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Research Productivity in a System of Universities

James D. ADAMS, Zvi GRILICHES *

ABSTRACT. – This paper considers research performance of U.S. universities for eight science fields. At the aggregate level we find that research output follows a constant returns to scale process. However, for individual universities we find evidence of diminishing returns. We offer two explanations for these differing results. First, data errors are more important at the individual level. Second, research spillovers exist between universities and fields that are captured only at the aggregate level.

Productivité de la recherche dans un système universitaire

RÉSUMÉ. – Cet article examine la performance de la recherche des universités américaines dans huit domaines scientifiques. Au niveau agrégé des domaines scientifiques, nous trouvons que les rendements de la recherche sont constants. Au niveau individuel des universités, nous découvrons cependant des preuves de rendements décroissants. Nous offrons deux explications à ces résultats divergents. Premièrement, les erreurs de données sont plus importantes au niveau individuel. Deuxièmement, il existe, entre universités et domaines, des retombées seulement perçues à un niveau d'ensemble.

* J. D. ADAMS: University of Florida, NBER; Z. GRILICHES: Harvard University, NBER.
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1 Introduction

The topic of this paper is the research productivity of a system of universities, where the particular system is a group of leading public and private universities in the United States. Broadly speaking, the measure of productivity that we use is the ratio of the "intermediate" outputs of the research – as measured by papers and citations to those papers – to lagged R&D expenditures. We also explore a multivariate specification of university productivity in a regression system. The two outputs are research and teaching in the form of advanced degrees.

It is important to study trends in university research and teaching productivity because universities account for about fifty percent of basic research in the United States (National Science Board, 1996, Table 4-5) and basic research is one of the mainsprings of industrial innovation. University research takes on additional importance in the United States because it shapes the training of graduate students, many of whom become industrial scientists and engineers. If university research productivity were to decline, then *for a given commitment of resources* to university research, a critical input into industrial research would grow more slowly. As a result new products and processes would tend to appear less frequently [1]. However, it is difficult to study the general relationship between industrial innovation and university research, and more difficult still to value the resulting innovations. Tracing the impact of science is a novelty for economists; we are apprentices in constructing the experiments that would isolate the connections between science and innovation, and a general methodology that reliably values the innovations remains over the horizon [2]. This is especially true given the location of universities in a public sector whose output is notoriously difficult to evaluate (GRILICHES [1994]).

For these reasons we study the more immediate connection between research output and lagged R&D of universities. And yet measuring research productivity even in this way is not a simple exercise. One problem is the unclear boundaries between different sciences and universities, since the results of research may, and hopefully do, show up in an entirely different university and field than their point of origin [3]. A second problem is that R&D statistics are subject to considerable error from the point of view of measuring basic research, and the errors can be of either sign. On the one hand, measured academic R&D underestimates the total value of R&D resources devoted to basic research because of implicitly funded research. On the other hand, measured R&D overstates the total value of resources devoted to basic research because some of the R&D is devoted to

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1. See EVENSON and KISLEV [1976] for a search-theoretic interpretation of the basic research, industry R&D linkage, and ADAMS (1993) for a cross-industry test of this relationship.
2. But see EVENSON and KISLEV [1975] and HUFFMAN and EVENSON [1993] for the relationship between biological science and agriculture. See STEPHAN [1996] for an excellent survey of the present state of the economics of science.
3. This is a familiar problem in the economics of industrial R&D. See GRILICHES [1979, 1992].

infrastructure and contract work rather than basic research. A third problem is that the various deflators for R&D do not agree, so the very definition of real R&D is at issue. Even the measure of what constitutes a scientific paper is an elastic yardstick of scientific achievement. Finally, our citation measurements depend on growth in the scientific professions; indeed they depend on the technology of carrying out the search underlying a citation. Citations are themselves an uncertain metric of the impact of an article, though they are the best measure that we have. We shall see that all of these problems haunt the data, and that some of the problems grow worse as we study the data in more detail.

The remainder of the paper is arranged as follows. Section 2 provides a graphical overview of the research output-research input relationship at the field level during the nineteen eighties in the US. Findings at the more detailed level of individual universities and fields over the same period are presented in Section 3. Section 4 is a summary and conclusion.

Section 2 presents field level graphs for eight broad sciences: agriculture, biology, chemistry, computer science, engineering, mathematics and statistics, medicine, and physics. These fields account for the majority of academic research expenditures, and the 109 universities that form the basis for these graphs account for three quarters of overall academic R&D in the United States. For the majority of sciences we find that papers and citations grow at *very roughly* the same rate as lagged R&D, with computer science and mathematics research being exceptions that grow more slowly than lagged R&D. Nevertheless, at the field level, given the R&D deflator that we use, the data suggest a constant returns to scale production process for research output: the elasticity of papers and citations with respect to lagged real R&D is essentially 1.0.

We report descriptive statistics and regressions based on samples of individual US. universities and fields in Section 3. The descriptive data strongly imply that average costs per citation, interpreted as costs per "quality adjusted" unit of research, are lower in the top ten universities than in universities of lesser rank, and that they are lower in private schools.

A key regression finding is that elasticities of research output with respect to R&D are smaller at the university and field level than for the entire system. The average elasticity is 0.6 for papers and 0.7 for citations at the university and field level, suggesting the possibility of diminishing returns at this level. The evidence at our disposal does not go deep enough to draw a firm conclusion at to why we see the *appearance* of diminishing returns at the level of the individual university but not at the aggregate level. In the course of our research we have been tempted to cite research externalities (R&D spillovers between fields and universities) as the source of this difference in results. According to this story, externalities convert individual diminishing returns to constant returns.

However, such a conclusion would be premature given the ready availability of alternative interpretations for the difference in results at the aggregate and individual levels. The incorrect assignment of R&D to papers and citations is undoubtedly a more important problem at the university level, and it could yield the illusion of diminishing returns at this level. For example, larger research programs may export Ph.D.s, and hence some of their research output, to smaller programs [4]. In general, university departments have rather weak intellectual property rights to the research output they produce.

The result that the citation-R&D elasticity is larger than the papers-R&D elasticity strongly suggests that larger research programs produce more cited, higher quality research. Another finding is that private schools generate more research output per dollar of R&D than public universities. These results in levels disappear when we account for individual school effects by regressing long differences of research outputs on long differences of lagged R&D. There is virtually no connection between growth of research output and growth of R&D input, implying that most of what we find at the university level between research output and input is linked with fixed university effects. To date we have little hold over changes in financial and other circumstances that bring about a change in the stream of a university's research output. Finally we examine the joint determination of research and graduate teaching outputs. We find modest correlations between the error terms in the research and teaching equations. We also show that both lagged R&D expenditures and lagged adanced degrees are factors that increase research output. Finally, in the equation for advanced degrees we find that both undergraduate science enrollments and lagged R&D expenditures in a university and field increase output of advanced degrees. With this summary in mind, we turn now to an examination of the findings.

2 Research Output and R&D at the Field Level

Figures 1 through 16 present graphs at the field level for eight fields of science. The underlying data are based on a constant sample of 109 universities having the largest R&D programs in the US. This set of universities accounts for three fourths of all university R&D; it is larger than the sub-samples of universities employed in Section 3, because of additional data required of the sub-samples. The graphs depict relationships between real R&D lagged two years and papers over the period 1981-1993; and they show the same relationship between real R&D and total citations to papers in the year of publication *and in four succeeding years*, over the period 1981-1989. Underlying data on nominal total and federal R&D derive from the CASPAR database of the National Science Foundation. We convert nominal R&D into constant dollar R&D using the recently constructed university R&D deflator of the Bureau of Economic Analysis (BEA, 1994). The papers and citations are taken from unpublished data of the Institute for Scientific Information (ISI), the source of the *Science Citation Index.*

4. The same statement could be true of fields: some sciences could be net contributors to other sciences. However, this problem would afflict the field level results as well as the university and field level results.

The BEA university deflator rises at 6.6 percent per year, almost twice as fast as the R&D deflator for industry, and more rapidly than the increase of 4.1 percent set by the implicit GDP deflator (see ADAMS and GRILICHES [1996]). We are not sure why the university deflator rises this quickly, but it is clear that if we had used the GDP deflator instead then the growth of real R&D would have been greater, and research productivity would have grown more slowly.

For each of the eight science fields we present two pairs of graphs. In each pair, time is on the horizontal axis and research output and lagged R&D are on the vertical axes. Both vertical axes use logarithmic scales. The upper pair of graphs shows the time path of our research output and R&D data in original units. The lower pair expresses all variables as ratios to their 1981 values. The purpose of the ratio specification is to provide a common scale in order to ease comparisons across fields. Left-hand graphs present R&D lagged two years on the left (log) scale and papers on the right (log) scale. Right-hand graphs repeat the curve of R&D lagged two years on the left scale but replace papers with total citations to those papers over a five year period on the right scale. Since vertical axes are in logs, slopes of the curves represent growth rates.

Referring to the *lower* pair of graphs in each field, Figures 1-16 allow us to reach the following conclusions. With the exception of Figures 7 and 8 (computer science) and Figures 11 and 12 (mathematics) most fields show growth in papers and citations that is roughly as fast as, or faster than, growth of lagged R&D. Computer science and mathematics papers and citations are the exception, in that outputs of these fields grow less rapidly than R&D. We are unsure as to the reasons why computer science and mathematics depart from the usual pattern. It is problematic that research output is growing more slowly than R&D dollars in these two fields in the very era when *past* mathematics is more useful than before, owing to its computer applications. This points out a weakness in current university R&D statistics, namely the lack of information on the *purpose* of the R&D. This has special relevance for computer science, given that some of its R&D could be infrastructure-driven research or contract work for industry rather than basic research. In the case of mathematics it is certainly possible that the mathematics of today comes at greater cost and is less useful than in the past; but if the nineteen eighties are an era of increased applications in research as well as industry, then this alone could account for slower growth of mathematics papers and citations, since the results of mathematics would be increasingly intertwined with other fields and more often misclassified. The difficulties of defining field boundaries are especially important for mathematics [5].

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5. The question is whether ISI omits applications of mathematics from its journal set at an increasing rate over time. We know that *some* applications of mathematics have long been covered by abstracts within mathematics. For example, *Jahrbuch uber die Fortschritte der Mathematik*, the main abstract service until 1940, regularly covered mathematical physics papers in the nineteenth and twentieth centuries. In the present era its successor *Mathematical Reviews* covers technical economics journals like *Econometrica*. See ADAMS [1990].

FIGURE 1

Agriculture

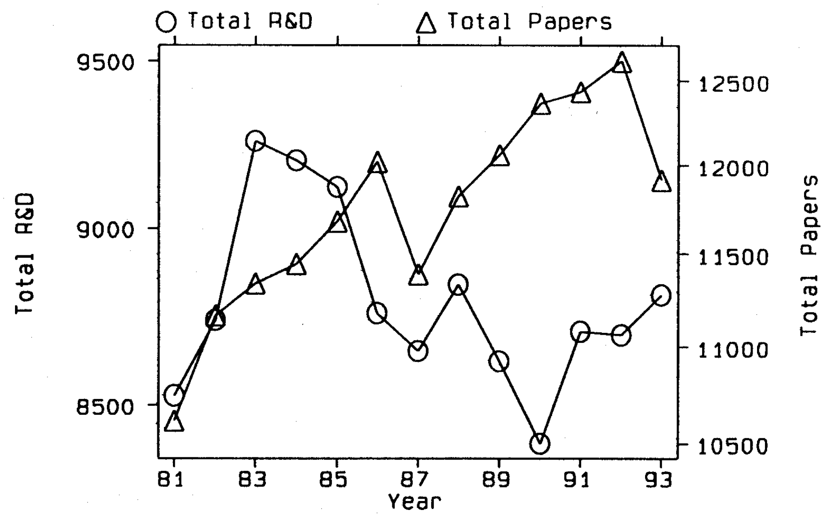

Fig 1a -- R&D and Papers

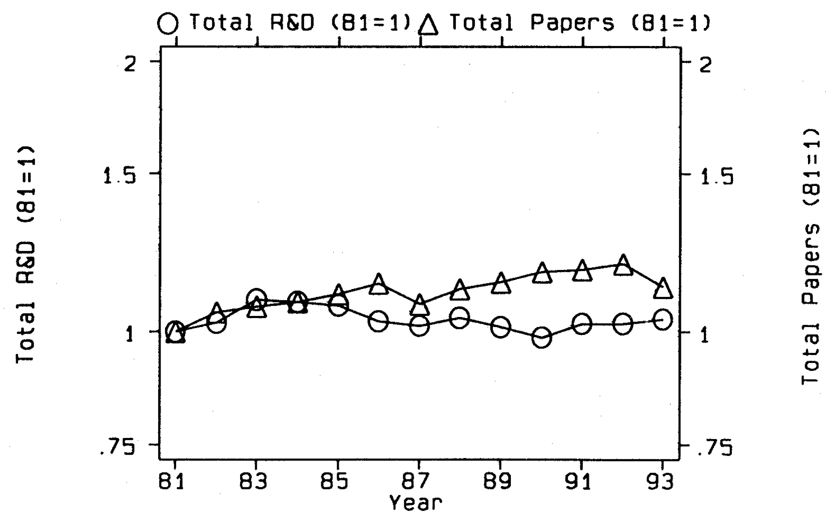

Fig 1b -- Normalized R&D and Papers

FIGURE 2

Agriculture

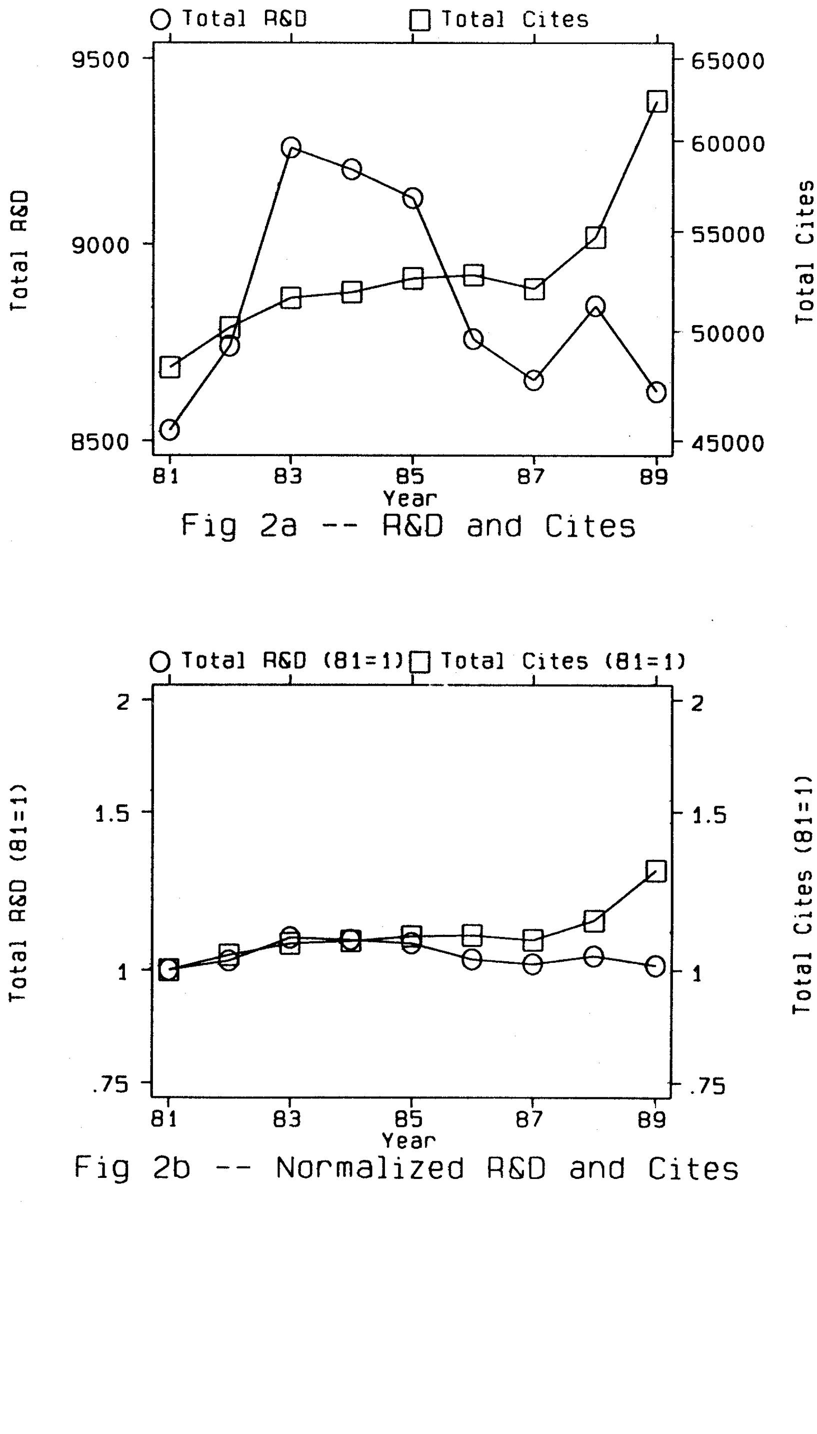

Fig 2a -- R&D and Cites

Fig 2b -- Normalized R&D and Cites

FIGURE 3

Biology

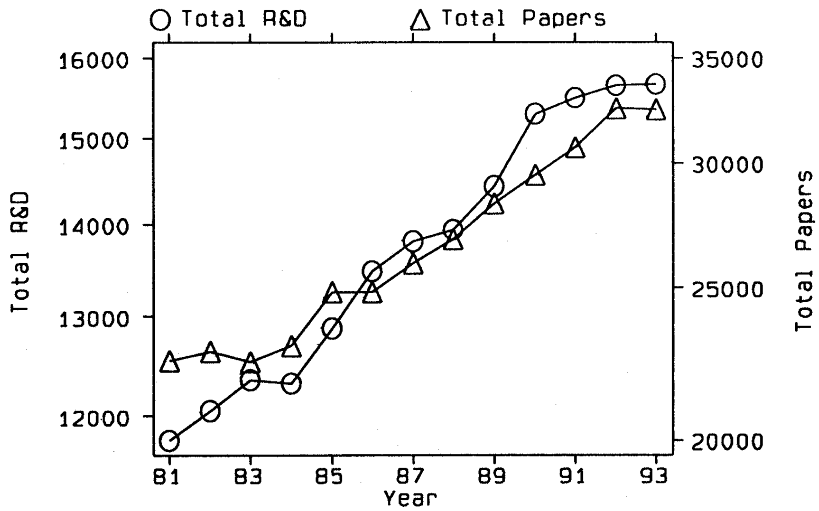

Fig 3a -- R&D and Papers

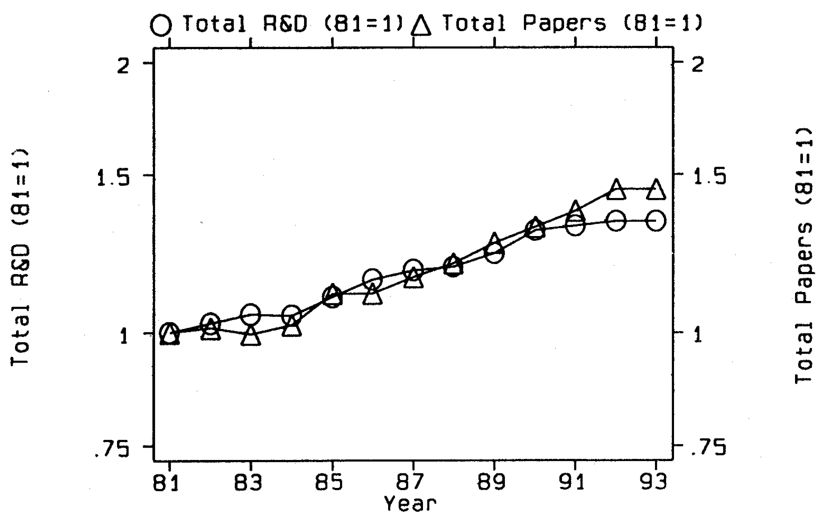

Fig 3b -- Normalized R&D and Papers

FIGURE 4

Biology

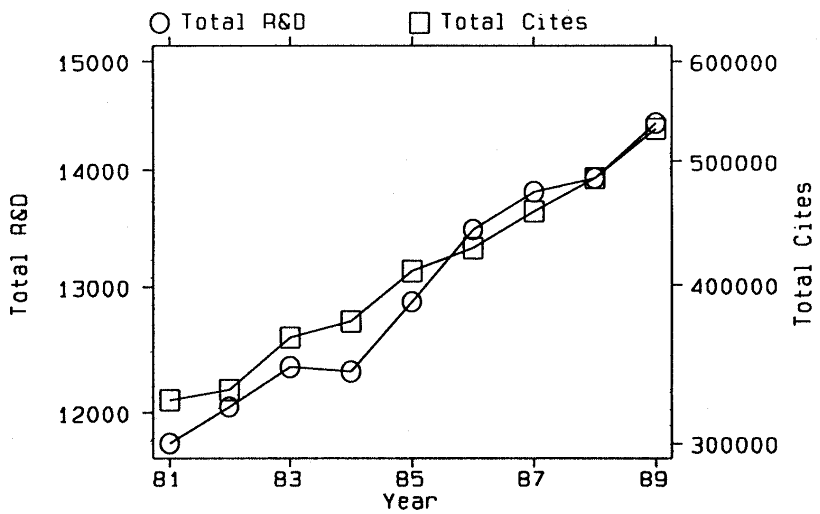

Fig 4a -- R&D and Cites

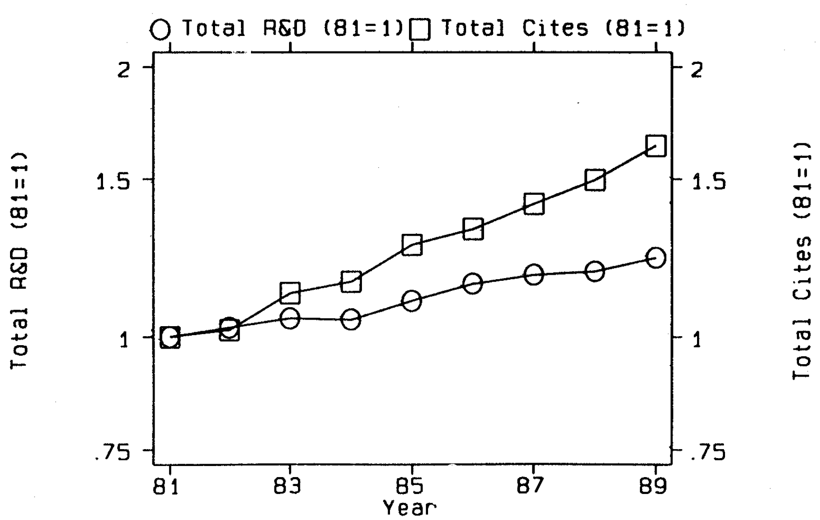

Fig 4b -- Normalized R&D and Cites

FIGURE 5

Chemistry

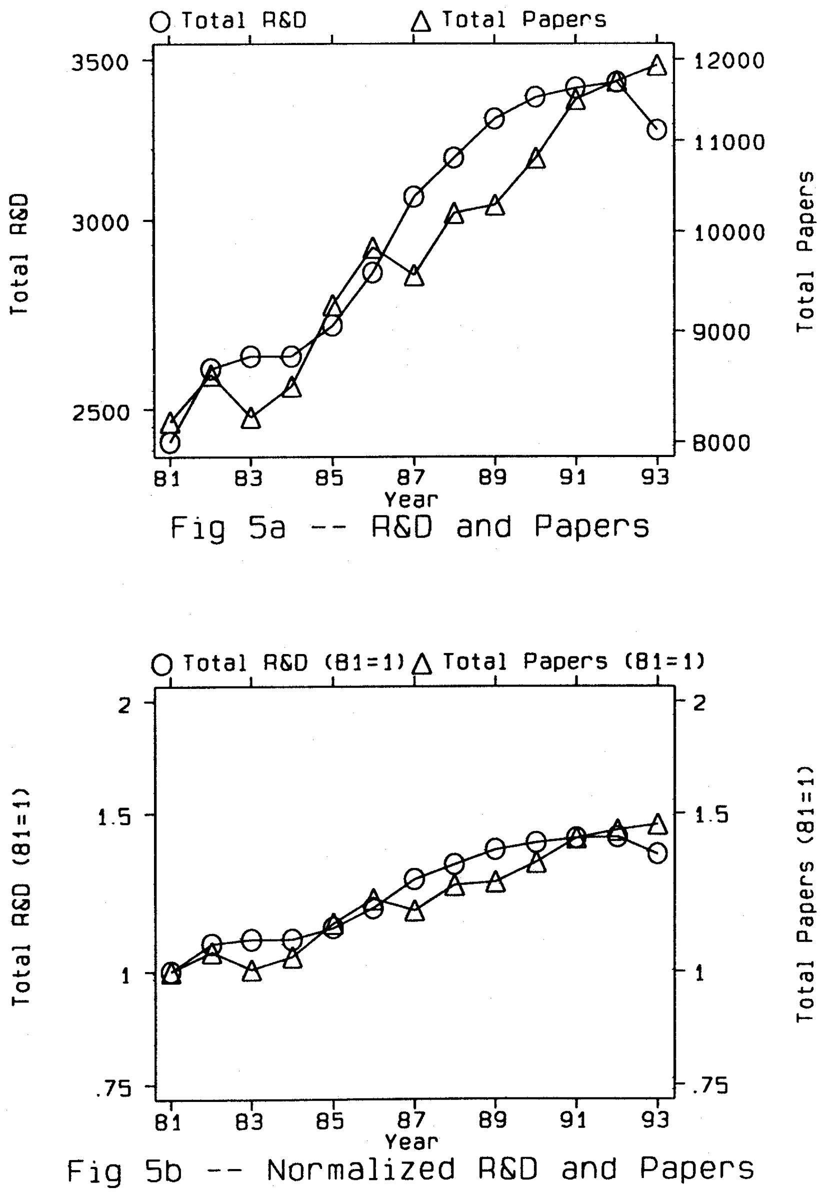

FIGURE 6

Chemistry

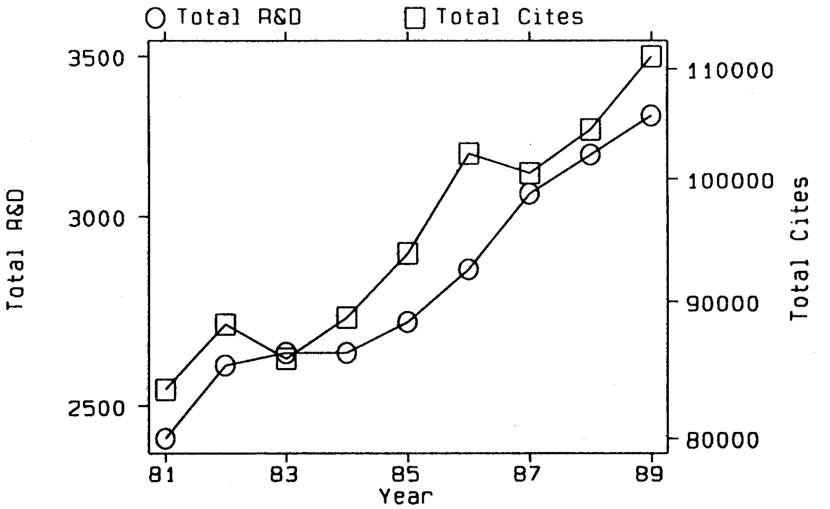

Fig 6a -- R&D and Cites

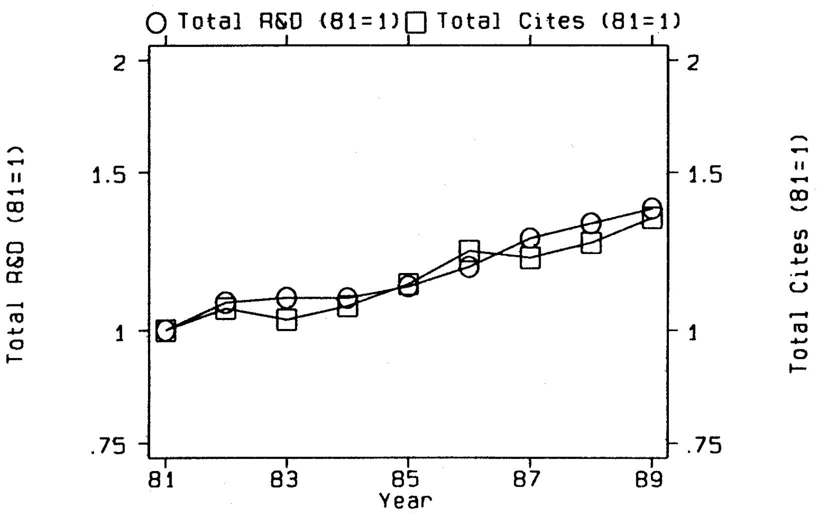

Fig 6b -- Normalized R&D and Cites

FIGURE 7

Computer Science

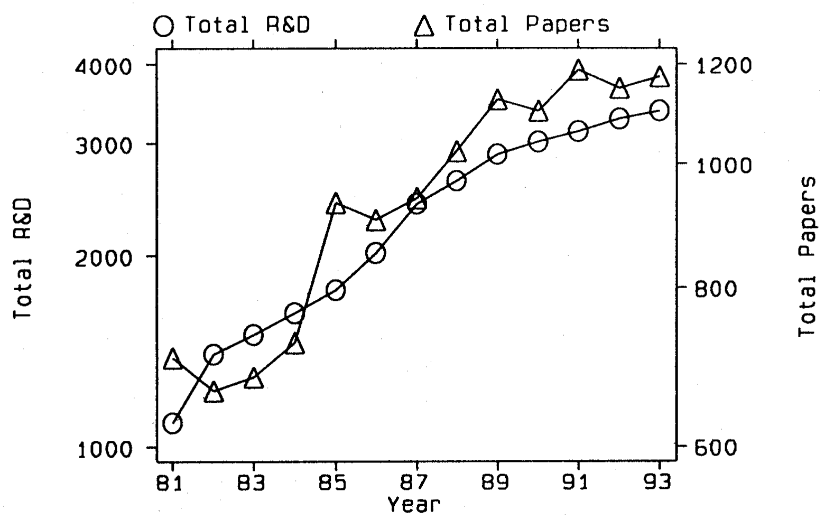

Fig 7a -- R&D and Papers

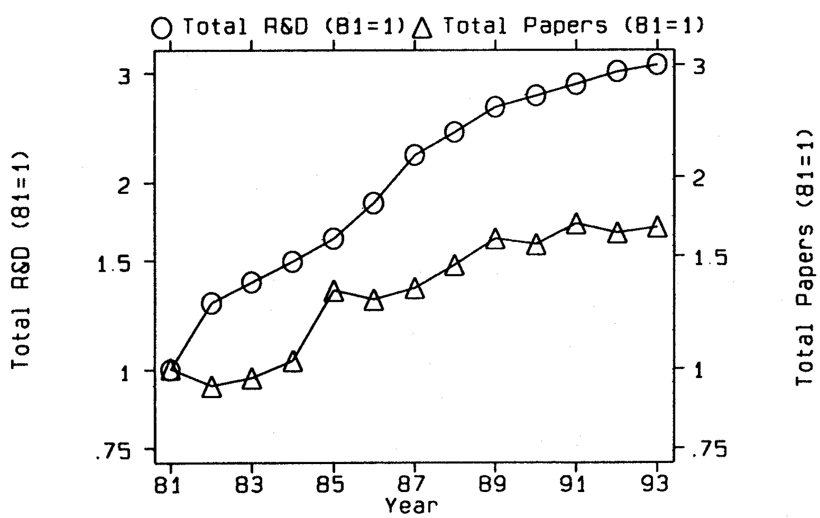

Fig 7b -- Normalized R&D and Papers

FIGURE 8

Computer Science

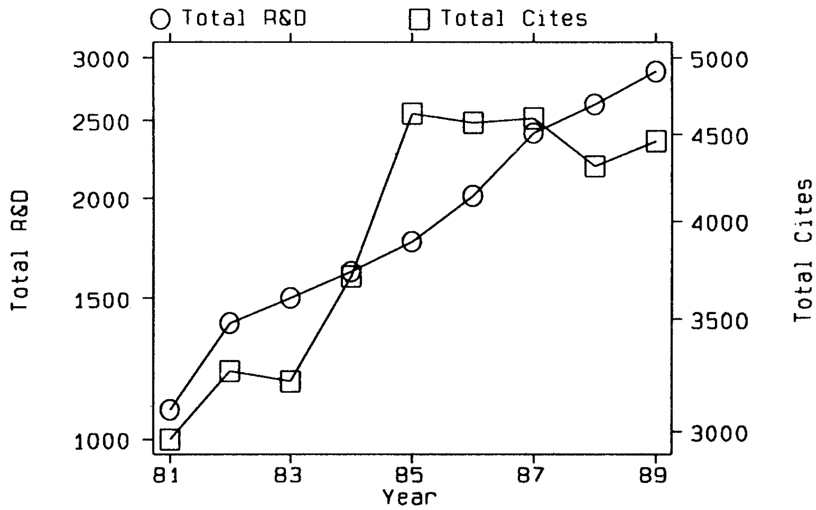

Fig 8a -- R&D and Cites

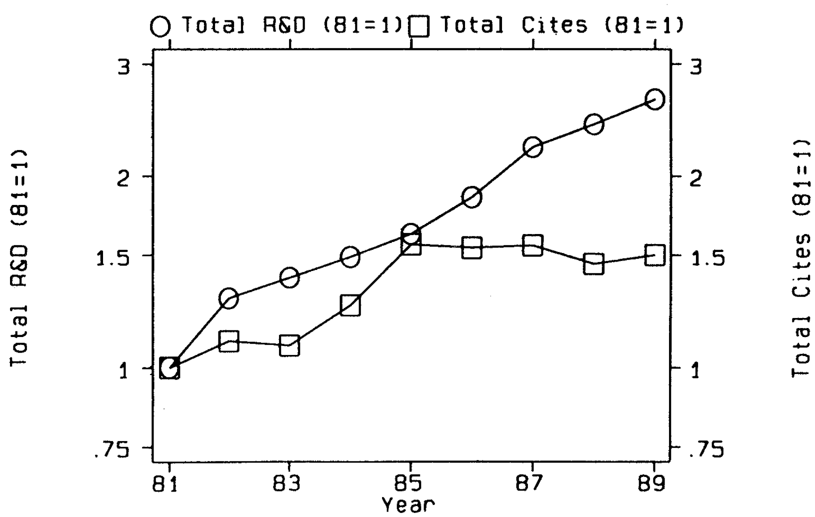

Fig 8b -- Normalized R&D and Cites

FIGURE 9

Engineering

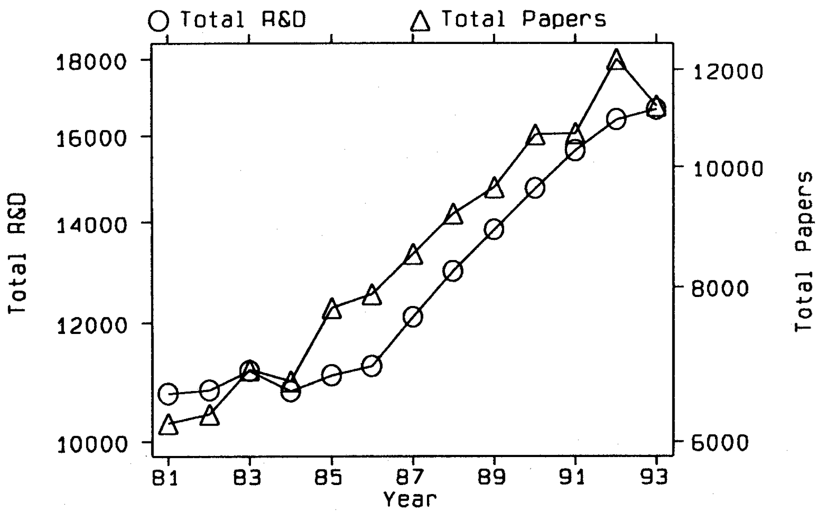

Fig 9a -- R&D and Papers

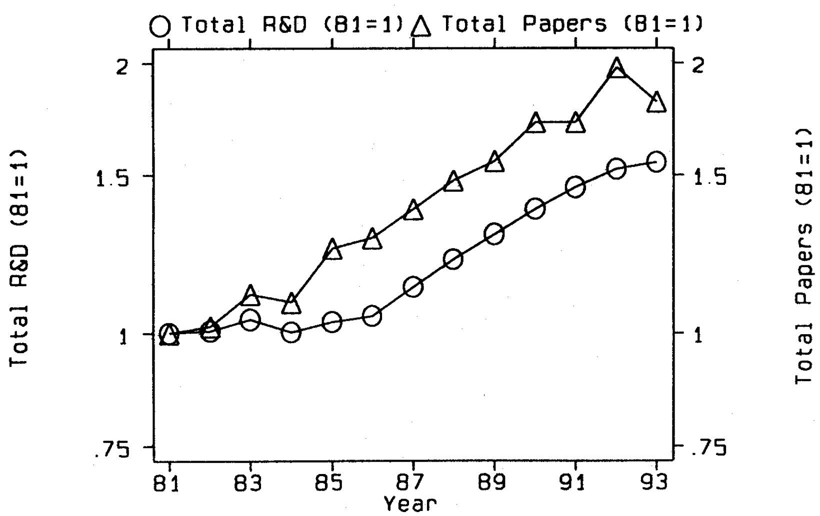

Fig 9b -- Normalized R&D and Papers

FIGURE 10

Engineering

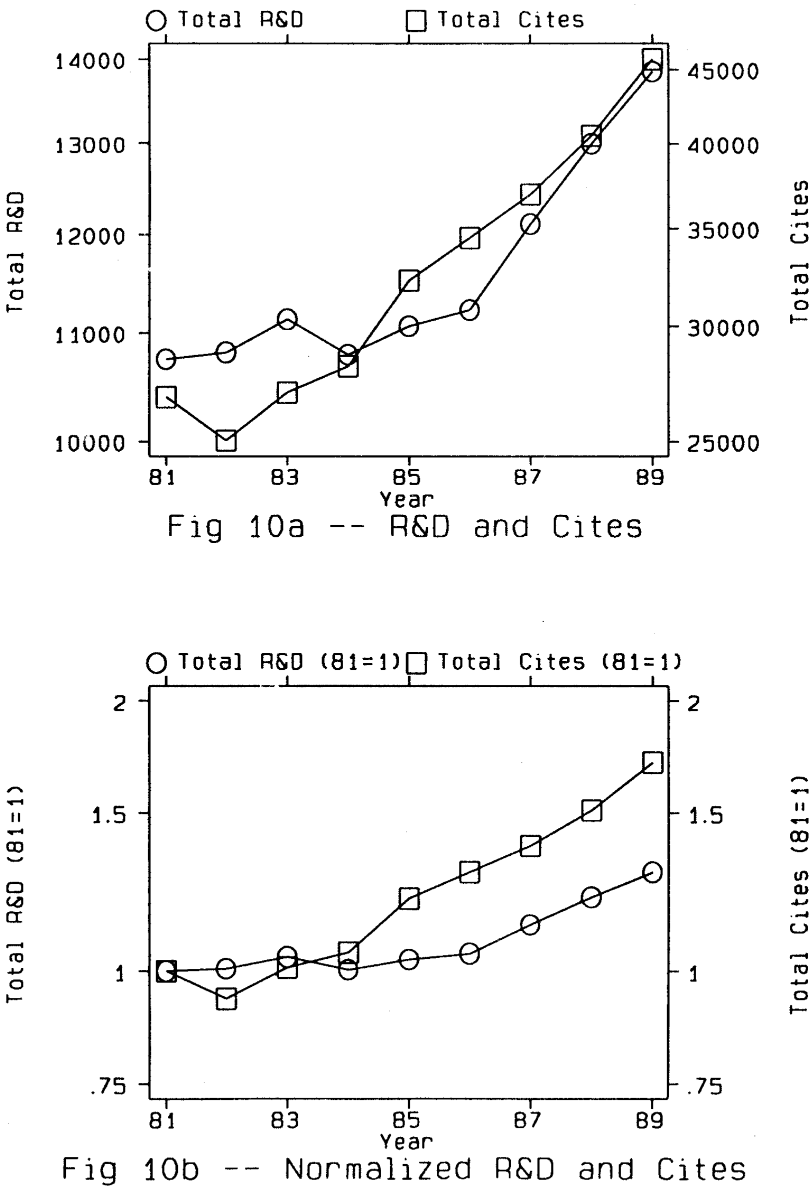

FIGURE 11

Mathematics

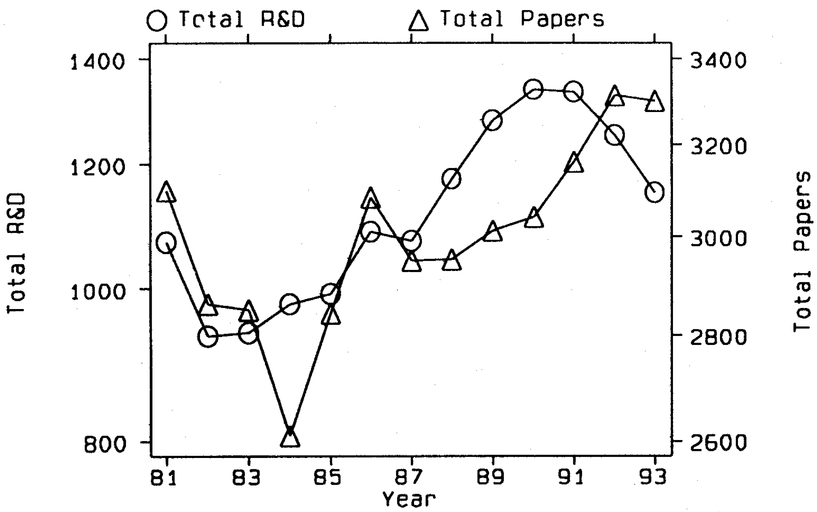

Fig 11a -- R&D and Papers

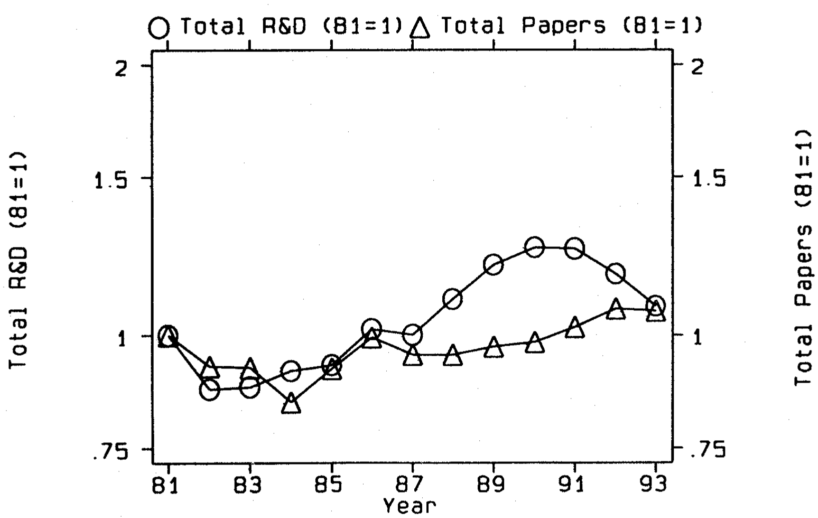

Fig 11b -- Normalized R&D and Papers

FIGURE 12

Mathematics

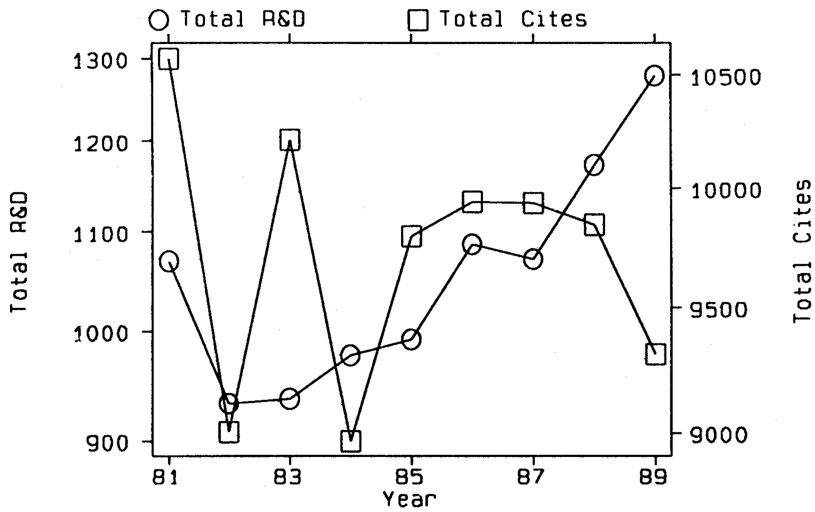

Fig 12a -- R&D and Cites

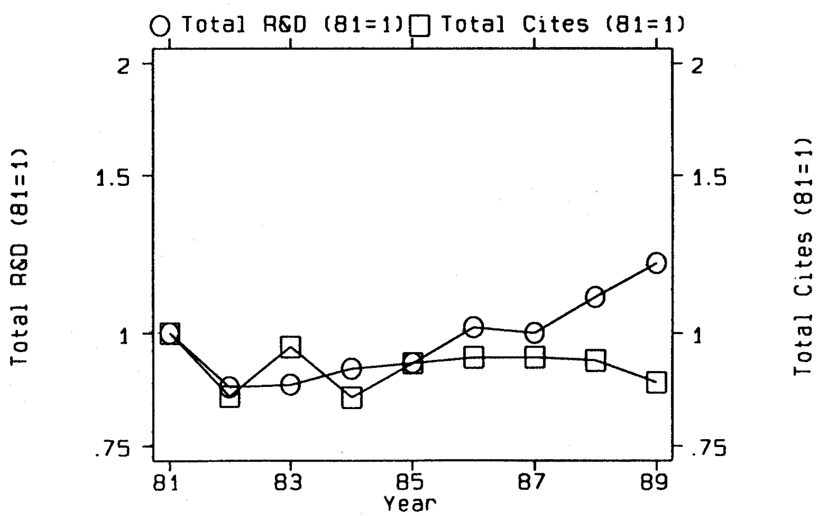

Fig 12b -- Normalized R&D and Cites

FIGURE 13

Medicine

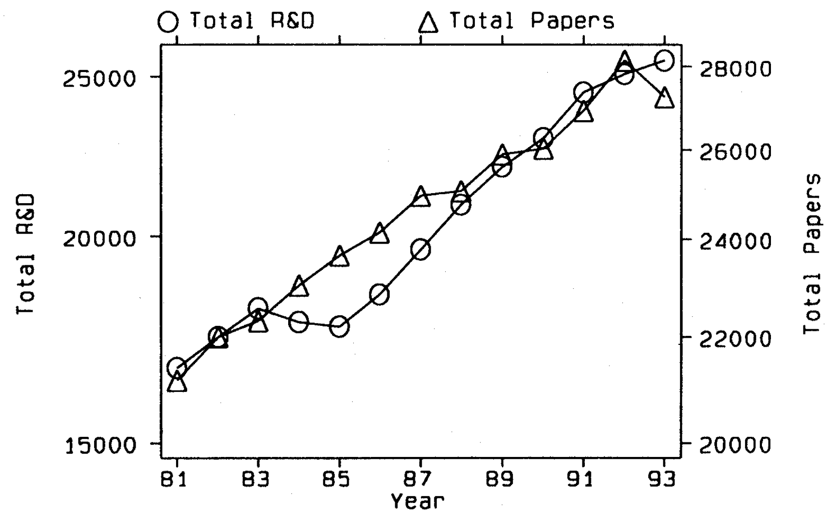

Fig 13a -- R&D and Papers

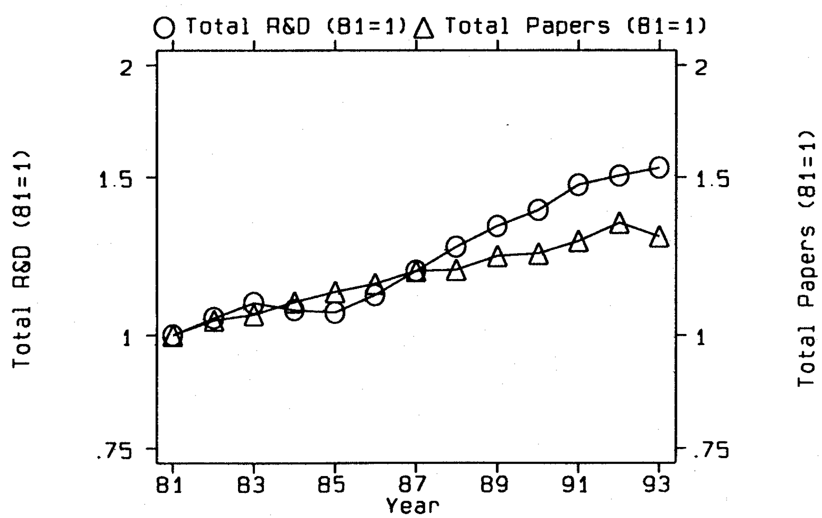

Fig 13b -- Normalized R&D and Papers

FIGURE 14

Medicine

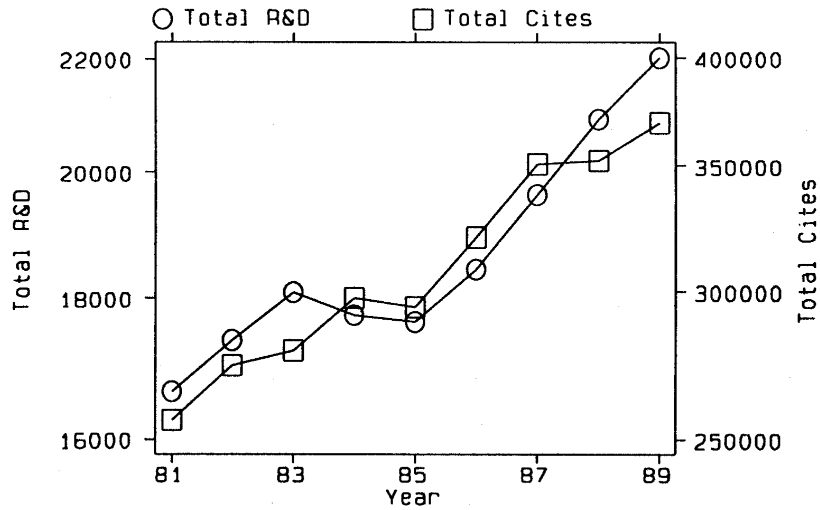

Fig 14a -- R&D and Cites

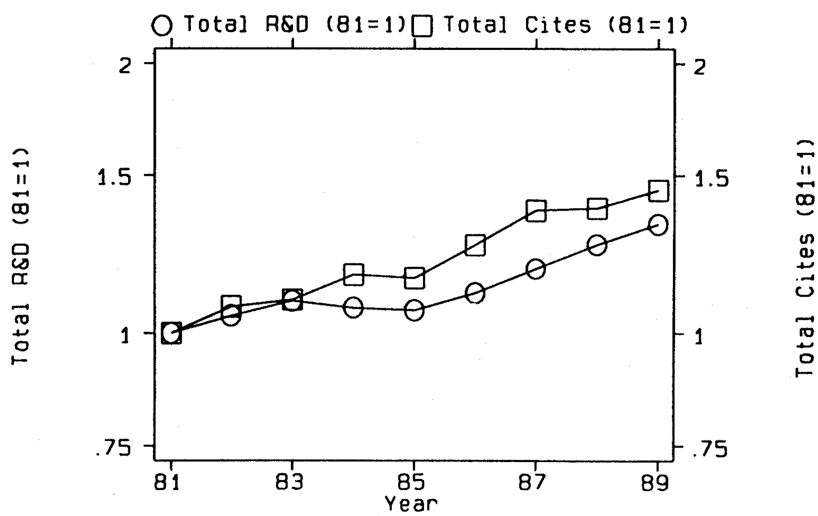

Fig 14b -- Normalized R&D and Cites

FIGURE 15

Physics

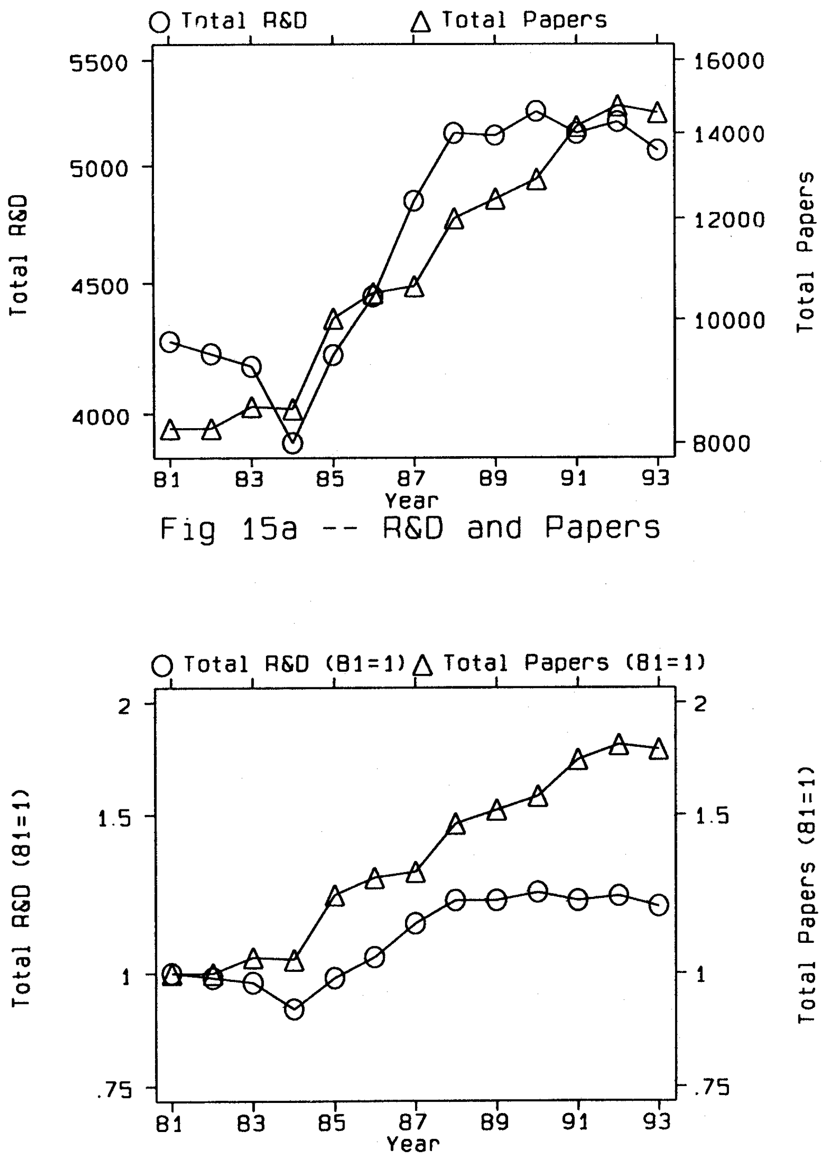

Fig 15a -- R&D and Papers

Fig 15b -- Normalized R&D and Papers

FIGURE 16

Physics

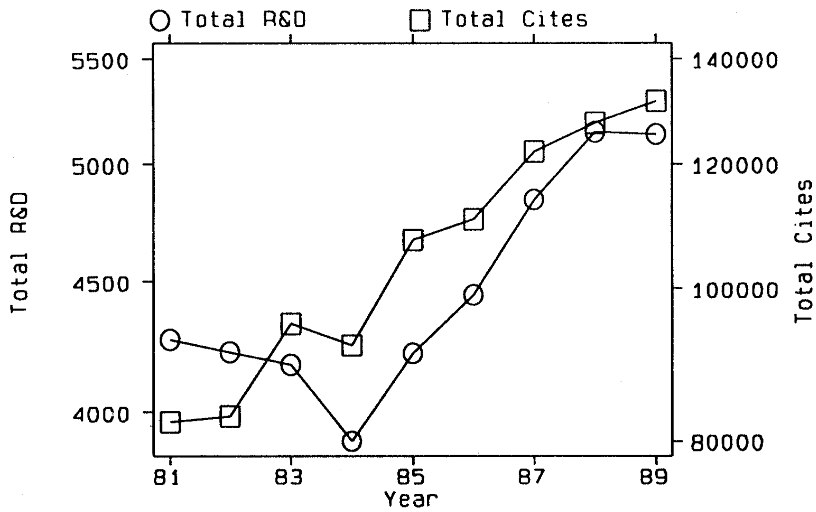

Fig 16a -- R&D and Cites

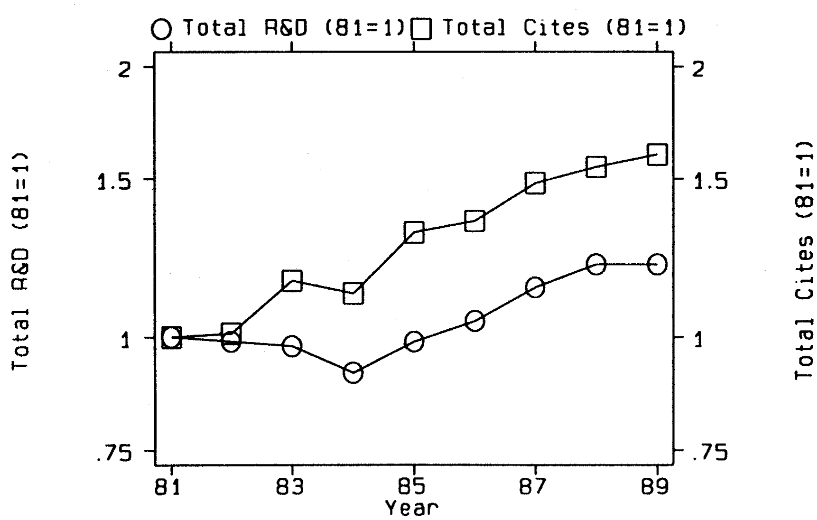

Fig 16b -- Normalized R&D and Cites

3 Findings at the Level of Universities and Fields

We now turn to the behavior of research output at the level of fields and universities. We have reasonably complete data on R&D and other characteristics for about thirty universities over the period 1973-1994, and we have consistent data on research outputs for the same schools over the period 1981-1993 [6]. Note that these samples at the individual university and field level are about one fourth of the 109 university sample on which Figures 1-16 are based.

The greater time span of R&D allows us to lag R&D spending relative to research outputs, although the final data are in fact restricted to the period 1981-1989 by the limited span of research output. Actual numbers of institutions are 24 in agriculture, 39 in biology, 41 in chemistry, 16 in computer science, 37 in engineering, 38 in mathematics, 33 in medicine, and 37 in physics. These numbers reflect the following selection criteria: (i), positive R&D; (ii), an active Ph. D. program (MD in medicine); and (iii), positive research output. We imposed these criteria to obtain consistent R&D data over time as well as samples that link up cleanly with the study of the joint determination of research and graduate teaching towards the end of the paper.

Panel A of Table 1 reports means of key variables. The typical field in a university produces one to two hundred papers per year with one to two thousand citations to those papers over five years. However, there is considerable variability across fields, with the life sciences being the most numerous producers of research and the mathematical sciences (mathematics, statistics, and computer science) the least numerous. The cross field differences arise partly from differences in the size of R&D programs: life sciences lead the group, while mathematics and computer science trail the other fields. Turning to teaching outputs as represented by undergraduate majors and Ph.D./MD degrees, we observe differing patterns by field. Engineering has large undergraduate and graduate programs, while medicine is concentrated at the graduate level. Programs in the mathematical and natural sciences tend to be small at both the graduate and undergraduate levels.

Panel B of Table 1 reports growth rates of research outputs, research funding, and teaching outputs for our regression samples. In most cases growth of research output equals or exceeds growth of research spending, the main exception being mathematics [7]. Turning to teaching outputs within

6. We have data on papers and citations over the period 1981-1993. We drop the data for 1990-1993 because we construct five years' worth of citations to papers published in each year, and this is clearly impossible for papers and citations to those papers after 1989.

7. It is important to point out that the samples of Table 1 comprise the upper tail of universities in Figures 1 to 16, and that their behavior is not precisely the same. This is readily seen for computer science, where growth of R&D is much closer to growth in research output in Table 1 than in Figures 7 and 8. Perhaps a larger fraction of computer science research is of a basic science nature in Table 1 than in these two figures.

fields, the pattern varies by discipline and presumably depends on differing market conditions. Life science degrees are flat over the period of the nineteen eighties at both levels, while the natural sciences, mathematical sciences, and engineering seem to shift towards increased focus on graduate education.

Table 2 examines average costs per paper and per citation in subsamples of the university and field level data. The average cost calculations remove scale of research programs from the data, facilitating comparisons across samples. Panel A breaks up the data by top ten research university and below [8]. Costs per paper are nearly the same in the top ten universities as in universities below this rank. Costs per citation are a different matter; on average these are thirty percent less in the top ten institutions [9]. These results suggest that top ten schools have a comparative advantage in producing more highly cited research.

Panel B breaks the data up into samples of private and public institutions. The comparisons exclude agriculture, since public universities dominate the latter field. The public-private comparisons suggest that private universities are more expensive at producing papers, yet cheaper at producing citations; indeed they are twenty percent cheaper [10].

Regression findings are presented in Tables 3 through 7. All the tables use a variant of the specification,

$$y = \alpha + \beta \cdot W(r) + \gamma \cdot X + u \tag{1}$$

where y is the logarithm of research output, comprised of papers or citations, $W(r)$ is the logarithm of a distributed lag function of real past R&D expenditures, and X is a vector of control variables. X includes year dummies to control for changes in the research production function over time. Sometimes it includes type of school (top ten, public, and so on). Our main interest centers on β, the elasticity of research output with respect to research input, and the measure of returns to scale in research in a field and university. Diminishing (constant or increasing) returns predominate at the university level for a given field when $\beta < 1$ ($\beta \geq 1$). As noted, the calculation of β is beset by multiple problems of measurement having to do with the horizon of the distributed lag, the mismeasurement of the R&D, the boundary of a field, the boundary of what constitutes the research

8. The top ten research universities were selected by the Institute for Scientific Information (ISI) on the following basis. First, universities were ranked among the top ten by *citation impact per paper* in each of twenty-one fields of science during the period 1981-1993. Second, those universities that ranked among the top ten most frequently, that is, based on number of appearances across the twenty-one fields, were awarded the title of top ten research university. The list includes the following private universities: Harvard, Yale, Chicago, MIT, Stanford, Princeton, Cornell, and the California Institute of Technology. The two public institutions are Berkeley and the University of Washington. Notice that a number of universities with large and successful research programs are excluded by this criterion, especially the University of Pennsylvania, Northwestern University, and Carnegie Mellon University, but also others.

9. Use the ratio of column means of costs per citation in Panel A: 11.3/16.4 = 0.69. Thus costs per citation are actually thirty-one percent lower in the top ten universities.

10. The ratio of the column means of costs per citation in Panel B is 14.1/17.8 = 0.79.

Table 1

Descriptive Statistics: Research Outputs, Research Funding, and Teaching Outputs of US Universities, 1981-1989.

	Variable					
		Research			Teaching	
Fields of Science	Number of Univer-sities [a] (1.1)	Papers per Year (1.2)	Cites over 5 years [b] (1.3)	5 Year Lagged R&D (1000$) [c] (1.4)	Bacc. Degrees in Field (1.5)	Ph.D./MD Degrees in Field (1.6)
Panel A. Means per University and Field, 1981-1989						
Agriculture	24	286	1223	23082	183	22
Biology	39	322	5759	19139	154	35
Chemistry	41	113	1249	4166	33	18
Computer Science	16	17	91	3882	80	7
Engineering	37	124	563	16223	436	47
Mathematics	38	45	166	1387	54	9
Medicine	33	355	5097	32277	55 [d]	180
Physics	37	148	1645	6887	18	11
Panel B. Annual Rates of Growth, 1981-1989						
Agriculture	24	0.024	0.031	0.006*	–0.093	0.017*
Biology	39	0.034	0.065	0.029	–0.003*	–0.002*
Chemistry	41	0.027	0.038	0.030	–0.034	0.019
Computer Science	16	0.071	0.042	0.061	0.006*	0.034
Engineering	37	0.053	0.067	–0.002*	0.005*	0.064
Mathematics	38	0.002*	0.001*	0.031	0.077	0.036
Medicine	33	0.021	0.046	–0.020	0.022 [d]	–0.013
Physics	37	0.052	0.058	0.010*	0.037	0.028

*Notes. Panel A reports means at the university and field level, Panel B reports mean annual rates of growth on data averaged across the set of universities in each row. * Variable is not significant at the 1% level for a one tailed test. [a] Number of schools is the number for which data are available. [b] Citations are to papers published in a given year over the current year and the next four years. [c] For papers and citations dated in year t, 5 year lagged R&D is the inverted V-lag of deflated R&D over years $t-1$ through $t-5$, where the weights are 0.111, 0.222, 0.333, 0.222, and 0.111. [d] Data on the number of pre-med baccalaureate degrees are available for a smaller number of medical schools than other medical data. Thus the number of observations is 178 here rather than 294.*

community of a university, and the very meaning of R&D expenditures. Likewise the assessment of diminishing return based on the size of β is clouded by exclusion of research externalities between fields and universities (spillovers) that bias our estimates of the *overall* returns to scale towards zero.

Table 3 presents estimates of β, where the type of school (public, private, top ten) is held constant. In this sense the regressions are "within group" estimates. For each measure of research output, papers and citations, we present results for five year distributed lags of R&D. The five year lag uses inverted V weights of 0.111, 0.222, 0.333, 0.222, and 0.111 on R&D dated

TABLE 2

Mean Research Costs per Unit of Research Output: Subsamples of US Universities, 1981-1989.

	Variable			
Field of Science	Research Dollars in 1000s per Paper	Research Dollars in 1000s per Citation [a]	Research Dollars in 1000s per Paper	Research Dollars in 1000s per Citation [a]
Subsamples of Panel A:	**Universities in the Top Ten** [b]		**Universities Below the Top Ten** [b]	
Agriculture	76.5	13.8	81.6	20.0
Biology	59.1	2.4	60.1	4.2
Chemistry	42.3	3.1	32.9	3.3
Computer Science	217.0	34.9	187.8	43.6
Engineering	163.1	30.1	136.2	35.7
Mathematics	30.9	6.7	28.0	9.0
Medicine	71.6	4.0	91.6	7.4
Physics	67.6	4.8	35.4	3.7
Column Means (All Fields)	**84.3**	**11.3**	**83.1**	**16.4**
Subsamples of Panel B:	**Private**		**Public**	
Biology	61.2	2.9	58.9	4.3
Chemistry	42.1	3.4	31.3	3.2
Computer Science	255.6	42.9	149.8	38.2
Engineering	162.9	31.4	133.7	35.4
Mathematics	34.8	8.2	25.4	8.4
Medicine	87.3	5.6	86.2	7.3
Physics	53.1	4.3	37.2	3.9
Column Means (excluding agriculture)	**99.6**	**14.1**	**74.6**	**17.8**

Notes. Field samples are the same as in Table 1. [a] *Citations are to papers published in a given year over the current year and the next four years.* [b] *The top ten research universities are selected by the Institute for Scientific Information (ISI). The criterion is the university rank among the top ten in terms of frequency of appearance among the top ten schools in 21 individual research fields measured by citation impact in each field.*

$t-5$, $t-4$, $t-3$, $t-2$, and $t-1$ relative to research output dated t or later. Five year lags yield a very slightly higher value for the research elasticity than three years lags (not reported here). This could indicate a longer lag in effect or else a fall in measurement error in $W(r)$ as length of lag r increases. The main finding is that research elasticities lie below 1. The difference is almost always significant at the 1% level, with the citation elasticities being about 0.1 higher than the paper elasticities. One interpretation of this finding is that papers "leak" out of the larger research programs as Ph.D. students move to faculty posts in other, usually smaller programs. Thus the R&D that generates these research papers is incorrectly assigned

TABLE 3

Research Output Regressions

	Papers per Year			Citations over 5 Years [a]		
Field of Science	Time Trend of Papers [b] (3.1)	Time Trend of Papers per $ of R&D [c] (3.2)	Coefficient of Lagged Total R&D [d] (3.3)	Time Trend of Citations [b] (3.4)	Time Trend of Citations per $ of R&D [c] (3.5)	Coefficient of Lagged Total R&D [d] (3.6)
Agriculture	0.020	0.018	0.90	0.032	0.031	0.93
Biology	0.015	0.006	0.67	0.041	0.036	0.83
Chemistry	0.011	−0.009	0.44	0.019	0.006	0.64
Computer Science	0.039	0.026	0.54	0.010	0.002	0.71
Engineering	0.050	0.048	0.57	0.059	0.058	0.68
Mathematics	−0.015	−0.037	0.38	−0.020	−0.037	0.53
Medicine	0.031	0.034	0.75	0.058	0.060	0.86
Physics	0.041	0.034	0.53	0.046	0.041	0.65

Notes. Variables and samples are defined in Table 1. Regressions include year dummies, 0-1 dummy variables for top ten research universities, for top ten private universities, and for other private universities. [a] *Citations over five years are citations in years t to $t+4$ for papers published in year t.* [b] *Time trend is the annualized effect of the time dummies. It is the difference between the 1989 year dummy and the 1981 year dummy divided by eight in a regression in which the log of lagged total R&D is a separate variable.* [c] *Time trend has the same interpretation as in note b, except that the log of papers or citations per dollar of R&D is the dependent variable. This constrains the research output elasticities to be 1.0.* [d] *Lagged total R&D is the log of total R&D lagged 5 years using an inverted V lag with weights of 0.111, 0.222, 0.333, 0.222, and 0.111 on R&D in years $t-5$, $t-4$, $t-3$, $t-2$, and $t-1$ respectively, for papers in year t and citations in years t and citations in years t through $t+4$.*

to different universities. Citations avoid this problem to an extent because research papers of young faculty cite papers in leading programs where their Ph.D. research was carried out. A second interpretation of the higher citation elasticity, by no means mutually exclusive, is that larger research programs focus on more basic research which produces occasionally bigger "hits". This could very well be an implication of the sorting of higher quality faculty to these institutions.

In addition, both the paper and citation elasticities are downward biased because the assignment of the papers and citations to fields is incorrect. Supporting evidence on this point is found in Tables 5 and 6 of ADAMS and GRILICHES [1996]. There it is shown that combining the fields of biology and medicine results in higher papers and citations elasticities than we find in either field separately, while combining the five fields of biology, chemistry, mathematics, medicine, and physics results in higher papers and citations elasticities than are observed for any of the five component fields.

Table 3 consists of regressions controlling for group effects, since the equations include dummies for type of institution. When we remove the dummies and introduce between group effects, research elasticities increase. This effect is important for biology, chemistry, engineering, and

TABLE 4

Eight Year Differences of Research Output: Coefficients of Papers per Year, and Citations over 5 Years, on Eight Year Differences of Lagged R&D

	Papers per Year	Citations over 5 Years [a]
Field of Science	Lagged Total R&D [b] (4.1)	Lagged Total R&D [b] (4.2)
Agriculture	0.08*	0.06*
Biology	0.14*	0.20*
Chemistry	0.17*	0.13*
Computer Science	–0.11*	–0.03*
Engineering	0.02*	0.17*
Mathematics	0.03*	0.06*
Medicine	–0.05*	–0.23*
Physics	0.21	0.31

*Notes. Samples are defined in Table 1. Eight year differences are the difference between 1981 and 1989 of the log of citations and papers regressed on the corresponding difference between 1981 and 1989 of the log of lagged R&D. *Coefficient is not significantly different from zero at the 3% level.* [a] *Citations over five years are citations in years t to $t+4$ for papers published in year t.* [b] *Lagged total R&D is the log of total R&D lagged 5 years using an inverted V lag with weights of 0.111, 0.222, 0.333, 0.222, and 0.111 on R&D in years $t-5$, $t-4$, $t-3$, $t-2$, and $t-1$ respectively, for papers in year t and citations in years t through $t+4$.*

mathematics [11]. Nevertheless, the elasticities remain below unity, indicating as before the *appearance* of diminishing returns to research at the university and field level.

Table 4 estimates eight year, long differences of research output on eight year, long differences of the distributed lag of R&D, thus taking out university and field fixed effects, including quality of university. As is often the case with panel data, the resulting elasticities fall by a large amount and are no longer different from zero. We are unable to control for changes in the financial, personnel, legal and other variables that drive changes in research productivity at this level. More fundamentally, R&D spending is correlated with a host of other factors; R&D spending captures the standing of a university and its faculty and is not therefore, a pure indicator of the effect of lagged research support on research output.

Table 5 departs from the earlier specification in (1) by allowing for separate effects of federal and non-federal R&D. In this case we use the nonlinear specification,

$$y = \alpha + \beta \cdot \ell n \left[W^* \left(r_f \right) + \delta \cdot W^* \left(r_n \right) \right] + \gamma \cdot X + u, \tag{2}$$

11. Taking the five year distributed lag of R&D as a benchmark we find that the within and between group elasticities for papers (citations) are 0.03 (0.08) higher in biology, 0.07 (0.11) higher in chemistry, 0.04 (0.06) higher in engineering, and 0.06 (0.09) higher in mathematics. None of the elasticities were lower than in Table 3.

TABLE 5

Nonlinear Research Output Regressions: Coefficients of Papers per Year and Citations over 5 Years, on Lagged Federal and Non-federal R&D.

Field of Science	Papers per Year: Coefficient of Lagged Total R&D (β) (5.1)	Papers per Year: Coefficient of Lagged Non-Federal R&D (δ) (5.2)	Citations over 5 Years: Coefficient of Lagged Total R&D (β) (5.3)	Citations over 5 Years: Coefficient of Lagged Non-federal R&D (δ) (5.4)
Agriculture	0.91	0.75 [c]	0.95	0.79 [c]
Biology	0.64	0.07 [b]	0.79	–0.09 [b]
Chemistry	0.44	1.42 [c]	0.63	0.61 [c]
Computer Science	0.56	0.46 [a]	0.75	0.13 [b]
Engineering	0.54	0.11 [b]	0.62	–0.03 [b]
Mathematics	0.41	0.12 [b]	0.57	0.04 [b]
Medicine	0.68	0.20 [a]	0.76	0.10 [b]
Physics	0.54	3.24 [d]	0.66	2.90 [d]

Notes. Variables and samples are defined in Table 1. Estimation method is NLLS. Regressions include 0-1 dummy variables for top ten research universities, for top ten private universities, and for other private universities. Specification of R&D is: log (Federal R&D+δ·NON-FEDERAL R&D). All coefficients are significantly different from zero at the 1% level unless otherwise noted. [a] *Coefficient is significantly greater than zero and less than one at the 1% level.* [b] *Coefficient is not significantly different from zero at the 1% level.* [c] *Coefficient is significantly greater than zero but is not significantly different from one at the 1% level.* [d] *Coefficient is significantly greater than one at the 1% level.*

where ℓn is the natural log, $W^*(r_f)$ is the *arithmetic* distributed lag of federal R&D and $W^*(r_n)$ is the *arithmetic* distributed lag of non-federal R&D. Throughout Table 5 we use a five year distributed lag of R&D.

Specification (2) allows the effect of non-federal R&D, δ, to differ from the effect of federal R&D, as given by β. The effect of non-federal R&D is smaller than the federal effect when $\delta < 1$, and at least equal when $\delta \geq 1$. However, we are obliged to point out that (2) is not the experiment we would conduct had we access to more detailed data. We cannot for example, decompose non-federal R&D into state government supported research, much of which could be targeted on service activities rather than publication; into funding by private industry that has an applied focus; and into funding by foundations, some of which may be given over to the most basic science. It is important to also see that any censoring effects on publication that might be due to industry supported R&D are included in the non-federal component of R&D, though we cannot separate industry-supported research from other non-federal sources. Nevertheless, (2) does separate federal R&D from non-federal, and it is the greatest detail of which our R&D data are capable [12].

12. Again we wish to emphasize that at the university and field level, non-federal R&D is not broken up into research that is funded by the university itself, by state and local governments, or by private foundations in the CASPAR database.

Columns (5.1) and (5.2) of Table 5 report the β and δ parameters of equation (2) for regressions in which papers are the dependent variable. Columns (5.3) and (5.4) report the β and δ parameters for total citations. Inspection of (5.1) and (5.3) shows that estimates of the effect of federal R&D are very similar to the overall research elasticities in Table 3. To see this, compare column (3.1) in Table 3 with column (5.1) of Table 5 and likewise the two columns labeled (3.3) and (5.3); these are precisely the same specification apart from the nonlinearity of the R&D term in (2) and Table 5.

The surprising result in Table 5 is the wide variation in the effect of non-federal R&D by field in comparison with federal. The non-federal effect, summarized by the parameter δ (see (2) above) is significantly less than the federal effect, summarized by β, in biology, computer science, engineering, mathematics, and medicine. Of the remaining three fields, federal and non-federal R&D have the same effect on research output in agriculture and chemistry, at conventional 1 per cent levels of significance. In the case of physics, non-federal R&D has a significantly greater effect than federal R&D: indeed, the point estimate says that a dollar of non-federal R&D has an effect three times larger than a dollar of federal R&D! Results for chemistry are qualitatively similar to physics, but the point estimate of $\delta = 1.4$ is not estimated with very much precision.

The large amount of variation in the non-federal effect δ that we observe in Table 5 calls for an explanation. Bearing in mind that any explanation must be speculative given the current evidence, there are some obvious candidates for the variation that we observe in δ. For example, the point estimate of the non-federal effect could be larger in chemistry and physics because a sizable part of non-federal R&D is targeted on basic research in these two fields. Nevertheless, the average effect of non-federal R&D across fields is inconsistent with this view: in most cases we observe $\delta < 1$ and a dollar of non-federal R&D is associated with lower observed research productivity compared with a dollar of federal R&D. However, one has to remember that what we call R&D consists of wide-ranging activities. In cases where $\delta < 1$ the non-federal R&D could be more directed towards applied research, even service activities that are less likely to result in publication. Examples are "R&D" funding for participation on public service commissions, consulting and contract research for business firms, and private funding for the construction of university plant and equipment that partly has a teaching function. In reality the results of Table 5 are still more diverse than we have implied. In biology, engineering, and mathematics, non-federal R&D is predicted to have *no* impact on research output. Again, we suspect that in these cases the non-federal component is aimed entirely at objectives other than basic research.

Table 6 stratifies the samples for private and public universities and compares elasticities of research output to lagged R&D in the two samples. In Table 6 alone we drop the dummy variable for top ten schools from the regressions. The reason is that we want to draw a full, "within and between group" comparison between private and public schools. If we control for the greater productivity of top ten schools, then we are making a biased comparison between public and private schools, because the private school sample is more homogeneous within its group. Top ten schools form about half of the private institutions in our private school samples and the remainder are similarly homogeneous within their class. Thus, the "within group" variation is smaller among the private schools than it is for public universities [13].

TABLE 6

Research Output Regressions for Private and Public Universities: Coefficients of Papers per Year and Citations over 5 Years, on Lagged R&D [a].

	Private Universities		Public Universities	
Field of Science [b]	Papers per Year (6.1)	Citations over 5 Years [c] (6.2)	Papers per Year (6.3)	Citations over 5 Years [c] (6.4)
Biology	0.77	0.95	0.64	0.90
Chemistry	0.67	0.91	0.37	0.60
Computer Science [d]	0.61	0.65	0.54	0.75
Engineering	0.62	0.72	0.60	0.75
Mathematics	0.46	0.61	0.41	0.64
Medicine	0.82	1.13	0.75	0.87
Physics	0.58	0.78	0.49	0.62

Notes. Variables and samples are defined in Table 1. All coefficients are significantly different from zero at the 1% level. These regressions omit the 0-1 dummies for top ten research universities, for top ten private universities, and for other private universities. [a] Total R&D is lagged 5 years, As in Table 1, this is an inverted V lag with weights of 0.111, 0.222, 0.333, 0.222, and 0.111 on R&D in years $t-5$, $t-4$, $t-3$, $t-2$, and $t-1$ respectively, for papers in year t and citations in years t through $t+4$. [b] Public and private university comparisons are not possible in agriculture, since public universities dominate the field. [c] Citations over five years are citations in years t to $t+4$ for papers published in year t. [d] Samples for computer science are relatively small. The private university sample consists of 5 schools over the 1981-1989 period. The public university sample consists of nearly complete observations on 10 schools over the period 1981-1989.

13. The same point can be made more formally as follows. Using standard notation for panel data (see for example BALTAGI [1995]), the within and between group, or total estimator is $\beta_T = (W_{XX} + B_{XX})^{-1}(W_{XY} + B_{XY})$, where W_{ij} and B_{ij} indicate within and between group data matrices. The within group estimator is then $\beta_W = W_{XX}^{-1} W_{XY}$ while the between group estimator is $\beta_B = B_{XX}^{-1} B_{XY}$. It follows that $\beta_T = \phi\beta_W + (1-\phi)\beta_B$, where ϕ is the relative weight on within group variation and $1-\phi$ the weight on the between group variation. Assume, as is correct for out data, that $\beta_W = \alpha\beta_B$, $\alpha < 1$. Now divide the data into two sets 1 and 2 that include both within and between group variation. Using the above relationships the ratio of the total estimators β_T for groups 1 and 2 is related to the ratio of the within estimators β_W by the following formula:
$$\frac{\beta_{T1}}{\beta_{T2}} = \left[\frac{\alpha_2}{\alpha_1}\,\frac{1-(1-\alpha_1)\,\phi_1}{1-(1-\alpha_2)\,\phi_2}\right]\frac{\beta_{W1}}{\beta_{W2}}.$$
Let set 1 be the private schools and set 2 the public schools and assume for simplicity that $\alpha_1 = \alpha_2$. Then the condition that the ratio of the total estimators on the left exceed the ratio of the within estimators on the right is that the bracketed term exceed 1.0, which comes down to $\phi_1 < \phi_2$, or that within group variation is smaller relative to the total variation for set 1, the private institutions.

Columns (6.1) and (6.3) are comparable regressions for private and public universities with papers as the dependent variable. Likewise (6.2) and (6.4) are comparable public-private regressions for citations. Clearly the elasticity of research output is greater in private schools whether we use papers or citations as the measure of output. In fact the private elasticities are about 0.1 higher than the public elasticities. Whether the result is due to smaller errors in the data from private schools or to a genuine difference in the ability to obtain output from given funding is unclear from the evidence, although the question clearly deserves further study, especially from a policy perspective.

So far the regressions we have reported assume that research output can be captured entirely by papers and citations. However, research universities place great emphasis on the production of Ph.D. students whose knowledge reflects recent innovations in research. These students clearly serve a valuable function by transmitting new techniques to researchers in other universities, industry, and government as well as through their own research. In this sense, graduate students comprise a kind of "intergenerational" research output. For all these reasons we conclude our presentation of findings with a table of multivariate results for papers or citations and Ph.D. degrees in a regression system. Our statistical method is Seemingly Unrelated Regression (SUR). As we have noted, the SUR system jointly estimates equations for research output and *graduate* teaching output measured by the logarithm of the number of advanced degrees [14]. In this case the specification consists of two production functions:

$$\begin{aligned} y_R &= \alpha_R + \beta_{RR} \cdot W_R(r) + \beta_{RA} \cdot W_A(r) + \gamma_R \cdot X + u_R \\ y_S &= \alpha_S + \beta_{SR} \cdot W_R(r) + \beta_{SU} \cdot W_U(s) + \gamma_S \cdot X + u_S, \end{aligned} \tag{3}$$

where the first equation is the research equation, the second is the graduate degrees equation, and the error terms are assumed to have mean zero, variances σ_{RR} and σ_{SS}, and covariance σ_{RS}.

We add the subscript R to the first equation to indicate research and S to the second to indicate graduate students. $W_R(r)$ is the log of five year lagged R&D, as in earlier tables. $W_A(r)$ is the log of five year lagged advanced degrees: this variable is based on the same inverted V weights as R&D [15]. X is the set of school dummies employed in earlier tables. The second equation expresses graduate student output y_S, the logarithm of the current number of advanced degrees, as a function of lagged R&D, $W_R(r)$, and $W_U(s)$, the log of a distributed *lead* of undergraduate science

14. The number of advanced degrees is the number of MD degrees in medicine, the number of Ph.D. degrees in other fields.

15. Thus $W_S(r)$ is the log of the sum of advanced degrees in years $t-5$ through $t-1$, with inverted V weights 0.111, 0.222, 0.333, 0.222, and 0.111, just as for R&D.

and engineering degrees in a university. Also included are the same set of controls X consisting of school dummies. The difference between the two equations therefore centers on the variables $W_A(r)$ and $W_U(s)$.

The research equation introduces both the distributed lag of both lagged R&D and lagged graduate students $W_A(r)$ because both research dollars and the pool of graduate students are important inputs into research. But why a distributed *lead* of undergraduate degrees $W_U(s)$ in the graduate degrees equation? We employ this variable since undergraduate degrees proxy for undergraduate teaching in the recent past and because reliable data on undergraduate enrollments are missing [16]. The particular form of the distributed *lead* $W_U(s)$ uses a constant weight of one third on undergraduate science degrees received in periods $t+1$, $t+2$, and $t+3$ relative to doctoral degrees received in period t. The rationale for this form of $W_U(s)$ is that undergraduate students receiving their diplomas in year t took their introductory science courses, in which graduate student teachers are concentrated, in year $t-3$. Likewise, undergraduates graduating in $t+2$ and $t+3$ are likely to have taken their introductory courses in years $t-2$ and $t-1$. In this way we construct a proxy for the introductory science and engineering teaching load over the course of the period t graduate student cohort. Thus, $W_U(s)$ is a demand variable for the services of graduate students in one interpretation, and a source of support, an "input" in another interpretation. The controls that enter the two equations of (3) as before include the year and institutional type dummies that we have already discussed. Of course this system is a reduced form and we do not pretend to have gone very much below the surface to reach the essence of the relationship between research and graduate teaching outputs. If we were to do so we would find that graduate students provide both teaching and research inputs, just as we would find that the services of teachers, including their stock of expertise from past R&D, are key inputs into graduate education. But this structural investigation would require better evidence and modeling of the dynamics of the research-teaching relationship than we have so far undertaken.

Table 7 reports findings for two systems of equations in each of our eight science fields. System A uses log (papers) as the measure of research output, while system B uses log (citations). Both systems use log (advanced degrees) as a proxy for graduate student output; this is the analogue to log (papers) or log (citations) on the research side. We have no readily available measure of quality of graduate degrees to compare with citations. We report regression coefficients of lagged R&D (both research and teaching equations), lagged advanced degrees (research output equation), and the distributed lead of total S&E degrees (teaching output equation). Each system is reported in two columns: the first is the research equation while the second is graduate teaching. For each field we report an estimate of

16. CASPAR collects data on undergraduate enrollments by university and field, but the quality of the data is uneven across schools. In addition the data are available over a very short period of time: this makes it impossible to construct meaningful leads of undergraduate enrollments.

the cross-equation correlation σ_{RS}. These are usually small, and they are essentially zero in the agriculture and medicine equations.

Since we introduce lagged advanced degrees as well as lagged R&D into the research equation, coefficients on lagged R&D in the research equations in columns (7.1) and (7.4) are less than their counterparts in Table 3, columns (3.1) and (3.3), though they remain statistically significant. For example the coefficient of lagged R&D in the biology papers equation is 0.28 rather than 0.67, and it is 0.18 in the physics equation, rather than 0.53. However, there is a secondary effct of R&D on research output that works through the advanced degrees equation (see (3) above). This is because lagged R&D raises future advanced degrees and thus future research output. We consider this point in the context of a steady state solution of (3) later on. The findings for citations in system B follow a similar pattern: the effects of lagged R&D in Table 3 are to an extent transferred to lagged advanced degrees in Table 7. It is interesting that the effect on research output of graduate students relative to lagged R&D differs so much by science: graduate students are more important in basic

TABLE 7

Systems of Research and Teaching Outputs: SUR Estimates

	System A		System B	
	Equation		Equation	
Field of Science, Variable	Log (papers) (7.1)	Log (Advanced Degs.) [a] (7.2)	Log (Cites over 5 Years) [b] (7.3)	Log (Advanced Degs.) [a] (7.4)
Agriculture				
Lagged R&D [c]	0.68	0.53	0.73	0.52
Lagged Advanced Degrees [d]	0.30		0.27	
Leading Undergraduate S&E Degrees [e]		0.48		0.49
σ_{RS}	**–0.00**		**–0.01**	
Biology				
Lagged R&D [c]	0.28	0.48	0.42	0.48
Lagged Advanced Degrees [d]	0.64		0.67	
Leading Undergraduate S&E Degrees [e]		0.59		0.58
σ_{RS}	**–0.07**		**–0.01**	
Chemistry				
Lagged R&D [c]	0.19	0.65	0.40	0.65
Lagged Advanced Degrees [d]	0.36		0.36	
Leading Undergraduate S&E Degrees [e]		0.33		0.33
σ_{RS}	**0.04**		**0.06**	
Computer Science				
Lagged R&D [c]	0.51	0.43	0.63	0.42
Lagged Advanced Degrees [d]	0.06*		0.13*	
Leading Undergraduate S&E Degrees [e]		0.67		0.75
σ_{RS}	**0.17**		**–0.06**	

TABLE 7 (cont.)

Systems of Research and Teaching Outputs: SUR Estimates

Field of Science, Variable	System A: Log (papers) (7.1)	System A: Log (Advanced Degs.) [a] (7.2)	System B: Log (Cites over 5 Years) [b] (7.3)	System B: Log (Advanced Degs.) [a] (7.4)
Engineering				
Lagged R&D [c]	0.08	0.73	0.15	0.73
Lagged Advanced Degrees [d]	0.62		0.67	
Leading Undergraduate S&E Degrees [e]		0.48		0.49
σ_{RS}	**0.10**		**0.11**	
Mathematics				
Lagged R&D [c]	0.27	0.48	0.41	0.49
Lagged Advanced Degrees [d]	0.20		0.22	
Leading Undergraduate S&E Degrees [e]		0.13*		0.10*
σ_{RS}	**0.05**		**0.11**	
Medicine				
Lagged R&D [c]	0.70	0.28	0.81	0.28
Lagged Advanced Degrees [d]	0.16		0.13	
Leading Undergraduate S&E Degrees [e]		0.22		0.22
σ_{RS}	**0.00**		**0.00**	
Physics				
Lagged R&D [c]	0.18	0.59	0.25	0.59
Lagged Advanced Degrees [d]	0.54		0.62	
Leading Undergraduate S&E Degrees [e]		0.53		0.53
σ_{RS}	**0.02**		**0.05**	

*Notes. Samples are slightly smaller than Table 1 due to missing values on new teaching and degree variables. Regressions include 0-1 dummy variables for top ten research universities, for top ten private universities, and for other private universities. σ_{RS} is the SUR estimate of the cross equation correlation between the residuals of the research and graduate teaching equations. * Not significant at the 1% level. [a] Advanced degrees consist of Ph.D. s in all science fields except medicine, and MD s in medicine itself. [b] Citations over five years are citations in years t to $t+4$ for papers published in year t. [c] Lagged R&D is the log of total R&D lagged 5 years, an inverted V lag with weights of 0.111, 0.222, 0.333, 0.222, and 0.111 on R&D in years $t-5$, $t-4$, $t-3$, $t-2$, and $t-1$ respectively, for papers in year t and citations in years t through $t+4$. [d] Lagged advanced degrees is the log of Ph.D. (MD in medicine) degrees lagged 5 years, an inverted V lag with weights of 0.111, 0.222, 0.333, 0.222, and 0.111 on advanced degrees in years $t-5$, $t-4$, $t-3$, $t-2$, and $t-1$ respectively, for papers in year t and citations in years t through $t+4$. [e] Leading undergraduate S&E degrees is the log of an average of undergraduates degrees in all science fields in a university 1, 2, 3 years in the future.*

sciences like biology, chemistry, mathematics, and physics than in more applied fields like agriculture, computer science, engineering, and medicine.

Now consider the advanced degrees equations, (7.2) and (7.4). We see that lagged R&D is consistently associated with larger outputs of advanced degrees in these equations. Also, leading undergraduate S&E degrees have a positive and generally significant effect on advanced degrees. If we use the "input" interpretation of lagged R&D and leading undergraduate degrees in the advanced degrees equation, then we see that advanced degrees follow a constant returns production process in Table 7. One reason for this contrast with the *appearance* of diminishing returns in the research equation is that errors of measurement are much less for advanced degrees. Students are usually assigned to the schools where they do most of their graduate work. This is not obviously the case for papers and citations.

It is interesting to consider further the relationships between research and graduate teaching that are implied by our results. It is easier to see these relations in a steady state setting, and we attach superscript zeroes to indicate steady state values. In a steady state we can assess the full effect of research on research output by incorporating the indirect effect on advanced degrees using (3) and two facts, that $y_S = W_A^0(s)$ and that $W_R(r) = W_R^0(r)$, to substitute the second equation into the first. This yields

$$y_R^0 = (\beta_{RR} + \beta_{RA}\beta_{SR})W_R^0 + Z_R^0, \tag{4}$$

where

$$Z_R^0 = \alpha_R + \gamma_R \cdot X^0 + \beta_{RA}[\alpha_S + W_U^0 + \gamma_S \cdot X^0]. \tag{5}$$

the term Z_R^0 in (5) encompasses steady state effects of variables other than lagged R&D. Equation (4) shows that the steady state, or "full" effect of lagged R&D on research output is $\beta_{RR} + \beta_{RA}\beta_{SR}$ rather than β_{RR}, since R&D affects graduate student output and thus indirectly research output, as well as research output directly. In the case of biology papers the full effect of lagged R&D is $\beta_{RR} + \beta_{RA}\beta_{SR} = 0.28 + 0.64 \times 0.48 = 0.59$, rather than $\beta_{RR} = 0.28$. For biology citations the full and direct effects are 0.74 and 0.42. In the case of physics papers, full and direct effects are 0.50 and 0.18, while for physics citations these effects are 0.62 and 0.25. Not surprisingly, the full effects are very close to the findings of Table 3, since we have in essence decomposed a nearly steady state effect in Table 3 into direct effects of lagged R&D on research output and lagged, indirect effects that work through the supply of graduate students.

5 Conclusion

The work that we have reported is, in a certain sense, an essay on of the difficulty of drawing distinctions. Many of the difficulties that hinder measurement of research productivity begin with distinctions between fields that are continuously blurred by spillovers and by collaborative ventures, and with distinctions between schools that are connected by the mutual exchange of students and ideas; indeed this is an essential part of the vitality of the university system. The puzzle of the seeming increase in cost of computer science and mathematics research during the nineteen eighties underscores the need to look at interrelationships of scientific research. In a different way, the close connection between fundamental biology and medicine points to a similar intertwining of research interests.

The same quandary shows up in yet another form. At the field level our typical finding *very roughly* approximates constant returns to scale, in contrast with our finding at the university and field level, which is one of diminishing returns. It is clear that both the research and the Ph.D. outputs are interdependent across institutions and time. The dynamics of these interrelationships are surely worthy of further exploration.

Our finding that there are differences between top ten and other universities, and between private and public universities, also deserves another look. It suggests at the very least, careful accounting for real R&D expenditures. Once having achieved that, the resulting evidence would call for a welfare analysis of the distribution of R&D among universities. The economics of universities promises to be a fertile ground for study for a long time to come.

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