Industrial Scientific Discovery

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November 2005

JEL Codes: D24, L33, O31, O33

Keywords: Science, Citations, Papers, Production Functions, R & D, Spillovers, Universities, Firms, Industries

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*The Andrew W. Mellon Foundation has generously supported this research. We thank Nancy Bayers and Henry Small of the Institute for Scientific Information (ISI) for assistance with the ISI data that is used in this paper.

Abstract

This paper estimates science production functions for top R&D firms in the United States. The data include estimated flows of basic science from universities to firms, from firms to other firms, and within firms. The underlying evidence consists of papers and citations from the Institute for Scientific Information (ISI) in Philadelphia, Pennsylvania. The data cover the top 200 R&D firms and the top 110 universities during 1981-1999. These account for most scientific research in the U.S. during this period.

Firms' papers and citation-weighted papers represent outputs of the science production functions, or the rate of industrial scientific discovery. Lagged indicators of (i) spillovers of science from universities; (ii) spillovers from other firms; as well as (iii) spillbacks of science within firms; and (iv) the firm's stock of R&D are used to explain the rate of discovery. The empirical estimates are based on a panel of firms, science fields, and years that is an extract from the papers and citations data. Using this panel we find that science spillovers from universities and other firms occur primarily within fields. Industry is much less of a barrier and in fact most knowledge flows occur between, rather than within industries.

Citation and collaboration spillovers from universities, citation spillovers from other firms, and citation spillbacks from firm's past research all make significant contributions to scientific discovery. Besides this, the paper uncovers a host of potential biases. First, the response of discovery to the firm's own R&D is biased upward by the failure to include science spillovers from universities and other firms. Second, the university citation spillover is biased upward by the failure to include collaboration between firms and universities. And third, the effects of spillovers and spillbacks are biased downward when zeroes of the spillovers and spillbacks are not considered by the estimation procedure.

The elasticity of firm's science output with respect to university citation spillovers is consistently larger than the firm spillover elasticity. In addition the marginal product of university spillovers exceeds the marginal product of firm spillovers, so that additional science output per dollar of university R&D is several times larger than additional output per dollar of firm R&D. University collaboration only serves to increase this productivity advantage of universities. Since university R&D is primarily funded by government, this potency of university spillovers appears to reassert the role of publicly funded science in propagating knowledge externalities throughout the U.S. economy.

I. Introduction

Let us begin with a hypothesis from the economics of search, that industrial science replenishes technological opportunity in firms and industries. Absorption of science, it is said, increases the arrival rate of ideas and the return to industrial R&D. Notice right away what this statement does not claim. It does not claim that industrial science is the only factor that replenishes technological opportunity just that it is one factor. Nor does it say that science matters to the same extent in all firms, for surely it matters in varying degrees. And lastly it does not say that only academic science matters, for it explicitly refers to industrial science and to the absorptive capacity of firms that this implies. Instead the statement simply asserts that the return to applied industrial R&D increases because of industrial science.

If the hypothesis is true scientific discovery boosts the arrival rate of inventions and new products[1]. Any resulting increase in major innovation would in turn promote growth. If science contributes to firm R&D, it follows that the productive sources of firms' scientific discoveries become a compelling question to address. It is the central question of this paper. In order to find a comprehensive answer, we adopt a flexible approach to it. As contributors to firms' scientific discoveries we allow for the firm's past scientific research, its stock of R&D, and the science research of universities as well as other firms. Knowledge is allowed to flow from any science, any university, and any firm to a given firm and field. We also provide for twin collaboration and citation channels of university influence on firms and fields. As a preface to the investigation, we offer a report on flows of scientific knowledge through the economy.

Our motivation is straightforward. We wish to understand the sources in basic science that firms draw on in doing their own science, and by this means characterize spillovers at the pre-technology stage. We are curious about the comparative contributions to firm research of the academic and industrial sectors, of particular fields of science, and of firms themselves to these science-based knowledge flows. The data give us the freedom to explore all of these dimensions. They are based on scientific papers, citations, and collaborations data during 1981-1999 as collected by the Institute for Scientific Information (ISI) in Philadelphia, Pennsylvania. The papers are written by scientists in the top 200 U.S. R&D firms and the top 110 U.S. universities. These institutions account for most scientific research conducted in the U.S.

[1] At present we are exploring linkages between science and patents in Adams and Clemmons (2005b).

The database includes 230 thousand papers written in the top 200 firms and 2.4 million papers written in the top 110 universities. The data report roughly one million citations of top 200 firms to papers of the top 110 universities, roughly 40 thousand collaborations between firms and universities, and over 600 thousand citations to firms. From these elemental data we extract a three-dimensional panel that consists of science outputs and inputs at the level of firms, fields, and years.

This paper draws on a large literature in productivity and technological change. Evenson and Kislev (1975, 1976) apply search theory (beginning with Stigler (1961, 1962)) to agricultural research and productivity and identify factors that limit the flow of agricultural research across geographical and technological space[2]. In results that presage later work on science and industry Mansfield (1980) and Griliches (1986) find that basic research is more potent than applied research in its contribution to firm output. Cohen and Levinthal (1989) introduce dual functions for R&D, innovation and learning. Their approach suggests that some of firm R&D goes to form a listening post in order that knowledge spillovers can take place, an idea which Adams (2005) applies to the division of learning effort between academic and industrial spillovers. Another strand of literature concerns itself with the influence of academic research on industrial research. Jaffe (1989) finds that university R&D increases firm patenting in the same state especially in drugs, chemicals, and electronics. Particularly at lags of 20-30 years, Adams (1990) finds that stocks of scientific papers weighted by science and engineering employment increase industrial productivity. Using survey evidence, Cohen, Nelson, and Walsh (2002) find that the most important channel of university research occurs through publications. Narin, Hamilton and Olivastro (1997) and Branstetter and Ogura (2005) find that patent citations to scientific literature have increased in recent years, but suggest that this spillover channel is specific to a few citing industries.

This paper has been influenced by the localization hypothesis. This is the notion that problems of adaptation impede knowledge flows across geographical and technological space. Adams and Jaffe (1996) find evidence for localization within firms, Adams (2002) uncovers localization effects of academic spillovers to firms, and Adams, Clemmons and Stephan (forthcoming) find that science fields constrain flows of knowledge among universities at the level of individual scientific papers. Peri (2005) underscores

[2] Papers by Kortum (1997), Klette and Griliches (1998), Jones (2002), and Klette and Kortum (2004) explore regularities in firm growth, aggregate growth, and interactions between the two and are at least partially inspired by the search theoretic approach.

these themes by showing that patent citations fall significantly with distance, region, national boundaries, and language[3].

The literature on patent measurement has taught us much about the use of citations to trace knowledge flows. Scherer (1982a, 1982b) constructed patent citation matrices that indicated the role of inter-industry knowledge flows and their contributions to invention. Trajtenberg (1990) found a positive correlation between citations to CT patents and the social value of CT scanner innovations. Jaffe and Trajtenberg (1999) used patent citations to trace knowledge flows between top R&D countries. Harhoff, Narin, Scherer, and Vopel (1999) calculated a direct relationship between citations to individual German patents and their value as drawn from surveys of the patent holders. All of this research has been useful for our work.

This paper makes six main contributions. First, we estimate science production functions at the firm and field level based on a sample of top U.S. R&D firms that cover manufacturing as well as trade and service industries. Second, we bring a comprehensive set of knowledge flows to bear on the problem of explaining scientific output in R&D-performing firms, and we confront these measures with each other and with a simple alternative, the firm's R&D stock (the new measures add considerably). Third, we do not assume the primacy of spillovers of outside basic science but instead test the spillovers against the flow of basic science inside the firm (spillovers matter). Fourth, we compare and contrast university science spillovers with spillovers from other firms (university spillovers are more potent). Fifth, rather than assume that citation spillovers alone matter, we explore the alternative of collaboration-based university spillovers (collaboration between firms is rare and hence neglected). Consistent with Adams, Black, Clemmons, and Stephan (2005) we find that collaboration also contributes to scientific discovery. Finally, the evidence confirms the importance of universities to industrial R&D, even as universities have lost share in recent years in U.S. science and engineering employment (Adams and Clemmons, 2005a).

Methodologically we find that citation and collaboration rates in science, while descriptive of the propensity to use the firm's research and the research of other institutions, fall short of a full accounting for scientific influence. Mean citation and collaboration rates do not capture frequency nor do they capture the

[3] Knowledge frictions imposed by industry are less clear. Certainly the evidence on inter-industry flows of patent citations in Scherer (1982a, 1982b) suggests the strength of flows of information among industries. Also, evidence in Von Hippel (1988) and in Klevorick, Levin, Nelson, and Winter (1995) implies that user and supplier "outside" industries are influential sources of innovation.

scale of the spillover. It is the citation- and collaboration-weighted sums of university and firm research that are more comprehensive as a metric of scientific influence.

We begin with descriptive findings that emerge from the goal of estimating science production functions. Reflecting university dominance in science most spillover interactions (citing/cited or collaborating/collaborated cells) involve universities. Interactions with firms are one-sixth as many. However this rate is larger than one would expect, given that firm papers are less than one-tenth as many as university papers. This finding and the fact that citation rates to other firms are five times greater than the citation rate to universities imply that firm's scientific research is more relevant to other firms.

Regarding science spillovers from firms, we find that most of these take place between rather than within industries. In contrast most spillovers originate in the same field of science rather than outside that field. Therefore, industrial spillovers seem to be little constrained by industry though they are strongly constrained by field. This field constraint applies even more strongly to citation spillovers from universities, suggesting that the firm-to-university citations are to theoretical research rather than applied interdisciplinary research. In regard to collaboration spillovers from universities to firms, we find that they average less than a tenth of citation spillovers. But in computer science and engineering the collaboration spillover exceeds 20 percent of the citation spillover.

The shares of fields in spillovers depend on the sending sector. As in Branstetter and Ogura (2005), most university citation spillovers derive from biomedicine. This agrees with the dominant role of biomedical funding in universities. Also, academic biomedicine spills over almost entirely to the drug industry. We find a very different pattern when we turn to collaboration spillovers from universities and to industrial spillovers. There engineering and natural science dominate. This is both evidence and a warning that spillovers depend on the industrial-scientific workforce. This is true even if citation-based spillovers cannot really capture this dimension as indeed they cannot when science publication is missing. Stephan, Summell, Black, and Adams (2004) explore the channel of graduate student migration from universities to firms in the late 1990s. They find it to be dominated by engineering and natural science.

The empirical work concludes with the science production functions. We estimate regressions on a three-dimensional panel of firms, sciences, and years. Logarithms of the firm's scientific papers or its citation-weighted scientific papers are the dependent variables. We find that the omission of knowledge spillovers biases upward the effect of the firm's R&D stock on scientific discovery. All spillovers are positive and all are highly significant. These results are robust. They stay about the same whether or not field and firm fixed effects are included. We find besides that failure to account for zero knowledge spillovers biases the effect of spillovers downward, especially for spillovers, such as collaboration, that occur rarely. For university spillovers we find that omitting collaboration spillovers biases upward the effect of citation-based spillovers, though both contribute to scientific discovery. We also find that spillbacks from the firms' past scientific research dominate the effect on scientific output of its own R&D stock.

University spillovers are especially potent. The elasticity of scientific discovery with respect to cited university research significantly exceeds that of other firms. Consistent with this the spillover effect *per dollar* of university research exceeds the effect per dollar of firm research. These findings emphasize the importance of publicly funded science as a source of knowledge spillovers in the U.S. economy.

The rest of the paper is divided into four sections. Section II provides a simple framework for the empirical study of industrial scientific discovery in firms. The keystone of this section is a firm-, field-, and year-level knowledge production function for industrial science that includes spillbacks of knowledge from the firm's past research and spillovers of knowledge from universities and other firms as essential arguments. In this section we also define the spillback and spillover variables that we use to study the sources of industrial discovery. Section III discusses the database and the panel data set that we have extracted from it. Section IV reports regression findings on scientific discovery in firms. Section V discusses directions for further research and concludes.

II. Analytical Framework

A. The Science Branch of a Firm

We now develop a model of the science branch of the firm, in order to frame the empirical work that follows. To an extent this branch is a "virtual" branch because industrial scientists work closely with applied researchers, line engineers, and management and often share their responsibilities (Adams, 2005). Though it is not always physically separate, the function of the science branch lies in scientific exploration and so. in a functional sense, it stands apart from the rest of the firm.

We use this model to study the production process for science discoveries in firms, the origin and meaning of knowledge spillovers in science, and the relationship of current scientific activity in the firm to its past scientific research as well as the firm's other R&D. This investigation will provide a bridge to the empirical work and it will explain the issues that are likely to arise in that work.

Scientific discovery in field i has an expected forward value EP_{it} at time t. Suppressing firm subscripts we write this as

(1) $$EP_{it} = EP_{it}(a_{it}, X_{it})$$

In (1) a_{it} is the stock of the firm's scientific knowledge and X_{it} is a vector of shifters of forward value that are exogenous to the science branch, including the firm's size and its stock of research, and the structure of the industry, including the size and knowledge stocks of competitors. EP_{it} is assumed to decrease with the knowledge stock a_{it} reflecting diminishing returns, but it is assumed to increase with firm size, representing appropriability. EP_{it} may increase with the firm's stock of applied research, owing to complementarity of different kinds of knowledge; and with other competencies, all of which we impound in the vector X_{it}.

The stock of scientific knowledge is

(2) $$a_{it} = g_{it} + (1-d)a_{it-1}$$

Here g_{it} is gross investment in science or the rate of discovery per year, and d is the rate of obsolescence. Gross investment in science i is

(3) $$g_{it} = \alpha \ell_{it}^{\beta_\ell} S_{it}^{\beta_S}$$

In (3) α captures technical efficiency, ℓ_{it} measures scientists and engineers engaged in internal work rather than a search for outside knowledge, S_{it} is the knowledge spillover, which depends on search, and the exponents β_ℓ, β_S are elasticities of scientific discovery with respect to the inputs. We assume diminishing returns so that $0 < \beta_\ell < 1, 0 < \beta_S < 1$ and $0 < \beta_\ell + \beta_S < 1$.

We make four assumptions concerning the spillover. We assume that spillovers from different sciences differ in intrinsic relevance c_{ij}; that spillovers require search; that specific science spillovers are subject to diminishing returns; and that pursuit of a particular science may not be justified by its expected monetary return. One example of the spillover is:

(4) $$S_{it} = \sum_j c_{ij} \mathrm{K}_{ijt}^{\gamma} A_{jt-1}$$

Its arguments are as follows: K_{ijt} is the proportion of the lagged stock of scientific knowledge A_{jt-1} that the firms chooses to absorb. If, as seems likely, search within the same science yields a larger return, then $c_{ii} > c_{ij}, j \neq i$. In order to satisfy the assumptions we require that $c_{ij} \neq c_{ik}, j \neq k$ (differences in intrinsic relevance), $\mathrm{K}_{ijt} > 0$ (positive search), and $0 < \gamma < 1$ (diminishing returns to a science).

Absorption K_{ijt} is controlled by firms. We assume a simple technology for it. One unit of search locates one scientific paper of sufficient quality to increase the rate of discovery. Since n_{jt} papers exist in science j at time t, and the probability that a paper is useful once searched is p_j this generates an "effective" sampling rate of $\kappa_{jt} = p_j / n_{jt}$. Summing we reach the total sampling rate

(5) $$\mathrm{K}_{ijt} = \sum \kappa_{jt}$$

Combining (1)-(5) the science branch maximizes a concave net return from discovery in each science in every period:

(6) $$\max_{\ell_{it}, \mathrm{K}_{ijt}} \left\{ EP_{it} \times \left[\alpha \ell_{it}^{\beta_\ell} \left(\sum_j \mathrm{K}_{ijt}^{\gamma} A_{jt-1} \right)^{\beta_S} \right] - w_R \left(\ell_{it} + \sum_j \mathrm{K}_{ijt} \right) \right\}$$

It is easy to show that the allocations which maximize (6) depend on knowledge, size of the firm and appropriability. Similarly, the range of sciences that yield an interior solution to (6) depends on the complexity of the firm's product structure and the degree of complementarity among different sciences.

Clearly the science inputs in (3) depend on the solution to (6) and are endogenous. But then, so are the inputs to every production function dependent. The relevant issue seems to be whether instruments are available that could improve on single equation estimates of (3). Another issue is collaboration. If search yields a likely academic partner (industrial collaboration is rare) then the arguments of (3) have to expand to include inputs of partners and (6) is likely to include costs of partners.

B. Empirical Science Production Function

The previous section has discussed the analytical relationship between scientific discovery and science inputs. But there are additional issues must be dealt with before we can estimate an empirical science production function. First, the inputs in (3) are not observable. This leads us to replace research labor ℓ_{it} with the firm's R&D stock and the spillback from its past science research. For related reasons we replace K_{ijt} with citation/collaboration rates. Second, instead of one spillover the data contain several. It is this mixture of constraints and opportunities that leads to the following empirical counterpart to (3):

$$n_{it} = \exp(\beta + Z'\delta + \alpha t) R_{t-1}^{\eta_R} B_{it-1}^{\eta_B} \prod_{v=1}^{V} S_{ivt-1}^{\eta_{sv}} \exp(u_{it}) \tag{7}$$

In (7) n_{it} is the number of papers or citation weighted papers produced by the firm in science i at time t, Z' is a vector of industry dummies whose coefficients are δ, t is time trend, R_t is the stock of the firm's R&D, B_{it-1} is the lagged spillback into i, or knowledge derived from the firm's stock of past science research, S_{ivt-1} is the stock of outside knowledge acquired from source v, and u_{it} is an error term. Here "acquired" refers to the sampling process described above. The η_i exponents are output elasticities.

A third issue is that the form of the spillover is nonlinear in (4) and (7). To avoid complications in the estimation procedures we express the approximate counterparts to the $\mathrm{K}_{ijt}^{\gamma}$ weights in the spillover/spillback indicators as linear citation or collaboration rates[4].

Features of the empirical knowledge spillovers are like this. First, in most cases the spillovers allow for cross-field effects. Collaboration is the exception. Its definition forces joint research to fall into

[4] Since the empirical work includes six sciences and at least four spillover and spillback variables, estimating a nonlinear regression based on (4) seems unpromising. Linear spillovers are simple to use in regression and are probably highly correlated with their nonlinear version in (7).

the field of the journal where the published paper appears, or in other words, the same field. Second, for spillover weights we rely on the citation/collaboration rate, which we define as c_{ij} / n_j. The numerator c_{ij} counts citations (or collaborations) between groups i and j. It is divided by n_j, the number of papers in group j that could be cited or jointly written. The citation/collaboration rate is preferable to the corresponding probability $c_{ij} / n_i n_j$ in the case of a group of papers n_i. The probability is more appropriate for a single paper, because it captures the average proportion of knowledge flowing from j to a paper in i (Adams, Clemmons, and Stephan, forthcoming). But if n_i papers cite n_j papers in j, then the average citation/collaboration probability $c_{ij} / n_i n_j$ sums to c_{ij} / n_j. We use the latter measure to study scientific influence over groups of papers n_i.

The citation spillover from universities takes the form:

$$(8) \qquad S_{ift-1}^{CU} = \sum_{j=1}^{N} \sum_{F=1}^{M} \sum_{\tau=1}^{t-1} \left(c_{iftjF\tau} / n_{jF\tau} \right) \mathrm{R}_{jF\tau}$$

It is the sum over all other groups j, all sciences F, and all previous years in the data τ of the citation rate times the stock of knowledge in the cited group, science, and year. As it happens, university R&D stocks have two advantages over Compustat R&D stocks for firms. One, university R&D stocks are available by field of science, and two, the stocks are science expenditures. This is true even though we compute an estimate of firms' basic research[5]. In the near future we plan to handicap the university data to test whether the potency of university research on industrial discovery partly derives from these advantages.

The collaboration spillover occurs within fields because in the data joint research is forced to take place within fields. Collaboration is also contemporaneous. It takes place at the same time as the jointly conducted research. However, to capture the lagged knowledge driving collaboration, we multiply the collaboration rate by the lagged R&D stock of the partner school and field. Since collaboration occurs

[5] The field and university R&D stocks are expressed in millions of 1992$ over the previous eight years. They are depreciated at 15 percent per year. We have R&D flows going back to 1973, though our analysis uses flows going back to 1980.

within field and is contemporaneous, the empirical collaboration spillover is a single sum over collaborated university R&D stocks in the same field, weighted by the collaboration rate:

(9) $$S^{JU}{}_{ift-1} = \sum_{j=1}^{N} \left(J_{ijft} / n_{jft} \right) b_{t-1} R_{jft-1} \ ,$$

In (9) the term J_{ifjt} stands for joint research between institutions i and j in field f .

The citation spillover from the rest of industry is:

(10) $$S^{I}_{ift-1} = \sum_{j=1}^{N} \sum\sum_{\tau=1}^{t-1} \left(\sum_{F=1}^{M} c_{iftjF\tau} \ / \ \sum_{F=1}^{M} n_{jF\tau} \right) b_{t-1} \mathrm{R}_{j\tau}$$

The citations are by papers in firm i , field f and time t to other firms' papers $n_{iF\tau}$ in any field F , in any previous time included in the data $\tau = 1 \ldots t-1$. The ratio in parentheses is the weighted average citation rate across fields: it is the number of papers in years t and $\tau = 1 \ldots t-1$ in *all* fields that are linked through citation, divided by the number of papers in *all* fields in that earlier year. We take the weighted average citation rate because firm R&D in Compustat is a total R&D measure, as is the R&D stock derived from it. Ideally we would like to have the firm's stock of basic science research broken out separately by field but this does not exist. Although we cannot obtain basic science research stocks by field, still we can obtain an estimate of the firm's overall stock of basic research. The estimate relies on b_{t-1} , the ratio of basic research to total research in the cited firm's primary industry times $R_{i\tau}$, the firm's stock of R&D in the cited year[6]. Given that R&D is not available by field, we use the weighted average citation rate times the estimated stock of the firm's basic research $b_{t-1} R_{i\tau}$ to approximate the spillover.

The citation spillback from the firm's own past scientific research is similar to (10):

[6] The firm R&D stock is the deflated stock of R&D in millions of 1992 $ over the previous eight years, and depreciated at a rate of 15 percent per year. We have these stocks going back as far as 1977, though we use data starting in 1980 and later depending on the year that the firm is first listed in Compustat.

(11) $$S^{B}_{ift-1} = \sum_{\tau=1}^{t-1} \left(\sum_{F=1}^{M} c^{Self}_{iftF\tau} / \sum_{F=1}^{M} n_{iF\tau} \right) b_{t-1} \mathrm{R}_{i\tau}$$

In (11) self-citations are written as $c^{Self}_{iftF\tau}$. Again (11) uses a weighted average citation rate because the R&D stock of the firm that is self-cited is a total stock taken from Compustat. As with (10) we use $b_{t-1}R_{j\tau}$ to estimate the total stock of basic research, on this occasion within the firm.

III. Database

The data consist of 230 thousand papers of the top 200 R&D firms and 2.43 million papers of the top 110 U.S. universities that are published during 1981-1999. The data source is ISI, the Institute for Scientific Information, in Philadelphia, Pennsylvania. The papers appear in 7,137 scientific journals. Each journal and all of its papers are assigned to a unique science field. The main alternative to this journal assignment method is to assign papers according to authors' fields. However this strategy fails because the information on authors' departments is inconsistent and incomplete[7].

The top 200 firms make one million citations to papers of top 110 universities, and 600 thousand citations to papers of top 200 firms, including themselves. As we have seen, spillovers entail citation and collaboration rates to papers by universities and other firms, which are accordingly "non-self" citations and collaborations. Self-citations are evidence of spillbacks.

Given that science teams among firms are rare, collaboration is limited to joint research between firms and universities. Such collaborations involve more than 40 of the 230 thousand firm papers. These are the linkages that we exploit first to construct the spillovers and spillbacks in (8)-(11) and later to estimate the science production function (7).

In building the spillovers and spillbacks we use data on research expenditures in universities by field from the NSF-CASPAR database, data on total R&D performed by firms from Compustat; and data on the ratio of basic to total research by industry from the 1980s to the present, also from NSF.

[7] As an experiment we tried to assign all papers of Harvard University to one of the science fields in our data using address information. About a third of the papers could not be assigned using information on authors' Harvard addresses. For this reason we abandoned the departmental assignment method.

We start off the description of the data with distributions of scientific papers by field. We report the industrial distributions by major industry group. We report the academic distribution as a whole. Table 1 describes these distributions. We indicate the top three sciences in each industry or sector in bold, with their ranks in parentheses to indicate dominant fields of in science publication. The first column lists sectors and industries and the second the total number of papers produced. Remaining columns report percentages out of the total number, for nine fields ranging from agriculture through physics. Note that three of the fields, agriculture, earth sciences, and mathematics and statistics, are quite rare in industry[8]. The six largest disciplines are biology, chemistry, computer science, engineering, medicine, and physics, and these disciplines that are the focus of our attention henceforward. The statistics reflect the private value of marginal product of different disciplines in industry. This is why engineering and natural science papers are more frequent in industry and biology and medicine less frequent (top line) than they are in universities (bottom line). Note that dominant fields in specific industries are as expected. Chemistry ranks first in petrochemicals, biology ranks first in drugs and biotechnology, and engineering ranks in the top three everywhere except drugs and biotechnology. One surprise is the high state of physics publication, about as frequent as in chemistry.

To undertake an empirical analysis of industrial scientific discovery we construct a panel data set made out of papers, citations, and collaborations. The dimensions of the panel are citing/collaborating firms, fields, and years. The fields are the primary ones of biology, chemistry, computer science, engineering, medicine, and physics. The maximum time period included in the panel ranges from 1988 to 1999, because of the desire to allow for citation and collaboration histories going back to 1981. Not all top 200 U.S. R&D firms have lengthy histories and indeed about 14 of the 200 firms lack a sufficient R&D history to be included in this study, so that 186 are left. The panel would be imbalanced for this reason alone but there is another reason as well. Since the data are at the level of sciences as well as firms and years, publication disappears in some years, especially for those sciences that are rarely practiced. This produces perforations in the panel even besides the fact that the length of the time series on different firms varies.

The dependent variables are counts of scientific papers and of papers weighted by citations over the first five years upon publication. The independent variables include time trend and field and firm fixed

[8] Three other fields, astronomy, economics, and psychology are more rarely represented still, and are dropped from Table 1 and after.

effects. Also included are logarithms of the various spillovers, the citation spillback, and the firm's R&D stock. After the exclusion of missing values the data consist of 5,273 observations on scientific papers and 3,288 observations on citation-weighted scientific papers[9].

We include Figures 1 to 8 to clarify the structure of the citation/collaboration rates and the spillovers/spillbacks derived from them. Each graph includes six industry groups that range from petrochemicals to transportation equipment each includes six sciences that range from biology to physics. The figures form natural pairs that report mean citation/collaboration rates in the first figure and the sum of citation/collaboration spillovers and spillbacks in the second. This arrangement is related to an important point of this paper. The average citation/collaboration rate cannot account for frequency of interaction, nor can it account for the volume of spillovers/spillbacks. This essential insight will become clear as the discussion proceeds.

Figure 1 reports mean citation rates by citing industry group and cited field of academic science. Figure 2 does the same for spillovers. Figure 1 shows that the rate of citation is highest by a wide margin to academic computer science. Secondary peaks occur in chemistry, engineering, and physics. But as Figure 2 shows, the volume of spillovers from academic biology and medicine far exceeds any of these fields. This is shown by the far lower secondary peaks observed for spillovers of academic computer science and physics in computers, communication, and software; for academic chemistry in chemicals, and for academic engineering in computer, communication, and software; electrical equipment and instruments; and transportation equipment. Nevertheless, about 63 percent of all academic *citation* spillovers take the form of biomedicine. Most are concentrated on drugs and biotechnology.

Figure 3 and Figure 4 show that we must take this finding with a grain of salt. In Figure 3 the rate of academic collaboration in computer science again overshadows that of other fields. Secondary peaks again take place in chemistry, engineering, and physics. But now the spikes of academic collaboration spillovers in biology and medicine are comparable with collaboration peaks in computer science and engineering and do not dominate them. In fact collaboration spillovers from academic biology and medicine comprise just

[9] Since citations received cover the first five years after publication, and since the data end in 1999, citation-weighted papers must end in 1995. This is the reason for the drop in the number of observations when we use citation-weighted papers.

35 percent of the total. The industrial workforce seems to condition university spillovers, considered apart from citation, because it reflects the distribution of scientific absorptive capacity in industry.

Figures 5 and 6 repeat the exercise for cited industrial fields of science. Compared with Figure 1 mean citation rates to industrial science in Figure 5 are higher than the citation rates to academic science and they are more equal across fields. We suspect that the first pattern results from the greater proximity and smaller scale of industrial science. Concerning the second, we conjecture that it shows the importance in industry of applied interdisciplinary research which implies higher cross-field citation.

Figures 7 and 8 conclude by reporting self-citation graphs to firm's own research. While not as evenly distributed as Figure 5 the citation rates in Figure 7 are more evenly distributed than for industry citations to academic science in Figure 1. Figure 8 shows that computers, communication, and software dominate self-citation spillbacks, with drugs and biotechnology, and petrochemicals coming in a distant second.

The figures illustrate the difference between citation/collaboration rates conditional on their having occurred and the aggregate volume of citation spillovers. Table 2 quantifies these findings using a simple format. In the table we report the number of citation/collaboration interactions, or cells in which interaction takes place, as well as mean and total spillovers. The underlying cells are defined by citing/collaborating firm, field and year, and by cited/collaborated institution, field, and year.

We start with the first column. There are 547 thousand citation interactions with universities compared with 89 thousand with other firms. The number of interactions with firms is more than one would expect by chance. The industrial frequency is one-sixth of the academic frequency, whereas industrial papers are one-tenth as many. This asymmetry is even greater when firms cite themselves. We attribute the excess frequency of firm citation to the greater proximity of firm research, especially one's own.

Interactions within industry are less common than between industry, but industrial interactions within field outnumber those between fields. Field constrains relevance to a greater extent than industry. Turning to interactions with universities, an even larger proportion of interactions take place within field, implying that interdisciplinary research is more common in industry. Collaboration is less frequent than citation, but then collaboration is more costly. It occurs in lumps and is always contemporaneous, whereas citation is distributed across past papers.

Column 2 reports mean citation/collaboration rates. The column shows that mean citation rates to firms are 0.05, about five times higher than to universities. Mean self-citation rates are 0.13, or 13 times higher than to universities. The mean firm-university collaboration rate is 0.01, roughly the same as the mean firm-university citation rate.

The third column shows the mean R&D spillover (in millions of 1992 dollars). As measured, the industry citation spillovers and spillbacks are quite a bit larger than university spillovers. This is partly due to the higher industrial citation rate, especially for self citations. However, the measure of industrial basic research that we use could be upward biased. It is true that we estimate basic research, so that we reduce the amount of cited industrial R&D to about five percent of Compustat R&D. However it is not clear that this basic research is the same as basic scientific research. The estimate could still be too large if basic research includes activities that are not science. But the official statistics do not record firm research on basic science. The estimate that we have seems to be the best that can be done.

Aggregate R&D spillovers summed over all citing/collaborating cells appear in the fourth column. More than 70 percent of industrial spillovers take place between industries, but more than half take place within fields, thus affirming the importance of field as a constraint on spillovers, but not industry. Field is also a constraint on citation spillovers from universities. Collaboration spillovers add another ten percent to university spillovers relative to industry, where collaboration is rare.

Table 3 reports aggregate spillovers and spillbacks from the six major sciences. Consistent with their importance in universities the table shows that biology and medicine account for over 60 percent of the university spillover. However, this proportion drops once the university-firm collaboration spillover is included. Collaboration spillovers are large in computer science and engineering compared with citation spillovers. The final two columns of Table 3 show total industrial spillovers and spillbacks by field. The greater importance in industry of natural science and engineering is clear.

The data description concludes with a presentation of university citation spillovers by citing industry. Table 4 shows the top four spillovers from universities. While spillovers from academic biology and medicine are large the table confirms once again their concentration in drugs and biotechnology. Across industries the most consistent spillover comes from engineering, followed by physics and chemistry.

Table 5 reports the top six spillovers from other firms, by industry. To bring out cross-industry effects the table reports cited industries as well as fields. Consistent with what has gone before most spillovers derive from outside the industry. Drugs and biotechnology are an exception. It is clear as well that most spillovers derive from the same field. Another point is that communications, and software and business services are the most common sources of industrial spillovers. Again biology and medicine are found to be less important in industry. The most broadly distributed sources of industrial spillovers are chemistry, engineering, and physics.

IV. Regression Findings

This section reports regression findings. Tables 6 and 7 report the regressions, while Tables 8 and 9 provide additional interpretation. The regressions fit the logarithm of the science production function (7) to the data as follows:

$$\ln(n_{it}) = \beta + Z'\delta + \alpha t + \eta_R \ln(R_{it-1}) + \eta_B \ln(B_{it-1}) + \sum_{v=1}^{V} \eta_{Sv} \ln(S_{ivt-1}) + u_{it} \tag{12}$$

To remind the reader the variable on the left is the logarithm of scientific papers or of citation-weighted papers. On the right following the intercept are the vector of field and firm fixed effects, time trend, and the logarithm of the firm's R&D stock. This is followed by the self-citation spillback from the firm's past basic research. Under the summation sign are logarithms of the vector of spillovers. They consist of citation-based spillovers from universities, collaboration-based spillovers from universities, and citation-based spillovers from other firms. The η_i coefficients are elasticities of scientific papers with respect to inside and outside R&D measures.

As noted in Section III, we reduce the elemental papers, citations, and collaborations data to a panel that consists of up to six sciences (biology, chemistry, computer science, engineering, medicine, and physics, of 186 firms that have adequate R&D data and histories, and of as many as 12 years of evidence from 1988-1999, depending on the date when firms go public in Compustat. The data include 5273 observations after dropping missing values. The mean number of papers is 25 and citation-weighted papers average 62. The means lie far above zero. They suggest that OLS estimation is adequate and Poisson estimation unnecessary. Since these are large R&D performing firms, their R&D stocks are positive and science publication is positive.

Nevertheless, for very many observations, one or more spillback/spillovers equals zero. To handle this problem of zeroes when taking logarithms we add 0.001 to the variables. Since all the R&D variables are denominated in millions, this adds a thousand dollars to a spillover measured in millions. However, in taking logarithms of the augmented measure, we create a mixture of positive and zero spillovers. To take care of this problem we create dummy indicators equal to one if the spillover is really zero, and zero if the spillover is positive. We multiply each dummy by the logarithm of the spillover. The resulting interaction terms handle the effect of a zero spillover on the production of scientific papers. To test this, in half of our specifications we include interaction terms. The interactions test for zero spillovers and spillbacks: we expect their absence to have a significantly negative effect on scientific discovery. Besides this, we expect omission of the interactions to bias the coefficients of the spillovers and spillbacks downward. We test for this and find that the predicted bias materializes.

Table 6 reports regression findings where the logarithm of scientific papers is the dependent variable. As already noted, all equations include time trend, and most include field and firm fixed effects, which are jointly significant at the 0.1 percent level. When we exclude the fixed effects, it is simply to show the effect that this has on the spillover, firm R&D, and spillback coefficients.

The table begins simply but progressively adds complexity moving from left to right. Equation 6.1 includes purely inside variables consisting of the firm's R&D stock and the self-citation spillback. Both are positive and highly significant. The elasticities are roughly equal (0.21 and 0.18). If the spillback is omitted however, the elasticity of papers with respect to the firm's un-weighted R&D stock equals 0.29. Much of the effect of firm's R&D stock is embodied in the spillback. This is true even before the zero spillback interaction term is taken into account, which biases down the effect of the spillback.

Equation 6.2 adds the logarithm of citation spillovers from universities and other firms to 6.1. The R&D elasticity drops to 0.09 and the spillback elasticity falls to 0.09. The university spillover elasticity is 0.20; the firm spillover elasticity is 0.09. This difference turns out to be highly significant so it is the university spillover that seems to be more potent. However the firm spillover elasticity may be biased downward by measurement errors to which it is subject.

Equation 6.3 adds the logarithm of the university collaboration spillover to 6.2. Both of the firm elasticities decline slightly, but it is the university citation spillover elasticity that drops most. Collaboration is an alternative to citation. It is interesting that the collaboration elasticity is 40 percent of the university citation elasticity, even though the collaboration spillover is just 10 percent of the citation spillover. Both the firm elasticities and the spillover elasticities remain positive and significant in this latest specification. The sum of the elasticities suggests that scientific discovery at the firm level is subject to diminishing returns and the returns to scale estimate in 6.3 is 0.67.

Equation 6.4 drops all the field and firm fixed effects from 6.3. Apart from an increase in the effect of firm's R&D stock, the surprise is that this makes very little difference to the spillover/spillback elasticities. In this sense it does not matter whether fixed effects are included or not, even though the fixed effects are jointly significant. The result comes as a surprise because firm fixed effects often make a large difference to the R&D estimates, and often render the R&D coefficients insignificant.

The second half of Table 6 adds zero interaction terms in order of appearance of each of the variables. The results are in line with expectations. In 6.5 we add the zero spillback interaction term to 6.1. The result is a large rise in the main effect of the spillback and a large fall in the R&D elasticity. It appears that once the spillback is properly accounted for it explains most of the firm's own effect on its rate of scientific discovery. As for the zero spillback interaction term, as expected this is negative and significant. Its absolute value is less than the main spillback elasticity, perhaps because firms with positive spillbacks come from a population that is more proficient in scientific research.

Equation 6.5 does not take spillovers and their zero interaction terms into account. Equation 6.6, the counterpart to 6.2, does exactly this. It adds main and zero interaction terms for citation spillovers from universities and other firms. The spillback elasticity declines compared with 6.5. Again the spillback is more important in the positive domain than the firm's R&D stock. As in 6.2 the university spillover elasticity is twice as large as the firm elasticity (0.38 versus 0.19). This difference turns out to be highly significant. The table continues with equation 6.7, which is the complement to 6.3. This adds the main collaboration spillover and its zero interaction term to 6.6. The result is striking: the collaboration spillover in its positive range has an elasticity of 0.22, almost as large as the main effect of the university citation spillover (0.26). The reason for the large increase in the collaboration elasticity lies in its rarity, which 6.7 accounts for. This addition takes away from the other elasticities. Nevertheless, both the firm elasticities and all of the spillover elasticities are positive and highly significant evaluated in the positive domain for each variable.

Table 7 revisits Table 6 using citation-weighted scientific papers as the dependent variable. To concentrate on industrial relevance of a paper the citations come from other firms[10]. The layout remains the same; complexity increases from left to right in the table. Besides exhibiting generally larger elasticities, the findings differ in several ways from Table 6. In equation 7.1, the twin of 6.1, the R&D stock has a larger elasticity (0.53) than the spillback (0.45). However, this firm R&D elasticity is sensitive to the inclusion of spillovers. This can be seen in 7.2, where we add citation spillovers from universities and firms. While the citation spillback and spillovers are highly significant, the firm's R&D stock becomes insignificant and this persists through the rest of the table. This also suggests that spillovers and spillbacks account almost entirely for firms' quality-adjusted research. Equation 7.3 is the counterpart to 6.3. It adds the collaboration-based university spillover to 7.2. As expected the elasticity of the citation-based university spillover declines. And yet all the spillover elasticities remain positive and significant. As before firm's R&D stock is insignificant while the citation spillback is positive and highly significant. In 7.3, the sum of the elasticities, the returns to scale estimate, is 0.91, indicating mildly diminishing returns. If we compare this finding with the equivalent estimate of 0.67 in 6.3, this suggests that past science yields part of its return in the form of higher quality research. Equation 7.4 drops firm and field fixed effects. As with 6.4 this makes little difference to the spillover and spillback elasticities.

Similar to equations 6.5-6.7, equations 7.5-7.7 include zero interaction terms. The main effect of the citation spillback jumps from 0.44 in 7.1 to 1.1 in 7.5. Consistent with this the sign of the zero spillback interaction term is negative and highly significant. The insignificance of the firm's R&D stock is nevertheless puzzling. Perhaps the key to interpreting it is to realize that R&D stock and the spillback both increase with firm R&D. Therefore, an increase in the firm's R&D stock holding the spillback constant implies that the citation rate of a firm to its own past papers *declines*. In other words, firm papers that the

[10] Notice that the citations received by the firm's papers from other firms in the future are completely distinct from the citations that it makes to papers in the past. The two sets of citations are mutually exclusive. This is an important point because it says that citation-weighted papers and citations do not betray a hidden dependency.

firm cites less are also cited less by other firms. The latter is the weight that we apply to firm papers. Controlling for the zero spillback interaction may bring out this correlation in scientific influence.

Equation 7.6 adds citation spillovers from universities and other firms as well as their zero interactions. All signs are as expected. Main elasticities of the spillback and spillovers are positive and significant while zero interaction effects are negative and significant. However, the main elasticities are larger than in 6.6. This suggests once again that spillovers and spillbacks increase the quality as well as quantity of research. Equation 7.7 adds the collaboration-based university spillover to 7.6. The main and interaction collaboration terms are significant, and as expected, are respectively positive and negative. Equation 7.8 drops field and firm fixed effects from 7.7. While the fixed effects are jointly significant, their exclusion leaves most spillover and spillback elasticities highly significant.

Table 8 collects formal tests for the equality of the regression coefficients. The upper panel of the table confirms that the university elasticities exceed the firm elasticities at more than the one percent level of significance. The lower panel indicates that very often, the main effect of the spillovers and spillbacks exceeds the zero interaction effect. This again suggests that firms that obtain spillovers and spillbacks are somewhat different from those that do not, and are better able to benefit from outside R&D.

So far we have discussed only elasticities. The elasticities record percent changes in papers or citation-weighted papers with respect to one percent changes in firm R&D, the citation spillback from firm research, and the spillover variables. And yet, we would like to have quantitative evidence on the marginal product of the R&D variables expressed in terms of the papers or citation-weighted papers, because this tells us the increase in the rate of scientific discovery per dollar of R&D of different types. The elasticities are $\eta_i = \partial \ln(Papers) / \partial \ln(Q_i)$. Here Q_i is one of the different types of R&D that we have studied. Solving for the marginal product of Q_i evaluated at the mean: $\partial\, papers / \partial Q_i = \eta_i \times (\overline{papers} / \overline{Q_i})$. Here the overbars indicate mean values. Table 9 calculates marginal products of the different R&D measures, evaluated at means, using equations 6.7 and 7.7 as its source. The table records means of papers, citation-weighted papers, and the R&D variables as well as the marginal products.

Looking at the first half of the table, the findings indicate that the marginal product—the payoff in additional counts of papers per million dollars of R&D—is largest for citation-based university spillovers, with spillovers from other firms a distant second, and the citation spillback third. Turning to the second half, we see that collaboration-based university spillovers have then largest marginal product, followed by citation-based university spillovers, and then by firm spillovers. In each of the two sets of estimates the citation-based university-spillover marginal product is about three times larger than the citation-based firm-spillover marginal product. Of course these estimates of firms' basic research and its marginal product are necessarily somewhat crude so the industry marginal product could be downward biased. But as it stands, the results suggest a strong role for university research in industrial scientific discovery, even in a setting which accounts for industrial scientific research to a greater extent than has been possible before now. In this sense, the results are a striking affirmation of publicly conducted science over most of industry.

V. Discussion and Conclusion

This paper has examined the structure of citation- and collaboration-based basic science knowledge flows to firms from universities, from other firms, and from the firm itself. In a broad view of the matter we find that industrial firms rely on both outside academic and industrial research, as well as on their own research. This is emphatically true in high-R&D intensity industries as petrochemicals, drugs and biotechnology, electrical equipment, and instruments, but this influence is present in other sectors as well, a point that has recently been emphasized by Cohen, Nelson, and Walsh (2002). The findings reinforce the sense of relevance of basic science for industrial progress.

We have shown that this influence operates both within and between industries. The results bear strong similarities with the findings of Scherer (1982a, b), and Klevorick, Levin, Nelson, and Winter (1995). All of these papers assert the importance of interindustry flows of technology for productivity growth and for the replenishment of technological opportunity. In the case of these citation-based knowledge spillovers from academia and elsewhere in industry, much influence originates within the same field of science. This is true in the sense that same-field spillovers are usually statistically significant, even while cross-field spillovers rarely are, compared with the number that might be significant. The same point holds for size of effect: usually within-field effects exceed between-field effects. Two exceptions are industrial biology and chemistry, which draw on four to five other sciences as well as themselves in both academia and industry.

The research reported in this paper leaves many questions unanswered. It is of course important to explore the availability of lagged instruments for the spillback and spillover indicators. Additional concerns can be considered under the headings of breadth of coverage, depth of explanation, and linkage to research outcomes in industry. Considering breadth of coverage first, we can easily think of alternative channels of scientific influence besides the citation and collaboration channels that we exploit in this paper. That channel rises and falls with publication. We already noted that Stephan, Black, Summell, and Adams (2004) consider placements of new PhDs to industry during in the late 199os. In these placements a far larger proportion consists of engineers and computer scientists than the proportion contributed by these fields to papers and citations. This raises the point of differing publication and citation practices by field of science, and the existence of mechanisms of influence that do not rely on citation. More could be done on this issue given time. While 60 percent of industrial citations to academic research go to biology and medicine, similar to the 60 percent share of these fields in academic research, a full 60 percent of the academic budget that is spent on graduate teaching and dissemination as well as research is not taken up by biomedicine. This raises the issue of bias in purely citation-based comparisons.

Questions of explanation also remain. Why are some industries more closely linked than others? Why are certain science fields more closely linked? Both are important questions to answer. While one would guess that research which uses common methods and overlapping materials creates these linkages, one would like to know more. Finally, this research does not address the outcomes of citation linkages and others for patents and new products, and other forms of scientific and technological creativity that strands of growth theory view as critical determinants of transitional and long term growth (Jones, 2002). All of these topics await further investigation.

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Figure 1--Mean Citation Rates By Citing Industry Group and Cited Field of Academic Science

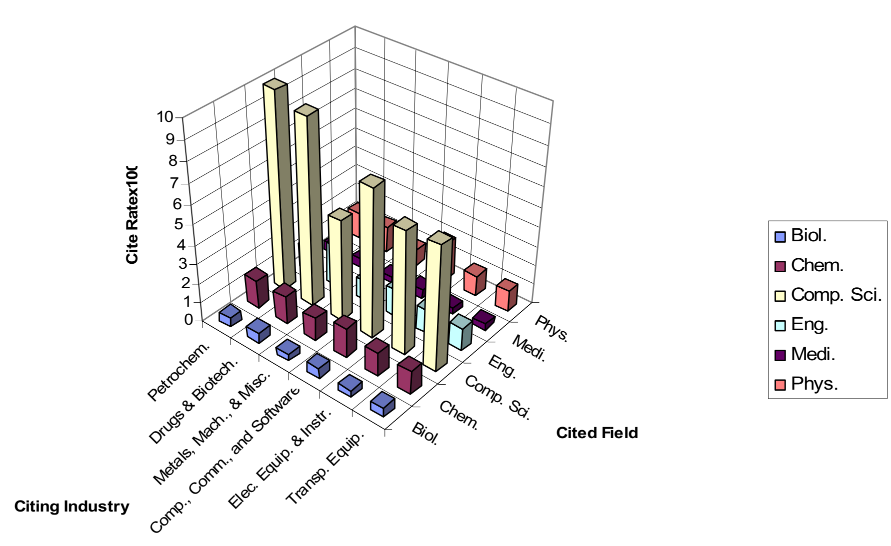
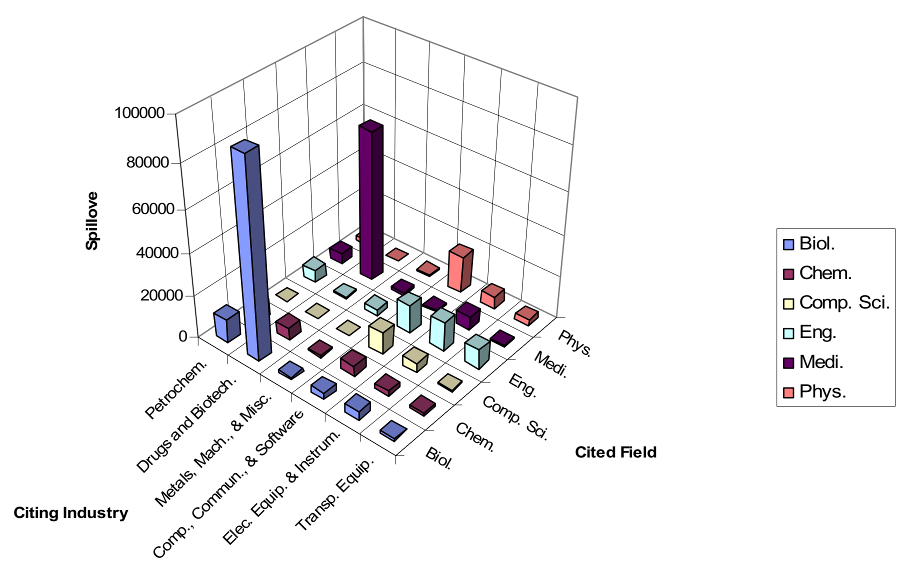


Figure 2--Citation Spillovers by Citing Industry Group And Cited Academic Field of Science



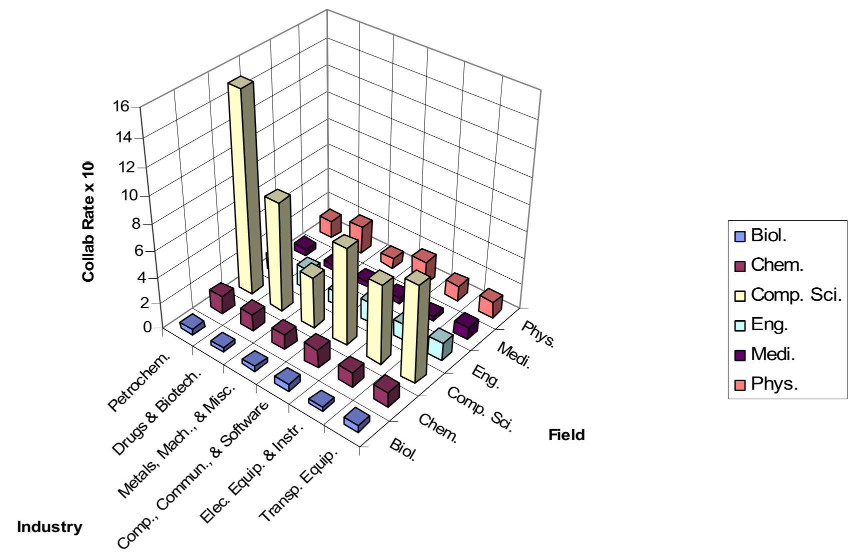


Figure 3--Mean Collaboration Rates by Industry Group And Field of Academic Science

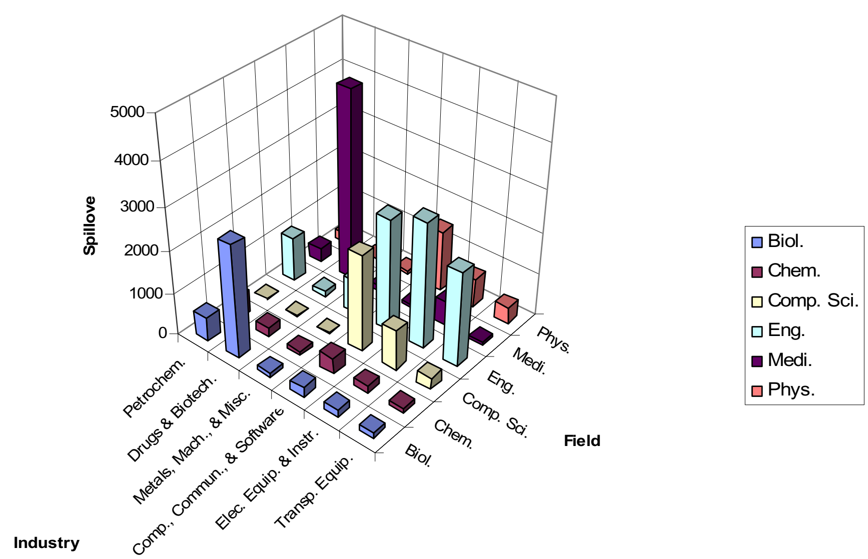


Figure 4--Collaboration Spillovers by Industry Group And Academic Field of Science

Figure 5--Mean Citation Rates by Citing Industry Group And Cited Industrial Field of Science

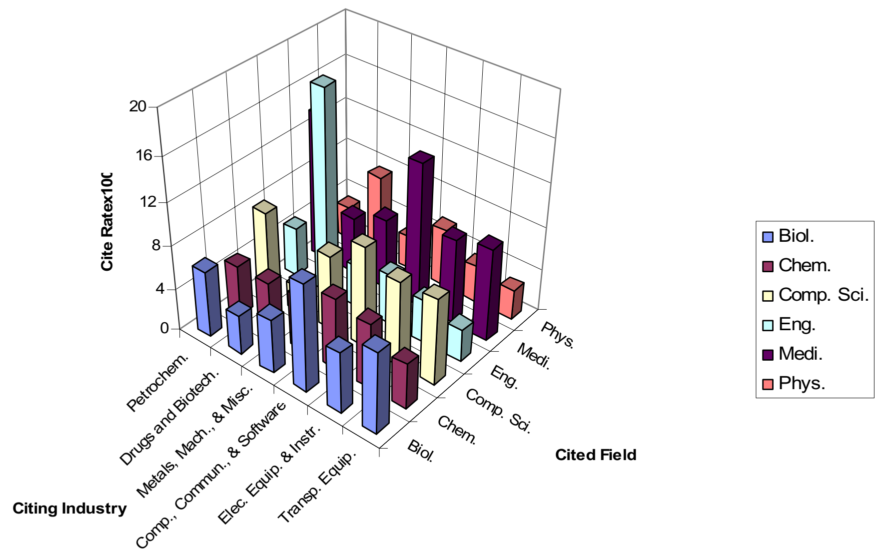
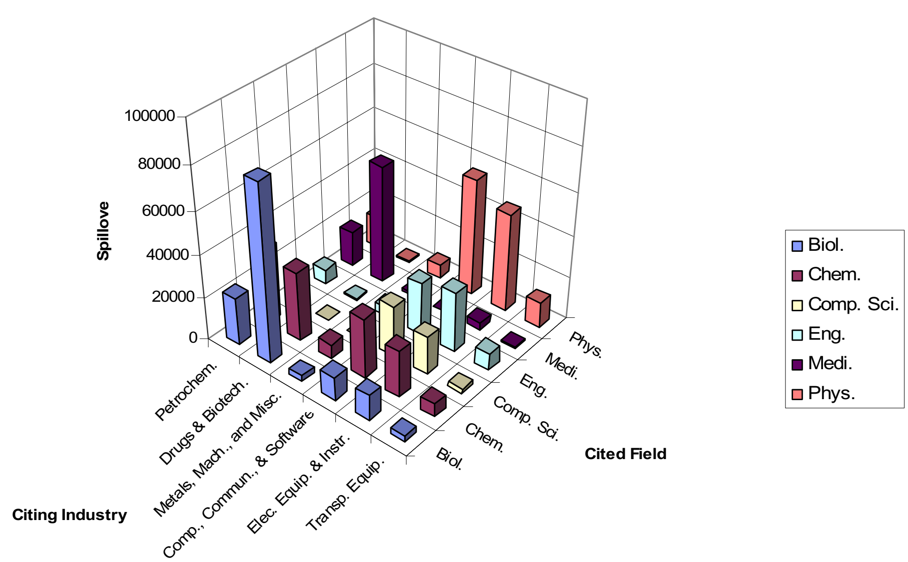


Figure 6--Citation Spillovers by Citing Industry Group And Cited Industrial Field of Science



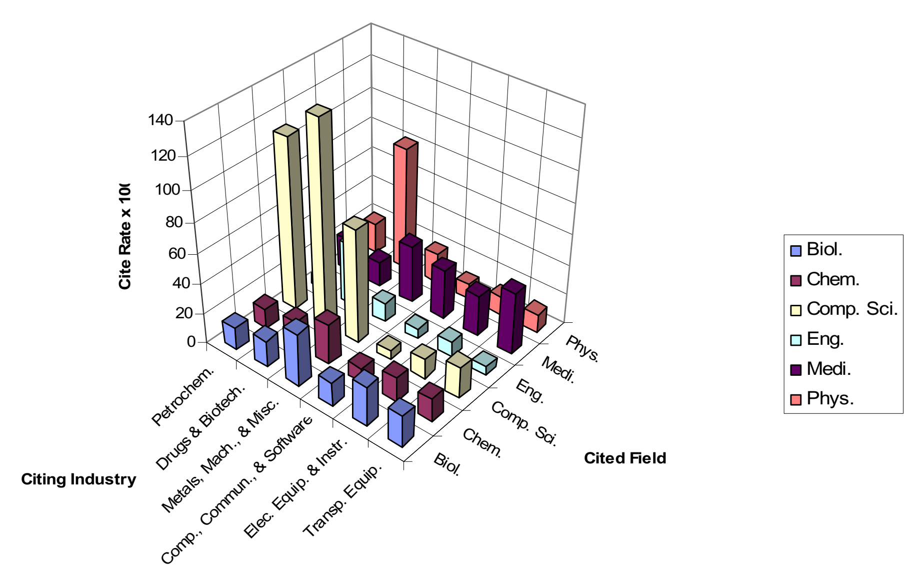


Figure 7--Mean Self-Citation Rates by Citing Industry Group and Cited Industrial Field of Science

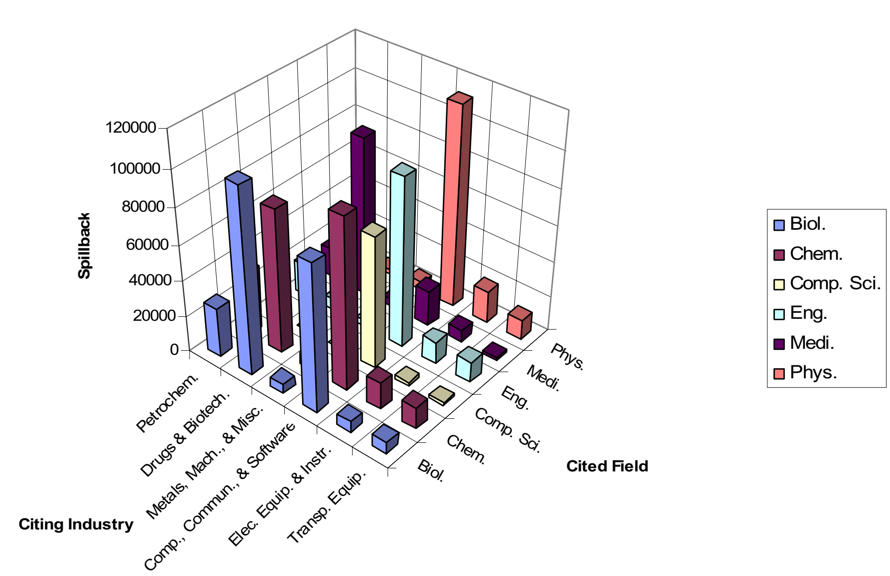


Figure 8--Self-Citation Spillbacks by Citing Industry Group and Cited Industrial Field of Science

Table 1
Distribution of Industrial Scientific Papers

Performing Sector And Industry	Number of Papers	Percentage Distribution by Field								
		Agriculture	Biology	Chemistry	Computer Science	Earth Science	Engineering	Mathematics and Statistics	Medicine	Physics
Industrial Sector	229,712	2.6%	**18.9% (3)**	16.8%	5.2%	1.5%	**21.2% (1.5)**	1.1%	11.4%	**21.2% (1.5)**
Petrochemicals	34,637	5.7%	**16.6% (3)**	**32.1% (1)**	0.2%	5.3%	**23.8% (2)**	0.5%	6.4%	9.5%
Drugs and Biotechnology	66,828	3.9%	**47.7% (1)**	**16.3% (3)**	0.0%	0.0%	0.9%	0.3%	**30.6% (2)**	0.3%
Metals	2,784	2.3%	9.0%	**20.2% (3)**	0.7%	0.8%	**41.2% (1)**	0.3%	4.9%	**20.5% (2)**
Machinery, Except Computers	1,768	2.3%	**6.4% (3)**	4.8%	2.0%	3.7%	**57.7% (1)**	0.2%	1.4%	**21.5% (2)**
Computers	9,382	0.6%	2.7%	**15.1% (3)**	13.4%	0.3%	**26.0% (2)**	0.9%	1.3%	**39.7% (1)**
Electrical Equipment	23,285	0.2%	2.0%	8.0%	**9.3% (3)**	0.6%	**49.5% (1)**	0.9%	2.4%	**27.4% (2)**
Transportation Equipment	22,421	0.5%	5.2%	**11.7% (3)**	3.6%	4.5%	**46.5% (1)**	0.8%	1.5%	**25.7% (2)**
Instruments	11,017	1.1%	11.6%	18.1%	2.6%	1.1%	**23.5% (2)**	0.4%	**15.2% (3)**	**26.3% (1)**
Misc. Agriculture and Manufacturing	4,026	**22.7% (2)**	14.7%	**24.8% (1)**	0.6%	0.6%	**15.2% (3)**	0.4%	10.6%	10.6%
Telecommunications Services	27,519	0.1%	3.0%	**11.6% (3)**	10.3%	0.6%	**21.2% (2)**	3.8%	0.3%	**49.1% (1)**
Software and Business Services	26,044	0.0%	2.9%	14.7%	**17.1% (2)**	0.5%	**16.6% (3)**	2.4%	0.7%	**44.9% (1)**
Academic Sector	2,430,001	7.8%	**26.3% (2)**	8.0%	1.2%	3.0%	7.0%	2.5%	**27.1% (1)**	**8.9% (3)**

Source: Institute for Scientific Information (ISI) and author's calculations. The three fields that contribute more papers to a sector or industry than any other are shown in bold. The rank of top fields within an industry or sector is indicated in parentheses.

Table 2
Science Spillover Indicators
By Industry, Sector and Field

Type and Level of Interaction	Number Of Interactions [a]	Mean Probability [b]	Mean R&D Spillover [c]	Aggregate R&D Spillover [d]
(1) Science Citations by Firms to Universities				
(a) Total	546,886	0.010	0.6	315,727.5
(b) Within Field	354,605	0.011	0.6	226,855.3
(c) Between Field	192,281	0.008	0.5	88,872.2
(2) Science Collaborations between Firms and Universities				
(a) Total (Within Field)	40,121	0.013	0.7	27,089.8
(3) Science Citations by Firms to Other Firms				
(a) Total	89,176	0.049	6.7	598,857.4
(b) Within Industry	38,197	0.047	4.5	173,216.0
(c) Between Industry	50,979	0.050	8.3	425,641.4
(d) Within Field	54,927	0.050	6.1	336,691.3
(e) Between Field	34,249	0.047	7.7	262,166.2
(4) Science Citations by Firms to Themselves				
(a) Total	30,047	0.131	33.5	1,005,909.0

Source: Institute for Scientific Information (ISI) and authors' calculations. [a] An interaction is defined as cell in which some citation or collaboration takes place, where cells are defined by the referencing firm, field and year, and the referenced institution, field, and year. [b] Mean probability is the average of the citation or collaboration rate for each cell, denoted $\bar{x}_i = \left(\overline{c_{ij} / n_j}\right)$. [c] Mean R&D spillover is the average by cell of the citation or collaboration rate times the stock of R&D (in millions of 1992 dollars) in the referenced institution, field, and year, with a lag of one year. [d] Aggregate R&D spillover is the sum over cells of the citation or collaboration rate times the referenced R&D stock (in millions of 1992 dollars). See the text for additional discussion.

Table 3
Aggregate R&D Spillovers and Spillbacks
By Channel of Transmission and Field of Science

Sending Field	Citation by Firms to Universities	Collaboration Between Firms and Universities	Citation by Firms to Other Firms	Citation by Firms to Themselves
Biology	114,219.9	3,861.1	133,677.5	230,193.6
Chemistry	22,979.2	1,509.3	132,079.7	245,408.8
Comp. Science	16,287.1	3,529.5	44,487.8	77,124.7
Engineering	46,511.9	9,736.1	73,331.9	146,339.7
Medicine	85,223.7	5,606.8	79,140.2	139,523.2
Physics	30,505.8	2,847.0	136,140.3	167,318.9

Notes: Aggregate R&D spillover is the sum over citing and cited (collaborating and collaborated) cells of the citation/collaboration rate times the cited R&D stock (in millions of 1992 dollars). The citation/collaboration rate c_{ij} / n_j is the number of citations from citing industry and industrial science field i to the cited academic science field j divided by the number of potentially cited papers.

Table 4
Top Four Academic Sciences by Size of R&D Spillover, Industry and Field, Firms Citing Universities

Citing Industry	Citing Field	Cited Field	Aggregate R&D Spillover [a]
Petrochemicals	Biology	Biology	8,507.8
	Chemistry	Chemistry	6,426.1
	Engineering	Engineering	3,916.2
	Medicine	Medicine	3,035.4
Drugs and Biotechnology	Biology	Biology	72,013.6
	Medicine	Medicine	45,169.1
	Biology	Medicine	24,016.5
	Medicine	Biology	17,528.2
Metals	Engineering	Engineering	1,095.1
	Biology	Biology	239.5
	Chemistry	Chemistry	225.7
	Physics	Physics	220.7
Machinery except Computers	Engineering	Engineering	822.3
	Physics	Physics	159.0
	Physics	Engineering	121.3
	Medicine	Medicine	40.6
Computers	Engineering	Engineering	2,033.0
	Physics	Physics	1,853.4
	Comp. Science	Comp. Science	1,492.1
	Chemistry	Chemistry	547.7
Electrical Equipment	Engineering	Engineering	8,420.7
	Physics	Physics	3,798.0
	Comp. Science	Comp. Science	3,249.3
	Physics	Engineering	1,972.9
Transportation Equipment	Engineering	Engineering	7,807.1
	Physics	Physics	2,224.8
	Physics	Engineering	1,087.2
	Chemistry	Chemistry	971.7
Instruments	Medicine	Medicine	3,508.5
	Biology	Biology	2,190.7
	Engineering	Engineering	1,500.5
	Chemistry	Chemistry	979.8
Telecommunications Services	Physics	Physics	6,383.7
	Engineering	Engineering	2,127.0
	Comp. Science	Comp. Science	1,998.2
	Chemistry	Chemistry	1,179.8

Table 4
Top Four Academic Sciences by Size of R&D Spillover, Industry and Field, Firms Citing Universities

Citing Industry	Citing Field	Cited Field	Aggregate R&D Spillover [a]
Software and Business Services	Physics	Physics	6,280.5
	Comp. Science	Comp. Science	4,649.6
	Engineering	Engineering	3,738.5
	Chemistry	Chemistry	1,831.5
Misc. Agriculture and Manufacturing	Biology	Biology	756.3
	Medicine	Medicine	612.9
	Chemistry	Chemistry	458.8
	Engineering	Engineering	388.6

Notes: Table reports the *top four* aggregate R&D spillovers by citing industry and citing and cited field.
[a] Aggregate R&D spillover is the sum over citing and cited cells of the citation rate times the cited R&D stock (in millions of 1992 dollars). The citation rate c_{ij} / n_j is the number of citations from citing industry and industrial science field i to the cited academic science field j divided by the number of potentially cited papers.

Table 5
Top Six Sciences by Industry and R&D Spillover,
Industry and Field, Firms Citing Other Firms

Citing Industry	Cited Industry	Citing Field	Cited Field	Aggregate R&D Spillover [a]
Petrochemicals	Petrochemicals	Chemistry	Chemistry	7,790.5
	Software and Bus. Services	Chemistry	Chemistry	6,049.3
	Petrochemicals	Medicine	Medicine	5,810.7
	Petrochemicals	Biology	Biology	5,608.0
	Petrochemicals	Biology	Medicine	4,774.8
	Communications Services	Chemistry	Chemistry	4,140.1
Drugs and Biotechnology	Drugs and Biotechnology	Biology	Biology	35,794.4
	Drugs and Biotechnology	Chemistry	Chemistry	17,373.6
	Drugs and Biotechnology	Medicine	Medicine	15,465.0
	Drugs and Biotechnology	Biology	Medicine	14,517.0
	Drugs and Biotechnology	Medicine	Biology	14,454.5
	Drugs and Biotechnology	Chemistry	Biology	8,275.2
Metals	Drugs and Biotechnology	Chemistry	Chemistry	704.3
	Petrochemicals	Chemistry	Chemistry	497.4
	Communications Services	Physics	Physics	389.5
	Software and Bus. Services	Chemistry	Chemistry	367.8
	Software and Bus. Services	Physics	Physics	337.8
	Petrochemicals	Physics	Physics	333.1
Machinery except Computers	Software and Bus. Services	Physics	Physics	686.4
	Software and Bus. Services	Engineering	Engineering	507.1
	Communications Services	Physics	Physics	292.0
	Electrical Equipment	Physics	Physics	264.6
	Communications Services	Engineering	Engineering	200.0
	Software and Bus. Services	Engineering	Physics	163.5
Computers	Software and Bus. Services	Physics	Physics	3,951.8
	Software and Bus. Services	Comp. Science	Comp. Science	2,475.7
	Software and Bus. Services	Chemistry	Chemistry	1,572.5
	Communications Services	Physics	Physics	1,564.3
	Software and Bus. Services	Engineering	Engineering	1,455.6
	Software and Bus. Services	Physics	Chemistry	1,287.2
Electrical Equipment	Software and Bus. Services	Physics	Physics	6,207.5
	Communications Services	Physics	Physics	5,245.6
	Software and Bus. Services	Comp. Science	Comp. Science	4,136.5
	Software and Bus. Services	Engineering	Engineering	4,067.6
	Communications Services	Engineering	Engineering	3,946.2
	Communications Services	Comp. Science	Comp. Science	3,534.1
Transportation Equipment	Software and Bus. Services	Physics	Physics	2,591.1
	Communications Services	Physics	Physics	1,933.2
	Software and Bus. Services	Engineering	Engineering	1,229.6
	Software and Bus. Services	Chemistry	Chemistry	1,217.7
	Transportation Equipment	Engineering	Engineering	1,102.6
	Electrical Equipment	Physics	Physics	930.3

Table 5
Top Six Sciences by Industry and R&D Spillover,
Industry and Field, Firms Citing Other Firms

Citing Industry	Cited Industry	Citing Field	Cited Field	Aggregate R&D Spillover [a]
Instruments	Drugs and Biotechnology	Engineering	Engineering	1,996.3
	Software and Bus. Services	Physics	Physics	1,677.7
	Software and Bus. Services	Chemistry	Chemistry	1,564.6
	Petrochemicals	Chemistry	Chemistry	1,030.3
	Communications Services	Physics	Physics	918.3
	Software and Bus. Services	Chemistry	Physics	785.7
Communications Services	Software and Bus. Services	Physics	Physics	3,401.7
	Software and Bus. Services	Comp. Science	Comp. Science	3,246.7
	Software and Bus. Services	Chemistry	Physics	2,938.8
	Software and Bus. Services	Engineering	Physics	2,907.5
	Software and Bus. Services	Chemistry	Chemistry	2,880.9
	Software and Bus. Services	Engineering	Engineering	2,812.9
Software and Bus. Services	Communications Services	Physics	Physics	2,518.9
	Communications Services	Comp. Science	Comp. Science	2,440.7
	Communications Services	Engineering	Engineering	2,046.8
	Communications Services	Chemistry	Chemistry	1,971.0
	Communications Services	Chemistry	Physics	1,929.3
	Communications Services	Physics	Chemistry	1,881.6
Misc. Agric. and Manuf.	Software and Bus. Services	Chemistry	Chemistry	804.6
	Drugs and Biotechnology	Physics	Physics	562.8
	Petrochemicals	Chemistry	Chemistry	535.5
	Petrochemicals	Chemistry	Physics	401.6
	Software and Bus. Services	Physics	Physics	372.2
	Instruments	Chemistry	Chemistry	308.0

Notes: Table reports the *top six* aggregate R&D spillovers by citing and cited industry and field.
[a] Aggregate R&D spillover is the sum over citing and cited cells of the citation rate times the cited R&D stock (in millions of 1992 dollars). The citation rate c_{ij} / n_j is the number of citations from citing industry and industrial science field i to the cited industry and industrial science field j divided by the number of potentially cited papers.

Table 6
Science Production Functions for Industrial Papers
(t-Statistics in Parentheses)

Variable or Statistic	Dependent Variable: Log (Scientific Papers of the Firm)							
	6.1	6.2	6.3	6.4	6.5	6.6	6.7	6.8
Time Trend	-0.038**	-0.058**	-0.055**	-0.059**	-0.043**	-0.065**	-0.062**	-0.063**
	(-7.8)	(-14.5)	(-14.1)	(-16.9)	(-9.4)	(-19.8)	(-19.6)	(-21.6)
Field and Firm Dummies Included	Yes	Yes	Yes	No	Yes	Yes	Yes	No
F-test for Joint Significance of Industry and Field Dummies	6.87^{+++}	6.60^{+++}	6.58^{+++}	n. a.	9.06^{+++}	9.20^{+++}	9.04^{+++}	n. a.
Log (Firm R&D Stock)	0.206**	0.088**	0.076**	0.131**	0.112**	0.043	0.053*	0.059**
	(5.6)	(3.0)	(2.6)	(13.6)	(3.3)	(1.7)	(2.2)	(6.6)
Log (Citation Spillback from Firm R&D) ($\beta_{firm,selfcit}$)	0.182**	0.090**	0.086**	0.088**	0.561**	0.185**	0.161**	0.111**
	(50.6)	(26.8)	(25.8)	(28.0)	(44.1)	(17.1)	(15.5)	(12.8)
Zero Spillback Dummy× Log (Citation Spillback from Firm R&D) ($\gamma_{firm,selfcit}$)					-0.571**	-0.177**	-0.148**	-0.071**
					(-30.8)	(-11.9)	(-10.4)	(-5.9)
Log (Citation Spillover from University R&D) ($\beta_{univ,cit}$)		0.200**	0.168**	0.170**		0.383**	0.315**	0.260**
		(33.8)	(27.0)	(27.0)		(42.7)	(30.8)	(25.1)
Zero University Citation Spillover Dummy× Log (Citation Spillovers from University R&D) ($\gamma_{univ,cit}$)						-0.364**	-0.289**	-0.235**
						(-31.6)	(-23.4)	(-18.1)
Log (Collaboration Spillover from University R&D) ($\beta_{univ,coll}$)			0.063**	0.065**			0.227**	0.224**
			(14.0)	(14.3)			(19.9)	(21.4)

Table 6
Science Production Functions for Industrial Papers
(t-Statistics in Parentheses)

Variable or Statistic	Dependent Variable: Log (Scientific Papers of the Firm)							
	6.1	6.2	6.3	6.4	6.5	6.6	6.7	6.8
Zero University Collaboration Spillover Dummy× Log (Collaboration Spillover from University R&D) ($\gamma_{univ,coll}$)							-0.230** (-21.8)	-0.227** (-22.7)
Log (Citation Spillover from Other Firms' R&D) ($\beta_{firm,cit}$)		0.087** (26.3)	0.080** (24.5)	0.084** (25.9)		0.189** (20.2)	0.149** (16.3)	0.190** (21.0)
Zero Firm Citation Spillover Dummy× Log (Citation Spillovers from Other Firms' R&D) ($\gamma_{firm,cit}$)						-0.202** (-15.9)	-0.149** (-12.0)	-0.187 (-14.7)
N	5273	5273	5273	5273	5273	5273	5273	5273
Root Mean Squared Error	0.988	0.794	0.779	0.854	0.907	0.655	0.626	0.711
Adjusted R^2	0.630	0.761	0.770	0.724	0.688	0.838	0.851	0.809
F Statistic	47.8**	87.6**	91.5**	2304.0**	61.4**	139.0**	152.8**	2226.5**

Notes: Time period is 1988-1999. Data are a panel of non-missing observations on numbers of papers produced in a given firm, science, and year. Firms are included in the top 200 R&D companies. Fields include biology, chemistry, computer science, engineering, medicine, and engineering. ** Variable is significantly different from zero at the one percent level. * Variable is significantly different from zero at the five percent level. $^{+++}$ F-statistic is significant at the 0.1 percent level.

Table 7
Science Production Functions for Citation-Weighted Industrial Papers
(t-Statistics in Parentheses)

Variable or Statistic	Dependent Variable: Log (Citation-Weighted Scientific Papers of the Firm)							
	7.1	7.2	7.3	7.4	7.5	7.6	7.7	7.8
Time Trend	-0.124** (-4.6)	-0.187** (-7.6)	-0.181** (-7.4)	-0.183** (-8.8)	-0.152** (-5.7)	-0.203** (-8.5)	-0.195** (-8.2)	-0.194** (-9.5)
Field and Firm Dummies Included	Yes	Yes	Yes	No	Yes	Yes	Yes	No
F-test for Joint Significance of Industry and Field Dummies	3.43+++	2.57+++	2.79+++	n. a.	3.85+++	2.21+++	2.91+++	n. a.
Log (Firm R&D Stock)	0.526** (2.6)	0.266 (1.5)	0.255 (1.4)	-0.043 (-1.2)	0.402* (2.0)	0.261 (1.5)	0.266 (1.5)	-0.084* (-2.0)
Log (Citation Spillback from Firm R&D) ($\beta_{firm,selfcit}$)	0.446** (32.3)	0.242** (16.8)	0.231** (16.1)	0.282** (21.9)	1.113** (20.8)	0.370** (6.5)	0.339** (6.0)	0.255** (6.0)
Zero Spillback Dummy× Log (Citation Spillback from Firm R&D) ($\gamma_{firm,\, selfcit}$)					-0.994** (-12.8)	-0.238 (-3.1)	-0.199 (-2.6)**	-0.017 (-0.3)
Log (Citation Spillover from University R&D) ($\beta_{univ,cit}$)		0.350** (14.5)	0.284** (11.1)	0.307** (12.6)		0.728** (16.5)	0.615** (11.7)	0.636** (13.1)
Zero University Citation Spillover Dummy× Log (Citation Spillovers from University R&D) ($\gamma_{univ,cit}$)						-0.640** (-11.6)	-0.527** (-8.5)	-0.547** (-9.3)
Log (Collaboration Spillover from University R&D) ($\beta_{univ,coll}$)			0.140** (7.2)	0.096** (5.3)			0.254 (4.3)	0.055 (1.1)

Table 7
Science Production Functions for Citation-Weighted Industrial Papers
(t-Statistics in Parentheses)

Variable or Statistic	Dependent Variable: Log (Citation-Weighted Scientific Papers of the Firm)							
	7.1	7.2	7.3	7.4	7.5	7.6	7.7	7.8
Zero University Collaboration Spillover Dummy× Log (Collaboration Spillover from University R&D) ($\gamma_{univ,coll}$)							-0.212** (-3.9)	-0.057 (-1.2)
Log (Citation Spillover from Other Firms' R&D) ($\beta_{firm,cit}$)		0.240** (17.4)	0.223** (16.1)	0.258** (19.7)		0.230** (5.0)	0.193** (4.1)	0.349** (8.1)
Zero Firm Citation Spillover Dummy× Log (Citation Spillovers from Other Firms' R&D) ($\gamma_{firm,cit}$)						-0.075** (-1.2)	-0.026 (-0.4)	-0.184** (-3.1)
N	3288	3288	3288	3288	3288	3288	3288	3288
Root Mean Squared Error	2.892	2.588	2.567	2.687	2.508	2.508	2.501	2.624
Adjusted R^2	0.534	0.627	0.633	0.598	0.650	0.650	0.652	0.616
F Statistic	22.3**	31.9**	32.5**	815.9**	34.5**	34.5**	34.4**	529.1**

Notes: Time period is 1988-1995. Data are a panel of non-missing observations on numbers of papers produced in a given firm, science, and year. Firms are included in the top 200 R&D companies. Fields include biology, chemistry, computer science, engineering, medicine, and engineering. Citation weights are citations received by papers in their first five years including the year of publication. Since the data end in 1999, papers published after 1995 have incomplete five year histories and hence are dropped from the data. ** Variable is significantly different from zero at the one percent level. * Variable is significantly different from zero at the five percent level. $^{+++}$ F-statistic is significant at the 0.1 percent level.

Table 8
F-Statistics for Tests of Equality of Coefficients,
Science Production Functions

Coefficient Restriction	Scientific Papers, Table 6, Equation 6.7	Citation-Weighted Scientific Papers, Table 7, Equation 7.7
Part A. Tests for Equality of University and Firm Main Effects		
$\beta_{univ,cit} = \beta_{firm,cit}$	115.2^{++++}	28.4^{++++}
$\beta_{univ,cit} + \beta_{univ,coll} = \beta_{firm,cit}$	509.6^{++++}	58.1^{++++}
$\beta_{univ,cit} + \beta_{univ,coll} = \beta_{firm,cit} + \beta_{firm,selfcit}$	124.7^{++++}	9.7^{+++}
Part B. Tests for Equality of Same Channel Main and Zero Interaction Effects		
$\beta_{univ,cit} = \gamma_{univ,cit}$	17.6^{++++}	8.5^{++++}
$\beta_{univ,coll} = \gamma_{univ,coll}$	0.4	4.1^{+}
$\beta_{firm,cit} = \gamma_{firm,cit}$	0.0	51.4^{++++}
$\beta_{firm,selfcit} = \gamma_{firm,selfcit}$	6.8^{++++}	28.1^{++++}

Notes: $^{+}$ Equality restriction is rejected at the five percent level. $^{+++}$ Equality restriction is rejected at the 0.2 percent level. $^{++++}$ Equality restriction is rejected at the 0.01 percent level.

Table 9
Marginal Products of Firm R&D, the Spillback of R&D,
And Spillovers from Universities and Firms

Variable	Papers [a]			Citation-Weighted Papers [b]		
	Means [c]	Main Effect Elasticities [d]	Marginal Products [d]	Means [c]	Main Effect Elasticities [d]	Marginal Products [d]
Firm R&D Stock	2920.4	0.053	0.0004	2797.1	0.266 [e]	0.0050 [e]
Citation Spillback from Firm R&D	181.1	0.161	0.0219	194.7	0.339	0.1080
Citation Spillover from University R&D	53.2	0.315	0.1457	45.9	0.615	0.8307
Collaboration Spillover from University R&D	4.1	0.227	1.3620	3.8	0.254	4.1442
Citation Spillover from Other Firms' R&D	105.5	0.149	0.0347	88.5	0.193	0.1352

Notes: [a] Source is equation 6.7. Mean number of papers is 24.6. [b] Source is equation 7.7. Mean number of citation-weighted papers is 62.0. [c] Means are means of right-hand side variables. [d] Main effect elasticities are the elasticities of the various R&D variables in the positive domain of these variables. Marginal products are marginal products of right-hand side variables. These are mean papers or citation-weighted papers, divided by means of each of the right-hand side variables, multiplied by their respective elasticities. For example, the marginal product of the citation spillback from firm R&D in terms of papers is (24.6/181.1)×0.161=0.0219. [e] Elasticity and marginal product are both insignificant at a P-value of 0.05.