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Learning, Internal Research, and Spillovers: Evidence from a Sample of Industrial R&D Laboratories

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Abstract

This paper presents new evidence on the practice of industrial Research and Development (R&D), especially the allocation between learning and internal research, and the role of outside knowledge, as represented by R&D spillovers, in reshaping this allocation. The evidence describes the sources of outside knowledge, portrays the flow of that knowledge into firms, and interprets the channels by which outside knowledge influences R&D.

The empirical work is based on a sample of 220 R&D laboratories owned by 115 firms in the U.S. chemicals, machinery, electrical equipment, and motor vehicles industries. The findings are consistent with the view that universities and firms generate technological opportunities in R&D laboratories. In addition to partnerships that define rather strict channels of opportunity, the paper uncovers broader effects of R&D spillovers. The results also suggest that academic spillovers drive learning about universities, and that industrial spillovers drive learning about industry. In this way externally derived opportunities reshape the rate and direction of R&D. Overall the findings paint an image of practitioners of industrial R&D reaching aggressively for opportunities, rather than waiting for opportunities to come to them.

I. Introduction

There can be little doubt as to the importance of industrial R&D for economic growth, given the present breadth of the knowledge-based industries and the number of countries that participate in them. The diffusion of R&D has seen to that. Less obvious perhaps, is the significance of the allocation of R&D between internal work and the study of R&D elsewhere, and of the influences that condition the practice of R&D. And yet these issues could be important if they influence normal discoveries and rare breakthroughs. In this paper I describe flows of outside knowledge into firms, interpret their effects on R&D, and explain the channels by which the flows take place.

To undertake an empirical study of these topics I collected evidence on industrial R&D laboratories[1]. Survey-based studies of industrial R&D are costly and hence rare, but they have often been effective. Edwin Mansfield and his associates have led this field. Using data collected from R&D executives they uncover high private and social returns from innovation (Mansfield et al., 1977), rapid diffusion of inventions to other firms (Mansfield et al., 1981), appreciable costs of imitation of new technologies (Mansfield, 1985), and an influence of academic research on innovation (Mansfield, 1991, 1995). Levin et al. (1987) use the Yale Survey of R&D Managers to explore methods of protecting intellectual property. In this respect they find that lead-time, speed of development, and sales and service efforts are more important than patent protection. Using the same data Klevorick et al. (1995) examine the sources of inter-industry differences in technological opportunity. Their view is that the origins of technological opportunity lie outside the industry and result from intrinsic differences in knowledge spillovers. More recently Cohen et al. (2000) apply the Carnegie-Mellon Survey of Industrial R&D to re-examine the efficacy of patents as a means of intellectual property protection. Their results suggest that patents have grown more important as a means of protection. And yet the reasons for seeking patent protection are complex. They include discouragement of entry and imitation, and usefulness in negotiations, besides direct contributions to profitability.

Economic historians have sifted the evidence on the limits of the firm in R&D and have emerged with some conclusions. Mueller (1962) observes that most of Du Pont's important products during 1920-1950 derived from external inventions. Hounshell and Smith (1988) confirm this and suggest that greater reliance on internal research after WW II led to a decline in Du Pont's research productivity. Mowery (1995) and Mowery and Rosenberg (1998, Chapter 2) study the boundaries of U.S firms' R&D in the early 20th century. They suggest that the boundaries expanded as U.S. antitrust policy became more stringent and as patent policy favored the accumulation of patent portfolios.

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[1] Throughout this paper the term "R&D laboratory" refers to any research group in a firm and not necessarily to a separately dedicated R&D establishment within a firm.

Cohen and Levinthal (1989) is very relevant to this research. Their work formulates R&D as both learning and innovation and highlight the role of "absorptive capacity" in the formation of the firm's stock of knowledge. The key element in their approach is that company research jointly produces innovation and learning. Innovation derives from additions to the firm's knowledge. But here the firm's R&D enters twice: once as it directly adds to the firm's knowledge, and again indirectly as it increases the absorption of additions to knowledge taking place outside the firm. Using this assumption they model the determination of R&D in non-cooperative oligopoly and explore empirically the effects of ease of learning, technological opportunity and intra-industry spillovers on firm R&D.

The literature on knowledge spillovers is also relevant since it determines the direction of R&D. In a pair of influential papers Griliches (1979, 1991) provides a penetrating discussion of the use of weighted external R&D as a measure of spillovers, and a survey of studies that use this approach. In past research I have found that spillovers of academic research exert their peak effect on productivity with a lag of a decade or more (Adams, 1990), that the impact of both spillovers and firm R&D on a firm's productivity are limited by geography and technology (Adams and Jaffe, 1996), and that firm R&D in the same product area as a plant's directly induces skill-biased technological change, while spillovers indirectly induce skill bias by stimulating accumulation of equipment capital (Adams, 1999).

The rest of the paper consists of five parts. Section II turns to historical case studies of petroleum refining and semiconductor R&D. The cases illustrate the allocation of R&D, especially the interplay between learning, internal research, and spillovers. They suggest that learning activity responds to perceived returns from the study of outside R&D, or knowledge spillovers. This material sets the stage for the empirical work to follow.

Section III describes the data. The discussion largely concerns a survey of R&D laboratories in the U.S. chemicals, machinery, electrical equipment, and motor vehicle industries. The section moves on to measurement of the allocation of R&D between learning and internal research, including cost shares devoted to learning about academic and industrial research and the employment of PhD scientists and engineers. The section concludes by discussing the construction of supplementary variables on unit prices of R&D and spillovers of academic and industrial R&D. One important feature of this section is the mapping from technology products to industries that is used to construct the industrial R&D spillover.

Section IV illustrates the linkages of the laboratories with universities and industries. It begins by describing the connections between universities, sciences and industries. In regard to academic science the paper finds that the influence of the engineering, chemistry and computer science disciplines is pervasive, except for specific sectors that draw on biology, medicine, mathematics and statistics, and physics. State universities in the South and Midwest are more important to traditional industries in the sample. Private universities and universities located in coastal regions of the U.S. are more important to newer industries consisting of pharmaceuticals and biotechnology, computers, and electrical equipment. These patterns are consistent with localization of university spillovers (Adams, 2002). The section concludes with a discussion of interactions between industries. The results indicate that computers and instruments are "General Purpose" industries on which many others rely. The results also suggest that intra-industry knowledge flows are larger than average.

Section V presents econometric findings. I begin with Translog estimates of equations for cost shares of learning about academic and industrial research. The econometric method is Ordered Probit since the cost shares consist of ordered categorical data. Larger laboratories spend more on learning. In addition faculty consulting, employment of graduate students, and other interactions with universities drive learning targeted on universities. Likewise contract research, the importance of customer and supplier problem-solving suggestions, and joint ventures drive learning targeted on other firms. But in addition the results are consistent with the view that academic R&D spillovers increase learning about academic research, while industrial R&D spillovers increase learning about industrial research. One limitation of these single equation findings is that cross-equation tests of hypotheses are not possible. For this reason I devise and implement a Bivariate Ordered Probit procedure that amounts to Seemingly Unrelated Regression for ordered categorical data. I find that the effect of the spillovers on learning activity differs significantly across the equations. Thus academic spillovers have a significantly larger effect on the academic learning-share and industrial spillovers a significantly larger effect on the industrial learning-share. The section concludes with equations that explain PhD employment in R&D laboratories. Using several methods I find that interactions with universities and academic R&D spillovers drive PhD employment, with the effect of the industrial spillover also important but somewhat less robust. Section VI is a summary and conclusion. An Appendix explains the Bivariate Ordered Probit likelihood function.

II. Case Studies of Learning, Internal Research and Spillovers

A. Petroleum Refining Research at Standard Oil of New Jersey, 1919-1942[2]

Cost reduction and improvement in yield have guided petroleum refining since the start of the industry. In its natural state crude oil is a heterogeneous mixture of hydrocarbons and residual impurities. Refining removes the impurities, "cracks" the hydrocarbons into more valuable light distillates, and separates the distillates into materials of similar weight. For example, gasoline is a blend of lighter weight isooctane, benzene, toluene and xylene[3].

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[2] This discussion draws on Enos (1962a, 1962b), Gornowski (1980), and Rosenberg (1998).
[3] The atomic weights of isooctane, benzene, toluene and xylene are clear from their formulas: C^8H^{18}, C^6H^6, C^7H^8 and C^8H^{10}. Atkins (1987), Chapter 3 contains a lucid discussion.

Improvement of refining occupied the first half of the 20th century. The Burton Process of 1910 applied heat and pressure to distill batches of petroleum. But for Standard Oil of New Jersey (Jersey Standard, later Exxon-Mobil) the 1911 breakup of the Standard Oil Trust contributed to mounting royalty fees. Partly to avoid these expenses Jersey Standard founded its central R&D laboratory, the Development Department (Enos, 1962b, P. 197). From the start the Department employed consultants to speed up its research. The most important was Warren K. Lewis, chairman of chemical engineering at the Massachusetts Institute of Technology (MIT) and an expert in distillation (Gornowski, 1980).

By 1922 the Department commercialized the Tube and Tank, a continuous thermal cracking process that reduced downtime, increased the output of gasoline and other light distillates, and expanded the range of input to include lower grade, higher viscosity petroleum. The Tube and Tank began to replace the Burton Process upon conclusion of a 1923 cross-licensing arrangement among the major oil companies.

Concerning this project, Enos (1962b, P. 126) observes that R&D costs were $150,000 per year over the period 1919-1923, while legal costs and costs of patent purchase were $90,000 per year. Expenditures for the services of Warren K. Lewis, the firm's most valued consultant, were about $2,500 per year or 1% of the project (Enos, 1962b, P. 105). If because of his knowledge of distillation the consultant was so valuable, why was so little spent on his services? The answer seems to be that other costs associated with the consulting were not reported. These include the opportunity cost of the time of refinery engineers. Such costs are hard to assess, because wages and time budget data are typically lacking. Enos (1962b, P. 104) writes the following:

> In general, it was expected that most of the ideas would come from outside Jersey Standard, for Howard [the director] felt that their own resources could best be allocated to applying the ideas of others rather than fostering basic research. The department was divided into four groups: one to search for new ideas, a second to carry out product development, a third to supply laboratory facilities, and a fourth to administer patents.

The search function of the laboratory suggests that consultants and related monetary expenses underestimate Exxon's total opportunity cost of search. This observation on implicit learning costs helps to guide the empirical work reported below.

Refining processes improved steadily during the 1920s, but the Department had other, longer run objectives. To conserve on apparently declining oil reserves, the Department explored the chemistry of synthetic fuels and catalytic cracking. Synthetic fuels built on the chemistry of hydrogenation, whose leader was the German firm I.G. Farben. Jersey Standard decided to pay stock plus a royalty on inventions resulting from the use of Farben's patents (Enos, 1962b, P. 190). Although hydrogenation turned out to be impractical, this research developed the Department's expertise in catalytic chemistry, which proved useful later on in Jersey Standard's development of petroleum refining.

Catalytic refining was another solution to declining reserves since it offered the possibility of improved yields. To this end, Jersey Standard negotiated with Eugene Houdry, the leading inventor in catalytic refining, but decided against licensing because of perceived technical problems. In 1936 however, Houdry commercialized catalytic cracking under the trade name of the Houdriflow process and showed that it improved gasoline quality compared with previous methods. Jersey Standard reopened negotiations but royalty fees were again seen as excessive. Moreover, the Socony-Mobil and Sun Oil Companies held rights to Houdriflow and thus enjoyed a competitive advantage (Enos, 1962b, P.189).

The company believed that it could invent around the Houdry patents. To accelerate its research the firm turned to Warren K. Lewis and the MIT department of chemical engineering. By 1938 the MIT researchers proposed a novel design for catalytic refining, in which particles of catalyst were mixed with airborne materials in vertical tubes to create a continuous process. Jersey Standard soon applied these results to actual refinery materials, crude oil in reaction with a liquid catalyst in production-sized vertical tubes. The new process handled more oil at lower cost and produced higher quality gasoline even than Houdriflow. In 1942 Exxon commercialized this invention, which became known as Fluidized Bed Catalytic Cracking. After World War II it was widely used in industry (Gornowski, 1980). But the critical point to see is that prior study and monitoring of external research built the research group needed for the invention.

B. Semiconductor Research at Bell Laboratories, 1930-1951[4]

Early in the 20th century the managers of Bell Laboratories became convinced that certain problems of the telephone system could only be solved by means of science. The invention of vacuum tube amplifiers in 1915 was a case in point. The research built on physical science yet it was a cornerstone of long distance telephony. Its success led Bell to increase support for other basic research. This took the form of a science library, the Bell System Technical Journal, seminars and lectures by distinguished visitors, and release time for study and travel to meetings.

During the 1930s a revolution in physics occurred that would profoundly influence research at Bell and transform the electronics and communications industries. This was the quantum theory of solids, the work of a small group of European physicists from 1926 to 1933. Efforts to test this theory’s implications for current amplification led to the unexpected discovery of the transistor effect during 1948-1951. This in turn gave rise to the semiconductor industry (Hoddeson, 1980, 1981).

Improvement of the vacuum tube was a major concern of the Bell Laboratories during the 1930s.

[4] This section draws on Nelson (1962) and Hoddeson (1980, 1981).

Vacuum tubes were the prevailing device for current amplification, but were problematic because of their lack of reliability, bulk, their drain on power, and sheer noise. Mervyn Kelly, director of Bell Laboratories from 1936, believed that replacement of vacuum tubes would require a deeper understanding of the physics of amplification, and an understanding of the physics of the solid state. To this end, Bell engaged in retraining of its established scientists, only to discover that this approach could not substitute for the hiring of new PhDs (Hoddeson, 1980). But owing to the Great Depression hiring did not resume until 1936. Among the researchers arriving that year was William Shockley, co-inventor of the transistor. In hindsight 1936 was a watershed year because of the hiring of scientists whose skills moved Bell to the frontiers of electronics.

Semiconductors are crystals that conduct electricity and direct or rectify current. They are said to semi-conduct because they conduct less well than metals. Work by Wilson, Mott and Schottky between 1931 and 1942 on the quantum theory of semiconductors influenced Bell's experiments leading to the transistor (Hoddeson, 1981). Also important were advances in Bell's metallurgy department, for these allowed the synthesis of precision crystals (Nelson, 1962). This was crucial, since the experiments were designed to test current amplification in theoretically precise crystals. The transistor's discovery resulted from tests of the quantum theory of semiconductors and yet the consequences were unrelated to the theory. Of course all these efforts were driven by a practical search for improved amplification (Nelson, 1962).

In summary, both cases emphasize the combination of learning and internal research in a sequential process of invention and innovation. Both suggest that the mix of learning and internal research is a decision partly made by firms. Furthermore, changes in science and technology appear to increase learning relative to internal research. Both point out that some learning costs are easily measured, while others are hard to measure. The cases differ in the relative importance of industrial versus academic research. The choice between learning and internal research is one focus of this paper's study of R&D laboratories. Determinants of the two types of R&D are a second focus.

III. Description of the Data

A. Survey of Industrial R&D Laboratories 1996

The case studies agree that industrial research serves dual functions of learning and innovation, but suggest that their relative importance is determined by technological opportunity as well as firm and laboratory capabilities. In this section I discuss survey data that were designed to explore these questions. The survey quantifies shares of learning and internal research in R&D and specifies sources of science and technology that the laboratories consider relevant.

Reflecting the fact that laboratories exist within firms, a sample was drawn in two stages. At the firm level the sample consists of 200 companies that were randomly selected from a set of 500 R&D performers in the U.S. chemicals, machinery, electrical equipment, and motor vehicles industries. Population firms consisted of companies in Standard and Poor 's 1995 Compustat database that reported R&D and sales and could be name-matched with assignees in the U.S. Patent and Trademark Office database. As a consequence the population consisted of publicly traded firms in the four industries whose size, R&D intensity, and U.S. patents were known. Motor vehicle firms were deliberately over-sampled compared with the other industries because of response-rate concerns. Largely as a result of this decision sample firms are larger than population firms. And yet a response bias analysis finds no significant difference between means of sales, R&D, or R&D intensity of firms in the sample and in the population [5].

At a second level it was discovered that the 200 firms owned about 600 R&D laboratories. The **Directory of American Research and Technolog**y (R.R. Bowker, 1997) contained this information. The laboratories were contacted and a mass mailing carried out[6]. This generated a return of 208 laboratories owned by 115 firms. Because three of the firms combined their responses, these observations actually account for 220 laboratories and imply a response rate of 37% (220/600). Twenty-nine of the 115 firms were publicly traded for less than 16 years, so that young companies form an important part of the sample. Respondents were experienced R&D managers with considerable knowledge of their companies, having been employed by them for an average of 15 years.

One might question whether the sample laboratories are representative of R&D in their companies. Answering this question is difficult. Information on the laboratories is proprietary, since R&D is part of corporate strategy. In addition Compustat and Survey R&D are hard to compare. Compustat R&D is affected by tax credits and includes non-R&D activities. In contrast, survey R&D excludes non-R&D charges in keeping with National Science Foundation (NSF) definitions. For these reasons I claim only that the data represent a sample of laboratories drawn from a sample of firms.

B. Descriptive Findings

Tables 1 and 2 describe industry and size characteristics of the laboratories. Table 1 shows the distribution of laboratories by industry of the parent firm. The distribution is uniform except for motor vehicles. As expected given its

[5] Survey firms reported an average of 211.1 million dollars of R&D and 4523.2 million in sales. Population firms reported an average of 114.6 million in R&D and 2274.6 million in sales. Two sample t-tests of the difference in means of R&D and sales (assuming unequal variances) were 1.43 and 1.48 respectively and thus were insignificant. Likewise weighted (un-weighted) R&D intensities were similar, 0.047 (0.084) for the sample, and 0.050 (0.077) for the population.

higher level of concentration, the motor vehicles industry includes fewer observations than other industries. Response rates are roughly equal across industries.

The top panel of Table 2 reports R&D inputs. In 1991 the laboratories employed 127 scientists and engineers, of which 19 held the PhD or MD, and spent 12 million dollars on R&D[7]. By 1996 the laboratories employed 142 scientists and 21 PhD researchers and had R&D budgets of 13 million so scientists and R&D increase by 10 percent over the period. The large standard deviations (shown in parentheses) indicate the positive skew of laboratory size. This may indicate stochastic processes that favor larger and more varied R&D programs (Cohen and Klepper, 1992).

The bottom panel reports U.S. patents granted and applied for in 1991 and 1996. Both measures include imputes for missing values based on U.S. Patent and Trademark Office (USPTO) patents for the firm, laboratory location and year. The **U.S. Patents Database** (Community of Science, 1999) is the source of the imputations. Current year patents are used to impute patent grants, while *next year's* patents are used to impute patent applications.

Details of the imputations are as follows. I start by matching two-digit zip codes to the addresses of inventors using the zip code database of the U.S. Postal Service. Next I assign the firm's patents to the laboratory if the zip code of inventors matches that of the laboratory. Finally I assign patents to the survey years 1991 and 1996 according to their issue dates[8]. It must be admitted that this method produces errors. If the inventor's zip code differs from that of the laboratory then the patents are ignored. Moreover, patents can be issued to inventors in different locations, while several laboratories in a firm can share the same zip code. In both cases the result overstates the laboratory's patents. I handle the first problem by multiplying patents by the fraction of the top four inventors living in the same zip code as the laboratory. I handle the second problem by distributing patents across laboratories by the shares of scientists in each of the firm's laboratories.

The sample of laboratories accounts for 2,000-4,000 patents. This amounts to a 5-10 per cent sample of U.S. industrial patents during the 1990s. Sample laboratories produce one patent for every 12 scientists and engineers, compared with an average for all industry of one patent for every 19 scientists and engineers[9]. Thus sample laboratories produce an above-average number of patents. However, other R&D in the firm contributes to laboratory patents, and this brings the patent-to-R&D ratio closer to the average.

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[6] The survey instrument was refined in three stages. A retired R&D manager read and critiqued the initial draft. Then a beta version was tested on 10 nearby laboratories. Using these comments a final draft was produced. The survey team then mailed the survey to all laboratories that granted permission to send the instrument.

[7] This figure, which follows NSF definitions, represents R&D purged of all overhead or non-research charges. It is a lower bound on figures for total R&D appropriations that are reported in Compustat. The survey figures on R&D used in this paper place less emphasis on production engineering and more on research than Compustat.

[8] Meg Fernando downloaded the patent data and translated the text fields into SAS™ data sets for further analysis.

R&D outputs rise faster than inputs over time. Mean numbers of patents granted are 8.9 in 1991 and 12.4 in 1996. Mean numbers of patent applications are 10.5 in 1991 and 14.5 in 1996. Thus patents rise by 40 per cent over the sample period, and by 30 percent relative to R&D inputs. This increase in productivity is consistent with Kortum and Lerner (1999) who attribute it to improvements in technological opportunity and the management of R&D.

The survey asked about shares of R&D spent learning about research in universities and other firms, hereafter referred to as learning-shares[10]. Examples of such costs are expenses of scientific and trade meetings, collaborations, books, journals, and consultants. Table 3 reports the results. The column on the far left reports intervals of the firm learning-share. The second through fifth columns report intervals of the university learning-share. Likewise, intervals of the firm learning-share are reported in the second through fifth rows. Interior entries display the joint distribution. The bottom row of the table is the marginal distribution of the university learning- share, while the column on the far right reports the marginal distribution of the firm learning-share. Internal research is the predominant and remaining fraction of budget, the interval for which is determined by one minus the minimum of each of the learning shares and their maximum.

Table 3 makes it clear that, as measured, learning costs comprise small shares of R&D, thinning rapidly as the shares rise above 1%. The marginal distributions show that learning about industry exceeds learning about universities, consistent with the larger scale of industry R&D. The table also stresses the categorical aspect of the shares. Marginal distributions are sparse beyond four categories, 0%, 0.1-1%, 2-3%, and 4+%. The joint distribution is sparse beyond three: 0%, 0.1-1%, and 2+%. The ordered response nature of the cost shares suggests the use of Ordered Probit procedures in empirical work that analyzes their behavior.

The learning-shares underestimate full learning costs. The case studies illustrate the difficulties standing in the way of a full accounting for such costs. Cohen and Levinthal (1989) provide an economic explanation of this based on the joint-ness of learning and internal research. Common sense points to the importance of shadow time costs of learning as well as monetary expenditures. The learning-share estimates are undoubtedly correlated with learning costs that remain implicit in the rest of laboratory R&D. This element of uncertainty underscores the polychotomous nature of the learning-share data.

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[9] See National Science Board (1998), Appendix tables 3-15 and 4-4.

[10] The survey asked respondents to identify shares of laboratory R&D budget for 1991 and 1996 that were spent on learning about research in universities. Respondents were asked to check or fill in one of the following categories: None, 0.1-1%, 2-3%, 4-5%, 6-7%, and Other% (fill in) _____. A second question, about research in other firms, is worded similarly.

C. Supplementary Variables

i. Price Indexes for R&D

I collected supplementary variables to extend the scope of the data. These include geographically detailed R&D prices and spillovers of academic and industrial R&D. The prices and spillovers play a useful role in the demand functions for learning-related components of industrial R&D reported below.

I construct two R&D prices. The first is a weekly wage for skilled engineers, which I use to represent the cost of learning and pure research[11]. The second is a unit cost index for R&D that covers administrative and production expenses in addition to the cost of pure learning and captures the cost of general industrial R&D activity. The engineering wage is provided by the Engineer V weekly wage series for 1991 and 1996 contained in the *Occupational Compensation Surveys* (OCS) of the U.S. Bureau of Labor Statistics (various years). The series has several advantages. First, the Engineer V occupation matches the responsibilities that are typical of industrial research. Its definition covers planning and coordination of engineering projects as well as wide-ranging research. Engineer V is a highly skilled occupation within engineering, the most common scientific field in industry. A second advantage is that the series is available by Standard Metropolitan Statistical Area (SMSA). Besides, SMSAs in the survey match Engineer V SMSAs more than 90 percent of the time. In the few remaining cases I imputed the Engineer V wage using a nearby SMSA of similar size[12].

Most R&D expense consists of costs other than research labor (Mansfield, Romeo, and Switzer, 1983; Jankowski, 1991). The additional costs include administrative wages, production worker wages, prices of equipment and structures, and materials prices. I collected weekly wages of administrative workers by SMSA and two-digit industry from the Current Population Survey for 1991 and 1996 (National Bureau of Economic Research, 2002). U.S. Bureau of Labor Statistics, *Employment and Earnings* (various years) contains weekly wages of production workers by SMSA and industry in 1991 and 1996. Prices of equipment and structures for 1991 and 1996 by industry (but not SMSA) are taken from the fixed asset tables of the U.S. Bureau of Economic Analysis (BEA, 2002), while materials and services price deflators by two-digit industry are included in the NBER Manufacturing Industry Database (NBER, 2002). Non-labor prices are deflated by 1991 prices in machinery while labor prices are deflated by 1991 wages in machinery in Pittsburgh, Pennsylvania.

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[11] One would like to have separate prices for learning about academic and industrial research, with the former weighted more heavily towards PhD scientists. But data on the wages of U.S. industrial scientists are scarce.

I calculate a Laspeyres R&D price index using the deflated R&D input prices based on the methodology of Jankowski (1991), who provides cost shares in R&D by industry of research scientists, administrative and professional workers, production workers, equipment, structures, and materials. The R&D cost index is

$$P_{ij}^{R} = \sum_{k} \alpha_{i}^{k} P_{ij}^{k} \tag{1}$$

where P_{ij}^{R} is the Laspeyres index of the unit cost of R&D in industry i and SMSA j, α_{i}^{k} is the cost share of factor k in industry i, and P_{ij}^{k} is the price of factor k in industry i and SMSA j. The ratio of the engineering wage P_{ij}^{e} to (1) provides a rough estimate of the cost of research labor relative to the cost of general R&D. The top panel of Table 4 presents the results. There is some variation in the Engineer V index. The maximum (relative to Pittsburgh) is 1.408 and occurs in the San Francisco-Oakland-San Jose, California; the minimum is 0.973 and occurs in Phoenix, Arizona. The R&D cost index varies less, since it is an average of three weekly wage series, which partially offset each other, and includes prices of equipment and structures capital and materials, for which no geographic detail is available.

ii. Academic R&D Spillovers

In this paper academic R&D spillovers are based on citations to sciences and universities that are specific to each laboratory. Recall that respondents check up to five science fields that they view as important[13]. R&D expenditures that match the cited fields and universities are taken from the NSF-CASPAR database. I accumulate R&D expenditures into stocks that cover the previous 17 years (the most available) using a 15 percent rate of depreciation. I choose federally funded R&D because this concept separates university R&D from company-financed R&D at universities. This is important since universities depend to an extent on industry support (Mansfield, 1995). By this means I avoid double counting of firm and laboratory support for universities in R&D budget and the university R&D spillover.

The data include up to five universities that are most influential for laboratory R&D. I combine this information and the information on fields to generate sums of federally funded R&D stocks across cited universities and sciences. I call this variable, federally funded academic R&D in closely affiliated universities. The academic spillovers are lagged one year, so that the 1991 spillover stock ends in 1990 and the 1996 spillover ends in 1995.

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[12] I thank Mircea Marcu for collecting the Engineer V wage series.

[13] Respondents drew from the following 16 science fields: aeronautical, chemical, civil, electrical, mechanical, and other engineering; chemistry, physics, and other physical sciences; computer science, mathematics and statistics; atmospheric sciences and earth sciences; and agriculture, biology, and medicine.

To illustrate, suppose that a laboratory cites Stanford, UC-Berkeley, and the University of Washington as the most significant universities for its research. Further suppose that electrical engineering, chemical engineering, computer science, and chemistry are its important science fields. Then I assign stocks of federally funded R&D for Stanford, UC-Berkeley and the University of Washington in the above fields to the laboratory. I sum across the four fields and three universities to obtain federally funded R&D in closely affiliated universities for that laboratory. In addition, I count up the number of cited science fields and divide the estimated spillover by this number to derive federally funded R&D in closely affiliated universities per science field. This variable removes a scale component from academic R&D. It is a useful check. Larger laboratories could cite a larger number of sciences because of the diversity of their research interests.

The middle panel of table 4 reports means and standard deviations of key variables associated with the academic spillover. The table finds that the mean academic spillover pool is about 302 million dollars (of 1987) that include an average of 4.5 academic fields over a period of 17 years. The mean spillover per science field is about 68 million.

iii. Industrial R&D Spillovers

The industrial R&D spillover consists of weighted R&D by industry in which the weights are specific to R&D laboratories. The calculation begins with the identification of relevant technologies by R&D managers. The industry weights result from a mapping of the technologies to industries. This linking process is necessary because statistics on industrial R&D are classified by industry rather than technology.

The survey asked respondents to identify technologies relevant to their laboratory. These are shown on the left of Table 5 and are based on technology products contained in CorpTech (1994). The mapping of technologies to industries is shown on the right. Respondents did not see this information, even though the technologies are included in the industries. Note that industries are identified by codes from the U.S. Standard Industrial Classification (SIC) System. The coding cascades, so that SIC 35 (Machinery, Computers and Office Equipment) includes SIC 357 (Computers and Office Equipment), which includes 3571 (Computers). Executive Office of the President (1987) describes the SIC system.

The technologies are more specific, detailed and tangible than the industries. They are the product of considerable thought as to the best way to present the data. In return, respondents understood the technologies and the response rate on this question was close to 100 percent. R&D managers also indicated their preference for technologies like Machine Tools or Presses, Industrial Gases, and Transducers over vaguely defined industries such as Metalworking Machinery and Equipment, Industrial Inorganic Chemicals, and Electronic Components and Accessories. This is in spite of the fact that the industries include the technologies. Another observation is that several technologies typically appear under the same industry. For example, nine technologies are included in Laboratory, Test, & Measuring Equipment, while five appear under Industrial Inorganic Chemicals. This suggests that fractions of technologies that are considered relevant be used as weights on R&D by industry, the only breakdown for the R&D statistics that is available.

The weights are laboratory-specific since they represent the opinions of R&D managers. Consider Computer Hardware. If a laboratory checked off one of the 10 categories under Computer Hardware as relevant, then a 1 is assigned to this technology, and a 0 otherwise. For example, Computer Memory Systems, a subclass of Computer Hardware, receives a 1 if checked, but otherwise receives a 0. Next I sum the number of relevant categories and divide this by the number of categories in computer hardware. If a respondent checked five of the 10 groups included in Computer Hardware then the importance weight is γ_j =0.5. If a different laboratory checked one group then γ_j =0.1 and likewise for all other technologies and laboratories.

The γ_j weights are fractions of technologies in each industry that are important to the laboratory. Griliches (1991) remarks that spillover variables are weighted sums of external R&D, where the weights depend on the available information. The weights used in this paper have three strengths. First, R&D managers decide which technologies are important based on information that is theirs and not the observer's. Second, the technologies are expressed in a terminology that is familiar to industrial researchers. And third, the technologies are clearly linked to the industries.

In the next step I multiply the weights times R&D stocks in cited industries minus R&D in the parent firm. The result is R&D spillovers from the rest of each industry. Finally I sum the net R&D stocks over industries weighted by their importance to the laboratory[14]. The R&D stocks for the 32 manufacturing industries derive from the R&D Survey of the U.S. Census and the National Science Foundation. Compustat provides R&D stocks for three R&D-intensive industries outside manufacturing that are not covered by Census. The industrial R&D spillover is

$$(2) \qquad \textit{R\&D in the Rest of Industry} = \sum_j \gamma_j \tilde{R}_j \, .$$

[14] The 35 industries include: agricultural chemicals; aircraft; communications equipment; construction and materials handling equipment; drugs; electrical components; electrical industrial apparatus; engines and turbines; electrical transmission and distribution equipment; fabricated metals; farm and garden equipment; primary ferrous metals; food and kindred products; inorganic and organic chemicals; missiles and space vehicles; motor vehicles; metalworking equipment; soap, paint, and miscellaneous chemicals; other electrical equipment, including appliances and wiring; computers and office equipment; optical, surgical, and photographic instruments; ordnance; special and general industry machinery; ships, railroads, and other transportation equipment; petroleum refining; plastics, resins, and fibers; primary nonferrous metals; audio, video, and radio equipment; rubber and plastics; search and detection equipment and lab apparatus; stone, clay, and glass; textiles; prepackaged software; computer services; and telecommunications services. The first 32 industries are the Census applied product fields in manufacturing. The last three industries, taken from Compustat, are R&D-intensive sectors outside manufacturing. Each of the 35 groups can be assigned to a two or three digit SIC major industry group.

The survey contains the γ_j weights for industry j. The stock of R&D in the rest of industry j, $\tilde{R}_j$, is the deflated stock of R&D in 1987 dollars, depreciated at 15 percent over a period of 13 years (the most available). The R&D stocks are lagged one year behind the survey data from 1991 and 1996. Thus the industrial spillover ends in 1990 and 1995.

The bottom panel of Table 4 reports means and standard deviations of the industrial spillover variables. The R&D spillover is 91 billion dollars of 1987. Slightly over nine of the 90 technologies are cited on average, so the mean R&D spillover per technology field is 10 billion dollars. Industrial R&D spillovers exceed academic spillovers in the middle panel by a considerable margin. This is due to the specific universities that enter into the academic calculations and the smaller scale of academic research.

IV. Linkages of R&D Laboratories to Universities and Firms

Recall that the data list up to five universities and sciences that were most important for laboratory research. Tables 6, 7 and 8 summarize these data. Table 6 lists the top 10 universities ranked by percent of citations received from the six industry groups in the sample: chemicals, pharmaceuticals and biotechnology, machinery, computers, electrical equipment, and motor vehicles. All of the universities listed are important centers of U.S. academic research. As the most cited university, MIT makes the list in five of the six industry groups.

Table 6 shows that state universities in the South and Midwest of the U.S. are leading sources of academic science for chemicals, machinery and motor vehicle laboratories. In contrast with these mature industries, research groups in pharmaceuticals and biotechnology, computers, and electronics more often rely on private universities and universities located in coastal regions, which are precisely the regions where these industries cluster.

Table 7 ranks the sciences by frequency of citation. Not surprisingly, the five most cited are mechanical, electrical, and chemical engineering, followed by computer science and chemistry. Fields that are mid-class include physics, other engineering (materials science), and mathematics and statistics. Other sciences are rarely cited. Table 8 describes the link between cited sciences and citing industries and includes a comparison between industry and overall citation ranks. Industries are linked with the sciences in accordance with expectations. Citations to chemistry and chemical engineering are higher than average among chemical laboratories. Pharmaceutical and biotechnology laboratories cite biology, medicine, and chemistry more frequently than laboratories elsewhere, and computer laboratories cite electrical engineering, computer science, and mathematics and statistics at a higher rate than usual.

Also recall that the survey includes citations to technologies and industries that R&D managers view as most important for their research. In contrast with the university data, references to closely affiliated firms are far less common. Apparently the identities of closely affiliated firms are regarded as proprietary information. This limitation makes the industrial R&D spillover less precise than the academic. But the industrial data have the advantage of an extensive mapping between technologies and industries. To an extent this sharpens the meaning of the industry spillover in spite of the missing evidence on specific firms.

Tables 9 and 10 report citations to industries. As explained in Section III the underlying methodology translates citations to technologies, which are more familiar to industrial researchers, into industry citations, which are more familiar to economists. For example, citations to any of the 10 technologies under Computer Hardware in Table 5 translate into citations to the Computer & Office Equipment Industry. Following this procedure, Table 9 lists the industries in order of citation frequency. Equipment and components manufacturers –computers, instruments (Search & Detection, Laboratory & Measuring Equipment), electrical components, chemicals, appliances, and communications equipment are the most cited industries. The high regard for instruments is striking since the sample does not include this industry. Citation frequencies decline rapidly: the middle ranked industry—Soaps, Paints & Other Chemicals—is cited one-tenth as computers. Table 9 suggests an input-output table in which highly cited industries provide General Purpose Technologies to others[15]. Table 10 shows that computers are the first or second most cited industry in each of the six groups. In contrast Motor Vehicles cites upstream technologies but its technologies are almost never cited.

Table 10 also shows that citation occurs at a higher rate within industries. Chemical laboratories cite chemicals, plastics, resins and fibers more often than usual, while pharmaceutical and biotechnology laboratories cite drugs and chemicals at a higher rate than average, and this pattern is universal in the table. This pattern suggests that intra-industry knowledge flows exceed representative knowledge flows from a given industry to others.

V. Econometric Results

This section presents estimates of demand functions for learning resources in the laboratories. I take two approaches. The more structured examines determinants of the learning cost shares using the Translog cost function. The less structured examines the demand for a key learning resource, PhD or MD scientists and engineers. One goal of the procedures is to investigate links between contractual arrangements, spillovers, and learning and internal research.

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[15] Scherer (1982) was among the first to construct an input-output table of technology flows through patent citations and trace their impact on productivity. See Bresnahan and Trajtenberg (1995) for an analysis of General Purpose Technologies.

A. Translog R&D Cost Function and Derived Demands

Following Cohen and Levinthal (1989), I assume that R&D serves two functions: learning about external R&D and innovation. Consistent with this concept of R&D and with the survey data discussed in Section III, I examine the behavior of the cost shares associated with learning activities and treat them as elements of a cost function for R&D.

The Translog cost function provides a flexible specification of the underlying technology[16]. The Translog has an advantage for this paper because the logarithmic derivative of the cost function with respect to input price equals the share of that input, and the data in this paper directly report learning shares. I assume that the cost of laboratory R&D can be approximated as follows:

$$
\begin{aligned}
\ln C_R &= \alpha_0 + \alpha_Q \ln Q + \alpha_S \ln S + \alpha_K \ln K + \sum_{i=A,M,N} \alpha_{it} D_t \ln w_i + \sum_{i=A,M,N} \sum_{h} \alpha_{ih} D_h \ln w_i \\
&+ \sum_{i=A,M,N} \gamma'_{iZ} Z \ln w_i + \tfrac{1}{2} \sum_{i=A,M,N} \sum_{j=A,M,N} \gamma_{ij} \ln w_i \ln w_j + \sum_{i=A,M,N} \gamma_{iQ} \ln w_i \ln Q \\
&+ \sum_{i=A,M,N} \gamma_{iS} \ln w_i \ln S + \sum_{i=A,M,N} \gamma_{iR} \ln w_i \ln R + \sum_{i=A,M,N} \ln w_i u_i + u_C
\end{aligned}
\tag{3}
$$

In (3) C_R is the cost of R&D, Q is the output of inventions measured by patents, S is the spillover, K is R&D in the rest of the firm, the subscripts A and M index factor prices associated with learning about academic and industrial research, and N stands for the price of internal research. In addition D_t is a dummy equal to 1 if the year is 1996 (rather than 1991), and 0 otherwise; and D_h is a dummy variable equal to 1 if the laboratory's parent firm is in industry h, and 0 otherwise. The dummy variables allow intercepts of the factor demand functions to differ over time and between industries. I include a vector of laboratory characteristics Z that are explained below. Prices are w_A, w_M, and w_N. Finally u_i and u_C are normally distributed error terms.

Since the cost function is homogeneous of degree one in the input prices, the following restrictions hold:

$$
\begin{aligned}
&\sum_{i=A,M,N} \alpha_{it} = 0, \quad \sum_{i=A,M,N} \alpha_{ih} = \sum_{i=A,M,N} \sum_{h} \alpha_{ih} D_h = 1, \\
&\sum_{i=A,M,N} \gamma'_{iZ} = 0, \quad \sum_{i=A,M,N} \gamma_{ij} = \sum_{j=A,M,N} \gamma_{ij} = \sum_{i=A,M,N} \sum_{j=A,M,N} \gamma_{ij} = 0, \\
&\sum_{i=A,M,N} \gamma_{iQ} = \sum_{i=A,M,N} \gamma_{iS} = \sum_{i=A,M,N} \gamma_{iR} = 0, \quad \sum_{i=A,M,N} u_i = 0
\end{aligned}
\tag{4}
$$

Substitution of (4) into (3) yields the normalized form of the Translog cost function:

[16] Christensen, Jorgenson and Lau (1973) introduce the Translog cost function.

(5)
$$\ln(C_R / w_N) = \alpha_0 + \alpha_Q \ln Q + \alpha_S \ln S + \alpha_R \ln R + \sum_{i=A,M} \alpha_{it} D_t \ln(w_l / w_N)$$
$$+ \sum_{i=\mathrm{A,M}} \sum_{h} \alpha_{lh} D_h \ln(w_i / w_N) + \sum_{i=A,M} \gamma'_{iZ} Z \ln\left(w_i / w_N\right)$$
$$+ \tfrac{1}{2} \sum_{i=A,M} \sum_{j=A,M} \gamma_{ij} \ln(w_i / w_N) \ln(w_j / w_N) + \sum_{i=A,M} \gamma_{iQ} \ln(w_i / w_N) \ln Q$$
$$+ \sum_{i=A,M} \gamma_{iS} \ln(w_i / w_N) \ln S + \sum_{i=A,M} \gamma_{iK} \ln(w_i / w_N) \ln K + \sum_{i=A,M} \ln(w_i / w_N) u_l + u_C$$

By Shephard's lemma the partial derivatives $\partial \ln\left(C_R / w_N\right) / \partial \ln\left(w_A / w_N\right)$ and $\partial \ln\left(C_R / w_N\right) / \partial \ln\left(w_M / w_N\right)$ are:

(6)
$$s*_A = \alpha_{it} D_t + \sum_{h} \alpha_{Ah} D_h + \gamma'_{AZ} Z + \gamma_{AA} \ln(w_A / w_N) + \gamma_{AM} \ln(w_M / w_N)$$
$$+ \gamma_{AQ} \ln Q + \gamma_{AS} \ln S + \gamma_{AK} \ln K + u_A$$
$$s*_M = \alpha_{it} D_t + \sum_{h} \alpha_{Ah} D_h + \gamma'_{MZ} Z + \gamma_{MA} \ln(w_A / w_N) + \gamma_{MM} \ln(w_M / w_N)$$
$$+ \gamma_{MQ} \ln Q + \gamma_{MS} \ln S + \gamma_{MK} \ln K + u_M$$

In (6), $s*_A$ is the academic learning-share while $s*_M$ is the industrial share. The share of internal research is left out since cost shares sum to 1.0. Asterisks indicate latent values of the cost shares, for which we observe interval-valued cost shares. This suggests that OLS and SUR estimation of (6) be replaced by Ordered Probit procedures, as is done below.

A few comments on (6) are useful. S forms a vector of academic and industrial spillovers in (6). In addition, I do not have separate learning prices (w_A and w_M). Instead I use the Engineer V wage to represent an average price of learning inputs. Therefore, I estimate the sum of γ_{AA} and γ_{AM} in the first equation and the sum of γ_{MA} and γ_{MM} in the second. I approximate the price of internal research w_N by the R&D cost index (1). Finally, notice that the coefficients of (6) represent the change in the cost share for a 100 percent change in the logarithm of a variable.

Table 11 reports single equation, Ordered Probit estimates of the learning shares (see Maddala, 1983 or Green, 2000). Following Table 3, the dependent variables are limited to the categories: 0%, 0.1-1%, 2-3%, and 4+%. Besides year and industry dummies I incorporate a number of controls for laboratory characteristics. The controls include dummy indicators (insignificant) for whether the firm owns other laboratories and whether the laboratory is jointly housed with manufacturing. The logarithm of the relative Engineer V wage is negative but also insignificant[17].

[17] Translog own and cross-price elasticities in the academic equation are $\sigma_{AA} = \dfrac{\gamma_{AA} + s*_A^2 - s*_A}{s*_A^2}$ and $\sigma_{AM} = \dfrac{\gamma_{AM} + s*_A\, s*_M}{s*_A\, s*_M}$. The elasticities cannot be identified, the same point holds for the industrial equation.

Equations 11.1 and 11.2 report the results of fitting the academic learning-share to the data. In both equations the logarithm of patent grants increases the share[18]. One can think of several reasons why larger laboratories spend proportionately more on learning and monitoring. These include increasing specialization, economies of scale, and simple recognition that the activity exists. R&D in the rest of the firm has little effect. The academic R&D spillover—the stock of federally funded R&D in closely affiliated universities and fields—drives learning about university research. However, R&D in the rest of industry—the stock of R&D in various industries weighted by the importance of their component technologies—has no significant effect on the academic learning-share. Equation 11.2 adds an indicator of partnership, the intensity of interactions with universities. This takes into account reasons for monitoring university research besides the spillover. Intensity ranges from 0 to 5 and is the sum of dummy indicators for the importance of: university science graduates, faculty consulting, contract research with universities, university collaborations, and university patents. Intensity is highly significant and improves the fit of the equation. And yet the university spillover remains significant.

Equations 11.3 and 11.4 report the industrial learning-share equations. Laboratories that issue more patents again spend a larger proportion on learning. R&D in the rest of industry increases learning and its effect is significant at the five percent level. This suggests that the industrial learning-share does respond to industrial research opportunities in relevant fields of technology. The cross effect of the university spillover is however, insignificant. Equation 11.4 adds indicators of partnership with other firms. The effect of engineering hours contributed by supplier firms is highly significant, and this implies that R&D laboratories study the work of suppliers who contribute to its research. Also significant is the intensity of interactions with other firms. Intensity ranges from 0 to 5 and is the sum of dummy indicators for the importance of: joint ventures, other firms' patents, outsourcing of R&D, R&D undertaken for other firms, and acquisition of other firms. Both of the interactions control for reasons to monitor firms besides spillovers. As before the spillover remains significant.

The implications of these results for the share of internal research are straightforward. Interactions between the laboratories, universities and other firms decrease the share of internal research. Larger laboratories, measured by number of patents granted, also have smaller internal research shares. A similar story applies to R&D spillovers. The academic spillover increases the university learning-share at the expense of internal research, just as the industrial spillover increases the industrial learning-share at the expense of internal research. These results are strongly reminiscent of the historical case studies that were discussed in Section II.

[18] The results stay about the same when patent applications are used instead of patent grants.

B. Bivariate Ordered Probit Estimates of the Cost Shares

The findings of Table 11 are subject to at least two limitations. They do not take into account the cross-equation correlation of the errors, and they do not permit cross-equation tests. To remedy these deficiencies I have devised a Bivariate Ordered Probit procedure. This bears the same relation to Ordered Probit that Seemingly Unrelated Regression bears to OLS regression. This section explains the procedure and presents the results.

The probability that $s*_A$ falls in interval j and $s*_M$ falls into interval k is given by

(7) $$\Pr(s_A = j, s_M = k) = \Pr(c_{Aj} > s*_A > c_{Aj-1},\ c_{Mk} > s*_M > c_{Mk-1})$$

The "cut points" for $s*_A$ are c_{Aj} while the cut points for $s*_M$ are c_{Mj}. The Bivariate Ordered Probit likelihood is then

(8) $$L = \prod_i \prod_j \prod_k \Pr(c_{Aj} > s*_A > c_{Aj-1},\ c_{Mk} > s*_M > c_{Mk-1})^{M_{ji} N_{ki}}$$

Here $M_{ij} = 1$ if the observation on s_A falls in bracket j, and 0 otherwise; and $N_{ik} = 1$ if the observation on s_M falls in bracket k, and 0 otherwise. The Appendix calculates (7) and (8) for the case where the values of s_A and s_M follow a "1, 2 or 3" scheme of 0%, 0.1-1%, or 2+%. As Table 3 has shown, this design is imposed by the scarcity of data above 2%.

Table 12 contains the results of the Bivariate Ordered Probit procedure[19]. The dependent variables are UNIVCAT, which assumes values ranging from 1 to 3, as above; and FIRMCAT, which also ranges from 1 to 3. As it happens the point estimates are similar to Table 11, and the cross-equation correlation is insignificant. New ground is gained, though, by the ability to conduct cross-equation tests. These are applied to the coefficients of patents and R&D spillovers, where I find that the patent coefficients are equal but that the spillover effects differ significantly. The university spillover has a significantly larger effect in the university equation; and similarly for the industry spillover in the firm equation. Equations 12.3 and 12.4 test the importance of spillovers per field of science and technology. The results stay about the same and reject the hypothesis that the spillover effect is the spurious result of a scale effect (number of fields). Of course, it would be premature to claim that these results prove that larger spillovers cause larger learning-shares. But at the very least, the findings suggest that active learning programs in industrial R&D find it worthwhile to align themselves with their counterparts in universities and other firms.

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[19] The STATA™ ML program that computes the estimates is available upon request. Gould and Sribney (1999) is an introduction to maximum likelihood estimation using STATA™.

C. Demands for PhD and MD Researchers

Since at least some learning is implicit in R&D, I explore the determinants of the employment of PhD (or MD) researchers. I assume that advanced degrees signal greater emphasis on learning about R&D elsewhere, especially academic R&D. One comment is that great inventors of the past such as Brunel, Edison or Watt achieved success without the doctorate.   My response to this comment is that our own times exhibit greater specialization, so that the PhD contributes to learning capabilities.

I approach the demand for PhD scientists using three different methods. I undertake Probit analysis of whether or not a laboratory employs PhD scientists. Next I estimate Tobit equations that examine whether or not and how many PhDs are employed. And finally I estimate weighted least squares (grouped Probit) equations of the odds that a researcher holds the PhD. In this instance the sample is confined to laboratories that report PhD employment.

Table 13 presents the findings, beginning with the Probit results. Equations 13.1 and 13.2 include dummy variables for whether the firm owns other laboratories and the laboratory is jointly housed with manufacturing, but neither is statistically significant. The logarithm of laboratory R&D budget increases the probability of PhD employment, but R&D in the rest of the firm does not. R&D spillovers increase the hiring probability, though the industrial spillover is marginally significant.

To further test the spillover contribution, equation 13.2 includes intensities of interaction with firms and universities. As before, these measure the strength of external linkages. The university intensity is positive and significant, suggesting that PhD skills provide a bridge between industry and academia. But the spillover effects remain intact.

Equations 13.3 and 13.4 contain Tobit estimates of the logarithm of the number of PhDs employed. The logarithms of R&D budget and spillovers increase the number of PhDs employed. Again the intensity of interactions with universities is associated with increased employment of PhDs, while the industrial intensity is insignificant. The other controls are not significant.

Weighted least squares estimates of the odds of PhD employment are reported in 13.5 and 13.6. Laboratories that are jointly housed with manufacturing and interaction with other firms, as well as larger laboratories in this sample employ a significantly smaller PhD proportion. The results on these variables are negative and significant in a way that they were not in 13.1-13.4. The reason is that use of proportions removes the effects of laboratory size, which are positively associated with joint housing, firm interactions, and laboratory R&D budget. The proportions data also changes the effect of R&D elsewhere in the firm, which seems to substitute for size of the laboratory in 13.1-13.4, but increase the shares of PhD personnel. Both spillovers are associated with a significant increase in the PhD proportion.

In separate equations not presented here, I undertake OLS estimates of the logarithm of the number of scientists and engineers not holding the PhD degree. Consistent with the idea that learning activities are concentrated among PhDs, I find that employment of non-PhDs is not affected by interactions with universities and firms, nor is it affected by R&D spillovers. One explanation is that active learners and inventors among non-PhDs are difficult to pick out from a crowd of personnel engaged in administration, production, and line engineering.

VI. Summary and Conclusion

This paper has presented new evidence on the practice of industrial R&D. This provides a description of the flow of outside knowledge into firms, and an interpretation of the specific channels by which the flows occur. The results are based on a sample of R&D laboratories in the U.S. chemicals, machinery, electrical equipment and motor vehicles industries. The paper has examined linkages of the laboratories with universities and other firms. While engineering, computer science, and chemistry are found to be pervasive, I find evidence of closer connections between fields and industries. Chemical engineering and chemistry are unusually important to chemical laboratories, while biology, chemistry, and medicine are more important than average to pharmaceutical and biotechnology laboratories. In addition the paper uncovers linkages between most cited universities and citing industries. For mature industries I find that state universities in the South and Midwest of the U.S. are more often cited. For younger industries the finding is that private universities and universities in coastal regions are more influential.

With respect to linkages between the laboratories and other industries, the paper finds that computers and instruments have the characteristics of General Purpose Technologies, since they are the most cited industries by every group in the survey. There is evidence besides, that intra-industry knowledge spillovers are larger than average. Chemical laboratories cite inorganic and organic chemicals, and plastics, resins and fibers, more frequently than other laboratories do. Likewise pharmaceutical and biotechnology laboratories cite ethical drugs more often than is usually the case.

The econometric findings suggest that the demand for learning resources in industrial R&D partly results from partnerships with universities and other firms. But the results suggest as well that learning activity responds to broader technological opportunities that are less subject to ownership. These “common property” opportunities are represented in this paper by estimates of academic and industrial R&D spillovers. Indeed the findings show that the academic learning-share responds to academic spillovers, but not to industrial spillovers. The converse is true of the industrial learning-share, where the industrial spillover predominates. These differences in the response to opportunities are highly significant both in the statistical sense, and in the sense of specificity of technological opportunity that they evoke. Other findings on the demand for PhD employment imply that technological opportunities, especially those offered by university research, contribute to the value of highly trained researchers. Overall the results are consistent with firms and laboratories aggressively responding to technological opportunities rather than waiting for opportunities to come to them.

Assuming that the mission of an R&D laboratory includes the study of external research, one might expect the firm to equate the marginal effect on expected present value of each type of R&D, learning and internal research, with price. However, one would also predict the existence of infra-marginal gains from learning and internal research and complementarities between the two[20]. Answers to these questions lie outside the scope of this paper and require panel data of a more elaborate nature than the data that I possess[21].

Also left for the future are questions about the division of labor among R&D laboratories, including the distinction between facilities devoted to routine testing and central laboratories concerned with basic and applied research as well as development. More work is likewise needed to improve the measurement of learning and internal research to include implicit time costs, as well as cases where the two are joint and inseparable, as Cohen and Levinthal (1989) have emphasized. There is much still to learn about the practice of R&D and its contributions to economic growth.

[20] Let $EPV(R_l, R_N) - w_l R_l - w_N R_N$ be the net expected present value as a function of learning and internal research R_l and R_N. Then $\partial EPV / \partial R_l = w_l, \partial EPV / \partial R_N = w_N$. Infra-marginal gains imply that $EPV(R_l, R_N) - w_l R_l - w_N R_N >$ $EPV(0,0)$. Complementarity says that $EPV(R_l, R_N) - w_l R_l - w_N R_N > \max\left[EPV(R_l, 0) - w_l R_l, EPV(0, R_N) - w_N R_N\right]$.

[21] Even assessing the effects of the allocation of R&D on invention is not a simple endeavor. In results not reported in this paper I find that learning about academic and industrial research has outsized positive effects on patents compared with internal research for the laboratories in my sample. This suggests that fixed effects of the laboratories are confounded with true effects of the learning activities. To separate the two would require fixed effects estimation in a panel that is large in both the cross sectional and time series dimensions. Of course this brief discussion ignores thorny questions about the measurement of invention, and the appropriate functional form to use in the estimation procedures.

Appendix
The Likelihood Function for Bivariate Ordered Probit

I adopt the following notation for the latent variables:

(A.1)
$$s^*_A = \beta'_A X_A + u_A$$
$$s^*_M = \beta'_M X_M + u_M$$

In a three-category example s_A and s_M equal 1,2 or 3, when s^*_A and s^*_M fall in the intervals $(-\infty, c_{A1})$, (c_{A1}, c_{A2}) or (c_{A2}, ∞). The likelihood has nine branches or probabilities corresponding to the elements (s_A , s_M) of (A.2):

(A.2)
$$\begin{pmatrix} 1{,}1 & 2{,}1 & 3{,}1 \\ 1{,}2 & 2{,}2 & 3{,}2 \\ 1{,}3 & 2{,}3 & 3{,}3 \end{pmatrix}$$

Below the probabilities (A.3)-(A.11)are written in terms of normal Cumulative Distribution Functions (CDFs). The univariate normal CDF is $\Phi(X)$ and the bivariate Normal CDF is $F(X, Y, \rho)$, where ρ is the correlation between X and Y. Both are standard normal since variances are not identified in Ordered Probit. The probabilities lie between 0 and 1 and one can show that they sum to 1 and form a proper probability distribution.

(A.3)
$$Pr(s_A = 1, s_M = 1) = P(c_{A1} > s^*_A = \beta'_A X_A + u_A, c_{M1} > s^*_M = \beta'_M X_M + u_M) =$$
$$P(c_{A1} - \beta'_A X_A > u_A, c_{M1} - \beta'_M X_M > u_M) = F(c_{A1} - \beta'_A X_A, c_{M1} - \beta'_M X_M, \rho)$$

(A.4)
$$Pr(s_A = 1, s_M = 2) = P(c_{A1} - \beta'_A X_A > u_A, c_{M2} - \beta'_M X_M > u_M > c_{M1} - \beta'_M X_M)$$
$$= P(c_{A1} - \beta'_A X_A > u_A, c_{M2} - \beta'_M X_M > u_M) - P(c_{A1} - \beta'_A X_A > u_A, c_{M1} - \beta'_M X_M > u_M)$$
$$= F(c_{A1} - \beta'_A X_A, c_{M2} - \beta'_M X_M, \rho) - F(c_{A1} - \beta'_A X_A, c_{M2} - \beta'_M X_M, \rho)$$

(A.5)
$$Pr(s_A = 1, s_M = 3) = P(c_{A1} - \beta'_A X_A > u_A, c_{M2} - \beta'_M X_M < u_M)$$
$$= P(c_{A1} - \beta'_A X_A > u_A) - P(c_{A1} - \beta'_A X_A > u_A, c_{M2} - \beta'_M X_M > u_M)$$
$$= \Phi(c_{A1} - \beta'_A X_A) - F(c_{A1} - \beta'_A X_A, c_{M2} - \beta'_M X_M, \rho)$$

(A.6)
$$Pr(s_A = 2, s_M = 1) = P(c_{A2} - \beta'_A X_A > u_A > c_{A1} - \beta'_A X_A, c_{M1} - \beta'_M X_M > u_M)$$
$$= P(c_{A2} - \beta'_A X_A > u_A, c_{M1} - \beta'_M X_M > u_M) - P(c_{A1} - \beta'_A X_A > u_A, c_{M1} - \beta'_M X_M > u_M)$$
$$= F(c_{A2} - \beta'_A X_A, c_{M1} - \beta'_M X_M, \rho) - F(c_{A1} - \beta'_A X_A, c_{M1} - \beta'_M X_M, \rho)$$

To illustrate the calculations I provide a more elaborate exposition for the case $s_A = 2$ and $s_M = 2$:

(A.7)
$$\Pr(s_A = 2, s_M = 2) = \int_{c_{A1} - \beta'_A X_A}^{c_{A2} - \beta'_A X_A} \int_{c_{M1} - \beta'_M X_M}^{c_{M2} - \beta'_M X_M} f(u_A, u_M) du_A u_M$$
$$= \left[\int_{-\infty}^{c_{A2} - \beta'_A X_A} \int_{c_{M1} - \beta'_M X_M}^{c_{M2} - \beta'_M X_M} f(u_A, u_M) du_A u_M \right] - \left[\int_{-\infty}^{c_{A1} - \beta'_A X_A} \int_{c_{M1} - \beta'_M X_M}^{c_{M2} - \beta'_M X_M} f(u_A, u_M) du_A u_M \right]$$
$$= \left[\int_{-\infty}^{c_{A2} - \beta'_A X_A} \int_{-\infty}^{c_{M2} - \beta'_M X_M} f(u_A, u_M) du_A u_M - \int_{-\infty}^{c_{A2} - \beta'_A X_A} \int_{-\infty}^{c_{M1} - \beta'_M X_M} f(u_A, u_M) du_A u_M \right] -$$
$$\left[\int_{-\infty}^{c_{A1} - \beta'_A X_A} \int_{-\infty}^{c_{M2} - \beta'_M X_M} f(u_A, u_M) du_A u_M - \int_{-\infty}^{c_{A1} - \beta'_A X_A} \int_{-\infty}^{c_{M1} - \beta'_M X_M} f(u_A, u_m) du_A u_M \right]$$

In more compact notation (A.7) is written as:

$$\text{(A.7}'\text{)}\quad \begin{aligned} &Pr(s_A = 2, s_M = 2) = P(c_{A2} - \beta_A' X_A > u_A > c_{A1} - \beta_A' X_A, c_{M2} - \beta_M' X_M > u_M > c_{M1} - \beta_M' X_M) \\ &= [P(c_{A2} - \beta_A' X_A > u_A, c_{M2} - \beta_M' X_M > u_M) - P(c_{A2} - \beta_A' X_A > u_A, c_{M1} - \beta_M' X_M > u_M)] - \\ &\quad [P(c_{A1} - \beta_A' X_A > u_A, c_{M2} - \beta_M' X_M > u_M) - P(c_{A1} - \beta_A' X_A > u_A, c_{M1} - \beta_M' X_M > u_M)] \\ &= [F(c_{A2} - \beta_A' X_A, c_{M2} - \beta_M' X_M, \rho) - F(c_{A2} - \beta_A' X_A, c_{M1} - \beta_M' X_M, \rho)] - \\ &\quad [F(c_{A1} - \beta_A' X_A, c_{M2} - \beta_M' X_M, \rho) - F(c_{A1} - \beta_A' X_A, c_{M1} - \beta_M' X_M, \rho)] \end{aligned}$$

The final equality of (A.7′) assumes that the CDFs are bivariate standard normal. The rest of the probabilities are:

$$\text{(A.8)}\quad \begin{aligned} &Pr(s_A = 2, s_M = 3) = P(c_{A2} - \beta_A' X_A > u_A > c_{A1} - \beta_A' X_A, u_M > c_{M2} - \beta_M' X_M) \\ &= P(c_{A2} - \beta_A' X_A > u_A > c_{A1} - \beta_A' X_A) - \\ &\quad P(c_{A2} - \beta_A' X_A > u_A > c_{A2} - \beta_A' X_A, c_{M2} - \beta_M' X_M > u_M) \\ &= [P(c_{A2} - \beta_A' X_A > u_A) - P(c_{A1} - \beta_A' X_A > u_A] - \\ &\quad [P(c_{A2} - \beta_A' X_A > u_A, c_{M2} - \beta_M' X_M > u_M) - P(c_{A1} - \beta_A' X_A > u_A, c_{M2} - \beta_M' X_M > u_M)] \\ &= [\Phi(c_{A2} - \beta_A' X_A) - \Phi(c_{A1} - \beta_A' X_A)] - \\ &\quad [F(c_{A2} - \beta_A' X_A, c_{M2} - \beta_M' X_M, \rho) - F(c_{A1} - \beta_A' X_A, c_{M2} - \beta_M' X_M, \rho)] \end{aligned}$$

$$\text{(A.9)}\quad \begin{aligned} &Pr(s_A = 3, s_M = 1) = P(c_{A2} - \beta_A' X_A < u_A, c_{M1} - \beta_M' X_M > u_M) \\ &= P(c_{M1} - \beta_M' X_M > u_M) - P(c_{A2} - \beta_A' X_A > u_A, c_{M1} - \beta_M' X_M > u_M) \\ &= \Phi(c_{M1} - \beta_M' X_M) - F(c_{A2} - \beta_A' X_A, c_{M1} - \beta_M' X_M, \rho) \end{aligned}$$

$$\text{(A.10)}\quad \begin{aligned} &Pr(s_A = 3, s_M = 2) = P(c_{A2} - \beta_A' X_A < u_A, c_{M2} - \beta_M' X_M > u_M > c_{M1} - \beta_M' X_M) \\ &= P(c_{M2} - \beta_M' X_M > u_M > c_{M1} - \beta_M' X_M) - \\ &\quad P(c_{M2} - \beta_M' X_M > u_M > c_{M1} - \beta_M' X_M, c_{A2} - \beta_A' X_A > u_A) \\ &= [P(c_{M2} - \beta_M' X_M > u_M) - P(c_{M1} - \beta_M' X_M > u_M] - \\ &\quad [P(c_{M2} - \beta_M' X_M > u_M, c_{A2} - \beta_A' X_A > u_A) - P(c_{M1} - \beta_M' X_M > u_M, c_{A2} - \beta_A' X_A > u_A)] \\ &= [\Phi(c_{M2} - \beta_M' X_M) - \Phi(c_{M1} - \beta_M' X_M)] - \\ &\quad [F(c_{M2} - \beta_M' X_M, c_{A2} - \beta_A' X_A, \rho) - F(c_{M1} - \beta_M' X_M, c_{A2} - \beta_A' X_A, \rho)] \end{aligned}$$

$$\text{(A.11)}\quad \begin{aligned} &Pr(s_A = 3, s_M = 3) = P(c_{A2} - \beta_A' X_A < u_A, c_{M2} - \beta_M' X_M < u_M) \\ &= P(c_{A2} - \beta_A' X_A < u_A) - P(c_{A2} - \beta_A' X_A < u_A, c_{M2} - \beta_M' X_M > u_M) \\ &= [1 - P(c_{A2} - \beta_A' X_A > u_A)] - \\ &\quad [P(c_{M2} - \beta_M' X_M > u_M) - P(c_{A2} - \beta_A' X_A > u_A, c_{M2} - \beta_M' X_M > u_M)] \\ &= [1 - \Phi(c_{A2} - \beta_A' X_A)] - [\Phi(c_{M2} - \beta_M' X_M) - F(c_{A2} - \beta_A' X_A, c_{M2} - \beta_M' X_M, \rho)] \end{aligned}$$

The calculations of Table 12 are based on (A.3)-(A.11) as summarized by the likelihood function:

$$\text{(A.12)}\qquad L = \prod_i \prod_j \prod_k \Pr\left(c_{Aj} > s*_{Ai} > c_{Aj-1},\ c_{Mk} > s*_{Mi} > c_{Mk-1}\right)^{M_{ji} N_{ki}}$$

where *i* represents the observation, $M_{ij} = 1$ if s_{Ai} falls in bracket j, and 0 otherwise, and $N_{ik} = 1$ if s_{Mi} falls in bracket k, and 0 otherwise.

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Table 1
Distribution of Firms and Laboratories by Industry

Industry	SIC Code	Number of Firms	Number of Observations*
Chemicals	28	32	59
Machinery	35	37	58
Electrical Equipment	36	33	57
Automobiles	37	14	34
All Industries	___	**116**	**208**

Source: *Survey of Industrial Laboratory Technologies 1996***.** * The 208 observations represent 220 laboratories owing to the aggregation of laboratories by several firms.

Table 2
Characteristics of the R&D Laboratories
(Standard Deviations in Parentheses)

Variable	Year 1991	Year 1996
R&D Inputs		
Number of Scientists and Engineers	126.9	142.1
	(385.2)	(421.5)
Number of PhD (or MD) Scientists and Engineers	19.1	21.4
	(108.3)	(99.2)
Fraction of Laboratory Scientists and Engineers Holding the PhD or MD	0.12	0.14
	(0.17)	(0.18)
Laboratory R&D Budget (in millions of ’87 $)	12.2	12.9
	(40.4)	(39.2)
Percent of Laboratories with PhD or MD Researchers	59.0%	66.2%
R&D Outputs		
Patent Grants [a]	8.9	12.4
	(30.4)	(40.6)
Patent Applications [b]	10.5	14.5
	(31.7)	(36.8)

Source: *Survey of Industrial Laboratory Technologies 1996.* Notes. [a] Missing values on patents granted are imputes from U.S. patents awarded to a locations. [b] Missing values on patent applications are imputes from next year’s U.S. patents awarded to a location.

Table 3
Distribution of Learning Shares in R&D Budget

Share of R&D Budget Spent Learning About Firms	Share of R&D Budget Spent Learning about Universities: None	0-1%	2-3%	4+%	Total Number of Laboratories
None	61	22	5	6	94
0-1%	62	28	10	4	106
2-3%	35	18	8	0	61
4+%	11	16	8	4	41
Total Number of Laboratories	169	84	35	14	302

Source: *Survey of Industrial Laboratory Technologies 1996.* Note. The 302 observations represent observations on the cost shares in both 1991 and 1996.

Table 4
Supplementary Variables: R&D Price Indexes,
Academic and Industrial R&D Spillovers
(Standard Errors in Parentheses)

Variable	**Mean (S.D.)**
R&D Price Indexes	
Engineer V Weekly Wage [a]	1.17 (0.12)
Unit R&D Cost Index [b]	1.05 (0.07)
Academic R&D Spillover	
R&D Spillover from Closely Affiliated Universities [c]	301.86 (543.57)
R&D Spillover from Closely Affiliated Universities per Field of Science [d]	68.37 (121.25)
Number of Science Fields Cited	4.46 (1.17)
Industrial R&D Spillover	
R&D Spillover from the Rest of Industry [e]	91,028.39 (78,118.60)
R&D Spillover from the Rest of Industry per Field of Technology [f]	10,305.95 (8,409.42)
Number of Field of Technology Cited	9.13 (5.41)

Sources: *Survey of Industrial Laboratory Technologies 1996, NSF CASPAR database of U.S. universities, Census-NSF R&D Survey, and Compustat.* Notes. [a] The Engineer V weekly wage is deflated by its value in Pittsburgh, Pennsylvania in machinery, in 1991. [b] The wage component of the unit R&D cost index is deflated by its value in Pittsburgh, Pennsylvania in machinery, in 1991. The non-wage component is deflated by its value in machinery, in 1991. [c] 17-year, federally funded R&D stock in millions of 1987 dollars. [d] The R&D spillover from closely affi1iated universities divided by the number of science fields cited. [e] 13-year, company funded R&D Stocks in millions of 1987 dollars. [f] The R&D spillover from the rest of industry divided by the number of technologies cited.

Table 5
Mapping from Technologies to Industries
The Survey of Industrial Laboratory Technologies 1996

	Technology	Industry (1987 Standard Industrial Classification)
Automation		
a1	Automatic Testing Equipment	Laboratory, Test, & Measuring Equipment (382)
a2	Manufacturing Automation & Robotics	General Industry Machinery (356)
a3	Manufacturing Control Systems	Electrical Industrial Apparatus (362)
a4	Manufacturing Measuring Equipment	Metalworking Machinery & Equipment (354)
a5	Materials Handling & Shipping Equipment	Construction, Mining, & Materials Handling Equipment (353)
a6	Machine Tools Or Presses	Metalworking Machinery & Equipment (354)
Biotechnology		
b1	Biotechnology Equipment	Laboratory, Test, & Measuring Equipment (382)
b2	Biotechnology Systems & Biomaterials	Drugs (283)
b3	Enzyme Technology Systems	Industrial Organic Chemicals (286)
Chemicals		
c1	Chemical Dyes or Pigments	Industrial Inorganic Chemicals (281)
c2	Explosive Chemicals	Miscellaneous Chemicals (289)
c3	Industrial Gases	Industrial Inorganic Chemicals (281)
c4	Other Inorganic Chemicals	" (281)
c5	Organic Chemicals	Industrial Organic Chemicals (286)
c6	Petrochemicals & Petroleum	Petroleum Refining and Related Industries (291)
Computer Hardware		
d1	Business Equipment	Computer & Office Equipment (357)
d2	Computer Accessories & Components	" (357)
d3	Computer Memory Systems	" (357)
d4	Central Processing Units	" (357)
d5	Computer Monitors & Input Devices	" (357)
d6	Microcomputers & Minicomputers	" (357)
d7	Mainframes & Supercomputers	" (357)
d8	Peripheral Controllers & Output Devices	" (357)
d9	Terminals	" (357)
d10	Computer Services	" (357)
Defense		
e1	Electronic Command & Control Equipment	Search, Detection, & Guidance Instruments (381)
e2	Defense Ground Support Equipment	Motor Vehicles (371)
e3	Missiles	Guided Missiles and Spacecraft (376)
e4	Ordnance Systems And Equipment	Ordnance (348)
Energy		
f1	Energy Management Systems	Laboratory, Test, & Measuring Equipment (382)
f2	Electric Motors & Generators	Electrical Industrial Apparatus (362)
f3	Electrical Power Transmission Equipment	Electrical Transmission and Distribution Equipment (361)
f4	Heating & Air Conditioning Equipment	Fabricated Metals Products (343)

Table 5
Mapping from Technologies to Industries
The Survey of Industrial Laboratory Technologies 1996

Technology		Industry (1987 Standard Industrial Classification)
f5	Energy Storage Equipment	Miscellaneous Electrical Machinery (369)
f6	Turbines	Engines & Turbines (351)
Environmental		
g1	Environmental Measuring Equipment	Laboratory, Test, & Measuring Equipment (382)
g2	Waste Treatment Equipment	Refrigeration & Service Industry Machinery (358)
Advanced Materials		
h1	Abrasives	Stone, Clay, & Glass Products (32)
h2	Adhesives	Miscellaneous Chemicals (289)
h3	Additives & Modifiers	“ (289)
h4	Ceramics & Nonmetallic Materials	Stone, Clay, & Glass Products (32)
h5	Composites & Foams	Rubber & Miscellaneous Plastics Products (30)
h6	Construction & Building Materials	Stone, Clay, & Glass Products (32)
h7	Coatings And Coating Materials	Paints & Varnishes (285)
h8	Desiccants	Industrial Inorganic Chemicals (281)
h9	Metals & Alloys	Primary Metals (330)
h10	Monomers & Polymers	Plastics Materials & Synthetic Resins, Rubber, & Fibers (282)
h11	Nuclear Materials	Industrial Inorganic Chemicals (281)
h12	Textiles & Textile Fibers	Textile Mill Products (220)
Medical		
i1	Dental Equipment	Medical & Surgical Equipment (384)
i2	Medical Diagnostic, Monitoring Other Equipment	“ (384)
i3	Handicap Aids & Prostheses	“ (384)
i4	Home Health Care Products or Rehabilitation	“ (384)
i5	Veterinary Equipment	Medical & Surgical Equipment (384)
Pharmaceuticals		
j1	Drugs	Drugs (283)
j2	Human & Veterinary Pharmaceuticals	“ (283)
j3	Diagnostic Agents	“ (283)
j4	Vaccines, Serums & Related Agents	“ (283)
Photonics		
k1	Cameras & Related Equipment	Optical Instruments (386)
k2	Displays & Optoelectronic Devices	Electronic Components & Accessories (367)
k3	Optics & Related Equipment	Laboratory, Test, & Measuring Equipment (382)
k4	Lasers & Laser Related Equipment	Miscellaneous Electrical Machinery (369)
Computer Software		
l1	Application Specific Software	Prepackaged Software (7372)
l2	Software-Related Services	Computer Programming, Data Processing; Other Services (737, except 7372)
Subassemblies and Components		
m1	Electronic Connectors	Electronic Components & Accessories (367)

Table 5
Mapping from Technologies to Industries
The Survey of Industrial Laboratory Technologies 1996

	Technology	Industry (1987 Standard Industrial Classification)
m2	Connectors for Electrical Devices	Electric Lighting & Wiring Equipment (364)
m3	Mechanical Connectors	Fabricated Metals Products (342)
m4	Electromechanical Devices	Miscellaneous Electrical Machinery (369)
m5	Electronic Subsystems	Electronic Components & Accessories (367)
m6	Non-Electronic Mechanical Devices	“ (367)
m7	Transducers	“ (367)
m8	Semiconductors & Semiconductor Devices	“ (367)
Test and Measurement		
n1	Analyzers & Counters	Laboratory, Test, & Measuring Equipment (382)
n2	Measuring Equipment	“ (382)
n3	Process Variable Controllers	“ (382)
n4	Scientific & Laboratory Equipment	“ (382)
n5	Security & Safety Equipment	Miscellaneous Manufacturing (399)
Telecommunications		
o1	Audio & Video Equipment	Communications Equipment (366)
o2	Broadcasting & Receiving Equipment	“ (366)
o3	Multiplexers & Modems	“ (366)
o4	Communications Networks & Related Equipment	“ (366)
o5	Signaling & Traffic Equipment	“ (366)
o6	Satellite & Microwave Communications	“ (366)
o7	Telecommunications Services	Communications (48)
o8	Telephone & Telegraph Equipment	Communications Equipment (366)
o9	Transmission Systems Equipment	“ (366)
Transportation		
p1	Aircraft & Aircraft Propulsion	Aircraft & Parts (372)
p2	Ground Transportation Equipment	Motor Vehicles (371)
p3	Ship Building & Repair	Ship Building (373)
p4	Space Vehicles	Guided Missiles and Spacecraft (376)

Source: *Survey of Industrial Laboratory Technologies 1996.* Note. See the text for a discussion of the system of SIC codes. The code is more aggregative when it contains fewer digits (i.e. 30, 48), and less aggregative when it contains more digits (i.e. 381, 7372).

Table 6
The Top 10 Most Cited Universities, By Industry Group

University	Percent of Citations by Industry	University	Percent of Citations by Industry
Chemicals (SIC 28, except SIC 283)		**Computers & Office Equipment (SIC 357)**	
Pennsylvania State University	9.2%	Stanford University	20%
Georgia Institute of Technology	4.0%	Carnegie Mellon University	10%
University of Minnesota	4.0%	University of California—Berkeley	10%
Case Western Reserve University	4.0%	University of Michigan	10%
North Carolina State University	4.0%	Boston University	5%
Clemson University	4.0%	Cornell University	5%
Virginia Polytechnic Institute	4.0%	Massachusetts Institute Of Technology (MIT)	5%
Purdue University	2.6%	University of California—Santa Barbara	5%
University of North Carolina—Chapel Hill	2.6%	University of Illinois at Urbana-Champaign	5%
University of Texas—Austin	2.6%	University of Washington	5%
Pharmaceuticals & Biotechnology (SIC 283)		**Electrical Equipment (SIC 36)**	
Harvard University	6.8%	Stanford University	8.6%
Massachusetts Institute Of Technology (MIT)	5.1%	Massachusetts Institute Of Technology (MIT)	7.4%
University of Illinois at Urbana-Champaign	5.1%	University of California—Berkeley	6.2%
Columbia University	3.4%	Rensselaer Polytechnic Institute	4.9%
Ohio State University	3.4%	Carnegie Mellon University	3.7%
University of California—San Diego	3.4%	Case Western Reserve University	3.7%
University of California—San Francisco	3.4%	University of Minnesota	3.7%
University of North Carolina—Chapel Hill	3.4%	Pennsylvania State University	3.7%
University of Pittsburgh	3.4%	Purdue University	3.7%
Yale University	3.4%	Ohio State University	2.5%
Machinery (SIC 35, except SIC 357)		**Motor Vehicles (SIC 371)**	
Purdue University	7.7%	University of Wisconsin—Madison	8.0%
Pennsylvania State University	5.8%	Ohio State University	6.0%
Virginia Polytechnic University	5.8%	University of California—Santa Barbara	6.0%
University of Minnesota	3.9%	Georgia Institute of Technology	4.0%
University of Virginia	3.9%	Purdue University	4.0%
Massachusetts Institute Of Technology (MIT)	3.9%	Massachusetts Institute Of Technology (MIT)	4.0%
Northwestern University	3.9%	University of Arizona	4.0%
Oregon State University	3.9%	University of California—Berkeley	4.0%
University of Massachusetts	3.9%	University of California—Los Angeles	4.0%
University of Wisconsin—Madison	3.9%	University of Missouri	4.0%

Source: *Survey of Industrial Laboratory Technologies 1996.*

Table 7
Fields of Academic Science Ranked by Citation

Field of Academic Science (Rank)	Percent of Citations
Mechanical Engineering **(1)**	16.3%
Electrical Engineering **(2)**	14.0%
Computer Science **(3)**	12.3%
Chemistry **(4)**	11.0%
Chemical Engineering **(5)**	9.8%
Physics **(6)**	8.8%
Other Engineering [a] **(7)**	8.7%
Mathematics & Statistics **(8)**	7.6%
Other Physical Sciences [b] **(9)**	2.8%
Biology **(10)**	2.6%
Medicine **(11)**	1.9%
Aeronautical Engineering **(12)**	1.4%
Civil Engineering **(13)**	1.2%
Agriculture **(14)**	0.8%
Earth Sciences **(15)**	0.6%
Atmospheric Sciences **(16)**	0.4%

Source: *Survey of Industrial Laboratory Technologies 1996***.** Notes. [a] Other Engineering includes materials science, industrial, biomedical, and safety engineering. [b] Other Physical Sciences include studies that combine Physics and Chemistry with other disciplines.

Table 8
The Top Five Most Cited Academic Fields, by Citing Industry

Field of Academic Science (*Industry*, Overall Rank)	**Percent of Citations By Industry**	**Field of Academic Science** (*Industry*, Overall Rank)	**Percent of Citations By Industry**
Chemicals (SIC 28, except SIC 283)		**Computers & Office Equipment (SIC 357)**	
Chemical Engineering (***1***,**5**)	19.2%	Electrical Engineering (***1***,**2**)	21.0%
Chemistry (***2***,**4**)	16.7%	Computer Science (***2***,**3**)	17.3%
Mechanical Engineering (***3***,**1**)	11.5%	Mechanical Engineering (***3***,**1**)	14.8%
Computer Science (***4***,**3**)	9.6%	Mathematics & Statistics (***4.5***,**8**)	12.4%
Mathematics & Statistics (***5***,**8**)	7.7%	Physics (***4.5***,**6**)	12.4%
Pharmaceuticals & Biotechnology (SIC 283)		**Electrical Equipment (SIC 36)**	
Biology (***1.5***,**10**)	16.9%	Electrical Engineering (***1***,**2**)	19.8%
Chemistry (***1.5***,**4**)	16.9%	Mechanical Engineering (***2***,**1**)	16.9%
Medicine (***3***,**11**)	15.7%	Computer Science (***3***,**3**)	12.9%
Chemical Engineering (***4***,**5**)	10.1%	Other Engineering (***4***,**7**)	11.3%
Mechanical Engineering (***5***,**1**)	9.0%	Physics (***5***,**6**)	10.5%
Machinery (SIC 35, except SIC 357)		**Motor Vehicles (SIC 371)**	
Mechanical Engineering (***1***,**1**)	21.2%	Mechanical Engineering (***1***,**1**)	20.9%
Computer Science (***2***,**3**)	12.8%	Electrical Engineering (***2***,**2**)	17.2%
Chemical Engineering (***3.5***,**5**)	12.2%	Computer Science (***3***,**3**)	14.9%
Electrical Engineering (***3.5***,**2**)	12.2%	Physics (***4***,**6**)	11.2%
Other Engineering (***5***,**7**)	11.5%	Other Engineering (***5***,**7**)	9.7%

Source: *Survey of Industrial Laboratory Technologies 1996*.

Table 9
Major Industries Ranked by Citation

Cited Industry (Overall Rank)	1987 SIC Codes	Percent of Citations
Computers & Office Equipment **(1)**	357	18.14%
Search, Detection, Lab & Measuring Equipment **(2)**	381-382	17.18%
Electrical Components **(3)**	367	8.28%
Inorganic & Organic Chemicals **(4)**	281,286	5.79%
Appliances, Wiring, and Other Electrical Equipment **(5.5)**	363-364,369	5.50%
Communications Equipment **(5.5)**	366	5.50%
Prepackaged Software **(7)**	7372	3.73%
Stone, Clay & Glass **(8)**	32	3.45%
Metalworking Equipment **(9)**	354	3.35%
Electrical Industrial Apparatus **(10)**	362	2.87%
Plastics, Resins & Fibers **(11)**	282	2.39%
Nonferrous Primary Metals **(12.5)**	333-335,339	2.35%
Primary Ferrous Metals **(12.5)**	331-332	2.35%
Special & General Industrial Equipment **(14)**	355-356,359	2.30%
Computer Services **(15)**	737, except 7372	1.96%
Soaps, Paints & Other Chemicals **(16)**	284-285,289	1.65%
Ethical Drugs **(17)**	283	1.58%
Fabricated Metals **(18.5)**	34, except 348	1.44%
Rubber & Plastics **(18.5)**	30	1.44%
Optical, Surgical and Photographic Instruments **(20)**	384-387	1.39%
Audio, Video & Radio Equipment **(21.5)**	365	1.29%
Miscellaneous Manufacturing **(21.5)**	39	1.29%
Construction & Materials Handling Equipment **(23.5)**	353	0.81%
Telecommunications Services **(23.5)**	48	0.81%
Textiles and Apparel **(25)**	22-23	0.72%
Motor Vehicles **(26)**	371	0.62%
Petroleum Refining **(27)**	13,30	0.57%
Aircraft **(28.5)**	372	0.38%
Missiles & Space Vehicles **(28.5)**	376	0.38%
Electrical Transmission & Distribution Equipment **(30.5)**	361	0.19%
Ordnance **(30.5)**	348	0.19%
Engines & Turbines **(32)**	351	0.10%

Source: *Survey of Industrial Laboratory Technologies 1996*. Notes. The citations to industries are derived from citations to technologies using the methodology of Section III.C.iii. Then the individual industries are combined as needed to match the product groupings by which R&D is reported in the Census-National Science Foundation R&D Survey; and in Compustat for Computer Services, Software, and Telecommunications Services. Thus the industries reported in this table match the groupings in the R&D statistics.

Table 10
The Top Five Most Cited Industries, by Citing Industry
[SIC Codes] (*Industry Rank*, Overall Rank)

Industry(*Industry*, Overall Rank)	**Percent of Citations by Industry**	**Industry**(*Industry*, Overall Rank)	**Percent of Citations by Industry**
Chemicals (SIC 28, less SIC 283)		**Computers (SIC 357)**	
Computers & Office Equipment [357] **(*1*,1)**	18.5%	Computers & Office Equipment [357] **(*1*,1)**	27.4%
Search & Detection, Laboratory & Measuring Equipment [381-382] **(*2*,2)**	18.2%	Search & Detection, Laboratory & Measuring Equipment [381-382] **(*2*,2)**	14.7%
Inorganic & Organic Chemicals [281,286] **(*3*,4)**	9.9%	Electrical Components [367] **(*3*,3)**	10.5%
Plastics, Resins & Fibers [282] **(*4*,11)**	5.2%	Communications Equipment [366] **(*4*,5.5)**	6.8%
Electrical Components [367] **(*5*,3)**	4.4%	Appliances, Wiring, & Other Electrical Equipment [363-364,369] **(*5*,5.5)**	5.8%
Pharmaceuticals and Biotechnology (SIC 283)		**Electrical Equipment (SIC 36)**	
Search & Detection, Laboratory & Measuring Equipment [381-382] **(*1*,2)**	20.0%	Computers & Office Equipment [357] **(*1*,1)**	19.5%
Computers & Office Equipment [357] **(*2*,1)**	13.2%	Search & Detection, Laboratory & Measuring Equipment [381-382] **(*2*,2)**	14.0%
Ethical Drugs [283] **(*3.5*,17)**	11.7%	Electrical Components [367] **(*3*,3)**	10.7%
Inorganic & Organic Chemicals [281,286] **(*3.5*,4)**	11.7%	Communications Equipment [366] **(*4*,5.5)**	9.2%
Communications Equipment [366] **(*5*,5.5)**	5.4%	Appliances, Wiring, & Other Electrical Equipment [363-364,369] **(*5*,5.5)**	6.8%
Machinery (SIC 35, less SIC 357)		**Motor Vehicles (SIC 371)**	
Search & Detection, Laboratory & Measuring Equipment [381-382] **(*1*,2)**	18.1%	Search & Detection, Laboratory & Measuring Equipment [381-382] **(*1*,2)**	19.9%
Computers & Office Equipment [357] **(*2*,1)**	13.5%	Computers & Office Equipment [357] **(*2*,1)**	17.6%
Electrical Components [367] **(*5*,3)**	9.2%	Electrical Components [367] **(*3*,3)**	8.8%
Appliances, Wiring, & Other Electrical Equipment [363-364,369] **(*4.5*,5.5)**	5.9%	Appliances, Wiring, & Other Electrical Equipment [363-364,369] **(*4*,5.5)**	6.4%
Metalworking Equipment [354] **(*4.5*,9)**	5.9%	Electrical Industrial Apparatus [362] **(*5*,10)**	3.8%

Source: *Survey of Industrial Laboratory Technologies 1996*. Notes. The citations to industries are derived from citations to technologies using the methodology of Section III.C.iii.

Table 11
Shares of Laboratory R&D Spent Learning about University and Firm Research
(Asymptotic Normal Statistics in Parentheses)

Variable or Statistic	Learning Share of R&D, Universities		Learning Share of R&D, Firms	
	Eq. 11.1	Eq. 11.2	Eq. 11.3	Eq. 11.4
Estimation Method	Ordered Probit			
Year, Industry Dummies	Yes	Yes	Yes	Yes
Firm Owns Other Laboratories	0.11	0.05	0.28	0.33
(1 if yes, 0 if no)	(0.7)	(0.3)	(1.9)	(2.1)
Laboratory is Housed with Manufacturing	0.17	0.24	0.24	0.23
(1 if yes, 0 if no)	(1.1)	(1.5)	(1.7)	(1.6)
Log (Relative Wage of Engineers/R&D	-3.23	-2.38	-0.61	0.38
Cost)	(-1.9)	(-1.3)	(-0.4)	(0.2)
Supplier Fraction of Engineering Hours				3.61
on New Products				(4.2)
Intensity of Interactions with Firms				0.12
				(2.3)
Intensity of Interactions with Universities		0.40		
		(6.7)		
Log (Patents Granted)	0.09	0.07	0.09	0.09
	(4.6)	(3.1)	(5.0)	(5.0)
Log (R&D in the Rest of the Firm)	0.02	0.01	-0.02	-0.01
	(0.9)	(0.3)	(-1.1)	(-0.8)
Log (Company-Financed R&D in the	-0.01	-0.03	0.04	0.04
Rest of Industry)	(-0.6)	(-1.6)	(2.1)	(2.1)
Log (Federally Funded R&D in Closely	0.07	0.06	0.00	0.00
Affiliated Universities)	(5.2)	(4.1)	(0.2)	(0.0)
Lower Cut Point	0.26	1.00	0.22	0.86
	(0.9)	(3.2)	(0.9)	(2.8)
Middle Cut Point	1.36	2.24	1.22	1.97
	(4.8)	(6.9)	(4.6)	(6.0)
Upper Cut Point	2.11	3.09	1.97	2.77
	(6.9)	(8.6)	(7.1)	(8.2)
Log Likelihood	-245.43	-221.98	-335.88	-323.67
Likelihood Ratio χ^2	81.62	128.52	49.85	74.26

Source: *Survey of Industrial Laboratory Technologies 1996*. Notes. Number of observations is N=271.

Table 12
Two Equation, Maximum Likelihood Estimates
Shares of Laboratory R&D Spent Learning about University and Firm Research
(Asymptotic Normal Statistics in Parentheses)

Variable or Statistic	UNIVCAT Eq. 12.1	FIRMCAT Eq. 12.2	UNIVCAT Eq. 12.3	FIRMCAT Eq. 12.4
Estimation Method		Bivariate Ordered Probit		
Year, Industry Dummies	Yes	Yes	Yes	Yes
Firm Owns Other Laboratories	0.03	0.21	0.03	0.21
(1 if yes, 0 if no)	(0.2)	(1.3)	(0.2)	(1.3)
Laboratory is Housed with Manufacturing	0.23	0.17	0.23	0.17
(1 if yes, 0 if no)	(1.4)	(1.2)	(1.4)	(1.2)
Log (Relative Wage of Engineers/R&D	-2.29	-0.35	-2.27	-0.27
Cost)	(-1.3)	(-0.2)	(-1.3)	(-0.2)
Supplier Fraction of Engineering Hours on		2.73		2.71
New Products		(3.0)		(3.0)
Intensity of Interactions with Firms		0.13		0.14
		(2.3)		(2.3)
Intensity of Interactions with Universities	0.40		0.40	
	(6.4)		(6.4)	
Log (Patents Granted)	0.07	0.09	0.07	0.09
	(3.4)	(4.9)	(3.4)	(5.0)
Log (R&D in the Rest of the Firm)	0.00	-0.01	0.00	-0.01
	(0.3)	(-0.7)	(0.2)	(-0.7)
Log (Company-Financed R&D in the Rest	-0.03*	0.04*		
of Industry)	(-1.7)	(2.1)		
Log (Federally Funded R&D in Closely	0.06*	0.00*		
Affiliated Universities)	(4.1)	(0.2)		
Log (Company-Financed R&D in the Rest			-0.04**	0.03**
of Industry per Field of Technology)			(-1.9)	(1.9)
Log (Federally Funded R&D in Closely			0.06**	0.00**
Affiliated Universities per Field of Science)			(4.0)	(0.1)
Lower Cut Point	0.91	0.70	0.86	0.62
	(2.9)	(2.2)	(2.8)	(2.0)
Upper Cut Point	2.15	1.74	2.10	1.65
	(6.5)	(5.3)	(6.6)	(5.2)
Log Likelihood	-464.73		-465.28	
Likelihood Ratio χ^2	98.87		99.07	
Cross-Equation Correlation	-0.002		0.00	
	(-0.02)		(0.0)	

Source: *Survey of Industrial Laboratory Technologies 1996*. Notes. Number of observations is N=271. * Coefficients in 12.1 and 12.2 are significantly different at greater than the 1 percent level. ** Coefficients in 12.3 and 12.4 are significantly different at greater than the 1 percent level.

Table 13
Determinants of the Demand for PhDs in the Laboratory
(Asymptotic Normal Statistics in Parentheses)

Variable or Statistic	PhD Employment (1 if yes, 0 if no)		Log (Number of PhDs Employed)		Log (PhD/ Non-PhD Scientists and Engineers)	
	13.1	13.2	13.3	13.4	13.5	13.6
Estimation Method	Probit		Tobit		Weighted Least Squares (Grouped Probit)	
Year, Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Firm Owns Other Laboratories	0.16	0.18	0.48	0.37	-0.06	-0.05
(1 if yes, 0 if no)	(0.8)	(0.8)	(0.8)	(0.6)	(-0.6)	(-0.6)
Laboratory is Housed with	0.14	0.17	0.65	0.69	-0.76	-0.76
Manufacturing (1 if yes, 0 if no)	(0.7)	(0.8)	(1.1)	(1.3)	(-6.3)	(-6.1)
Intensity of Interactions with Firms		-0.06		0.01		-0.14
		(-0.8)		(0.0)		(-3.6)
Intensity of Interactions with		0.17		0.60		0.06
Universities		(2.3)		(2.8)		(1.9)
Log (Laboratory R&D Budget)	0.39	0.36	1.66	1.49	-0.11	-0.14
	(5.6)	(5.0)	(8.8)	(7.7)	(-2.6)	(-3.3)
Log (Company-Financed R&D in the	-0.02	-0.02	-0.05	-0.05	0.05	0.04
Rest of the Firm)	(-0.7)	(-0.8)	(-0.7)	(-0.8)	(5.3)	(4.9)
Log (Company-Financed R&D in the	0.05	0.05	0.19	0.16	0.03	0.04
Rest of Industry)	(2.1)	(1.9)	(2.5)	(2.1)	(3.1)	(3.5)
Log (Federally Funded R&D in	0.06	0.05	0.25	0.20	0.06	0.05
Closely Affiliated Universities)	(4.0)	(3.3)	(4.9)	(3.9)	(5.7)	(4.9)
Log Likelihood	-122.42	-119.80	-619.61	-615.61		
Likelihood Ratio χ^2	104.47	109.71	149.55	157.54		
Adjusted R^2					0.54	0.57
F Statistic					20.99	20.07
Number of Observations	277	277	277	277	187	187

Source: *Survey of Industrial Laboratory Technologies 1996*. Note. The number of zero or left censored observations in equations 13.1-13.4 is 90 out of 277, or 32.5 percent.