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RESEARCH PRODUCTIVITY IN A SYSTEM OF UNIVERSITIES

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ABSTRACT

The focus of this paper is the research performance of a system of universities and sciences. Using data from the United States during the nineteen eighties we study the relationship between research output and R&D in eight different fields of science. We begin at the field level by examining the time series behavior of outputs measured by papers and citations in relation to R&D. At this level we find approximate parity between growth rates of papers and citations and the rate of growth of R&D, with the exceptions of mathematics and agriculture, which diverge from parity in opposite directions. This suggests the predominance of a CRS production process for new scientific results.

We then conduct an analysis at the university and field level. For this purpose we use small samples of leading U.S. research universities. We now find that returns to R&D are diminishing in nearly every case. Two explanations are offered for the divergence in results. The first explanation points to the importance of research spillovers between universities and fields, which are excluded at the university level but not at the system level. The second explanation is that errors in R&D are more important at the university level. The errors arise mostly from misclassification of R&D by university and field. Together these explanations emphasize the relevance of research spillovers and of the system-wide aspects of university research. They also pinpoint the sources of the many failings of contemporary data on science resources and stress the value of better accounting for university R&D, resources, and outputs.

In addition we explore some efficiency aspects of the university system. Our findings suggest that leading schools have lower average and marginal costs of performing research than lesser institutions, and that leading institutions have a comparative advantage at generating higher quality, more highly cited research. In our comparisons of private and public institutions the results are not as one-sided, yet they suggest once again that private schools have a comparative advantage at generating more highly cited research.

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I. 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-- measured by papers and citations to those papers-- to lagged R&D expenditures. Along the way we explore the joint determination of the related outputs of research and advanced degrees in a regression system.

It is important to study trends in university research productivity because universities account for 50 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 assumes additional importance in the United States because it conditions 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 still 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 could reliably value the innovations

[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.

remains over the horizon[2]. This is especially true given the participation of universities in a public sector whose output is notoriously difficult to estimate (Griliches, 1994).

For these reasons we study the connection between research output and lagged R&D of universities. And yet measuring research productivity even in this way is not a simple exercise. In part the problems are due to the unclear boundaries between different sciences and universities, since the results of research may show up in an entirely different location than their point of origin[3]. Another difficulty is the inadequate accounting for resources that contribute to research output: officially measured R&D fails to capture the total value of R&D resources, and this is especially true of internally funded research. Furthermore, some academic R&D is undoubtedly devoted to "infrastructure" rather than basic research. Still another 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 makes for 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 finer detail.

The remainder of the paper is arranged as follows. Section II provides a graphical

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[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).

overview of the research output-research input relationship at the field level during the nineteen eighties in the U.S. Findings at the more detailed university and field level over the same period are presented in Section III. Section IV is a summary and conclusion.

Section II presents field level graphs for eight broad sciences: agriculture, biology, chemistry, computer science, engineering, mathematics and statistics, medicine, and physics. As a whole these fields account for the majority of academic research expenditures, while the 109 universities that form the basis for these graphs account for about three quarters of overall academic R&D in the U.S. For the majority of sciences we find that papers and citations grow at about the same rate as lagged R&D, with agriculture and mathematics being notable exceptions that diverge from this pattern in opposite directions. 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 U.S. universities and fields in Section III. 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 also 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. Given our results at the field level, this explanation suggests that individual diminishing returns are converted to constant returns by R&D spillovers between fields and universities. But there is an alternative interpretation. This is that incorrect assignment of

R&D to papers and citations is a more important problem at the university level, yielding the illusion of individually diminishing returns.

The result that the citation-R&D elasticity is larger than the papers-R&D elasticity suggests that larger research programs produce research that is more cited and of higher quality. Another finding is that private schools generate more research output per additional 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 evidence of correlation in the error terms in the research and teaching output equations, and we find that undergraduate science enrollments as well as quality rank of a university in a particular field increase the output of advanced degrees With this summary of results in mind, we now turn to an examination of the findings.

II. 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 with the largest and most successful R&D programs in the U.S. 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 III. The graphs depict relationships between lagged R&D and papers published in single years over the period 1981-1989; and they show a parallel relationship between lagged R&D and total citations to papers in the year of publication and four succeeding years. The data on nominal total and federal R&D derive from the CASPAR database of the National Science Foundation. The papers and citation are taken from unpublished data of the Institute for Scientific Information (ISI), the source of the **Science Citation Index**.

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 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, forthcoming). We are not sure why the 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 the outlook for research productivity correspondingly gloomier.

For each of our eight science fields we present a pair of graphs. Time is on the horizontal axis and research output as well as lagged R&D are on the vertical axes. Both vertical axes use logarithmic scales. The left-hand graph presents R&D lagged two years on the left (log) scale and papers on the right (log) scale. The right-hand graph again draws the curve of R&D lagged two years on the left scale but replaces 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, permitting comparisons of growth in research outputs and inputs.

With the exception of Figures 1 and 2 (agriculture) and Figures 11 and 12 (Mathematics and Statistics combined) most fields show *rough* equality between growth of papers and citations, and growth of lagged R&D. Agricultural papers and citations are the exception: these grow more rapidly than R&D. The reverse holds true for mathematics; thus there is a crude cancellation of the divergence from constant returns across all fields. We are unsure as to the reasons why agriculture and mathematics depart from the prevailing appearance of constant returns. The continued growth of agricultural papers and citations after the funding interruption in Figures 1 and 2 could be a simple case of research output feeding off a stock of lagged funding, with the effects of the funding slowdown showing up in the nineteen nineties after our sample period concludes.

Diminishing returns to mathematics and statistics are more problematic, especially in an era when past mathematics is more useful than ever due to its computer applications. Should we give in quickly, and believe that expenditures on mathematics are less effective than before? It is possible that the mathematics of today comes at greater cost and is less useful than past mathematics; but if the nineteen eighties are an era of increased applications in research as well as in industry, this alone could account for slower growth of mathematics papers and citations. For then the results of mathematics would be increasingly intertwined with those of other fields and accordingly, more often misclassified. The difficulties of defining field boundaries are likely to be especially important for mathematics[4].

Another ambiguity is brought out by Figures 7 and 8 for computer science. The citation graph suggests mildly decreasing returns to computer research, and yet computer science has also

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[4] The question is whether the ISI mathematics journal set is less inclusive over time of applications penned by mathematicians. 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 19th and 20th centuries. In the present era its successor **Mathematical Reviews** covers technical economics journals like **Econometrica**. See Adams (1990).

become more useful in recent years. There is a mixture of objectives targeted by R&D in general, but especially by computer science R&D. If the R&D is devoted to the building of infrastructure within the university rather than original research, then this could account for the finding of more rapid growth of computer science "research" than research "output." Falling costs of computing could in fact drive up infrastructure research relative to original research.

III. Findings at the Level of Universities and Fields

We turn next to the behavior of research output at the level of fields and universities. We have reasonably complete data on R&D and some other characteristics for about 40 universities over the period 1973-1994, and we have consistent data on research outputs for the same schools over the period 1981-1989[5]. Notice that these samples are about one third the size of the 109 university sample on which Figures 1-16 are based.

The long time span over which R&D is available allows us to lag R&D spending relative to research outputs, even though the final data set is restricted by research output to the period 1981-1989. 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 PhD program (MD in medicine); and (iii), positive research output. We imposed these criteria in order 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 teaching outputs towards the end of the paper.

[5] In reality we have data on papers and citations over the period 1981-1993. We drop the data for 1990-1993 because we wanted to construct five years' worth of citations to papers published in each year, which is not possible for papers and citations to those papers after 1989.

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 in both respects 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: here the life sciences again lead the pack, and the mathematical sciences again trail the others. Turning to teaching outputs as represented by undergraduate majors and PhD/MD degrees, we observe differing concentrations by field. Engineering has large undergraduate and graduate programs, medicine of course is concentrated at the graduate level. Programs in the mathematical and natural sciences tend to be small at both levels.

Panel B of Table 1 reports growth rates of research outputs, research funding, and teaching outputs for our regression samples. In the majority of cases growth of research outputs equals or exceeds growth of research spending, the main exceptions again being the mathematical sciences. Turning to teaching outputs within fields, the pattern is quite mixed and presumably depends on market conditions that vary across specialties. Life science degrees are roughly stagnant over the period of the nineteen eighties at both levels, while the natural sciences, mathematical sciences, and engineering seem to shift towards graduate education.

Table 2 examines average costs per paper and per citation in various sub-samples of our university and field level data. The average cost calculations remove scale of research programs from the data and they facilitate comparisons across samples. Panel A breaks up the data by top ten research university and below[6]. Costs per paper appear 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[7]. The result suggests that top ten schools have a comparative advantage in producing more cited research. But these unit cost comparisons understate the advantage of top ten universities. Schools below the top ten have a larger share of informally funded, off-budget R&D. Thus the advantage is entirely on the side of the top ten schools for papers as well as citations, though the extent of the advantage is unknown.

Panel B breaks the data up into samples of private and public institutions excluding agriculture, since the public universities dominate this field. The public-private comparison suggest that private universities are more expensive at producing papers, yet cheaper at producing citations. The same caveat applies as before: again it is likely that a larger fraction of research is informally funded in public universities and that R&D costs are understated there to a larger extent. We are left feeling unsure as to whether private schools are really the more costly producers of research papers, but we are confident that they are the less expensive producers of citations; even neglecting the likely bias in research costs, private schools are twenty percent

[6] 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.

[7] 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.

cheaper[8].

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

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

where y is the logarithm of research "intermediate" output, 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 always includes year dummies to control for changes in the research production function over time and 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 local 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 $\beta<1$ ($\beta \geq 1$). Still, 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 community of a university, and the very meaning of R&D expenditures. The assessment of diminishing returns based on the size of β is also clouded by exclusion of research externalities between fields and universities (spillovers) that bias *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 some sense then, these are "within group" estimates. For each measure of research output, papers and citations, we present results for three and five year distributed lags of R&D.

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

The three year lag uses inverted V weights of 0.25, 0.5, and 0.25 on R&D dated t-3, t-2, and t-1 for outputs dated t and later, while the five year lag uses weights of 0.111, 0.222, 0.333, 0.222, and 0.111 on R&D dated t-5, t-4, t-3, t-2, and t-1. Five year lags yield a higher value for the research elasticity, indicating either a truly longer lag in effect or a fall in measurement error in W(r) as length of lag increases. The main finding is that research elasticities lie uniformly below 1, and the difference is almost always significant at the 1% level, with the citation elasticities about 0.1 higher than the paper elasticities. One interpretation of this finding is that papers "leak" out of the larger research programs as doctoral students move to faculty posts in other, generally smaller programs. Thus the R&D that generates these research papers is incorrectly assigned between different universities. Citations avoid this problem to an extent because research papers of young faculty cite papers in leading programs where the doctoral 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 highly cited research, on bigger "hits", which could very well be an implication of the sorting of higher quality faculty to these institutions.

Table 3 consists of regressions controlling for group effects since all equations include dummies for type of institution. When we remove these dummies, research elasticities increase somewhat. This effect is important for biology, chemistry, engineering, and mathematics[9]. Nevertheless, the elasticities remain below unity, indicating as before diminishing returns to research at the university and field level.

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[9] 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 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. 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 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 the nonlinear specification is,

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

where ℓn is the natural log, $W^*(r_f)$ is the *arithmetic* distributed lag of federal R&D and $W^*(r_n)$ is the same 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 to differ from the effect of federal R&D, which is again given by β. The effect of non-federal R&D is smaller than the federal effect when $\delta<1$, and at least equal when $\delta \geq 1$. It is important to see that (2) is not the experiment we would attempt if we had better data. We cannot for example, decompose non-federal R&D into state supported research, much of which could be targeted on service or infrastructure rather than publication, and into funding by private foundations, much of which may be devoted to the most basic science, and for which competition is intense. Nevertheless, (2) does separate federal R&D

from non-federal, and it is the greatest detail of which our R&D data are capable[10].

Consider the results of Table 5. Inspection 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 equation (3) and Table 5. Surprisingly, the effect of non-federal R&D varies widely by field and is significantly less than the federal effect 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% levels of significance. In the case of physics, non-federal R&D has a significantly greater effect than federal R&D; 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! The results for chemistry are qualitatively similar to physics, but the point estimate of $\delta=1.4$ is not estimated with very much precision. One guess as to why the point estimate of the non-federal effect is larger in these two fields is that a sizable part of non-federal chemistry and physics research is targeted on basic science. Nevertheless, the average effect of non-federal R&D across fields is inconsistent with this view: see the column means. Usually, as we have noted, non-federal R&D has an effect less than or equal to the federal effect. In reality the results of Table 5 are even more diverse than we have implied. In biology, engineering, and mathematics, non-federal R&D is predicted to have *no* impact on research output. We suspect that in these fields the non-federal component is aimed at other objectives besides basic research. It is tantalizing that in these three fields and none other, regressions that include the deflated market

[10] Non-federal R&D is not broken up by CASPAR at the university and field level.

value of endowment reveal a significant effect of endowment on research output. This implies a compensatory role for endowment in fields where non-federal support for research is otherwise weak.

A comparison of research output of private and public universities forms the heart of Table 6. Here we drop the remaining dummy for top ten schools from the regressions. The reason is that we want to draw a full comparison between private and public schools. If we control for the greater productivity of top ten, then we are making a biased comparison between public and private schools, because the private school sample is more homogeneous within groups. 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[11].

[11] 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 our 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:

Columns (6.1) and (6.3), (6.2) and (6.4) are comparable regressions for private and public universities. It is clear that 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 0.1 higher. 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 again unclear from the evidence at hand, but the question is worth further investigation.

We conclude our presentation of findings with a table of SUR estimates. The system jointly estimates equations for research output and *graduate* teaching output, measured by the logarithm of advanced degrees (MD s in medicine, PhD s in other fields). The specification in this case is

$$\begin{aligned} y_R &= \alpha_R + \beta_R \bullet W(r) + \gamma_R \bullet X_R + u_R \\ y_S &= \alpha_S + \beta_S \bullet W(s) + \gamma_S \bullet X_S + u_S, \end{aligned} \tag{3}$$

where the first equation of (3) represents the research production function (1). We add the subscript R to indicate research and note that X_R is the usual set of control variables. The second equation expresses graduate teaching output y_S as a function of W(s), the logarithm of a distributed *lead* of undergraduate science and engineering (US&E) degrees in a university, and a

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$$\frac{\beta_{T1}}{\beta_{T2}} = \left[\frac{\alpha_2}{\alpha_1} \frac{1-(1-\alpha_1)\phi_1}{1-(1-\alpha_2)\phi_2}\right] \frac{\beta_{W1}}{\beta_{W2}}.$$

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.

set of controls X_S and is indicated by subscript S; the difference between the two equations centers on the variable W(s) and the set of controls, which differ in the two equations.

But why a distributed *lead* of undergraduate degrees in the graduate degrees equation? We employ this variable because future degrees proxy for the undergraduate teaching load in the past, and because reliable data on undergraduate enrollments are missing[12]. The particular form of the distributed lead W(s) uses a constant weight of one third on US&E degrees received in periods t+1, t+2, and t+3 for doctoral degrees received in period t. The idea 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(s) is a demand variable for the services of graduate students. The controls that enter the two equations of (3) are for the most part the same as before and include the year dummies and institutional type dummies that we have already discussed, with one difference. We include a variable for the quality rank of a field in a given institution among the controls in X_S when in it is available as an indicator of the success of an institution and field; unfortunately, ranks are not available in the data for agriculture and medicine. Quality rank is the mean outcome of a survey of department chairs in a given field and varies by construction between 5.0 and 1.0 in gradations of 0.1, with 5.0 being the highest rank and 1.0 being the lowest. The majority of schools, even in rated fields, are unranked, but for our

[12] 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.

data sets this is not a problem since our schools are in the set of research "contenders." 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 graduate 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.

Table 7 reports the findings for the 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 teaching output; this is the analogue to log (papers) on the research side, but we have no readily available measure of the quality of graduate degrees. We report regression coefficients of lagged R&D (research output equation), the distributed lead of total S&E degrees (teaching output equation), and quality rank (teaching output equation). Each system is reported in three columns: the first is the research output equation, the second is the teaching output equation, and the third is the estimate of the cross-equation correlation of the error terms u_R and u_S.

The coefficients on lagged R&D in the research output equations in columns (7.1) and (7.4) are similar to their counterparts in Table 3, columns (3.1) and (3.3). Considering the log of leading undergraduate S&E degrees in the teaching output equation, three-fourths of the time its effect is positive and significant at the 1 percent level. In the six fields where we have a quality rank indicator, its effect is positive and highly significant for the number of degrees. This is not surprising; it indicates that highly ranked programs attract larger numbers of students. The cross equation correlations are typically small and larger in absolute value in the two fields (agriculture and medicine) that lack the quality rank indicator. This suggests that quality rank successfully proxies for unmeasured attributes of an institution that drive research and teaching outputs.

IV. Conclusion

This work we have reported is, in a certain sense, an essay on of the difficulty of drawing distinctions. Many of the difficulties that hinder our measurements 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 in reality connected by the mutual exchange of students and ideas. The puzzle of the seemingly rising costs of mathematics research underscores the need to look at interrelationships of scientific research. In a different way, the close connection between fundamental biology and medicine points to the same intertwining of research interests.

The same quandary shows up in yet another form. At the field level our typical finding 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 the system of universities is a general equilibrium system, and this system moreover has dynamic properties that are surely worthy of further exploration.

The 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, and once having achieved that, the resulting cleaner 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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Agriculture

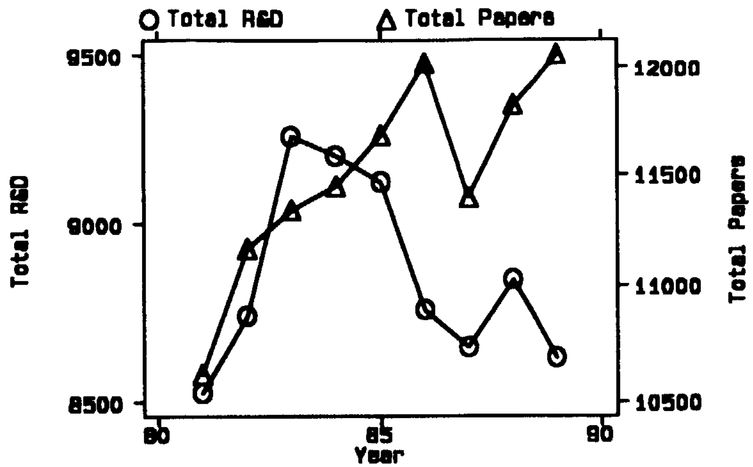

Fig 1-- Agriculture R&D and Papers

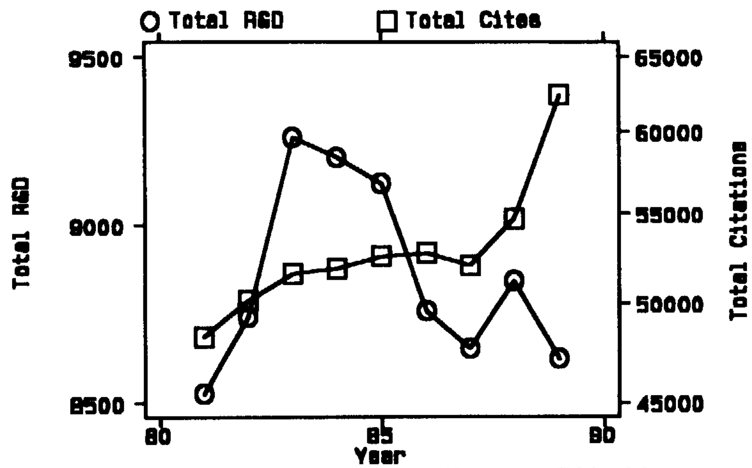

Fig 2-- Agriculture R&D and Citations

Biology

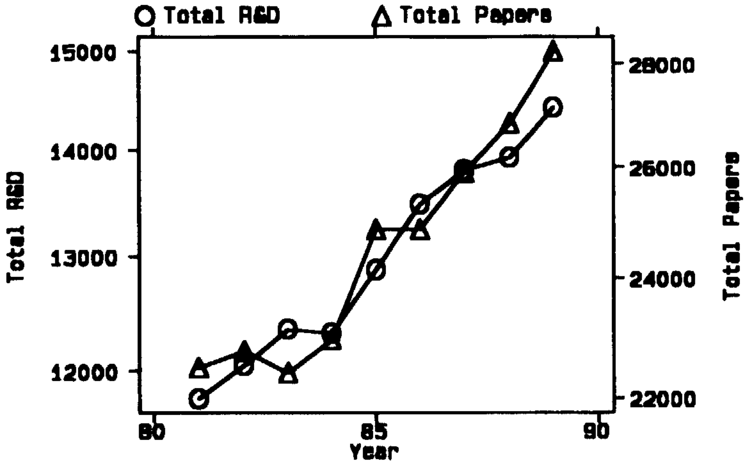

Fig 3-- Biology R&D and Papers

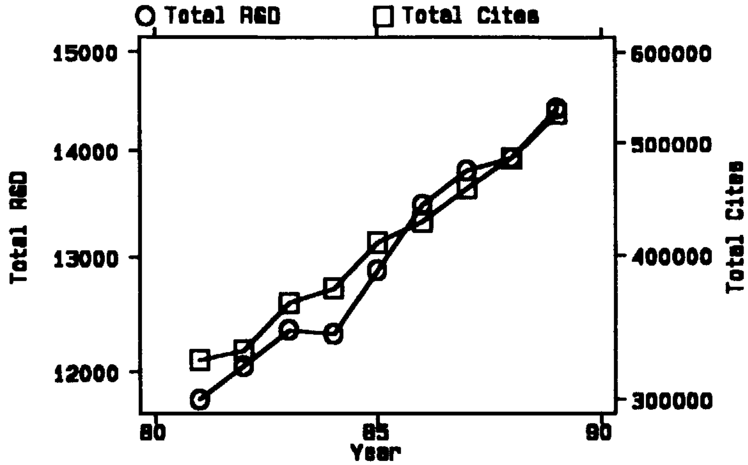

Fig 4-- Biology R&D and Citations

Chemistry

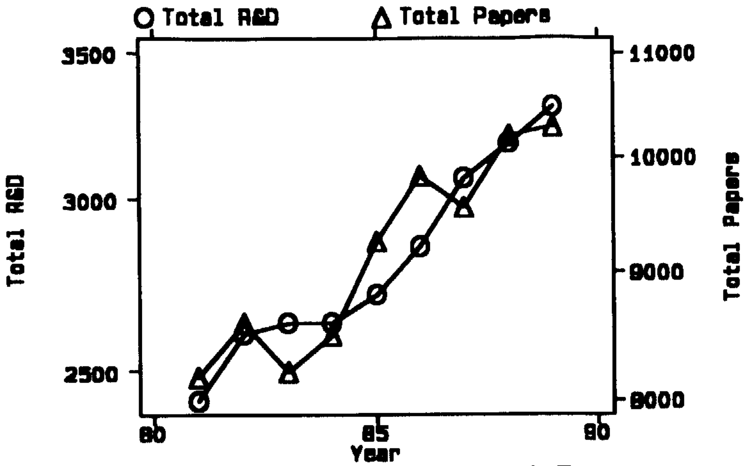

Fig 5-- Chemistry R&D and Papers

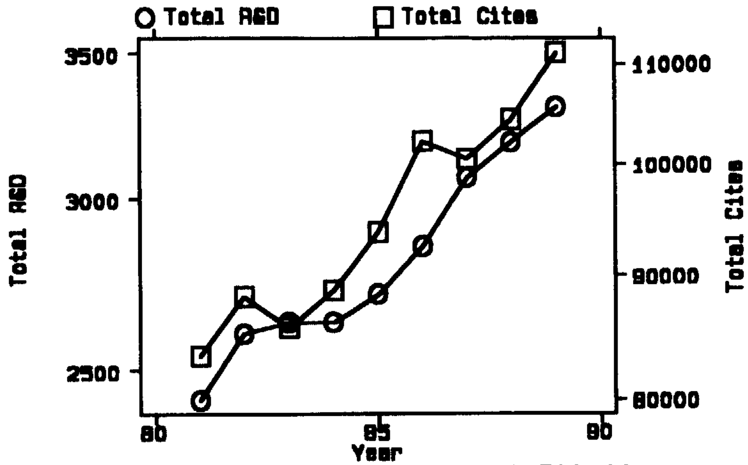

Fig 6-- Chemistry R&D and Citations

Computer Science

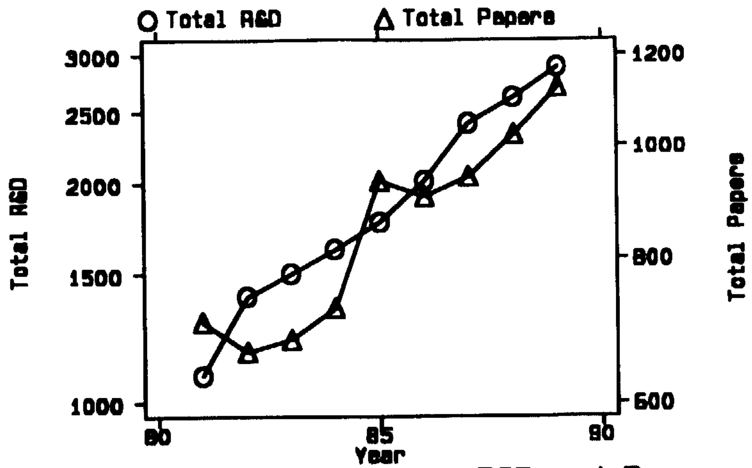

Fig 7-- Computer Science R&D and Papers

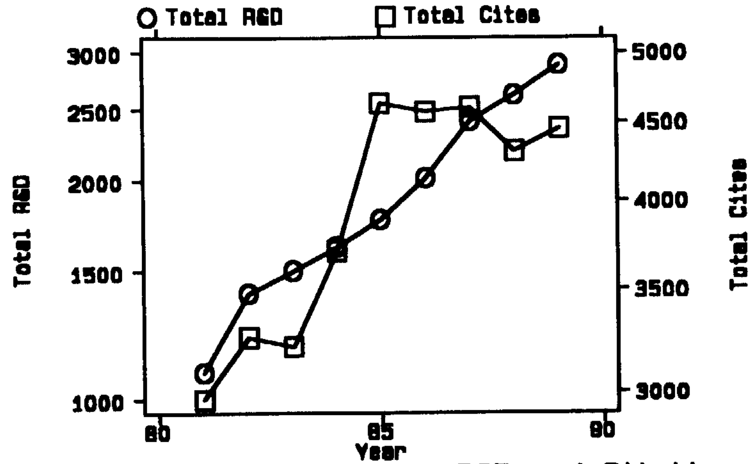

Fig 8-- Computer Science R&D and Citations

Engineering

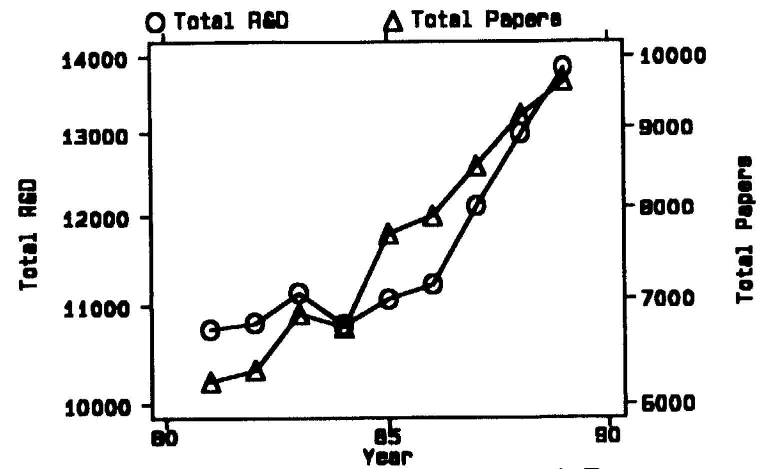

Fig 9-- Engineering R&D and Papers

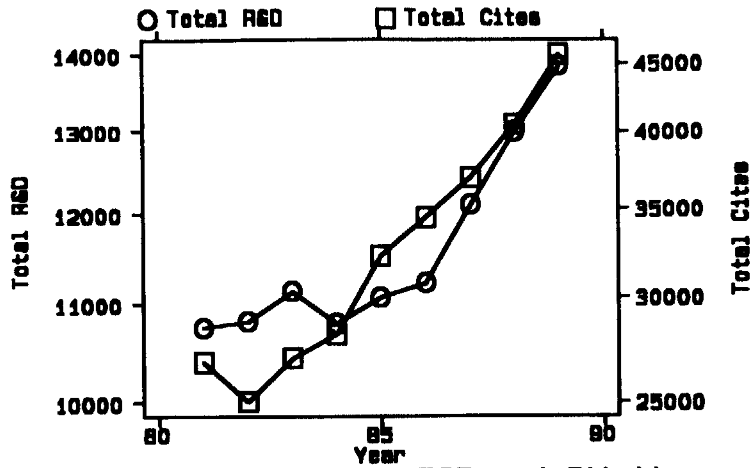

Fig 10-- Engineering R&D and Citations

Mathematics

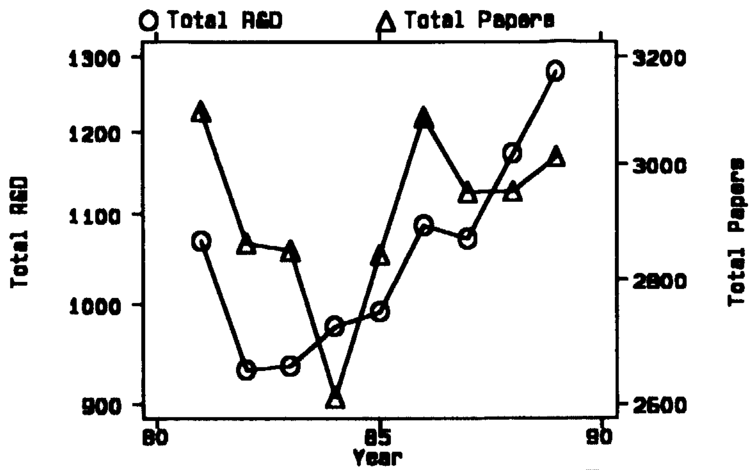

Fig 11-- Mathematics R&D and Papers

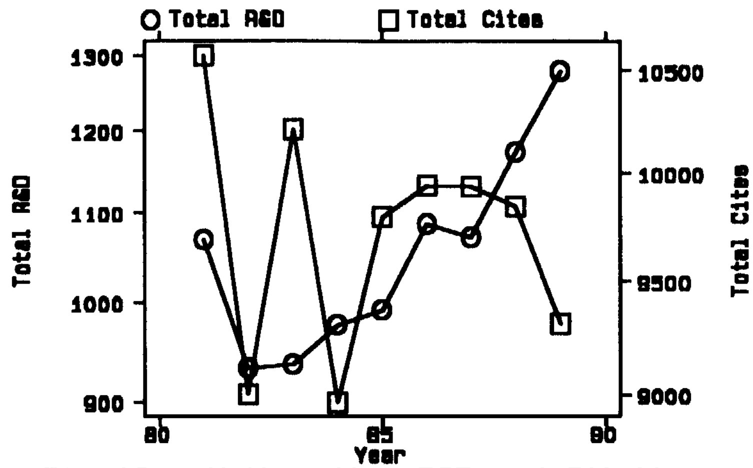

Fig 12-- Mathematics R&D and Citations

Medicine

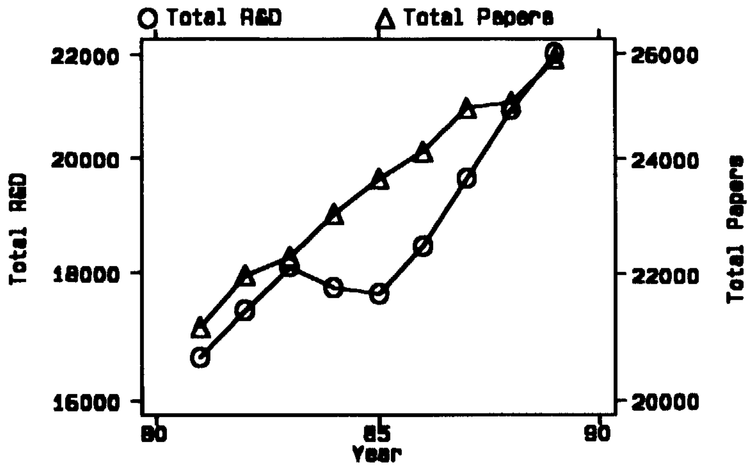

Fig 13-- Medical R&D and Papers

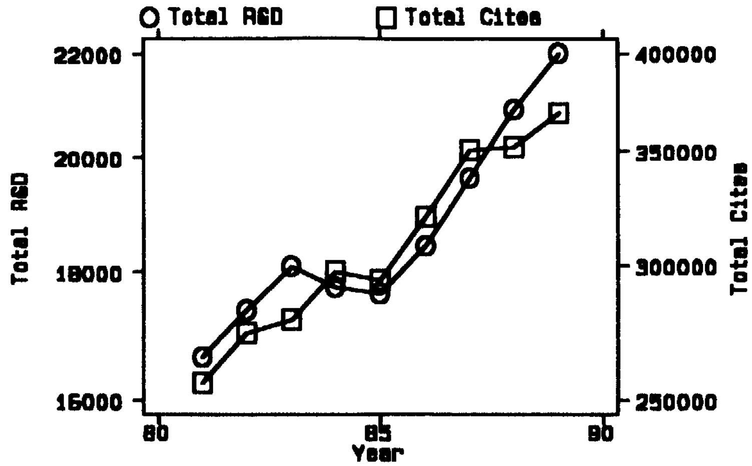

Fig 14-- Medical R&D and Citations

Physics

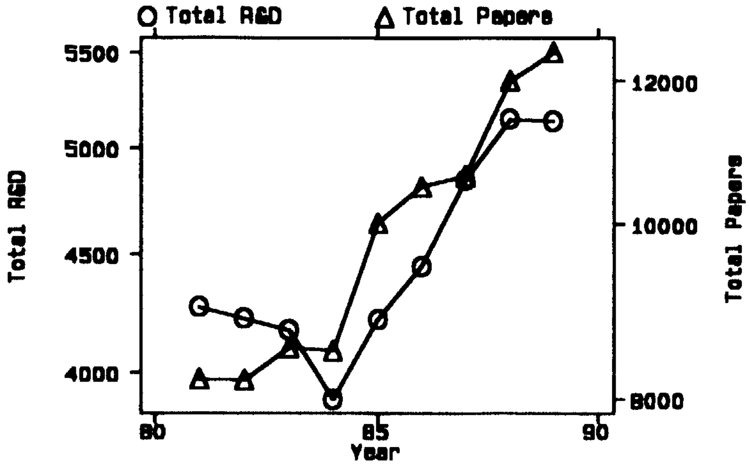

Fig 15-- Physics R&D and Papers

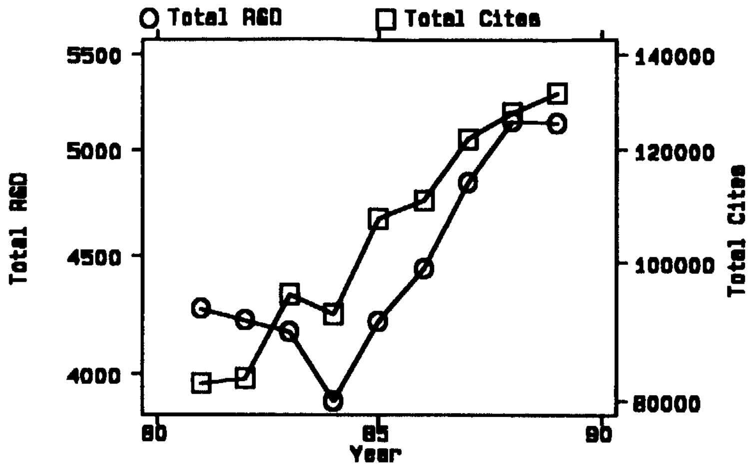

Fig 16-- Physics R&D and Citations

Table 1
Descriptive Statistics: Research Outputs, Research Funding, and Teaching Outputs of U.S. Universities, 1981-1989

Field of Science	Variable					
	Research				Teaching	
	Number of Universities[a]	Papers per Year	Cites over 5 years[b]	5 Year Lagged R&D (1000$)[c]	Bacc. Degrees in Field	PhD Degrees in Field
	(1.1)	(1.2)	(1.3)	(1.4)	(1.7)	(1.8)
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 Percentage Rates of Growth, 1981-1989						
Agriculture	24	2.4	3.1	0.6*	-9.3	1.7*
Biology	39	3.4	6.5	2.9	-0.3*	-0.2*
Chemistry	41	2.7	3.8	3.0	-3.4	1.9
Computer Science	16	7.1	4.2	6.1	0.6*	3.4
Engineering	37	5.3	6.7	-0.2*	0.5*	6.4
Mathematics	38	0.2*	0.1*	3.1	7.7	3.6
Medicine	33	2.1	4.6	-2.0	2.2[d]	-1.3
Physics	37	5.2	5.8	1.0*	3.7	2.8

Notes. Panel A reports means at the university and field level, Panel B reports mean annual percentage rates of growth on data averaged across universities. * 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.

Table 2
Mean Research Costs per Unit of Research Output: Subsamples of U.S. Universities, 1981-1989

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.

Table 3
Research Output Regressions: Coefficients of Papers per Year and Citations over 5 Years, on Lagged R&D

Field of Science	Papers per Year		Citations over 5 Years[a]	
	5 year lagged Total R&D[b] (3.1)	3 year lagged Total R&D[c] (3.2)	5 year lagged Total R&D[b] (3.3)	3 year lagged Total R&D[c] (3.4)
Agriculture	0.90	0.88	0.93	0.90
Biology	0.67	0.64	0.83	0.79
Chemistry	0.44	0.45	0.64	0.66
Computer Science	0.54	0.39	0.71	0.50
Engineering	0.57	0.56	0.68	0.66
Mathematics	0.38	0.37	0.53	0.52
Medicine	0.75	0.72	0.86	0.82
Physics	0.53	0.52	0.65	0.63
Column Means	**0.60**	**0.57**	**0.73**	**0.69**

Notes. Variables and samples are defined in Table 1. All coefficients are significantly different from zero at the 1% level. Within group regressions include 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] Total R&D lagged 5 years 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. [c] Total R&D lagged 3 years is an inverted V lag with weights of 0.25, 0.5, 0.25 on R&D in years t-3, t-2, and t-1 respectively, for papers in year t and citations in years t through t+4.

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

Field of Science	Papers per Year	Citations over 5 Years[a]
	5 year lagged Total R&D[b] (4.1)	5 year 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
Column Means	**0.06**	**0.08**

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] Total R&D lagged 5 years 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. [c] Total R&D lagged 3 years is an inverted V lag with weights of 0.25, 0.5, 0.25 on R&D in years t-3, t-2, and t-1 respectively, for papers in year t and citations in years t through t+4.

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

	Papers per Year		Citations over 5 Years	
Field of Science	5 year lagged Total R&D	5 year lagged Non-federal R&D	5 year lagged Total R&D	5 year lagged Non-federal R&D
	(5.1)	(5.2)	(5.3)	(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]
Column Means	**0.59**	**0.80**	**0.72**	**0.56**

Notes. Variables and samples are defined in Table 1. Estimation method is NLLS. Within group regressions include the 0-1 dummy variables for top ten research universities, for top ten private universities, for other private universities. Specification of R&D is: log (Federal R&D+b•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.

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
Column Mean	**0.65**	**0.82**	**0.54**	**0.73**

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.

Table 7
Regression Systems of Research and Teaching Outputs: SUR Estimates

Field of Science, Variable	System A			System B		
	Equation		Cross Eq. Corr.	Equation		Cross Eq. Corr.
	Log(papers)	Log(Advanced Degs.)[a]		Log(Cites over 5 Years)[b]	Log(Advanced Degs.)[a]	
	(7.1)	(7.2)	(7.3)	(7.4)	(7.5)	(7.6)
Agriculture			0.25			0.15
Lagged R&D[c]	0.84			0.89		
Leading Total S&E Degrees[d]		0.71			0.79	
Biology			-0.01			-0.12
Lagged R&D[c]	0.56			0.74		
Quality Rank[e]		0.61			0.67	
Leading Total S&E Degrees[d]		0.11*			0.11*	
Chemistry			0.05			-0.01
Lagged R&D[c]	0.43			0.64		
Quality Rank[e]		0.72			0.72	
Leading Total S&E Degrees[d]		0.19			0.21	
Computer Science			0.01			0.00
Lagged R&D[c]	0.53			0.63		
Quality Rank[e]		0.61			0.61	
Leading Total S&E Degrees[d]		0.75			0.74	
Engineering			0.09			-0.01
Lagged R&D[c]	0.55			0.71		
Quality Rank[e]		0.80			0.83	
Leading Total S&E Degrees[d]		0.48			0.52	

Table 7
Regression Systems of Research and Teaching Outputs: SUR Estimates

Field of Science, Variable	System A			System B		
	Equation		Cross Eq. Corr.	Equation		Cross Eq. Corr.
	Log(papers)	Log(Advanced Degs.)[a]		Log(Cites over 5 Years)[b]	Log(Advanced Degs.)[a]	
	(7.1)	(7.2)	(7.3)	(7.4)	(7.5)	(7.6)
Mathematics			-0.06			-0.02
Lagged R&D[c]	0.37			0.51		
Quality Rank[e]		0.75			0.74	
Leading Total S&E Degrees[d]		0.07*			0.04*	
Medicine			0.16			-0.12
Lagged R&D[c]	0.71			0.82		
Leading Total S&E Degrees[d]		0.32			0.33	
Physics			-0.05			-0.09
Lagged R&D[c]	0.48			0.60		
Quality Rank[e]		0.80			0.81	
Leading Total S&E Degrees[d]		0.41			0.42	

Notes. Samples are slightly smaller than Table 1 due to missing values on new teaching and rank variables. All regressions include 0-1 dummy variables for top ten research universities, for top ten private universities, and for other private universities. * Not significant at the 1% level. [a] Advanced degrees consist of PhD s in fields other than 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] Total R&D lagged 5 years 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. [d] Leading total S&E degrees is the average of undergraduates degrees in all science fields in a university 1, 2, 3 years in the future. [e] Quality rank is an ordinal scale ranging from 5.0 (highest rank) to 1.0 (lowest rank) within a field.