Negbin_I: Electrical, Mechanical and Other patents.

	Electrical		Mechanical		Other	
	Poisson	Negbin_I	Poisson	Negbin_I	Poisson	Negbin_I
β_0	-7.47	-6.14	-7.95	-7.78	-7.16	-6.91
	(1.04)	(0.79)	(1.25)	(1.14)	(0.70)	(0.72)
β_1	0.86	0.72	0.8	0.78	0.68	0.66
	(0.11)	(0.09)	(0.13)	(0.12)	(0.07)	(0.08)
α		2.58		1.28		0.76
		(0.8)		(0.47)		(0.3)
Loglik.	-256	-210	-139	-122	-160	-148
#obs.	304	304	230	230	363	363
#obs>0	63	63	38	38	46	46

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, however, we find elasticities that are smaller than those we estimated for the university level. And for three out of these four, we can even reject the constant returns to scale hypothesis. Using citations, we get slightly higher coefficient but still are able to reject the hypothesis of constant returns to scale for both Computer patents and Other patents.

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.

[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.

Fixed effects: pooling disciplines

Next we pool the six disciplines, using those departments that had positive expenditures, of the 112 universities that had positive expenditures in at least 2 of the categories and received at least one patent. These conditions provide us with an unbalanced 'panel' of 629 observations. 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 11: the results of the pooled Poisson regression - Patents.

	Pooled Poisson Patent				cites
β_0	-3.79 (0.47)	-	-	-	-
β_1	0.47 (0.04)	0.6 (0.06)	0.3 (0.04)	0.31 (0.05)	0.43 (0.07)
DiscDum	NO	YES	NO	YES	YES
UniDum	NO	NO	YES	YES	YES
Loglik	-1250	-1090	-944	-819	-1059
#obs	629	629	629	629	542

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, a doubling of the budget only leads to an increase of 47% in the number of patents. Including subject dummies increases the elasticity to about .6. However, when also including university specific intercepts we get a point estimate of only .3. The citation production function has again a slightly higher point estimate of .4.

Using the specification of column 5, the dummies of the individual disciplines further show that the 'Other' is the least productive discipline. For a given amount of money, chemistry gives 4.5 times more patents, 'Electrical' and 'Drugs' about 3 times and Computer Sciences about 2 times more patents. The university-effects also cover a wide range: the university with the highest effect produces 60 times more patents, with the same amount of money, than the one with the lowest effect.

Instead of including a fixed effect, we can also look at the spillovers between different disciplines[14]. We do this by including the R&D expenditures by the university in other disciplines.

Table 12: Spillovers between disciplines.

	Poisson	Poisson	Poisson cites	Negbin1	Negbin1	Negbin1 cites
β_0	-5.85 (0.73)	-	-	-4.48 (0.54)	-	-
β_1	0.41 (0.05)	0.48 (0.08)	0.43 (0.07)	0.34 (0.4)	0.37 (0.06)	0.39 (0.05)
β_2 (R&D other depts)	0.23 (0.07)	0.21 (0.08)	0.25 (0.1)	0.17 (0.05)	0.22 (0.06)	0.09 (0.08)
α	-	-		2.2 (0.34)	1.56 (0.27)	6.7 (0.88)
DiscDum	NO	YES	Yes	NO	YES	YES
UniDum	NO	NO	NO	NO	NO	NO
Loglik	-1220	-1075	-1449	-1220	-937	-854
#obs	629	629	524	629	629	524

As one can see from table 12, given the amount of research in the department, more research in the other departments has a positive effect on the patent production but not on the citation production of the department. However, even with spillovers, the evidence for decreasing returns to scale are quite striking. Note also that the drop in coefficients that we observed when controlling for fixed effects is also observed when using firm data.

[14] As we measure our variables in logarithms, it would in principle be possible to include university specific effects. However, this results in a non-significant effect of the departmental R&D and a negative spillover effect

Time series

So far we only used data for 1994 and 1990. However, we have data about R&D expenditures have been collected since 1972. From 1973, data are available for the 'Science and Engineering' disciplines though the subdivision of the engineering disciplines started only in 1980.

Table 13: R&D expenditures in million 1998 US $: descriptive statistics

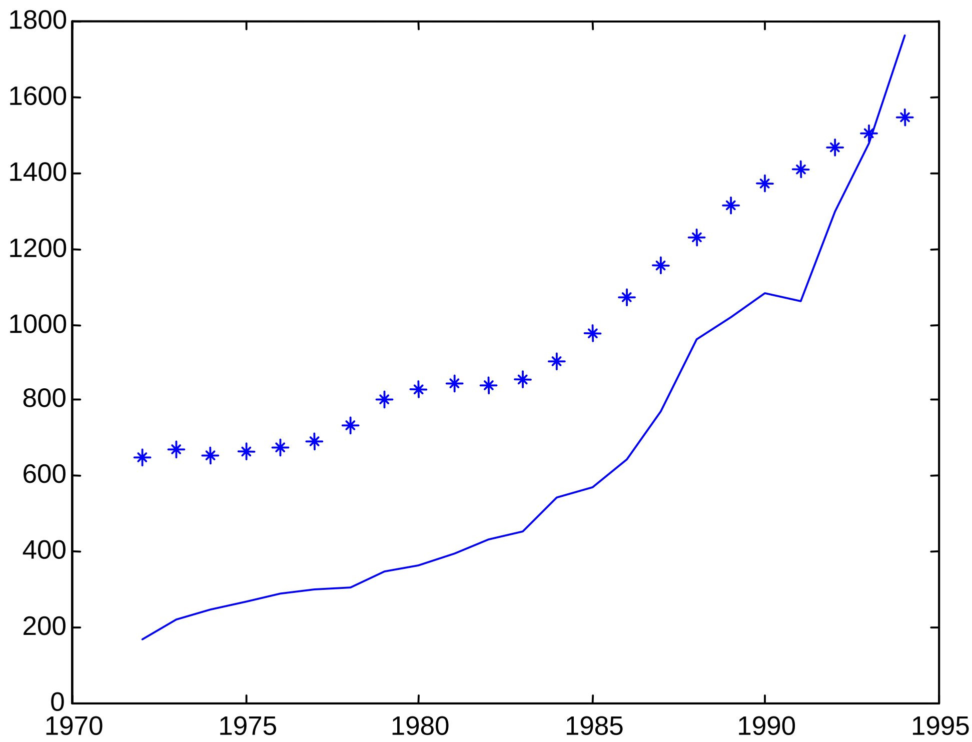
	1972	1980	1990	1994
#median R&D of institutions with positive R&D 1972-1990	12136	13738	23929	30742
#institutions with positive R&D 1972-1990	212	212	212	212
#median R&D of institutions with positive R&D in year X	1028	1993	2560	3516
#institutions with positive R&D in year X	440	389	429	415

For 212 institutions[15], we have complete histories of R&D expenditures between 1972 and 1994. The budget of the median department more than doubled since 1972. Note that these 212 institutions clearly are the bigger spenders: if we take all institutions with positive R&D expenditures in a given year, the median budget is about 10 times smaller.

From the USPTO we also have data on patents from 1972 until 1994. However, there's an additional complication. Some universities allowed patent management companies, most notably Research Corporation and University Patent Inc. (See Nelson and Sampat (1999)) to manage their inventions. An important consequence of this is that several patents based on university inventions have been assigned to these patent management organizations rather than to the university. In the USPTO-university patents data, 470 patents are assigned to Research Corporation (between 1972 and 1988) and 218 to University Patents Inc (period 1972-1994, 1 in 1994). While this should not influence our cross-sectional results, it could be important for our panel results. Indeed, the USPTO patent counts will underestimate the real number of patented university inventions for some universities. This might be especially important for our estimate of the TTO effect (and for the Bayh-Dole effect). If universities that leave a patent management organization, establish a TTO, we will see an increase in patents going together with the presence of TTO's. Note that this also means that we have to interpret a TTO effect as the effect of doing patent management in-house in contrast to 'buying' patent management rather than in contrast to no patent management at all.

To solve this problem, we asked both Research Corporation and University Patent Inc. for the name of the originating university of each of the patent numbers that have been assigned to them and are considered by the USPTO as university patents. Research Corporation Technologies was able to provide this for most of these patents, University Patents Inc advised us to use the location of the inventors as the indicator for the university[16,17,18].

Fig 2 plots the sum of the patents ((-),between 1972-1994) and the sum of the R&D expenditures ((*),between 1972 and 1994, in 10 millions of 1998 US$, deflated by GDP-deflator) for those 212 universities for which we have complete R&D data over that period.

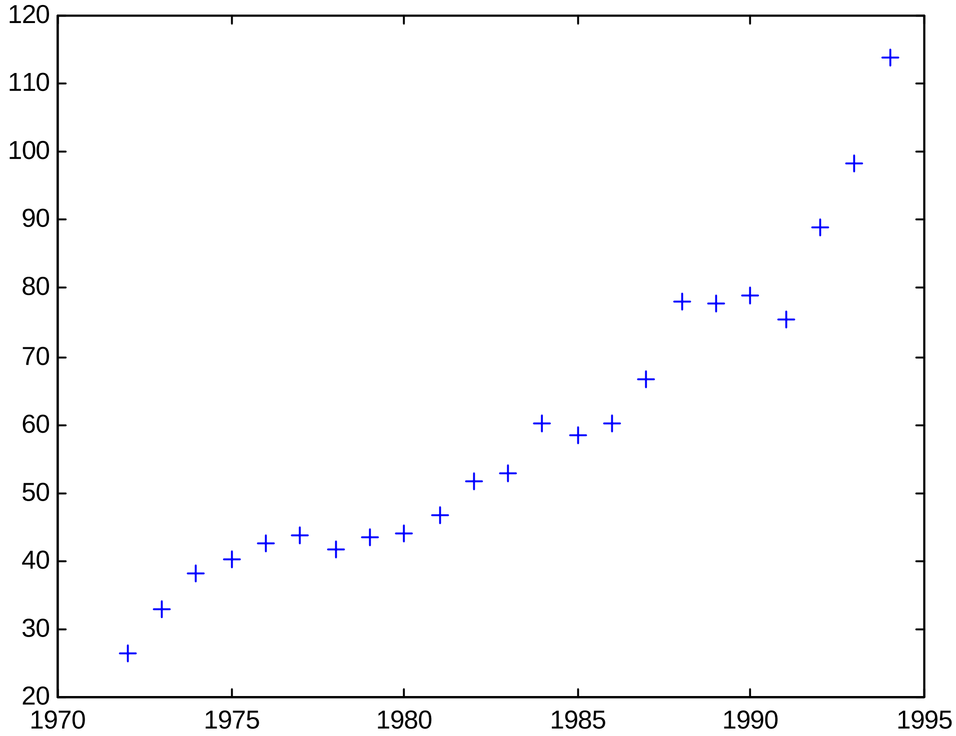


[15] excluded are the universities that use one assignee name for several branches.
[16] I thank John Perchorowicz of RCT for his help in obtaining the RCT data.
[17] The location indeed is a good indicator: when looking at the webpages of the inventors, we indeed found that they were working at that university around that time. For multiple inventors, we took the the location of the first inventor. A small disadvantage might be that we attribute some 'independent' inventions to a university.
[18] The USPTO includes Research Corporation in its publication on university patents. The organization that took over the patent management business of Research corporation, Research Corporation Technologies, however, is not included.

Fig 2 shows clearly how both patents and R&D increased substantially over the last two decades. While the growth-rate of patents has been consistently above that of R&D, the turning point seems to be somewhere around 1985: while real R&D resources grew faster than ever before, patenting at universities started to grow exponentially.

Next we look at the ratio patents per billion US$.

Fig 3: the number of patents per billion US$



While universities applied for about 20 patents per billion US$ in 1972, the same amount lead to about 40 patents by 1985, arriving at more than 100 by 1994. From the above pictures, on would get the impression of increasing returns to scale: over time both R&D and the ratio patents over R&D increased. Note that this is contrary to the picture one gets for the US industry in the seventies, where the growth in R&D was faster than the growth in patents.

However, first sights might be misleading in this case: Geiger and Feller (1995) show how in the seventies and the eighties there was a dispersion of the academic R&D over more and more universities. Together with the increasing patent-R&D ratio, this would seem to indicate decreasing returns to scale on the ‘university’-level.

Next, we look at the individual universities. Table 14 gives the distribution of the universities that had positive R&D between 1972-1990.

Tabel 14: distribution of universities over the number of patents.

	1972	1980	1990	1990
Mean	0.81	1.72	5.11	8.3
Median	0	0	1	2
Mean(>0)	3.89	4.93	9.58	13.24
Median(>0)	2	3	6	8
0	168	138	99	79
1-5	40	53	53	58
6-10	1	11	31	22
11-15	0	7	8	14
16-20	2	1	9	15
>20	1	2	12	24
#	212	212	212	212

The number of universities that applied for a patent in a given year has risen steadily from 44 (21%) in 1972 to 133 (62%) in 1994[19]. Moreover, the average number of patents also increased considerably. Taken over the period 1972-1994, we have 47 universities or 22 % of our sample that spend money on R&D but never applied for a patent[20].

Econometrics

A standard way to analyze panels of count data is to use conditional Poisson (see HHG(1984)).

First, we compare the results of simply pooling the 22 years of observations we have on 212 universities with those of the fixed effects specification (conditional Poisson, where conditioning is on total number of patents granted to the university over the whole time-period).

[19] Compare to HGH (1986) sample of US firms, where "over 20% of the firms did not apply for patents in 1976" and the median number of patents was 3. Cincera's (1997) 181 big international firms have a mean of 69.5 patents in the period 87-91, with 21% having at most one patent.
[20] We do not show a similar table for cites as it's difficult to compare aggregates over time because the number of citations per patent has increased over time (see Jaffe and Traitenberg ()) and because the time-period over which a patent can be cited is shorter for more recent patents.

Table 15: panel estimates

	Poisson			
	Pooled		Fixed	
Const	-10.86 (0.35)	-14.5 (0.48)		
Time		0.05 (0.005)		0.082 (0.01)
Exp	1.11 (0.03)	1.025 (0.03)	1.75 (0.12)	0.44 (0.16)
Loglik	-11030	-10329	-6300	-5818
# obs.	212*22	212*22	212*22	212*22

Tstats base on Eicker-White standard errors that allow for misspecification

Simply pooling the different years shows increasing returns to scale, and including university-specific effects even reinforces this conclusion. This indicates that (part of) the increase in university patents can also be attributed to a production function with increasing returns to scale.

Next, we also include a time-trend to catch exogeneous increases in patents (like HHG (1984))[21]. This changes the results quite dramatically. The pooled sample gives constant returns to scale while the fixed effects specification gives decreasing returns to scale.

Recently, Mowery and Ziedonis (2000) have tried to look for the effects of the Bayh-Dole Act. They conclude: “Although our evidence suggest little if any change in the content of academic research, the effects of the Bayh-Dole on the marketing effects of these two universities nevertheless have been considerable. Our evidence suggests that both UC and Stanford university administrators intensified their effort to market faculty inventions in the wake of Bayh-Dole. These intensified marketing efforts expanded the pool of university inventions for which patent applications were made and licensees actively sought”.

By including a dummy that takes the value one from 1981 onwards (and zero before) or interact this dummy with the with the expenditures, we can see whether there’s a difference between the pre-Bayh-Dole period and the post-Bayh-Dole period with

[21] “Non-stationary stochastic trends have not been studied for count regression. Non-stationarity is instead accomodated by deterministic trends, in which the usual asymptotic theory still applies” (Cameron and Trivedi, 1998).

respect to the sensitivity of the number of patents to R&D expenditures. Indeed, if Bayh-Dole made it more attractive to patent, we should expect more patents per US-dollar.

Table 16: Bayh-Dole effect and TTO-effect

	Patents			
Time		0.09 (0.01)		0.09 (0.01)
Exp	1.41 (0.12)	0.41 (0.16)	1.38 (0.13)	0.42 (0.16)
Expenditures*(year>81)			0.04 (0.01)	-0.014 (0.075)
(year>81)	0.44 (0.11)	-0.15 (0.08)		
Loglik	-6170	-5810	-6169	-5808
#observations	212*22	212*22	212*22	212*22

Conditional Poisson estimates. Eicker-White standard errors between brackets.

The inclusion of a trend is again very influential. Without a trend, we get a significant positive effect of Bayh-Dole but once we include a trend, we find that after 1981 money had less effect than before…We would get such an effect if Bayh-Dole only pushed ‘smaller’ universities to patent inventions.

Other studies have tried to evaluate the effectiveness of the Technology Transfer Offices of universities. Thursby and Thursby (2000) for example find that “ increased licensing is due primarily to an increased willingness of faculty and administrators to license and increased business reliance on external R&D rather than a shift in faculty research.” Similarly, Siegel et al. (2000) state: “the most critical organizational factors are likely to be reward systems for faculty, TTO staffing and compensation practices, and actions taken by administrators to extirpate informational and cultural barriers between universities and firms”.

From the AUTM-survey, we have the date of establishment of the TTO’s of 97 universities (out of our 212). Hence, a dummy taking the value one from the year after the TTO has been established (and then again multiplied by expenditures), should learn us something about the effectiveness of TTO in bringing out more patents.

Indeed, one can expect that a university with a TTO should have a higher number of patents per dollar spent[22]. Column 3 of table 15 confirms this: a university with TTO that spends the mean expenditures (11.3 (logs!) in 1994) will have an expected number of patents that is about 45% higher than the same university without TTO (exp(11.3*0.43)/exp(11.3*0.4)) higher! Hence, the Bayh-Dole act doesn't seem to have a positive effect per se. However, to the extent that it induced the establishment of TTO offices in some universities, it did have a significant effect (in 1980, 20% of the institutions in the sample had a TTO against 85% in 1994).

Table 17: TTO-effect

	Patents			
Time		0.066 (0.01)		0.065 (0.01)
Exp	1.36 (0.13)	0.41 (0.16)	1.33 (0.13)	0.40 (0.16)
Expenditures*TTO			0.054 (0.01)	0.034 (0.1)
TTO	0.61 (0.12)	0.39 (0.1)		
Loglik	-4504	-4271	-4497	-4272
#observations	19*97	19*97	19*97	19*97

Conditional Poisson estimates. Eicker-White standard errors between brackets.

Of course, one might claim however that we have an endogeneity problem here[23]: there might be a shock that simultaneously leads to the establishment of a TTO and that affects the patent awareness of a university. Suppose for example that a scientist

[22] Of course, in this way we only look at one of the 'outputs' of a TTO. Siegel et al. (2000) note that about half of the TTO administrators they interviewed saw patents as one of their outputs. Licenses and royalties get 67 resp 87%. Similarly, Jensen and Thursby (1999) find that patents are considered relatively unimportant. The word 'relative' is important here as they find some 70% of TTO's that consider patents to be moderately or extreme important (revenues/licenses score higher). They note further that industrial surveys gave similar results. And more important: '…we expect the reasons for the patent ranking in these studies to be different. Many of the managers interviewed said that for financial reasons their policy is to apply for patents only after the invention has been licensed'. This implies that patent counts themselves might be considered as quality weighted counts of innovations.

[23] Nelson and Sampat (1999) give a number of reasons for the rise in the number of TTO's. First, during the sixties the idea that university research would only be exploited if ownership rights were given to the university became more and more accepted and lead some funding agencies to allow universities to do so. Second, Research Corporation started to stimulate universities to take care of the first stages of the screening of inventions themselves. Third, the patenting of some superstar inventions and the income those patents generated made universities aware of possible benefits. Finally, the universities expected that the rise of biotechnology would lead to a more steady stream of patents.

at a university does a break-through invention. This might trigger an increased awareness among the scientists of that university that patenting might be profitable. However, it might also cause an increased awareness among the managers of that university that patenting might be profitable. The first can then lead to more patents, the second to the establishment of a TTO. However, the positive correlation one will then find obviously should not be attributed to the TTO. Similarly, the original patent that gave rise to the establishment of the TTO, might lead to some off-spring patents. Also in this case we will observe an increased number of patents going together with the founding of the TTO.

While we can not distinguish between a shock with long lasting consequences and the establishing of a TTO, we can show that our TTO-effect is not a consequence of an exogenous shock that has only a short-run effect on the number of patents or citations. Note that a TTO should have a lasting effect while awareness shocks should only have a temporary effect. Therefor, we create a dummy variable that takes the value 1 only from three years after the TTO date. The idea being that it's unlikely that three years after the break-through finding there are still these off-spring patents or awareness effects.

Table 18: TTO-effect

Patents			
Time	0.06 (0.01)	Time	0.06 (0.01)
Exp	0.38 (0.15)	Exp	0.38 (0.15)
TTO	0.29 (0.09)	TTO*exp	0.026 (0.008)
TTO (+3)	0.2 (0.1)	TTO (+3)*exp	0.017 (0.009)
Loglik	-4260	Loglik	-4261
#observations	19*97	#observations	19*97

Conditional Poisson estimates. Eicker-White standard errors between brackets.

As one can see, rather than decreasing the effect of the TTO increases over time (from +34% to +69% in the dummy specification), which gives extra weight to the TTO effect explanation.

Conclusions and ideas for further research.

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 of 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 much smaller coefficients indicating decreasing returns to scale. Cincera (1997) looks at several firm-studies and cites elasticities between 0.25 and 0.6, a range that also includes our fixed effects specification[24].

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 in several aspects the (research-intensive) firms.

So far the university-patent relationship has been studied mainly for US universities. As far as we know, empirical studies about university patenting in Europe are nonexistent[25]. 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.

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

[25] 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

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 spill-overs. Hence, one would expect that the introduction of Bayh-Dole did reduce such spill-overs.

Finally, Jensen and Thursby (1999) stress the importance of royalties to induce further effort of the scientist in developing his invention. However, as it is the scientist that has to do the further development, it is the scientist that should be motivated rather than the university. University patent policies differ a lot in the share of money they give to the inventors. Table 1 gives some statistics based on a sample of the patent policies of 97 universities[26]. Of these 97 distribution rules 7 are based on gross income, 90 on net income. Of these 90, 53 have a percentage that is independent from the amount of net income, 36 have a 'progressive income taxes' (lower shares for the inventor as the net income increases). In the next table, we give some descriptive statistics on what percentage the inventor gets when the revenues are 100 thousand, 500 thousand and 1 million $.

Table 13: Share of the Inventor.

	Fixed	50	100	500	1000
Nr of univ	53	37	37	37	37
Mean	39.7	46.6	44.7	35.4	32.8
Std	9.3	9.3	9.9	7.1	6.6
Max	60	77	77	51	50
Min	15	25	25	22	21

For the universities that use a fixed percentage, the inventor gets about 40% of the average net revenues of licenses. The inventors at universities that use scales are on average better off for 'small' inventions but worse off for 'big' inventions. Note that there's quite some variation over universities.

If Jensen and Thursby (1999) are correct, we should find that those universities that allow their scientist to keep a large part of the income, should have more patents.

universities!). BMBF(1998) includes a graph that shows that the patent-applications of German universities increased from about 400 in 3 to about 1600 in 97.

[26] I used the AUTM TTO-addresses page to select the universities.

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Appendix

Mapping of NSF disciplines into the Jaffe Classification. (* not assessed by the NRC)

Jaffe's patent classification	NSF Disciplines
Chemical	Chemistry
	Chemical Engineering
Computers & Communications	Computer Science
Drugs & Medical	Biology
	Medicine*
	Agricultural Sciences*
	Other Life Sciences*
Electrical & Electronic	Electrical Engineering
	Astronomy
	Physics
Mechanical	Mechanical Engineering
	Civil engineering
	Materials Engineering
	Aerospace Engineering
	Other Engineering
	Other Physical Sciences*
Other	Atmospheric Sciences*
	Earth Sciences
	Oceanography
	Other Geosciences*
	Mathematics and Statistics
	Psychology
	Economics
	Political Science
	Sociology
	Other Social Sciences
	Interdisciplinary or Other Sciences*