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ABSTRACT

This paper explores the implications of a simple model of learning and innovation by firms. In this model R&D spillovers are partly determined by firms, rather than by the given economic environment. According to this approach the full effect of spillovers on research productivity of firms exceeds the structural effect because it includes an "active learning" response of firms to new information. Furthermore, effective spillovers grow faster or slower than potential spillovers, depending on the returns to scale of production processes for learning and invention.

The empirical work is based on a sample of R&D laboratories in the chemicals, machinery, electrical equipment, and transportation equipment industries. I estimate negative binomial regressions for the number of patents as a function of academic and industrial spillover pools, learning expenditures and internal research expenditures. The findings are consistent with the view that learning expenditures transmit the effect of spillovers. I also perform tobit, ordered probit and grouped probit estimation of learning effort. I find that learning effort increases in response to industrial and academic R&D spillovers. Lastly, academic spillovers appear to have a more pervasive effect on R&D than do industrial spillovers.

Overall these results suggest a sequence of events underlying learning and innovation, with learning responding to opportunities, innovation responding to learning and own R&D, and a stream of innovations leading to the accumulation of new product introductions that ultimately are reflected in the value of enterprise.

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I. Introduction

In recent years a growing literature has studied knowledge spillovers and their effect on the performance of industrial firms. This literature finds consistent evidence for increases in patenting and productivity due to spillovers, holding firm research and development (R&D) constant[1]. In spite of these results few economists have studied how spillovers occur and what this implies about the behavior and performance of firms[2]. And yet firms decide how much to learn from external R&D and how much knowledge spills over, just as they decide the extent of their involvement in many other activities, including investment, advertising and diversification. As a result, exogenous spillovers may be unimportant when compared with spillovers that firms generate by their own efforts.

This paper provides new evidence on the endogeneity of knowledge spillovers. I show that firms actively seek new information and that they increase their learning efforts when there is more to learn and thus more to be gained from learning. Furthermore, by responding to these opportunities, firms amplify the effects of spillovers on their patenting and innovation. This "*magnification of spillovers effect*" is later transmitted to process and product innovation, to profits, and finally to general economic growth as the results of learning and internal research spread from enterprise to enterprise[3]. According to this description of the learning process, spillovers affect the firm and economy through a sequence of events. Learning effort increases first in response to knowledge spillovers. Later on learning and internal research enlarge the flow of innovation. Over time profits increase in such a way that the short run effect of innovation on profits is small, though the long run effect is substantial. Current innovation contributes little to current profits, because most of the firm's products date from earlier years, so that profits are determined by the stock of innovation and by market forces.

By design R&D laboratories are centers of innovation within their firms[4]. Accordingly, section II builds a simple model to describe the behavior of industrial R&D laboratories, and to guide the empirical work. The key

[1] Griliches (1979) introduces the cosine measure of spillovers used in much subsequent research, while Griliches (1991) is a history of spillover research. Mansfield (1991) discusses the effect of academic research on the speed of industrial research, which complements the work of Mansfield, et al. (1977) on the high rate of return to industrial research. See also Jaffe (1986), Adams (1990), Adams and Jaffe (1996), and Adams (1999) for more on academic and industrial spillovers.

[2] Two exceptions that I know of are Cohen and Levinthal (1989) and Sakakibara (1998). These papers focus on learning and research in non-cooperative oligopoly. Mowery (1995) provides an historical perspective on this topic.

[3] See Becker and Murphy (1992) for a related analysis of economic growth through the division of labor, which is driven by increases in the aggregate stock of knowledge.

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

assumption is that the different components of R&D are not perfect substitutes, so that innovation depends on the allocation of laboratory R&D as well as its level. As a consequence, I take a different view of the knowledge production function, one where innovation is primarily a function of laboratory learning from external R&D and internal research. Learning effort is itself a function of potential spillovers. This approach contrasts with a single stage specification that treats innovation as a function of firm R&D and spillovers. The most important implication of the new approach is that the full effect of spillovers exceeds the structural effect. The firm's indirect innovation function embodies this implication and results from substituting the optimized R&D components, which are increasing functions of the spillovers, into the original innovation function. Spillovers have primary and secondary effects in the indirect innovation function. The secondary effect results from induced learning in the laboratory that is brought about by spillovers, and is the source of the magnification effect discussed above.

Section III describes the database. This section also spells out definitions of learning, internal research, and spillovers of academic and industrial R&D. Most of the discussion concerns a recent survey of R&D laboratories in the chemicals, machinery, electrical equipment, and transportation equipment industries. The survey was designed to quantify learning, internal research, spillovers, and output of the laboratories. It serves as the principal data source for this paper. Section III concludes by discussing data on academic R&D, industrial R&D, and patents of parent firms that supplements the survey evidence.

Section IV presents the results. I find that the elasticity of patent counts with respect to laboratory R&D is about 0.6. We shall see that this appearance of diminishing returns is partly due to the exclusion of value weights on patents. The core of the work on patents explores a decomposition of laboratory budget between learning and internal research. In the most refined estimates I find that learning accounts for about 12% of the effect of R&D. I uncover substantial evidence that learning contributes to patents, in addition to internal research and spillovers. These findings for patents suggest that learning is important for the transmission of knowledge to the firm. In addition, both learning expenditures and the fraction of laboratory workforce composed of Ph.D. researchers increase in response to potential spillovers. Learning expenditures are to an extent specific to particular spillovers. Learning about university R&D tends to be more sensitive to university spillovers, while industrial learning responds more to industry spillovers. Finally there is evidence that learning directed towards university research is more pervasive than industrial learning efforts. Spillovers of university research bring about a strong increase in general R&D spending, unlike industrial spillovers.

The empirical work concludes with an analysis of the value of new products and cost savings generated by the laboratories. I find that the elasticity of value of new products and cost savings with respect to laboratory R&D is about 1.0, suggesting that the patenting elasticity of 0.6 is downward biased because it omits value weights for the patents. In this analysis, I do not find a robust and significant effect of learning effort on values of new products and cost savings of the laboratory. I believe that this provides further support for the multi-stage nature of innovation, since cost savings and value of new products are the result of a series of innovations extending into the past.

Section V engages in a general discussion. The section compares the approach taken in this paper with related literature on innovation and growth, and fits our approach into that literature. The empirical findings of section IV are further explored in light of this comparative discussion. In particular, I quantify the magnification of spillovers by endogenous learning effort. Consistent with the approach taken here, the estimates suggest that the secondary effects of spillovers significantly add to primary effects. This is especially true of academic spillovers, whose secondary effect on the laboratory is pervasive, and about double the primary effect. Section VI concludes and discusses extensions of the research reported in this paper.

II. Analytical Framework

A. R&D Composition and the Knowledge Production Function

Consider an R&D laboratory that serves a firm or a line of business within a firm. Following Cohen and Levinthal (1989), R&D is comprised of learning about external R&D and internal research. I assume that the laboratory learns from academia, indicated by A, and industry, indicated by M. Suppressing time subscripts the laboratory R&D budget R is given by

$$R = \ell_A + \ell_M + R_F \tag{1}$$

where ℓ_A is academic learning effort, ℓ_M is industrial learning effort and R_F is internal research.

The firm has a production function that generates innovations as a function of R&D. In a practical sense one might identify innovation with patents, although with two caveats. Counts of patents leave out innovations that are not patented and they fail to take the differing importance of innovations into account. Therefore, I prefer to think of innovations more generally, perhaps weighted by their importance, though patent counts do serve as one of the measures of innovation in this paper. One common approach writes innovations n, as a function of R&D and potential spillovers:

(2) $$n = A_n R^{\alpha_R} K_A^{\alpha_A} K_M^{\alpha_M} K_F^{\alpha_F} e^u ,$$

where R is R&D, academic spillovers are K_A, industrial spillovers are K_M, the firm's stock of knowledge is K_F and u is a random error term[5]. This is the "exogenous spillovers" view of innovation.

This paper departs from (2) by writing innovation as a function of learning expenditures and internal research. The learning components of R&D are the primary transmitters of spillovers, while internal research brings the firm's stock of knowledge to bear on innovation. Therefore, innovations are produced according to

(3) $$n = B_n \ell_A^{\beta_A} \ell_M^{\beta_M} R_F^{\beta_F} e^v ,$$

where B_n stands for neutral efficiency and v is random error in innovation. Note that small positive numbers increment the R&D components, so that the firm can innovate, even though it spends nothing on one or more of the learning components. The exponents β_i, while constant from the firm's point of view, exhibit gradual change as spillovers and the firm's stock of knowledge increase. Variations in applicable spillovers and past research at individual laboratories, as well as their growth, drive the β_i and therefore learning and internal research. Compared with (2), equation (3) depends more on the allocation of R&D, and less on external knowledge. Although B_n may still be a function of spillovers, much of the effect of knowledge disappears when ℓ_A, ℓ_M, and R_F equal zero. To take the possibility of exogenous spillovers into account, I write

(4) $$B_n = D_n K_A^{\delta_A} K_M^{\delta_M} K_F^{\delta_F} .$$

Equation (4) specifies the exogenous contribution of spillovers to innovation[6]. The rest of (3), apart from B_n, specifies the endogenous component.

Spillovers increase learning effort, but learning could increase selectively. Thus academic spillovers may increase the particular returns to learning about academic R&D, industrial spillovers may increase the returns to industrial learning, while the firm's knowledge drives internal research. In the purest case, β_A increases with the academic spillover K_A, β_M increases with the industrial spillover K_M, and β_F increases with K_F, the firm's stock of knowledge.

[5] For example, several studies in Griliches, ed. (1984) express this view of patenting.
[6] Audretsch and Stephan (1996) and Zucker, Darby, and Brewer (1998) discuss mobility of academic scientists to industry. Some of this mobility could lead to unintended and exogenous spillovers that contribute to (4), while some is fully intended and part of (3). Klette (1996) introduces complementarity between past industrial research of the firm and current research productivity of the firm, which figures in (3) and (4).

In this case, spillovers and the firm's knowledge increase the returns to scale to innovation; but as long as the returns to scale to innovation are diminishing in (3), so that $\sum_i b_i \leq 1.0$, there are limits to this contribution. This suggests that spillovers could *reduce* the other exponents of (3). For example, academic spillovers could reduce β_M and β_F while increasing β_A.

The pair of equations, (3) and (4), comprise the "endogenous spillovers" view of patenting. Section IV reports estimates of the two models, comprised of (2) and (3)-(4). According to the estimates (3)-(4) dominates the exogenous model (2) by a wide margin. The allocation of firm R&D between learning and internal research has incremental ability to explain patents. As a result, and in an immediate sense, spillovers are less important to innovation. And yet indirectly they are more important, through the stimulus they provide to R&D effort. Section IV goes on to estimate equations for learning and internal research as functions of spillovers, the firm's R&D history, firm size and other variables. In these equations spillovers are important determinants of learning expenditures. But before I explore the determinants of the various R&D components, the nature of their dependence on the firm's environment and past history must be specified.

B. Vintage Product Model of the R&D Firm

A simple model illustrates the determinants of learning and internal research as well as the events underlying innovation, cost savings, and the revenues from new products. Clearly, more than one model is able to link learning and internal research to innovation, and ultimately, to link innovation to future profits. The model that I use represents a way to express these connections, one that I believe is correct in broad outline.

The firm produces different vintages of goods in any period t. These goods were new product introductions at various times in the past, and they reflect the firm's know-how at each period of introduction, since new and improved models are later introductions. Products are assumed to have a finite life of L years, reflecting obsolescence from product improvements. The assumption that products disappear after L years limits the number of vintages that are produced in a given year and helps to limit total profits.

Consider total profits in period t. These are written as $\Pi^*(t)$, where the asterisk represents maximization over output, and therefore "indirect" profits. Total profits are the sum over τ of profits $\Pi^*_\tau(t)$ from product introductions in year τ, where $t \geq \tau \geq t-L$, minus R&D in the current period, R (t):

(5) $$\Pi^*(t) = \sum_{t=v-L}^{t} \Pi_t^*(t) - R(t)\,.$$

I assume that more recent goods embody higher quality because the firm’s knowledge grows over time. Quality reflects the firm’s innovations, including patents, at the time of introduction.

The firm chooses the level and composition of R&D to maximize discounted present value PV,

(6) $$PV = \sum_{t=0}^{\infty} (1+r)^{-t}\, \Pi^*(t)\,.$$

C. Choice between Learning and Internal Research

Now substitute (1) and (3)-(5) into (6) and maximize over the components of R&D. Allowing for corner solutions the first order conditions at time t satisfy

(7) $$\begin{aligned} \frac{\partial PV}{\partial \ell_A(t)} &= MB_n(t) \bullet \frac{b_A n(t)}{\ell_A(t)} - 1 \le 0 \\ \frac{\partial PV}{\partial \ell_M(t)} &= MB_n(t) \bullet \frac{b_M n(t)}{\ell_M(t)} - 1 \le 0 \quad, \\ \frac{\partial PV}{\partial R_F(t)} &= MB_n(t) \bullet \frac{b_F n(t)}{R_F(t)} - 1 \le 0 \end{aligned}$$

where $MB_n(t)$ is the discounted present value, or marginal benefit of an innovation. Marginal benefit is multiplied by ratios that are marginal products of the R&D components, all based on the innovation production function (3).

Not all laboratories engage in deliberate learning, but consider one that does. To a first approximation I assume that optimal learning and internal research are the following functions of spillovers, the firm’s stock of knowledge, and the marginal benefit of a patent. Suppressing time subscripts these are

(8) $$\begin{aligned} \ell_A &= K_A^{g_{AA}} K_M^{g_{AM}} K_F^{g_{AF}} MB_n^{g_{An}} e^{w_A} \\ \ell_M &= K_A^{g_{MA}} K_M^{g_{MM}} K_F^{g_{MF}} MB_n^{g_{Mn}} e^{w_M} \quad, \\ R_F &= K_A^{g_{FA}} K_M^{g_{FM}} K_F^{g_{FF}} MB_n^{g_{Fn}} e^{w_F} \end{aligned}$$

where w_A, w_M, and w_F are error terms. These are due to errors in variables, errors in functional form, omitted variables, and the like. In the empirical work I allow for corner solutions in (8) using tobit analysis.

The empirical work concentrates on the explanation of patents, which are one observable part of innovation, but also I explore the determinants of learning and internal research. It follows that (3) and (8) are at the heart of the empirical work.

D. Behavior of Learning, Internal Research, and Innovation

Several implications follow from (8). Learning and internal research are generally increasing functions of the spillovers, since knowledge raises the productivity of R&D. Firm size raises the marginal benefit of innovation and R&D as one might expect. Furthermore, information technology that raises at least one of the exponents of (8) increases effective spillovers because learning expenditure increases, holding constant potential spillovers.

Academic spillovers may increase academic learning effort as compared to industrial learning effort. In terms of (8), this occurs when β_{AA} increases relative to β_{MA}. Conversely, industrial spillovers increase industrial learning effort relative to academic if β_{MM} increases relative to β_{AM}.

Reduced form effects of spillovers and the firm's stock of knowledge exceed structural effects, since learning and internal research respond to learning opportunities, causing effective spillovers to rise more than potential spillovers. All this shows in the *indirect innovation function*, the result of substituting (4) and (8) into (3):

(9) $$n^* = D_n\, K_A^{\delta_A + \sum_i \beta_i \gamma_{iA}}\, K_M^{\delta_M + \sum_i \beta_i \gamma_{iM}}\, K_F^{\delta_F + \sum_i \beta_i \gamma_{iF}}\, MB_n^{\sum_i \beta_i \gamma_{in}}\, e^{v + \sum_i \omega_i}$$

Spillovers have "primary" effects that are caught by the δ_i terms in the exponents, and "secondary" effects that show up as remainder terms. As a result of these secondary effects, spillovers tend to be more powerful in (9) than (3). This follows from the fact that (9) approximates a maximum value function. A standard property of such functions is that state variables have larger effects than in the original functions, if the controls are increasing functions of the states[7]. In (9), the state variables are spillovers and the controls are R&D components that increase with spillovers.

Thus far I have assumed that external research is complementary to internal research; a different approach emphasizes R&D partnerships rather than spillovers. According to this view, firms subcontract research or perform research for other firms[8]. By this logic, internal and external R&D could be substitutes rather than complements. The following innovation production function shows how subcontracting might work:

[7] See Dixit (1990), Chapter 5, for a lucid treatment.
[8] Conversely, R&D partnerships may exploit complementarities of R&D and follow the previous model. This is the model of "complementary capabilities" that seems to shape many R&D joint ventures. Branstetter and Sakakibara (1998) contain a useful discussion.

$$n = B_n \ell_A^{\,b_A} \ell_M^{\,b_M} \left(R_F + g\ R_E^{\,k}\right)^{b_F}. \qquad (10)$$

where R_E is R&D purchased from other firms while R_F is internal research. To avoid knife-edge solutions, I assume that $\kappa<1$, so that R_E has a diminishing effect in (10). Internal and external firm R&D are substitutes, and the firm chooses between the two based on cost. This is an analysis of R&D in the spirit of Coase (1937).

For the data used in this study external R&D is likely to be complementary with internal research. I calculate spillovers of academic R&D based on national stocks of federally funded R&D; similarly, industry spillovers are based on company-financed R&D stocks in the rest of industry. R&D substitution is a trace element within broad specifications of external R&D like the ones used in this paper.

III. Description of the Data

A. Measurement of Learning and Internal Research

The empirical work depends on a recent survey of industrial R&D laboratories. The survey quantifies learning effort and internal research, as well as potential spillovers of the laboratories[9]. I selected 600 laboratories owned by 200 firms as potential subjects for analysis. The laboratories were taken from the **Directory of American Research and Technolog**y (R.R. Bowker, 1997). Parent firms were performers of R&D and manufacturers of chemicals, machinery, electrical goods, or transportation equipment. Firms had to be (1) in Compustat and report R&D and sales in that database, and (2), had be patent assignees with matching records in the U.S. Patent Office database. These criteria allow for cross-validation of the data while focusing the sample on innovative companies.

Responses include 208 laboratory aggregates owned by 116 firms. The 208 responses account for 220 laboratories because three firms combined their responses into one, yielding a response rate of 37% (220/600). Of the 116 firms, 29 were publicly traded for less than 16 years in 1996, so that young companies form a significant part of the sample. Respondents were R&D managers with considerable knowledge of their firms who had been in industrial research an average of 17 years and with their firms for 15 years.

Tables 1 to 5 describe the data. All the data have been flagged for missing values, checked against outside sources and any errors corrected. The most important corrections involved re-scaling of dollar variables. In 25

[9] The survey instrument was refined in three stages. A former R&D manager critiqued the initial draft. After this a beta version was tested on 10 laboratories. Using their comments, we produced a final draft, and proceeded to contact the bulk of the laboratories by phone. A mass mailing was then made to all laboratories that granted permission to send the instrument.

cases I discovered reporting of monetary variables in whole dollars or in millions, even though respondents were asked to report in thousands of dollars.

Table 1 shows the distribution of firms and laboratories by industry of the parent firm. The distribution is uniform except for a smaller number of firms and laboratories in transportation equipment. This was to be expected given that a smaller number of firms were in transportation equipment than in other industries. The number of responses by industry is in fact, roughly proportional to the number of laboratories surveyed.

Table 2 reports the size characteristics of the laboratories. Consider R&D inputs: the average laboratory employed 127 scientists and engineers in 1991, of whom 19 held the Ph.D. (or MD) degree. The average R&D budget was 12 million dollars[10]. By 1996 the number of scientists was 142, the number of Ph.D. researchers was 21, and R&D was 13 million. Thus scientists, Ph.D.s, and R&D all increased by 6 to 9% over the sample period. Standard deviations appear in parentheses. These imply a positive skew of laboratory size that may be the result of cumulative processes favoring large and diverse R&D programs (Cohen and Klepper, 1992).

Now turn to R&D outputs. Two measures of patents are shown in Table 2. The first line shows patents granted in the years 1991 and 1996 as reported in the survey. Not all laboratories, especially several of the larger ones, knew their patents in these two years. The second line replaces missing patents with an estimate based on U.S. patents for the firm, laboratory location, and year. The data were downloaded from the **U.S. Patents Database** (Community of Science, 1999).

The method for obtaining the patent estimates is as follows. I begin by matching two digit zip codes to text addresses of the inventors in the patent data for a given company using the electronic zip code database of the U.S. postal service. Next I assign patents of the parent firm to the laboratory location if the two-digit zip code of inventors matches the two-digit zip code of the laboratory. Finally I assign patents to the years 1991 and 1996 according to their issue dates[11].

I believe that this is the best available way to impute the missing patents, but it is not a perfect assignment. For an example of this, consider laboratories in small states. Their inventors often live in a different two-digit zip code and state than the laboratory, and their patents are irrevocably lost according to this method.

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

[11] I am indebted to Margaret Lister Fernando for downloading the patent data and for translation of the text fields into SAS™ data sets for further analysis.

Furthermore, patents often include multiple inventors in different locations, and different laboratories in a firm may cluster in the same two-digit zip code. Both situations lead to over counts of the firm's patents. I handle the first problem by multiplying the patents by the fraction of the top four inventors on a patent who reside in the same two-digit zip code as the laboratory, although this adjustment makes little difference to the results. I handle the problem of geographic clustering of laboratories in the same firm and multiple counting of patents as follows. I catalog laboratories in the survey that are in the same firm and two-digit zip code, and I apportion the patents according to the shares of scientists and engineers that are employed in the same firm within this area.

The sample of laboratories accounts for 2,000-4,000 patents. This is a 5-10% sample of U.S. industrial patents during the middle 1990s. Using the more comprehensive figure for patents, which includes all the large laboratories in the sample, the laboratories produce one patent for every 12 scientists and engineers. Based on National Science Board (1998), Appendix Tables 3-15 and 4-4, the average for industry is one patent for every 19 scientists and engineers. Thus the sample of laboratories produces a number of patents that is above the average for their size class. But there is evidence that other R&D in the firm contributes to laboratory patents. This "virtual" R&D brings the patent to R&D ratio closer to the national average.

Table 2 shows that R&D outputs rise faster than inputs during the sample period. Mean numbers of patents granted in the survey and supplemented are 5.2 and 8.9 in 1991. The same figures are 7.7 and 12.4 in 1996. Value of sales rises from 95 million to 131 million. Thus patents and value of new products both rise by 40- 50% over the sample period, and both increase relative to R&D inputs.

Table 3 measures learning effort by the laboratories. **Direct** learning expenditures are reported fractions of budget spent on learning about spillover i (i=A, M) times laboratory R&D budget:

(11) $$\mathit{Direct\ Learning\ Expenditure}_i = \mathit{Direct\ Learning\ Fraction}_i \times \mathit{R\&D\ Budget}.$$

Examples of direct learning include travel to and attendance at meetings, expenditures on journals, books, technical reports, and on salaries of student interns and of consultants.

While concrete and easily grasped by respondents, direct expenditures underestimate learning effort. R&D laboratories learn from recently hired graduate students and they conduct internal research jointly with a study of the science and engineering literature. The joint conduct of practical research with theoretical study makes it quite hard to separate learning from internal research. **Total** learning expenditures devoted to spillover i (i=A, M) are

$$Total\ Learning\ Expenditure_i \ = \ (Direct\ Learning\ Fraction_i + Indirect\ Learning\ Fraction_i) \times R\&D\ Budget.$$

$$(12) \qquad Indirect\ Learning\ Fraction_i \ = \ F_i \times 0.2 \times \frac{Ph.D.\ scientists}{all\ scientists}$$

$$F_i = \frac{Direct\ Learning\ Fraction\ on\ i}{\sum_{i=A,M} Direct\ Learning\ Fraction\ on\ i}$$

Total expenditures are the sum of direct and indirect learning expenditures—the corresponding total budget fractions times R&D budget. I assume that indirect expenditure fractions stand in the same ratio as the direct fractions. This yields F_i as shown in the third equation of (12). The second equation estimates the indirect learning fraction by multiplying F_i by 20 percent of the fraction of scientists that hold the Ph.D. This assumes that Ph.D. scientists spend 20 percent of their time learning. Assuming a 60 hour week, Ph.D.s spend 12 hours learning about external research by reading, going to meetings, meeting with consultants, visiting research installations, and so on. On average eight of these 12 hours are spent on industrial research while four are spent on academic research. Only doctoral researchers are permitted this release time. Both assumptions are conservative, and I explore estimates assuming fractions of time spent learning of 0.4 and 0.6 besides 0.2. These results are similar to (12).

Table 3 has three panels. The top panel describes academic learning effort. The direct percent of R&D budget spent on learning about academic research rises from 0.6% in 1991 to 0.8% in 1996. Direct learning expenditures increase from 0.12 million to 0.16 million dollars, or 33%. The total percent of budget spent on academic R&D is more than twice the direct percent, 1.5% compared with 0.6%, and total learning expenditures are correspondingly larger.

The middle panel of Table 3 describes industrial learning effort. Direct percent of budget spent on learning about industrial R&D rises from 1.0% in 1991 to 1.6% by 1996. Direct industrial learning expenditures increase from 0.21 to 0.26 million dollars. The total percent of budget spent on industrial R&D rises from 1.9% to 2.8% in 1996. The two panels suggest that laboratories spend more on learning about industrial R&D than on university R&D. Table 5 shows that spillovers of industrial R&D are nine times larger than academic spillovers, suggesting that laboratories have a greater incentive to learn about industrial research.

The bottom panel of table 3 reports employment of Ph.D. scientists. Since Ph.D.s increase the capacity to learn about new developments in science and technology, Ph.D. employment signals an increase in linkages to

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
Transportation Equipment	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
Size 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 (385.2)	142.1 (421.5)
Number of Ph.D. (or MD) Scientists and Engineers	19.1 (108.3)	21.4 (99.2)
Laboratory R&D Budget (in millions of ’87 $)	12.2 (40.4)	12.9 (39.2)
R&D Outputs		
Patents Granted from the Survey	5.2 (11.5)	7.7 (18.3)
Patents Granted from the Survey, Supplemented by estimated USPTO Patents by Firm and Laboratory Location	8.9 (30.4)	12.4 (40.6)
Sales from New Products Originating in the Laboratory (in millions of ‘87 $)	94.9 (511.9)	131.0 (626.2)

Source: *Survey of Industrial Laboratory Technologies 1996*. Note: the same laboratories appear in the 1991 and 1996 calculations for each variable.

Table 3
Learning Efforts of the R&D Laboratories and Linkages to External R&D Performers (Standard Deviations in Parentheses)

Measure	Year	
	1991	**1996**
Learning Effort, Laboratory with University		
Direct Percent of Budget Spent on Learning about University R&D [a]	0.6% (1.4%)	0.8% (1.7%)
Direct Learning Expenditures on University R&D (in Millions of '87 $) [b]	0.12 (0.47)	0.16 (0.60)
Total Percent of Budget Spent on Learning about University R&D [a]	1.5% (3.2%)	1.8% (3.7%)
Total Learning Expenditures on University R&D (in millions of '87 $) [b]	0.21 (0.79)	0.27 (1.04)
Learning Effort, Laboratory with Industry		
Direct Percent of Budget Spent on Learning about Industry R&D [a]	1.0% (1.9%)	1.6% (2.2%)
Direct Learning Expenditures on Industry R&D (in millions of '87 $) [b]	0.21 (1.08)	0.26 (1.14)
Total Percent of Budget Spent on Learning about Industry R&D [a]	1.9% (3.0%)	2.8% (3.5%)
Total Learning Expenditures on Industry R&D (in millions of '87 $) [b]	0.27 (1.22)	0.37 (140)
Linkages to Industry and University		
Percent of Laboratories with Ph.D. or MD Researchers	59.0%	66.2%
Fraction of Laboratory Scientists and Engineers Holding the Ph.D. or MD	0.12 (0.17)	0.14 (0.18)

Source: *Survey of Industrial Laboratory Technologies 1996*. Note: for each variable, the same laboratories appear in the calculations for 1991 and 1996. [a] Percent of budget as estimated by the laboratory. [b] Estimated percent of budget times R&D budget estimated by the laboratory.

external R&D. Ph.D. employment as a share of laboratory workforce rose slightly, from 13% to 14%, over the sample period. The percent of laboratories that employed Ph.D. researchers increased somewhat more, from 59% to 66%. Together these findings suggest that the Ph.D. share of smaller laboratories increased over the sample period.

Table 4 combines the statistics of tables 2 and 3 for the subsample of laboratories that employ at least one Ph.D. Doctoral laboratories are larger than average: the number of scientists and R&D budget are 50% larger than in table 2, as are patenting and the value of new products. Some of this reflects industry distinctions, but most of it survives industry effects in the regressions reported below.

Not surprisingly, employment of Ph.D.s and direct learning expenditures are related to each other. To see this compare table 3 with table 4. Expenditures on learning, and especially academic learning, are larger both as a percent of budget and in dollar terms.

So far I have focused on learning expenditures, but now consider internal research. Internal research is the portion of R&D budget ostensibly *not* devoted to learning:

$$\textit{Internal Research} = \textit{R\&D Budget} - \sum_{i=A,M} \textit{Learning Expenditure}_i, \tag{13}$$

where A and M again refer to academia and industry.

B. Construction of Potential Spillovers

The empirical work focuses on innovation and learning by R&D laboratories. In support of such an investigation, the data were designed to contain citations to particular sciences, universities, and areas of technology that the R&D managers view as important. I use this information to construct the spillovers.

The academic spillover is the easiest to construct. Respondents identified up to five of 18 science and engineering fields that they regarded as most relevant to their laboratory[12]. Matching R&D expenditures by field of science are taken from the NSF-CASPAR database for the top 225 research universities ranked by size of their R&D programs. These data cover nearly all of academic R&D and span the period 1972-1995[13].

[12] Science disciplines include astronomy, chemistry, physics, other physical sciences; computer science, mathematics and statistics; atmospheric sciences, earth sciences, and oceanography; and agriculture, biology, and medicine. Engineering disciplines include aeronautical, chemical, civil, electrical, mechanical, and other engineering.

Table 4
Learning Effort and Size Of Doctoral R&D Laboratories
(Standard Deviations in Parentheses)

Characteristic	Year 1991	Year 1996
R&D Inputs		
Number of Scientists and Engineers	181.0	203.4
	(461.8)	(504.7)
Number of Ph.D. (or MD) Scientists and Engineers	28.6	32.1
	(131.6)	(120.0)
R&D Budget (in millions of '87 $)	16.8	18.4
	(48.9)	(47.7)
R&D Outputs		
Patents Granted from the Survey	7.7	11.4
	(13.6)	(21.9)
Patents Granted from the Survey, Supplemented by estimated USPTO Patents by Firm and Laboratory Location	12.8	17.5
	(37.7)	(46.7)
Sales from New Products Originating in the Lab (in millions of '87 $)	143.0	197.7
	(634.8)	(779.5)
Learning Effort, Laboratory with University		
Direct Percent of Budget Spent on University R&D	0.9%	1.2%
	(1.7%)	(2.0%)
Direct Learning Expenditures on University R&D (in Millions of '87 $)	0.18	0.24
	(0.58)	(0.73)
Total Percent of Budget Spent on University R&D	2.1%	2.7%
	(3.8%)	(4.4%)
Total Learning Expenditures on University R&D (in Millions of '87 $)	0.31	0.41
	(0.96)	(1.26)
Learning Effort, Laboratory with Industry		
Direct Percent of Budget Spent on Industry R&D	1.1%	2.0%
	(1.8%)	(2.3%)
Direct Learning Expenditures on Industry R&D (in Millions of '87 $)	0.27	0.37
	(1.28)	(1.39)
Total Percent of Budget Spent on Industry R&D	2.5%	3.9%
	(3.2%)	(3.8%)
Total Learning Expenditures on Industry R&D (in Millions of '87 $)	0.40	0.54
	(1.49)	(1.70)

Source: *Survey of Industrial Laboratory Technologies 1996*. Note: for each variable the same laboratories appear in the calculations for 1991 and 1996.

[13] For more on the university data see Adams and Griliches (1996,1998).

The academic spillover is the sum of federally funded academic R&D accumulated into stocks over a period of 17 years (the most available) for up to five sciences that managers regard as important. The choice of federally funded R&D separates university R&D from company-financed R&D in industry. This separation is important to maintain, since smaller universities depend heavily on industry support (Mansfield, 1995). I refer to this measure of academic spillovers as federally funded academic R&D.

The laboratories also report up to five universities that were most influential for their R&D. I sum federally funded 17-year R&D stocks across these universities for as many as five sciences. I call this, federally funded academic R&D in closely affiliated universities.

The industry R&D spillover is a more involved calculation that relies partly on the Census-NSF R&D survey of industrial research. The estimated spillover is the sum of company R&D stocks over 35 product groups weighted by the importance of each group to the laboratory[14]. Thus,

(14) $$R\&D\ in\ the\ Rest\ of\ Industry = \sum_j g_j \tilde{R}_j \ .$$

Here $\tilde{R}_j$ is the stock of R&D over a period of 13 years (the most available) in product j, net of parent firm R&D. The g_j are laboratory-specific, so that the industry spillover is laboratory-specific. The g_j are fractions of technologies in each SIC group that are important both to the laboratory and as sources of technology transfer. The technologies have been mapped to four digit SIC codes by **CorpTech** (Corporate Technology Information Services, 1994). Therefore, the technology codes can be aggregated to the SIC groups used in the Census-NSF R&D data.

Equation (14) requires $\tilde{R}_j$—R&D in product group j in the rest of industry. To compute $\tilde{R}_j$ I rely on Compustat to correct the Census-NSF R&D data for changing samples and falling response rates (see Adams and

[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.

Peck, 1994). The calculation of $\tilde{R}_j$ begins with the distribution of R&D across 32 product fields reported in the Census-NSF data. I sum these data over firms by product field. This yields an estimate $\overline{R}_j$ of R&D in product j. The rest of the calculation corrects errors in $\overline{R}_j$.

The Compustat extension that achieves this correction is comprised of the three equations,

$$
\begin{aligned}
\hat{R}_{ij} &= \frac{\overline{R}_j}{\overline{S}_j} \times S_{ij} \\
\tilde{R}_{ij} &= \frac{\hat{R}_{ij}}{\sum_j \hat{R}_{ij}} \times R_i. \qquad (15) \\
\tilde{R}_j &= \sum_j \tilde{R}_{ij}
\end{aligned}
$$

Definitions of the terms are

$$
\begin{aligned}
\overline{R}_j &= \textit{aggregate Census R \& D in product } j \\
\overline{S}_j &= \textit{aggregate sales in } j \textit{ from Compustat line of business data} \\
S_{ij} &= \textit{sales of firm } i \textit{ in } j \textit{ from Compustat line of business data} \\
R_i &= \textit{R \& D of company } i \textit{ from Compustat} \\
\hat{R}_{ij} &= \textit{estimated R \& D of firm } i \textit{ in product } j\textit{, not controlled to total R \& D of firm } i \\
\tilde{R}_{ij} &= \textit{estimated R \& D of firm } i \textit{ in product } j\textit{, controlled to total R \& D of firm } i \\
\tilde{R}_j &= \textit{final estimate of aggregate R \& D in } j.
\end{aligned}
$$

The first equation of (15) multiplies the aggregate R&D to sales ratio in product j by sales of firm i in that product, yielding imputed R&D, $\hat{R}_{ij}$, of the firm in product j. This assumes that the ratio of firm R&D to sales in a given product group equals the industry ratio. And yet the first stage estimates of firm R&D by product do not sum to total firm R&D.

The second equation handles the adding up problem. I multiply company R&D reported from Compustat, R_i, by the first stage *shares* of firm R&D in product j. By necessity these second stage estimates add up to total firm R&D. The third equation of (15) sums the corrected estimates across firms to reach estimated company-financed R&D by applied product, $\tilde{R}_j$. I deflate $\tilde{R}_j$ and accumulate flows into stocks over a 13-year period (the most available) using a depreciation rate of 15%. Finally I subtract 13-year stocks of parent firm R&D from $\tilde{R}_j$ to obtain R&D in the rest of industry.

In addition to R&D in the 32 product fields defined by Census, I include deflated stocks of company-financed R&D (depreciated at 15%) in prepackaged software, software services, and telecommunications services, all taken from Compustat. The Census-NSF R&D data do not cover firms in these important high technology products. Deflated R&D stocks in these three products improve the quality of the industry spillover by expanding its coverage outside manufacturing.

The result of all these calculations is (14), R&D in the rest of industry. This is the best measure of industry spillovers available to us, even though it contains sizable errors. As we have seen, the underlying Census-NSF R&D data suffer from incomplete coverage of product groups, from variable rates of sampling, and from a falling response rate over time[15].

Table 5 reports means and standard deviations of spillover variables for the laboratories. All the spillovers increase from 1991 to 1996, with industrial spillovers increasing at the most rapid rate. As expected, academic spillovers are less than industrial spillovers, and of course spillovers from closely affiliated universities are smaller than general academic spillovers. Not surprisingly, spillovers to doctoral laboratories are larger than average.

IV. Innovation, Learning, and Internal Research

Tables 6-10 report regression-style estimates that explain innovation, learning, and internal research. Tables 6 and 7 use negative binomial regression to explain numbers of patents granted to the laboratories, while tables 8 and 9 use tobit, OLS, and various probit techniques to explain learning and internal research. Table 10 concludes with the analysis of the value of new products and cost savings contributed by the laboratories.

I begin with the regression analysis of patents in tables 6 and 7. As is typically the case for count data, many of the laboratories do not patent, mean numbers of patents are close to zero, and there are large differences among the laboratories in the numbers of patents issued.

Given the differences a regression method is required that can handle over-dispersed count data. Negative binomial regression generalizes Poisson regression by allowing for over-dispersion of counts between the

[15] The interaction of the Census R&D data with Compustat R&D remedies problems of variable sampling and response in the Census data. It does this by requiring that estimated firm R&D by industry sum to total firm R&D in Compustat. This last figure is clean of response rate problems, but notice that Compustat R&D omits government-financed R&D. This is concentrated differently among industries than company-financed R&D.

Table 5
Academic and Industrial R&D Spillovers
(Standard Deviations in Parentheses)

Spillover Variable	Year 1991	Year 1996
All Laboratories		
Spillover of R&D from Closely affiliated Universities (17 year, federally funded R&D stocks in millions of '87 $)	237.1 (456.3)	290.5 (542.2)
Spillover of R&D from all Universities (17 year, federally funded R&D stocks in millions of '87 $)	8,779.3 (6,186.6)	11,075.8 (7,668.0)
Spillover of R&D from the Rest of Industry (13 year, company funded stocks in millions of '87 $)	72,687.0 (63,478.9)	97,053.7 (84,562.6)
Doctoral Laboratories		
Spillover of R&D from Closely affiliated Universities (17 year, federally funded R&D stocks in millions of '87 $)	337.6 (536.2)	412.3 (633.6)
Spillover of R&D from All Universities (17 year, federally funded R&D stocks in millions of '87 $)	9,737.4 (7,067.4)	12,267.3 (8,773.1)
Spillover of R&D from the Rest of Industry (13 year, company funded stocks in millions of '87 $)	77,062.0 (64,903.2)	102,349.5 (85,863.7)

Sources: *Survey of Industrial Laboratory Technologies 1996, NSF CASPAR database of universities, Census-NSF R&D Survey, and Compustat.* Note: for each variable the same laboratories appear in the calculations for 1991 and 1996.

observations[16]. Tests of over-dispersion support the negative binomial over the Poisson in all the regressions reported in tables 6 and 7.

The dependent variable of table 6 is patents granted to the laboratories, supplemented by estimated patents for firms and laboratories if the patent data are missing. When I use patents granted from the survey alone, the results are similar to those shown, though slightly less significant given the smaller sample. All the equations include year and industry dummies. In addition, all include two dummies that control for laboratory specialization. The first controls for specialization in testing rather than research. For laboratories primarily devoted to testing the dummy equals 1. For all other laboratories the testing dummy equals 0. As one would expect, patenting is less in laboratories whose main function is testing. The second dummy equals 1 when a laboratory is jointly housed with a manufacturing facility. Otherwise the jointly housed dummy equals 0. While negative, this variable is never significant in the patent equations. All the equations include besides a dummy coded 1 if patents are imputed for the laboratory from the U.S. Patent Office data and 0 otherwise. This variable has a positive coefficient, reflecting in part the large size of laboratories whose patents are assigned.

Finally, in some of the equations I include a third variable that captures specialization. This is the fraction of academic fields cited by respondents as important, which are outside engineering. This variable picks up science orientation of the laboratory. However, this is insignificant.

Besides the above controls I include two measures of size of the parent firm. Both are taken from Compustat. The first is the logarithm of recent sales in the firm. This is the depreciated stock of firm sales in millions of 1987 dollars over the preceding 13 years (the most available), assuming a depreciation rate of 15 percent. The second size variable is the logarithm of company-financed R&D in the rest of the firm. This is the 13-year stock of firm R&D outside the laboratory in millions of 1987 dollars assuming a depreciation rate of 15 percent.

Equations 6.1 to 6.4 of table 6 report "exogenous" spillover regressions. As in equation (2) patents are functions of laboratory R&D, firm size and R&D, and potential spillovers. Equations 6.5 to 6.8 are endogenous spillover regressions in which I divide R&D budget into learning and internal research components. Under the null

[16] Assume that the number of events conditional on λ is Poisson distributed, and that the λ parameter follows the Gamma distribution. Integration over λ yields the unconditional distribution for the number of events, and this follows the negative binomial distribution. For a derivation see Johnson and Kotz (1969). For a discussion of the application of the Poisson family of distributions to patents, see Hausman, Hall, and Griliches (1984).

hypothesis of endogenous spillovers one would expect learning expenditures to matter in addition to internal research, because they transmit spillovers to patents. Likewise, spillovers should be less significant in the endogenous specifications.

Equations 6.1 and 6.2 are the simplest specifications in the table. These include controls for year, industry, and laboratory specialization, laboratory R&D, and the two measures of firm size. Since the controls have already been explained, I concentrate on laboratory R&D and firm size. The coefficient of the logarithm of laboratory R&D is the elasticity of patents with respect to laboratory R&D in this regression method[17]. While highly significant, the point estimate is 0.6, significantly less than 1.0, indicating diminishing returns to laboratory R&D, or errors in the measurement of the importance of inventions, or perhaps, a declining propensity to patent. However the results in table 10 paint a different picture. There the elasticity of value of new products or of cost savings with respect to laboratory R&D is not significantly different from 1.0. These results suggest that the value of innovation follows constant returns to scale, and that not measuring value is the source of the problem.

I enter the logarithm of recent sales in 6.1 without R&D in the rest of the firm, and its effect on patents is positive and highly significant. But when R&D in the rest of the firm is also introduced, as in 6.2, the significance of recent sales disappears. R&D in the rest of the firm contributes to laboratory patents, probably through shared projects with other laboratories in the firm. At most, recent sales of the firm capture the effect of rest of firm R&D.

Equations 6.3 and 6.4 add the spillovers of section III to 6.1 and 6.2. Of the three, company financed R&D in the rest of industry is positive and significant, federally funded academic R&D is marginally significant, and R&D in closely affiliated universities is never significant. Adding the spillovers to the regressions lowers the coefficient on laboratory R&D slightly.

The endogenous spillover specifications consist of equations 6.5 to 6.8. Equations 6.5 and 6.6 break up laboratory R&D into direct learning expenditures (see section III) on industrial and academic R&D and the remainder of budget, or internal research. All three components of R&D budget are highly significant. The results are striking: learning expenditures assume a large proportion of the effect of patents, while own research, which

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[17] The mean of dependent variable in negative binomial regression is λ_i. This is parameterized as

$$\log \lambda_i = x_i' \beta .$$

Thus $x_{ij} = \log z_{ij}$ implies that β_{ij} is the elasticity of the dependent variable with respect to z_{ij}.

Table 6
Patents Granted
(Asymptotic Normal Statistics in Parentheses)

Variable or Statistic	Specification							
	Exogenous Spillovers				Endogenous Spillovers			
	Eq. 6.1	Eq. 6.2	Eq. 6.3	Eq.6.4	Eq. 6.5	Eq. 6.6	Eq. 6.7	Eq.6.8
Estimation Method	Negative Binomial Regression							
Year and Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lab is Primarily a Testing Facility (1 if yes, 0 if no)	-1.75 (-2.4)	-1.44 (-2.0)	-1.76 (-2.5)	-1.52 (-2.1)	-1.68 (-2.4)	-1.43 (-2.1)	-1.56 (-2.2)	-1.30 (-1.9)
Lab Housed With Manufacturing (1 if yes, 0 if no)	0.01 (0.1)	-0.02 (-0.1)	-0.04 (-0.2)	-0.06 (-0.4)	-0.03 (-0.2)	-0.08 (-0.5)	-0.01 (-0.1)	-0.09 (-0.5)
Patents Imputed (1 if yes, 0 if no)	0.63 (2.6)	0.61 (2.6)	0.56 (2.3)	0.54 (2.3)	0.79 (3.0)	0.83 (2.9)	0.78 (2.9)	0.86 (3.0)
Importance of Science Relative to Engineering (Range: 0 to 1)						-0.21 (-0.5)		-0.37 (-0.8)
Log (Recent Sales of the Firm)	0.18 (3.8)	0.04 (0.6)	0.20 (4.2)	0.08 (1.3)	0.18 (3.7)	0.05 (0.8)	0.18 (3.7)	0.05 (0.7)
Log (Company Financed R&D in the Rest of the Firm)		0.08 (3.2)		0.07 (2.6)		0.07 (2.8)		0.07 (2.8)
Log (Laboratory R&D budget)	0.60 (10.5)	0.64 (11.1)	0.55 (9.9)	0.60 (10.3)				
Log (**Direct** Learning Expenditures, Industrial R&D)					0.16 (3.5)	0.16 (3.7)		
Log (**Direct** Learning Expenditures, Academic R&D					0.11 (2.5)	0.11 (2.4)		
Log (**Direct** Internal Research)					0.31 (4.1)	0.36 (4.6)		
Log (**Total** Learning Expenditures, Industrial R&D)							0.16 (4.1)	0.16 (4.3)

Table 6
Patents Granted
(Asymptotic Normal Statistics in Parentheses)

Variable or Statistic	Specification							
	Exogenous Spillovers				Endogenous Spillovers			
	Eq. 6.1	Eq. 6.2	Eq. 6.3	Eq.6.4	Eq. 6.5	Eq. 6.6	Eq. 6.7	Eq.6.8
Log (**Total** Learning Expenditures, Academic R&D							0.10 (2.8)	0.11 (2.9)
Log (**Total** Internal Research)							0.31 (4.2)	0.35 (4.6)
Log (Company Financed R&D in the Rest of Industry)			0.06 (2.9)	0.06 (2.9)	0.05 (2.5)	0.05 (2.4)	0.05 (2.3)	0.04 (2.1)
Log (Federally funded Academic R&D)			0.37 (2.2)	0.33 (1.9)	0.24 (1.3)	0.23 (1.1)	0.20 (1.1)	0.22 (1.1)
Log (Federally funded Academic R&D in Closely Affiliated Universities)			0.003 (0.2)	0.001 (0.1)	-0.011 (-0.7)	-0.011 (-0.7)	-0.010 (-0.6)	-0.010 (-0.6)
Number of Observations	288	288	288	288	268	268	268	268
Log Likelihood	-730.3	-725.7	-721.9	-718.8	-646.2	-642.7	-644.9	-641.1

Note: data are derived from *Survey of Industrial Laboratory Technologies 1996,* the Census-NSF R&D survey, Compustat, and the NSF CASPAR database of university research. See the text for a discussion of the variables.

accounts for most of R&D budget, falls sharply. Industrial learning is the more powerful of the two learning expenditures. This result is consistent with the fact that industrial R&D is the largest spillover source. Equation 6.6 adds R&D in the rest of the firm and science orientation of the laboratory, though the latter is insignificant. As before, R&D elsewhere in the firm eliminates the effect of firm sales, indicating the importance of other R&D units in the firm to patents. Equations 6.5 and 6.6 include the spillovers. Since learning effort is held constant the spillovers are now less significant. Equations 6.7 and 6.8 replace direct learning expenditures with total learning expenditures[18]. The new measures of learning are a better fit to laboratory patents based on the log likelihood; otherwise the results are similar to 6.5 and 6.6. Consistent with this better fit the spillover constructs are still weaker. They are at best marginally significant in 6.7 and 6.8.

The large effect of learning expenditures in table 6, while consistent with the hypothesis that learning contributes to laboratory productivity, is still a cause for concern. The percent of budget contributed by each type of learning expenditure is small—on the order of 1-5% depending on the measure. And yet the elasticities of patents with respect to the learning expenditures are a third to a half of the elasticity for internal research, a much larger component of R&D budget.

Three hypotheses are candidates to explain the outsized effect of learning on patents. First, learning expenditures may capture excluded aspects of laboratory specialization or size that have little to do with learning. I am fairly sure that variables of this kind are not driving the results, because the equations include a battery of controls for laboratory specialization and size. I include testing, joint housing with manufacturing, and laboratory orientation towards science as controls for laboratory specialization. I include laboratory R&D, R&D in the rest of the firm, and firm sales as controls for size.

A second and more plausible hypothesis is that learning expenditures are underestimated in the data. There is evidence to support this hypothesis. Total learning expenditures have at least as strong an effect on patents as direct learning expenditures, even though total expenditures exceed direct expenditures. As I increase the fraction of time spent learning by Ph.D. researchers in (14) from 0.2 to 0.4 or 0.6 the results stay about the same. This suggests that I underestimate *informal* learning expenditures. Table 8 provides further evidence on this point. The table shows that internal research as well as learning responds to spillovers, implying that learning activity permeates

[18] Compare (11) and (12): these define, respectively, direct and total learning expenditures.

R&D budget. The difficulty of separating learning from internal research occurs for a good reason, the inherent joint-ness of the two activities.

A third hypothesis I believe also has validity. Since learning expenditures are products of the fractions spent on learning and R&D budget, these expenditures may simply pick up the effect of R&D budget. To examine this hypothesis I introduce logarithms of *fractions* of budget spent on learning in the patent equations, which are independent of the logarithm of laboratory R&D budget. This is done in Table 7. Equations 7.1 and 7.3 introduce direct and total *fractions* of budget spent on learning about industrial and academic R&D. The learning fractions are highly significant in both equations. The industrial learning fraction remains the more potent of the two, consistent with the larger size of industrial spillovers. Notice also that the effect of R&D budget declines from about 0.6 in 6.1 to 6.4 of table 6, to 0.53 in 7.1 and 7.2. This is a drop of 0.07, or 12 percent of the effect of laboratory budget. Turning the result the other way, learning activities seem to account for about 12 percent of budget.

I conclude that learning effects are outsized in table 6 for two reasons. First, respondents underestimate learning expenditures. They ignore activities like the reading of scientific journals that are jointly carried out with internal research. They do not regard these activities as a cost of learning, though they require scarce time and are essential to invention. Second, learning *expenditures* cannot be separated from total R&D budget. However, the results in table 7 suggest that, as a fraction of budget, learning does matter for patents. As it turns out, research "not invented here" has a crucial bearing on how industry goes about the business of invention.

Also in table 7, I combine the fractions of budget spent on learning about academic and industrial R&D into a single learning fraction. Respondents may find it hard to separate the two types of learning, and one would like to test for this. The results, equations 7.2 and 7.4, produce a slightly better fit than equations 7.1 and 7.3, and the combined fraction spent learning has a positive and highly significant effect on patents. These results suggest that respondents find it a challenge to separate industrial from academic learning, though the problem does not appear to be a serious one.

Table 8 fits the various components of laboratory R&D budget to the data[19]. The logarithms of laboratory learning and internal research are treated as functions of firm sales, R&D elsewhere in the firm, and the various spillovers. The fitted equations are the log-linear approximations to laboratory R&D found in (8) of section III.

[19] I am estimating patents and R&D in a recursive system. This is because I assume that R&D precedes patents, implying that learning, and internal research, are predetermined in the patent equations.

Table 7
Patents Granted As a Function of Fractions Spent on Learning
And Laboratory R&D
(Asymptotic Normal Statistics in Parentheses)

Variable or Statistic	Eq. 7.1	Eq. 7.2	Eq. 7.3	Eq. 7.4
Estimation Method	Negative Binomial Regression			
Year, Industry, Test, Lab, Patent Imputation Dummies	Yes	Yes	Yes	Yes
Industrial and Academic Spillovers	Included	Included	Included	Included
Log (Recent Sales of the Parent Firm)	0.07 (1.1)	0.08 (1.2)	0.07 (1.1)	0.08 (1.2)
Log (R&D in the Rest of the Firm)	0.06 (2.5)	0.06 (2.4)	0.06 (2.4)	0.06 (2.5)
Log (**Direct** Learning about Industrial R&D as a fraction of Laboratory Budget)	0.21 (3.3)			
Log (**Direct** Learning about Academic R&D as a fraction of Laboratory Budget)	0.17 (2.4)			
Log (**Combined Direct** Learning as a fraction of Laboratory Budget)		0.32 (4.4)		
Log (**Total** Learning about Industrial R&D as a fraction of Laboratory Budget)			0.22 (4.0)	
Log (**Total** Learning about Academic R&D as a fraction of Laboratory Budget)			0.15 (2.7)	
Log (**Combined Total** Learning as a fraction of Laboratory Budget)				0.29 (4.7)
Log (Laboratory R&D Budget)	0.53 (8.6)	0.55 (9.3)	0.52 (8.6)	0.56 (9.5)
Number of Observations	268	268	268	268
Log Likelihood	-644.5	-643.0	-642.6	-642.0

Note: data are derived from *Survey of Industrial Laboratory Technologies 1996***,** the Census-NSF R&D survey, Compustat, and the NSF CASPAR database of universities. See the text for a discussion of the variables.

Table 8
Determinants of Learning and Internal Research Expenditures
(t-Statistics in Parentheses)

Variable or Statistic	Learning Expenditures, Industrial R&D		Learning Expenditures, Academic R&D		Internal Research Expenditures	
	Direct	**Total**	**Direct**	**Total**	**Direct**	**Total**
	Eq. 8.1	Eq. 8.2	Eq. 8.3	Eq. 8.4	Eq. 8.5	Eq. 8.6
Estimation Method	Tobit		Tobit		OLS	
Year, Industry, Test, Jointly Housed Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log (Stock of Recent Sales of the Company)	0.40 (3.3)	0.41 (3.0)	0.74 (4.3)	0.83 (4.2)	0.43 (8.2)	0.43 (8.2)
Log (Stock of R&D in the Rest of the Firm)	-0.09 (-1.7)	-0.09 (-1.4)	-0.09 (-1.2)	-0.10 (-1.1)	-0.09 (-3.9)	-0.10 (-4.0)
Log (Company Financed R&D in the Rest of Industry)	0.11 (2.3)	0.14 (2.6)	-0.01 (-0.2)	0.00 (0.1)	0.03 (1.4)	0.03 (1.3)
Log (Federally funded Academic R&D)	1.03 (2.5)	1.36 (2.9)	1.41 (2.4)	1.51 (2.2)	0.55 (3.1)	0.55 (3.1)
Log (Federally funded Academic R&D in Closely Affiliated Universities)	0.07 (2.2)	0.08 (2.2)	0.28 (5.4)	0.32 (5.3)	0.04 (2.4)	0.03 (2.4)
Number of Observations	268	268	268	268	268	268
Percent of Observations Left Censored at Zero	0.31	0.31	0.56	0.56	--	--
Root MSE	2.96	3.28	3.73	4.38	1.35	1.35
Log Likelihood	-536.6	-557.0	-404.1	-424.0	--	--
Adjusted R^2	--	--	--	--	0.36	0.36

Note: data are derived from *Survey of Industrial Laboratory Technologies 1996*, the Census-NSF RD-1 survey, Compustat, and NSF CASPAR database of universities. See the text for a discussion of the variables.

I estimate learning expenditures using tobit analysis rather than ordinary least squares, because 31 percent of the R&D laboratories report zero expenditures on learning about industrial R&D, while 56 percent report zero expenditures on learning about academic R&D. The internal research equations use ordinary least squares since this part of budget is not censored. All equations include dummy variables for year and industry. All include dummies for testing and joint housing with a manufacturing facility, though these are insignificant in table 8.

Equations 8.1-8.2 report findings for industrial learning expenditures. As throughout the table, recent sales of the firm promote learning effort, whereas R&D in the rest of the firm has no effect on learning about industrial research. This is in contrast to patents, where rest of firm R&D was the significant variable, and not sales. The difference partly reflects the dominance of incentives to perform R&D in table 8, whereas in the patent regressions of tables 6 and 7, R&D budget already captures incentives. Another difference is that R&D elsewhere in the firm has a direct bearing on outputs such as patents, but little bearing on learning effort. Turning to the spillover variables, company financed R&D elsewhere in industry stimulates industrial learning, but academic spillovers also have this effect. This is perhaps not surprising. Basic research in industry is large, about half that of universities during the 1990s[20]. Thus there is some overlap in the type of research conducted in the two sectors.

Equations 8.3-8.4 report estimates for academic learning expenditures. Qualitative patterns are similar to the results for industrial learning. The main exception is that industrial spillovers have no effect on academic learning. This is consistent with the notion that industrial learning may be specific to industrial spillovers.

Quantitative comparison of the results for industrial learning with those for academic learning requires estimates of marginal effects. In tobit analysis marginal effects are the estimated coefficients multiplied by the fraction of observations that are not censored[21]. The fraction not censored is 0.69 for industrial learning and 0.44 for academic learning. Thus, for example, the marginal effect of recent sales is only slightly greater for academic learning than industrial, 0.34 versus 0.28. Surprisingly, federally funded academic R&D has a slightly smaller effect on academic than industrial learning, about 0.64 versus 0.82. However, the marginal effect of federally funded R&D in closely affiliated universities is almost three times larger for academic learning, 0.13 versus 0.05. Overall the results suggest that industrial spillovers increase industrial learning effort more than academic. The specificity

[20] See National Science Board (1998), appendix Table 4-7, page A-125.

[21] Where β is the Tobit coefficient and $1-\Phi$ is the fraction of observations not censored, the expected marginal effect is $\beta \bullet (1-\Phi)$. Compare this result with OLS, where β is both the regression coefficient and the marginal effect. Greene (2000), Theorem 20.4, page 909 contains a proof of this result.

of academic learning effort is not as clear, perhaps because of the presence of basic research in industry. Still, academic learning responds strongly to federally funded R&D in closely affiliated universities.

It is much more important to see that the results strongly suggest that learning expenditures respond to learning opportunities, so that spillovers are endogenous. Since tables 6 and 7 indicate that learning expenditures are a determinant of patents, spillovers have a secondary effect on innovation that bolsters their primary effect. I return to this theme in section V of the paper.

Equations 8.5 and 8.6 show the estimates for internal research. Until now R&D in the rest of the firm has had no discernable effect on laboratory effort. But in these results the effect is negative and highly significant, perhaps reflecting the substitution of other units' R&D for the laboratory. Another finding is that academic spillovers increase the internal research of the laboratory. In fact, academic research pervades laboratory R&D, while industrial spillovers specifically promote industrial learning expenditures. The influence of university research is therefore strongly understated by academic learning expenditures.

Equations 8.1 to 8.4 have used learning expenditures as the dependent variable. To separate learning effort from budget I grouped the fractions of budget assigned to learning and treated them as an ordered categorical variable. The categorized learning fractions were then fitted to the data using ordered probit. To save space I do not provide a separate table, but simply state that the results generally confirm the findings using tobit analysis. The industrial spillover significantly increases the fraction of budget devoted to learning about industrial research but not the fraction devoted to academic learning. As above, academic spillovers tend to increase both academic and industrial learning fractions. Also as before, the spillover from closely affiliated universities exerts an extraordinary effect on the academic learning fraction.

Table 9 reports estimates of the determinants of Ph.D. employment. The idea is to see whether spillovers increase the fraction of laboratory workforce consisting of Ph.D. researchers, since Ph.D. scientists have a comparative advantage in learning about external research. The technique is grouped probit. The sample consists of laboratories that employ Ph.D. scientists. The dependent variable in equations 9.1 to 9.4 is the fraction of the workforce composed of Ph.D. scientists[22].

Notice that the dummy variable for joint housing with manufacturing is negative and significant in all the equations. This shows that jointly housed laboratories are oriented towards development rather than basic and

[22] For a discussion of grouped Probit see Maddala (1983), Chapter 2.

Table 9
Relative Employment of Ph.D. Scientists
(t-Statistics in Parentheses)

Variable or Statistic	Log (Ph.D. Scientists /Non-Ph.D. Scientists)			
	Eq. 9.1	Eq. 9.2	Eq. 9.3	Eq. 9.4
Estimation method	Grouped Probit			
Year, Industry Dummies	Yes	Yes	Yes	Yes
Lab Housed With Manufacturing (1 if yes, 0 if no)	-0.53 (-4.9)	-0.64 (-5.3)	-0.64 (-6.1)	-0.68 (-6.0)
Log (Lab R&D Budget)		-0.09 (-2.0)		-0.05 (-1.0)
Log (Recent Sales of the Firm)	-0.00 (-0.1)	0.03 (1.0)	-0.12 (-3.5)	-0.10 (-2.4)
Log (Company Financed R&D in the Rest of the Firm)			0.06 (5.0)	0.06 (4.6)
Log (R&D in the Rest of Industry)	0.03 (2.7)	0.03 (3.0)	0.02 (2.0)	0.02 (2.2)
Log (Federally funded Academic R&D)	0.84 (5.1)	0.84 (5.1)	0.58 (3.5)	0.59 (3.6)
Log (Federally funded Academic R&D in Closely Affiliated Universities)	0.06 (5.6)	0.06 (6.0)	0.05 (5.3)	0.05 (5.4)
Number of Observations	187	187	187	187
Root MSE	0.49	0.49	0.46	0.46
Adjusted R^2	0.53	0.54	0.59	0.59

Note: data are derived from *Survey of Industrial Laboratory Technologies 1996*, the Census-NSF R&D survey, Compustat, and the NSF CASPAR database of university research. See the text for a discussion of the variables. The dummy variable for testing is omitted because none of the Ph.D. laboratories specialize in testing.

applied research. For this reason laboratories that are jointly housed with manufacturing employ a smaller fraction of Ph.D. scientists.

The key finding of table 9 is that R&D spillovers, especially those originating in academia, are the most important drivers of Ph.D. employment. In addition, R&D in the rest of the firm increases the fraction comprised of Ph.D. researchers. This suggests that larger R&D firms carry out more skill intensive research. However, when firm R&D is held constant, as in 9.3 and 9.4, larger sales of the firm decrease the share of Ph.D. employment. Holding R&D constant, firm size seems to increase the demand for production engineering and not research.

The empirical work concludes with the analysis of data on value of new products and cost savings originating in the laboratory. The findings, shown in table 10, are different than before, and the sample more restricted. Though I find a strong effect of overall laboratory budget, the effects of learning effort and spillovers are not separately identified, and hence omitted from the table.

Our best guess is that the lack of an effect for learning and spillovers follows from the multi-stage nature by which value of new products and cost savings come about. Inevitably, data of this kind are more distant in time and space from current patents and the division of R&D within the laboratory. Most of the evidence concerns research laboratories within firms, which are usually a small part of enterprise. And yet the value of new products and cost savings are the result of applying labor, capital, and other inputs that are frequently arrayed throughout the parent firm and suppliers. As a consequence, many of the relevant inputs are difficult to identify. In addition to this, the value of new products is a stock variable composed of the value of products introduced in the past. At the very least this suggests the use of panel data on inputs, including past learning effort and internal research of the laboratory.

Table 10 contains the results. Equations 10.1 and 10.2 report OLS regressions for the logarithm of the value of new products. The logarithm of laboratory R&D is positive and significant in these equations, while R&D in the rest of the firm is insignificant. The elasticity of value of new products with respect to laboratory R&D is indistinguishable from 1.0, implying that the value of new products increases in proportion to laboratory R&D. This contrasts with the results for patents, where the patent R&D elasticity is on the order of 0.6, and significantly less than 1.0. The difference in elasticities highlights the importance of attaching values to patents. Larger laboratories seem to have more valuable patents.

Since the value of new products has a stock dimension, owing to the introduction of new products over time, I difference these data. I take the five-year difference of the value of new products in 1996 and 1991 and of

R&D in the laboratory and the rest of the firm. I estimate growth of the value of new products as a function of growth in R&D effort in the firm and laboratory. The five-year differences have two effects on the results. First, individual fixed effects of the laboratories are eliminated. And second, the data focus now on recent products as well as recent research. Equations 10.3 and 10.4 display the results for 102 laboratories that report all relevant data in both years. Laboratory R&D budget enters more weakly in differenced form, though it would be significant in a larger sample, and R&D in the rest of the firm is significant for the first time. These results are closer to the results for patents, also a flow variable, where laboratory R&D and R&D in the rest of the firm both contribute, with laboratory R&D the more important of the two.

The presentation of the findings concludes with OLS regressions explaining the logarithm of the value of cost savings created by the laboratory. Equations 10.5 and 10.6 contain the results. As held true for new products, the value of cost savings increases in proportion to laboratory R&D and the elasticity of cost savings with respect to laboratory R&D is not significantly different from 1.0. Rest of firm R&D is insignificant in 10.6. The principal message of table 10 is that R&D laboratories seem to be subject to constant returns to scale production processes for the *value* of their innovations.

V. Discussion

Let us take stock of the results and interpret them in the light of the key equations, (3), (8), and (9). To begin with, the results for patents provide support for the endogenous innovation function (3). According to the estimates in tables 6 and 7, outcomes of learning from academia and industry, as well as internal research, are recombined in the innovation function. To this extent, the results convey the spirit if not the letter of Weitzman (1998), who argues that aggregate growth proceeds by combinatorial means. As he shows, this growth eventually dominates any exponential growth process. The innovation function in this paper as well, where disparate ideas are brought together in unexpected ways, is effectively recombinant and mutually reinforcing of the different learning processes. For inside (3), ideas from multiple sources in academia and industry, as well as ideas hatched within the laboratory, effectively meet and give rise to still other ideas. With laboratories in a large number of companies so engaged all at once, the economy is a sea of recombinant growth.

Second, the results of tables 8 and 9 suggest that learning expenditures, fractions of budget disposed towards learning, and learning resources all increase in response to potential spillovers. It follows that the indirect innovation function (9) exhibits returns to scale that exceed that of the original innovation function (3). This result

Table 10
Log (Value of New Products) and Log (Value of Cost Savings)
(t-Statistics in Parentheses)

Variable or Statistic	Log (Value of New Products)		Five Year Difference in Log (Value of New Products)		Log (Value of Cost Savings)	
	Eq.10.1	Eq. 10.2	Eq. 10.3	Eq. 10.4	Eq. 10.5	Eq. 10.6
Estimation Method			OLS			
Year, Industry, Test, Jointly Housed Dummies	Yes	Yes	No	No	Yes	Yes
Log (R&D in the Rest of the Firm)		0.03 (0.6)				-0.09 (-1.5)
Log (Laboratory R&D Budget)	1.19 (8.7)	1.18 (8.4)			0.90 (4.8)	0.96 (5.0)
Five Year Difference in Log (R&D in the Rest of the Firm)				0.22 (2.8)		
Five Year Difference in Log (Laboratory R&D Budget)			0.71 (1.8)	0.82 (2.2)		
Number of Observations	216	216	102	102	158	158
Root MSE	3.06	3.07	2.06	2.00	3.31	3.30
Adjusted R^2	0.28	0.28	0.02	0.09	0.22	0.23
F Statistic	11.4	10.2	3.4	5.8	6.5	6.1

Note: data are derived from *Survey of Industrial Laboratory Technologies 1996,* the Census-NSF R&D survey, Compustat, and NSF CASPAR database of university research. See the text for a discussion of the variables.

formally resembles that of Becker and Murphy (1992) in their analysis of growth by means of specialization. However, the results differ from theirs, in that learning from disparate sources places a limit on specialization. In this sense, the results bear a closer resemblance to those of Cohen and Levinthal (1989) in their work on innovation and learning, the two faces of R&D.

I now combine the results of the different tables to obtain point estimates of the primary and secondary effects of industrial and academic spillovers. Since the tables are the first to undertake estimates of this kind, the following calculations should be viewed as tentative and illustrative in nature. The measurement of secondary effects will allow us to gain a quantitative reading on the magnification of spillovers by the response of learning effort to learning opportunities represented by the spillovers. Recall that these effects are combined in the exponents of the indirect innovation function (9), which is reproduced below for convenience:

$$n^* = D_n K_M^{d_M + \sum_i b_i g_{iM}} \; K_A^{d_A + \sum_i b_i g_{iA}} K_F^{d_F + \sum_i b_i g_{iF}} MB_n^{\sum_i b_i g_{in}} e^{v + \sum_i w_i} \tag{9}$$

Using the results of table 6 and 8, the primary effect of industrial spillovers is $d_M = 0.05$. The secondary effect is

$$b_M g_{MM} + b_A g_{AM} + b_F g_{FM} = 0.16 \times 0.09 + 0.11 \times 0.00 + 0.31 \times 0.03 = 0.02 \,.$$

These results multiply the g_{iM} coefficients by fractions of observations that are not censored (see table 8). In any event, the contribution of industrial spillovers is largely the primary effect.

I now repeat this exercise for academic spillovers. Remember that these include federally funded R&D both in general and for closely affiliated universities of the laboratories. The primary effect is $d_A = 0.22$. The secondary effect is

$$b_M g_{MA} + b_A g_{AA} + b_F g_{FA} = 0.16 \times 0.89 + 0.11 \times 0.77 + 0.31 \times 0.69 = 0.43 \,.$$

In quantifying these secondary effects I once again multiply the g_{iA} coefficients by fractions of observations not censored (see table 8) to obtain marginal effects. The results suggest that the secondary contribution is more important for academic spillovers. More important, they show that secondary effects of spillovers are comparable with the primary effects. Thus the returns to scale to innovation are enhanced by the endogeneity of knowledge spillovers.

One further note concerns the comparison of the two spillover effects. The above calculations suggest that the academic spillover effect is about 0.65, about nine times larger than the industrial effect of 0.07. However, these estimates are elasticities of patents with respect to one-percent increases in each type of spillover. Given that the industrial spillover is on average nine times larger than the academic spillover (see table 5), per dollar, the two effects are about equal at the mean of the sample.

Finally, a complete sequential story that accounts for the process by which firms discover new products and processes is desirable, but out of reach at this time. The stages by which research progresses within the firm cannot be traced, since the data are not sufficient to link the value of new products and of cost savings backward to the myriad of learning activities as described by repeated access to spillovers. Instead laboratory R&D budget, which demonstrates a high degree of serial correlation, is the dominant effect on the value-based measures of innovation reported in table 10[23]. This part of the analysis is clearly in need of further improvement. At the very least this will require a panel of data on firms that is of a very detailed nature.

VI. Conclusion

This paper has presented theory and evidence concerning endogenous R&D spillovers. While more can be done on this topic, I hazard a few conclusions from the work to date. First, academic research does seem to have a profound significance for the rate of innovation and for the amount of learning carried out by the laboratory. Consistent with this point of view, an increasing fraction of the laboratories in the sample have included doctoral scientists and engineers in their research programs over time. Second, the evidence is consistent with the idea that spillovers, especially academic spillovers, are endogenous. I find that learning expenditures increase in response to spillovers. Third, the results imply that learning is somewhat specific, in that learning aimed at a particular spillover seems to respond intensively to that source. But I also find that academic spillovers exert a broader impact on laboratory R&D than industrial spillovers. Fourth, the findings are supportive of a sequential view of learning and innovation, in which spillovers and firm R&D lead to increased learning, learning and own research lead to innovation, and a stream of innovation supports the cumulative introduction of new products over time. Fifth, not all laboratories have the same orientation and not all have the same demand for learning about external R&D. Part of this has to do with the particular industry and with presumed opportunities for learning, but part has to do with a mission of the laboratory that is skewed towards testing rather than research, perhaps because other, larger facilities within the same firm shoulder the main load of research.

[23] See Adams and Jaffe (1996) for evidence on the high degree of serial correlation in R&D data at the firm and divisional level.

References

Adams, James D., “Fundamental Stocks of Knowledge and Productivity Growth,” **Journal of Political Economy** (August 1990): 673-702.

_______________, “The Structure of Firm R&D, the Factor Intensity of Production, and Skill Bias,” **The Review of Economics and Statistics** 81 (August 1999): 499-510.

_______________, and Adam B. Jaffe, “Bounding the Effects of R&D: An Investigation Using Matched Firm and Establishment Data,” **RAND Journal of Economics** 27 (Winter 1996): 700-721.

_______________, and Suzanne Peck, “A Guide to R&D Data at the Center for Economic Studies,” U.S. Bureau of the Census, Center for Economic Studies Working Paper 94-9, 1994.

_______________, and Zvi Griliches, “Measuring Science: An Exploration,” **Proceedings of the National Academy of Sciences** 93 (November 1996): 12664-12670.

________________________________, “Research Productivity in a System of Universities,” **Annals of INSEE** 49/50 (October 1998): 127-162.

Audretsch, David A., and Paula E. Stephan, “Company-Scientist Locational Links: The Case of Biotechnology,” **American Economic Review** 86 (June 1996): 641-652.

Becker, Gary S., and Kevin M. Murphy, “The Division of Labor, Coordination Costs, and Specialization,” **Quarterly Journal of Economics** 107 (August 1992): 1137-1160.

Branstetter, Lee, and Mariko Sakakibara, “Japanese Research Consortia: A Microeconometric Analysis of Industrial Policy,” **The Journal of Industrial Economics** 16 (June 1998): 207-234.

Coase, Ronald H., “The Limits of the Firm,” **Economica** 4 (November 1937): 386-405.

Cohen, Wesley M., and Daniel A. Levinthal, “Innovation and Learning: The Two Faces of R&D,” **The Economic Journal** 99 (September 1989): 569-596.

________________, and Steven Klepper, “The Anatomy of Industry R&D Intensity Distributions,” **American Economic Review** 82 (September 1992): 773-799.

CorpTech: Corporate Technology Database, Woburn, Massachusetts, Corporate Technology Information Services, Inc., 1994.

Directory of American Research and Technology, 31st Edition, New Providence, New Jersey: R.R. Bowker, Inc., 1997.

Dixit, Avinash K., **Optimization in Economic Theory**, Oxford, UK, Oxford University Press, 1990.

Greene, William H., **Econometric Analysis**, 4th ed., Upper Saddle River, New Jersey, Prentice-Hall, 2000.

Griliches, Zvi, "Issues in Addressing the Contribution of Research and Development to Productivity Growth," **Bell Journal of Economics** 10 (1979): 92-116.

____________, Editor, **R&D, Patents, and Productivity**, Chicago, University of Chicago Press for NBER, 1984.

____________, "The Search for R&D Spillovers," **Scandinavian Journal of Economics** 94 (Supplement 1991): 29-47.

Hausman, Jerry, Bronwyn Hall, and Zvi Griliches, "Economic Models for Count Data with an Application to the Patents-R&D Relationship," **Econometrica** 52 (July 1984): 909-938.

Hicks, Diana, "Published Papers, Tacit Competencies, and Corporate Management of the Public/Private Character of Knowledge," in **Innovation in Complex Systems Industries**, Oxford, UK: Oxford University Press, 1995.

Hounshell, David A., and John Kenley Smith, **Science and Corporate Strategy: DuPont R&D, 1902-1980**, Cambridge, UK: Cambridge University Press, 1988.

Jaffe, Adam B., "Technological Opportunity and Spillovers of R&D," **American Economic Review** 76 (December 1986): 984-1001.

Johnson, Norman L., and Samuel Kotz, **Distributions in Statistics: Discrete Distributions**, Boston: Houghton-Mifflin, 1969.

Klette, Tor J., "R&D, Scope Economies, and Plant Performance," **RAND Journal of Economics** 27 (1996): 502-522.

Maddala, G. S., **Limited-Dependent and Qualitative Variables in Econometrics**, Cambridge, U.K.: Cambridge University Press, 1983.

Mansfield, Edwin, "Academic Research and Industrial Innovation," **Research Policy** 20 (1991): 1-12.

______________, "Academic Research Underlying Industrial Innovations: Sources, Characteristics, and Financing,"

The Review of Economics and Statistics 77 (February 1995): 55-65.

Mansfield, Edwin, John Rapoport, Anthony Romeo, Samuel Wagner, and George Beardsley, “Social and Private Rates of Return from Industrial Innovations,” **Quarterly Journal of Economics** 91 (May 1977): 221-240.

Mowery, David C., “The Boundaries of the Firm in R&D,” in N. R. Lamoureaux and D. M. G. Raff, editors, **Coordination and Information: Historical Perspectives on the Organization of Enterprise**. Chicago: University of Chicago Press for NBER, 1995.

National Science Board, **Science and Engineering Indicators 1998**, Washington D.C., U.S. Government Printing Office, 1998.

Sakakibara, Mariko, “Knowledge Sharing in Cooperative Research and Development,” working paper, Anderson Graduate School of Management, UCLA, September 1998.

U.S. Patents Database, Baltimore, Maryland: Community of Science, Inc., 1999.

Weitzman, Martin L., “Recombinant Growth,” **Quarterly Journal of Economics** 113 (May 1998): 331-360.

Zucker, Lynn G., Michael R. Darby, and Marilynn B. Brewer, “Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises,” **American Economic Review** 88 (March 1998): 290-306.