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COMPARATIVE LOCALIZATION OF ACADEMIC AND INDUSTRIAL SPILLOVERS

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Comparative Localization of Academic and Industrial Spillovers
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ABSTRACT

This paper studies localization of academic and industrial knowledge spillovers. Using data on U.S. Research and Development laboratories, that quantify spatial aspects of learning about universities and firms as well as their locations, I find that academic spillovers are more localized than industrial spillovers. I also find that localization is increased by nearby stocks of R&D, but reduced by laboratory and firm size. These results on localized academic spillovers reflect open science and the industry-university cooperative movement, which encourage firms to work with local universities, so that localization coincides with the public goods nature of science. This situation contrasts with relations to other firms, where contractual arrangements are needed to access proprietary information, often at a considerable distance.

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I. Introduction

An expanding literature in economic geography studies the spatial concentration of production and innovation and the role that such localization plays in urban and regional growth. Geographic limits on knowledge spillovers, where these are defined as flows of ideas between agents at less than the original cost (Griliches, 1992), are one factor that may cause localization in innovation and output. According to this hypothesis spillovers are at least temporarily localized or bounded by geography. As a result nearby firms benefit disproportionately from the spillovers, giving rise to knowledge-based agglomeration economies that contribute to regional growth (Feldman, 1999). As with agglomeration economies in general (Jacobs, 1969 and Mills, 1972) geographic limits on knowledge spillovers become a policy issue. If localization of spillovers matters, then growth depends on aspects of urbanization that are beyond the decision-making abilities of individual firms and industries.

This paper characterizes the localization of spillovers to firms. It partly does so by describing the spatial dimension of firms' learning activities, which include consultation, travel to conferences, expenditures on books and journals, and the like. Electronic communication is not the same as contact with industrial inventors and university scientists. But traveling further to consult, collaborate, or outsource is costly. These considerations imply that geographic limits to learning and spillovers are flexible and respond to incentives, so that localization is endogenous to the firm (Adams, 2000).

The empirical results are based on new evidence from a sample of Research and Development (R&D) laboratories owned by U.S. manufacturing firms[1]. R&D laboratories engage in learning and innovation and are an interface between firms and external R&D performers. An

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

advantage of the data is that localization of learning and spillovers from universities and firms can be compared net of treatment effects for the same laboratories.

Findings from the investigation are the following. First, university spillovers and learning about universities are significantly more localized than industrial spillovers and learning about industry. Second, R&D of cited universities is localized compared with other university R&D. Third, distances between cited universities and citing R&D laboratories are less than distances to cited firms. Together these findings suggest that firms go to local universities for advice, research, and students. In contrast industrial partnerships take place over a greater distance and occur selectively, as a result of specific personnel movements and collaborative ventures. Since academic research is usually regarded as more of a public good than firm research, this poses a puzzle. The solution requires one to see that localization of university science represents ease of dissemination and its public goods nature.

The fourth finding is that the stock of federal university R&D near the firm drives localization of academic spillovers, and likewise for industrial spillovers. Fifth, the evidence implies localization of spillovers on laboratory patents, with university spillovers again more localized. Sixth, spillovers are weaker and still more localized for new products. These findings suggest that spillovers occur during the early phase of research. Later, development uses mostly internal research, consistent with the rising value of secrecy as commercialization draws near.

The rest of the paper consists of five parts. Section II reviews the literature on localized production, innovation, and knowledge spillovers. Section III describes new data on industrial R&D laboratories, whose tasks include learning from academia and industry. Section IV presents descriptive findings on localization. Section V reports regression-style findings on localization of laboratory learning from academia and industry, as well as localization effects on laboratory patents and innovations. Section VI discusses the findings, draws some implications for policy, and concludes the paper. A brief appendix explains the calculations in the text.

II. Review of the Localization Literature

The localization literature is partly concerned with the causes behind growth of firms, cities, and regions. A second part focuses on regional innovation as a function of regional knowledge-based inputs. A final strand of the literature searches for evidence of knowledge spillovers in the form of patent citations, movements of scientists and engineers, and R&D expenditures. Below is a partial review of findings in these areas.

Zucker, Darby and Brewer (1998) study firm formation in biotechnology, an industry that is closely linked to fundamental molecular biology. Their analysis of biotechnology startups in 183 regions shows that top university researchers in a region contribute to firm formation even after controlling for regional factors such as skill-intensity, supply of venture capital, and growth. Using data on U.S. regions, Swann and Prevezer (1996) compare firm formation and growth in computing and biotechnology. They find that feedback across sectors of computing (such as hardware, software and peripherals) contributes to entry in any one sector. The same pattern does not hold for biotechnology. While computing includes complementary sectors, biotechnology consists of distinct applications. Unlike computing, however, Swann and Prevezer find that entry in biotechnology relies on regional universities, consistent with the findings of Zucker, Darby and Brewer (1998). The results of Swann and Prevezer suggest that knowledge spillovers are localized, but are industrial in origin for computing, academic in origin for biotechnology. Harhoff (1999) analyzes firm formation in regions of West Germany. His study contrasts entry into high technology industries with that of other industries, finding that the regional diversity of industries and scientific personnel are important mainly for high technology entry. Coupled with his finding that regional specialization matters less in high technology, the Harhoff study finds that localized cross-industry spillovers drive high technology growth.

Glaeser, Kallal, Scheinkman and Shleifer (1992) study growth in cities. Their results are based on a cross section of roughly 1,000 U.S. city-industries whose wage and employment growth is measured between 1956 and 1987. The heart of their work compares the effects of industrial specialization, competition and diversity on city growth. While competition and diversity contribute to growth, specialization does not. This suggests, like Harhoff (1999), that localized cross-industry spillovers ("Jacobs externalities") are a key to growth. They argue that regions specialize for other reasons: labor market pooling of specialized skills and the reduced expense of specialized intermediate inputs, as pointed out by Marshall (1920) and recently re-emphasized by Krugman (1991).

A second strand of literature explains the workings of regional innovation. Jaffe (1989) examines the interaction between corporate patenting and R&D and university R&D in a panel of U.S. states. His main findings are that geographic coincidence between universities and industrial laboratories contributes to corporate patents in addition to the main effect of university research. Perhaps more important, university R&D stimulates corporate R&D and indirectly corporate patents. Audretsch and Feldman (1996) explore the determinants of regional concentration of innovation in 163 manufacturing industries. Using a cross section of U.S. innovation counts in 1982 classified by location and industry, they find that Gini coefficients for the 163 industries, a measure of concentration, increase as a function of skilled labor requirements and university research that is relevant to firms, where relevance is based on the Yale Survey of R&D Managers. Both Jaffe and Audretsch and Feldman suggest the importance of local university research to industrial innovation in a region.

Finally, the literature seeks to measure localized spillovers. Jaffe, Trajtenberg, and Henderson (1993) examine patent citations to nearby and distant industrial firms. Their measure of localization is the excess frequency of citations to patents of nearby firms over and above a sample of control patents in the same patent class and year of issue. They find that the excess frequency of localized citation is significant. They also find that the excess frequency tends to disappear as patents age, implying that localization of knowledge spillovers in industrial patents fades over time with diffusion of ideas. This finding is consistent with Mansfield, Schwartz and Wagner (1981) and Mansfield (1985) on imitation and the rate at which industrial technology leaks out.

Audretsch and Stephan (1996) explore localized employment of university scientists working for biotechnology firms that were Initial Public Offerings (IPOs) in the early 1990s. Their data are unusually precise. Linkages of firms with scientists, locations of the firms and scientists, and the roles served by scientists—including founder, scientific advisor, or consultant—all these are known. Audretsch and Stephan find that scientists are more likely to be from the same region as firms if they are founders, chairs of scientific advisory boards, or Nobel Prize winners. But older scientists are not as localized and are probably consultants. These results suggest that *time-intensity* of university-firm relations is a determinant of localization of university spillovers.

Adams and Jaffe (1996) explore localization of the effects of R&D within the firm on total factor productivity of the firm's manufacturing plants. They find that R&D in the same state or within a 100-mile radius is more potent than distant R&D of the same firm. They also find that R&D in the same general product area as the plant has a stronger effect on productivity than R&D in other product areas. Thus, the effects of R&D do not flow unimpeded through the firm but are hampered by geographic and technological distance, just as spillovers seem to be hampered by geography and technological dissimilarity.

Mansfield and Lee (1996) follow R&D expenditure trails from firms to universities. Their principal finding is that firms prefer to work with local university researchers, usually within 100 miles of the firm's R&D laboratories, though this fadeout in firm support of universities, as one might expect, is less for basic research than for applied research. Another finding is that firms support applied research of less distinguished faculties nearly as much as faculty in top schools, though basic research supported by firms takes place mostly at top universities.

In summary, a variety of studies suggest that localization of knowledge spillovers contributes to firm formation, growth, and innovation. The contribution of this paper lies in comparing localization of spillovers from academic and industrial sources and in interpreting this comparison. By this means insight may be gained into the determinants of localization.

III. Description of the Data

A. Survey of R&D Laboratories

The empirical work is based on a 1997 survey of R&D laboratories. The survey quantified learning activities of the laboratories as well as the sources of spillovers from universities and firms[2]. Learning expenditures include meeting with university scientists, joint research, travel to conferences and meetings, and so on. There is in them an important element of search and exploration, rather than production of commercialized invention. It is not surprising that managers regard these expenditures as a modest component of budget, on the order of 5%. But in characterizing these expenditures by academic and industrial source and distance from the R&D

[2] The survey instrument was refined in three stages. A former R&D manager critiqued the initial draft. Afterwards the survey team tested a beta version of the instrument on 10 laboratories. Using these comments we produced a third and final version of the survey instrument. We then contacted the laboratories by phone. A mass mailing was then made to all laboratories that granted permission to send the instrument.

laboratory, information on localization comes to light that would otherwise remain hidden. I exploit this information below.

I selected 600 laboratories owned by 200 firms as subjects for analysis. Parent firms were sampled from Standard and Poor 's Compustat database of publicly traded firms. Laboratory addresses within the firms were drawn 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 report R&D and sales in Compustat and had to be patent assignees in the U.S. Patent and Trademark Office (USPTO) database. These criteria allow for cross-validation of the survey data on R&D, sales, and employment from the years 1991 and 1996.

Responses include 220 laboratories owned by 116 firms, yielding a response rate of 37 percent (220/600). However, three firms aggregated their responses to the firm level, resulting in 208 observations. Twenty-nine of the 116 firms were publicly traded for under 16 years in 1996 so that young companies are a large part of the sample. Nevertheless, respondents were experienced R&D managers who had been with the firm for about 15 years.

Tables 1 and 2 describe the return on the survey and laboratory size characteristics. Table 1 shows the distribution of firms and laboratories by industry of the parent firm. The distribution is uniform except for the smaller number of firms and laboratories in transportation equipment. This pattern is to be expected given the greater concentration of transportation equipment compared with other industries. The number of responses by industry is roughly proportional to the number of laboratories surveyed[3].

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[3] The exception to the rule is pharmaceuticals, where the response rate was lower. Pharmaceutical firms declined to respond because of a large volume of surveys received, and because of the cross-industry nature of this survey, not exclusively focused on ethical drugs.

Table 2 reports characteristics of the laboratories averaged over 1991 and 1996. Consider R&D inputs first. The average laboratory employed 157 scientists and engineers, of which 23 held the Ph.D. (or MD) degree. Average R&D was 14 million dollars of 1987[4]. Standard deviations are in parentheses. These imply positively skewed laboratory size, perhaps because of processes favoring large R&D programs (Cohen and Klepper, 1992).

Now turn to R&D outputs. Table 2 reports two measures of patents. The first line shows patents granted as reported in the survey. These average 8.3 per laboratory. Some of the laboratories, especially several larger ones, did not report their patents. The second line replaces missing patents with an estimate based on U.S.-issued patents for the firm, laboratory location and year. The data were downloaded from the **U.S. Patents Database** (Community of Science (COS), 1999). Patents including imputes average 12.6 per laboratory.

The method for imputing patents is this. I match two digit zip codes to addresses of all inventors in the U.S. patent data for a given company using the electronic zip code database of the U.S. post office. Next I match patents of the parent firm by the two-digit zip code of the laboratory. Finally I assign the imputed patents to the years in the survey (1991 and 1996) according to their issue dates[5].

This is the best way that I know to impute the missing patents, but the method is imperfect. To see this, consider laboratories in small states. Often their inventors live in a different state and two-digit zip code than the laboratory. The imputation method fails to pick up these patents.

Two other problems are that patents often include 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

[4] 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 applied research.

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. I handle the second problem by cataloguing laboratories that are in the same firm and two-digit zip code. I then apportion the patents to the laboratories by the shares of scientists and engineers employed in the same firm and two-digit zip code.

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. Including imputed patents 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 industry average 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.

In addition to patent counts we obtained counts of new products produced by the laboratory in 1991 and 1996. This provides an estimate of innovation that is closer to commercialization. Understandably, fewer managers were able to estimate new product counts than patents. For those who answered, the average number of new products was 6.6 per laboratory (compared with 12.6 for patents). This pattern agrees with British data used in Van Reenan (1996), where innovation counts are also fewer than patents, not all of which become products.

B. Calculation of the Variables

In the empirical work I focus on localization of learning, which guides spillovers into the laboratory, spillover sources, and their effect on innovation. To undertake this analysis I designed a questionnaire that would measure expenditures on learning and identify spillover sources and

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[5] I thank Meg Fernando for downloading the COS data and Janet Galvez for translating them into SAS™ format.

their location relative to the laboratory.

i. Measurement of Laboratory Learning and Its Localization

Besides laboratory R&D budget the survey asked for percentages of budget earmarked for various purposes. Specifically the questionnaire asked respondents to check the percent of budget devoted to learning about academic R&D and to learning about academic R&D within 200 miles of the laboratory. Likewise the questionnaire asked respondents to check the percent of budget devoted to learning about industrial R&D and to learning about industrial R&D confined to a region within 200 miles of the laboratory[6]. Estimated laboratory learning expenditures are the fraction of budget times R&D budget. The estimated fractions of budget accounted for by learning were about five percent, and of course smaller still for learning within 200 miles of the laboratory.

I measure localization of learning expenditures as the logarithm of learning about research within 200 miles of the lab minus the logarithm of learning about research beyond 200 miles of the laboratory. I repeat this procedure for learning about academic and industrial sources.

ii. Measurement of Distance to Cited Universities and Firms

The questionnaire asked R&D managers to list up to five universities and up to five firms, with their city and state locations, which were influential for the laboratory's R&D[7]. Respondents

[6] An example is as follows: "Check the percent of your laboratory's R&D budget for 1991 and 1996 that was spent on learning about research *in firms within 200 miles of your lab*. Fill in 'Other' if the percent exceeds those listed.

Budget Percent	1991	1996
1. None	___	___
2. 0.1-1%	___	___
3. 2-3%	___	___
4. 4-5%	___	___
5. 6-7%	___	___
6. Other%	______	______."

[7] An excerpt from this type of question is this: "List as many as five firms and locations whose research was most important for the conduct of your laboratory's R&D over the past five years. *Please print*.

named closely affiliated universities more often than firms. Moreover, R&D expenditures of universities by field of science are available through NSF's CASPAR database and can be assigned to locations. In contrast, data on firm R&D can be difficult to obtain, especially by location. For these reasons the data on cited universities are more complete and more useful than the data on cited firms.

If the laboratory cites particular universities and firms I calculate distances from the laboratory as follows. First I assign zip codes to citing R&D laboratories and to cited U.S. universities and firms. I exclude foreign universities and firms from these calculations because of missing R&D and location data. Next I assign latitudes and longitudes to zip codes using the Places file of the U.S. Census Bureau. At this stage I have reasonable data on the locations of citing and cited parties. Finally I use the locations to compute distances between the laboratories and cited universities and firms. Later on I compare distances from citing laboratories to closely affiliated universities and firms and I use these distances to construct nearby and distant spillovers as a means of assessing localization. The appendix to this paper explains the calculations.

iii. Measurement of Academic and Industrial Spillovers

The academic spillover is constructed as follows. Respondents identified up to five of 18 science and engineering fields that they regarded as most relevant to their laboratory[8]. Matching R&D expenditures by field of science are taken from NSF's CASPAR database for the closely affiliated universities indicated by the laboratories as most important for their research. The CASPAR data span the period 1972-1995[9].

Firm #1 ____

City, State, Country ______________________________________."

[8] 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.

[9] For more details on the university data see Adams and Griliches (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 the sciences (up to five out of 18) and universities (up to five) cited by the R&D managers. Thus, the measure of the relevant stock of academic R&D is

$$(1) \qquad AcademicR\,\&\,D = \sum_{j=1}^{18} \delta_j K_j$$

Here K_j is the stock of federally funded R&D in field j summed over the cited universities. The term δ_j equals one if the laboratory rates a field as important and zero otherwise. So (1) is the sum of the R&D stocks, weighted by the laboratory-specific δ_j, over the 18 fields of science. Chosen to avoid double counting, federally funded R&D separates university R&D from company R&D. This is important since U.S. universities rely on industry for seven percent of their research support (Mansfield, 1996).

In addition to (1) I construct the local academic spillover as the sum over the relevant sciences' stocks of R&D, but only for closely affiliated universities that are within 200 miles of the laboratory. This distance matches that of localized learning expenditures and may drive these expenditures. Likewise I construct the distant academic spillover as the sum over the relevant sciences' stocks of R&D but for closely affiliated universities that are beyond 200 miles of the laboratory. This variable serves as a likely driver of distant learning expenditures.

There is no corresponding data on cited firm R&D by location to match that of universities. Instead I rely on the Census-NSF R&D survey to construct an estimate of the industry R&D spillover by location. At the first step the estimated spillover is the sum of company R&D stocks over 35 product groups that are included in the U.S. SIC system of classification, weighted by the importance of each group to the laboratory[10]. Thus,

(2) $$R\&D \text{ in the Rest of Industry} = \sum_{j=1}^{35} \gamma_j \widetilde{R}_j \ .$$

Here $\widetilde{R}_j$ is the stock of R&D over a period of 13 years in product j (net of parent firm R&D). The γ_j weights are fractions of technologies in an SIC group that are relevant to each laboratory[11]. The survey technologies have been mapped into 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.

At the second stage I estimate the amount of industrial R&D within and outside 200 miles of the laboratory. In order to do this I construct the fraction of state level industrial R&D within 200 miles and the fraction outside 200 miles. Industrial R&D by state is contained in **Research**

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10 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.

11 To clarify the meaning of the γ_j weights, consider SIC 357, Office Machines and Computing, one of the applied product groups in the Census-NSF R&D data. The following 10 technologies in the survey fall within SIC 357: business equipment, computer accessories/components, computer memory systems, central processing units, computer monitors and input devices, microcomputers/minicomputers, mainframes/semiconductors, peripheral controllers and output devices, computer related services, and terminals. If an R&D manager indicates that three of the above sectors are important, then γ_j=0.3. If the manager indicates seven, then γ_j=0.7. Thus the γ_j weights are laboratory-specific. Similar calculations apply to other technologies that form technologies within the Census-NSF product groups described in footnote 10.

and Development in Industry (National Science Foundation, various years)[12]. I assign a center that is near the largest city in each state[13].

I then assign latitude and longitude coordinates to the state centers and as above, compute distances from the laboratories to these centers. If any distance is less than or equal to 200 miles, then all the R&D data for that state is brought inside the circle 200 miles around the laboratory. The R&D data for the different nearby states is then summed to create state level industry R&D within 200 miles of the laboratory.

One problem is that state level R&D includes all the different areas of technology carried on by industry[14]. Only some are relevant to the laboratory, and this varies by laboratory, as (2) points out. To handle this problem I estimate Industry R&D Within 200 miles of each R&D laboratory as the product of the share of state level R&D within 200 miles of the laboratory, times (2):

$$\begin{aligned}\text{Industry } R\,\&\,D \text{ Within 200 Miles} = {} & \frac{\text{State Level Industry R \& D Within 200 Miles}}{\text{State Level Industry R \& D}} \\ & \times \text{R \& D in the Rest of Industry}\end{aligned} \tag{3}$$

R&D in the Rest of Industry differs by laboratory as noted in (2), because the γ_j weights are specific to laboratories. This estimate of industry R&D within 200 miles of the laboratory exploits information on relevance contained in the γ_j weights and on proximity to the laboratory using the state level R&D data. Equation (3) contains errors but it is the best measure that I have. Finally, Industry R&D Beyond 200 miles of the laboratory is (2) minus (3).

[12] The state is the most detailed level of geographic detail in the NSF data on industrial R&D by industry. This creates some errors in the measure of localized R&D, defined as within 200 miles of the laboratory, but nothing can be done about it.

[13] Nearly all the laboratories are in densely populated states that have moderate to large amounts of R&D and are consistently non-missing and not subject to disclosure problems. Thus, most of the NSF geographic data that are needed for the calculations are present. For small states I interpolate between non-missing years

IV. Descriptive Findings on Localization

Tables 3 through 7 describe localization of laboratory linkages to universities and firms. Table 3 records mean expenditures on learning from universities and firms by 200-mile radius from the laboratory. These expenditures as noted above, amount to five percent of laboratory budget, or about 600 thousand dollars (of 1987) per year. Their distribution by distance depends on the spillover source. Lines 1 and 2, column (A), show that university learning is concentrated within 200 miles of the laboratory, while the reverse is true of industrial learning in column (B). Line 3 is the "localization ratio" or ratio of nearby learning to distant learning, while line 4 is its logarithm. If we treat the logarithm as normally distributed we can apply a paired t-test to the difference in localization ratios in columns (A) and (B)[15]. The statistic is t=3.35, significant at more than the one percent level.

Earlier I remarked that laboratories cite up to five closely affiliated universities that they consider most influential for their R&D. How localized is the R&D of these universities? To answer this question I accumulate the R&D of universities that are and are not cited by the laboratories within and outside circles that are 200 miles from the laboratory. In this comparison the set of relevant sciences is the same for closely affiliated and all other universities, as indicated in each case by the R&D managers. Table 4 displays R&D by distance from the laboratory for closely affiliated universities in column (A) and for other universities in column (B). The first three lines show the amounts within 200 miles of the laboratory, outside 200 miles, and their ratio. Clearly the R&D of closely affiliated universities is closer to the laboratory than university R&D taken at random. I take the logarithm of these "localization ratios" on line 4. If I treat this log

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[14] R&D by state and by applied product are collected independently in the Census-NSF survey of industrial R&D that yields state level R&D.

[15] This test is at best approximate because the logarithm of the localization ratio is essentially the difference in the logarithms of two budget proportions.

difference as approximately normally distributed and take the difference of the log differences in (A) and (B), the paired t-statistic for the difference in means is t=7.67. Thus the R&D of closely affiliated universities is significantly more localized than university R&D taken at random.

Table 5 reports mean distances from the laboratories to cited universities and firms. Even keeping in mind the small sample for firms, the data allow us to compare distances to universities and firms. This again suggests that university spillovers are more localized. All U.S. universities and firms that could be identified are included in the tabulations[16]. However, the table excludes citations to other divisions in the same firm and citations to foreign universities and firms so as to concentrate on distances to U.S. spillover sources, for which data are available.

Line 1 of Table 5 reports distances to U.S. universities and firms separately. Mean distances to universities and firms are respectively 493 and 851 miles. The second line compares university and firm distances for a sample of 48 observations from the same laboratories. Mean distances to universities and firms are 478 and 827 miles, about the same as above. Line three calculates means of the logarithm of distances to universities and firms in the paired data and performs a t-test on the mean difference. The result is t=-3.16, indicating a significantly shorter distance to universities than to firms. From different perspectives tables 3 to 5 imply that academic spillovers are more localized than industrial spillovers.

Tables 6 and 7 conclude the presentation of descriptive statistics. The tables report correlation coefficients between localized learning and indicators of university and firm influence. Localization is measured by the logarithm of learning expenditures within 200 miles of the laboratory minus the logarithm of learning expenditures beyond 200 miles. These indicators of university and firm influence are derived from Likert scale indicators of the importance of each

[16] Privately held companies, many of them startups, are difficult to identify in standard business directories.

channel[17]. If respondents indicated a score of three or better out of five, then a value of one was assigned the channel to indicate its importance, and zero otherwise. The table lists four interactions between the laboratory and universities: engineering graduates, patent licensing, outsourcing of R&D to universities, and faculty consulting. Likewise technical publications, patents, joint research with other firms, and outsourcing of R&D to other firms are four interactions between the laboratory and other firms.

Table 6 reports correlations between localization of learning about university research and the four channels of university influence. Nearly all the channels increase localization. Table 7 reports correlations between localization of learning about firm research and the four channels of firm influence. Unlike table 6, some channels (technical papers and patents) reduce localization. Tables 6 and 7 suggest in yet another way that linkages between laboratories and universities are more localized than linkages with firms.

V. Localized Learning and Innovation

Tables 8 to 10 study the determinants of localized learning and innovation. Tables 8 and 9 explain localization of learning of about academic and industrial research. Table 10 explains numbers of patents and new products as functions of nearby and distant learning academic and industrial R&D, and other variables.

Table 8 reports findings for learning about academic R&D. Explanatory variables include industry and time dummy variables and the logarithms of non-PhD and PhD laboratory scientists, which together control for laboratory size and research intensiveness. In addition I include the

[17] An excerpt from the question about university channels is, 'Below are some firm-university interactions. *Circle the number to indicate the importance of each to your lab*.'

Firm-University Interaction	**Not Applicable**	**Unimportant**		**Important**	**Very Important**
Engineering Graduates	1	2	3	4	5."

four channels of university influence already noted: outsourcing of R&D to universities, faculty consulting, licensing of university patents, and engineering graduates.

The dependent variables of 8.1 and 8.2 are the logarithms of learning about academic R&D within and beyond 200 miles of the laboratory. The estimation method is Tobit analysis, since over half of the observations are left censored. The higher proportion of censoring in 8.2 indicates localization of laboratory linkages to universities, since many of the laboratories do not find it worthwhile to learn about university research at a distance.

According to 8.1 and 8.2 most of the channels of university influence contribute to localization. Outsourcing to universities, licensing of university patents and engineering graduates all seem to contribute more to nearby learning, though the coefficients are not significantly different. The number of non-PhD scientists however, does contribute to localization, while PhD researchers have no effect. Combining these results laboratories that are less PhD intensive learn more locally from university research. Presumably such laboratories seek advice on "normal" (and widely available) science and engineering. In addition the equations include a dummy variable for whether the firm owns other laboratories. This variable diminishes localization, perhaps because larger firms are geographically dispersed in both research and production.

Finally I include the logarithms of nearby and distant R&D in closely affiliated universities as determinants of benefits of learning from nearby and distant universities. Consistent with expectations, R&D in nearby universities increases localization, while distant R&D decreases localization.

Table 9 presents parallel findings on learning about industrial research. As before logarithms of learning about nearby and distant industrial research are the dependent variables. The equations include year and time dummies and channels of interaction with other firms, the

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The question for firm-firm interactions is worded similarly.

logarithms of non-PhD and PhD scientists, and the dummy, as above, for whether the firm owns other laboratories. I also include nearby and distant industrial R&D, although, as pointed out in the discussion of equations (2) and (3), this evidence on industrial spillovers is not as specific as that on university spillovers. R&D of closely affiliated firms, unlike closely affiliated universities, is usually missing and when available is not easy to assign to a place. In addition table 9 includes two controls, the dummy for other laboratories in the firm, and an indicator of frequency of meeting with other laboratories that equals one if the laboratory meets at least monthly with other R&D units in the firm, and zero otherwise. These variables control for firm size and focus of the laboratory on its locality.

Equations 9.1 and 9.2 are Tobit estimates of the logarithms of nearby and distant learning about industrial R&D. Tobit is the preferred method since half or more of industrial learning expenditures are left censored[18]. Outsourcing of R&D to other firms and joint research contribute to localization. Importance of other firm's technical papers, on the other hand, diminishes localization perhaps because it indicates interest in joint or external research in industry. As measures of laboratory size both non-PhD and PhD scientists increase learning expenditures. But neither contributes to localization. Nearby and distant industrial R&D have the expected effects, increasing and decreasing localization, though only the former difference is significant across equations.

Consistent with its interpretation as a measure of the parent firm's size and geographic dispersion, ownership of other laboratories diminishes localization in 9.1 and 9.2. Consistent with its interpretation of the time-intensity of intra-firm interactions, frequency of meeting increases localization.

[18] The increase in left censoring from 50 to 59 percent as learning changes from nearby to distant indicates some degree of localization.

Table 10 explores implications of localized learning for laboratory patents and number of new products. The dependent variables are counts of patents and new products. These are non-negative, include many zeroes and are positively skewed. The Poisson family of distributions fits this class of variable well. But the Poisson itself assumes that the mean equals the variance and ignores the fact that the variance exceeds the mean in most micro-data. The Negative Binomial distribution handles the "over-dispersion" problem and is the method used in table 10[19]. The dependent variable in 10.1 and 10.2 is patents granted, with missing values imputed by USPTO patents as described in section II of this paper. The dependent variable in 10.3 and 10.4 is the number of new products originating in the laboratory.

The idea behind this table is that to invent or innovate, the laboratory must first learn from the outside and engage in internal research[20]. Seen in this light, expenditures on academic and industrial learning, as well as own laboratory and parent firm research should intermediate the effects of spillovers. Consistent with this approach the spillover variables that I have are generally insignificant in explaining patents and new products. Thus table 10 concentrates on learning and internal research, as well as localization in learning, on patents and new products.

The explanatory variables are nearly the same in the two pairs of equations, the only difference being the patent imputation dummy in 10.1 and 10.2. This imputation dummy is associated with more patents because imputation occurs in several of the larger laboratories and because the procedure tends to include research conducted elsewhere in the firm.

Otherwise independent variables are the same in the patents and new products equations. The explanatory variables include learning about industrial and academic R&D differentiated by

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[19] The Negative Binomial is derived by assuming that the Poisson parameter is Gamma distributed. Integrating over the Gamma error term, the marginal distribution is found to be Negative Binomial (Johnson and Kotz, 1969). For references see Maddala (1983) or Green (2000). For applications of random effects Poisson (Negative Binomial) and fixed effects Poisson (Conditional Logit) regression to patents, see Hausman, Hall and Griliches (1984).
[20] Cohen and Levinthal (1989) and Adams (2000) pursue this idea further.

distance from the laboratory. Equations 10.1 and 10.2 (and likewise 10.3 and 10.4) follow two approaches to differentiation by distance. In 10.1 I enter the logarithms of nearby and distant learning as separate variables. In 10.2 I construct "composites" of academic and industrial learning expenditures that are of the form $\log(\ell_n + \beta\ell_d)$ ("n"=nearby, "d"=distant). To pin down β, I perform a grid search over values of β ranging over 0.0, 0.2 … 1.0 in the case of academic and industrial research. This procedure is a way to allow for nonlinear effects of learning in Negative Binomial regression, and it provides a comparison between effects of nearby and distant R&D.

Using separate variables does not work well for academic research in the patent equation, 10.1: both nearby and distant R&D are insignificant and their effects are not estimated very precisely. The results for industrial R&D suggest some fadeout with distance, but this fadeout is not significant. The grid search in 10.2 turns up a best-fitting combination of β=1.0 for distant learning about industrial research, and β=0.6 for distant learning about academic research. This is suggestive of the notion that learning is primarily localized in the case of academic research, though the sample is small and the estimates imprecise.

Equations 10.3 and 10.4 explain the number of new products. I enter separate variables in 10.3 for nearby and distant learning about academic and industrial research. It seems clear that localization of learning is greater for new products than patents. Indeed, distant learning about academic research has a negative effect on patents, the interpretation being that laboratories engaged in learning about distant university research are engaged in more basic research that precedes new products. A fadeout of industrial learning with distance is again apparent, though the estimates are again imprecise.

Equation 10.4 applies the grid search methodology to new products. Again I construct "composites" of academic and industrial learning expenditures ℓ that are of the form $\log(\ell_n + \beta\ell_d)$

("n"=nearby, "d"=distant), for which I perform a grid search over values of β ranging over –0.4, -0.2, … 1.0 for academic learning (given the negative sign in 10.3) and over β ranging over 0.0, 0.2, … 1.0 for industrial learning. The best fitting equation indicates β=0, or no effect of distant learning about industrial research and $\beta = -0.2$ for distant academic learning[21].

These results are indicative of greater localization at the commercialization stage than the invention stage. As the firm approaches commercialization and secrecy becomes more valuable, it seems plausible that most of the research in the laboratory would be internal development work.

VI. Policy Discussion and Conclusion

The results of previous sections offer solid evidence for localization of academic knowledge spillovers. The spillovers are more localized than one would expect on the basis of the geographic distribution of university R&D and they are more localized than industrial knowledge spillovers. This judgment is based on the behavior of laboratory learning effort differentiated by distance and on the distance of closely affiliated universities and firms from the laboratories. We attribute part of this difference to the system of open science, which makes it possible for firms to go to local universities to obtain information that is reasonably current and close to the frontiers of knowledge. But to attribute all localization in this way is an overstatement. Open science is standard in many countries yet it does not require the tight industry-university linkages that one observes in these data. I believe that the missing element that conditions the data is the industry-university cooperative movement.

This movement formally began in the United States with the Morrill Act (1862), which provided grants of land for the establishment of one college in a state with its primary objective

[21] The additional constraint is imposed that *Academic Spillover* $= \max(0, \ell_n + \beta\ell_d)$. This is required to take the logarithm.

the teaching of courses in the agricultural and mechanical arts[22]. Around the same time Congress passed the act founding the U.S. Department of Agriculture, which interacted through the years with the Land Grant colleges.

Somewhat later the Hatch Act (1887) established the state agricultural experiment stations on the campuses of Land Grant colleges. This act joined together teaching and research functions within the same institution, enabling diffusion of research results to the various states. The charters of the Land Grant colleges were to serve the agriculture and industry by providing practical education and research. As employment shifted away from agriculture, training in Land Grant universities shifted with it, but maintained an applied focus in research and teaching, in keeping with continuing funding pressures by state governments. The industry-university cooperative movement seems from the first to have been an expression of state interests' demands for jointly exercised, practical training and research. And since private and Land Grant universities compete for students and research dollars, the Land Grant system very likely pressured private universities in a similar pragmatic direction. These developments laid the foundations for the close industry-university ties that we observe in the present data and elsewhere.

This was the setting up to World War II. World War II vastly increased federal support for university research. The National Science Foundation and the expansion of the National Institutes of Health, both extensive sources of funding, were the direct result of success in harnessing university research to wartime needs[23]. But by 1980 complaints began to mount that federal funding, which led universities in a more basic direction, also distanced the universities,

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[22] Chapter 1 of Huffman and Evenson (1993) documents earlier initiatives that were precursors of the Land Grant act. The agricultural division of the U.S. Patent Office almost from the start undertook seed collection, experimentation and diffusion—activities that were later included in the research of agricultural colleges. Early agricultural colleges allowed for institutional experimentation that contributed to the Land Grant colleges.

[23] For a discussion see Mowery and Rosenberg (1998).

especially schools of engineering, from firms, and were a threat to competitiveness[24]. In 1980 Congress passed the Bayh-Dole Act, which allowed universities to patent inventions from federal research. At the same time NSF and other agencies began to found Industry-University Cooperative Research Centers (IUCRCs). The IUCRCs compensated engineering faculty for working closely with firms and moved the schools of engineering towards service activities. By these and other means, the federal government has recently tried to bolster the cooperative movement in relation to the modern equivalents of the "agricultural and mechanical arts[25]."

This paper has presented evidence on the localization of R&D spillovers using data from a sample of R&D laboratories. As part of this research I examined forces that determine the concentration of learning effort in the vicinity of the research group, as opposed to more distant locations, thereby hoping to shed light on behavioral aspects of localization. Perhaps the most important of this paper's findings are that university spillovers are more localized than firm spillovers and more localized than the general distribution of university R&D. This evidence can be viewed as consistent with policies that have coupled scientific training and research with state agricultural and industrial interests (the industry-university cooperative movement), strongly complementing the results of open science. The paradox is that a form of knowledge that is more a public good than almost any other should be so localized. The resolution to the paradox is that localization of university research represents the dissemination of this knowledge, which, if it is not free, is certainly cheaper than carrying out the research over again.

This evidence raises several policy issues. Perhaps the main one is, how local should the university-firm connection be? University research that is primarily supported at the state level internalizes benefits to one state. Clearly, research that has a wider scope than this, including much

[24] See Dertouzos and others (1989).
[25] See Adams, Chiang, and Starkey (2001) for an analysis of contributions of IUCRCs to firm R&D.

basic research, is better funded at the national or international levels, where more of the benefits can be internalized. This way of putting it explains the trend away from state funding of research and suggests limits to the arguments underlying the industry-university cooperative movement[26]. Perhaps the best combination is that of universities serving state and local interests through training and dissemination, with all the duplication which this necessarily entails, coupled with national and international funding of more wide-ranging research that almost without notice crosses political boundaries.

[26] National Science Board (1998), appendix table 5-2 does in fact show that the share of academic research accounted for by states fell from 13.2% in 1960 to 7.6% by 1997.

Appendix
Distance Calculations

This appendix explains the distance calculations in the text. While the methods of spherical trigonometry that underlie them are quite old, the applications below are not easy to find in one reference. Define a curved triangle ABC on a sphere whose radius OA equals 1 and whose center is at O as in Figure 1. Point A of the triangle is the "pole" of the sphere since latitude and longitude coordinates are assumed. Construct the plane triangle ADE tangent to point A so that

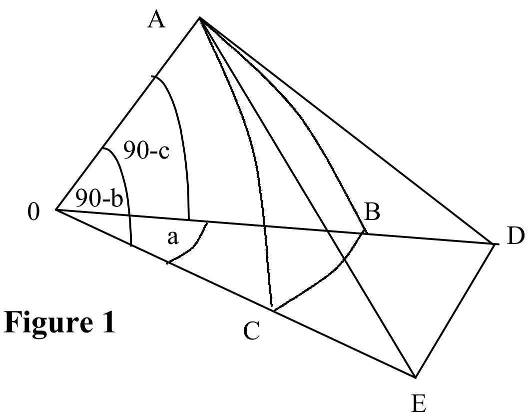

Figure 1

OAD and OAE are plane right triangles. Also construct the plane triangle ODE passing through the great circle connecting O, B and C forming the floor of solid angle OABC. We seek the distance separating C from B. Note that for angle a specified in radians, distance CB is also equal to a, since ABC lies on a sphere of unit radius[27]. Thus the arc cosine of the cosine of a, where a is in radians, yields the distance CB. The cosine of angle a (measured in degrees of longitude) is given by the formula

(A.1) $$\cos a = \cos A \bullet \sin(90 - b) \bullet \sin(90 - c) + \cos(90 - b) \bullet \cos(90 - c),$$

[27] Since there are 2π radians on a circle of arbitrary dimension and since the circumference of a circle is $2\pi r$ for a circle of radius r, when r=1 (as on the unit sphere) radian measure equals distance measure.

where 90-b and 90-c are the colatitudes of angles AOC and AOB. Equation (A.1) uses the plane cosine formula applied to triangles ODE and ADE and the Pythagorean theorem applied to OAD and OAE (Cotter, 1966, Ch. 3). The proof of (A.1) is as follows. From Figure 1,

(A.2) $$DE^2=OD^2+OE^2-2\bullet OD \bullet OE\bullet \cos a$$

by the plane cosine formula applied to triangle ODE. Also from Figure 1,

(A.3) $$DE^2=AD^2+AE^2-2\bullet AD \bullet AE\bullet \cos A$$

by the plane cosine formula applied to triangle ADE. Subtracting (A.3) from (A.2) yields

(A.4) $$0=(OD^2-AD^2)+(OE^2-AE^2) +2\bullet AD \bullet AE\bullet \cos A- 2\bullet OD \bullet OE\bullet \cos a.$$

But since OAD and OAE are right triangles,

(A.5) $$OD^2=OA^2+AD^2$$
$$OE^2=OA^2+AE^2$$

Substitution of (A.5) into the first two terms on the right of (A.4) yields

(A.6) $$0=2\bullet OA^2+2\bullet AD \bullet AE\bullet \cos A- 2\bullet OD \bullet OE\bullet \cos a$$

Solving (A.6) for cos a and recognizing that cos (90-b)=OA/OE, cos (90-c)=OA/OD, sin (90-b)=AE/OE, and sin (90-c)=AD/OD yields (A.1) above. But since sin (90-x)=cos x and cos (90-x)=sin x, (A.1) is equivalent to

(A.7) $$\cos a = \cos A \bullet \cos b \bullet \cos c + \sin b \bullet \sin c .$$

To apply (A.7) to the problem of computing distances on the earth, assume an R&D laboratory at C and a cited university or firm at B. Then two operations must be applied to determine CB: conversion from latitude-longitude coordinates to radians and scaling of the unit sphere to the size of the Earth. These are shown in (A.8) below.

$$lablat = \frac{2\pi}{360} \times latitude \text{ in degrees of the laboratory}$$

$$lablong = \frac{2\pi}{360} \times longitude \text{ in degrees of the laboratory}$$

$$zlat = \frac{2\pi}{360} \times latitude \text{ in degrees of (university or firm) z}$$

(A.8) $$zlong = \frac{2\pi}{360} \times longitude \text{ in degrees of (university or firm) z}$$

$$\cos(lab, z) = \{[\cos(|\, lablong - zlong \,|)] \times \cos(lablat) \times \cos(zlat)\} + \sin(lablat) \times \sin(zlat)$$

$$dist(lab, z) = 3953.424 \times \text{arcos}\left[\cos(\text{lab}, \text{z})\right]$$

The first four equations of (A.8) convert the unit of measure from degrees to radians. The conversion factor is $2\pi/360$ since there are 2π radians in a circle of 360^{o}. The fifth equation is (A.7) with angles rewritten in terms of radian measure and with C and B identified with laboratory and cited university or firm coordinates. Thus for example cos (lab, z) in (A.8) equals cos a in (A.7). This formula calculates the cosine of the distance in *radians* on a unit sphere between the laboratory and university or firm z. The final equation of (A.8) scales distance to the size of the Earth by converting radians into miles using 3953.424=360/2π (=57.296) times 69, the approximate number of miles per degree on the surface of the earth and multiplying by the arcos of cos (lab, z). Equation (A.8) is the method for finding distances used in the text and by cartographers, given the spherical approximation.

Table 1
Distribution of Firms and R&D Laboratories
By Industry

Industry	SIC Code	Number of Firms	Number of Laboratories*
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 because of the aggregation of laboratories under a single response by several firms.

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

Variable	Mean (S.D.)
R&D Inputs	
Number of Scientists and Engineers	157.3 (442.7)
Number of Ph.D. (or MD) Scientists and Engineers	22.9 (113.8)
Laboratory R&D Budget (in millions of '87 $)	14.0 (41.7)
R&D Outputs	
Patents Granted from the Survey	8.3 (23.3)
Patents Granted from the Survey, Supplemented by USPTO Patents for Firm and Laboratory Locations	12.6 (40.2)
Number of New Products from the Survey	6.6 (17.9)

Source: *Survey of Industrial Laboratory Technologies 1996.* The data are averages across 1991 and 1996.

Table 3
Localization of Learning Expenditures
On Industrial and Academic Research (In Millions of '87 $)
(Standard Deviations in Parentheses)

Variable	Mean Expenditures on Learning about Academic Research (A)	Mean Expenditures on Learning about Industrial Research (B)
(1) Learning Expenditures Within 200 Miles of the Laboratory	0.169	0.126
	(0.630)	(0.490)
(2) Learning Expenditures Beyond 200 Miles of the Laboratory	0.109	0.224
	(0.637)	(1.129)
(3) Nearby Learning/Distant Learning, (1)÷(2)	1.551	0.563
(4) Log (Nearby Learning/Distant Learning), Log [(1)÷(2)]	0.925*	0.102*

Source: *Survey of Industrial Laboratory Technologies 1996.* * T-test for the difference in means between (A) and (B) is t=3.35 (N=293), significant at greater than the one percent level.

Table 4
Localization of Federal R&D in Closely Affiliated Universities
(In Millions of '87 $)
(Standard Deviations in Parentheses)

Variable	Mean Federal R&D in Closely Affiliated Universities (A)	Mean Federal R&D in All Other Universities (B)
(1) Federally Funded Academic R&D Within 200 Miles of the Laboratory	229.3	972.9
	(409.7)	(1435.1)
(2) Federally Funded Academic R&D Beyond 200 Miles of the Laboratory	246.5	9395.3
	(461.2)	(6245.1)
(3) Nearby Federal R&D/Distant Federal R&D, (1)÷(2)	0.93	0.10
(4) Log (Nearby Federal R&D/Distant Federal R&D), Log [(1)÷(2)]	1.10*	-3.22*

Source: *Survey of Industrial Laboratory Technologies 1996.* * Approximate t-test for the difference in means between (A) and (B) is t=7.67 (N=203), significant at greater than the one percent level.

Table 5
Distances Between Citing Laboratories and Cited Universities and Firms
(Standard Deviations in Parentheses)
[Number of Observations in Brackets]

Sample	Variable	Distance to Cited Universities in Miles (A)	Distance to Cited Firms in Miles (B)
(1) Unpaired Data, self and international citations excluded	Distance	492.5 (488.4) [N=117]	851.2 (526.0) [N=66]
(2) Paired Data, self and international citations excluded	Distance	477.8 (409.1) [N=48]	826.5 (527.0) [N=48]
(3) Paired Data, self and international citations excluded	Log (Distance)	5.35* (2.34) [N=48]	6.49* (0.74) [N=48]

Source: *Survey of Industrial Laboratory Technologies 1996.* Note: N is the number of laboratories meeting the sample criteria. * T-test for the difference in means between the logarithm of columns (A) and (B) is t=-3.16 (N=48), significant at greater than the one percent level.

Table 6
Correlations Between Localization of Laboratory Learning About Academic Research
And Channels of Interaction with Universities

Measure of Localization of Learning About Academic Research	Channel of Interaction With Universities	Correlation (P-value)
Log (Nearby Learning/(Distant Learning)	Outsourcing of R&D to Universities Important (1 if yes, 0 if no)	0.229 (0.001)
“	Faculty Consulting Important (1 if yes, 0 if no)	0.157 (0.007)
“	Licensing of University Patents Important (1 if yes, 0 if no)	0.096 (0.098)
“	Engineering Graduates Important (1 if yes, 0 if no)	0.169 (0.004)

Source: *Survey of Industrial Laboratory Technologies 1996.* Note: channels are dummy variables coded as 1 if a respondent indicates that a particular interaction is important and 0 otherwise. See the text for a discussion.

Table 7
Correlations Between Localization of Laboratory Learning About Industrial Research And Channels of Interaction with Other Firms

Measure of Localization of Learning About Industrial Research	**Channel of Interaction With Other Firms**	**Correlation (P-value)**
Log (Nearby Learning/ Distant Learning)	Outsourcing of R&D to Other Firms Important (1 if yes, 0 if no)	0.060 (0.304)
"	Joint Research with Other Firms	0.073 (0.335)
"	Other Firms' Technical Publications Important (1 if yes, 0 if no)	-0.153 (0.009)
"	Other Firms' Patents Important (1 if yes, 0 if no)	-0.097 (0.096)

Source: *Survey of Industrial Laboratory Technologies 1996.* Note: channels are dummy variables coded as 1 if a respondent indicates that a particular interaction is important and 0 otherwise. See text for a discussion.

Table 8
Localization of Learning About Academic Research
(Asymptotic Normal Statistics in Parentheses)

Variable or Statistic	Log (Learning about Academic R&D Within 200 Miles)	Log (Learning About Academic R&D Beyond 200 Miles)
	8.1	8.2
Estimation Method	Tobit	
Year and Time Dummies	Yes	Yes
Outsourcing of R&D to Universities Important (1 if yes, 0 if no)	1.43 (2.1)	0.41 (0.3)
Faculty Consulting Important (1 if yes, 0 if no)	2.46 (2.7)	2.74 (1.6)
Licensing of University Patents Important (1 if yes, 0 if no)	2.02 (3.0)	0.80 (0.6)
Engineering Graduates Important (1 if yes, 0 if no)	-1.27 (-1.5)	-4.81 (-3.0)
Log (Non-PhD Laboratory Scientists and Engineers)	1.17* (5.4)	-0.42* (-1.1)
Log (Ph D Laboratory Scientists and Engineers)	0.46 (4.3)	0.56 (2.8)
Firm Owns Other R&D Laboratories (1 if yes, 0 if no)	-0.51 (-0.9)	2.68 (2.1)
Log (Closely Affiliated University R&D Within 200 miles of the Laboratory)	0.16* (2.8)	-0.18* (-1.5)
Log (Closely Affiliated University R&D Beyond 200 miles of the Laboratory)	0.03 (0.6)	0.43 (3.6)
Fraction of Left Censored Observations	0.64	0.83
Log Likelihood	-323.9	-206.2
χ^2	175.3	58.0
Root MSE	3.52	5.84

Source: *Survey of Industrial Laboratory Technologies 1996*, the Census-NSF survey, and the NSF-CASPAR database of universities. The number of observations is N=269. *Estimated coefficients in 8.1 and 8.2 differ at greater than the one percent level of significance.

Table 9
Localization of Learning About Industrial Research
(Asymptotic Normal Statistics in Parentheses)

Variable or Statistic	Log (Learning about Industrial R&D Within 200 Miles)	Log (Learning About Industrial R&D Beyond 200 Miles)
	9.1	9.2
Estimation Method	Tobit	
Year and Time Dummies	Yes	Yes
Outsourcing of R&D to Other Firms Important (1 if yes, 0 if no)	1.33* (2.9)	-0.60* (-0.9)
Joint Research with Other Firms Important (1 if yes, 0 if no)	-0.05 (-0.1)	-1.41 (-1.9)
Other Firm's Technical Publications Important (1 if yes, 0 if no)	-0.36** (-0.5)	3.25** (3.0)
Other Firm's Patents Important (1 if yes, 0 if no)	0.44 (0.7)	0.93 (1.1)
Log (Non-PhD Laboratory Scientists and Engineers)	0.83 (4.7)	0.84 (3.4)
Log (Ph D Laboratory Scientists and Engineers)	0.31 (4.4)	0.27 (2.6)
Firm Owns Other R&D Laboratories (1 if yes, 0 if no)	-0.54* (-1.0)	3.03* (3.6)
Laboratory Meets at least Weekly with Other Labs in the Firm (1 if yes, 0 if no)	0.71** (1.2)	-2.19** (-2.5)
Log (Industry R&D Within 200 miles of the Laboratory)	0.40** (2.5)	-0.06** (-0.3)
Log (Industry R&D Beyond 200 miles of the Laboratory)	-0.23 (-1.6)	0.16 (0.8)
Fraction of Left Censored Observations	0.50	0.59
Log Likelihood	-430.1	-407.3
χ^2	108.2	66.6
Root MSE	3.20	4.45

Source: *Survey of Industrial Laboratory Technologies 1996*, the Census-NSF R&D survey, and the NSF-CASPAR database of universities. The number of observations is N=269. *Estimated coefficients in 9.1 and 9.2 differ at greater than the one percent level of significance. **Estimated coefficients in 9.1 and 9.2 differ at greater than the five percent level of significance.

Table 10
Laboratory Innovation and Localized Learning
(Asymptotic Normal Statistics in Parentheses)

Variable or Statistic	Patents Granted		Number of New Products	
	10.1	10.2	10.3	10.4
Estimation Method	Negative Binomial Regression			
Year and Time Dummies	Yes	Yes	Yes	Yes
Patent Imputation Dummy (1 if yes, 0 if no)	0.87	0.89		
	(3.5)	(3.5)		
Log (Learning about Academic R&D Within 200 Miles)	0.07		0.08	
	(1.8)		(2.1)	
Log (Learning about Academic R&D Beyond 200 Miles)	0.06		-0.12	
	(1.4)		(-3.3)	
Log ("Composite" Learning about Academic R&D) [b]		0.09		0.08
		(2.6)		(2.1)
Log (Learning about Industrial R&D Within 200 Miles)	0.12		0.05	
	(3.1)		(1.5)	
Log (Learning about Industrial R&D Beyond 200 Miles)	0.09		0.01	
	(2.8)		(0.2)	
Log ("Composite" Learning about Industrial R&D) [a]		0.19		0.07
		(5.0)		(2.0)
Log (Internal Research of the Laboratory)	0.44	0.38	0.39	0.36
	(6.3)	(5.4)	(5.6)	(5.0)
Log (Stock of R&D in the Rest of the Firm)	0.09	0.09	-0.00	-0.00
	(4.7)	(4.8)	(-0.1)	(-0.2)
N	262	262	202	202
Log (Likelihood)	-630.0	-626.5	-511.7	-511.6
χ^2	212.3	219.5	144.0	144.3

Sources: *Survey of Industrial Laboratory Technologies 1996*, Standard and Poor 's Compustat, and the NSF-CASPAR database of universities. [a] In 10.2 and 10.4 "Composite Learning about Industrial R&D" is simply the sum of learning about industrial R&D within 200 miles of the laboratory, plus learning about industrial R&D beyond 200 miles. [b] In 10.2 "Composite Learning about Academic R&D" is the sum of learning about academic R&D within 200 miles of the laboratory, plus 0.6 times learning about academic R&D beyond 200 miles. See the text for a discussion. In 10.4 "Composite Learning about Academic R&D" is the sum of learning about academic R&D within 200 miles of the laboratory, minus 0.2 times learning about academic research beyond 200 miles. See the text for further discussion.

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