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ABSTRACT

Over the past 60 years the United States has created the world's largest system of government laboratories. The impact of the laboratories on the private economy has been little studied though their research accounts for 14% of total U.S. R&D, more than the R&D of all colleges and universities combined. In this paper we study the influence of federal laboratory R&D on industrial research using a sample of industrial laboratories.

In head-to-head comparisons with alternative measures, we find that Cooperative Research and Development Agreements or CRADAs, are the primary channel by which federal laboratories increase the patenting and R&D of industrial laboratories. With a CRADA industrial laboratories patent more, spend more on company-financed R&D and spend more of their own money on federal laboratories. Without a CRADA patenting stays about the same and only federally funded R&D increases, mostly because of direct subsidies by government.

These results are consistent with the literature on endogenous R&D spillovers, which emphasizes that knowledge spills over when recipients work at making it spill over. CRADAs are legal agreements between federal laboratories and firms to work together on joint research. They are backed by real budgets and accompanied by cost sharing that could bind the parties together in joint research. Moreover, the CRADA instrument is the main form of such agreements. Thus, both in theory and in fact CRADAs may be more beneficial to firms than other public- private interactions, precisely because of the mutual effort that they require of firms and government laboratories.

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I. Introduction

Over the past 60 years the United States has created the world's largest system of government laboratories. To see how large the system is, consider that federal laboratory research amounted to 25.7 billion dollars in 1995 or 14% of U.S. research and development (R&D), larger than the combined R&D of universities. In spite of their size the impact of the laboratories has been little studied. This paper seeks to remedy this neglect by examining the influence of federal laboratory R&D on industrial research.

The programs of the federal laboratories are wide-ranging. Included are weapons development, the study of alternative sources of energy, pollution measurement and abatement, basic research in mathematics, computer science, astronomy, physics, molecular biology, genetics, and other fields of science; the containment and eradication of disease, improvement of the system of measures, and much else.

Basic research is usually defined as research designed to gain understanding without specific applications in mind. Defined this way, the share of basic research in federal laboratories lies between that of universities and industrial firms. In 1995 basic research contributed 67% of university R&D, 23% of federal laboratory R&D, and 4% of industrial R&D[1]. Furthermore, in federal laboratories with a more basic orientation researchers publish in scientific journals at a rate like that of top research universities. Thus the research of federal laboratories is a composite of academic and industrial research.

Recent political changes could have predicted a difficult future for the federal laboratories, especially given the end of the Cold War and the predictable decline in demand for weapons research. But these negative trends have been partly offset by an increase in technology transfer from federal laboratories, a form of "peace dividend," but also a way to protect the laboratory budgets (Cohen and Noll, 1996). A separate factor contributing to increased interest in technology transfer was a widespread belief during the 1980s in declining U.S. productivity and competitiveness in high technology products (Krugman, 1994). This belief probably led to some shift towards technology transfer from the federal government.

Thus recent legislation has sought to increase the assistance offered by federal laboratories to industry. The Stephenson-Wydler Technology Innovation Act of 1980 made technology transfer a mission of all federal laboratories, though it embodied few concrete incentives. The Federal Technology Transfer Act of 1986 was the

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[1] See National Science Board (1998), table 4-3, p. A-121 for statistics on R&D in federal laboratories and in other sectors; and table 4-7, p. A-125 for statistics on basic research performed in federal laboratories and in other sectors.

first to give incentives to Government Owned and Government Operated laboratories (GOGOs) to commercialize. It did so by establishing a budgetary function for Cooperative Research and Development Agreements (CRADAs), annual reviews of CRADAs at the agency level and set-asides for the agreements. The National Competitiveness Technology Transfer Act of 1989 extended similar rules to Government Owned and Contractor Operated laboratories (GOCOs). These laboratories account for most of the R&D conducted in the federal government.

Parallel legislation relaxed the application of antitrust to jointly conducted R&D. The National Cooperative R&D Act of 1984 sheltered R&D joint ventures from antitrust action. The National Cooperative Research and Production Act of 1993 extended this protection to joint production for the purpose of commercializing the results of R&D joint ventures. Both laws could increase technology transfer from federal laboratories to industry. With antitrust protection alliances of firms can share benefits from working with federal laboratories, thereby muting the protests of firms outside the alliances. Without this protection the protests of outsider firms are more likely to shut down attempts to transfer federal technology.

Still, the increase in cooperative R&D has not solved the problem of creating winners and losers through federal technology transfer and to claim so would be an overstatement. Some evidence for this is the peaking in the number of CRADAs by 1998, a result that was predicted by Cohen and Noll (1996)[2].

Rather little is known about the effect of federal laboratories on innovation and growth. And yet federal laboratory technologies could be valuable under the right conditions. Government laboratories are large, diverse and rather different from industrial laboratories. The two sets of capabilities could be complementary and federal laboratory R&D could be beneficial to firms. But the relevant conditions ensuring that this benefit occurs are more complex than a simple handing down of information from the federal laboratories.

The type of interaction also matters. Government contractors manufacture products to federal guidelines but this does not imply technology transfer. Furthermore in some contractual relationships the firm does not retain intellectual property in inventions that it creates under government contract and does not patent, because this would disclose information that compromises national security. Again the firm could license government patents and be granted access to test facilities of government laboratories, but neither interaction necessarily implies the transfer of technology.

[2] The total number of active CRADAs for all agencies of the federal government rose from 34 in 1987 to 3688 in 1996. But this number declined to 3186 by 1998. We are indebted to Walt Polanski of the U.S. Department of Energy for these tabulations.

Joint research offers greater promise of creating new technologies than most interactions between firms and government laboratories[3]. The CRADA or Cooperative Research and Development Agreement, is a legal contract that enables federal laboratories to conduct joint research with firms. Under the usual terms of a CRADA the private-firm partner is assigned the intellectual property that results from the joint research. Some CRADAs are multi-firm while others involve a single firm. Many CRADAs include cost sharing requirements that if enforced, imply matching of company with federal laboratory resources, often on a dollar for dollar basis. CRADAs could set up the close interactions between public and private R&D that are most likely to result in technology transfer. The selection process is unclear that determines CRADAs yet it seems likely that the government laboratories know the firms through previous contractor and other relationships. To see why, consider the timeline of CRADAs. The 1986 Federal Technology Transfer Act rewarded government operated GOGO laboratories for CRADA activity and yet the GOCO laboratories issued CRADAs only with the 1989 National Competitiveness Technology Transfer Act. Given the greater size and prominence of the GOCOs and given likely delays in carrying out legislation, it is fair to say that CRADAs have been in operation for about a decade.

The literature on endogenous R&D spillovers suggests that CRADAs could be an important means of technology transfer. Cohen and Levinthal (1989) emphasize the two faces of R&D, innovation and learning. In order to benefit from spillovers generated by external performers of R&D, the firm must dedicate resources to learning about the R&D. As a result knowledge spillovers are neither exogenous nor free. Adams (1999b) shows that multiple learning efforts contribute to industrial research productivity and that the learning efforts are mutually enhancing and responsive to learning opportunities. Consistent with the endogenous spillover literature Cockburn and Henderson (1996) find evidence of *reciprocal* interactions between publicly funded scientists and researchers in pharmaceutical companies in the form of co-authorship by the two sets of researchers.

While there have been a few studies of federal laboratories, none to our knowledge have explored the *statistical* impact of the laboratories on the research productivity of industrial firms, which is the primary focus of this paper. Ham and Mowery (1998) present five case studies of CRADAs signed by a prominent weapons laboratory with industrial firms. Their view is that not all CRADAs are created equal. They argue that the most effective CRADAs draw on the historic capabilities of the federal laboratories, allow for managerial flexibility,

[3] An alternative and very important channel is spin-offs from federal laboratories. One way to measure spin-offs is to trace the migration of government scientists to established firms and as founders of new firms.

contain incentives that reward commitment of both the firm and the laboratory and acquaint federal researchers with the needs of firms[4]. Cohen and Noll (1996) as we have seen discuss the future of the national laboratories, arguing that the end of the Cold War has weakened support for weapons research. They predict declining expenditures on federal laboratories. Jaffe and Lerner (1999) study patenting of two Department of Energy laboratories. They find that federal technology transfer initiatives increased patents per dollar of R&D to the level of research universities.

This paper provides evidence on the *channels* by which federal laboratories affect industrial laboratories. Since private laboratories are early points of contact between firms and federal laboratories, this evidence relates to the first results of federal laboratory R&D, long before the effects on prices, costs, and consumer and producer's surplus have worked themselves out (Klette, Moen, and Griliches, 1999). Given the decade or so that CRADAs have been around, industrial laboratories are likely places to look for effects of federal laboratories.

Results from the investigation are these. First, the influence of the federal laboratories on industrial patenting and R&D effort seems to depend on the extent of interaction between the two sets of laboratories. In head-to-head comparisons of CRADAs with alternative measures of federal laboratory effects we find that CRADAs are the principal means by which federal laboratories influence patenting and company-financed R&D of industrial laboratories. Since CRADAs are formal agreements that require cost sharing and an ongoing commitment to be successful (Ham and Mowery, 1998) this suggests that intensive interaction is necessary for government laboratories to have an effect. Second, government contractor interactions have effects ranging from zero to negative on industrial patents and no effect on industrial R&D except for publicly funded budget. In contrast, CRADAs increase patents, usually with significance, and also increase company-financed and publicly funded laboratory budget.

At the outset we would like to comment on what we cannot do. We are unable to calculate a stream of costs and benefits from CRADAs and other associations between firms and federal laboratories and cannot do a cost-benefit analysis. Required are aggregate public and private outlays as well as their social and returns, but the data for this do not exist. CRADAs in particular are too new for the monetary returns to be measured, and firm and government laboratory partnerships are generally not a matter of public record.

[4] The results of research projects are hard to predict and no one should expect CRADAs to differ in this respect. Mansfield and Beardsley (1978) study the size of forecasting errors at the level of industrial projects. They compare forecasts of discounted profits by the sponsoring firm with actual discounted profits, using a sample of R&D projects undertaken by a large equipment manufacturer. The regression of forecasted profits on actual profits yielded an adjusted R^2 of 0.14 and a slope coefficient of 0.24 (t=2.4) for new product innovations.

The rest of the paper is organized as follows. Section II describes the surveys that yield most of the data. In addition we discuss external data on patenting of the laboratories as well as R&D in the rest of the firm. Section II includes descriptive tables that illustrate firm and federal laboratory interactions. Section III presents single equation estimates of the federal laboratory effect on industrial patents. The findings show the importance of CRADAs for patenting and cast doubt on the importance of other interactions. Section IV explores extensions of the patent equations. We report on a study of the effect of federal laboratories by agency. We estimate a two-equation Ordered Probit-Probit model, which was previously unknown to us, of the effect of CRADAs on laboratory patents that also accounts for the effect of industrial productivity on CRADAs. Section V explores the federal laboratory impact on R&D effort of the laboratory. Similar to the findings for patents, we find that CRADAs alone increase company-financed R&D. Section VI is a discussion, summary and conclusion.

II. Description of the Data

Most of the data used in this paper derive from two surveys. Here we describe the surveys and the data drawn from them. We also discuss data taken from published sources that supplement the surveys, and we explain our uses for the additional evidence.

The first survey concerns a sample of industrial laboratories. The data include R&D, patents, and other laboratory characteristics. Most important they include a rich set of interactions between industrial and federal laboratories. The data contain two sources of information. First, the industrial laboratories were asked to rank an array of interactions on a scale of 1 to 5 in order of importance. Second and conditional on some interaction, the industrial laboratories were asked to cite particular federal laboratories that were influential for their research.

The second survey collected data on the on-site R&D carried out in federally funded laboratories—the very ones that are cited by the industrial laboratories in the first survey[5]. The follow-up survey was necessary because there is no comprehensive source of information on the R&D of federal laboratories. Later we describe which federal laboratories were included in published sources and which had to be surveyed.

A. Survey of Industrial Laboratory Technologies 1996

A survey of industrial R&D laboratories is our primary data source (Adams, 1997). The survey provides

[5] On-site federal laboratory R&D is our preferred measure since the remainder of laboratory R&D is spent on contractor firms and universities and double-counted among the R&D budgets of the recipient institutions.

size and organizational characteristics of the private laboratories and quantifies their linkages with government research facilities. At the start of the investigation 600 laboratories owned by 200 firms were selected as subjects for analysis. Parent firms were manufacturers of chemicals, machinery, electrical equipment, or transportation equipment. The laboratories were taken from the Directory of American Research and Technology (R.R. Bowker, 1997). Parent firms had to be in Compustat and had to report sales and R&D in that database. Firms also had to be patent assignees with matching records in the U.S. Patent Office database. These criteria allow for some degree of cross-validation of the data while focusing the sample on innovative firms.

A total of 208 laboratory aggregates owned by 116 firms responded to the survey. The responses in fact account for 220 laboratories because three of the firms combined their responses into one, yielding a response rate of 37% (220/600). Of the 116 firms 29 were public for less than 16 years in 1996 so that young companies form a significant part of the sample. Respondents were R&D managers who had been in industrial research for an average of 17 years and with their firms for 15 years, and were knowledgeable about their companies during the 1991-1996 period of the survey.

Table 1 shows the distribution of firms and laboratories by industry of parent firm. The distribution is fairly uniform except for the smaller number of firms in transportation equipment, expected because of the smaller number of firms in this industry. Across industries responding laboratories lie in about the same proportion as the number surveyed. Note that the numbers of laboratories are an upper bound on numbers of observations in the regression tables, since missing values are ignored in the descriptive tables. About two-thirds of the laboratories in fact remain in the regression samples.

Table 2 displays size characteristics of the R&D laboratories classified by linkage to federal laboratories. Since the data in this table were collected for 1991 and 1996 we are averaging over years as well as laboratories in the calculations. The top panel shows R&D inputs: the number of scientists and engineers, number of Ph.D. or MD researchers and laboratory R&D budget in millions of 1987 dollars[6]. The bottom panel shows R&D outputs: the number of patents issued and the value of sales from new products originating in the laboratories.

Table 2 shows two measures of patents issued. The first line is the average of patents granted in 1991 and 1996 as reported in the survey. Not all laboratories, especially a number of the larger ones, reported their patents in both years. The second line replaces missing patents with an estimate for the firm, laboratory location and year using patents of parent firms. Imputed patents derive from U.S. Patent and Trademark Office data and were downloaded from the **U.S. Patents Database** (Community of Science, 1999). The method for obtaining the estimate is this. We begin by matching two digit zip codes to the addresses of all inventors for a company using the electronic zip code database of the U.S. postal service. Next we assign all patents of the parent firm to the laboratory location given in the survey if the inventor two-digit postal zip code matches that of the laboratory. Finally we assign patents to years 1991 and 1996 according to their issue dates[7]. We call this result hybrid patents.

While this is the best way to impute the missing patents that we could think of, it is not a perfect assignment. Inventors employed by firms in smaller states often live in a different two-digit zip code and state than the laboratory. These patents are lost according to our method. Patents often include multiple inventors in different locations and different laboratories in the same firm cluster in the same city for obvious reasons. Both factors lead to over counts of the firm's patents. We handled the first problem by multiplying patents by the fraction of the top four inventors in the same two-digit zip code as the laboratory, even though this adjustment made little difference to our results. We dealt with the problem of clustering of different laboratories in the same firm as follows. We identified laboratories in the survey that were in the same two digit zip code and apportioned the total number of patents according to their share in total scientists and engineers. Despite these improvements the estimates contain errors. The main problem is that imputed patents are partly the result of R&D elsewhere in the firm.

Larger industrial laboratories are more likely to be associated with federal laboratories. Federally connected labs have three times as many scientists, almost seven times as many Ph.D. or MD researchers, and R&D budgets that are more than twice as large as R&D budgets of other laboratories. Patents issued are also more than twice as large as industrial laboratories associated with government. Value of new products is almost eight times larger, this large difference perhaps reflecting industry composition. Given the role of size (and research excellence) in the selection process for government laboratory affiliations, it is imperative that we control for laboratory size and we are careful to do so in the regressions reported below.

Table 3 describes ten interactions between federal and industrial laboratories and the percent of industrial laboratories that rate these interactions as important. Of these the use of test facilities in government laboratories,

[6] While R&D in the laboratory survey is otherwise defined according to NSF guidelines, total R&D is net of overhead expenses and non-R&D charges in the survey data.

[7] We are indebted to Margaret Lister Fernando for downloading the patent data from the Community of Science web site and for translating the text fields into SAS™ for further analysis.

Cooperative Research and Development Agreements (CRADAs), government contractor, inflows of ideas from government laboratories, and use of industry-government technology transfer centers stand out as the most common. Interaction does not necessarily imply technology transfer. For example government contractors manufacture products to meet government specifications. In this case the government finances, but does not necessarily *stimulate* new product development. Similarly SBIR awards finance small projects in universities and startups but they do not provide the projects. Likewise use of test facilities in government laboratories, outflows of scientists to government laboratories, and outflows of ideas to government laboratories do not indicate technology transfer to industry.

Of the interactions listed in table 3 licensing of government patents, CRADAs, inflows of scientists from government laboratories, inflows of ideas from government laboratories, and use of industry-government technology transfer centers are the most likely channels of technology transfer. We mark these accordingly in table 3 and examine their frequency distribution among industrial laboratories in table 4. Fifty-eight percent of laboratories rank none of the technology transfer indicators as important. Among the remaining 42 percent the tail of the distribution of number of indicators is flat. This suggests that the technology transfer indicators are independent of each other and that interactions with federal laboratories are not driven by a single underlying factor.

In the empirical work we code each of the interactions as dummy variables equal to 1 if the private laboratories rated an interaction as important, and 0 otherwise. For some purposes we sum across dummy variables coding for technology transfer, or we recode the individual indicators to show technology transfer of a certain kind. These variations are spelled out in sections III, IV and V on findings from the investigation.

Of the coded interaction dummies the empirical work suggests the importance of government contractor and CRADA interactions for the industrial laboratories. Accordingly table 5 breaks out sub-samples based on these interactions and calculates the ratio of patents to R&D. The most striking aspect of the table is that the patents to R&D ratio doubles when CRADA=1, but drops down to a normal level when GOVERNMENT CONTRACTOR=1: compare the top and middle entries of the second column. This theme recurs in the work to follow and suggests that GOVERNMENT CONTRACTOR conceals the positive effects of CRADA, perhaps because of restrictions on patenting associated with defense R&D. This finding shows the importance of separating contractor from CRADA.

B. Survey of Government Laboratory R&D 1998

Separately from the above information the industrial laboratories were asked to write down particular federal laboratories that had a significant effect on their research. The result was a name and address list of federal laboratories. Using this information we set out to identify cited laboratories by department or agency of the federal government using U.S. General Accounting Office (1996). The majority of laboratories were in the Department of Energy (DOE) or Department of Defense (DOD) with lesser numbers in NASA, Commerce, Health and Human Services (HHS), Agriculture, Interior, and the Environmental Protection Agency (EPA) by citation frequency. This ranking is not surprising given the dominant role of DOE and DOD in government research. But the citations also reflect the concentration of private laboratories in the sample in the machinery, computers, electrical equipment, and transportation equipment industries rather than in biotechnology and pharmaceuticals. This lowers the citation rate to HHS and agriculture. In six cases we found citations to large non-profit laboratories that were private, but receiving most of their funding from federal government. We call these federally funded R&D laboratories.

Given the list of cited federal laboratories we sought to construct spillover "pools" of R&D from published data on federal laboratories in order to test a simple model of public-private interactions. The idea is that larger pools represent a larger source of knowledge than smaller pools and automatically transmit more knowledge to the industrial laboratories working with them[8].

The chief alternative to this model is that knowledge spills over only if a firm devotes resources to *making* the knowledge spill over (Cohen and Levinthal, 1989). In our context the argument suggests that the firm is interested in the small part of federal laboratory research that is opened up by research collaboration.

We needed several pieces of evidence in order to test the hypothesis that larger laboratories provide larger spillovers. We required (1) a history of government laboratory R&D that extended at least a decade before the 1991 and 1996 data on the industrial laboratories. This would allow us to compute a partial R&D stock for the laboratory. In addition we required (2) data on on-site or "intramural" R&D. This internally conducted R&D would attract the private laboratories in the pool analogy. Note that on-site R&D is separate from contracts and grants to firms and avoids double counting in the budgets of private and federal laboratories. And (3), we wanted data on research divisions or *directorates* in a laboratory to capture diversity of R&D effort within federal laboratories and to serve as a "real" deflator of that R&D[9]. However, we were soon frustrated in our efforts to construct a spillover "pool" for each cited government laboratory that could be matched to private laboratories. Only the Department of Defense

[8] See Cockburn and Henderson (1996), Ham and Mowery (1998), and Adams (1999b) on the list of references for a critique of this view.

[9] This idea seems to have first appeared in Evenson and Kislev (1973). Adams and Jaffe (1996) and Adams (1999a) make extensive use of "real" deflators of R&D in Census data classified by location or by area of technology. In their case the deflators are numbers of plants by location or technology.

records such information in the form of its RDT&E reports (see Defense Technical Information Center, various years).

Thus we lacked reasonable spillover pools for most of the individual government laboratories apart from the DOD data and a few exceptions contained in National Science Foundation (various years). It was for the sole purpose of constructing these spillover pools of government laboratory R&D that we conducted the **Survey of Government Laboratory R&D 1998** (Adams, 1998). This survey, which polled the chief financial officers (CFOs) of the non-DOD federal and federally funded laboratories, had a response rate of 97%[10].

The resulting data on the R&D of federal laboratories are prone to several sources of error. Respondent error by the industrial laboratories is probably the most important since citations are usually to all of a federal laboratory rather than to the "sending" division of the laboratory. The size of this aggregation error is likely to vary from one respondent to another but little can be done about the problem. In addition the data on federal laboratories may be variously aggregated, leading to a different source of error. Finally the quality of data concerning on-site R&D varies according to agency and by responding CFO in the federal laboratory survey.

Table 6 describes general interactions between the two sets of laboratories, including the average size of the R&D "pool" facing the private laboratories as taken from the published sources and the **Survey of Government Laboratory R&D 1998**. Forty-five percent of private laboratories report some interaction with federal laboratories. Of these nearly all or 42% report that at least one of the technology transfer channels (see table 3) was important for their research. Of the 45% having a federal lab connection two thirds or 31% describe particular federal laboratories that were influential for their research. We refer to these as closely affiliated federal laboratories.

Contingent on the citation of particular federal laboratories table 6 indicates the average number of federal laboratories cited and the average number of directorates. These are 3.5 and 20.5 respectively indicating six directorates in the average federal laboratory. The table also reports R&D stocks for the set of closely affiliated federal laboratories that are cited by the industrial laboratories. For each cited government laboratory we constructed 10- year stocks of R&D in millions of 1987 dollars, that end one year prior to the survey evidence dated as of 1991 and 1996, and discounted at a rate of 15 percent. Reported stocks are means of the sum over the R&D stocks of federal laboratories cited by *private* laboratories. Total R&D stock is 8.8 billion $ in 1991 and 9.2 billion

[10] In some cases we obtained data on federal laboratory R&D from both the survey and published sources. In all such cases the two sets of figures matched quite closely. This is because the CFOs of the laboratories were the source for the survey data on the federal laboratories.

$ in 1996. The more relevant on-site or intramural figure is about 4 billion $ in both years[11]. Per directorate the stock of total federal laboratory is slightly less than 500 million $. The preferred on-site R&D stocks per directorate are just over 200 million $. These figures indicate the extraordinary size of the federal laboratories.

Table 7 reports the distribution of cited laboratories by category and the number of citations by the private laboratories from the industrial laboratory survey. For comparison the table includes aggregate data on the number of CRADAs and patent applications in the third and fourth columns [12]. Since biotechnology and pharmaceutical firms are a minority of the industrial laboratories HHS and agriculture are less important agencies for this sample. Otherwise the citations seem closely related to the aggregate number of CRADAs. So while the number of cited laboratories is largest for DOD the number of DOD citations comes in second to Department of Energy, much like the distribution of CRADAs in column (3).

Before studying the regressions note the policy that we adopt for keeping observations that include data on particular cited federal laboratories. First, if an industrial laboratory declared a federal laboratory connection and cited federal laboratories, then we include the observation. If the laboratory said there was no federal laboratory connection that observation was also included. But if a connection was declared and no federal laboratory was cited then we exclude the observation. For in this case the laboratories censored the data on particular federal laboratories. We treat the information on federal laboratories as missing in such cases.

C. Supplemental Data

Besides evidence from surveys we introduced R&D and sales of parent firms from Compustat (Standard and Poor, 1999) and matched this with the survey data. This gave us two variables that play a useful role in the empirical work. The first is the logarithm of R&D in the rest of the firm in millions of 1987 dollars. This variable controls for R&D effort elsewhere in the firm, which could contribute to laboratory patents in addition to laboratory budget. The second is the logarithm of the stock of recent sales of the firm. To construct this variable we expressed sales in millions of 1987 dollars from the previous 12 years, depreciated them at a rate of 15%, summed the result, and took logarithms. Recent firm sales control for size of the firm. Another measure of size from Compustat, stock market value, performed in a similar way to recent sales.

[11] The fraction of total R&D that is conducted on-site ranges from 1 to 99 percent across the cited group of federal laboratories. This indicates the heterogeneity of the laboratories in the degree to which they farm out research and the importance of obtaining intramural R&D to disclose true laboratory R&D effort.

III. The Influence of Federal Laboratories on Industrial Patents

Tables 8 and 9 show the single equation results for patents issued to the private laboratories. After all missing values are accounted for the samples include two-thirds of responding laboratories for up to two years. The estimation method we use is negative binomial regression—a type of random effects Poisson. Many of the laboratories do not patent and the mean number of patents is close to zero. Poisson regression is one way of handling such count data, but it has a major drawback[13]. The Poisson assumption fails to account for over-dispersion of observed counts in microdata. Negative binomial regression corrects for this problem. In all the regressions test statistics for over-dispersion of the Poisson are highly significant, indicating support for the negative binomial over the Poisson.

Given the non-linearity of the negative binomial we find it useful to give an interpretation of the estimated regression parameters. To ensure non-negativity, the computational algorithm writes the logarithm of the Poisson parameter, which determines the expected number of patents, as a regression function:

(1) $$\log \lambda_i = x_i' \beta$$

It follows that if x_{ij} is specified in logarithmic form, then β_j is the constant elasticity of patents with respect to x_{ij}.

We provide a more elaborate analysis for x_{ij} a dummy variable, since the federal laboratory interactions take this form and are a cornerstone of the analysis. Take the antilogarithm of (1) to find the expected number of patents for the ith observation λ_i. Let $\lambda_i^{\,1}$ stand for expected patents when x_{ij} =1 and let $\lambda_i^{\,0}$ when x_{ij} =0.

Then the change in the number of patents due to x_{ij} changing from 0 to 1 is:

(2) $$\Delta\lambda_i \equiv \lambda_i^{\,1} - \lambda_i^{\,0} = e^{x_{i.j}\beta_{.j}+\beta_j} - e^{x_{i.j}\beta_{.j}} = \lambda_i^{\,0}\left(e^{\beta_j} - 1\right)$$

The third expression uses the notation $x_i'\beta = x_{i.j}\beta_{.j} + x_{ij}\beta_j$ to partition the regression function as well as x_{ij} =1 to write $\lambda_i^{\,1}$ and x_{ij} =0 to write $\lambda_i^{\,0}$. The expression on the far right then follows from the definition of $\lambda_i^{\,0}$.

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[12] We thank Walt Polanski of the U.S. Department of Energy for providing the aggregate data appearing in columns (3) and (4) of Table 7.

[13] Maddala (1983), Ch. 2 is a basic treatment of Poisson regression. Hausman, Hall and Griliches (1984) discuss the extension to the negative binomial. Johnson and Kotz (1969) derive the negative binomial as follows. Assume that the count data are Poisson distributed for a given parameter λ, and further assume that λ is a random variable that follows the Gamma distribution. Then the unconditional distribution of the data follows a negative binomial.

Equation (2) gives the expected change in the number of patents for the ith observation due to the dummy variable. But we are more interested in the *mean* effect of a change in the dummy variable for the sample of observations where the dummy equals zero. Let $\overline{\lambda}^0$ stand for mean patents for the x_j =0 sub-sample and let $\widetilde{\lambda}^1$ represent the mean effect on patents of a change in x_j from 0 to 1. Using (2) we can write the predicted change in patents as

(3) $$\Delta\overline{\lambda}^0 \equiv \widetilde{\lambda}^1 - \overline{\lambda}^0 = \overline{\lambda}^0\left(e^{\beta_j} - 1\right)$$

The ratio of (3) to the difference in mean patents in samples where the dummy is 1 and 0 respectively ($\overline{\lambda}^1 - \overline{\lambda}^0$) is a useful comparison function, helpful for gauging the mean effect of the dummy:

(4) $$R_{\Delta\overline{\lambda}^0} \equiv \frac{\widetilde{\lambda}^1 - \overline{\lambda}^0}{\overline{\lambda}^1 - \overline{\lambda}^0} = \frac{\overline{\lambda}^0}{\overline{\lambda}^1 - \overline{\lambda}^0}\left(e^{\beta_j} - 1\right)$$

We make frequent use of (1), (3) and (4) in discussing the impact of CRADAs on patents below.

Equations 8.1 to 8.4 use reported patents as the dependent variable while 8.5 to 8.8 use hybrid patents. Recall that hybrid patents replace reported patents with an estimate for the location and firm from U.S. Patent and Trademark Office data when reported patents are missing. Thus we include an imputation dummy in 8.5 to 8.8 to absorb the effect of imputation. The imputation dummy is positive and significant, partly indicating the larger size of laboratories in imputed cases but also the fact that imputed patents are more inclusive than reported patents. All equations include dummy variables for year and industry. In addition, two dummy variables measure specialization of the laboratory. These measure whether the laboratory is primarily engaged in testing and whether the laboratory is jointly housed with manufacturing. The testing dummy lowers patenting, as one would expect, although the effect is not significant. The joint housing dummy, which reflects proximity to manufacturing and distance from science-based R&D, makes little difference to patenting once laboratory budget is held constant, as is done throughout. While separately housed laboratories are more focused on research, making them more prone to patent, they are also more likely to be engaged in basic science and less prone to patent, so the net effect is zero.

The rest of the table considers the effect on patenting of laboratory R&D, rest of firm R&D and the interactions with federal laboratories. Throughout table 8 the logarithm of laboratory R&D has a positive, highly significant effect though the elasticity (about 0.7) is significantly less than 1.0. This could mean that there are diminishing returns to patenting or that larger laboratories have a lower propensity to patent or that larger laboratories focus on more significant inventions though we cannot distinguish these explanations. Equations 8.4

and 8.8 split laboratory R&D budget into company-financed and federally funded components. Only the company-financed component increases patenting. This indicates that federally funded R&D is dominated by government contracts, for which either patent rights or technological opportunities are limited.

In all the equations we introduce the logarithm of R&D in the rest of the firm to control for firm size and for cross-divisional benefits from research conducted elsewhere in the company. This variable is net of R&D in the laboratory[14]. Its effect on laboratory patents is positive and significant, though its elasticity of 0.06 is less than a tenth of the elasticity of laboratory R&D. As we have suggested, the effect of rest of firm R&D could capture the firm's ability to capture returns to its R&D as reflected in firm size. Alternatively, the effect of rest of firm R&D could represent knowledge transfer within the enterprise. In regressions not shown where we include recent sales of the firm to capture size of firm, sales are insignificant but rest of firm R&D remains positive and significant. This suggests that rest of firm R&D measures knowledge transfer within the firm.

Table 8 contains three indicators of government laboratory interaction. GOVERNMENT CONTRACTOR is a dummy equal to 1 (and 0 otherwise) when a private lab indicates that a contractor relationship with the federal laboratories is important. GOVERNMENT CONTRACTOR is negative to insignificant for patents, suggesting perhaps, that the property rights to government-sponsored R&D do not reside with the firm.

CRADA equals 1 (and 0 otherwise) when an industrial laboratory indicates the importance of cooperative research agreements with federal labs. CRADA is associated with a significant increase in patents, consistent with its interpretation as a legal arrangement that expedites technology transfer. This effect weakens (see 8.4 and 8.8) when federally funded laboratory budget is included as a separate variable, presumably because federal support includes CRADA funding. The remaining indicator, the logarithm of on-site R&D in closely affiliated government laboratories per directorate, is never significant. CRADA is the only indicator in table 7 associated with increased patenting by industrial laboratories. To see how large the effect of CRADA is, use β_j =0.4 or 0.5 in equation (3),

[14] We suspect, though we cannot prove, that R&D in the rest of the firm contains a larger component of production engineering than research, compared with laboratory R&D. This is because Compustat R&D probably contains much of the engineering budget as well as the research of central laboratories. The latter is longer term R&D. The grounds for our suspicions derive from a visit by one of us to the only central research laboratory of an important firm. The budget of this laboratory, where most of the firm's basic and applied research was performed, accounted for 1/10 of Compustat R&D. The company-financed portion of budget derived from a tax on the engineering budget, supplemented by external grants. The tax led to conflict with production engineers over the use of company funds. The central laboratory focus on basic and applied research, along with the nature of the conflict suggests that production engineering accounted for most of 10K R&D reported in Compustat.

along with $\bar{\lambda}_0$=5.93 from the third row, first column of table 5. The estimated effect of the importance of CRADAs ($\Delta\bar{\lambda}_0$) is 2.91 or 3.85 patents. Since the CRADA dummy stands for several CRADA agreements, and since an agreement is worth an amount on the order of one million $ (Ham and Mowery, 1998), these figures seem reasonable. Furthermore we can use the measure $R_{\Delta\bar{\lambda}^0}$ (see (4) above) of the fraction of the mean difference in patents in the samples without and without CRADAs that is accounted for by the CRADA dummy, to gauge the relative contribution of CRADAs. From the third row, second and first columns of table 5, $\bar{\lambda}_1$=17.80 and $\bar{\lambda}_0$=5.93. Substituting these values and $\Delta\bar{\lambda}_0$ into (4) we see that $R_{\Delta\bar{\lambda}^0}$ ranges from 0.25 to 0.32 and that most of the difference in patents between the samples is due to the laboratories rather than CRADA. This again seems reasonable.

Table 9 digs deeper into the effect of CRADA. In this table we set up a competition between CRADA and other technology transfer indicators to see which dominates. The collection of indicators on each line is extracted from regressions specified as in table 8. We omit the other variables since their effect remains the same as before. The technology transfer indicators are shown on the left. Estimated coefficients are shown on the right, with t-statistics in parentheses. Eight combinations of government laboratory interactions are reported in table 9.

WEAK is a dummy variable equal to 1 if any of the technology-transfer indicators in table 3 (licensing of government patents, use of CRADAs, inflows of ideas from government laboratories, inflows of government scientists, and use of industry-government technology transfer centers) are important[15]. Otherwise WEAK equals 0. WEAK is insignificant unless GOVERNMENT CONTRACTOR is introduced, as on the second line.

STRONG is the sum of the five technology transfer indicators and accordingly ranges from 0 to 5. STRONG is a more significant contributor to patents than WEAK, especially when GOVERNMENT CONTRACTOR is introduced. This is because STRONG captures intensity of interactions with government laboratories in a way that WEAK cannot.

The last four lines of table 9 separate CRADA from WEAK and STRONG. RESIDUAL WEAK is a dummy variable equal to 1 if any of the technology transfer indicators besides CRADA are important (licensing of government patents, inflows of ideas from government laboratories, inflows of government scientists and use of industry-government technology transfer centers). Otherwise RESIDUAL WEAK equals 0. The fifth line of table 9 breaks up WEAK as shown on the first line into RESIDUAL WEAK and CRADA. RESIDUAL WEAK is negative and insignificant indicating the meager contribution of other technology transfer indicators, while CRADA remains positive and significant as before. The sixth line adds GOVERNMENT CONTRACTOR to the specification. RESIDUAL WEAK is insignificant while CRADA remains positive and significant. At best GOVERNMENT CONTRACTOR is associated with the same number of laboratory patents.

Lines seven and eight separate CRADA from STRONG. We decompose STRONG into RESIDUAL STRONG and CRADA; otherwise the regressions are comparable to lines three and four. Unlike STRONG, RESIDUAL STRONG is insignificant. We have consistently seen that CRADA increases laboratory patents, while GOVERNMENT CONTRACTOR lowers patenting, sometimes with significance.

Table 9 offers more support for the hypothesis that the effect of federal technology transfer on patenting resides *only* in the CRADA indicator. Once CRADA is separated out neither WEAK nor STRONG matters. The results strengthen those of table 8 and more generally the case for the endogenous R&D spillovers interpretation of public-private interactions, since CRADA is one of the most resource intensive indicators shown. But in spite of all the controls for laboratory size and specialization, CRADA could still reflect unobserved aspects of the laboratory.

IV. Further Investigation of Federal Laboratory Effects on Patents

According to the above results the mean effect of R&D in closely affiliated laboratories is zero, yet patents increase as a result of CRADA. In this section we explore these contrasting findings. We argue that the mean effect of federal laboratory R&D equals zero because linkages to federal laboratories represent combinations of relationships that both raise and lower patenting in industry. Some industrial laboratories are engaged in defense research and this censors their patents. In others the firm has a contractor relationship that has no bearing on patents. In still others the firm engages in a CRADA relationship that seems to encourage industrial patents. To an extent the separation of federal laboratory R&D into different agencies unmasks these relationships.

A. Agency Effects

We extended the results of Tables 8 and 9 by decomposing R&D of closely affiliated federal laboratories into the R&D of Energy, NASA, Defense, Commerce and all other agencies.[16] The particular measure of federal R&D remained on-site R&D per division. To save space we do not include a table but merely summarize the results.

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[15] WEAK and STRONG is tongue in cheek for weak and strong indicators of interaction with federal laboratories.
[16] All other consists of R&D in Agriculture, EPA, HHS and private non-profit laboratories that are primarily funded by federal government.

The main result was that the R&D of the NASA laboratories has a consistent, positive and significant effect on industrial patenting, whereas Energy and especially Defense laboratories have a negative and sometimes significant effect. One has to be careful in interpreting the results since several explanations could account for them. The pattern of the results is nevertheless surprising, since Energy and Defense are more active in CRADA issuance than other departments (see table 7). But Energy and Defense laboratories are involved in highly sensitive research and these aspects seem to negate the effect of CRADAs. Throughout it is the agencies that are not involved in defense whose R&D has the more positive effect. This suggests that restrictions on patenting from publicly financed R&D decrease the observed impact on industrial patents. Therefore, one interpretation is *not* that Energy and Defense affiliations result in fewer patents but rather that the type of affiliation leads to greater censoring of patenting, or contractor activity not focused on patenting. An alternative view is that agency effects simply proxy for various industrial laboratories' propensity to patent.

B. Simultaneity between Industrial Patents and CRADAs

So far we have found that CRADAs increase patents, but we have not explored the possibility that CRADAs are influenced by research proficiency, evidenced in part by patents. And yet the industrial laboratories working with federal laboratories are larger than average (see table 2) and probably more successful than average. One view of the process generating the observations is that CRADA is a dummy variable in a simultaneous equation system[17]. According to this interpretation patents are a function of laboratory R&D budget, CRADA, industry and year dummies and specialization of the laboratory[18]. At the same time CRADAs are a function of laboratory R&D budget; industry and year dummies; and other interactions with federal laboratories, including GOVERNMENT CONTRACTOR. Both equations are part of a two-equation system that allows for cross-correlation of the errors.

The equation system for this type of model does not allow for any feedback from patents to CRADA and the following discussion shows why. To fix ideas in the course of this discussion we shall model the patent

[17] Heckman (1978) develops the theory of endogenous dummy variables in a simultaneous equation system and applies the theory to anti-discrimination laws. Maddala (1983) Ch. 5 contains a survey of the literature.

[18] An alternative view emphasizes the role of selectivity. According to this view, the error term of the patent equation of (1), which may be interpreted as unobserved research productivity, can be expressed as a function of CRADA. The reason is that the propensity to receive CRADAs and to regard them as important is a function of unobserved patent productivity. As long as the CRADA propensity can be inverted to solve out the error term, the solution exhibits a positive correlation with the CRADA dummy. See Olley and Pakes (1996) for an exposition of this approach and its application to the telecommunications equipment industry. But in our case, unlike theirs, there is no obvious sample selection: R&D labs do not disappear from the sample as a result of not receiving a CRADA.

indicator as an Ordered Probit variable in which patents fall into increasing intervals. This assumption allows us to estimate the correlation between the Ordered Probit indicator for patents and the standard Probit indicator for the importance of CRADAs using bivariate normal theory. The two-equation system is

$$(5)\quad \begin{aligned} y_1^* &= \beta_2 y_2 + \gamma_1' X_1 + u_1 \\ y_2^* &= \gamma_2' X_2 + u_2 \end{aligned}$$

Here y_1^* is the latent indicator of patents, y_2 is the observed 0-1 indicator for the importance of CRADAs to the laboratory and y_2^* is the latent indicator for CRADA interactions. Also, X_1 and X_2 are the independent variables and u_1 and u_2 are the error terms. The reason why patents do not feedback to CRADAs, so that $\beta_1 y_1$ does not appear in the second equation of (5), is that the probabilities do not sum to unity unless β_1 equals zero[19]. This logical consistency condition, which is necessary if the model is to have a proper distribution, leads some writers to call models like (5) recursive models, even though the errors are not assumed to be independent and the term "recursive" is usually reserved for the independent case. Indeed, the principal gain from using (5) in place of single equation methods is that it permits us to estimate the correlation between u_1 and u_2, as in Seemingly Unrelated Regression.

Turning to the estimation procedure, the probability that patents lie in interval j and that CRADAs are important is

$$\Pr(y_1 = j, y_2 = 1) = P(c_j > y_1^* > c_{j-1}, y_2^* > 0)$$

$$= P(c_j > y_1^* > c_{j-1}) - P(c_j > y_1^* > c_{j-1}, y_2^* < 0)$$

$$(6)\quad = \left[P(c_j > y_1^*) - P(c_j > y_1^*, y_2^* < 0)\right] - \left[P(c_{j-1} > y_1^*) - P(c_{j-1} > y_1^*, y_2^* < 0)\right]$$

$$= \left[\Phi\left(c_j - \beta_2 - \gamma_2' x_2\right) - F\left(c_j - \beta_2 - \gamma_2' x_2, -\gamma_1' x_1, \rho\right)\right]$$

$$- \left[\Phi\left(c_{j-1} - \beta_2 - \gamma_2' x_2\right) - F\left(c_{j-1} - \beta_2 - \gamma_2' x_2, -\gamma_1' x_1, \rho\right)\right]$$

The equality sign on the first line of (6) states the equivalence between observable and latent indicators, as determined in part by the "cut points" c_j and c_{j-1}. The equality on the second line shows the conversion between the probability of y_2^* exceeding 0 and its equivalent, 1 minus the probability that y_2^* is less than 0. The equality on the third line of (6) expresses the bracketed probability that y_1^* lies between two cut points as the corresponding difference in probabilities that y_1^* is less than each cut point. Thus lines two and three rewrite the probability of jointly observing $y_1 = j$ and $y_2 = 1$ in terms of univariate and bivariate cumulative distribution functions (CDFs). This is necessary in order to maximize the log likelihood, because standard software catalogues only the CDFs. The fourth and fifth lines impose the assumption of normality on each of the CDFs since $\Phi(\bullet)$ is the standard univariate normal CDF and $F(\bullet)$ is the standard bivariate normal CDF assuming a correlation coefficient of ρ. We assume standardized normal distributions since Probit analysis does not identify the variances.

Equation (6) specifies the branch of the likelihood function where CRADAs are observed to be important to the laboratory. The probability of observing the other branch, where CRADAs are not important, is

$$\begin{aligned} &\Pr(y_1 = j, y_2 = 0) = P(c_j > y_1^* > c_{j-1}, y_2^* < 0) \\ (7) \qquad &= \left[P(c_j > y_1^*, y_2^* < 0) - P(c_{j-1} > y_1^*, y_2^* < 0) \right] \\ &= \left[F\left(c_j - \gamma_2' x_2, -\gamma_1' x_1, \rho\right) - F\left(c_{j-1} - \gamma_2' x_2, -\gamma_1' x_1, \rho\right) \right] \end{aligned}$$

As in (6) the first line states the equivalence between the observable and latent indicators. The second line again expresses the bracketed probability that y_1^* lies between two "cut points" as the equivalent difference in probabilities that y_1^* is less than each cut point and translates the probabilities into computable CDFs. The last line imposes normality on the CDFs, where $F(\bullet)$ is the standard bivariate normal CDF, assuming a correlation coefficient of ρ.

The likelihood function is the product of (6) and (7) across observations:

$$(8) \qquad L = \prod_i \prod_j \left[P(c_j > y_{1i}^* > c_{j-1}, y_{2i}^* > 0) \right]^{Z_{ij}} \bullet \left[P(c_j > y_{1i}^* > c_{j-1}, y_{2i}^* < 0) \right]^{Z_{ij}},$$

where i is the observation and $Z_{ij} = 1$ if y_{1i}^* falls in category j of patents and 0 otherwise.

Table 10 contains the results for the two equation econometric model consisting of (5)-(8)[20]. Equation 10.1 presents the single equation, Ordered Probit estimate of the patent equation in which categorical patents are

[19] For a proof using a simplified version of (5), see Maddala (1983), p. 119.
[20] The STATA™ program that computes the estimates is available on request. See Gould and Sribney (1999) for an introduction to maximum likelihood estimation using STATA™.

PATCAT[21]. In this equation, as before, CRADA is highly significant. Equation 10.2 reports the single equation Probit estimate of the CRADA equation, with a battery of other interactions with government labs serving as instruments and treated as predetermined. These interactions include GOVERNMENT CONTRACTOR, inflows of ideas from government labs, inflows of scientists from federal labs, licensing of government patents, test facilities in government laboratories, and industry-government technology transfer centers. The logarithm of R&D conducted elsewhere in the firm is excluded from 10.2 on the ground that the size and research proficiency of the laboratory attracts CRADAs, not research elsewhere in the firm[22]. The results of 10.2 suggest that GOVERNMENT CONTRACTOR, inflows of ideas from government labs, and licensing of government patents are the most important determinants of CRADAs.

Equations 10.3 and 10.4 contain the two equation maximum likelihood estimates of PATCAT and CRADA. The key result is that taking cross-equation correlation into account increases the point estimate of CRADA in the patent equation. And while the standard errors of the estimated coefficients increase in 10.3, especially for R&D budget and CRADA, both these variables remain significant. The correlation between the error terms of the patent and CRADA equations, while negative, is insignificant[23].

We also estimated the system comprised of (5)-(8) using the broader sample that includes imputed patents from the U.S. Patent and Trademark Office when reported patents are missing. The results for hybrid patents are similar to those for reported patents in table 10. In the single equation results for PATCAT the coefficient for CRADA is 0.33 (t=2.4). In the two equation maximum likelihood results, the coefficient of CRADA is 0.41 (t=2.0). The cross-equation correlation is –0.09 (t=-0.5). Thus as before the point estimate of the CRADA effect is larger in the two equation results, though the standard errors increase.

V. The Effect of Federal Research on Laboratory R&D

Table 11 studies the determinants of laboratory R&D[24]. The table reports five specifications of laboratory R&D: total, company-financed, company-financed net of expenditures on federal laboratories, federally funded and

[21] The 10 categories of PATCAT correspond to 0, 1, 2, 3, and 4 patents, 5-7 patents, 8-10 patents, 11-20 patents, 21-40 patents, and 41+ patents. The intervals are selected to avoid small cells on the patent observations.
[22] The instruments and the exclusion restrictions identify the probabilities for this model. Again see Maddala (1983), p. 122-123.
[23] As expected the estimates of the "cut points" are monotonically increasing and are –0.02, 0.47, 0.92, 1.37, 1.64, 1.99, 2.32, 2.87 and 3.43.
[24] Laboratory R&D and patents are treated as a recursive system in tables 8-12, with R&D preceding patents.

company expenditures on federal laboratories. Interactions with federal laboratories influence the budgetary components differently. Total laboratory R&D averages the influences across components. Company-financed R&D forms most of laboratory budget and is driven the most by profitability of the firm's research, as well as any incentives from interactions with the government. Net company-financed R&D takes out company expenditures on federal laboratories; but the net amount is very close to company-financed R&D. Government support has a mechanical effect on federally funded R&D. But federally funded R&D is also influenced by characteristics of the firm and laboratory that attract the funding. Although a minor part of budget, company expenditures on federal R&D are probably the most affected by contact with government laboratories.

Thus table 11 compares effects for the different types of laboratory expenditures of the dummy federal laboratory interactions and the logarithm of R&D in closely affiliated federal laboratories. We believe that the impact of public-private interactions differs for the various categories of R&D and we would like to see if these beliefs are confirmed. We would also like to know whether federal laboratory interactions have effects on R&D expenditures that differ from those for industrial patents.

Equations 11.1 and 11.2 are OLS regressions that explain total R&D of the industrial laboratories. R&D spending is significantly smaller in laboratories that specialize in testing and are housed jointly with manufacturing plants. All the equations in tables 11 and 12 include the logarithm of the number of Ph.D. scientists in the laboratory to control for size and excellence of the laboratory. Otherwise, since laboratory R&D is now a dependent variable the effect of laboratory size is transmitted to the other independent variables, including the federal laboratory interactions. Consistent with this, the number of Ph.D. scientists has a highly significant effect on laboratory R&D and likewise the effect of the other variables generally declines as a result of its inclusion.

Larger amounts of R&D in the rest of the firm lead to a reduction in laboratory budget holding constant recent sales of the firm. This effect suggests diversion of firm R&D to other laboratories as rest of firm R&D increases. Recent sales of the firm, a measure of firm size and the incentives to do research, increase laboratory R&D. Building on previous research that suggests R&D intensity is unrelated to firm size, the *joint* effect of rest of firm R&D and recent sales is positive for laboratory R&D[25]. We show this by imposing constancy of firm R&D intensity through the assumption of an equal percentage increase in R&D in the rest of the firm and in recent sales of

[25] See Bound et al. (1984), for a discussion and empirical results at the firm level that suggest R&D intensity relative to sales is nearly constant across different firm sizes.

the firm. Then table 11's finding of a larger elasticity of laboratory R&D with respect to sales than rest of firm R&D implies that the joint effect of the two variables is positive for laboratory R&D.

The pattern of government laboratory interactions in equations 11.1 and 11.2 is similar to that for patents (see table 8). GOVERNMENT CONTRACTOR is insignificant whereas CRADA contributes strongly to laboratory budget. Just as in the patent equations on-site federal R&D in closely affiliated federal laboratories has essentially no effect on R&D expenditures.

Equations 11.3 and 11.4 explore the determinants of company-financed R&D. Since most R&D is company-financed the results are similar to 11.1 and 11.2. Among the three government laboratory indicators, only CRADA increases company-financed R&D, perhaps reflecting the cost-sharing provisions of cooperative agreements that were discussed in the introduction to this paper. Equations 11.5 and 11.6 examine company-financed R&D net of expenditures on federal laboratories. These results are about the same as for 11.3 and 11.4.

Equations 11.7 and 11.8 study the behavior of federally funded R&D. The estimation method is Tobit analysis since 80% of the laboratories receive no federal funding[26]. Clearly firms with larger sales attract larger amounts of federal funding. In 11.7 the CONTRACTOR and CRADA dummies are associated with an increase in federal funding, since government contracts as well as CRADAs contribute to federally funded budget. Equation 11.8 introduces R&D of closely affiliated federal laboratories, along with GOVERNMENT CONTRACTOR and CRADA. As before, federal laboratory R&D is insignificant.

The Tobit coefficients are considerably larger than the OLS coefficients. However, unlike OLS, mean effects in Tobit analysis are the estimated coefficients multiplied by the fraction of observations not censored[27]. The marginal effect of CRADA on company-financed R&D is 0.65 in 11.3, but the marginal effect of CRADA on federally funded R&D is $0.2\times3.79=0.76$ in 11.7. The same comparison holds for the other variables. All the Tobit coefficients must be multiplied by the fraction of observations not censored to obtain expected marginal effects that can be compared with OLS coefficients.

Table 11 concludes with expenditures by the private laboratories on federal laboratories. While a minor part of R&D budget, one would expect a strong reaction of this type of expenditure to public-private interactions,

[26] Tobit is a mixture of probit and regression analysis. See any standard textbook of econometrics for a discussion.
[27] 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 proposition.

partly because of the exploratory nature of these expenditures. Tobit is the estimation method since expenditures on federal laboratories equal zero for 83% of the observations.

Equations 11.9-11.11 show the results. Equation 11.9 includes only GOVERNMENT CONTRACTOR and CRADA, 11.10 includes only the logarithm of federal laboratory R&D and 11.11 includes all of three public-private interactions. GOVERNMENT CONTRACTOR is insignificant, suggesting that contractor R&D is fully funded by government. CRADA encourages expenditures on federal laboratories, consistent with its interpretation as an indicator of joint research. For the first time, R&D of closely affiliated federal laboratories adds to a component of industrial research. This is due perhaps, to larger federal laboratories awarding larger CRADAs, or to larger federal laboratories attracting more interest from industrial laboratories. But these effects apply to a minor component of R&D and as a result, they are absent from 11.1 and 11.2, the findings for total R&D.

Overall table 11 suggests that CRADA alone stimulates company R&D spending. As a mechanical matter, government contractors receive more federal support. As a contractual matter and as a matter of incentives private laboratories that participate in CRADAs spend more on their own, receive more government support, and are more energetic in finding out about research in government laboratories.

To gauge the effect of CRADA we use a formula that is very like (3) for patents. Just as $\log \lambda = x'\beta$ so here, $\log R\&D = z'\delta$. Thus we can replace mean λ with mean $R\&D$ throughout (3), yielding

$$\Delta\overline{R\&D}^{0} \equiv \tilde{R}\tilde{\&}\tilde{D}^{1} - \overline{R\&D}^{0} = \overline{R\&D}^{0}\left(e^{\delta_j} - 1\right) \tag{9}$$

As in (3), $\Delta\overline{R\&D}^{0}$ is the mean increase in R&D due to CRADA, $\tilde{R}\tilde{\&}\tilde{D}^{1}$ is additional R&D in non-recipient laboratories brought about by CRADA and $\overline{R\&D}^{0}$ is mean R&D in non-recipient laboratories. Superscript 0 stands for the group where CRADA=0, superscript 1 stands for the group where CRADA=1, and δ_j is the coefficient of CRADA.

Therefore (9) gives the mean effect on laboratory R&D of CRADA, using mean R&D of laboratories where CRADA=0 ($\overline{R\&D}^{0}$) as the base. We now calculate (9). From the third row, first column of table 5, $\overline{R\&D}^{0}$ =4.48. For the CRADA effect we use δ_j=0.62 from 11.5, the results for net company-financed R&D in 11.5. This concept of R&D is freest of federal support and thus the most reliable for estimating the effect of CRADA. Substituting these numbers into (9), $\Delta\overline{R\&D}^{0}$=4.48(1.62-1)=3.85.

To gauge the size of this effect we use a formula that parallels (4):

$$R_{\Delta\overline{R\&D}^0} \equiv \frac{\widetilde{R}\,\widetilde{\&}\,\widetilde{D}^1 - \overline{R\&D}^0}{\overline{R\&D}^1 - \overline{R\&D}^0} = \frac{\overline{R\&D}^0}{\overline{R\&D}^1 - \overline{R\&D}^0}\left(e^{\delta_j} - 1\right) \tag{10}$$

This is the fraction of the difference in R&D in laboratories where CRADA=1 (superscript 1) and CRADA=0 (superscript 0) that is due to CRADA itself. Since (9) gives the numerator of the middle element of (10), and since $\overline{R\&D}^0$ =4.48, all we need to complete the calculation of (10) is $\overline{R\&D}^1$. From the third row, second column of table 5 mean R&D for the sample where CRADA=1 is $\overline{R\&D}^1$ =23.13. From the above calculations $R_{\Delta\overline{R\&D}^o}$ =3.85/(23.13-4.48)=0.21.

If we repeat the calculations using δ_j =0.74 from 11.6 then the results are $\Delta\overline{R\&D}^0$ =4.93, and $R_{\Delta\overline{R\&D}^o}$ =4.93/(23.13-4.48)=0.26. Thus CRADA accounts for 0.21-0.26 of the difference in R&D between groups of laboratories where CRADA as important. This seems realistic given that CRADA contributes one-fifth of the gap between R&D budget of the two groups and given that CRADA likely represents several cooperative agreements.

Table 12 further explores the implications of federal laboratory interactions for industrial R&D. The table is in a similar form to table 9 for patents granted except that there are five dependent variables made up of the five types of laboratory R&D. The different expenditures are listed along the top of the table. Table 12 reports eight regressions, specified otherwise as in table 11. Regression coefficients and t-statistics are limited to the government laboratory interactions. As before their purpose is to test the importance of the other technology transfer indicators (licensing of government patents, inflows of ideas from government laboratories, inflows of government scientists, and use of industry-government technology transfer centers) against that of CRADA. Throughout CRADA continues to be positive and usually significant for every category of R&D. GOVERNMENT CONTRACTOR has the same effect on federally funded R&D as in table 11.

Now consider the combined indicators of technology transfer. Recall that WEAK is equal to 1 if any of the technology transfer dummies equals 1 and 0 otherwise. STRONG is the sum of the five dummies, ranges from 0 to 5, and captures intensity of interactions with government laboratories. RESIDUAL WEAK and RESIDUAL STRONG take CRADA out of WEAK and STRONG respectively, leaving other technology transfer indicators besides CRADA in the two variables. WEAK and STRONG are significant alone and in combination with

GOVERNMENT CONTRACTOR in lines 1-4 of the table. When CRADA is taken out of WEAK AND STRONG in lines 5 and 7, RESIDUAL WEAK and RESIDUAL STRONG are insignificant in columns (1), (2) and (3), representing total laboratory R&D, company-financed R&D and net company-financed R&D. But in columns (4) and (5), consisting of federally funded R&D and company expenditures on federal laboratory R&D, lines 5 and 7 show that RESIDUAL WEAK and RESIDUAL STRONG remain significant.

Lines 6 and 8 reintroduce the GOVERNMENT CONTRACTOR variable. RESIDUAL WEAK and RESIDUAL STRONG, while no longer significant for federally financed R&D—that effect is absorbed by GOVERNMENT CONTRACTOR—still matter for company expenditures on federal laboratories.

In general WEAK and STRONG are more powerful for R&D expenditures than for patents granted. And yet, most of their effect is due to CRADA and GOVERNMENT CONTRACTOR, of which the latter only obtains significance in the federally funded part of budget. Once these two effects are accounted for the residual indicators of technology transfer (licensing of government patents, inflows of ideas from government laboratories, inflows of government scientists, and use of industry-government technology transfer centers) influence just the part of budget devoted to expenditures on government labs. But this effect disappears in total R&D budget where RESIDUAL WEAK and RESDUAL STRONG are insignificant. This shows how small company expenditures on federal laboratories are.

VI. Summary, Discussion and Conclusion

The technology transfer efforts of the federal government intensified starting some two decades ago with the passage of the Stephenson-Wydler Act. This transformation in policy continued with the Federal Technology Transfer and National Competitiveness Technology Transfer Acts of 1986 and 1989. The findings of this paper suggest the importance of CRADAs to the success of these technology transfer efforts. The results also suggest that arrangements ensuring effort on the part of both firms and federal laboratories are essential to the success of technology transfer. These results are clear enough that further space need not be devoted to them. Instead we turn to behavior underlying the results and to some unanswered questions about the effect of federal laboratory R&D.

The CRADA effect that we observe is almost certainly not a random experiment. Instead a double selection mechanism operates that yields CRADAs between pairs of firms and federal laboratories. One can readily imagine that firms are reluctant to apply for CRADAs unless the expected returns are large enough to justify the costs of applying for and administering the agreements. Likewise federal laboratories probably choose among potential CRADAs given a limited budget with which to manage the agreements and establish a cutoff for different projects. Therefore, the CRADAs that we observe may be more productive than CRADAs awarded at random. While present evidence cannot settle the issue, this line of thought suggests that more effort needs to be devoted to observable criteria for the double selection mechanism. Firms that apply for CRADAs are more likely to gain from the agreement and to be more attractive to federal laboratory selection committees. In addition we suspect that firms are attracted to particular federal laboratories whose capabilities they know from previous encounters, perhaps as contractors. Likewise federal laboratories are more likely to select industrial firms whose work is already known and trusted. For both reasons CRADAs, especially the more successful ones, probably spring from long term relationships between federal laboratories and firms in which the latter have served as suppliers of manufactures needed by federal laboratories. It follows that detailed histories of the individual relationships between firms and federal laboratories are needed to deepen the study of the cooperative agreements. The Probit equations of table 10 try to get at this, but complete evidence on the relevant conditioning factors is missing.

Eventually one would like to do a cost benefit analysis of CRADAs and other agreements that are intended to promote technology transfer from publicly funded science. But to undertake such an analysis one would have to be able, on the benefit side, to calculate the stream of producer's and consumer's surplus from innovations launched by CRADAs and the rate of decay in both forms of surplus. On the cost side one would have to know all the costs incurred by firms in carrying the CRADAs to commercialization, including the costs of those CRADAs that turned out to be unsuccessful, and likewise the costs of federal laboratories in administering all the CRADAs. More deeply one would like to know which portions of the federal laboratory system are able to sustain a stream of successful CRADAs and why, including those aspects of contract design that are most successful in ensuring technology transfer. We have scratched the surface of public-private interactions in research, but there is still much to be learned underneath the surface about the factors determining success and failure of the interactions. Together these constitute a notable social experiment of our own time.

Table 1
Distribution of Firms and R&D Laboratories
by Industry Group of the Parent Firm

Industry Group	SIC Code	Number of Firms	Number of R&D 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 or research groups, owing to the grouping of laboratories by several firms.

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

Variable	Industrial R&D Laboratories	
	Linked to Federal Laboratories	**Not linked to Federal Laboratories**
R&D Inputs		
Number of Scientists and Engineers	241.9 (563.5)	77.0 (261.8)
Number of Ph.D. (or MD) Scientists and Engineers	40.8 (160.2)	5.9 (18.4)
Laboratory R&D Budget (in millions of '87 $)	20.2 (52.8)	8.1 (26.3)
R&D Outputs		
Patents Granted from the Survey	11.3 (29.6)	5.4 (5.4)
Patents Granted from the Survey, Supplemented by USPTO Patents for Firm and Laboratory Location	17.5 (49.1)	8.0 (29.0)
Sales from New Products Originating in the Laboratory (in millions of '87 $)	226.2 (848.1)	32.1 (78.1)

Source: ***Survey of Industrial Laboratory Technologies 1996***.

Table 3
Types of Interactions between R&D Laboratories and Federal Laboratories

Type of Interaction	Percent of Industrial R&D Laboratories Ranking Type of Interaction as Important [a]
Test Facilities in Government Laboratories	32.7
Licensing of Government Patents [b]	15.7
Cooperative Research and Development Agreement (CRADA) [b]	28.4
Inflows of Scientists from Government Labs [b]	14.9
Outflows of Scientists to Government Labs	7.2
Small Business Innovation Research Program (SBIR)	10.6
GOVERNMENT CONTRACTOR	26.4
Inflows of Ideas from Government Labs [b]	34.6
Outflows of Ideas to Government Labs	21.2
Industry-Government Technology Transfer Centers [b]	25.0

Source: ***Survey of Industrial Laboratory Technologies 1996***. [a] An interaction is classified as important when it receives a score of 3-5 on a five point Likert scale. Sample consists of all reporting labs in the survey. [b] Indicator of technology transfer.

Table 4
Frequency Distribution of Technology Transfer Indicators, Federal Laboratories and R&D Laboratories

Number of Technology Transfer Indicators Rated as Important [a]	Percent of All Industrial R&D Labs
0	58.2
1	6.7
2	12.0
3	8.7
4	10.1
5	4.3

Source: ***Survey of Industrial Laboratory Technologies 1996***. [a] The technology transfer indicators are licensing of government patents, cooperative research and development agreements (CRADAs), inflows of scientists from government labs, inflows of ideas from government labs, and participation in industry-government technology transfer centers, all as noted in Table 4. An indicator of technology transfer is rated as important if it receives a score of 3-5 on a 5 point Likert scale. Sample consists of all labs that report in the survey.

Table 5
Patenting and R&D Budget of Industrial Laboratories Classified by CRADA and GOVERNMENT CONTRACTOR Indicators

	CRADA=0	CRADA=1	CRADA=0 or 1
GOVERNMENT CONTRACTOR=0	Patents Granted=4.39 Lab. R&D Budget=5.70 (mill. $) Patents/R&D=0.77 N=176	Patents Granted=9.17 Lab. R&D Budget=5.37 (mill. $) Patents/R&D=1.71 N=30	Patents Granted=5.08 Lab. R&D Budget=5.66 (mill. $) Patents/R&D=0.90 N=206
GOVERNMENT CONTRACTOR=1	Patents Granted=7.42 Lab. R&D Budget=5.07 (mill. $) Patents/R&D=0.68 N=27	Patents Granted=22.88 Lab. R&D Budget=33.58 (mill. $) Patents/R&D=0.68 N=51	Patents Granted=5.93 Lab. R&D Budget=4.48 (mill. $) Patents/R&D=0.68 N=78
GOVERNMENT CONTRACTOR= 0 or 1	Patents Granted=5.93 Lab. R&D Budget=4.48 (mill. $) Patents/R&D=0.76 N=203	Patents Granted=17.80 Lab. R&D Budget=23.13 (mill. $) Patents/R&D=0.77 N=81	Patents Granted=8.28 Lab. R&D Budget=10.83 (mill. $) Patents/R&D=0.76 N=284

Source: ***Survey of Industrial Laboratory Technologies 1996***. Patents/R&D= cell mean of the number of patents granted in the survey divided by the cell mean of laboratory R&D, in millions of dollars.

Table 6
Linkages between Federal Laboratories and Private R&D Laboratories

Variable	**Year**	
	1991	**1996**
Percent of Private R&D Laboratories that Indicate Linkage to Federal Laboratories [a]	45.2%	
Percent of Private R&D Laboratories that indicate Linkage to Particular Federal Laboratories	30.8%	
Number of Cited Federal Laboratories, Contingent on Linkage to particular Federal Laboratories	3.5	
Number of Directorates in Cited Labs, Contingent on linkage To particular Federal Laboratories [b]	20.5	
Total R&D of Cited Federal Laboratories, 12 Year Stocks (in millions of '87 $) [b]	8823.9	9226.2
On-Site R&D of Cited Federal Laboratories, 12 Year Stocks (in millions of '87 $) [b]	4025.2	4036.0
Total R&D, ***per directorate***, of Cited Federal Laboratories, 12 year Stocks (in millions of '87 $) [b]	475.6	484.1
On-Site R&D, ***per directorate***, of Cited Federal Laboratories, 12 year Stocks (in millions of '87 $) [b]	209.7	208.7

Sources: ***Survey of Industrial Laboratory Technologies 1996***, Defense Technical Information Center (various years), National Science Foundation (various years), and ***Survey of Government Laboratory R&D 1998***.
[a] Sample consists of all reporting labs in the survey. [b] Sample consists of the subset of industrial R&D labs that report particular federal laboratories which they considered important to their research.

Table 7
Distribution of Cited Federal Laboratories
And of Citations to Federal Laboratories
By Department or Category

Federal Department or Category	(1) Number of Cited Laboratories (% of Labs)	(2) Number of Citations in Survey (% of Cites)	(3) Number of Active CRADAs in 1995	(4) Patent App. for Fed. Inventions in 1995
Agriculture	2 (4.6%)	2 (1.3%)	229	80
Commerce	3 (6.8%)	9 (5.9%)	407	35
Defense	22 (50.0%)	48 (31.4%)	845	759
Energy	8 (18.2%)	57 (37.3%)	1392	571
EPA	1 (2.3%)	1 (0.7%)	30	24
HHS	3 (6.8%)	7 (4.6%)	152	166
Interior	2 (4.6%)	2 (1.3%)	15	2
NASA	5 (11.4%)	17 (11.1%)	N/A	101
Private, Non-Profit, Federally Funded Laboratories	6 (13.6%)	10 (6.5%)	N/A	N/A

Sources, columns (1) and (2): ***Survey of Industrial Laboratory Technologies 1996***, columns (3) and (4): unpublished U.S. Department of Energy Tabulations. N/A means not appropriate or not available.

Table 8
Patents Issued to Industrial Laboratories
(Asymptotic t-Statistics in Parentheses)

Variable or Statistic	Patents Granted				Hybrid Patents			
	Eq. 8.1	Eq. 8.2	Eq. 8.3	Eq. 8.4	Eq. 8.5	Eq. 8.6	Eq. 8.7	Eq. 8.8
Estimation Method	Negative Binomial Regression							
Year, Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lab is primarily a Testing Facility (1 if yes, 0 if no)	-1.21 (-2.0)	-1.10 (-1.8)	-1.09 (-1.8)	-1.11 (-1.8)	-1.32 (-2.1)	-1.24 (-1.9)	-1.23 (-1.9)	-1.29 (-2.0)
Lab Housed With Manufacturing (1 if yes, 0 if no)	0.11 (0.7)	0.03 (0.2)	0.07 (0.4)	0.12 (0.7)	-0.03 (-0.2)	-0.08 (-0.5)	-0.06 (-0.4)	-0.06 (-0.3)
Log (Laboratory R&D budget)	0.75 (14.8)	0.70 (14.3)	0.73 (14.5)		0.71 (14.5)	0.67 (14.0)	0.69 (14.2)	
Log (Company-Financed Laboratory R&D Budget)				0.69 (12.0)				0.64 (11.5)
Log (Federally-Funded Laboratory R&D Budget)				0.03 (0.5)				0.04 (0.8)
Log (R&D in the Rest of the Firm)	0.07 (4.4)	0.06 (4.0)	0.07 (4.2)	0.05 (2.7)	0.08 (4.7)	0.07 (4.4)	0.07 (4.6)	0.06 (3.2)
GOVERNMENT CONTRACTOR (1 if yes, 0 if no)	-0.18 (-1.0)		-0.44 (-2.2)	-0.57 (-2.2)	-0.18 (-0.9)		-0.44 (-2.0)	-0.47 (-1.6)

Table 8
Patents Issued to Industrial Laboratories
(Asymptotic t-Statistics in Parentheses)

Variable or Statistic	Patents Granted				Hybrid Patents			
	Eq. 8.1	Eq. 8.2	Eq. 8.3	Eq. 8.4	Eq. 8.5	Eq. 8.6	Eq. 8.7	Eq. 8.8
CRADA (1 if yes, 0 if no)		0.44 (2.6)	0.59 (3.3)	0.48 (2.2)		0.35 (2.0)	0.53 (2.7)	0.44 (1.8)
Patents Imputed from USPTO for Parent Firm and Location (1 if yes, 0 if no)					0.57 (2.4)	0.64 (2.8)	0.61 (2.6)	0.81 (3.2)
Log (R&D in Closely Affiliated Gov. Labs ***per Directorate***)				0.019 (0.5)				-0.009 (-0.2)
Number of Observations	268	268	268	243	306	306	306	274
Log Likelihood	-620.9	-618.0	-615.5	-531.3	-758.5	-757.0	-755.0	-645.8

Sources: ***Survey of Industrial Laboratory Technologies 1996*** and ***Survey of Government Laboratory R&D 1998***.

Table 9
Patents Issued to Industrial Laboratories
Variations on the Federal Laboratory Interactions
(Asymptotic t-Statistics in Parentheses)

Line Number	Federal Laboratory Interactions, Entered Alone or in Groups	Coefficients (t-Statistics)
1	WEAK (1 if yes, 0 if no)	0.22 (1.4)
2	WEAK (1 if yes, 0 if no)	0.40 (2.1)
	GOVERNMENT CONTRACTOR (1 if yes, 0 if no)	-0.41 (-1.9)
3	STRONG (Range from 0 to 5)	0.10 (2.1)
4	STRONG (Range from 0 to 5)	0.14 (2.8)
	GOVERNMENT CONTRACTOR (1 if yes, 0 if no)	-0.42 (-2.0)
5	RESIDUAL WEAK (1 if yes, 0 if no)	-0.13 (-0.6)
	CRADA (1 if yes, 0 if no)	0.52 (2.4)
6	RESIDUAL WEAK (1 if yes, 0 if no)	0.01 (0.0)
	CRADA (1 if yes, 0 if no)	0.59 (2.7)
	GOVERNMENT CONTRACTOR (1 if yes, 0 if no)	-0.44 (-2.1)
7	RESIDUAL STRONG (Range from 0 to 4)	0.01 (0.1)
	CRADA (1 if yes, 0 if no)	0.42 (1.9)
8	RESIDUAL STRONG (Range from 0 to 4)	0.04 (0.5)
	CRADA (1 if yes, 0 if no)	0.53 (2.4)
	GOVERNMENT CONTRACTOR (1 if yes, 0 if no)	-0.46 (-2.3)

Sources: ***Survey of Industrial Laboratory Technologies 1996*** and ***Survey of Government Laboratory R&D 1998***.
Note: each group is part of a negative binomial regression, specified as in table 8.

Table 10
Two Equation, Maximum Likelihood Estimates of
Patents Issued by Size Class and CRADAs
(Asymptotic t-Statistics in Parentheses)

Variable or Statistic	PATCAT Eq. 10.1	CRADA Eq. 10.2	PATCAT Eq. 10.3	CRADA Eq. 10.4
Estimation Method	Ordered Probit	Probit	Two Equation, Maximum Likelihood	
Year, Industry Dummies	Yes	Yes	Yes	Yes
Lab Housed With Manufacturing (1 if yes, 0 if no)	0.12 (0.8)	0.41 (1.5)	0.10 (0.7)	0.41 (1.6)
Log (Laboratory R&D Budget)	0.62 (11.4)	0.13 (1.6)	0.61 (10.6)	0.13 (1.6)
Log (R&D in the Rest of the Firm)	0.05 (3.5)		0.05 (3.5)	
CRADA (1 if yes, 0 if no)	0.46 (3.1)		0.59 (2.4)	
GOVERNMENT CONTRACTOR (1 if yes, 0 if no)		0.66 (2.5)		0.66 (2.5)
Inflows of Ideas from Government Labs (1 if yes, 0 if no)		1.00 (3.2)		0.99 (3.2)
Inflows of Scientists from Government Labs (1 if yes, 0 if no)		0.47 (1.5)		0.49 (1.5)
Licensing of Government Patents (1 if yes, 0 if no)		0.91 (3.3)		0.90 (3.3)
Test Facilities in Government Laboratories (1 if yes, 0 if no)		0.41 (1.5)		0.41 (1.5)
Industry-Government Technology Transfer Centers (1 if yes, 0 if no)		0.04 (0.1)		0.07 (0.2)
Log Likelihood	-453.0	-89.9	-542.8	
Cross-Equation Correlation			-0.13 (-0.6)	

Sources: **Survey of Industrial Laboratory Technologies 1996** and **Survey of Government Laboratory R&D 1998**. The number of observations is N=268.

Table 11
R&D Expenditures of Industrial Laboratories,
Subdivided by Source of Funding and Function
(t-Statistics in Parentheses)

Variable or Statistic	Log (Laboratory R&D Budget)		Log (Company-Financed Lab. R&D Budget)		Log (*Net* Company-Financed Lab. R&D Budget)		Log (Federally-Funded Lab. R&D Budget)		Log (Expenditures on Federal Laboratory R&D)		
	Eq. 11.1	Eq. 11.2	Eq. 11.3	Eq. 11.4	Eq. 11.5	Eq. 11.6	Eq. 11.7	Eq. 11.8	Eq. 11.9	Eq. 11.10	Eq. 11.11
Estimation Method	OLS		OLS		OLS		Tobit		Tobit		
Year, Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lab is primarily a Testing Facility (1 if yes, 0 if no)	-0.50 (-1.3)	-0.50 (-1.3)	-0.50 (-1.3)	-0.49 (-1.3)	-0.53 (-1.4)	-0.52 (-1.3)	2.50 (1.1)	2.50 (1.1)	2.54 (1.2)	1.20 (0.5)	2.43 (1.2)
Lab Housed With Manufactu-Ring (1 if yes, 0 if no)	-0.82 (-5.2)	-0.83 (-5.3)	-0.84 (-5.1)	-0.86 (-5.2)	-0.82 (-5.0)	-0.82 (-5.0)	1.47 (1.4)	1.40 (1.4)	-0.45 (-0.5)	-0.16 (-0.2)	-0.44 (-0.5)
Log (Number of Ph.D. scientists in the Lab)	0.15 (7.7)	0.15 (7.7)	0.15 (6.9)	0.15 (6.9)	0.14 (6.6)	0.14 (6.6)	0.41 (3.2)	0.40 (3.2)	0.22 (2.0)	0.31 (2.7)	0.21 (2.0)
Log (R&D in the Rest of the Firm)	-0.06 (-3.1)	-0.06 (-3.0)	-0.07 (-3.2)	-0.07 (-3.1)	-0.07 (-3.3)	-0.07 (-3.2)	-0.03 (-0.3)	-0.05 (-0.4)	-0.09 (-0.8)	-0.17 (-1.5)	-0.12 (-1.1)
Log (Recent Sales of the Firm)	0.36 (7.5)	0.36 (7.5)	0.35 (7.2)	0.36 (7.2)	0.35 (7.1)	0.35 (7.1)	0.47 (1.5)	0.48 (1.6)	0.51 (1.9)	0.43 (1.6)	0.52 (1.9)
GOVERNMENT CON-TRACTOR (1 if yes, 0 if no)	0.02 (0.1)	0.09 (0.4)	-0.09 (-0.4)	-0.02 (-0.1)	-0.13 (-0.6)	-0.05 (-0.2)	6.28 (5.5)	5.91 (5.2)	0.97 (1.0)		0.70 (0.7)
CRADA (1 if yes, 0 if no)	0.67 (3.2)	0.81 (3.5)	0.65 (2.9)	0.79 (3.2)	0.62 (2.8)	0.74 (3.0)	3.79 (3.4)	3.41 (3.0)	5.75 (5.4)		4.61 (4.2)

Table 11
R&D Expenditures of Industrial Laboratories,
Subdivided by Source of Funding and Function
(t-Statistics in Parentheses)

Variable or Statistic	Log (Laboratory R&D Budget)		Log (Company-Financed Lab. R&D Budget)		Log (*Net* Company-Financed Lab. R&D Budget)		Log (Federally-Funded Lab. R&D Budget)		Log (Expenditures on Federal Laboratory R&D)		
	Eq. 11.1	Eq. 11.2	Eq. 11.3	Eq. 11.4	Eq. 11.5	Eq. 11.6	Eq. 11.7	Eq. 11.8	Eq. 11.9	Eq. 11.10	Eq. 11.11
Estimation Method	OLS		OLS		OLS		Tobit		Tobit		
Log (R&D in Closely Affiliated Government Labs ***per Directorate***)		-0.06 (-1.4)		-0.06 (-1.4)		-0.05 (-1.1)		0.24 (1.3)		0.99 (5.3)	0.41 (2.2)
Number of Observations	280	280	266	266	263	263	266	266	271	271	271
Adjusted R^2	0.53	0.53	0.49	0.49	0.46	0.46	--	--	--	--	--
Root MSE	1.24	1.24	1.26	1.26	1.26	1.26	3.77	3.76	4.25	4.63	4.16
Percent of Left Censored Observations	--	--	--	--	--	--	0.83	0.83	0.80	0.80	0.80
Log Likelihood	--	--	--	--	--	--	-156.1	-155.3	-211.1	-221.9	-208.7

Sources: ***Survey of Industrial Laboratory Technologies 1996*** and ***Survey of Government Laboratory R&D 1998***.

Table 12
R&D Expenditures of Industrial Laboratories
Variations on Federal Laboratory Interactions
(Asymptotic t-Statistics in Parentheses)

Line Number	Federal Laboratory Interactions, Entered Alone or in Groups	(1) Log (Lab. R&D Budget) Coefficients (t-Statistics)	(2) Log (Comp.-Fin. Lab. R&D Budget) Coefficients (t-Statistics)	(3) Log (*Net* Comp.-Fin. Lab. R&D Budget) Coefficients (t-Statistics)	(4) Log (Fed-Funded Lab. R&D Budget) Coefficients (t-Statistics)	(5) Log (Lab. Expend. On Fed. Lab. R&D) Coefficients (t-Statistics)
1	WEAK (1 if yes, 0 if no)	0.41 (2.5)	0.35 (2.1)	0.32 (1.9)	9.38 (5.7)	7.48 (6.4)
2	WEAK (1 if yes, 0 if no)	0.31 (1.5)	0.32 (1.5)	0.33 (1.5)	3.96 (2.6)	7.53 (5.9)
	GOVERNMENT CONTRACTOR (1 if yes, 0 if no)	0.18 (0.8)	0.05 (0.2)	-0.02 (-0.1)	5.96 (4.7)	-0.09 (-0.1)
3	STRONG (Range from 0 to 5)	0.18 (3.6)	0.17 (3.2)	0.15 (2.9)	2.24 (5.8)	1.95 (6.8)
4	STRONG (Range from 0 to 5)	0.18 (2.9)	0.19 (2.9)	0.18 (2.8)	0.67 (1.8)	1.93 (6.1)
	GOVERNMENT CONTRACTOR (1 if yes, 0 if no)	0.03 (0.1)	-0.15 (-0.6)	-0.19 (-0.8)	6.96 (5.4)	0.14 (0.1)
5	RESIDUAL WEAK (1 if yes, 0 if no)	0.16 (0.8)	0.15 (0.7)	0.15 (0.7)	4.39 (3.4)	3.51 (3.4)
	CRADA (1 if yes, 0 if no)	0.56 (2.5)	0.50 (2.1)	0.45 (1.9)	5.77 (4.6)	4.14 (4.1)
6	RESIDUAL WEAK (1 if yes, 0 if no)	0.18 (0.8)	0.23 (1.0)	0.24 (1.0)	0.86 (0.6)	3.61 (3.3)
	CRADA (1 if yes, 0 if no)	0.58 (2.5)	0.55 (2.2)	0.51 (2.1)	3.64 (3.2)	4.21 (4.0)
	GOVERNMENT CONTRACTOR (1 if yes, 0 if no)	-0.05 (-0.2)	-0.20 (-0.8)	-0.24 (-0.9)	5.82 (4.5)	-0.29 (-0.3)
7	RESIDUAL STRONG (Range from 0 to 4)	0.07 (0.9)	0.09 (1.0)	0.08 (0.9)	0.86 (1.9)	1.45 (3.9)
	CRADA (1 if yes, 0 if no)	0.54 (2.4)	0.45 (1.9)	0.41 (1.7)	6.76 (4.9)	3.65 (3.7)
8	RESIDUAL STRONG (Range from 0 to 4)	0.08 (0.9)	0.11 (1.2)	0.11 (1.2)	-0.13 (-0.3)	1.46 (3.8)
	CRADA (1 if yes, 0 if no)	0.56 (2.3)	0.51 (2.0)	0.48 (1.9)	3.89 (3.3)	3.70 (3.6)
	GOVERNMENT CONTRACTOR (1 if yes, 0 if no)	-0.04 (-0.2)	-0.20 (-0.8)	-0.23 (-0.9)	6.43 (5.1)	-0.14 (-0.2)

Sources: ***Survey of Industrial Laboratory Technologies 1996*** and ***Survey of Government Laboratory R&D 1998***. Note: each group is part of OLS or Tobit regression specified as in table 11.

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