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JAPANESE RESEARCH CONSORTIA: A MICROECONOMETRIC ANALYSIS OF INDUSTRIAL POLICY

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ABSTRACT

The existence of strong "spillover" effects of private R&D increases the potential social contribution of R&D but may depress the private incentives to undertake it. R&D consortia offer a potentially effective means of internalizing this externality, and a number of prominent economists have argued for public support of such consortia (e.g., Romer, 1993). Governments in Europe and North America have adopted policies to promote the formation of such consortia, motivated less by economic theory than by the perception that the Japanese government has used such policies to great effect (Tyson, 1992). Despite the existence of a large theoretical literature analyzing the potential benefits and costs of R&D consortia, there has been little corresponding empirical work on their efficacy.

In this paper, we undertake the *first* large-sample econometric study of Japanese government-sponsored research consortia which uses firm-level data on research inputs and outputs to measure the impact of participation on the *ex-post* research productivity of the firm. We are able to find evidence that frequent participation in these consortia has a positive impact on research expenditure and research productivity. These results hold after controlling for the potential endogeneity of the intensity of participation in consortia to participating firms' research productivity. Furthermore, we find evidence that part of this impact arises from the increased knowledge spillovers that take place within these consortia. Not only are these results useful in providing empirical evidence on the theory of research joint ventures, but they are also useful in shedding light on the question of what role Japanese "industrial policy" played in Japanese technological innovation during the 1980s. We conclude with directions for further research.

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I. Introduction:

If some or most of the benefits of new industrial R&D spill over to a firm's competitors, customers, or suppliers, then the ensuing appropriation problem can lead the firm to undersupply R&D relative to the social optimum. Following Spence (1984), a large theoretical literature has developed over the last decade which has analyzed the possible benefits of research consortia as tools by which R&D externalities could be internalized. Up to this point, however, little has been done to confront this substantial theoretical literature with the data in a systematic way. The empirical research that has been done has tended to focus on small numbers of highly publicized (and quite possibly atypical) case studies.[2] An exception to this is Sakakibara (1994, 1997a,b), which compiled a comprehensive list of consortia and participating firms. Going further, Sakakibara used a survey of R&D managers of Japanese firms participating in government-sponsored consortia to obtain detailed qualitative evidence about the perceived benefits of participation.

We contribute to the literature with this microeconometric analysis of the actual effects of research consortia on a panel of Japanese firms. By combining Sakakibara's data on firm participation in these projects with a rich set of firm-level data on the research inputs and outputs of a subset of the participating firms and a control group of non-participants, we have created a data set that will allow us to test a variety of hypotheses derived from the current theory about the operation and effectiveness of research consortia in Japan.

This data set is useful in testing the predictions of the theory of research consortia. We also use it to contribute to economists' understanding of postwar Japanese industrial policy. Despite the contention of a number of political scientists and others that Japanese postwar economic performance is primarily the result of skillful government intervention, theoretical and empirical economic analysis has tended to support the view that Japanese industrial policy played a small role, if any, in Japan's industrial development.[3] However, publicly supported research consortia are precisely the kind of intervention for which economic

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[2] For a recent example, see Scott Callon's *Divided Sun: MITI and the Decline of Japanese Industrial Policy 1975-1993* (1995). Also, for example, see Ouchi and Bolton (1988).

[3] Beason and Weinstein (1996) provide particularly compelling evidence at the 2-digit industry level.

theory offers some justification.[4] It is our hope that our empirical results will not only shed light on the relevance of theoretical work on research consortia, but also provide policy lessons for other countries seeking to emulate Japan's success through application of this particular kind of industrial policy.

II. Review of the Literature

Spence (1984) clearly established the two countervailing market failures that characterize R&D activities. The first issue is that of appropriation. The existence of R&D spillovers makes it difficult for innovators to capture the full social benefits of their innovation. Even when innovators can capture the full benefits, through patents or other kinds of strongly-enforced intellectual property rights, however, there is another market failure. The social cost of new knowledge, once it is produced, is the cost of transmission, which is often, though not always, close to zero. Hence, attempts to correct the inadequacy of appropriation incentives by strengthening intellectual property rights can exacerbate the second market failure, leading firms to charge too much for their new knowledge, such that the diffusion of new knowledge that takes place is less than the social optimum. Thus, there is a tradeoff between incentives for the socially efficient production of new knowledge and the incentives for its socially efficient diffusion. Given this dilemma, research consortia in which firms pool their research resources to share both the costs and benefits of R&D, may offer a solution. By joining forces, firms internalize the externality created through spillovers. Since each participant is privy to the research results, the "transmission" problem is solved as well.

Unfortunately, the theoretical contribution by Katz (1986) revealed that research consortia have problems of their own. If firms cooperate in R&D, but compete in the product market, then the increased incentive to do R&D is possibly vitiated by the impact of the shared R&D output on subsequent market competition. If that higher level of R&D makes *ex post* market competition more intense, either by lowering firms' marginal cost of production or "crowding" the product space with larger numbers of differentiated products, then the resulting decline in profits, if internalized by the firms, will reduce their incentives to do R&D. Katz showed that research consortia can, under some conditions, result in *less* R&D as firms seek to lessen the severity of competition in the product market and raise profits.

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[4] More generally, there is a literature in international trade which examines the potential role of R&D rivalry in "strategic trade" policies. See the pioneering work by Spencer and Brander (1983).

Katz assumed that the amount of spillovers received by a firm did not depend on its level of R&D spending. Subsequent contributions to this theoretical literature, notably the contribution by Cohen and Levinthal (1989) argued that this is unlikely. If the amount of spillovers received by a firm depends (positively) on its level of R&D spending, then the presence of spillovers in general and participation in spillover-enhancing consortia in particular might lead to *increased* rather than decreased levels of R&D spending. In the empirical model of spillovers that we present in this paper, we implicitly follow Cohen and Levinthal in assuming that the level of potential R&D spillovers depends on current and past levels of R&D spending. We will also argue below that Japanese research consortia tend into fit into that class of consortia which tend to raise R&D spending, even in Katz's more restrictive framework.

In general, Japanese R&D consortia involved some government subsidization of consortia R&D expenditures, lowering the effective cost of R&D. This strengthens the "effective R&D cost-reducing" effect of participation which comes from economies of scale, avoidance of wasteful duplication, and ease of access of the necessary complementary resources for R&D in Katz's framework. Secondly, the government generally sought (not always successfully) to encourage complete dissemination of all research results to the participating firms. Furthermore, in selecting participants, the government generally sought to bring together firms with complementary research assets. This tendency has been especially strong since the early 1980s, which is the focus of our analysis. This implies that the level of intra-consortia spillover could be quite high. These two factors augment the spillover-enhancing aspect of participation. Finally, we would argue that the potentially vitiating effects of consortia R&D on second-stage industry profits are small. Consortia have frequently brought together firms that were not direct rivals in the product market. For instance, suppliers would come together with downstream firms to improve the efficiency of the production process. In some cases, the product market relationships between participants were complementary rather than rivalrous. Consortia also sought to target markets in which Japanese firms played a small role in global production and trade.[5] If we assume that foreign firms received no spillovers from consortia R&D, then the impact on industry profits following Japanese entry would come solely from the impact of new Japanese

[5] By the late 1970s, government assistance to established firms and industries had become increasingly difficult to justify both to the Japanese public and to Japan's trading partners. The 1980s and 1990s were marked by a redirection of government assistance toward new businesses and precommercial technological research.

products on the industry--but if the Japanese competitors were starting from a very small base, then this effect is second order in importance, whereas the spillover-enhancing and cost-reducing aspects of participation on Japanese consortia participants are first-order.

Even having made this assumption, theory does not necessarily guarantee that participation will lead firms to increase their R&D spending. Both the spillovers-enhancing and cost-reducing aspects of participation in consortia can be viewed as having both "income" and "substitution" effects. If participation allows firms to realize greater benefits from a given level of R&D, firms may choose to increase R&D spending if the "substitution effect" dominates. On the other hand, they may actually reduce their R&D spending if the "income effect" dominates. Based on our reading of the theoretical literature (especially Cohen and Levinthal) and on Sakakibara's interviews with R&D managers from these firms, we think that substitution effects are likely to be more important.[6] However, the data do not yield unambiguous evidence on this point.

We therefore establish the following predictions:

1. Participation in research consortia augments knowledge spillovers.

2. The spillover-augmenting effect of research consortia raises the "research productivity" of participating firms, controlling for their R&D expenditures.

3. As a result of 1 and 2, participation in research consortia may lead to an increase in R&D spending.

Our paper will test predictions 1-3 using microdata drawn from a sample of participating and nonparticipating firms. We find evidence in favor of all three.

III. R&D Consortia in Japan

Since the late 1970s, governments throughout the developed world have adopted policies to spur the development of cooperative R&D, albeit with mixed success. The United States granted broad antitrust exemption to groups of firms collaborating in joint research projects by passing the National Cooperative

[6] The balance between the "income" and "substitution" effects cannot be deduced analytically. There is an extensive theoretical literature which examines the determinants of R&D intensity (for a summary of this literature, see Reinganum, 1989). The outcomes of these models are highly assumption-sensitive, and these models cannot be easily nested (Cockburn and Henderson, 1994).

Research Act of 1984[7]. A successor bill, the National Cooperative Research and Production Act, was passed in 1993. While the expected number of research joint ventures failed to materialize, a few famous examples, including SEMATECH, a consortia of semiconductor manufacturers, received substantial direct subsidies from the federal government.[8] The Clinton Administration generally sought to strengthen federal government intervention in this area by vastly increasing the budget of the Advanced Technology Program (ATP). This program funds proposals for collaborative research from the private sector. European governments also attempted to foster the development of research consortia. ESPRIT (European Strategic Program for R&D in Information Technologies) and EUREKA are two famous examples of European multinational projects.[9]

However, the nation that has most assiduously and consistently fostered R&D through the policy instrument of R&D consortia is undoubtedly Japan. To a great extent, the adoption by European governments and U.S. administrations of policies promoting R&D consortia was prompted by the perceived success of this policy instrument in Japan. The promotion of R&D consortia in Japan has a long history, reaching all the way back to late 1950s. We focus on its recent history for two reasons. First, Japanese observers of R&D consortia point out that until the later 1970s, the focus of Japanese firms' R&D efforts was not on creating new technology so much as understanding, catching up to, or adapting Western technology for use in Japanese markets. Wakasugi, in particular, notes that prior to the 1980s, much emphasis was placed on R&D close to commercialization (Wakasugi, 1986). While R&D consortia may have been successful at *diffusing* Western technology, that is less applicable now that Japan has reached the technological frontier. The second reason is more practical: prior to the early 1980s, data on Japanese R&D spending and patenting at the firm level is generally of poor quality.

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[7] See the study undertaken by Scott (1988) for an empirical analysis of these research joint ventures.

[8] Irwin and Klenow (1996) have studied the impact of Sematech on semiconductor firms' R&D, profits, and labor productivity and concluded, on the basis of mixed evidence, that it did not have the desired effect. Albert Link, David Teece, and William Finan, using participating firms' estimates of the rate of return of individual Sematech research projects, have come to a very different conclusion (1996).

[9] Despite this increase in the incidence of cooperative R&D, there have been few empirical studies which have attempted to estimate the effects of this cooperative R&D on research productivity. Most of the few empirical papers that have appeared in the literature draw upon "one-time" surveys of firms. The general lack of any time-series dimension in the data severely constrains the ability of prior researchers to control for left out variables or endogeneity. Furthermore, most researchers lack any micro-level measure of research "output," and therefore concentrate on the effects of participation on R&D spending or undertake

Compared to the overall level of government intervention in R&D in the West, the level of Japanese government support of R&D is relatively small.[10] Between 1960 and 1991, for example, the average level of US government spending on R&D, as a percentage of GDP, was 1.32%, while in Japan it was 0.47%. The contribution of government-sponsored R&D consortia to total R&D spending in Japan is also small, accounting for only 1.6% of total R&D expenditure during the same period (Sakakibara, 1997a,b).

Mariko Sakakibara (1994) has presented a detailed breakdown of the distribution of projects by industry, time, and budget. Her results are summarized in Tables 1 and 2. A number of trends are evident from this sectoral distribution of projects and spending. First, government spending rose rapidly and peaked in the 1970s. In the 1980s, there was a substantial real decline in spending. To some extent this mirrored the general real decline in Japanese government discretionary spending in the 1980s as Japan's Ministry of Finance successfully labored to bring the overall budget into balance. Secondly, projects and spending were concentrated in a few sectors. The semiconductors/computers cluster stands out as a sector which has received a consistently high level of support over time. In particular, telecommunications and semiconductors/computers together constituted 41 of the 143 total projects during the 1980s (the period for which our microdata is most complete) and nearly 30% of total government R&D spending on cooperative research projects (Sakakibara, 1994).[11]

IV. Empirical Challenges

an analysis of the "motives for participation" using probit and ordered probit models. Our paper represents an important departure from this tradition.

[10] A sizable component of this difference can be traced to the role of defense-related R&D spending in the U.S., and to a lesser extent, in the UK and France. Japan is perhaps unique among large advanced countries in the extent to which national R&D spending has been financed by the private sector. This is changing somewhat in the very recent past as Japanese firms have responded to the prolonged 1990s recession in Japan by curtailing R&D expenditures and the Japanese government has increased its overall contribution to the national R&D effort.

[11] This data set was originally prepared for *The Two Japans: Reexamining the Japanese Model of Competitiveness*, by Michael Porter and Hirotaka Takeuchi, with Mariko Sakakibara, forthcoming.

There are two substantial challenges to empirical estimation of the impact of participation in consortia on research productivity and research intensity.[12] The first is the problem of *measurement.* Technological innovation, *per se*, is not observed. We observe instead the economic manifestations of this innovation, such as patenting and increases in revenue from the introduction of new products and processes or the refinement of existing ones. These empirical proxies are imperfect, and potentially fraught with significant errors of measurement. As is well known, the *ex-post* economic value of patents varies enormously, with many patents never leading to new products and others leading to billions in new revenues. Our measures of revenue increases are clouded by the lack of hedonic price deflators which adjust for improvements in quality.[13]

On the input side, there are measurement issues as well. Our measures of capital input are taken directly from firm accounts and deflated by a capital price index. As such, they are the product of numerous acts of creative accounting which may not accurately reflect economic fundamentals. Our measures of R&D input represent a vast improvement over the commercially available data series, such as the NEEDS database or the Japan Development Bank Corporate Finance Data Base. Having supplemented data from these sources with Japanese language primary sources, we believe that our data are the best nonconfidential data available.[14] Nevertheless, there are likely to be errors of measurement here too, since firms vary considerably in the extent to which "informal" research and "process engineering" is recorded in the formal R&D budget.

These measurement problems are common to all micro studies of innovation. In our case, there are a few additional measurement issues particular to the topic at hand. First, especially prior to 1990, many if not most of the patents to *directly* emerge from the research undertaken within government-sponsored research consortia were, by government directive, assigned not to the participating firms but instead to the research joint ventures themselves. We are still in the process of obtaining data on patents assigned to these

[12] Saxonhouse (forthcoming) seeks to measure the financial impact of a small number of projects by conducting an "event study" which examines the reactions of participating firms' stock prices to the announcement of formation of a consortia.
[13] Furthermore, the more "basic" nature of the R&D undertaken in the consortia implies that the current consortia research will only have an impact on revenue years later, when the technology is further developed and commercialized through the introduction of new or improved products or processes.

joint ventures. In our estimates reported in this paper, we include only data on patents assigned directly to firms. This means that we may systematically undermeasure the total *direct* benefits of the consortia.[15] We are also missing, in this version, data on the government subsidy received per firm per project per year. This subsidy is not straightforward to compute, as the effective level of the subsidy differs across firms, projects, and years, and the typical participating firm is involved in more than one project per year in our sample. However, the average level of the subsidies has been quite high -- on the order of two thirds of the total project budgets have been contributed by the government. Thus, we may also be undermeasuring the total social costs of the consortia. This is unfortunate, and if our goal were to undertake a comprehensive "social" cost/benefit analysis of these research consortia, this data problem would severely constrain our analysis.[16] However, our goal in *this* paper is to undertake the more modest task of estimating the impact of participation on the research inputs and innovation of the firms themselves. We *do* have sufficient data on the *private* costs and benefits of the consortia, direct and indirect, to begin to undertake such analysis.

If the theoretical models of research consortia are at all correct, then the knowledge spillovers that take place through participation in consortia should have an impact on firm research inputs and research productivity that goes beyond the narrow topics investigated by the consortia. In other words, even if we do not observe all of the patents a firm generates through direct involvement in a certain project (because they are assigned to a research joint venture), we certainly observe the lingering effect of the project on the firm's subsequent research activities, and the subsidiary research activities that grow out of the initial project, as well as the costs associated with them. If these "indirect" effects are large, then we should find them in the data, even without complete information on the direct costs and benefits of the consortia. As it turns out, we find evidence of such effects in the data.

As mentioned above, the theoretical literature on research consortia suggests that one of the primary benefits of these organizations will be to increase the impact of knowledge spillovers. Like

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[14] Much of this data came from the R&D survey undertaken by Toyo Keizai as well as data reported in various issues of *Nikkei Kaisha Joho*. We thank Kazuyuki Suzuki, formerly of the Japan Development Bank, for guidance regarding these and other data sources.

[15] Of course, firms had an incentive to "delay" patenting until after the official conclusion of the project so that they could secure the intellectual property rights to their innovations. To the extent that this happened, our measures of the direct benefits of consortia are complete.

innovation, spillovers are not observed *per se*. We utilize the micro-econometric framework pioneered by Jaffe (1986) and modified by Branstetter (1996a,b) to *empirically estimate* the differential impact of knowledge spillovers on firms which frequently participate in consortia and those which do not. This framework allows us to identify a significant and positive effect on knowledge spillovers associated with frequent participation in research consortia.

The final measurement issue has to do with aggregation. Even though we do empirical analysis at the level of the *firm*, there is reason to believe that this is still too aggregated. The reason is that the typical participant in research consortia is a fairly large firm with a fairly large research and product portfolio. The typical project targets only part of this research and product portfolio. Thus, one might expect, *ex ante*, that it would be hard to identify the impact of participation in consortia on the overall R&D effort, sales, and patenting of the firm as a whole.[17] In this paper, we do find such "overall" effects, but the interpretation of these effects is rendered more problematic by this aggregation problem. As part of our research agenda on Japanese research consortia, we are currently gathering detailed data at the project level that will allow us to get around this aggregation problem.

In addition to problems of measurement, there is also the problem of the potential *endogeneity* of the intensity of participation in research joint ventures. The process by which the goals of R&D consortia and the participating firms are selected is a complex one, involving input from interested firms, academics, and MITI's own experts. Ultimately, however, MITI decides which firms participate in which projects. This assignment is not random. To the extent that they can observe it, it is quite likely that MITI officials pick firms with higher "research quality" for participation in more consortia. If we find that research productivity is 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.[18]

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[16] We are currently engaged in building a project-level data base including information on patents assigned to the research joint ventures and government subsidies per project that will, at least in principle, allow us to undertake such a cost/benefit analysis.

[17] This is particularly a problem with R&D spending. Survey evidence at the project level suggests that firms see R&D subsidies as a complement to their own R&D spending rather than a substitute for it. However, if the overall firm R&D budget is fixed, then, at least in the short term, an increase in private consortia-related R&D spending may "crowd out" private R&D spending that is not consortia related.

[18] There is also the problem of confounding the effects of consortia with exogenous changes in technological opportunity. If consortia are quickly established in "hot" fields, it may be that our estimates are picking up not the direct effect of consortia but the indirect effect of these changes in technological

This is a difficult issue to surmount, especially at our level of aggregation. We take two approaches. The first is the fixed effect approach, in which we assume that, whatever "research quality" is, it evolves slowly over time, so much so that it does not change in the 5-7 years of our sample period. If this assumption is correct, we can obtain consistent estimates of the impact of consortia on research productivity by looking only at the "within" dimension of the data. The second is the standard two-stage least squares (2SLS) approach, in which we first use exogenous and lagged endogenous variables to predict the number of research consortia a given firm will be involved in during a given year. In the second stage, we instrument our measure of participation using these predicted values. This allows us to utilize the cross-section dimension of our data. It also allows, in principle, for research quality to evolve over time. If both approaches, which make quite different assumptions, give us the same results, then we have reasonably robust evidence of an effect of participation on research productivity. This is precisely what we find.

V. Perceptions of Japanese R&D Managers

Sakakibara has examined the perceptions of Japanese R&D managers concerning the costs and benefits of participation in consortia by distributing a confidential survey directly to the R&D managers of participating firms. While we lack the space here to relate all of the results from this survey, we summarize several key points. Details of the survey are provided in Sakakibara (1994) and some important results are discussed in Sakakibara (1997a,b). The survey, conducted in 1993, obtained the replies of 67 firms concerning 86 separate projects.

The first key result is evidence on the firms' motives for participating in consortia. While firm R&D managers listed a number of motivations for seeking to participate in consortia, the most highly cited reason for seeking to participate in consortia was access to complementary knowledge assets of other participants.[19] In particular, these firms consistently ranked this as a stronger motivation than that of sharing the costs of research with other firms. This survey evidence has been strongly reinforced by more anecdotal evidence obtained from conversations with Japanese R&D managers, industry observers, and MITI officials. It is primarily this fact which leads us to look for a specification that can directly test the effects of knowledge spillovers.

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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.

The second is the effect of participation on the firm's own R&D spending. We have already noted that government subsidies constituted as much as two-thirds of the total budget of the projects on average. This figure masks considerable heterogeneity within projects. There are some projects in which government provided 100 percent of the project budget, and there were others in which the government provided much less than half of the total budget. Nevertheless, in the majority of projects, government provided an important share of total costs. How do firms respond to these subsidies? Survey evidence and more anecdotal evidence strongly suggests that firms do not view government funding as a substitute for their own R&D spending. Rather, survey evidence indicates that firms, on average, undertook private R&D spending on consortia-related research by an amount equal to nearly ninety percent of the government contribution.[20] This increase in expenditure arises in two ways. First, the typical project budget involves costs not accounted for in the government budget which must be born by the firms. Second, firms often choose to invest in private R&D closely related to the consortia research in hopes of appropriating the benefits of that research.

This increase in private R&D spending arises from two motivations. One is the direct substitution effect of the subsidy. The other, potentially more important factor is the spillover-augmenting interaction among firms that arise through participation in consortia.[21] Of course, these two effects are not mutually exclusive; in fact, they as mutually reinforcing. With the available data, it is not possible to distinguish precisely between these two effects. However, we do present evidence which suggests that "spillover augmentation" is the primary component of the overall impact of participation.

The third important result arising from survey evidence is the firms' own subjective evaluation of consortia. Typically, firms R&D managers see the projects as being modestly beneficial to the firms, but not critical to their commercial success. A frequent criticism is that the focus of the projects on research close to the technological frontier often fails to generate immediate financial gains. In terms of costs, firms

[19] See Sakakibara (1997a) pp. 13-18 for details.

[20] The survey data also suggest that, on average, participation in consortia raises private R&D spending on consortia-related topics by nearly 40% more than the level which firms would have undertaken in the absence of participation. See Sakakibara (1997b) pp. 16-18 for details. This is to be contrasted with the finding of Irwin and Klenow (1996) that participants in the Sematech consortia reduced their R&D spending. Wallsten (1996) finds that recipients of SBIR research grants *reduce* their R&D spending substantially as a result of receiving the grant.

seem quite sensitive to the direct costs and the opportunity costs of participation in consortia. In particular, coordinating research activities across several different firm laboratories tends to pose a substantial burden on the time of key senior research personnel.

Finally, while it is difficult to document quantitatively, discussions with managers and MITI officials frequently drew attention to the issue of *adverse selection*.[22] This arises both in terms of the selection of participants and the selection of projects. Firms which are technology leaders are understandably more reluctant to participate in projects in which they perceive that they have relatively little to gain. This problem seems to have become more pronounced in recent years.[23] In the same way, especially promising projects that can be profitably undertaken by the firms themselves are typically *not* the focus of government consortia. Instead, especially in the 1980s and 1990s, consortia projects have tended to involve more frontier research with greater uncertainty in the expected outcomes.

VI. Empirical Models for Estimating the Impact of Research Consortia

Our basic empirical strategy is two-fold. First, we establish that the intensity of participation in research consortia raises both the level of research input and the level of research output, with the latter measured by patents. Our analysis of patenting controls for both private research input and industry characteristics. Thus, the intensity of participation is found to have a modest, but significant impact on both research input and research productivity.

Next, we attempt to identify the extent to which this positive impact on research productivity is produced by the augmenting or strengthening of spillover effects within consortia. To that end we introduce an empirical framework which allows us to measure spillovers, albeit indirectly, and infer their effects on research output.

A Model of Research Productivity

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21 Sakakibara (1997a) showed evidence from the survey data that, after controlling for the government subsidy effect, the learning motive from other participants is likely to increase a firm's R&D spending.
22 See Sakakibara (1997b) pp. 23-26.
23 It may be that as Japanese firms have become large players in many high-tech global product markets, they have increasingly internalized the "competition-enhancing/profit-reducing" effects technological cooperation might have on industry equilibrium output and profits.

The first step requires us to develop a model of research productivity. To do so, we postulate the following simple "knowledge production function," suppressing time subscripts for the moment to simplify notation.

$$N_i = R_i^{\beta} e^{\gamma C_i} \Phi_i \tag{1}$$

where N is innovation, R is firm-level R&D spending, C is our measure of the intensity of participation in research consortia, and

$$\Phi_i = e^{\sum_d \delta_d D_{id}} e^{\varepsilon_i} \tag{2}$$

where the δ's are the coefficients on our industry dummy variables. Taking the logs of both sides of (1) provides us with a simple log-linear functional form

$$n_{it} = \beta r_{it} + \gamma c_{it} + \sum_d \delta_d D_{id} + \varepsilon_{it} \tag{3}$$

in which the estimation of fixed and random effects is straightforward. Now, n is not observed, but if firms patent a certain fixed portion of their new ideas then, allowing this propensity to patent to vary across industries and firms, we can use the relationship

$$P_{it} = e^{\sum_d \delta_d D_{id}} e^{\xi_i} N_{it} \tag{4}$$

to substitute patents, which we do observe, for innovation, which we do not observe.[24] Taking the logs of both sides of (4) and substituting into (3), and putting the time subscripts back in gives us

$$p_{it} = \beta r_{it} + \gamma c_{it} + \sum_d \delta_d D_{id} + \mu_{it} \tag{5}$$

and we allow the error term μ to consist of unmeasured firm effects as well as a truly random, iid error term which satisfies the usual assumptions of the Gauss-Markov theorem. Thus, μ can be rewritten as

$$\mu_{it} = q_i + u_{it} \tag{6}$$

where q_i might have the interpretation of the unmeasured "quality" of firm i's research team. The presence of q_i in the error term raises the specter of omitted variables bias. In particular, it may be that MITI tends to

[24] Here the δ's represent industry effects and the ξ's represent firm effects in the propensity to patent.

pick "high q" firms more frequently for participation in research consortia, so that our measure of intensity of participation in consortia is correlated with the error term.

There are two relatively straightforward "fixes" for this problem. One is to use the "fixed effects" estimator pioneered by Mundlak. We define transformations of our variables such that, for each firm in each year, we subtract the mean of the variable for that firm over time. Thus

$$p_{it}^{*} = p_{it} - \frac{1}{T}\sum_{t} p_{it}$$

$$r_{it}^{*} = r_{it} - \frac{1}{T}\sum_{t} r_{it}$$

$$c_{it}^{*} = c_{it} - \frac{1}{T}\sum_{t} c_{it} \qquad (7)$$

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$$\mu_{it}^{*} = \mu_{it} - \frac{1}{T}\sum_{t} \mu_{it}$$

Note that our industry dummies fall out, since they do not vary "within firms" over time. Note also that the individual effect falls out of the error term, because it also, by assumption, does not vary over time. Performing least squares on our transformed equation

$$p^{*}_{it} = \beta r^{*}_{it} + \gamma c^{*}_{it} + \mu^{*}_{it} \qquad (8)$$

Gives us potentially unbiased and consistent estimates of all parameters, albeit at the cost of throwing away the cross-sectional variance in our data, which is most of the total variance. Unfortunately, as Griliches and Hausman (1986) have shown, the fixed estimator may itself be biased in the presence of measurement error. Given the aforementioned 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. It is difficult to judge just how severe this problem is, but the existence of this problem suggests the need for another approach.

An alternative method is to view our measure of intensity of participation in consortia as itself a function of research quality, R&D investment, and industry characteristics such that

$$c_{it} = \theta_0 + \theta_1 q_{it} + \theta_2 r_{it} + \sum_d \theta_d D_{id} + v_{it} \tag{9}$$

In which case, OLS gives us inconsistent results and even fixed effects estimates are not guaranteed to be consistent, because in this specification the individual effect is allowed to evolve over time -- it is not, in fact, *fixed*. If (9) truly describes the movement of our measure of participation, then we cannot identify its impact. Let us suppose though, that the movement of c is actually described by

$$c_{it} = \theta_0 + \theta_1 q_{it} + \theta_2 r_{it} + \theta_3 c_{i,t-k} + \theta_4 c_{i,t-k-1} + \theta_5 c_{i,t-k-2} + \sum_d \theta_d D_{id} + v_{it} \tag{10}$$

Equation (10) implies that there is some "bureaucratic" inertia to the selection process. Firms that were frequently picked in the past are more likely to be picked in the present regardless of their true research quality. This sort of behavior, perhaps the result of slow adjustment of firms' reputations within MITI to actual changes in research quality, is quite consistent with the experience of the authors, both of whom have had official connections to MITI in the past. It is also consistent with the autoregressive properties of the c_{it} series. Thus, even if q_{it} evolves partially as a function of participation in consortia, 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 q. The proper procedure to employ is two stage least squares. Thus, we estimate a version of (10) using only the exogenous variables

$$\hat{c}_{it} = \theta_0 + \theta_2 r_{it} + \theta_3 c_{i,t-k} + \theta_4 c_{i,t-k-1} + \theta_5 c_{i,t-k-2} + \sum_d \theta_d D_{id} + v_{it} \tag{11}$$

We obtain from (11) a predicted value for c_{it}, $\hat{c}_{it}$, which we can substitute into equation (5) to obtain consistent estimates through 2SLS.[25]

Heretofore we have used linear regression models. However, patent data are actually count data whose distribution is quite skewed. Problems arise in applying linear regression models to such data, particularly when there are a nontrivial number of firm-years for which the number of patents recorded, either in the U.S. or in Japan, is zero. Of course, the natural log of zero is not identified, so the dependent variable for such observations is set to zero. Concerns that this sort of arbitrary transformation, which is standard in the older patents-R&D literature, might affect the results motivated us to estimate a set of nonlinear versions of (5), using empirical models based on the Poisson and Negative Binomial distributions. We also estimate the fixed-effects version of the Negative Binomial model developed by Hausman, Hall, and Griliches (1984). These models are developed in the Technical Appendix. As the reader will see, these models give us results very similar to our linear models.

An Empirical Framework for Measuring Knowledge Spillovers

Now we turn to the issue of what is behind the positive, significant effects associated with participation. Is it merely the result of government subsidies or do consortia actually increase the impact of knowledge spillovers, as is alleged by their supporters? Here we introduce an empirical framework which allows us to examine this question econometrically. This framework was pioneered by Adam Jaffe (1986) and modified by Branstetter (1996a,b).[26]

The typical firm conducts R&D in a number of technological fields simultaneously. We could obtain a measure of a firm's location in "technology space" by measuring the distribution of its R&D effort across various technological fields. Let a firm's R&D program be described by the vector F, where

$$F_i = (f_1 \dots f_k) \qquad (12)$$

and each of the k elements of F represent the firm's research resources and expertise in the kth technological area. We can infer from the number of patents taken out in different technological areas what the distribution of R&D investment and technological expertise across different technical fields has been. In other words, by counting the number of patents held by a firm in a narrowly defined technological field, we can obtain a quantitative measure of the firm's level of technological expertise in that field.

We assume that, in the short run, a firm's position in technology space is fixed. Over time, of course, a firm can change its position by building technological expertise in new areas, but this takes time and the "adjustment costs" associated with this kind of change can be high. For this reason, we calculate for

[25] The use of three lagged terms is not dictated so much by theoretical considerations as by the limitation in the time series dimension of our data on firm participation.

[26] This section borrows heavily from Branstetter (1996b).

each firm in our sample a single location vector based on its patenting behavior over the entire sample period.

We can measure the "technological proximity" between two firms by measuring the degree of similarity in their patent portfolios. Firms working on the same technologies will tend to patent in the same technological areas. We can state this more precisely: the "distance" in "technology space" between two firms i and j can be approximated by T_{ij} where T_{ij} is the uncentered correlation coefficient of the F vectors of the two firms, or

$$T_{ij} = \frac{F_i F_j'}{[(F_i F_i')(F_j F_j')]^{1/2}} \tag{13}$$

Other things being equal, firm i will receive more "R&D spillovers" from firm j if firm j is doing a substantial amount of investment in new technologies. Firm i will also receive more R&D spillovers if its research program is very similar to that of firm j. Thus, the total potential pool of R&D spillovers for a firm can be proxied by calculating the weighted sum of the R&D performed by all other firms with the "similarity coefficients" for each pair of firms, T_{ij}, used as weights. More simply, suppressing time subscripts here and in the equations below for expositional convenience, the spillover pool for the ith firm is K_i, where K_i is

$$K_i = \sum_{i \neq j} T_{ij} R_j \tag{14}$$

Here R_j is the R&D spending of the jth firm (j not equal to i) and T_{ij} is the "similarity coefficient" which measures the correlation in patent portfolios between i and j as in the previous expression.

Assume that innovation is a function of own R&D and external knowledge. Then, the "innovation production function" for the ith firm is

$$N_i = R_i^{\beta} K_i^{\gamma_i} \Phi_i \tag{15}$$

where

$$\Phi_i = e^{\sum_d \delta_d D_{id}} e^{\varepsilon_i} \tag{16}$$

Here the δ's can be thought of as exogenous differences in the "technological fecundity" of *d* different industries. Taking the logs of both sides of (15) and adding time subscripts yields the following log-linear equation

$$n_{it} = \beta r_{it} + \gamma(c_i)k_{it} + \sum_d \delta_d D_{id} + \varepsilon_{it} \tag{17}$$

Here, n_{it} is innovation, r_{it} is the firm's own R&D investment, k_{it} is the potential spillover pool, the D's are dummy variables to control for differences in the propensity to generate new knowledge across industries (indicated by the subscript d), and ε is an error term. However, we hypothesize that the impact of spillovers on innovative output, γ, is an increasing function of the "intensity" with which firm i participates in research consortia ($\gamma'(c_i) > 0$), such that frequent participants enjoy a higher innovation output elasticity for a given level of potential knowledge spillovers. The reasoning behind this is straightforward: spillovers are not automatic. To monitor and understand other firms' R&D can be a difficult task. It may be facilitated by participation in consortia, in which the cost of accessing other firm's knowledge assets is reduced.

As in equation (6), we substitute observed patents for unobserved innovation, so that we are left with

$$p_{it} = \beta r_{it} + \gamma(c_{it})k_{it} + \sum_d \delta_d D_{id} + \mu_{it} \tag{18}$$

Again, we allow for μ to contain an individual effect as well as a truly random error component.

Real technological spillovers should lead not only to more patents but also higher levels of revenue, by increasing product quality, and thus product demand, or lowering production costs. To measure this effect, we estimate a standard Cobb-Douglas production function in its "growth rate" (difference) form, again assuming that the impact of spillovers is a function of the intensity of participation in research consortia. We allow the revenue elasticity of spillovers to vary as an increasing function of the intensity of participation in research joint ventures. We start with the log transformation of our Cobb-Douglas production function.

$$q_i = \alpha\kappa_i + \beta l_i + \phi r_i + \varphi(c_i)k_i + \varepsilon_i \tag{19}$$

Here q is output, κ is capital, l is labor input, r is the firms' own R&D stock, and k is the domestic spillover stock.[27] Again, we allow for the existence of individual effects which are potentially correlated with the right hand side regressors, such that

$$\varepsilon_i = q_i + u_i \tag{20}$$

Following Griliches and Hausman (1986), we use the so-called "long difference" estimator, regressing the log difference in the starting and ending levels of firms' sales on the "long" log difference in levels of capital and labor inputs, etc.

$$q_{iT} - q_{i0} = \alpha(\kappa_{iT} - \kappa_{i0}) + \beta(l_{iT} - l_{i0}) + \phi(r_{iT} - r_{i0}) + \varphi(c_i)(k_{iT} - k_{i0}) + (q_i - q_i) + u_{iT} - u_{i0}$$

(21)

Here, T is the last period in the panel, while 0 is the first period. Thus our estimates are, it is hoped, less biased in the presence of measurement error as well as individual effects which are correlated with firm's levels of capital, employment, or R&D.[28]

Revenue growth is subject to idiosyncratic and systematic demand and input supply shocks. In particular, unmeasured growth in the quality of capital and labor inputs, the level of capacity utilization, or the effective demand for the firm's products can all show up in the "residual" as productivity growth.[29] As a result of this additional noise, it may be considerably more difficult to distill a relationship between spillovers and firm-level innovation from the data. If, however, our production function regressions give us results similar to those of the patent equations, we have strong confirmation that we may be observing a "real" effect.

Note that, in practice, we do not have enough degrees of freedom to allow γ to vary with the number of project-years. Instead, we divide our sample into nonparticipants/infrequent participants and frequent participants and allow the parameter γ to vary across the two subsamples. In some specifications,

[27] Here, we use the perpetual inventory method to calculate R&D and spillover "stocks" from the R&D expenditure series. We do this in the case of the production function because, while the impact of R&D on patenting might be largely contemporaneous, the impact of R&D (and spillovers) on revenues is likely to be subject to longer lags, with past R&D, appropriately depreciated, having some effect on current revenue growth. In doing this, we follow the conventions of the economic literature on patents and R&D.

[28] See Griliches and Hausman (1986) for a thorough exposition of this econometric problem.

we allow the overall intercept term to differ for the two subsamples as well. Then we can construct a standard Chow test whether or not these parameters are significantly different across the two subsamples.

VII. Empirical Estimates of the Impact of Consortia

We have collected data on approximately 230 firms' R&D spending, sales, capital stock, labor and materials usage, and patenting in the U.S. as well as in Japan, for the years 1983-1989. Of the firms, over 140 participated in at least one consortia.[30] Data on participation in consortia come from Mariko Sakakibara's data base, the construction of which is documented in Sakakibara (1997b). The other data come from the same sources and are prepared in the same way as in Branstetter (1996b). Unfortunately, data are not available for all variables on all firms in all years. In particular, data on R&D spending at the firm level and data on patent applications in Japan are not available for all firm-years.[31] Thus, some of our regressions will be run on a smaller "balanced" panel with 208 firms.[32]

Our analysis proceeds as follows. First, we divide our sample firms into nonparticipants/occasional participants and frequent participants as measured by their involvement in consortia over the entire sample period, 1983-1989. We present sample statistics for these two samples in Tables 3 and 4. Then, we attempt to quantify the effects of participation on the R&D input and output variables of the firm. Controlling for industry effects and R&D spending, we estimate a "patent" production function to assess the extent to which participation improves "R&D efficiency." Finally, we attempt to test if spillovers are stronger, on average, among participating firms.[33]

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[29] In order to reduce the impact of these fluctuations, we attempt to "average them out." Equation (21) is actually estimated using data averaged over three early years of the sample, as the "first period," and four later years of the sample, as the "last period."

[30] Supplementary Table A-1 gives the distribution of projects across industry clusters for only the firms for which we have micro data. A comparison of this table with Table 1 shows that we have reasonably representative coverage of the universe of projects in our data for the 1980s.

[31] Our data on the Japanese patents of Japanese firms is considerably more limited than our data on their U.S. patents due to the difficulty and expense of obtaining Japanese patent data by firm.

[32] Our sample was selected on the basis of availability of micro data on research inputs and outputs. It thus consists of firms that are, on average, larger and more R&D intensive than is generally the case in the "universe" of Japanese manufacturing firms. This is especially true for the "infrequent participants." We are currently working to expand the data set in both the cross-section and time series dimension.

[33] One potential problem we do not address in this paper is the issue of unmeasured technological collaboration outside the official consortia sanctioned and subsidized by MITI. It is well known that Japanese firms are actively involved in interfirm technological collaboration. Frequently, but not always, this cooperation takes place within so-called "production *keiretsu*," in which firms and their suppliers engage in the deliberate exchange of proprietary information and research personnel to enhance the efficiency of product and process innovation. The effects of this knowledge transfer on research

A. Sample Statistics

Table 3 gives data on firms that were infrequent participants in MITI-organized research consortia. Since the typical consortia lasted more than one calendar year, we made our division on the basis of "project years." Using Sakakibara's data, for each firm in each year we noted how many consortia it was concurrently involved in. We summed these "project-years" over the entire sample period for each firm. Firms with 11 or fewer project-years over the entire sample period were deemed infrequent participants. Firms with more than 11 project years were deemed frequent participants.[34] Table 4 shows data on frequent participants.

It is immediately obvious that frequent participants were significantly larger and more R&D intensive than nonparticipants. Frequent participants also tended to take out more patents in the U.S. and in Japan. Do frequent participants tend to do significantly more R&D? One traditional measure of R&D intensity is the R&D/sales ratio. A Wilcoxon sign-rank test for the equality of the median R&D/sales ratio in both subsamples *strongly rejected the hypothesis of equality*, providing us with our first statistical evidence that they do, though the actual magnitude of the difference is relatively small. Nevertheless, in terms of absolute yen expenditures, the frequent participants spend much more since, at the median, they are more than 5 times as large as the nonparticipants as measured by size. Because of this clear size difference as well as differences in the industry mix of frequent participants and others, we need to make this comparison using control variables.

B. Effect of Participation on R&D Spending

We have run such a regression, using the log of firm i's capital stock to control for size and using industry dummies as additional control variables. Thus, our equation is

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productivity and spillovers are explored in Branstetter (1996b) and compared with the impact of participation in the research consortia studied here. However, Branstetter's (1996b) preliminary results indicate that the knowledge transfer which takes place within *keiretsu* seems is qualitatively different from that which takes place in the research consortia modeled here. Thus, concerns that omitting variables on *keiretsu* affiliation might substantially bias the results reported here are not supported by the data.

[34] This cutoff number is the 75 percentile in our sample data.

$$\log(R\&D_{it}) = \alpha_i + \beta_1 \log(capital_{it}) + \beta_2(c_{it}) + \sum \delta_d D_d + \varepsilon_i \qquad (22)$$

where α_i is the individual effect, c_{it} is the number of consortia in which firm i is involved in year t and the δ's are the coefficients on our industry dummy variables.[35] This equation is not meant to be a realistic model of firm level R&D spending, and it is certainly not meant as a structural model. We do not believe, for instance, that firms "optimize" R&D on the basis of their capital stock.[36] This regression is run only to test the hypothesis that increases in the intensity of participation is associated with increases in R&D. Given the ad hoc nature of our specification, we realize our results are open to a number of interpretations.

The results in Table 5 come from our "unbalanced" panel, with 1,486 observations from 226 firms. Here, as in later equations, "c" is simply a count variable showing the number of projects in which the *i*th firm was involved in the *t*th year. As in subsequent tables, standard errors are given in parentheses. It seems clear from our results that, at the margin, participation in an additional consortia has a statistically positive and significant impact on R&D spending. Firms which participate in more consortia do spend more on R&D even after controlling for size and industry effects. We explore whether or not the same kind of relationship exists in the "within" dimension of the data and find that it does. (Naturally, the industry effects fall out as part of the fixed effect in this and other "within" regressions). Results did not qualitatively change when we restricted our data to firms for which we have data on all variables in all years. The coefficient on c (about .02 in the fixed effects model) is small, but the reader should recall that the interpretation of the coefficient is the impact of an additional project-year on annual R&D spending. Some firms participate in more than 10 projects per year, so the cumulative effect of a transition from being a nonparticipant to a frequent participant could be quite substantial. For instance, an increase in intensity of participation on the order of an additional 5 projects per year is associated with an increase in total R&D

[35] The industry dummies used are, in numerical order, chemicals/pharmaceuticals, general machinery, transportation, and precision instruments. The reference industry is the electronics sector.

[36] Of course, there are other potential indices of firm size, including log of sales and log of employment. All of these indices have problems as measures of "size." Sales can fluctuate quite dramatically relative to capital stock for various reasons. Our measures of employment include only "full time" workers whereas

spending of over 10%. However, we must note that while our random effects estimates are robust to the inclusion of a full set of time dummies, our fixed effects results are not. This arises partially because a fixed effects model sweeps out all of the cross-sectional variance, which is most of the total variance in the data. Taking out common time series variance leaves relatively little "signal" in the data relative to the "noise." However, we acknowledge that the evidence for the impact of participation on R&D spending is not as robust as some of the other evidence we present in this paper.

C. Patent production function

We have found some evidence that participating firms are more R&D-intensive, a result that is consistent with the predictions of theory. Can we also make statistical inference regarding the productivity of that R&D spending? Here, we continue our exploration of the data by looking for a statistical relationship between a firm's "productivity" of R&D and its "intensity" of participation in R&D consortia. We measure productivity as patents generated per year, controlling for R&D spending, industry effects, and firm effects. Results from both a random effects specification and a fixed effects specification are provided. The equation we seek to estimate is

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

which is based on equation (5). Results are given in Table 6.

The results in Table 6 show a positive and significant relationship between participation and patenting.[37] Here we use the numbers of U.S. patents granted to Japanese firms as our dependent variable, though the results using Japanese patent applications are qualitatively similar. The third column shows the results when we use a dummy variable to identify the most frequent participants. It is, of course, difficult to assign any causal interpretation to the results in this column because of the likelihood that "research quality"

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many Japanese firms use large numbers of part time workers. Still, we note that the results of Table 5 are not sensitive to the use of sales or employment as alternative measures of size.

[37] In these equations, we regress patents by the ith firm in the tth year on the number of research joint ventures that firm has participated in during that year. If research consortia augment firm patenting through R&D spillovers, then one might expect its effects to enter with some lag. The short time series dimension

is correlated with the intensity of participation in consortia. Because of this, in fact, the random effects estimates may be inconsistent. A fixed effect model removes all constant factors, like industry affiliation and, hopefully, research quality, from the regression, although this may worsen the bias that arises from measurement error. The results from the fixed effects model are broadly consistent with our earlier regressions and suggest that at least some of the impact of participation on patenting is, in fact, driven by participation rather than some left out variable like "quality of the research team."[38]

The point estimate from the fixed effect model suggests that participation in an additional consortia increases patenting by about 5%, holding other variables constant.[39] This seems like a small effect, but the cumulative effect of an increase in the intensity of participation from 1 to 5 projects per year could have a substantial cumulative effect on research productivity.[40]

While there are a number of reasons to think that at least some of the effect of participation on patenting is practically contemporaneous[41], as we have modeled it, there are also reasons to believe that the full impact only comes after a lag of one or two years. In particular, a two-year lag makes sense because research personnel are typically rotated into research consortia, then rotated back to the parent firm on a two-year cycle. When these research personnel return to the firm, they presumably bring with them a substantial amount of explicit and "tacit" knowledge about the new technology being developed within the consortia. To allow for these lags in a simple way, we substituted one and two-period lagged measures of participation in place of our contemporaneous measures and re-estimated our fixed effect model. The results are qualitatively similar to the ones reported in Table 6. Our lagged measure of "c" remains positive and significant, with a coefficient of approximately the same magnitude as in Table 6.

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of the data and the limited variation in participation in that dimension are such that the lag structure is difficult to estimate.

[38] A Hausman test rejects the equivalence of random effects and fixed effects models. The Hausman test is distributed Chi-square with two degrees of freedom. The p-value of our test statistic of 13.52 is on the order of 0.0012.

[39] These results are robust to the inclusion of a measure of firm size, such as the log of capital stock or the log of employment.

[40] The positive, significant impact of particpation remains even after controlling for the possible effects of Japan's "bubble economy" of the late 1980s. Even after the inclusion of a full set of time dummies, which sweeps out the common "within" variance as well as the cross-sectional variance, the effect of participation remains positive and "marginally" significant (the p-value is approx. .07).

[41] For example, there is anecdotal evidence that researchers in consortia frequently communicate with their parent companies, sometimes daily. When an consortium is formed as a dispersed organization whose research facilities are located at participants' research labs, this communication can be even more frequent.

The alternative to a fixed effects approach is to use instrumental variables. In Table 7 we present results based on the 2SLS model we developed in equations (9)-(11). The table presents results using both the log of patents registered by Japanese firms in the U.S. and results using firms' patent applications to the Japanese patent office. The results are qualitatively similar to the fixed effects results, though the magnitudes are larger. The R^2 from our first stage regression of research consortia on our vector of exogenous variables and instruments is slightly more than .7, indicating a reasonably good fit. In our results, we used 7, 8, and 9 period lags of counts of project-years as instruments. Note that the point estimates of the impact of an additional consortia on research productivity are, in the case of the regression using Japanese patent applications, more than twice as high as those which we obtained in our fixed effects model. These estimates imply that an increase in intensity of participation on the order of two projects per year would increase research productivity (as measured by patents per R&D dollar) by between 10% and 16%.[42] We found that the 2SLS results do not qualitatively change when time dummies are included. We also found that the results do not qualitatively change when we use two-period lagged measures of participation rather than a contemporaneous measure of participation.[43]

The linear model has a great advantage in that the estimation of fixed and random effects is quite straightforward. However, the linear model has a serious drawback in estimation. Not a few firms take out no patents in any given year. The alternative to this is to use a model in which 0's are a natural and predicted outcome. The canonical model is the Poisson model and its generalizations, which are developed further in the Technical Appendix. Results based on these models, using Japanese patent applications are presented in Table 8. Regressions run using U.S. patents were qualitatively similar.[44]

[42] We used a Lagrange Multiplier test to test the validity of our instruments by regressing the residuals from the second stage of our two-stage least squares regression on the instruments used in the first stage. The null hypothesis that our instruments were valid is strongly supported by the data.
[43] The results of this and other supplementary regressions mentioned in the text are available from the authors upon request.
[44] The results of the Poisson models are robust to the inclusion of time dummies.

It is possible to exploit panel data to run "fixed effect" versions of the Poisson model and more general models based on it. The results of such an estimate are presented above in the fourth column of Table 8. As we can see, this result is completely congruent with both the linear fixed effect results and the Poisson pooled results and indicates that, even in the "within" dimension, participation has a reasonably strong and robust positive effect on research output even after controlling for private research input.

Of course, we do not include in these regressions measures of the government subsidies provided to the firms. An alternative interpretation of our results is that we are simply picking up the output effects of unmeasured subsidies. A "back of the envelope" calculation *strongly* suggests that this interpretation is unlikely to be true. While we do not have precise data on the subsidies offered per firm per project per year, we can roughly approximate it. There are 131 consortia in which the firms in our sample participated during the years 1983 to 1989. If we allocate the total project budgets for these consortia equally over the planned duration of the projects, we obtain a figure of 503,484 million yen (in constant prices) in government subsidies for these projects over the seven years of our sample period. In order to obtain a subsidy figure per firm per year, we divide this sum by the number of firms which participated in these projects in each year (including participating firms for which we do not have R&D or patent data). Thus, the average per firm per project per year government subsidy is only 68.3 million yen.[45] In contrast, the average level of R&D spending for our 226 firms is 13,211 million yen. Since the average firm in our data set is involved in slightly less than one project per year, on average, the government subsidy per firm per year only accounts for about 0.52% of annual firm R&D expenditure.[46] This magnitude is much smaller than the estimated effect of participation on innovative output, which ranges from 3% to 8%.[47] Though the government subsidy increased the effective R&D input for firms, the *much* more substantial increase of firm

[45] Even if we assume that subsidies were given entirely to the larger, listed firms that participated in the project, the per firm per project per year subsidy rises to only 95.2 million yen. This adjustment raises the per firm per project per year subsidy to 0.72%.
[46] This may explain why Saxonhouse (forthcoming) has failed to find robust evidence of a strong effect of project announcements on participating firms' stock prices. The subsidies provided to the firms are small enough and the nature of research done within consortia far enough removed from commercialization that the immediate impact on stock prices is not large relative to day-to-day fluctuations in stock prices.
[47] Recall that the estimated innovative output elasticity of own R&D spending is less than 1. This implies that our estimate of the incidence of the government subsidy would have to underestimate the 'true' incidence by a factor of 4 to 6 in order to fully explain even the *lower* bound of our range of estimates of the effect of participation on innovative output.

R&D output implies the presence of an effect of consortia participation that is greater than a simple "subsidy effect."

D. Patents and Spillovers

Finally, we present indirect estimates of the impact of consortia on knowledge spillovers. We do not have enough degrees of freedom to allow γ to vary with the number of project-years. Instead, we divide our sample into nonparticipants/infrequent participants and frequent participants and allow the parameter γ to vary across the two subsamples. Then we construct a Chow test to identify whether or not the parameters are significantly different. In practice, this is done by running a regression including an *interaction term* in which the spillover term is multiplied by a dummy variable signifying whether or not the firm is a "frequent" participant. An F test on the significance of the coefficient of the interaction term is equivalent to a Chow test of a difference in that parameter, holding others constant. In some specifications, we also allow the *intercept terms* of frequent participants to differ from those of other firms.

In the regression results presented in Table 9, it does seem that the patent output elasticity of spillovers, as we measure them, is much higher for the frequent participant subsample. We interpret these results as suggesting that it is indeed through the channel of augmenting spillovers that research consortia raise both R&D levels and R&D productivity. We estimated

$$p_{it} = \beta_0 + \beta_1 freq_i + \beta_2 r_{it} + \gamma_0 k_{it} + \gamma_1 k_{it} * freq_i + \sum_d \delta_d D_{id} + \mu_{it}$$

which is the econometric analog of equation (18). The results reported in Table 9 are representative of our findings. In the OLS model, the interaction term is positive and significant, but small in magnitude. In general, allowing the constant term to vary as well as the spillover parameter results in very large differences in the innovation output elasticity of the spillover term in the subsample. Allowing a separate constant term does have a useful interpretation. The managerial literature suggests that there are substantial "coordination costs" associated with the management of research consortia.[48] Research personnel must invest considerable time and energy in coordinating research activities across firm boundaries and overcoming the natural tendency to free-ride on the efforts of other participants. It is quite likely that the separate intercept term for frequent participants is picking up the effects of these coordination costs. The sign and magnitude of the coefficient suggest that these costs are quite substantial, a finding completely in accordance with the view of the managerial literature.[49] Furthermore, as we mentioned, firms were not generally permitted to apply for patents on research conducted within the consortia. Instead, those patents were frequently assigned to the consortia. This may have lead frequent participants to lower their propensity to patent.

Finally, we note that, in a fixed effects version of (18), the interaction term is positive and of reasonably high magnitude, but is statistically insignificant. This result is not surprising, given our small sample size and the fact that our spillover term is certainly measured with error, a problem which is exacerbated when we use fixed effects models. These results suggest that participation is associated with increased impact of spillovers, but the evidence is not conclusive.

TFP Growth and Spillovers

Here the equation being estimated is a modification of the general model in which spillovers, as proxied above, enter directly into a Cobb-Douglas production function. As in the patent equation, however, the impact of spillovers is a function of participation in research consortia. Thus, we estimate

$$q_{iT} - q_{i0} = \theta_0 + \theta_1 freq_i + \alpha(\kappa_{iT} - \kappa_{i0}) + \beta(l_{iT} - l_{i0}) + \phi(r_{iT} - r_{i0}) +$$
$$\varphi_0(k_{iT} - k_{i0}) + \varphi_1(k_{iT} - k_{i0}) * freq_i + (\lambda_i - \lambda_i) + u_{iT} - u_{i0}$$

based on equation (21), where we allow the parameter on the change in spillover stocks to vary between nonparticpants/infrequent participants and frequent participants. The results are summarized in Table 10. We find results very consistent with the previous results from the patent equation. Furthermore, these results are less vulnerable to the problem of reverse causality, since the fixed effect is differenced away.

[48] See the cited works by Doz (1987), Hladik (1988), and Jorde and Teece (1990) for evidence.

[49] Sakakibara has found direct evidence of this in her interviews with Japanese R&D managers. She also cites the work of other researchers which confirms the existence and importance of these costs in Sakakibara (1997a).

Here again a Chow test allows us to reject at the 1% level the equality of the spillover parameters across the two subsamples when we also allow the intercept to differ across the subsamples. Otherwise, the interaction term is statistically indistinguishable from zero.[50] The spillover coefficient in the third column seems implausibly high. We note, however, that the 95% confidence interval for this estimate is rather wide and contains a substantial range of more plausible values. We do not place too much stock in the exact point estimate, but we note that we could still reject the hypothesis of equality across the two subsamples even if the coefficient were substantially lower. Here the allowance of a separate constant term for frequent participants also has a potentially plausible interpretation: frequent participants are, in fact, much larger and more "mature" than nonparticipants, and can be expected to have, on average, lower rates of revenue growth as we measured it (difference in logs of sales) for that reason alone.

VIII. Conclusions and Extensions

Our preliminary exploration of the data suggests that the predictions we made about the effect of participation in research consortia on R&D performance find support in the data. Namely,

1. *Participation in R&D consortia tends to be associated with higher levels of R&D spending of participating firms.*

2. *Participation in R&D consortia also seems to raise the research productivity of participating firms.*

3. *Finally, our results suggest that at least one channel by which consortia have these positive effects may be through effectively augmenting knowledge spillovers.*

Based on our empirical results we can assign numbers to these effects. The estimated elasticity of participation in an additional consortia on R&D spending from our fixed effects and 2SLS estimates suggests that if a firm participates in an additional project per year, it will raise its total R&D spending by about 2% and its patenting per R&D dollar (i.e., its research productivity) by between 4% and 8%. These sound like small effects, but the cumulative impact of a large increase in the intensity of participation in research consortia could be substantial. Although we do not actually observe many such changes in our

[50] Since the research consortia that are the focus of our study generally targeted "precommercial" research projects, it generally took years for the innovations developed as a result of consortia research to be brought to market. Because of these long and variable lags and because the typical firm in our data base has a

data, we should point out that an increase of five projects per year will raise R&D spending by more than 10%, patenting per R&D dollar (adjusted for industry effects) by between 20% and 40%, and could more than double the estimated elasticity of knowledge spillovers on the firm's own innovation.

In addition to the benefits of consortia, however, we have also found evidence of their costs. The managerial literature suggests that the coordination of research across firms can impose substantial administrative burdens on the research personnel of participating firms. We have presented econometric evidence consistent with this view in Table 9, which suggests that frequent participation in research consortia increases the impact of R&D spillovers, but does impose other costs on the firms. The previous paragraph suggests that the *net* benefits of participation are positive.

Viewed as an instrument of industrial policy, our results to date suggest that the consortia did have the effect of stimulating innovative activity by the selected firms. We have not included a measure of the cost of government subsidies or the administrative costs incurred nor do we yet have measures of the patents assigned directly to the joint ventures, so that a true "social" cost/benefit analysis of consortia is beyond the scope of the present paper. However, the finding of a positive effect of participation on innovation is a necessary, though not sufficient, condition for demonstrating that subsidizing consortia was a worthwhile social investment. Between 1960 and 1991, the average government contribution to government sponsored R&D consortia accounts for only 1.1 % of total R&D expenditure in Japan, suggesting the small magnitude of the costs incurred by the government.

This initial exploration of the data strongly suggests future directions for research. R&D consortia tend to target technologies that are only a small part of a firm's total research effort and one might not expect to find clear effects of the consortia on the entire R&D and product portfolio of whole firm. We do find small, but statistically robust, effects of participation on research inputs, productivity, and spillovers at the firm level. Nevertheless, a better approach, and one which allows us more leverage over the nettlesome issue of causal interpretation, would be to undertake our analysis at the *project* level.[51]

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diversified product portfolio, it is perhaps not surprising that the measured direct effect of participation on revenue growth is small.

[51] For a pioneering work which measures research productivity and identifies spillover effects at the research project level, see Henderson and Cockburn (1996).

By classifying projects and patents by technological area and obtaining data on patent applications submitted by the research joint ventures, we could examine the effect of participation in a particular project on *ex-post* patenting *in that area.* Since we could observe the participating firms before and after participation in the given project, it would be much easier to give our analytical results a causal interpretation. It would also be much easier to compute the effective government subsidies accruing to each participant. Finally, at the project level we would be able to analyze the important question of why some projects succeeded in stimulating innovation and others did not. We could fully exploit the cross-sectional and time series variation in the organizational design of the consortia, the industry and size mix of the participants, the technological goals, and the level of government support to determine what factors are predictors of success and what factors are predictors of failure. Updating our data set through the early 1990s is feasible, as is broadening it by increasing the coverage of firms and industries, and we are currently engaged in such a data collection effort.

On the whole, our preliminary results suggest that this is a fruitful area of research. As all advanced nations struggle to maintain growth and innovation in the face of changing technology and increasing international competition, policies to enhance R&D spending and bridge the gap between the social and private benefits of R&D offer one of the few methods governments have of promoting sustainable growth. Our review of the policy history in this area suggests that governments throughout the advanced world will continue to resort to consortia. We may have much to learn from the successes and failures of the Japanese experience.

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Technical Appendix **Nonlinear Models for Patent Data**
Poisson and Negative Binomial Models

Patent data are "count data" - non-negative integers - and in any given year a number of firms perform R&D but generate no patents. The distribution of patents is highly skewed with most firms generating far fewer than the mean number of patents in a given year. The linear model was not designed to handle such data. Over the past decade a set of regression models have been developed expressly for the purpose of handling this kind of data. A sketch derivation of the technique used here, a generalization of the Poisson model known as the "negative binomial" estimator, is given below. For a more formal development of this model, please consult Hausman, Hall, and Griliches (1984). Here, I summarize their results, borrowing extensively from the presentation of these basic results found in Montalvo and Yafeh (1994).

The Poisson estimator posits a relationship between the dependent and independent variables such that

$$pr(n_{it}) = f(n_{it}) = \frac{e^{-\lambda_{it}} \lambda^{nit}{}_{it}}{n_{it}\,!} \tag{23}$$

where $\lambda_{it} = e^{X_{it}\beta}$ (24)

Econometric estimation is possible by estimating the log likelihood function using standard maximum likelihood techniques. The negative binomial estimator generalizes the Poisson by allowing an additional source of variance. We allow the Poisson parameter lambda to be randomly distributed according to a gamma distribution. Thus defining lambda as before

$$\lambda_{it} = e^{X_{it}\beta} + \varepsilon_i \tag{25}$$

Using the relationship between the marginal and conditional distributions, we can write

$$\Pr[N_{it} = n_{it}] = \int \Pr[N_{it} = n_{it} \mid \lambda_{it}] f(\lambda_{it}) d\lambda_{it} \tag{26}$$

If the density function is assumed to follow a gamma distribution, then the Poisson model becomes a Negative Binomial model:

$$\lambda_{it} = \Gamma(\alpha_{it}\varphi_{it}) \tag{27}$$

where

$$\alpha_{it} = e^{X_{it}\beta} \tag{28}$$

then

$$\Pr(n) = \int_0^{\infty} \frac{e^{-\lambda_{it}} \lambda_{it}}{n_{it}!} \frac{\lambda_{it}^{-1}}{\Gamma(\varphi_{it})} [\frac{\varphi_{it} \lambda_{it}}{\alpha_{it}}]^{\phi_{it}} e^{\phi_{it}\lambda_{it} \int \alpha_{it}} d\lambda_{it} \tag{29}$$

where

$$E(\lambda_{it}) = \alpha_{it} V(\lambda_{it}) = \frac{\alpha_{it}^2}{\phi_{it}} \tag{30}$$

Integrating by parts and using the fact that

$$\Gamma(\alpha) = \alpha\Gamma(\alpha - 1) = (\alpha - 1)! \tag{31}$$

yields the following distribution

$$\Pr(n_{it}) = \frac{\Gamma(n_{it} + \phi_{it})}{\Gamma(n_{it} + 1)\Gamma(\phi_{it})} [\frac{\phi_i}{\alpha_{it} + \phi_{it}}]^{\phi_{it}} [\frac{\alpha_{it}}{\phi_{it} + \alpha_{it}}]^{n_{it}} \tag{32}$$

with

$$E(n_{it}) = \alpha_{it} \tag{33}$$

and

$$V(n_{it}) = \alpha_{it} + \alpha_{it}^2 / \phi_{it} \tag{34}$$

This can also be estimated using maximum likelihood techniques. The log likelihood function becomes

$$L(\beta) = \sum_i \sum_t \log\Gamma(\lambda_{it} + n_{it}) - \log\Gamma(\lambda_{it}) - \log\Gamma(n_{it} + 1) + \lambda_{it} \log(\delta) - (\lambda_{it} + n_{it}) \log(1 + \delta) \tag{35}$$

with

$$V(n_{it}) = e^{X_{it}\beta}(1 + \delta) / \delta \tag{36}$$

Thus, the coefficients are estimated using standard maximum likelihood techniques.

Fixed Effects Negative Binomial Model

In this section I present a sketch derivation of the "conditional" or "fixed-effects" negative binomial estimator. The derivation and the notation very closely follow Hausman, Hall, and Griliches (1984) and is merely intended to be a summary of their analysis. For a more complete treatment of the topic, the reader is referred to that paper.

Let the moment generating function for the negative binomial distribution be

$$m(t) = \left(\frac{1+\delta+e^{t}}{\delta}\right)^{-\gamma} \tag{37}$$

Now consider a simple case with two observations. If γ is common for two independent negative binomial random variables w_1 and w_2, then $w_1+w_2=z$ is distributed as a negative binomial with parameters $(\gamma_1+\gamma_2,\delta)$. This is due to the fact that the moment generating function of a sum of independent random variables equals the product of their moment generating functions. We derive the distribution for the two observations case.

$$pr(w_1 | z = w_1 + w_2) = \frac{pr(w_1)pr(z-w_1)}{pr(z)}$$

$$= \frac{\dfrac{\Gamma(\gamma_1+w_1)}{\Gamma(\gamma_1)\Gamma(w_1+1)}(1+\delta)^{-(w_1+w_2)}\left(\dfrac{\delta}{1+\delta}\right)^{\gamma_1+\gamma_2}\dfrac{\Gamma(\gamma_2+w_2)}{\Gamma(\gamma_2)\Gamma(w_2+1)}}{\dfrac{\Gamma(\gamma_1+\gamma_2+z)}{\Gamma(\gamma_1+\gamma_2)\Gamma(z+1)}(1+\delta)^{-z}\left(\dfrac{\delta}{1+\delta}\right)^{\gamma_1+\gamma_2}}$$

$$= \frac{\Gamma(\gamma_1+w_1)\Gamma(\gamma_1+w_2)\Gamma(\gamma_1+\gamma_2)\Gamma(w_1+w_2+1)}{\Gamma(\gamma_1+\gamma_2+z)\Gamma(\gamma_1)\Gamma(\gamma_2)\Gamma(w_1+1)\Gamma(w_2+1)} \tag{38}$$

Here each firm can have its own delta so long as this delta does not vary over time. The delta has been eliminated by the conditioning argument. More generally, considering the joint probability of a given firm's patents conditional on the 4 year total, we can obtain the following distribution.

$$pr(n_{i1},\ldots,n_{iT} \Big| \sum n_{it}) = \left(\prod_t t\frac{\Gamma(\gamma_{it}+n_{it})}{\Gamma(\gamma_{it})\Gamma(n_{it}+1)}\right)\left(\frac{\Gamma(\sum_t \gamma_{it})\Gamma(\sum_t n_{it}+1)}{\Gamma(\sum_t \gamma_{it}+\sum_t n_{it}}\right) \tag{39}$$

Given this, we are able to do estimation of the following log likelihood function

$$\log L = \sum_i \sum_t \log\Gamma(\lambda_{it} + n_{it}) - \log\Gamma(\lambda_{it}) - \log\Gamma(n_{it}+1) + \log\Gamma(\sum_t \lambda_{it}) +$$

$$\log\Gamma(\sum_t n_{it} + 1) - \log\Gamma(\sum_t \lambda_{it} + \sum_t n_{it}) \qquad (40)$$

where

$$\lambda_{it} = e^{X_{it}\beta} \qquad (41)$$

Table 1 **Number of Projects by Industry Cluster and Starting Year**

Cluster Name	1960s	1970s	1980s	1990-92	Total
Materials/Metals	4	3	14	0	21
Petroleum/Chemicals	5	6	18	3	32
Semicon/Computers	2	5	20	5	32
Transportation	2	6	8	2	18
Telecommunications	0	0	21	5	26
Food/Beverage	1	1	14	12	28
Health Care	0	2	14	5	21
Power Generation	0	6	9	2	17
Other	4	7	25	6	42
Total	18	36	143	40	237

Table 2 Project Budget (Government Contribution) by Cluster and Starting Year (figures given in millions of 1985 yen)

Cluster Name	1960s	1970s	1980s	1990-92	Total
Materials/Metals	434	25,142	71,372	0	96,949
Petroleum/Chemicals	11,140	294,794	80,744	4,926	391,603
Semicon/Computers	29,520	212,596	136,585	30,253	408,954
Transportation	17,427	44,659	93,738	1,204	157,028
Telecommunications	0	0	75,169	29,254	104,423
Food/Beverage	16,427	102	6,200	5,487	28,216
Health Care	0	18,109	36,424	5,443	59,975
Power Generation	0	398,201	116,535	6,566	521,302
Other	419	51,580	118,386	36,804	207,189
Total	75,367	1,045,182	735,153	119,938	1,975,641

Table 3 Summary Statistics for Infrequent/nonparticipants

Variable	Observations	Mean	Median	Standard dev.
Rnd/sales	1095	.042	.034	.030
Sales	1196	112,013	59,683	191,382
Japanese Patents	1062	199.6	60	486.7
U.S. Patents	1196	15.4	3	39

Table 4 Summary Statistics for Frequent participants (Participated in more than 11 project-years)

Variable	Observations	Mean	Median	Standard dev.
Rnd/sales	392	.045	.040	.025
Sales	414	742,200	375,012	1,073,775
Japanese Patents	341	2,051.4	460	4,166.7
U.S. Patents	414	92	24	171.4

Table 5 Estimation of R&D expenditure equation

Variable	**Random Effects**	**Fixed Effects**
Constant	-1.34 (.346)	-1.13 (.425)
log(capital)	.975 (.030)	.931 (.043)
ind1	-.145 (.212)	n.a.
ind2	-.545 (.226)	n.a.
ind3	.085 (.215)	n.a.
ind4	-.645 (.223)	n.a.
c	**.0215 (.006)**	**.019 (.007)**

Here the dependent variable is the log of real R&D spending by firms in the fiscal years 1983-89. Regression includes industry dummy variables.

Table 6 **Estimation of a "patent production function"**

Variable	**Random effects**	**Random Effects - dummy**	**Fixed effects**
log(R&D)	.605 (.0352)	.622 (.0339)	.507 (.044)
c	**.053 (.011)**	n.a.	**.0460 (.012)**
freq	n.a.	**.501 (.170)**	n.a.
cons	-2.45 (.371)	-2.66 (.371)	-2.30 (.356)
ind1	-.886 (.291)	-.873 (.294)	n.a.
ind2	-.431 (.311)	-.432 (.314)	n.a.
ind3	-.655 (.295)	-.571 (.297)	n.a.
ind4	-.635 (.304)	-.629 (.307)	n.a.

The dependent variable is the log of patents granted in the U.S. per firm classified by year of application, 1983-89. Independent variables are the log of R&D spending, the number of consortia the firm is affiliated with in a given year (c), a dummy variable signifying a "frequent participant" (freq), a constant, and 4 industry dummies.

Table 7 **Two-Stage Least Squares Estimates**

Variables	**U.S. patent grants**	**Japanese patent applications**
c	**.0492 (.0118)**	**.0804 (.0099)**
lrnd	.7096 (.0254)	.7838 (.0236)
ind1	-.9122 (.1240)	-.9702 (.1133)
ind2	-.3856 (.1334)	-.1148 (.1219)
ind3	-.7155 (.1285)	-.2036 (.1171)
ind4	-.6561 (.1311)	-.2608 (.1210)
cons	-3.286 (.2278)	-1.423 (.2093)

The dependent variables are log of patents granted in the U.S. per firm classified by year of application (first column), and log of patent applications made by firms to the Japanese patent office classified by year of application. Independent variables are the log of R&D spending, the number of consortia the firm is affiliated with in a given year (c), and 4 industry dummies. R&D, industry dummies, and 7, 8, and 9 period lagged "c" values are used as instruments in the first stage regression.

Table 8 Estimation of Poisson/Negative Binomial Patent Production Functions

Variable	Poisson	Negative Binomial fixed effects model
log(R&D)	.948 (.001)	.613 (.0042)
c	**.012 (.0001)**	**.093 (.0104)**
cons	-2.05 (.011)	
ind1	-1.09 (.007)	n.a.
ind2	-.263 (.007)	n.a.
ind3	-.248 (.007)	n.a.
ind4	-1.14 (.007)	n.a.

Here the dependent variable is the count of applications to the Japanese patent office by firm by year. The other variables are the same as in Table 6.

Table 9 Estimation of Spillovers Model with Patents as Dependent Variable

Variable	OLS Model with interaction term	Random Effects with interaction & dummy	Fixed Effects with interaction term
log(R&D)	.716 (.030)	.591 (.049)	.356 (.084))
Spillover pool	**.448 (.094)**	**.570 (.141)**	**.949 (.215)**
Spillover*frequent	**.027 (.008)**	**.571 (.277)**	**.139 (.400)**
industry 1	-.556 (.167)	-.390 (.296)	n.a.
industry 2	-.122 (.176)	-.118 (.310)	n.a.
industry 3	-.538 (.163)	-.580 (.296)	n.a.
industry 4	-.525 (.179)	-.498 (.308)	n.a.
Frequent (dummy)	n.a.	-7.17 (3.71)	n.a.
constant	-9.47 (1.21)	-8.06 (1.26)	n.a.

The dependent variable is patents granted in the U.S. to firms by date of application. Spillover variables are defined in section IV.

Table 10
Estimation of Spillovers Model with Revenue Growth as Dependent Variable

Variable	Separate slope term	Separate slope and intercept terms
change in capital	.220 (.072)	.220 (.071)
change in labor	.427 (.107)	.383 (.112)
change in own R&D	.068 (.047)	.079 (.048)
change in spillovers	.689 (.363)	.362 (.393)
interaction term	**-.092 (.076)**	**2.27 (1.05)**
freq (dummy)	n.a.	-.752 (.333)
constant	-.101 (.116)	-.000 (.124)
Adj R-squared	.3553	.3684

Supplementary Tables

Table A-1 **Number of Projects by Industry Cluster and Starting Year for the Firms in Our Sample**

Cluster Name	1960s	1970s	**1980s**	1990-92	Total
Materials/Metals	1	2	**11**	0	14
Petroleum/Chemicals	4	5	**15**	1	25
Semicon/Computers	2	4	**17**	5	28
Transportation	2	6	**8**	2	18
Telecommunications	0	0	**15**	5	20
Food/Beverage	1	1	**13**	10	25
Health Care	0	2	**12**	4	18
Power Generation	0	2	**7**	2	11
Other	3	6	**21**	6	36
Total	13	28	**119**	35	195