NIST GCR 02-830

Measuring the Impact of ATP-Funded Research Consortia on Research Productivity of Participating Firms:

A Framework Using Both U.S. and Japanese Data

December 2002

National Institute of Standards and Technology • Technology Administration • U.S. Department of Commerce

NIST GCR 02-830

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Prepared for
Economic Assessment Office
Advanced Technology Program
National Institute of Standards and Technology
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Grant 56SBNB760338

November 2002

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TECHNOLOGY ADMINISTRATION
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NATIONAL INSTITUTE OF STANDARDS AND TECHNOLOGY
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Abstract

This study empirically evaluates the impact of consortia funded by the U.S. Advanced Technology Program (ATP) on the research productivity of participating firms. We find that there is a positive association between the intensity of participation in research consortia and the overall research productivity of participants. Our analysis suggests that participation in one additional ATP-funded research consortium per year would generate an increase in patenting for that firm in that year of nearly 8%. We also find that consortia have a positive impact on the research productivity of participants in the technological areas targeted by the consortia. This positive impact of consortia is higher when the average technological proximity (as measured by the degree to which the patenting portfolios of participating firms are similar) of participants is high. There is preliminary evidence that large firms conducting intensive research and development (R&D) tend to benefit more from their participation in consortia.

Japanese data validate the findings of data from ATP projects regarding the positive association between the average technological proximity of firms in a consortium and patenting in the technological areas targeted by the consortium, as well as an increase in patenting outcomes (i.e., increase in patenting activity) over pre-consortium levels in the technologies targeted by the consortium. Japanese data support ATP's focus on pre-commercial research. Qualitative data show a positive association between patenting outcomes and research projects that Japanese firms perceive to be more "basic" or "pre-commercial," as opposed to projects that are close to commercialization. In addition, Japanese data suggest that bringing makers of rival products for the same market into the same consortium is detrimental to patenting outcomes. Few ATP projects have this type of horizontal structure. The results of the authors' research on Japanese research consortia were published in the American Economic Review in March 2002.

Acknowledgments

No research effort of this magnitude is ever accomplished without the help of many people. We would like to first express our gratitude to the staff of the Economic Assessment Office of ATP. Special thanks go to Holly Jackson and Jeanne Powell for help with initial data acquisition, to Robert Sienkiewicz and Richard Spivack for help in arranging interviews, obtaining additional data, and providing us with excellent feedback at several points in the research process, and to John Hewes, Jack Boudreaux, Connie Chang, and other reviewers at ATP who helped shape the final study. We also wish to thank Adam Jaffe of Brandeis University and the National Bureau of Economic Research (NBER) for his guidance and suggestions. Susan Colligan and Julie Peters of the NBER helped administer our grant efficiently and effectively, and we are grateful for their efforts.

To protect the confidentiality of our interviewees, we are unable to acknowledge by name the government officials and firm managers we interviewed in both the United States and Japan to obtain invaluable insights on how both ATP and Japan's Ministry of Trade and Industry (MITI, now known as the Ministry of Economy, Trade and Industry, or METI) research consortia actually operated. However, this information was a critical input to our research. We are therefore very grateful to the numerous officials and executives who generously shared their insights with us.

The staff of the Japanese Patent Office shared their vast information resources with us at a fraction of the cost normally charged to private sector data users. Officers at the Japanese Patent Office also helped us create a mapping to link the technological goals of Japanese research consortia with the International Patent Classification system. In generating a similar "mapping" for ATP-sponsored consortia in the United States, we benefited from the excellent assistance of Bailey Services, Inc. We also benefited from informal discussions with Sam Petuchowski of Bromberg and Sunstein, LLP. We also acknowledge the generosity of Bronwyn Hall at the University of California, Berkeley, and Adam Jaffe in sharing their data resources with us. We could not have completed this project without their help.

Finally, a number of research assistants worked on assembling much of the data used in this report. We would like to thank Shun-Li Yao and, especially, Kaoru Nabeshima, both Ph.D. students in the UC-Davis doctoral program in economics, for their outstanding research assistance. Mariko Sakakibara received help from Makoto Nakayama, Jina Kang, and Heather Berry of the UCLA Management Ph.D. program, Jon Wolf at the UCLA Department of Economics, and Yumiko Kawanishi in the doctoral program of East Asian Languages and Cultures at UCLA.

Executive Summary

In pursuit of its legislative mandate to strengthen the competitiveness of technology-intensive U.S. firms and industries, the Advanced Technology Program (ATP) supports research consortia to promote and stimulate "pre-commercial" research by private firms. A number of theoretical arguments in the economic literature support the use of this policy instrument. ATP's funding decisions and evaluation efforts, however, must be based on empirical facts rather than theoretical appeal. In this study, we describe the results of our empirical evaluation of the impact of ATP-funded consortia on the research productivity of participating firms.

This study builds upon our earlier work (Branstetter and Sakakibara, 1998, 2000) where we examine the impact of the Japanese government–sponsored research consortia. To extract as much useful information as possible from our quantitative data set, we analyze the ATP-funded consortia at three different levels of aggregation:

- the impact of consortia participation on the overall research productivity of the participating firm;
- the impact of participation at the consortium level; and
- the impact of consortia participation at the level of the firm-consortium pair.

We describe below our analytical framework, our findings using both U.S. and Japanese data, and their implications. We acknowledge the limitations of our study and make a number of suggestions on how future ATP-affiliated researchers could build upon and extend our results. Finally, we point to complete documentation of the database we used to study the impact of ATP-funded research consortia.

THE IMPACT OF CONSORTIA PARTICIPATION ON THE OVERALL RESEARCH PRODUCTIVITY OF FIRMS

To what extent did participation in an ATP-funded research consortium contribute to an overall expansion of research productivity among participating firms? We pursued this question by developing an original, firm-level data set of research inputs and outputs for a set of firms that participated in ATP-funded research consortia and a set of control firms that were never involved. Using such data, we analyzed the statistical relationship between the frequency of participation in ATP-funded consortia and the relative research productivity of industrial firms. Our analysis used a conceptual framework known in the economic literature as the “knowledge production function.” Innovative output was measured using patent data. Innovative input was measured as research and development (R&D) spending. We fully recognize the many shortcomings of patent data as a measure of innovative output. Our decision to base our analysis on patent data is discussed and defended in the body of the report.

We found the relationship between participation and research productivity to be positive, statistically significant, and robust to changes in the specification of our statistical model. In other words, holding all other factors constant, we find evidence that firms participating in more ATP-funded research consortia generate more patents per unit of R&D spending than firms that participate in fewer ATP consortia or do not participate at all. Our econometric estimates suggest that, at the margin, a firm that participates in an ATP-funded consortium will realize a nearly 8% increase in research productivity per year.

THE IMPACT OF PARTICIPATION AT THE CONSORTIUM LEVEL

What is the impact of participation in ATP consortia on the collective patenting of participating firms in the technological areas targeted by the consortia? What kinds of consortia are the most successful at promoting the research productivity of participating firms? With the help of outside experts, we constructed a mapping from the stated technological goals of ATP-funded consortia to the relevant patent classes of the U.S. Patent and Trademark Office (USPTO) patent classification system. This mapping allows us to examine patenting in the technological areas targeted by a consortium. Our results indicate that consortium participation increased patenting in the targeted areas above pre-consortium levels. In addition, “technological proximity” of consortia, as measured by the degree to which the patenting portfolios of participating firms are similar, and “pre-consortium technology strength” are positively associated with patenting in the technological areas targeted by the consortium.

THE IMPACT OF CONSORTIA PARTICIPATION ON FIRM-CONSORTIUM PAIRS

What type of firm receives the largest benefits from participation in an ATP-funded research consortium? We examine the constituent firms of each consortium and analyze the impact of the consortium on each firm separately. Our preliminary results indicate that larger firms with higher R&D budgets (i.e., technologically more progressive firms) tend to benefit more from participation than other firms. In the absence of panel data on the research inputs and outputs of smaller firms, it is difficult, however, to come to any definitive conclusions about the effect of size or overall R&D spending on research outcomes.

ADDITIONAL WORK USING JAPANESE DATA

Japanese data were used as a statistical “testing ground” for the analytical framework that was applied to U.S. data. Japanese government support of research consortia began in the late

1950s, which allows us to examine the long-run effects of consortia. (ATP's first projects began in 1990–91 and the time series data used in our U.S. analysis extend only through 1995.) Results from Japanese data suggest that much of the impact of research consortia is felt long after the inception of the project. In fact, evidence from Japanese consortia suggests that some of the strongest effects are felt *after the official cessation of the consortia*. This means that the relatively short time series of data available on participating firms in ATP-funded research consortia will tend to underestimate the total impact of the consortia.

RESULTS AND IMPLICATIONS

We find evidence that the impact of participation in ATP-funded consortia on the research productivity of participating firms is positive at all three levels of analysis examined in this paper:

- the impact of consortia participation on the overall research productivity of the participating firm;
- the impact of participation at the consortium level; and
- the impact on the firm-consortium pair.

First, we find that there is a positive statistical association between the intensity of participation in research consortia and the overall research productivity of the participating firms. Second, at the consortia level, we find a positive impact of consortia on the research productivity of participating firms in the technological areas targeted by the consortia. Furthermore, we find that this positive impact of consortia is higher when the average "technological proximity" of participating firms is high. This is a measure that ATP could calculate for prospective firms as a screening device for selecting the most meritorious project proposals. Third, we find less clear-cut evidence concerning which types of firms benefit most from participation. Our preliminary results suggest that larger firms with higher R&D budgets benefit more from participation than other firms. However, this finding should be viewed with caution given the inherent flaws in our data set regarding research inputs and outputs for smaller, private firms.

Results from these three levels of analysis demonstrate that participation in ATP-funded consortia is leading to verifiable, measurable increases in research productivity, an indication that ATP is accomplishing its mission.

LIMITATIONS OF THE STUDY AND ISSUES FOR FURTHER ANALYSIS

We confronted three important limitations in our data. The first most serious problem is that our data series covers only a four-year period, from 1991 to 1995. Information on the total patenting of participating firms is based on relevant data that extend to 1994 or early 1995 from the Regional Economic Issues (REI) Patent Database developed and maintained at the Case Western Reserve University Center for the Study of Regional Economic Issues. Information on the total R&D spending of participating firms is based on Standard & Poor's COMPUSTAT database of financial, statistical, and market information on more than 7,500 publicly held companies; information taken from COMPUSTAT extends to 1995 (but could have been expanded to 1997). Relatively few ATP projects began before 1995, and almost none were completed by then. Our patent data effectively end in 1995, just as ATP was expanding its support of research consortia. Results from our Japanese data indicate that the full impact of participation in a research consortium is only realized over fairly long periods of time. A large share—perhaps the largest share—of the benefits from participation in ATP is missing from the data set. This means that the data are likely to underestimate the overall impact of ATP-funded research consortia. The fact that we find positive, statistically significant benefits of participation in spite of this data truncation problem suggests that the positive effects are real.

Second, the data set lacks information on the research inputs and outputs of some smaller firms involved in ATP-supported research consortia. While it is relatively easy to obtain data on the large, publicly traded firms that were part of these projects, it is difficult to obtain similar data on small, privately held firms that were often leaders of the joint ventures. Lack of data on smaller firms limits our ability to estimate the impact of ATP-funded consortia on their research productivity. If smaller firms benefit more from consortia participation than do larger firms, then our data may underestimate the impact of ATP-funded consortia on smaller firms.

Finally, we were unable to analyze the ATP's Business Reporting System (BRS) survey data to its fullest extent due to confidentiality constraints. As a result, we used consortium-level averages, rather than individual firm responses, in our analysis of firms' perceptions of the benefits of consortium participation on research outcomes. Using individual firm responses would have enhanced our ability to establish statistical links between survey variables and research outcomes.

Future ATP-affiliated researchers could expand our data set in ways that would solve some of these problems. First, publicly available databases on firm patenting and other firm characteristics could be used to expand the time series dimension of our data set beyond 1995. This would allow a more comprehensive analysis of the long-term benefits of ATP-funded projects. Second, ATP is addressing the coverage of small- and medium-size, private firms through the extension of BRS. Third, ATP staff could conduct additional firm-level analysis using BRS survey data to fully utilize the available data and avoid compromising data confidentiality.

DATABASE CONSTRUCTION

The Appendix documents the database developed for this project, which was provided to ATP with the first draft of the study in October 1998. The database contains two key components.

Table A is a mapping from the stated technological goals of ATP-funded research consortia to the corresponding patent classes in the U.S. patent classification system. This mapping, completed with the assistance of Bailey Services, Inc., allows us to measure patenting by participating firms in the targeted classes before, during, and, in principle, after the cessation of a consortium. Table B is a list of ATP-funded consortium projects, the firms participating in those projects, and their associated Standard & Poor's CUSIP (Committee on Uniform Security Identification Procedures) identifying codes. The CUSIP codes, a standard method in identifying issuers of securities, in conjunction with Standard & Poor's COMPUSTAT database, may be used to update our data set. The Appendix also contains a complete description of the way in which key variables were constructed and the statistical software package used in our analysis. We hope these tables and documentation will be a useful, enduring data resource for ATP.

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1. Introduction

In pursuit of its legislative mandate to strengthen the competitiveness of technology-intensive U.S. firms and industries for future economic growth, the Department of Commerce's Advanced Technology Program (ATP) supports research consortia to promote "pre-commercial" research by private firms. A number of theoretical arguments in the economic literature support the use of this policy instrument. Spence's (1984) pioneering work analyzed the possible benefits of research consortia as tools by which R&D externalities could be internalized. Subsequent contributions include Katz (1986), d'Aspremont and Jacquemin (1988), Suzumura (1992), Kamien, Muller, and Zang (1992), Kamien and Zang (2000), Leahy and Neary (1997), and Katsoulacos and Ulph (1998).[1] Much of this theoretical literature identifies the conditions under which consortia are likely to lead to improvements that benefit the economy. However, little has been done to confront the empirical predictions or implications of this literature with data in a systematic way.[2]

This study empirically evaluates the impact of ATP-funded consortia[3] on the research productivity of participating firms by building upon our earlier work (Branstetter and Sakakibara, 1998, 2000) where we examine the impact of Japanese government–sponsored research consortia. We analyze the ATP-funded research consortia at three different levels of aggregation—the impact of consortia participation on the overall research productivity of the participating firm, the impact of participation at the consortium level, and at the level of the firm-consortium pair—in an attempt to extract as much useful information as possible from our quantitative data set.

We find that there is a positive association between the participation in research consortia and research productivity of the participating firms at all levels of aggregation. Furthermore, we find that this positive impact of consortia is higher when the average technological proximity (the degree to which the patenting portfolios of participating firms are similar) of participating firms is high. We find less clear-cut evidence concerning which kinds of firms benefit most from participation. However, our results demonstrate that participation in ATP-funded research consortia leads to verifiable and measurable increases in research productivity of the participating firms.

The rest of the study is organized as follows: Section 2 provides background information on this study. Section 3 describes our approach to estimate the overall impact of consortia participation and presents the results. Section 4 examines the relationship between consortium characteristics and consortium outcomes. Section 5 presents results relating the characteristics of participating firms to the benefits those firms receive from participation. Section 6 presents findings from Japanese data on government-sponsored research consortia. Section 7 offers some conclusions and suggests issues for future research.

NOTES

1. For a comprehensive review of this literature or related papers, see Martin (2000).
2. Much of empirical work has been qualitative or descriptive rather than econometric (e.g., Ouchi and Bolton, 1988; Callon, 1995; Ham and Mowery, 1995). Much of the econometric work in the received literature has focused on a *single* research consortium, such as in Irwin and Klenow (1996).
3. We use the words “consortium” and “project” interchangeably.

2. Brief Background of Study

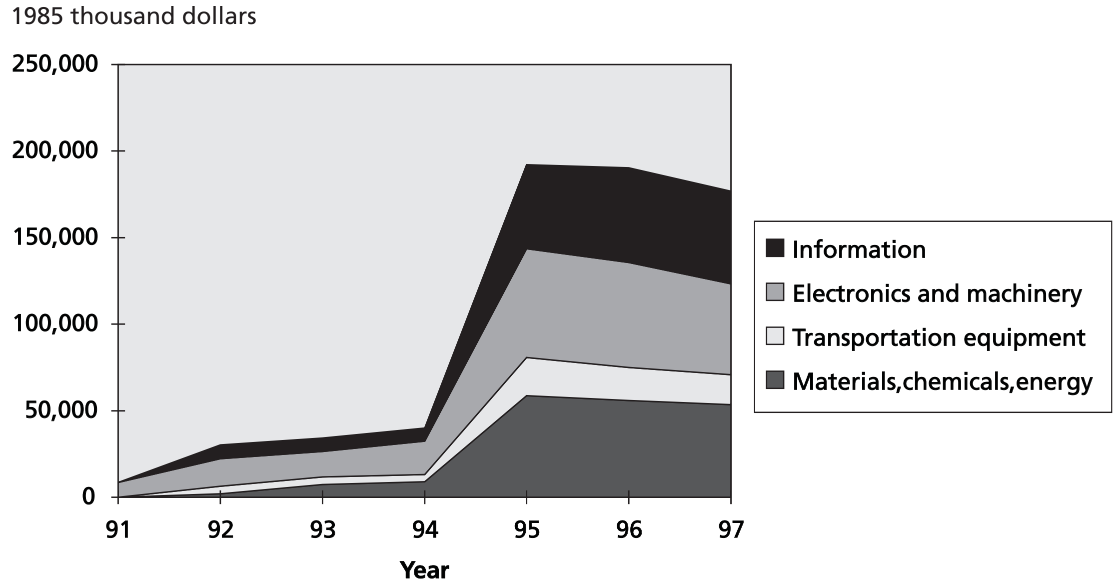
In the late 1980s, low-cost, high-quality Asian production was eroding U.S. high-tech markets. Policy makers and corporate leaders believed that U.S. firms needed to improve their productivity, and that sustained economic growth through new product and process innovation would best achieve this goal. There was evidence that firms were systematically underinvesting in leading-edge technologies and failing to commercialize the products of their own research activities effectively (e.g., Deretouzos, Solow, and Lester, 1989). These concerns, buttressed by academic arguments pointing to a potential market failure in the area of early-stage technological developments, motivated new proposals to modify the role of government in the innovation system. A key legislative initiative resulting from this process was the creation of the Advanced Technology Program (ATP) through the passage of the Omnibus Trade and Competitiveness Act of 1988.

The ATP commenced in 1990 with the mission to foster the development and broad dissemination of high-risk technologies that offer the potential for significant, broad-based economic benefit to the United States. One important policy tool is to fund research consortia. From 1990 to 1995, 96 research consortia received funding from ATP. Figure 1 shows the total budget of ATP-funded research consortia by sector from 1991 to 1997, revealing that the total budget for consortia funding increased substantially in later years.

Similar data are shown in Figure 2 for Japanese R&D consortia. The comparison between U.S. and Japanese R&D consortia is made because Japan's involvement in publicly supported research consortia predates U.S. involvement and provides long-term data on the impact of research consortia on research outcomes. These data were used to develop a framework for analysis of U.S. data. Figure 2 shows that Japanese funding for R&D consortia peaked in the late 1970s and the early 1980s. A comparison of Figures 1 and 2 suggests that the funding of U.S. consortia is more evenly distributed by sector than Japanese funding.[1]

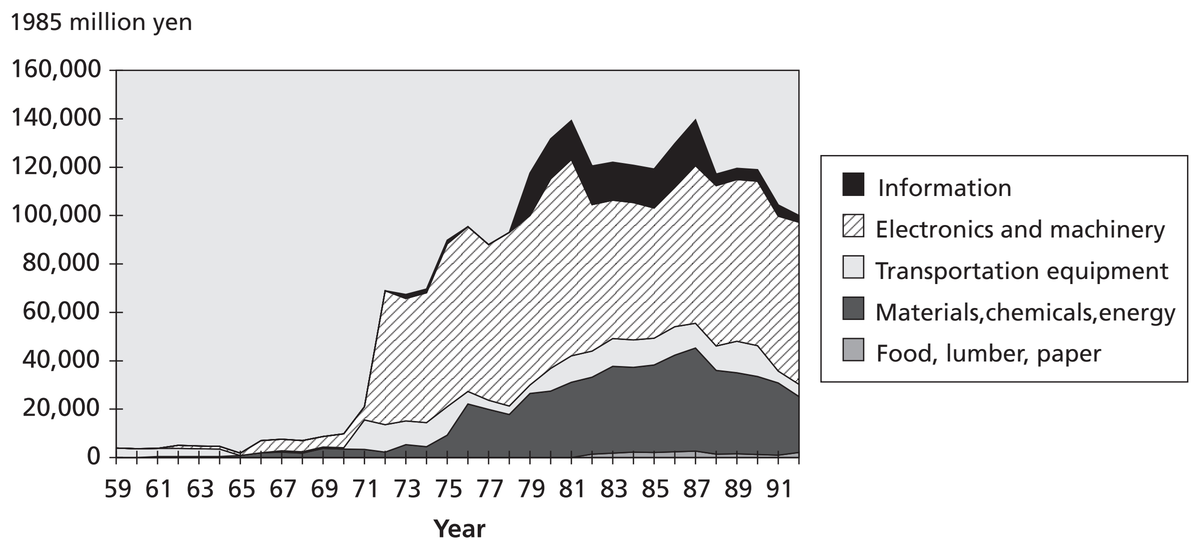
Other differences are also evident between U.S. and Japanese research consortia. The average duration of ATP-funded research consortia is just over 4 years, as compared to 7 years for Japanese consortia. Furthermore, a typical ATP-funded research consortium tends to include a large firm and several small firms plus university participants, while the size of participating firms in a typical Japanese consortium is more evenly distributed. This discrepancy may reflect ATP's emphasis on the inclusion of smaller firms among consortium participants.

Figure 1. **ATP-Funded Research Consortia, Total Budget by Sector**



Source: ATP's Business Reporting System.

Figure 2. **Japanese R&D Consortia Total Budget by Sector**



Source: Sakakibara (1994).

NOTES

1. Perhaps this reflects the underlying R&D structure of both countries. Between 1987 and 1996, for example, the coefficient of variation of U.S. R&D expenditures by industry is 1.1 on average, compared with 1.7 in Japan.

3. Overall Benefits from Research Consortia

METHODOLOGY

If ATP-funded consortia enhance the research productivity of member firms by promoting research spillovers among members, then we may observe a statistical relationship between the intensity of participation and the firm's patent output in that year.[1] We seek to directly test this hypothesis using panel data on participating firms and a control group of non-participants.

We draw heavily from the methodology developed in Branstetter and Sakakibara (1998) and use the following simple log-linear equation, derived from a knowledge production function to estimate patenting output:

$$p_{it} = \beta_0 + \beta_1 r_{it} + \beta_2 C_{it} + \sum_d \delta_d D_{id} + \mu_{it} \tag{1}$$

where p_{it} is the natural log of the number of patents generated by firm i in year t; r_{it} is the natural log of firm-level R&D spending; C_{it} is the intensity of participation in research consortia, measured as the count of concurrent projects in which firm i was involved in year t; δ's are the coefficients on our industry dummy variables (Ds), and μ is an error term. The δ terms represent industry-level differences in the propensity to patent.

The process by which firms select one another as joint venture partners and the process by which ATP selects joint venture proposals for funding are not processes of random assignment. When seeking out joint venture partners, firms would logically seek to affiliate with firms that conduct high-quality research. Moreover, it is quite likely that ATP funds consortia consisting of high research quality firms. If research productivity is positively correlated with the intensity of participation in consortia, it may be that the chain of causality *runs from research productivity to participation* rather than the other way around.[2]

To deal with this problem, we could, in principle, take two approaches. One is to use a model with firm "fixed effects" (which also removes industry effects). A fixed-effects estimate gives us potentially unbiased and consistent estimates of all parameters, albeit at the cost of losing the cross-sectional variance in our data, which is most of the total variance. As Griliches and Hausman (1986) have shown, however, the fixed-effects estimator may itself be biased in the presence of measurement error. Given the imperfections of patents as indicators of innovative output and our measures of firm-level R&D spending as measures of innovative input, some level of measurement error is virtually certain.

Unfortunately, this is not the only shortcoming of this framework. At least some firms that participated in ATP consortia were large firms with large, diversified research portfolios. The technological focus of the ATP consortia may be only a small part of their total research agenda, and hence account for only a small or even trivial fraction of their total patenting. Thus, movements in the measure of output used here—total patents—could be partially or entirely unrelated to the actual outcomes of the firm's research program that is involved in the ATP consortium. This argues for a more disaggregated approach to the data that focuses on patenting only in the areas targeted by the ATP consortia, which is the subject of the next two sections.

At *this* level of aggregation, the empirical alternative to a fixed-effects model is an instrumental variables approach. Such an approach assumes that changes in the intensity of participation in research consortia (*C)* is actually described by lagged values of *C*s as well as other observable variables. This assumption implies that there is some "inertia" to the selection process. Perhaps firms that participated in the past would be more likely to participate in present projects regardless of their true research quality. Thus, we can achieve identification by using "predetermined" or *k*-lagged values of C_{it} as instruments, where *k* is a lag long enough to be exogenous with respect to research quality. It is not possible, however, to apply this alternative approach to our current U.S. data. At this stage, we do not possess long lags in the "participation" variable. Therefore, inference in the U.S. data will be based on fixed- and random-effects estimates.[3]

DATA

Our data consists of an unbalanced panel of 249 firms, 65 of which have participated in at least one ATP project. Data cover the years from 1985 through 1995. (Additional information regarding the data sources and construction of the panel data are explained in the Appendix.) The ATP provided information on 96 ATP-funded consortia, including the members of the consortia, the total budget, the time frame of the project, and the technological goals of each research joint venture.[4]

Information on total R&D spending, sales, and capital investment of participating and non-participating firms was obtained from Standard & Poor's COMPUSTAT database. We do *not* have information on all participants for all years for several reasons: first, a number of smaller ATP project participants do not show up in the COMPUSTAT database in any year; second, some small firms only have data for the most recent years; and third, the data we obtained from COMPUSTAT only extend through 1995.

Information on the total patenting of firms was obtained from the REI Patent Database developed and maintained at the Case Western Reserve University Center for the Study of Regional Economic Issues. This database allows us to date patents by the date of application rather than the date of grant. This is important because the lag between the development of an idea by a firm (at which point the patent is applied for) and the granting of a patent by the USPTO can be as long as two to three years. At the time of this analysis, the REI Patent Database only contained information on patents granted through 1996. This means that our information on patents applied for effectively only goes up to 1994 or early 1995.

Thus, we confront two sources of "truncation" in the data. First, there is truncation in the cross-section dimension of our data. Many small firms are completely absent from our panel. Second, there is truncation in the time-series dimension of our data. Effectively, our data on the research inputs and outputs of the firm end in 1995 and do not capture the large number of ATP projects begun after 1995. Moreover, few projects that had begun before 1995 had actually ended by 1995. If the effects of participation continue long after the official end of a joint venture, we will likely *underestimate* the impact of consortia participation in our empirical analysis due to truncation of the data. To the extent that participation led to the strongest enhancement of research productivity in smaller firms, the lack of data on small firms could also lead to an underestimate of the total impact of consortia.

RESULTS

Table 1 presents some sample statistics of participants in ATP-funded research consortia versus non-participants. *T*-tests comparing these two groups indicate that firms in the participant sample are larger (as measured by nominal and inflation-adjusted sales), conduct

Table 1. Summary Statistics for Non-Participants and Participants of ATP-Funded Consortia

	Non-participants			*ATP participants*		
Variables	*Mean (Std. dev.)*	*Min.*	*Max.*	*Mean (Std. dev.)*	*Min.*	*Max.*
Patents	37.71	0.00	942.00	131.51	0.00	1,413.00
	(89.22)			(204.31)		
Real R&D	106.37	0.00	1,490.14	436.51	0.03	6,667.64
	(215.10)			(912.65)		
Sales	2,911.33	0.05	69,276.00	12,912.94	1.29	16,5370.0
	(6,996.35)			(24,036.08)		0
Real sales 2589.07	0.05	59,279.66	11,451.88	1.07	127,501.9	
	(6,156.09)			(21,043.83)		0
Real net capital stock	2,273.38	0.00	161,717.30	8,835.99	0.37	95,607.25
	(8,110.09)		0	(15,904.86)		
Number of observations	1,898			684		

Note: Units are millions of U.S. dollars. Patents are measured as total grants per year by date of application. These sample statistics are drawn from only one of several alternative approaches employed in this study.

more R&D, and generate more patents than firms in the non-participant sample. Given ATP's emphasis on the inclusion of smaller firms as joint venture partners, these findings appear contrary to expectations. Larger firms, however, are often partners in research consortia even though they are rarely joint venture leaders, and participation of subsidiaries in a joint venture is "credited" to the larger parent firm. In addition, smaller firms that do not publicly report R&D expenditures or generate patents do not show up in our database because there is no publicly available data on them in our original sources.

Table 2 presents various specifications of equation (1). We add a full set of year dummies to our regression, which partly controls for the time-truncation effect in our patent data. Industries are classified into seven sectors. Given our earlier concerns about reverse causality, we estimate a random-effects specification (column 1) and a fixed-effects specification (column 2). In both cases, the measure of intensity of participation, C, is positively correlated with patenting. The coefficient is statistically significant in both specifications.

Columns 3 and 4 give the results when we include the log of the deflated net capital stock as a control for the size of the participating firms. This variable is included because previous research indicates a positive correlation between firm size and the propensity to patent. Controlling for firm size, the impact of participation in ATP-funded consortia on research output remains positive and significant in all specifications. These results are quite striking given the many imperfections of our data. It suggests that there may indeed be substantial spillover-enhancing effects achieved through these research consortia.

IMPLICATIONS

This section gives us a measure of the extent to which involvement in ATP projects impacts the entire research portfolio of participating firms. Since the participants in our data set include large firms with quite diversified research portfolios, we will only observe large, significant impacts in this analytical framework if the effect of participation is the generation of knowledge spillovers that transcend the generally narrow technical focus of the project itself. So how large is the effect of consortia participation on the overall patenting of participating firms? Perhaps it is most instructive to look at column 4 of Table 3—the results from the fixed-effects specification with all controls in place. The coefficient on the variable C is 0.075. This suggests that participation in one additional ATP-funded research consortium per year would generate an increase in patenting in that year of nearly 8%. We note that the causal interpretation that we give in this statistical relationship between research productivity and participation is not the only possible interpretation. In the absence of a randomized experiment in which ATP makes awards to research consortia without regard to research quality, it is difficult to *prove* that the statistical relationship we document is causal. Nevertheless, our best efforts within the context of this framework suggest that ATP has a positive impact on the research productivity of the firms participating in its research consortia. We are not able, within this framework, to undertake a full cost-benefit analysis of ATP's funding; however, the statistical link we find between consortia participation and overall patenting is a necessary, though certainly not sufficient, condition of establishing that ATP's investment is socially productive.

Table 2. Estimation of a Patent Production Function: Overall Effect of Participation
Dependent variable: Log of patents granted per firm classified by the year of application

Variables	(1) Random Effects	(2) Fixed Effects	(3) Random Effects	(4) Fixed Effects
Real R&D	.567	.425	.315	.265
	(.019)	(.027)	(.029)	(.034)
Real net capital stock	—	—	.351	.311
			(.030)	(.04)
C	**.081**	**.066**	**.088**	**.075**
	(.026)	**(.026)**	**(.026)**	**(.026)**
Chemicals	.353	—	–.089	—
	(.148)		(.143)	
Machinery	.185	—	–.101	—
	(.160)		(.152)	
Transportation	.031	—	–.41	—
	(.202)		(.193)	
Precision instruments	–.071	—	.041	—
	(.171)		(.160)	
Fabricated metals	–.286	—	–.577	—
	(.435)		(.408)	
Other manufacturing	.526	—	–.011	—
	(.498)	—	(.469)	
Year 1986 dummy	.028	.036	.0322	.036
	(.049)	(.048)	(.048)	(.048)
Year 1987 dummy	.124	.139	.115	.124
	(.049)	(.048)	(.048)	(.048)
Year 1988 dummy	.082	.108	.061	.088
	(.049)	(.048)	(.048)	(.048)
Year 1989 dummy	.120	.151	.088	.109
	(.049)	(.049)	(.048)	(.048)
Year 1990 dummy	.131	.161	.082	.104
	(.049)	(.049)	(.048)	(.049)
Year 1991 dummy	.121	.152	.077	.100
	(.049)	(.049)	(.048)	(.049)
Year 1992 dummy	.115	.154	.066	.093
	(.05)	(.05)	(.049)	(.049)
Year 1993 dummy	.051	.093	.009	.038
	(.05)	(.05)	(.049)	(.05)
Year 1994 dummy	–.058	–.012	–.126	–.093
	(.051)	(.050)	(.050)	(.051)
Year 1995 dummy	–.808	–.746	–.895	–.849
	(.053)	(.053)	(.053)	(.054)
Constant	.594	1.20	–.473	–.149
	(.120)	(.096)	(.145)	(.198)
***R*-squared**	.7004	.6958	.7281	.7190

Note: Standard errors in parentheses. The reference sector of industry dummies is electronics. *C* is the count of concurrent projects in which firm *i* was involved in year *t*. Both R&D and net capital stock are measured in logs.

NOTES

1. A logical question here is the role of "lags" in our results. Unfortunately, the limited time-series dimension of our data does not allow us to adequately explore this question, but we do introduce a lag structure in subsequent empirical sections.

2. If consortia are established in technologically promising fields, it may be that our estimates are picking up not the direct effects of consortia but the indirect effects of the changes in technological opportunity. Our ability to control for this at the firm level is limited, though we believe that some of these technological opportunity effects are likely captured in our year and industry dummy variables.

3. Branstetter and Sakakibara (1998) used a 2SLS (two-stage least squares) approach with the Japanese data, in which there are long lags in the participation variable that can be used as instruments in the model.

4. Note that in some cases, individual subsidiaries of the same larger firm would participate in more than one ATP project in a given year. We also have cases where two subsidiaries of the same firm participate in the same project in a given year. In both cases, we measure intensity of participation by the firm by summing up the participation of its subsidiaries. Because, in general, U.S. firms are not required to break down their sales, investment, or R&D by division or business unit, it was not possible to conduct this analysis at the subsidiary level.

4. Effects of Consortium Characteristics on Consortium Performance

METHODOLOGY

The methodology presented in the previous section examines the impact of consortia participating on overall patenting. It does not, however, allow us to answer two important questions: (1) What is the impact of participation on the collective patenting of participating firms in the technological areas targeted by the consortia? (2) What kinds of consortia are most successful at promoting research productivity of participating firms?

To answer these questions, we need to measure the impact of consortium participation on patenting outcomes *in the technological areas targeted by the research consortia,* and compare the outcomes of different consortia projects.

The methodology used in this section and the subsequent one draws heavily from Branstetter and Sakakibara (2000). Below we define our dependent variable and discuss its strengths and weaknesses. Next, we discuss the independent variables used in this analysis. Then, we present our basic estimating equations followed by our results.

DEPENDENT VARIABLE

Innovative output, our dependent variable, is a measure of patenting by consortia participants in the technological areas targeted by the consortia.[1] We mapped the technological goals of ATP projects to their corresponding patent classes in order to create our dependent variable. The USPTO assigns each patent to a patent class that categorizes the technology. After assigning the stated technological objectives of an ATP-funded research consortium to the appropriate patent class or classes, we counted the number of patents taken out by participating firms in the targeted technologies before, during, and after the projects. This provided a panel dimension to the data on research outcomes.

Creating this mapping from ATP project technological goals to patent classes was not easy because of the complexity of the USPTO classification system and the broad range of technologies targeted by different ATP projects. We relied on the expertise of outside consultants to create this mapping.[2]

To the extent that our mapping is imprecise, we measure patenting in the targeted areas with error. The mapping we constructed likely includes more patents than are, in reality, *directly* connected technologically to the goals of the ATP project. The imputed level of patenting in the targeted area may overstate the impact of the project on firm patenting; however, the behavior of this variable *over time within a project* should be an accurate measure of impact.

INDEPENDENT VARIABLES

Time path of benefits. If a consortium had a significant impact on participating firms' innovative performance, we should be able to observe a consortium-induced upturn in the patenting of participating firms in the targeted area. Did the "consortium boost" to patenting merely occur during the first few years of the project, or do we observe a lasting impact on the level of patenting in the targeted area? Obviously, the "time path" of benefits from consortium participation is of interest. The time path was traced in two ways and is explained more fully under "Model" below.

Pre-project patenting in the targeted class. Measuring the impact of a consortium requires that we control for the patenting of participating firms in the targeted areas prior to the start of the project.

Project budgets. We control for the total public and private resources channeled into consortia research. We have information on the total budget of each project and the government's share. In the panel regressions, we divide the total budget by the number of years in which this budget was active in order to create an annualized budget series. All R&D numbers are adjusted for inflation.

Technological proximity of participants. The strongest potential for R&D spillovers may exist among firms that pursue research in the same technological areas.[3]

To measure proximity of firms in technology space, we followed the framework developed by Jaffe. A firm's R&D program may be described by the vector F, where $F_i = (f_1 \ldots f_k)$ and each of the k elements of F represents the firm's research resources and expertise in the k^{th} technological area. This is measured by the number of patents held by a firm in a narrowly defined technological field. We measure the "technological proximity" between two firms by measuring the degree of similarity in their patent portfolios. More precisely, the "distance" in technology space between two firms i and j is approximated by T_{ij} where T_{ij} is the uncentered correlation coefficient of the F vectors of the two firms, or

$$T_{ij} = \frac{F_i F_j'}{[(F_i F_i')(F_j F_j')]^{1/2}} \tag{2}$$

We calculated average T_{ij} measures for each project for which we had sufficient data.

Resources from overlapping consortia. Some firms participated in multiple consortia and some consortia tended to target similar classes of technologies. Therefore, simply looking at the output of a project while controlling only for the inputs participating firms received as a function of their participation in that project may understate the total resources being devoted to research in a particular class of technologies. We used information on the overlap in projects, both in terms of participating firms and targeted classes, to impute the variable "indirect inputs." [4]

Firms' perceptions of consortia impact. ATP's Business Reporting System (BRS)[5] provides information on firms' perceptions of the impact of consortia participation on research outcomes. Using responses to the survey questions listed below, we address the following question: Are positive *perceptions* of value correlated with empirical measures of research outcomes?

- *Stimulate_creative_thinking—To what extent has collaboration enabled your firm to stimulate creative thinking?* Here, and in most cases below, firms were asked to give an ordinal response, i.e., "significantly," "moderately," "little/none," or "unsure."

- *Avoid_redundant_R&D—To what extent has collaboration enabled your firm to avoid redundant R&D expenses*?

- *R&D_cost_saving—How much (in dollars) has your company saved in R&D expenses through collaboration?*

- *Time_saving—To what extent has collaboration allowed your company to save time in general?*

- *Delayed_product_entry—To what extent has collaboration delayed product entry into the marketplace?*

- *Delayed_R&D_phase—To what extent has collaboration contributed to a delay in the R&D phase?*

To protect the confidentiality of firms' responses, ATP disguised firm identity in these data. As a result, we averaged firm-level responses by consortium and linked this averaged response to other data.

The firms' responses came from different ATP reports; some came from the closeout report, others came from reports during the operation of the project. The relative success or failure of a consortium may affect a manager's perceptions of the consortium's attributes; thus, these qualitative data are not necessarily exogenous, in a statistical sense, to our measures of project outcomes. Nevertheless, we present our regressions as a way of assessing statistical relationships between these variables and research outcomes, without necessarily being able to prove anything about the causal nature of the relationship.

MODEL

The basic empirical model used in this section is as follows:

$$P_{it} = \alpha_0 + \beta_1 project\_duration_{it} + \beta_2 years\_passed_{it} + \beta_3 years\_passed^2{}_{it}$$
$$+\chi_0 budget_{it} + \lambda pre\_project\_patenting_i + \delta_c \sum_c L_{ci} + \varepsilon_{it} \quad (3)$$

Here P_{it} denotes the sum of U.S. patent grants generated by member firms of consortium *i* in year *t* in the technological areas targeted by the consortium. P_{it} is given as a simple count. $Budget_{it}$ represents the total research resources expended by the consortium. $Pre\_project\_patenting_i$ denotes the average patenting in the targeted classes, with the average taken over a 5-year window prior to the official start date of the project. Our qualitative variables are represented in the sigma term.

The spillover-inducing effect of the consortia is captured with a method borrowed from the macroeconomics literature on impulse response function.[6] A skeptical view of the benefits of research consortia maintains that any positive impact on the innovative output of participating firms is produced entirely by the combination of subsidies granted to the participants and the research resources expended by the participating firms out of their own R&D budgets. A positive view of the benefits of research consortia maintains that, in addition to the public and private financial resources expended, the process of bringing firms with complementary research assets into contact should itself enhance the innovative activity of the firms involved.

$Project\_duration_{it}$ is a dummy variable set equal to one during the years, *t*, for which project *i* is active. The regression coefficient on $project\_duration_{it}$ measures the boost to patenting in the targeted area sustained by the participating firms *during the duration of the project*. If this variable is positive and significant, then we interpret this as evidence that participation in consortia promotes spillovers of complementary knowledge among participants, enhancing the productivity of their collective research effort, and that these effects generate a more or less immediate impact on the patenting of consortium members.

Presumably, a boost to patenting in the targeted area that endures past the conclusion of the project is of greater social value than one that ends with the project. To get a sense of the average time path of benefits, we constructed two additional variables: $years\_passed_{it}$ and $years\_passed^2{}_{it}$. $Years\_passed_{it}$ measures the years elapsed since the start of a given project. A positive coefficient on $years\_passed_{it}$ and a negative coefficient on $years\_passed^2{}_{it}$ imply that the boost to patenting has a quadratic shape: it rises initially after the start of the project, but peaks and then declines at some later date.[7] A large, positive coefficient on $years\_passed_{it}$ and a relatively small, negative coefficient on $years\_passed^2{}_{it}$ would imply that a relatively long-lasting boost is obtained from consortia participation.

Another way to estimate the time path of benefits is to include a number of dummy variables corresponding to periods of set length after the inception of a project, and to examine the coefficients on these various dummies. This more flexible approach does not impose a quadratic structure on the benefits stream. Due to the time-truncation problem in our U.S. data, we are only able to estimate lags up to four years in length.

RESULTS

In our initial regression, we estimate the "stripped down" version of equation (3), leaving out, for the moment, our qualitative data on the nature of the consortia. Results are given in column 1 of Table 3. A Poisson regression model is used to explicitly allow for the "count data" characteristics of the dependent variable. The coefficient on *project_duration* has the interpretation of the additional patents generated per year that a consortium is in operation. In column 1, the coefficient on *project_duration* is positive and significant, though rather small in magnitude.[8]

The coefficient on *budget* is negative and significant, suggesting that a larger budget for a consortium paradoxically results in fewer patents. We believe this to be an artifact of the data, driven by trends in ATP's budget. When ATP began sponsoring its first projects during the first Bush Administration, it had a modest budget. The ATP considerably expanded during the Clinton Administration; however, our patent coverage for these later years is truncated. The negative coefficient for *budget*, which appears in most of our succeeding specifications, is probably driven by truncation of patents resulting from later projects rather than strongly decreasing returns to R&D subsidies.

The coefficient on *years_passed* is positive and significant, and the coefficient on *years_passed*^{2} is negative and significant. These coefficients imply a boost to patenting that is small initially, grows fairly rapidly, peaks within 2–3 years of the inception of a project, and declines thereafter. Our interpretation of the coefficients on *project_duration*, *years_passed*, and *years_passed*^{2} are all clouded by the time truncation problem in our patent data. With a longer post-project time series, we may very well observe more long-lived effects.

In column 2, we implement a more flexible version of the impulse response function, using dummy variables to represent time lags instead of the quadratic form used in column 1. The results of this model are quite consistent with the results of the quadratic time path of benefits estimated. The impact of participation in the first year is small and not statistically significant. Thereafter, the measured impact grows rapidly, peaking in the second year, and declining rapidly thereafter. Because of the time truncation in our data, the actual decline may be less rapid than the apparent decline shown in this model. This concern notwithstanding, these results support the evidence presented in the previous section: *participation in ATP-funded consortia has a positive, statistically significant impact on patenting by participating firms in the targeted technology*.

Column 3 adds our measure of average technological proximity to our baseline specification. Column 4 adds calendar year as a control variable to capture any overall time trend in

Table 3. Consortium-Level Analysis
Poisson regression
Dependent variable: Sum of patent grants by consortium participants in the targeted area

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Budget	–7.08e-08 (1.44e-09)	–7.09e-08 (1.44e-09)	–6.88e-08 (1.46e-09)	–6.88e-08 (1.51e-09)	–6.71e-08 (1.45e-09)
Pre-project patenting	.004 (.0000104)	.004 (.0000104)	.003 (.0000114)	.003 (.0000116)	.004 (.0000106)
Project duration dummy	**.054** **(.012)**	—	**.046** **(.013)**	**.319** **(.015)**	—
Years passed	**.431** **(.018)**	—	**.445** **(.019)**	**.452** **(.018)**	—
Years passed^2	**–.104** **(.005)**	—	**–.111** **(.005)**	**–.101** **(.005)**	—
Year 0 dummy[(a)] **(.013)**	—	**.019**	— **(.014)**	—	**.258**
Year 1 dummy	—	**.383** **(.016)**	—	—	**.573** **(.016)**
Year 2 dummy	—	**.558** **(.017)**	—	—	**.659** **(.017)**
Year 3 dummy	—	**.283** **(.02)**	—	—	**.716** **(.022)**
Year 4 dummy	—	**.254** **(.033)**	—	—	**.510** **(.033)**
Average technological proximity	—	—	.343 (.019)	.091 (.020)	—
Calendar year	—	—	—	–.096 (.002)	—
Real indirect inputs	—	—	—	—	–1.18e-07 (3.41e-09)
Constant	3.72 (.008)	3.72 (.008)	3.90 (.011)	194.341 (.618)	3.66 (.008)
***R*-squared**	.7726	.7730	.8062	.8192	.7808

Note: Standard errors in parentheses. The *R*-squared measure for the Poisson regression given here is a pseudo-*R*-squared measure.
(a) Year 0 indicates the year of the inception of a consortium.

patenting. In both cases, higher measured technological proximity is positively and significantly associated with higher levels of patenting in the targeted technologies. This suggests that the measure of average proximity we constructed here can be used to help predict the likelihood of project success ex ante.

We test the robustness of our baseline specification by including indirect resources received by project participants from other overlapping projects. Results are given in column 5. The basic results of our regression are unaffected by including this additional control variable.

Lastly, we include firms' responses to survey questions in the BRS while controlling for project *budget* and *pre_project_patenting* in the targeted area. Results presented in Table 4 are grouped by survey content. The model in column 1 shows that the coefficient on *stimulate_creative_thinking* is positively and significantly associated with patenting in the targeted area. The model in column 2 includes the variables *avoid_redundant_R&D*, *R&D_cost_saving*, and *time_saving*. Two of the three variables are positively and significantly correlated with project outcomes, suggesting that the perception of enhanced efficiency from collaboration is indeed correlated with higher levels of patenting in the targeted areas. The coefficient on *avoid_redundant_R&D* is negative. This result is difficult to interpret without further research, and is potentially contaminated by its collinearity with *R&D_cost_saving*. The model in column 3 measures the association between perceptions of problems or delays due to collaboration and project outcomes. As expected, the coefficient on *delayed_product_entry* is negative, suggesting that perceptions of delays in getting products to

Table 4. Consortium-Level Analysis: Qualitative Characteristics of Consortia
Poisson regression
Dependent variable: Sum of patent grants by consortium participants in the targeted area

Variables	*(1)*	*(2)*	*(3)*
Budget	–1.39e-07 (5.85e-09)	–1.58e-07 (8.64e-09)	–1.27e-07 (5.42e-09)
Pre-project patenting	.004 (.0000555)	.005 (.0000555)	.004 (.0000505)
Stimulate creative thinking	.382 (.0896)	— —	— —
Avoid redundant R&D	—	–.285 (.054)	—
R&D cost saving	—	2.74e-07 (4.14e-08)	—
Time saving	—	.428 (.083)	—
Delayed product entry	—	—	–.508 (.259)
Delayed R&D phase	—	—	.747 (.0483)
Constant	2.273 (.1623)	2.520 (.128)	2.666 (.0408)
***R*-squared**	.8308	.8376	.8469

Note: Standard errors in parentheses. The *R*-squared measure for the Poisson regression given here is a pseudo-*R*-squared measure.

the marketplace as a result of collaboration are associated with reduced patenting outcomes. In contrast, the coefficient on *delayed_R&D_phase* is positive, suggesting that perceptions of delays in the R&D phase of a project are associated with increased patenting outcomes. Although this result is difficult to explain without additional research, it is possible that technologically ambitious projects tend to fall behind schedule, but in the end generate greater technological payoffs.[9]

IMPLICATIONS

In this section, we showed that the establishment of an ATP-funded research consortium stimulates patenting by participating firms *in the targeted technological areas*. We identified some characteristics of consortia that lead to greater relative levels of success. Our results suggest that technological proximity, as measured by the degree to which the patenting portfolios of participating firms are similar, fosters spillovers; this, in turn, enhances the research productivity of the participating firms in the consortium. We also find a strong link between pre-consortium patenting in the targeted area and subsequent success. These results suggest that policy makers can use technological proximity and pre-consortium patenting in the targeted area as a criterion for selecting projects and member firms.[10]

We established a statistical link between some of the survey response variables in the BRS and quantitative outcome measures. The relationship between total project budgets and total project outcomes is less clear. The ATP faces a tradeoff between investing relatively large amounts of money in a small number of projects versus investing smaller amounts of money in larger numbers of projects. The evidence we present does not suggest that the projects with the biggest budgets generate the highest levels of patent output. However, the measured relationship between budget and outcomes is quite possibly distorted in our data by the time truncation problem in our patent data. More research will be necessary to clarify the nature of this important relationship.

NOTES

1. An alternative to this measure would be revenues obtained by corporations from the sales of products whose design and development were stimulated by participation in consortia. The mapping from consortia to commercial products, however, is a challenging task because even the participating firms themselves would have difficulty tracing the changes in their annual revenues due to products growing out of their participation in a consortium.

2. We acknowledge with gratitude the superb work done for us on this by the staff of Bailey Services, Inc.

3. However, it is certainly possible that there may be important technological complementarities between "distant" technologies that this index fails to measure.

4. We do not (and *cannot*) control for the spillover-stimulating effect of overlapping consortia. Thus, the estimated "spillover" effect attributed to one project may, in fact, partially reflect the "spillover enhancing" impact of the overlapping consortia.

5. In early 1994, ATP implemented the Business Reporting System (BRS), an electronically administered data collection tool for tracking progress of projects selected for ATP awards from 1993 to the present. BRS tracks the progress participants are making on their business plans and projected economic benefits that were originally outlined in their project proposals and updated over the course of conducting the research. Data are collected on a routine and regular basis at the individual participant level within a project to ensure maximum confidentiality of information.

6. We thank Oscar Jorda of UC-Davis for this suggestion.

7. It may be that the impact on firm patenting observed during the duration of the project is negligible, such that the estimated coefficient on *project_duration* is small. However, after the official cessation of the project, we may observe a substantial increase in patenting in the targeted area, as the research results obtained through the consortia are incorporated in the firms' own research programs.

8. Recall in the Poisson model, the regression coefficients have a semi-elasticity interpretation. The coefficients represent the percentage change in firm patenting associated with a unit change in the independent variable.

9. To facilitate interpretation of the coefficients on the survey response variables, we restrict our time dimension in *these* regressions to observations after the start of an individual project.

10. In other regressions not shown here, we estimated the elasticity of consortium outcomes with respect to pre-consortium patenting to be approximately 100%.

5. Firm Characteristics and Outcomes

METHODOLOGY

In this section, we examine the firms within a consortium to answer the question: What kind of firm benefits the most from participation? Here, the unit of observation is a firm's participation in an individual project. We seek to identify firm characteristics that are associated with measures of research success in the targeted areas during and after participation in a particular research project.

This component of our research faces one important data problem; we do *not* have good data on the division of individual firms' R&D budgets across research projects, including that fraction of the R&D budget spent on consortia-related research. What we *do* know is each firm's total R&D spending per year. We also know the total R&D budget for each consortium and how this total was divided between the government and the private sector. Using this information, we imputed a firm-level, project-specific R&D budget (inclusive of subsidies) by dividing the total *annualized* budget by the number of participants. While this will not necessarily be an accurate measure of the actual individual firm's investment in project-related technology in every year, this is the best that can be done with the current data. Our firm-level variables are defined below.

Pre-project patenting in the targeted area. The same logic applies here as in the case of the more aggregated consortium-level data. In order to isolate the impact of the project on the firm, we need a quantitative measure of its research competence in the targeted area. To measure pre-existing patenting levels in the targeted area, we use an average measure of pre-project patenting in the targeted area taken over a five-year window prior to the official start date of the project, or as much of this window as the available data permit.

Total R&D spending. For a large number of firms, we have high-quality panel data on overall research and development spending. A positive association of this variable with the outcome measure would suggest that the technologically more progressive firms are the prime beneficiaries of the projects. A negative association would suggest that it is the technological followers that benefit rather than the technological leaders.

Industry effects. Due to large and persistent differences in the propensities of firms in different industries to patent, we include industry fixed effects[1] in our regression analysis. Each participating firm is classified into one of seven industry classes. The inclusion of industry effects enables us to determine whether consortia in some industries are substantially more productive than other industries.

Capital stock. This is included primarily as a measure of firm size. We also have data on employment for a large number of participating firms, which can serve as an alternative measure of size. This is included to get some insight into whether large firms or small firms benefit most from consortia participation and to partially control for other unmeasured firm characteristics that are correlated with size.

Effects of overlapping projects. Firms may have a particularly high output in a certain project, controlling for inputs, but this may simply reflect the firm's simultaneous participation in another consortium that targets the same technologies. We control for overlapping projects by imputing the firm's subsidies and private contributions to each overlapping project. This measure is included in the variable *real_indirect_inputs*.

RESULTS

Our baseline empirical specification for analysis at the consortium-firm level resembles that of the consortium-level analysis. The essential difference is, of course, that we have an additional dimension of variance: we observe multiple firms participating in the same projects and, conversely, multiple projects impacting the same firms. We initially estimate:

$$\begin{aligned} P_{jit} &= \alpha_0 + \beta_1 project\_duration_{jit} + \beta_2 years\_passed_{jit} \\ &+ \beta_3 years\_passed^2{}_{jit} + \chi_0 budget_{jit} + \lambda pre\_project\_patenting_{ji} + \varepsilon_{jit} \end{aligned} \tag{4}$$

where *j* denotes the firm, *i* denotes the project, and *t* denotes the year. As in the previous analyses, we allow the project boost effect to have three components: an initial boost contemporaneous with the duration of firm *j*'s involvement in project *i* ($project\_duration_{jit}$); an effect that captures the—possibly lagged—increase in patenting as years since the inception of the project increase ($years\_passed_{jit}$); and a quadratic term in years elapsed since the inception of project *i* to allow for the decline in patenting that eventually sets in ($years\_passed^2{}_{jit}$). We also include as controls firm *j*'s share of the total budget (private outlays and public subsidy) for project *i* ($budget_{jit}$) and firm *j*'s pre-project level of patenting in the technologies targeted by project *i* ($pre\_project\_patenting_{jit}$).

The results of our initial regression are given in column 1 of Table 5. The coefficient on *project_duration* is positive but not statistically significant. The effects on *years_passed* and $years\_passed^2$ are statistically significant and have the expected sign. The results suggest the boost to firm patenting stemming from participation is not immediate, but takes place with a lag. As in the consortium-level regressions, the regression coefficients suggest an effect that peaks about two years after the inception of the project and then declines.

Table 5. **Firm-Consortium Level Analysis**
Poisson regression
Dependent variable: firm patenting in the targeted area

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Budget	–1.01e-06 (2.15e-08)	–1.56e-07 (7.75e-09)	–3.19e-07 (9.63e-09)	.003 (.0000167)	–2.19e-07 (7.84e-09)
Pre project patenting	.005 (.0000218)	.0042 (8.64e-06)	.004 (.0000142)	–1.24e-07 (8.41e-09)	.004 (9.77e-06)
Project duration dummy	**11.86** **(26.74)**	—	—	—	—
Years passed	**.566** **(.019)**	—	—	—	—
Years passed^2	**–.120** **(.005)**	—	—	—	—
Year 0 dummy[(a)]	—	.065 (.013)	.084 (.014)	.008 (.013)	.141 (.013)
Year 1 dummy	—	.772 (.015)	.574 (.016)	.469 (.016)	.930 (.016)
Year 2 dummy	—	.9998 (.017)	.901 (.018)	.777 (.017)	1.01 (.017)
Year 3 dummy	—	.745 (.02)	.558 (.020)	.474 (.020)	.915 (.020)
Year 4 dummy	—	.710 (.033)	.505 (.034)	.300 (.033)	.999 (.033)
Chemicals	—	—	—	–1.08 (.029)	—
Machinery	—	—	—	–.036 (.018)	—
Transportation	—	—	—	–1.169 (.021)	—
Precision instruments	—	—	—	.111 (.018)	—
Fabricated metals	—	—	—	-2.986 (.139)	—
Other manufacturing	—	—	—	–.423 (.030)	—
Average technological proximity	—	—	.987 (.020)	—	—
R&D spending	—	—	.0000966 (3.92e-06)	.000284 (3.79e-06)	—
Real net capital stock	—	—	2.41e-06 (3.04e-07)	—	—
Real indirect inputs	—	—	—	—	–1.28e-08 (2.66e-10)
Constant	–8.766 (26.738)	2.950 (.007)	2.771 (.012)	3.335 (.0130)	2.943 (.007)
R-squared	.6990	.6646	.7450	.7583	.6780

Note: Standard errors in parentheses. The *R*-squared measure for the Poisson regression given here is a pseudo-*R*-squared measure. The reference sector of industry dummies is electronics.
(a) Year 0 indicates the year of the inception of a consortium.

As a check on the robustness of the results, we estimate a more flexible "time path of benefits" structure using the set of year dummy variables. The results are given in column 2. These results are generally consistent with the picture we obtained from the results of column 1. Again, we have a boost that affects firms with a lag, peaks relatively early, and then declines.

Column 3 includes controls for the average technological proximity of firms within projects, overall R&D spending, and firm size as measured by net deflated capital stock. *Average_technological_proximity* is the same variable used in the previous section. *R&D_spending* measures firm *j*'s overall R&D spending in year *t*. This helps control for changes in the overall R&D intensity (and, potentially, R&D productivity) of firm *j* over time. Because we do not have R&D data for all firms in all years, our total number of observations declines in this specification. The results indicate that all three variables are positively associated with research outcomes. The results for *R&D_spending* and *real_net_capital_stock* imply that larger firms benefit more from consortium participation. However, the magnitude of the positive coefficient on the *real_net_capital_stock* variable is quite small, so it is not immediately obvious what its economic significance is.

Column 4 includes the industry dummy variables. A negative coefficient on an industry dummy variable suggests that, relative to the reference sector (electronics), firms generate fewer patents as a consequence of participation in a consortium. However, the coefficients on these industry dummy variables represent not only the differential effects of participation, but also the differential extent to which innovation resulting from participation is codified into patents.

We conducted two robustness tests, one that includes our measure of indirect inputs and a second that includes firm fixed effects. The former is presented in column 5 and indicates that our basic result survives this robustness check. The latter is shown in Table 6. The number of parameters needed to estimate firm fixed effects makes Poisson regression computationally impossible. Table 6 compares column 2 from Table 5 to a linear specification of the model with the firm effects added (but the fixed effects coefficients suppressed). The time path of benefits is essentially unchanged. These results are inconsistent with the view that project success is simply driven by the inclusion of "good" firms. Rather we find that, controlling for the unobserved research quality of firms within the targeted area, participation is associated with an increase in patenting in that area.[2]

In some cases, measuring the patent output of a particular firm, in a particular project, in a particular year is not disaggregated enough. A number of frequent participants in ATP-funded consortia were subsidiaries of large firms. The subsidiary's participation may constitute a small part of the larger firm's total research effort. Although the subsidiary's participation may have little impact on the entire firm's research effort, it may play a significant role in the subsidiary's research effort. We thus sought to isolate the patenting of the participating subsidiary as our measure of research output. To do this, we took the patents assigned to the corporation and selected out that subset of patents invented by individuals residing in the same geographic area as the participating subsidiary. This, we reasoned, was as close to the subsidiary's patents as the available data would allow us to get. The results are presented in Table 7 and are quite similar to the results presented in columns 2 and 3 of Table 5.

Table 6. Firm-Consortium Level Analysis: Comparison of Poisson and OLS Regression Models*
Dependent variable: firm patenting in the targeted area

Variables	(1) Poisson	(2) OLS
Budget	–1.56e-07	–9.25e-06
(7.75e-09)	(4.25e-06)	
Pre project patenting	.0042	.961
	(8.64e-06)	(.019)
Year 0 dummy[(a)]	.065	–1.651
	(.013)	(3.79)
Year 1 dummy	.772	17.548
	(.015)	(7.095)
Year 2 dummy	.9998	23.918
	(.017)	(7.899)
Year 3 dummy	.745	3.445
	(.02)	(8.263)
Year 4 dummy	.710	–31.758
	(.033)	(14.790)
Constant	2.950	41.061
	(.007)	(28.229)
***R*-squared**	.6646	.8831

Note: Standard errors in parentheses. The *R*-squared measure for the Poisson regression given here is a pseudo-*R*-squared measure.
* The OLS model is computed with the firm effects added, but the model is presented here with the coefficients suppressed.

IMPLICATIONS

In this section, we demonstrated that there is a statistical link between a firm's participation in an ATP project *and that firm's patenting in the technologies targeted by the ATP consortium*. This approach gets us as close as we can to causal identification between consortia participation and patenting outcomes without randomized experiments. We also demonstrated that this positive association between participation and patent output is not simply the result of "better" firms being systematically selected for more frequent participation. The patent boost from participation remains positive and statistically significant even when controlling for unobserved firm fixed effects, such as the firms' research productivity in the targeted technologies.

We also began to address the kinds of firms that benefit most from consortia participation. We find that our measure of technological proximity is positively and significantly correlated with research outcomes in the presence of other control variables, suggesting that firms participating in consortia composed of other firms with similar patenting portfolios tend to do

Table 7. Subsidiary-Consortium Level Analysis*
Poisson Regression
Dependent variable: firm patenting in the targeted area

Variables	*(1)*	*(2)*
Budget	2.07e-07 (1.07e-08)	1.70e-07 (1.52e-08)
Pre project patenting	.009 (.0000276)	.007 (.0000471)
Year 0 dummy[(a)]	.105 (.020)	–.060 (.022)
Year 1 dummy	.811 (.025)	.446 (.026)
Year 2 dummy	.956 (.0259)	.734 (.027)
Year 3 dummy	.668 (.030)	.308 (.032)
Year 4 dummy	.664 (.049)	.136 (.051)
Average technological proximity	—	1.160 (.030)
R&D spending	—	.0002905 (6.87e-06)
Real net capital stock	—	–9.34e-06 (6.04e-07)

* Measuring the subsidiary's patents is not possible with the current data. This analysis uses patents invented by individuals residing in the same geographic area as the participating subsidiary as a proxy measure of the subsidiary's patents.
Note: Standard errors in parentheses. The *R*-squared measure for the Poisson regression given here is a pseudo-*R*-squared measure.

better. We also find some evidence that firms' total R&D spending and firm size are also positively correlated with research outcomes. However, the economic significance of these coefficients is not clear given that our sample of ATP participants is not complete. In the absence of panel data on the research inputs and outputs of smaller firms, it is difficult to come to any definitive conclusions about the role of size or overall R&D spending in effecting research outcomes.

NOTES

1. A fixed-effects estimate gives us potentially unbiased and consistent estimates of all parameters, albeit at the cost of losing the cross-sectional variance in our data, which is most of the total variance. The fixed-effects estimator may itself be biased, however, in the presence of measurement error.
2. Results that are not presented here are available from the authors upon request.

6. Lessons from Japanese Data

TIME PATH OF BENEFITS FROM CONSORTIA

Our analytical framework for analysis of U.S. data was developed and pre-tested on Japanese data.[1] Japanese government involvement in publicly supported research consortia dates back to the late 1950's; examining this data will enable us to observe the long-run impact of consortia on patenting outcomes.

Using a model similar to that presented in Table 4, column 2, we estimated the time path benefits of consortia participation up to 13 years after inception of the consortia. Figures 3 and 4 graph the coefficients from the project duration dummy variables against the time since inception of the project. The regression coefficients represent the percentage increase in patenting in the targeted area associated with that year. Figure 3 shows a linear specification along with three alternative negative binomial specifications. Figure 4 shows one of the negative binomial specifications and the 95% confidence interval associated with each estimated coefficient.

Figure 3. Alternative Specifications of the Time Path of Benefits from Japanese Data

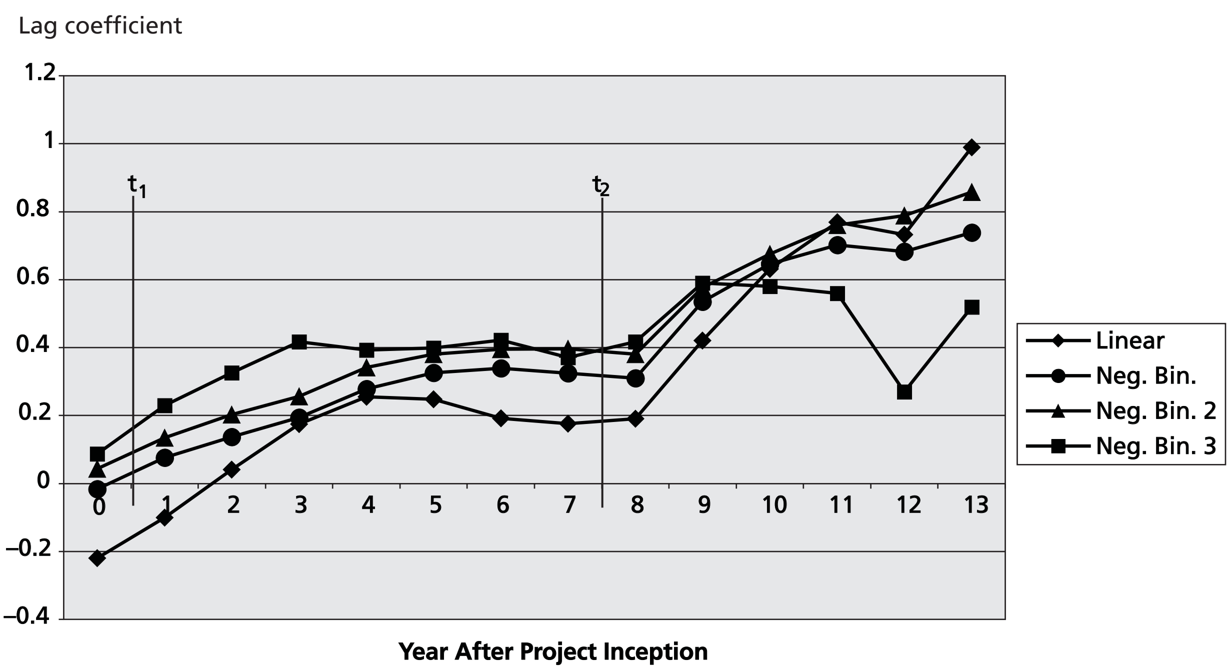
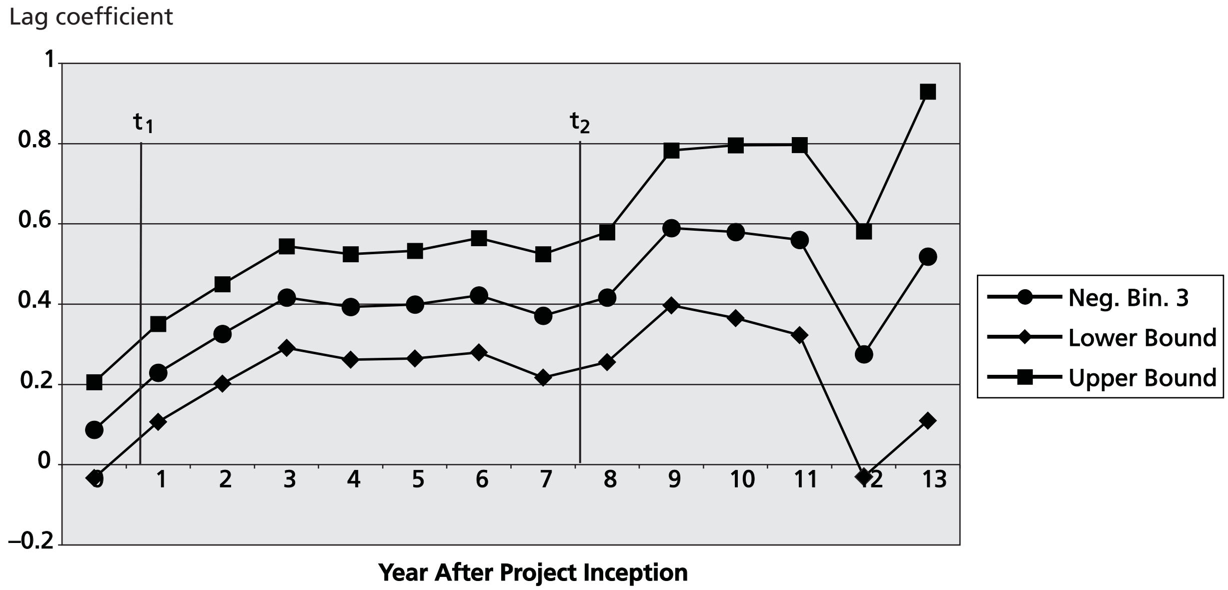


Figure 4. Time Path of Benefits from Japanese Data with Confidence Interval



Results from Japanese data indicate that the effect of consortia on patenting outcomes tends to persist for relatively long periods of time. In fact, patenting in the targeted area seems to *increase* a bit after the cessation of the consortium, before leveling off again in later years. This may be due to the rules under which subsidies were disbursed to firms in Japan. Any idea conceived as a direct result of the consortia was supposed to be patented in the name of the consortium itself rather than in the name of the participating firms. This created an incentive for firms to delay patenting some of their most useful ideas until after the official end of the consortium. For our purposes, the important point to keep in mind is that the effect of consortia can be quite long lasting. This suggests that our estimates of the impact of ATP-funded consortia, based on only four years of data, may underestimate the total impact of research consortia on patenting outcomes of the firms that were involved.

CONSORTIA CHARACTERISTICS

Using Japanese data, we examined the impact of two consortia characteristics on patenting outcomes: spillover potential and product market proximity. Economic theory predicts a positive association between spillover potential and patenting outcomes, and a negative association between product market proximity and patenting outcomes. Research consortia may intensify competition in the industry, in turn lowering profits. Firms that are direct competitors might conduct less R&D in a consortium than they would individually.

Spillover potential is assessed using the measure of technological proximity defined previously. Product market proximity measures “competitive distance” between each pair of firms in a consortium by dividing the number of product markets in which two firms in a consortium “meet” by the total number of product markets in which each firm is active. Two firms that meet one another in a large number of product markets are presumed to be more proximate to each another than firms with few or no overlapping products.[2] Based on data from 591 distinct product markets, we constructed an average measure of proximity for firms within a consortium.[3]

Many of the variables on consortium characteristics do not change over time. Including them in a panel regression creates statistical problems (see Moulton, 1986). For that reason, we collapsed the time series dimension of the data. Consortium outcomes are measured as the cumulative sum of patenting in the targeted classes, taken over a fifteen-year horizon from the official inception of the project (or for as long as the data allowed). This sum was regressed on summed measures of direct and indirect research inputs, pre-consortium technological strength, and time-invariant consortium characteristics.

The first two columns of Table 8 illustrate the impact of *technological_proximity* and p*roduct_market_proximity* on patenting outcomes.[4] Consistent with theoretical predictions, the first variable has a positive impact on consortium outcomes, whereas the second variable has a negative impact, albeit one that is only marginally significant in a statistical sense.

These results have important implications for our previous analysis of U.S. data. First, it confirms the importance and robustness of technological proximity as a predictor of consortium success in a data set with a much longer, more complete time series dimension.

Table 8. Firm-Consortium Level Analysis Using Japanese Data
Negative binomial models
Dependent variable: Patenting in the targeted area

Variables	*(1)*	*(2)*	*(3)*
Budget	.068	.196	—
	(.039)	(.045)	
Pre project patenting	.799	.756	—
	(.026)	(.030)	
Real indirect inputs	.028	.020	—
	(.011)	(.013)	
Technological proximity	.497	.020	1.16
	(.250)	(.284)	(.41)
Product market proximity	–.323	–.552	–.164
	(.298)	(.341)	(.524)
Technological goal	—	—	.254
		(.121)	
Cumulative total patents	.103	.142	—
	(.042)	(.051)	
Year	–.114	—	—
	(0.14)	—	—

Second, the negative effect of product market proximity on consortium outcomes suggests that bringing product market rivals into a consortium is unlikely to produce a successful pattern. Few ATP-funded consortia have this structure, and that is probably a good thing.

The third column adds an additional variable to the regression equation that measures participating firms' perceptions concerning the degree to which the technological goals of a given consortium are "close to commercialization" versus "pre-commercial" or "basic." The positive, statistically significant coefficient on this variable suggests that projects focusing on pre-commercial research are likely to yield better outcomes. Thus, Japanese data lend support to ATP's focus on pre-commercial research.

CAVEATS IN APPLYING JAPANESE LESSONS TO U.S. CONSORTIA

When comparing results from Japanese consortia to the U.S. experience, a number of caveats apply. Research consortia may have a larger impact on Japanese research productivity than they would in the United States because of the very different structure of the labor market in Japan. Most scientists and engineers employed in Japanese corporations are part of the so-called "lifetime employment system," spending most of their careers with a single company. In contrast, U.S. scientific labor tends to be quite mobile across firms. The movement of scientists and engineers between U.S. companies is an important mechanism by which new technology diffuses in manufacturing industries. Because the same mechanism is less operative in Japan, research consortia may play a particularly important role in enabling new technological innovation to flow across firm boundaries.

There is also greater involvement of the Japanese government in establishing consortia, selecting members, directing research, and ensuring that the results are widely diffused throughout Japanese industry than in the United States. The ATP model of consortium governance is essentially a "bottom-up" model, in which the burden of organization falls upon the participating firms—in particular, the joint venture lead participant. By contrast, Japanese consortia are run according to a more "top-down" approach, in which the sponsoring ministry is generally more involved in directing the activities of the consortium. Our preliminary investigations suggest that the degree of centralization is *negatively* correlated with good outcomes, which, again, validates ATP's approach to consortium management.

NOTES

1. A complete discussion of the Japanese data and our analysis of it are available as a separate paper:see Branstetter and Sakakibara (1998,1999,and 2000).

2. However, our measure of proximity does not guarantee symmetry. For any pair of firms, *i* may be closer to *j* than *j* is to *i* if *i* is in only one product market (and meets *j* in that market), while *j* is in one hundred product markets, in only one of which it meets *i*.

3. *Market Share in Japan* by Yano Keizai Kenkyusho was the reference manual consulted in determining Japanese product markets.

4. Other variables included in the regressions include measures of the total consortium budget, levels of pre-consortium patenting in the targeted areas, and "indirect inputs," as in the previous section. The dependent variable is the level of patenting in the targeted area. The statistical model used is a negative binomial model.

7. Conclusions and Issues for Future Research

This study empirically evaluates the impact of ATP-funded consortia on the research productivity of participating firms. We find evidence that *the impact of participation on research productivity of participating firms is positive at all levels*. There is a positive association between the intensity of participation in research consortia and the overall research productivity of the participating firms. At the consortium level, we continue to find a positive impact of consortia on the research productivity of participating firms in the technological areas targeted by the consortia. Furthermore, this positive impact of consortia is higher when the average technological proximity (that is, the degree to which patenting portfolios of participating firms are similar) of participating firms is high, and when consortia participation stimulates the participants' creative thinking and contributes to their R&D cost and time saving. Larger firms with higher R&D budgets tend to benefit more from participation than other firms. The economic significance of this finding is unclear due to the flaws of our data set. Viewed together, however, our results demonstrate that consortia participation is leading to verifiable, measurable increases in research productivity.

We compared our U.S. findings to results from Japanese government–sponsored R&D consortia, which allowed us to examine the long-run impact of consortia on patenting outcomes. Japanese data indicate that participation in an additional consortium increases patenting between 4% and 8%, similar to our finding in this study. Japanese data also suggest that the benefits of research consortia are observed long after the inception of the project, with a surge in patenting following the official cessation of the consortia. This implies that the relatively short time series of data available on firms that participated in ATP-funded research consortia will tend to underestimate the total impact of participation.

We also examined the impact of two consortium characteristics using Japanese data: spillover potential (as measured by average technological proximity of firms within a consortium) and product market proximity. As expected, Japanese data show a positive association between technological proximity and research outcomes and a negative association between product market proximity and research outcomes. These results have important implications for our analysis of U.S. data. First, they confirm the importance and robustness of technological proximity as a predictor of consortium success in a data set with a much longer, more complete time-series dimension. Second, the negative effect of product market proximity on consortium outcomes suggests that bringing product market rivals into a consortium is unlikely to produce a successful pattern. Few ATP-funded consortia have this structure, and that is probably beneficial for ATP.

Although Japanese data confirm several of our U.S. findings, we are mindful of the limitations of our analysis due to several data constraints. First, the lack of information on a number of small, privately held firms that were involved in ATP-funded consortia affects the cross-sectional dimension of our data set. Second, the REI patent data effectively ends in 1995, just as the ATP was expanding its support of research consortia. This affects the time series dimension of our data. Measurements of consortium outcomes based on only a few years' data are likely to underestimate the full effect of consortia participation on member firms. In addition, our analysis using ATP's Business Reporting System (BRS) survey data on firms' perceptions of the impact of participation in consortia on their own research and development was limited because of confidentiality constraints.

The limitations in our data set could be addressed in several ways. First, the USPTO's Automated Patent System is an on-line database that allows users to download data on hundreds of thousands of recent patents. Using this database, our patent series could be updated to include recent granted patents.

Second, ATP staff economists could analyze individual firm-level responses to BRS survey questions without jeopardizing the confidentiality of these data. Combing the qualitative BRS data with quantitative measures developed in this study will create a richer, more complete picture of the impact of consortia than we were able to achieve.

Third, future work could extend the time-series dimension of our analysis by updating firm R&D spending, capital investment, and industry affiliation through Standard & Poor's COMPUSTAT database. Firms' innovative inputs could be updated using the most recent version of this database.

Fourth, the consortium-level and firm-level analyses discussed in this report depend on the construction of a mapping from the stated technological goals of ATP-funded research consortia to the relevant patent classes of the U.S. Patent and Trademark Office's patent classification system. As described in the Appendix on data construction, we employed an outside consultant, Bailey Services, Inc., to construct this mapping at a nominal price. We believe that the accuracy of the mapping they provided is high enough for the exploratory analysis conducted in this report. However, we strongly suggest that ATP's Economic Assessment Office consider investing an additional $5,000–$10,000 in the creation of a truly comprehensive patent mapping. Such a document could be a useful evaluation tool for years to come.

In this study, we have accomplished our mission of developing a framework that allows ATP to quantitatively measure the impact of research consortia on the research productivity of participating firms. We hope that ATP researchers will be able to apply this framework, build upon our work, and extend it in order to ensure that ATP maximizes the benefits of its investments in new technology.

Appendix: Documentation of the Data

1. MAPPING PROJECTS TO PATENT CLASSES

Bailey Services, Inc., mapped the technological goals of ATP-funded research consortia to the U.S. Patent and Trademark Office's patent classification system. This firm, based in Texas and Washington, D.C., consists of Ph.D.-level scientists with many years of professional experience in obtaining patent data for corporate clients.

2. DATA CONSTRUCTION DESCRIPTION

With this mapping in hand, we sought to acquire patent data for U.S. firms in our sample. Unfortunately, patents assigned to U.S. corporations by the U.S. Patent and Trademark Office (USPTO) are not indexed by Standard & Poor's COMPUSTAT code but by an "assignee code" which corresponds to the name of the firm as it appears on the patent grant document. Often firms will take out patents in the name of a subsidiary firm. Alternatively, firms may use variants of their name on the patent document ("International Business Machines, Incorporated" vs. "IBM"). Thus, obtaining the total number of U.S. patents of participating firms required a rather extensive, sophisticated search through publicly available data sources, as a single firm can have patents assigned to any one of several dozen separate "assignee codes." Bronwyn Hall at the University of California, Berkeley allowed us to use her proprietary "mapping" from firm COMPUSTAT codes to USPTO assignee codes to quickly identify the assignee codes for the firms in our data set.

With these assignee codes, we were able to obtain patent data directly in electronic form through the use of the REI Patent Database developed and maintained at Case Western Reserve University's Center for the Study of Regional Economic Issues. This database allowed us to date patents by the date of application rather than the date of grant. This is important, because the lag between the development of an idea by a firm (at which point the patent is applied for) and the granting of a patent by the patent office can be as long as 2–3 years. Unfortunately, at the time of this analysis, the REI database only contained information on patents *granted* through 1996. This means that our information on patents applied for effectively only goes up to 1994 or early 1995.

Our patent data initially consisted of observations on individual patents. For each patent granted to firms in our database after 1980, we obtained information on the "primary" technology class of the patent, the date of application, and, in some cases, the address of the inventor. Managing this data was quite complicated, because some of our firms had literally thousands of patents, and we were obtaining this data on hundreds of firms. We used the PERL text processing language to process the original text files submitted with each patent application. Then, we converted our data into STATA format. The STATA statistical analysis software package was used in all of our regressions.

These patent data were aggregated in a number of ways. To provide the dependent variable for our firm-level regressions, we added up all patents taken out by a given firm in a given year for the years 1985–1995. To provide the dependent variable for our consortium-level regressions, we added up all patents taken out by all firms participating in a given project in all targeted patent classes during a given year for the years 1985–1995. To provide the dependent variable for our firm-consortium level regressions, we added up the patents taken out by individual firms participating in a given project in the targeted patent classes in a given year. In this case, a firm's participation in one project was taken as the unit of observation—the same firm could show up multiple times in the data set if it participated in more than one project. Finally, to calculate our measures of "average proximity," each firm's total patents over the 1980–1995 period were aggregated into 50 technology clusters to create the *F* vector defined in the body of the report. The measure of technological proximity was derived from the average uncentered correlation coefficient of the *F* vectors of firms participating in the projects.

As for the data on research input and other firm characteristics, the original source for our data is the COMPUSTAT data file, but we actually obtained our data from Bronwyn Hall, who did some substantial cleaning of the raw data and provided us with deflators.

One issue we had to deal with was the fact that some participating firms in the ATP-funded research consortia were subsidiaries of much larger corporations. To identify the patent output of participating subsidiaries, we used data from the REI patent database on the geographic location of the inventor. We took patents assigned to a participating firm and then identified the subset of patents assigned to that firm *which were invented by persons in the same geographic area (CMSA code) as the location of the participating subsidiary*.

Firms can participate in multiple consortia and multiple consortia can target similar classes of technologies. Thus, there was an overlap in the consortia, both in terms of participating firms and targeted technology classes. Controlling only for the inputs directly invested in a particular consortium may make some consortia look successful simply because they are located in the center of a cluster of related consortia, and innovative output is high because resources are seeping in from these related projects. We control for this overlapping in our measure of *real_indirect_inputs,* which was calculated as follows. If two consortia, *X* and *Y*, have two common firms, then these firms' share of the total budget for consortium *Y* is multiplied by the degree of technological overlap between *X* and *Y* in terms of targeted patent classes, and this product is imputed to *X* as "indirect inputs." A similar imputation is done for consortia that follow *X* and target some of the same firms and classes.

Table A1. Mapping of Projects to Patent Classes

Project	*Associated Patent Classes*
90-01-0060	349 428 345 359 445 313 361 324 348 364 702 395 156 206
90-01-0126	430 204 315 378 250 372 347 355 356 73 359 385 428
90-01-0154	174 257 439 361 338 148 228 29 156 428 355
90-01-0154	174 257 439 361 338 148 228 29 156 428 355
90-01-0154	174 257 439 361 338 148 228 29 156 428 355
90-01-0154	174 257 439 361 338 148 228 29 156 428 355
90-01-0154	174 257 439 361 338 148 228 29 156 428 355
90-01-0231	365 369 711 346 395 372 257 359 364
90-01-0231	365 369 711 346 395 372 257 359 364
91-01-0016	364 360 365 386 396 348 345 395 346
91-01-0016	364 360 365 386 396 348 345 395 346
91-01-0016	364 360 365 386 396 348 345 395 346
91-01-0016	364 360 365 386 396 348 345 395 346
91-01-0016	364 360 365 386 396 348 345 395 346
91-01-0016	364 360 365 386 396 348 345 395 346
91-01-0016	364 360 365 386 396 348 345 395 346
91-01-0069	706 73 364 252 438
91-01-0069	706 73 364 252 438
91-01-0069	706 73 364 252 438
91-01-0069	706 73 364 252 438
91-01-0083	706 395 364
91-01-0083	706 395 364
91-01-0083	706 395 364
91-01-0083	706 395 364
91-01-0176	257 345 347 348 353 355 358 359 364 365 369 372 385 386 395 438
91-01-0177	73 702 364 706 356
91-01-0177	73 702 364 706 356
91-01-0177	73 702 364 706 356
91-01-0178	264 427 428 442 521 523 526 296
91-01-0261	204 427 117 118 428 423
91-01-0267	364 395 706 707 438
91-01-0267	364 395 706 707 438
92-01-0040	156 364 395 425 706
92-01-0040	156 364 395 425 706
92-01-0044	435 536 382 364 436
92-01-0123	359 204
93-01-0089	427 118 407 51 75 216 30
93-01-0089	427 118 407 51 75 216 30
93-01-0089	427 118 407 51 75 216 30
93-01-0151	359 364 395 707 701 385 340 375

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Table A1 continued

Project	*Associated Patent Classes*
93-01-0151	359 364 395 707 701 385 340 375
93-01-0244	82 83 29 318 184 501 279
93-01-0244	82 83 29 318 184 501 279
93-01-0244	82 83 29 318 184 501 279
93-01-0244	82 83 29 318 184 501 279
94-01-0079	384 148 428 501 420
94-01-0079	384 148 428 501 420
94-01-0079	384 148 428 501 420
94-01-0135	95 96 204 252 423 428 501 502
94-01-0169	706 705 364 395 345 702
94-01-0169	706 705 364 395 345 702
94-01-0169	706 705 364 395 345 702
94-01-0169	706 705 364 395 345 702
94-01-0169	706 705 364 395 345 702
94-01-0169	706 705 364 395 345 702
94-01-0178	356 395 73 707 702 318 369
94-01-0178	356 395 73 707 702 318 369
94-01-0178	356 395 73 707 702 318 369
94-01-0178	356 395 73 707 702 318 369
94-01-0190	502 423 252 585
94-01-0228	128 600 408 382 364
94-01-0282	141 313 349 395 445 324 345 427 364
94-01-0304	345 348 353 359 361 445 257
94-01-0305	428 106 216 252 427 244
94-01-0340	505 428 427 148 257
94-01-0357	427 118 428 51 219
94-02-0027	296 156 425 411 264 252 52
94-02-0027	296 156 425 411 264 252 52
94-02-0027	296 156 425 411 264 252 52
94-02-0030	75 420 428 74 164 264 442 475 60
94-02-0032	405 166 137 138 285 156 420
94-02-0032	405 166 137 138 285 156 420
94-02-0032	405 166 137 138 285 156 420
94-02-0032	405 166 137 138 285 156 420
94-02-0033	156 264 428 442 164 702 364 324 340
94-02-0038	405 166 137 138 285 156 420
94-02-0038	405 166 137 138 285 156 420
94-02-0038	405 166 137 138 285 156 420
94-02-0039	156 420 52 156 264 428 442
94-02-0039	156 420 52 156 264 428 442

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Table A1 continued

Project	*Associated Patent Classes*
94-02-0043	14 52 292 403 156 428 442 702 364 324 340
94-02-0048	405 166 137 138 285 156 420
94-02-0048	405 166 137 138 285 156 420
94-02-0048	405 166 137 138 285 156 420
94-04-0028	706 707 395
94-04-0041	707 705
94-04-0041	707 705
94-05-0004	372 359 385 430 347 355 257
94-05-0030	204 436 435
95-01-0108	385 359 372 455 356 73 228 324 148 235
95-01-0108	385 359 372 455 356 73 228 324 148 235
95-01-0126	313 445 437 385 359 501 257 438 345
95-01-0150	62 361 417 60 165
95-01-0152	257 438 437 359 445 349 378
95-02-0008	29 72 101 180 280 296 423
95-02-0008	29 72 101 180 280 296 423
95-02-0008	29 72 101 180 280 296 423
95-02-0008	29 72 101 180 280 296 423
95-02-0008	29 72 101 180 280 296 423
95-02-0008	29 72 101 180 280 296 423
95-02-0008	29 72 101 180 280 296 423
95-02-0009	419 75 428 148 29 72 74 180 301
95-02-0013	219 706 364 395 29 180 280 296
95-02-0013	219 706 364 395 29 180 280 296
95-02-0013	219 706 364 395 29 180 280 296
95-02-0013	219 706 364 395 29 180 280 296
95-02-0013	219 706 364 395 29 180 280 296
95-02-0013	219 706 364 395 29 180 280 296
95-02-0013	219 706 364 395 29 180 280 296
95-02-0013	219 706 364 395 29 180 280 296
95-02-0013	219 706 364 395 29 180 280 296
95-02-0035	420 148 72 73 29 702
95-02-0035	420 148 72 73 29 702
95-02-0035	420 148 72 73 29 702
95-02-0035	420 148 72 73 29 702
95-02-0035	420 148 72 73 29 702
95-02-0036	250 118 427 216 148 76 315 219 156
95-02-0036	250 118 427 216 148 76 315 219 156
95-02-0036	250 118 427 216 148 76 315 219 156
95-02-0036	250 118 427 216 148 76 315 219 156

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Table A1 continued

Project	*Associated Patent Classes*
95-02-0040	501 75 427 428 117 118 407 51
95-02-0058	123 451 73 702
95-02-0058	123 451 73 702
95-02-0062	378 250 257 364 382 74
95-02-0062	378 250 257 364 382 74
95-02-0062	378 250 257 364 382 74
95-03-0017	348 364 365 369 386 345 370 707 711 375 395 382 346 359
95-03-0018	360 364 346 395 386 348 324 711 427
95-03-0018	360 364 346 395 386 348 324 711 427
95-03-0022	369 360 364 346 395 386 348 385 707 711 235
95-03-0022	369 360 364 346 395 386 348 385 707 711 235
95-03-0022	369 360 364 346 395 386 348 385 707 711 235
95-03-0022	369 360 364 346 395 386 348 385 707 711 235
95-04-0001	348 375 386 395 455 379 370 342 343 382
95-04-0026	348 375 386 395 455 379 370 385 342 343 345 364 382
95-04-0026	348 375 386 395 455 379 370 385 342 343 345 364 382
95-04-0026	348 375 386 395 455 379 370 385 342 343 345 364 382
95-04-0037	348 375 386 395 455 379 370 385 342 343 345 364 382
95-04-0037	348 375 386 395 455 379 370 385 342 343 345 364 382
95-05-0038	524 525 526 264 502
95-05-0038	524 525 526 264 502
95-05-0039	502 524 525
95-05-0040	502 585 560 568
95-05-0040	502 585 560 568
95-06-0010	62 165 415 384 137 417 361
95-06-0010	62 165 415 384 137 417 361
95-06-0010	62 165 415 384 137 417 361
95-06-0010	62 165 415 384 137 417 361
95-06-0011	62 73 356 250
95-07-0004	228 219 324 148 395 235
95-07-0004	228 219 324 148 395 235
95-07-0017	164 416 29 415 60
95-07-0020	164 364 73
95-08-0006	435 436 707 704 705 364
95-08-0023	435 436 382 364
95-10-0030	455 707 395 386 364
95-11-0010	405 166 137 138 285 156 420
95-11-0024	156 425 264 252 52 296 428 442 423
95-11-0024	156 425 264 252 52 296 428 442 423

(Table continued on next page)

Table A1 continued

Project	*Associated Patent Classes*
95-12-0024	364 702 706 705 395 340 370
95-12-0024	364 702 706 705 395 340 370
95-12-0027	156 264 428 442 164 702 364 324 340
95-12-0027	156 264 428 442 164 702 364 324 340
95-12-0030	705 706 364 395
95-12-0030	705 706 364 395
95-12-0030	705 706 364 395
95-12-0030	705 706 364 395
96-01-0257	378 250 257 364 382 345 358
96-01-0257	378 250 257 364 382 345 358

Table A2. U.S. Projects and Firms in Our Data Sets

Project Number	Project Title	CUSIP	Company Name
90-01-0060	Advanced Manufacturing Technology for Low-Cost Flat-Panel Display	913017	United Technologies Corp
90-01-0126	Solid-State Laser Technology for Point-Source X-Ray Lithography	580169	McDonnell Douglas Corp
90-01-0154	Printed Wiring Board Interconnect Systems	19512	Allied Signal Inc
90-01-0154	Printed Wiring Board Interconnect Systems	370442	General Motors Corp
90-01-0154	Printed Wiring Board Interconnect Systems	459200	Intl Business Machines Co
90-01-0154	Printed Wiring Board Interconnect Systems	882508	Texas Instruments Inc
90-01-0154	Printed Wiring Board Interconnect Systems	913017	United Technologies Corp
90-01-0231	Short-Wavelength Sources for Optical Recording	277461	Eastman Kodak Co
90-01-0231	Short-Wavelength Sources for Optical Recording	459200	Intl Business Machines Co
91-01-0016	Ultra-High Density Magnetic Recording Heads	38213	Applied Magnetics Co
91-01-0016	Ultra-High Density Magnetic Recording Heads	277461	Eastman Kodak Co
91-01-0016	Ultra-High Density Magnetic Recording Heads	428236	Hewlett-Packard
91-01-0016	Ultra-High Density Magnetic Recording Heads	459200	Intl Business Machines Co
91-01-0016	Ultra-High Density Magnetic Recording Heads	747906	Quantum Corp
91-01-0016	Ultra-High Density Magnetic Recording Heads	811804	Seagate Technology
91-01-0016	Ultra-High Density Magnetic Recording Heads	862111	Storage Technology
91-01-0069	Neural Network Control and Sensors for Complex Materials	18804	Alliant Techsystems
91-01-0069	Neural Network Control and Sensors for Complex Materials	438506	Honeywell Inc
91-01-0069	Neural Network Control and Sensors for Complex Materials	604059	3m Company
91-01-0069	Neural Network Control and Sensors for Complex Materials	822440	Sheldahl
91-01-0083	NCMS Rapid Response Manufacturing	345370	Ford Motor Co
91-01-0083	NCMS Rapid Response Manufacturing	370442	General Motors Corp
91-01-0083	NCMS Rapid Response Manufacturing	882508	Texas Instruments Inc
91-01-0083	NCMS Rapid Response Manufacturing	913017	United Technologies Corp
91-01-0176	Monolithic Multiwavelength Laser Diode Array Spanning 430 to 1100nm	984121	Xerox Corp
91-01-0177	Development of Advanced Technologies and Systems for Controlling Dimensional Variation	171196	Chrysler Corp
91-01-0177	Development of Advanced Technologies and Systems for Controlling Dimensional Variation	370442	General Motors Corp
91-01-0177	Development of Advanced Technologies and Systems for Controlling Dimensional Variation	71361F	Perceptron, Inc.
91-01-0178	Cyclic Thermoplastic Liquid Composite Molding for Automotive Structures	71361F	Perceptron, Inc.
91-01-0261	Plasma Technology for Low-Cost Diamond Production	960402	Westinghouse Electric Corp

(Table continued on next page)

Table A2 continued

Project Number	Project Title	CUSIP	Company Name
91-01-0267	PREAMP - Pre-Competitive Advanced Manufacturing of Electrical Products	97023	Boeing Co
91-01-0267	PREAMP - Pre-Competitive Advanced Manufacturing of Electrical Products	774347	Rockwell International Corp
92-01-0040	Engineering Design with Injection-Molded Thermoplastics	369604	General Electric Co
92-01-0040	Engineering Design with Injection-Molded Thermoplastics	370442	General Motors Corp
92-01-0044	Genosensor Technology Development	75816	Beckman Instruments
92-01-0123	Electrochromic Materials	604059	3m Company
93-01-0089	CVD Diamond-Coated Rotating Tools for Machining Advanced Composite Materials	345370	Ford Motor Co
93-01-0089	CVD Diamond-Coated Rotating Tools for Machining Advanced Composite Materials	370442	General Motors Corp
93-01-0089	CVD Diamond-Coated Rotating Tools for Machining Advanced Composite Materials	775133	Rogers Corp
93-01-0151	Jitney: A Low-Cost, High-Performance Optical Bus	459200	Intl Business Machines Co
93-01-0151	Jitney: A Low-Cost, High-Performance Optical Bus	604059	3m Company
93-01-0244	Strategic Machine Tool Technologies: Spindles	345370	Ford Motor Co
93-01-0244	Strategic Machine Tool Technologies: Spindles	370442	General Motors Corp
93-01-0244	Strategic Machine Tool Technologies: Spindles	375046	Giddings & Lewis, Inc., Automation Technology
93-01-0244	Strategic Machine Tool Technologies: Spindles	456866	Ingersoll-Rand Co
94-01-0079	Engineered Surfaces for Rolling and Sliding Contacts	149123	Caterpillar Inc
94-01-0079	Engineered Surfaces for Rolling and Sliding Contacts	370442	General Motors Corp
94-01-0079	Engineered Surfaces for Rolling and Sliding Contacts	887389	Timken Co
94-01-0135	Dual Purpose Ceramic Membranes	74005P	Praxair Technology, Inc.
94-01-0169	Collaborative Decision Support for Industrial Process Control	31905	Amoco Corp
94-01-0169	Collaborative Decision Support for Industrial Process Control	166751	Chevron Corp
94-01-0169	Collaborative Decision Support for Industrial Process Control	302290	Exxon Corp
94-01-0169	Collaborative Decision Support for Industrial Process Control	438506	Honeywell Inc
94-01-0169	Collaborative Decision Support for Industrial Process Control	822635	Shell Oil Company

(Table continued on next page)

Table A2 continued

Project Number	Project Title	CUSIP	Company Name
94-01-0169	Collaborative Decision Support for Industrial Process Control	881694	Texaco Inc
94-01-0178	Rapid Agile Metrology for Manufacturing	115223	Brown & Sharpe Manufacturing Company
94-01-0178	Rapid Agile Metrology for Manufacturing	149123	Caterpillar Inc
94-01-0178	Rapid Agile Metrology for Manufacturing	278058	Eaton Corp
94-01-0178	Rapid Agile Metrology for Manufacturing	369604	General Electric Co
94-01-0190	Development of Improved Catalysts using Nanometer-Scale Technology	595073	Microfluidics International Corporation
94-01-0228	Computer-Integrated Revision Total Hip Replacement Surgery	459200	Intl Business Machines Co
94-01-0282	Diamond Diode Field Emission Display Process Technology Development	868532	Supertex, Inc.
94-01-0304	High Information Content Display Technology	657045	North America Philips Lighting Corp.
94-01-0305	Film Technologies to Replace Paint on Aircraft	604059	3m Company
94-01-0340	Technologies for HTS Components for Magnetic Resonance Applications	458771	Intermagnetics General Corporation
94-01-0357	Accelerated Commercialization of Diamond-Coated Round Tools and Wear Parts	489170	Kennametal Inc
94-02-0027	Automotive Composite Structures: Development of High-Volume Manufacturing Technology	171196	Chrysler Corp
94-02-0027	Automotive Composite Structures: Development of High-Volume Manufacturing Technology	345370	Ford Motor Co
94-02-0027	Automotive Composite Structures: Development of High-Volume Manufacturing Technology	370442	General Motors Corp
94-02-0030	Polymer Matrix Composite Power Transmission Devices	428290	Hexcel Corporation
94-02-0032	Composite Production Risers	31905	Amoco Corp
94-02-0032	Composite Production Risers	208251	Conoco, Inc.
94-02-0032	Composite Production Risers	428290	Hexcel Corporation
94-02-0032	Composite Production Risers	822635	Shell Oil Company
94-02-0033	High-Performance Composites for Large Commercial Structures	260543	Dow Chemical
94-02-0038	Spoolable Composite Tubing	31905	Amoco Corp
94-02-0038	Spoolable Composite Tubing	718507	Phillips Petroleum Co
94-02-0038	Spoolable Composite Tubing	822635	Shell Oil Company
94-02-0039	Low-Cost Advanced Composite Process for Light Transit Vehicle Manufacturing	345370	Ford Motor Co
94-02-0039	Low-Cost Advanced Composite Process for Light Transit Vehicle Manufacturing	369604	General Electric Co

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Table A2 continued

Project Number	Project Title	CUSIP	Company Name
94-02-0043	Low Cost Manufacturing and Design/Sensor Technologies for Seismic Upgrade of Bridge Columns	428290	Hexcel Corporation
94-02-0048	Manufacturing Composite Structures for the Offshore Oil Industry	428290	Hexcel Corporation
94-02-0048	Manufacturing Composite Structures for the Offshore Oil Industry	666807	Northrop Corporation
94-02-0048	Manufacturing Composite Structures for the Offshore Oil Industry	881694	Texaco Inc
94-04-0028	Development of an Episode Grouper	604059	3m Company
94-04-0041	Enterprise Integration Tool Set (EITS) for Healthcare Professionals	253912	Digital Systems Resources, Inc.
94-04-0041	Enterprise Integration Tool Set (EITS) for Healthcare Professionals	909214	Unisys Corp
94-05-0004	Compact Blue Laser for Diagnostics	714041	Perkin-Elmer Corp
94-05-0030	Diagnostic Laser Desorption Mass Spectrometry Detection of Multiplex Electrophore	372430	Genome Therapeutics Corporation
95-01-0108	Precision Optoelectronics Assembly	97023	Boeing Co
95-01-0108	Precision Optoelectronics Assembly	261597	Dresser Industries Inc
95-01-0126	Technology Development for the Smart Display - A Versatile High-Performance Video Display Integrated with Electronics	382388	Goodrich (B.F.) Co
95-01-0150	Development of Closed Cycle Air Refrigeration Technology for Refrigeration Market	9158	Air Products & Chemicals Inc
95-01-0152	Low-Cost Amorphous Silicon Manufacturing Technology	369604	General Electric Co
95-02-0008	Agile Precision Sheet-Metal Stamping	17634	Allen Bradley Company, Inc.
95-02-0008	Agile Precision Sheet-Metal Stamping	52770	Autodie International, Inc.
95-02-0008	Agile Precision Sheet-Metal Stamping	171196	Chrysler Corp
95-02-0008	Agile Precision Sheet-Metal Stamping	345370	Ford Motor Co
95-02-0008	Agile Precision Sheet-Metal Stamping	370442	General Motors Corp
95-02-0008	Agile Precision Sheet-Metal Stamping	538021	Litton Industries, Inc.
95-02-0008	Agile Precision Sheet-Metal Stamping	71361F	Perceptron, Inc.
95-02-0009	The Next-Generation Industrial Production Process for High-Density Powder Metal Products	370442	General Motors Corp
95-02-0013	Intelligent Resistance Welding	17634	Allen Bradley Company, Inc.
95-02-0013	Intelligent Resistance Welding	171196	Chrysler Corp
95-02-0013	Intelligent Resistance Welding	345370	Ford Motor Co
95-02-0013	Intelligent Resistance Welding	370442	General Motors Corp
95-02-0013	Intelligent Resistance Welding	382388	Goodrich (B.F.) Co
95-02-0013	Intelligent Resistance Welding	458095	Intech R&D U.S.A.

(Table continued on next page)

Table A2 continued

Project Number	Project Title	CUSIP	Company Name
95-02-0013	Intelligent Resistance Welding	478366	Johnson Controls, Inc., Automotive Systems Group
95-02-0013	Intelligent Resistance Welding	538021	Litton Industries, Inc.
95-02-0013	Intelligent Resistance Welding	584029	Medar, Inc.
95-02-0035	Springback Predictability in Automotive Manufacturing	22249	Aluminum Company Of America
95-02-0035	Springback Predictability in Automotive Manufacturing	118835	Budd Company, Technical Center
95-02-0035	Springback Predictability in Automotive Manufacturing	171196	Chrysler Corp
95-02-0035	Springback Predictability in Automotive Manufacturing	345370	Ford Motor Co
95-02-0035	Springback Predictability in Automotive Manufacturing	370442	General Motors Corp
95-02-0036	Plasma-Based Processing of Lightweight Materials for Motor-Vehicle Components and Manufacturing Applications	370442	General Motors Corp
95-02-0036	Plasma-Based Processing of Lightweight Materials for Motor-Vehicle Components and Manufacturing Applications	412822	Harley-Davidson, Inc.
95-02-0036	Plasma-Based Processing of Lightweight Materials for Motor-Vehicle Components and Manufacturing Applications	538021	Litton Industries, Inc.
95-02-0036	Plasma-Based Processing of Lightweight Materials for Motor-Vehicle Components and Manufacturing Applications	831865	A.O. Smith Corp.
95-02-0040	Cubic Boron Nitride (cBN) Coatings for Cutting and Specialty Tools	489170	Kennametal Inc
95-02-0058	Flow-Control Machining	345370	Ford Motor Co
95-02-0058	Flow-Control Machining	370442	General Motors Corp
95-02-0062	Fast, Volumetric X-Ray Scanner for Three-Dimensional Characterization of Critical Objects	369604	General Electric Co
95-02-0062	Fast, Volumetric X-Ray Scanner for Three-Dimensional Characterization of Critical Objects	370442	General Motors Corp
95-02-0062	Fast, Volumetric X-Ray Scanner for Three-Dimensional Characterization of Critical Objects	808766	Scientific Measurement Systems, Inc.
95-03-0017	Ultrahigh-Capacity Optical Disk: Multilayer Short-Wavelength Write-Once and Erasable Optical Disk Recording System	277461	Eastman Kodak Co

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Table A2 continued

Project Number	Project Title	CUSIP	Company Name
95-03-0018	High-Performance, Variable-Data-Rate, Multimedia Magnetic Tape Recorder	811804	Seagate Technology
95-03-0018	High-Performance, Variable-Data-Rate, Multimedia Magnetic Tape Recorder	862111	Storage Technology
95-03-0022	Technology Development for Optical-Tape-Based Rapid Access Affordable Mass Storage	292659	Energy Conversion Devices, Inc. (ECD)
95-03-0022	Technology Development for Optical-Tape-Based Rapid Access Affordable Mass Storage	620076	Motorola Inc
95-03-0022	Technology Development for Optical-Tape-Based Rapid Access Affordable Mass Storage	731095	Polaroid Corp
95-03-0022	Technology Development for Optical-Tape-Based Rapid Access Affordable Mass Storage	984121	Xerox Corp
95-04-0001	Mobile Information Infrastructure for Digital Video and Multimedia Applications	866810	Sun Microsystems Computer Corporation
95-04-0026	HDTV Broadcast Technology	459200	Intl Business Machines Co
95-04-0026	HDTV Broadcast Technology	657045	North America Philips Lighting Corp.
95-04-0026	HDTV Broadcast Technology	866810	Sun Microsystems Computer Corporation
95-04-0037	Perceptual-Based Video Encoding and Quality Measurement	866810	Sun Microsystems Computer Corporation
95-04-0037	Perceptual-Based Video Encoding and Quality Measurement	882508	Texas Instruments Inc
95-05-0038	Tailored Optical Polymers Through a Novel Catalyst System (TOPCAT)	382388	Goodrich (B.F.) Co
95-05-0038	Tailored Optical Polymers Through a Novel Catalyst System (TOPCAT)	604059	3M Company
95-05-0039	Elastomeric Polypropylene and Elastic Non-wovens Venture	31905	Amoco Corp
95-05-0040	Breakthrough Technology for Oxidation of Alkanes	775371	Rohm & Haas Co
95-05-0040	Breakthrough Technology for Oxidation of Alkanes	866762	Sun Company, Inc. (R&M)
95-06-0010	Innovative, Small, High-Speed, Centrifugal Compressor and Integrated Heat-Exchange	19512	Allied Signal Inc
95-06-0010	Innovative, Small, High-Speed, Centrifugal Compressor and Integrated Heat-Exchange	144465	Carrier Corporation
95-06-0010	Innovative, Small, High-Speed, Centrifugal Compressor and Integrated Heat-Exchange	369604	General Electric Co
95-06-0010	Innovative, Small, High-Speed, Centrifugal Compressor and Integrated Heat-Exchange	913017	United Technologies Corp

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Table A2 continued

Project Number	Project Title	CUSIP	Company Name
95-06-0011	Novel Leak Detection Technology Development	913017	United Technologies Corp
95-07-0004	Fabrication of Advanced Structures Using Intelligent and Synergistic Materials Processing	149123	Caterpillar Inc
95-07-0004	Fabrication of Advanced Structures Using Intelligent and Synergistic Materials Processing	533543	Lincoln Electric Company
95-07-0017	Cost-Effective Blade Manufacturing for Combustion Turbine Applications	960402	Westinghouse Electric Corp
95-07-0020	Low-Cost, Near Net-Shape Aluminum Casting Processes for Automotive and Truck Components	19512	Allied Signal Inc
95-08-0006	Real-Time Micro-PCR Analysis System	714041	Perkin-Elmer Corp
95-08-0023	Arrayed Primer Extension (APEX): The Next Generation DNA Analysis System for Sequencing in DNA Diagnosis	716941	Pharmacia Biotech, Inc.
95-10-0030	Development of National Medical Practice Knowledge Banks	628862	NCR Corp
95-11-0010	Composite Drill Pipes	718507	Phillips Petroleum Co
95-11-0024	Vapor-Grown Carbon-Fiber Composites for Automotive Applications	370442	General Motors Corp
95-11-0024	Vapor-Grown Carbon-Fiber Composites for Automotive Applications	382550	Goodyear Aerospace Corporation
95-12-0024	An Agent-Based Framework for Integrated Intelligent Planning - Execution	456866	Ingersoll-Rand Co
95-12-0024	An Agent-Based Framework for Integrated Intelligent Planning - Execution	459200	Intl Business Machines Co
95-12-0027	Advanced Process Control Framework Initiative	7903	Advanced Micro Devices
95-12-0027	Advanced Process Control Framework Initiative	438506	Honeywell Inc
95-12-0030	Solutions for MES-Adaptable Replicable Technology (SMART)	31897	Amp Inc
95-12-0030	Solutions for MES-Adaptable Replicable Technology (SMART)	459200	Intl Business Machines Co
95-12-0030	Solutions for MES-Adaptable Replicable Technology (SMART)	871660	Synquest
95-12-0030	Solutions for MES-Adaptable Replicable Technology (SMART)	878377	International Technegroup, Inc.
96-01-0257	High Performance Sensor Arrays for Digital X-Ray and Visible Light Imaging	883666	Thermotrex Corporation
96-01-0257	High Performance Sensor Arrays for Digital X-Ray and Visible Light Imaging	984121	Xerox Corp

References

Branstetter, L., and M. Sakakibara. 1998. “Japanese Research Consortia: A Microeconometric Analysis of Industrial Policy.” *Journal of Industrial Economics* 46: 207–233.

———. 1999. “Analyzing Research Consortia at the Project Level: Microeconometric Evidence from Japan.” Working paper. UC Davis, CA.

———. 2000. “When Do Research Consortia Work Well and Why? Evidence from Japanese Panel Data.” Working paper presented at the American Economic Association annual meeting, Boston, MA.

Callon, S., 1995. *Divided Sun: MITI and the Breakdown of Japanese Industrial Policy, 1975–1993*. Stanford, CT: Stanford University Press.

d’Aspremont, C., and A. Jacquemin. 1988. “Cooperative and Noncooperative R&D in a Duopoly with Spillovers.” *American Economic Review* 78: 1133–1137.

Dertouzos, M.L., R.M. Solow, and R.K. Lester. 1989. *Made in America: Regaining the Productive Edge*. Cambridge, MA: MIT Press.

Griliches, Z., and J. Hausman. 1986. “Errors in Variables in Panel Data.” *Journal of Econometrics* 31: 93–118.

Ham, R. M., and D. Mowery. 1995. “Enduring Dilemmas in U.S. Technology Policy.” *California Management Review* 37: 89–107.

Irwin, D., and P. Klenow. 1996. “High Tech R&D Subsidies: The Effects of Sematech.” *Journal of International Economics* 40: 323–344.

Jaffe, A.B., 1986. “Technological Opportunity and Spillover of R&D: Evidence from Firms’ Patents, Profits, and Market Value.” *American Economic Review* 76: 984–1,001.

Kamien, M., E. Muller, and I. Zang. 1992. “Research Joint Ventures and R&D Cartels.” *American Economic Review* 82: 1293–1306.

Kamien, M., and I. Zang. 2000. "Meet Me Halfway: Research Joint Ventures and Absorptive Capacity." *International Journal of Industrial Organization* 18: 995–1012.

Katsoulacos, Y., and D. Ulph. 1998. "Endogenous Spillovers and Research Joint Ventures." *Journal of Industrial Economics* 44: 333–357.

Katz, M.L. 1986. "An Analysis of Cooperative Research and Development." *RAND Journal of Economics* 17: 527–543.

Leahy, D., and J.P. Neary. 1997. "Public Policy towards R&D in Oligopolistic Industries." *American Economic Review* 87: 642–662.

Martin, S. 2000. "Spillovers, Appropriability, and R&D." Working paper presented at the American Economic Association annual meeting, Boston, MA.

Moulton, B. 1986. "Random Group Effects and the Precision of Regression Estimates." *Journal of Econometrics* 32: 385–397.

Ouchi, W.G., and M.K. Bolton. 1988. "The Logic of Joint Research and Development." *California Management Review* 30: 9–33.

Sakakibara, M. 1994. "Cooperative Research and Development: Theory and Evidence on Japanese Practice." Ph.D. Thesis, Harvard University.

Spence, A.M. 1984. "Cost Reduction, Competition, and Industry Performance." *Econometrica* 52: 101–121.

Suzumura, K. 1992. "Cooperative and Noncooperative R&D in an Oligopoly with Spillovers." *American Economic Review* 82: 1307–20.

Related Reading

Beason, R., and D. Weinstein. 1996. "Growth, Economies of Scale, and Targeting in Japan (1955-1990)." *Review of Economics and Statistics* (August): 286-95.

Branstetter, L. 1996a. "Are Knowledge Spillovers Intranational or International in Scope: Microeconometric Evidence from the United States and Japan" National Bureau of Economic Research (NBER) Working Paper.

———. 1996b. "Innovation, Knowledge Spillovers, and Dynamic Comparative Advantage: Evidence from Japan and the United States." Ph.D. thesis, Harvard University.

Chang, C. 1993. "The Advanced Technology Program Compared with Technology Development Programs Abroad." Advanced Technology Program (ATP) Staff Report.

Cockburn, I., and R. Henderson. 1994. "Racing to Invest? The Dynamics of Competition in Ethical Drug Discovery." *Journal of Economics and Management Strategy* 3(3): 481–519.

Cohen, W., and D. Levinthal. 1989. "The Two Faces of R&D." *Economic Journal* 99 (September): 569-610.

Doz, Y. 1987. "Technology Partnerships between Larger and Smaller Firms: Some Critical Issues." *International Studies of Management and Organization* 17(4): 31–57.

Hausman, J., B. Hall, and Z. Griliches. 1984. "Econometric Models for Count Data with an Application to the Patents-R&D Relationship." *Econometrica* 52: 4.

Henderson, R., and I. Cockburn. 1996. "Scale, Scope, and Spillovers: the Determinants of Research Productivity in Drug Discovery." *Rand Journal of Economics* 27(1): 32–59.

Hladik, K.J. 1988. "R&D and International Joint Ventures." In F.J. Contractor and P. Lorange, eds, *Cooperative Strategies in International Business*. Lexington, MA: Lexington Books (99–109).

Jorde, T.M., and D.J. Teece. 1990. "Innovation and Cooperation: Implications for Cooperation and Antitrust." *Journal of Economic Perspectives* 4: 75–96.

Link, A.N., D. Teece, and W.F. Finan. 1996. "Estimating the Benefits from Collaboration: The Case of Sematech." *Review of Industrial Organization* 11(5): 737–751.

Montalvo, J., and Y. Yafeh. 1994. "A Micro-Econometric Analysis of Technology Transfer: The Case of Licensing Agreements of Japanese Firms." *International Journal of Industrial Organization* 12(2).

Porter, M.E., H. Takeuchi, and M. Sakakibara. Forthcoming *The Two Japans: Reexamining the Japanese Model of Competitiveness.*

Reinganum, J. 1989. "The Timing of Innovation: Research, Development and Diffusion." In R. Schmalensee and R.D. Willig, eds., *Handbook of Industrial Organization*. Volume 1. Amsterdam: North Holland (849–908).

Romer, P. 1993. "Implementing a National Technology Strategy with Self-Organizing Industry Investment Boards." *Brookings Papers on Economic Activity*: Microeconomics 2, 1993.

Ruegg, R. 1996. "Guidelines for Economic Evaluation of the Advanced Technology Program." NISTIR-5896.

Sakakibara, M. 1997a. "Heterogeneity of Firm Capabilities and Cooperative Research and Development: An Empirical Examination of Motives." *Strategic Management Journal* (special summer issue): 143–164.

———. 1997b. "Evaluating Government Sponsored R&D Consortia in Japan: Who Benefits and How." *Research Policy.* Forthcoming.

Saxonhouse, G. Forthcoming. "A Market Evaluation of Government High-Technology Policy: Opto-Electronics in Japan." In a volume of essays in honor of Hugh Patrick, to be edited by G. Saxonhouse and M. Aoki.

Scott, J.T. 1988. "Diversification versus Cooperation in R&D Investment." *Managerial and Decision Economics* 9: 173–186.

Scherer, F.M., D. Harhoff, and J. Kukies. 1998. "The Size Distribution of Profits from Innovation." Working paper.

Spencer, B., and J. Brander. "International R&D Rivalry and Industrial Strategy." *Review of Economic Studies* 50: 707–22.

Trajtenberg, M. 1989. "The Welfare Analysis of Product Innovations, with an Application to CT Scanners." *Journal of Political Economy* (summer): 444–479.

Tyson, L.D. 1992. *Who's Bashing Whom?: Trade Conflict in High-Technology Industries*. Washington, DC: Institute for International Economics.

Wakasugi, R. 1986. *Gijutsu Kakushin to Kenkyu Kaihatsu no Keizai Bunseki: Nihon no Kigyo Kodo to Sangyo Seisaku* (The Economic Analysis of Research and Development and Technological Progress: Japanese Firm Activity and Industrial Policy). Tokyo: Toyo Keizai Shimposha.

About the Advanced Technology Program

The Advanced Technology Program (ATP) is a partnership between government and private industry to conduct high-risk research to develop enabling technologies that promise significant commercial payoffs and widespread benefits for the economy. The ATP provides a mechanism for industry to extend its technological reach and push the envelope beyond what it otherwise would attempt.

Promising future technologies are the domain of ATP:

- Enabling technologies that are essential to the development of future new and substantially improved projects, processes, and services across diverse application areas;
- Technologies for which there are challenging technical issues standing in the way of success;
- Technologies whose development often involves complex "systems" problems requiring a collaborative effort by multiple organizations;
- Technologies which will go undeveloped and/or proceed too slowly to be competitive in global markets without ATP.

The ATP funds technical research, but it does not fund product developmentæthat is the domain of the company partners. The ATP is industry driven, and that keeps it grounded in real-world needs. For-profit companies conceive, propose, co-fund, and execute all of the projects cost-shared by ATP.

Smaller firms working on single-company projects pay a minimum of all the indirect costs associated with the project. Large, "Fortune 500" companies participating as a single company pay at least 60% of total project costs. Joint ventures pay at least half of total project costs. Single-company projects can last up to three years; joint ventures can last as long as five years. Companies of all sizes participate in ATP-funded projects. To date, more than half of ATP awards have gone to individual small businesses or to joint ventures led by a small business.

Each project has specific goals, funding allocations, and completion dates established at the outset. Projects are monitored and can be terminated for cause before completion. All projects are selected in rigorous, competitions, which use peer review to identify those that score highest against technical and economic criteria.

Contact ATP for more information:

- On the Internet: http://www.atp.nist.gov
- By e-mail: atp@nist.gov
- By phone: 1-800-ATP-FUND (1-800-287-3863)
- By writing: Advanced Technology Program, National Institute of Standards and Technology, 100 Bureau Drive, Mail Stop 4701, Gaithersburg, MD 20899-4701

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