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# Are knowledge spillovers international or intranational in scope? Microeconometric evidence from the U.S. and Japan ☆

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**Abstract**

In this paper, I provide new estimates of the relative impact of intranational and international knowledge spillovers on innovation and productivity at the firm level, using previously unexploited panel data from the U.S. and Japan. My estimates suggest that knowledge spillovers are primarily *intranational* in scope, providing empirical confirmation of an important assumption in much of the theoretical literature. The implications of this finding are discussed in the conclusion. © 2001 Elsevier Science B.V. All rights reserved.

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## 1. Introduction

The theoretical literature in international economics and economic growth over the last decade has given considerable attention to the potential role of technological externalities in generating endogenous growth and determining the pattern of trade. In a number of contexts, it has been shown that assuming externalities of this type can have dramatic effects on the equilibrium pattern of trade and production. In these models, there are multiple equilibria, and comparative advantage can itself be endogenously determined.

The sort of technological externality on which this paper focuses is most closely related to the theoretical contributions of Grossman and Helpman, particularly the model presented in Grossman and Helpman (1990). These authors have developed growth models in which the number of products (and/or product quality) expands over time due to the innovative activity of profit-seeking firms. In these models, decreasing returns to innovation never sets in because the innovative activities of firms not only lead to new products (whose benefits the firms can appropriate), but also contribute to a general stock of knowledge upon which subsequent innovators can build. Over time, the foundation of general knowledge grows, allowing more differentiated products to be introduced *without* a continual increase in the research resources that must be expended. This is referred to as ''knowledge spillovers,'' so-called because the benefit of innovation accrues not only to the innovator, but ''spills over'' to other firms by raising the level of knowledge upon which new innovations can be based. Thus, knowledge spillovers serve as the ''engine of endogenous economic growth.''[1]

In their work, Grossman and Helpman have demonstrated that even in a model in which innovation is fully endogenous, trade can still be determined by factor endowments if new ideas flow as quickly to other nations as they flow within nations. On the other hand, if knowledge spillovers are purely intranational, then trade patterns can exhibit path dependence. For example, a country which acquires a temporary advantage in R&D-intensive sectors can build on that advantage, eventually developing a position of enduring comparative advantage. Once this country's firms begin to innovate at a faster rate than those outside the country, these new innovations become the foundation upon which more ideas can be created. Because this ''foundation'' is higher than it is elsewhere, firms in this country have a powerful advantage over foreign rivals — they are likely to continue to generate more ideas than their foreign rivals, further enlarging and broadening the national ''stock'' of knowledge from which they can draw and further cementing their technological advantage.

Even in models in which any nonzero level of international knowledge spillover rules out multiple equilibria in the long run steady-state equilibrium, it is still true

[1]The phrase ''engine of endogenous growth'' comes from Grossman and Helpman (1995).

that the extent of the differential in international and intranational spillovers will affect both the speed and the nature of the convergence to the steady-state. As Grossman and Helpman (1995) put it, ''an accident of history'' or a temporary policy that provides one country with a temporary advantage in the R&D-intensive sector ''can have long-lasting implications for trade when there is a national component to the knowledge stock.''[2]

This paper seeks to measure the extent of this ''national component'' of the knowledge stock. Following the spirit of these models, I derive an empirical framework that allows us to estimate the relationship of new increments to the general knowledge stock, or ''flows'' of spillovers, from foreign and domestic sources, to the innovative performance of firms in Japan and the United States. The paper then obtains estimates of the impact of ''international'' and ''intranational'' knowledge spillovers on innovation and technological change at the firm level, using previously unexploited panel data from the U.S. and Japan. I find robust evidence that knowledge spillovers are primarily an *intranational* phenomenon. The implications of this finding for the theoretical literature and for policy are discussed in the conclusion.

## 2. Previous literature

An alternative mechanism for endogenous growth and endogenous comparative advantage is some form of ''learning-by-doing.'' Taking a focus very similar in spirit to that of the current paper, Irwin and Klenow (1994) examine the relative strength of intranational and international *learning-by-doing* spillovers in the Dynamic Random Access Memory Chip industry. Noting that considerable anecdotal and empirical evidence suggests that learning-by-doing is an important feature of production in this industry, Irwin and Klenow proceed to examine the extent to which learning-by-doing by one firm ''spills over'' to other producers within the same country and the extent to which it spills over internationally. Unfortunately, the data limitations they confront in their study are substantial. Because they lack any direct measure of firms' marginal cost, the dependent variable in their regressions, they are forced to impute it by assuming that the global DRAM industry is at all times characterized by strict Cournot competition in quantities with no capacity constraints. Irwin and Klenow also lack any firm-level data on R&D. They are thus unable to assess the degree to which R&D contributes to marginal cost reduction or product innovation in this industry.

In one of the most interesting and well-done recent papers on a related topic, Jonathan Eaton and Sam Kortum derive a formal model of technology diffusion, which is then parameterized around data on country-level international ''cross-

[2] These quotes are taken from Grossman and Helpman (1995).

patenting'' in 8 OECD countries. However, the authors quite explicitly see their work as a measurement of technology transfer or diffusion, rather than knowledge spillovers. There is little focus on the extent to which knowledge which diffuses abroad begats further innovation abroad.

There is also a set of papers in the literature which have sought to measure ''R&D spillovers.'' Coe and Helpman (1995), Coe et al. (1995), and Bernstein and Mohnen (1998) have done so, using country-level data to assess the statistical relationship between aggregate R&D capital accumulation abroad and own country growth in total factor productivity.[3] Keller (1998) has taken a similar approach using approximately 2-digit industry data from 8 countries. In the influential paper by Coe and Helpman and much subsequent work, an explicit emphasis is placed on the role of intermediate inputs as conduits of spillovers. Information on the flow of goods, either between countries, between industrial sectors, or between countries and sectors, is used to predict the flow of knowledge. However, the flow of knowledge does not necessarily closely correspond to the flow of goods.[4] Wolfgang Keller's (1998) paper, ''Are International R&D Spillovers Trade-Related?'' provides econometric evidence on the potential dangers of relying too heavily on flows of goods to infer flows of knowledge spillovers.[5]

It is useful here to invoke the distinction made by Griliches (1992) between ''pecuniary'' spillovers and knowledge spillovers. When an upstream firm or industry, through its R&D efforts, produces a higher quality good (or a larger range of specialized goods) which is then utilized by a downstream industry or firm, a pecuniary external can be said to have occurred if the upstream innovator is unable to appropriate all of the surplus from this invention. In practice, competitive pressures and the impossibility of perfect price discrimination even in the absence of strong competition will insure that some surplus ''leaks'' downstream. However, unless that downstream user is able to reverse engineer the technology embodied in this newly improved product, and use that knowledge to further its own inventive activity, one cannot say that a ''knowledge spillover'' has taken place. One can obtain substantial productive gains (in the sense of cost reduction) from the use of an improved input, but this can be a static gain analogous to the benefit to producers when energy prices decline. The ''engine of endogenous growth'' is not operative in such a case.

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[3] Using a methodology similar to that of Bernstein and Mohnen (1998), Bernstein has estimated international spillovers for several other country pairs and groups of countries. This methodology utilizes a cost function approach rather than a production function approach.

[4] To cite a trivial but illustrative example, I purchase much more on an annual basis from my landlord, my mechanic, and my physician than from my fellow economists. However, these transactions have taught me little about real estate, medicine, or auto repair.

[5] Using the Coe–Helpman data set, Keller creates ''random'' measures of bilateral trade by which he weights the ''foreign'' spillover term. The estimated output elasticity of this ''randomly'' weighted spillover term is often higher than that of the actual bilateral trade-weighted spillover term used by Coe and Helpman.

There is also a practical problem with econometric work at the level of aggregation used in these papers. Within countries and even within 2-digit industries, there is considerable technological heterogeneity. This requires us to be careful in measuring spillovers. For instance, a maker of industrial solvents is unlikely to directly benefit from the research of pharmaceuticals companies on psychoactive drugs, even though both are in the ''chemical'' industry. If we find no relationship between the productivity of our industrial solvent manufacturer and research and development by the pharmaceuticals manufacturer, that does not mean there are no knowledge spillovers. On the other hand, if we find a relationship, and these authors generally do, it is difficult to give it a causal interpretation.[6] We are more likely to be observing common demand or input price shocks or a common time trend rather than actual knowledge spillovers.[7]

Separating the ''signal'' of real knowledge spillovers from the ''noise'' of potentially spurious correlation requires a measure of technological proximity by which to weight the R&D, domestic and foreign, which is done external to the firm. Obtaining such a measure requires the use of data at the level of the producer which provides a rich description of the R&D activities of individual firms and the distribution of that effort across different technological fields. Fortunately, such data exist and are exploited in this paper.

In concluding this section, I note that a number of researchers have recently taken alternative approaches to the measurement of knowledge spillovers. Adam Jaffe and a number of co-authors have examined knowledge spillovers through the econometric analysis of patent citations in U.S. patent data.[8] These researchers have generally found that innovators in the same country have a much higher propensity to cite one another than would be expected given the distribution of research resources across countries, fields, and time. Narin (1995) has found similar evidence of primarily intranational knowledge spillovers in his bibliometric studies of citations in the academic literature of the biological sciences. Finally, Goto and Nagata (1997) directly surveyed R&D managers in Japan and the U.S.

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[6]Working with aggregate data does not necessarily bias one toward *not* finding a significant result. Recent work by Funk (1998) demonstrates that the aggregate data used by Coe and Helpman to obtain fairly large and statistically significant estimates of spillover effects are non-stationary; that is, they contain a unit root. The use of standard linear regression techniques with such data creates standard errors that are biased downwards. Using recently developed techniques for panel data analysis in the presence of unit roots, Funk re-estimates the regressions of Coe and Helpman, finding *no* statistically significant evidence of international R&D spillovers.

[7]This general problem is exacerbated by the way R&D data is collected in some countries. In the U.S., R&D is collected at the firm level and assigned to the industry which the firm identifies as its primary industry. However, most of the private sector R&D in the U.S. is done by large firms that span several 3-digit and even 2-digit sectors. Working at the industry level can lead to what F.M. Scherer has referred to as ''mismeasurement spillovers'' — correlations resulting from the misclassification of R&D data at the industry level.

[8]See Jaffe et al. (1993) and Jaffe and Trajtenberg (1996).

concerning where they perceived their ''spillovers'' to be coming from. The survey responses indicate that managers learn much more from other domestic firms than from foreign-based ones. Taken together, these results suggest that knowledge spillovers have a substantial ''intranational'' component. My empirical results will support this view.

## 3. Empirical methodology

This paper builds on the methodologies suggested by the late Zvi Griliches (1979) and first implemented by Jaffe (1986). I note that this description of my methodology borrows heavily from Branstetter (1996) and overlaps substantially with Branstetter (2000a) and Branstetter (2000b). The typical firm conducts R&D in a number of technological fields simultaneously. We can construct 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

$$F_i = (f_i \cdots f_k) \tag{1}$$

and where the $k$ elements of $F$ represent the firm's research resources and expertise in the $k$th technological area.[9] 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.[10]

Of course, a firm can change its position in technology space by building technological expertise in new areas, but the ''adjustment costs'' associated with this kind of change are likely to be high and such change is likely to be time consuming. I therefore assume that a firm's position in technology space is effectively fixed in the short term. Based on this assumption, I calculate for each firm in my sample a single location vector based on its patenting behavior over the

[9]The $k$ areas represent technological areas (based on the technology classification scheme of the U.S. patent office) rather than industry classifications. We do control for industry effects elsewhere, but here we aim to measure *technological proximity* rather than proximity in a ''product market'' sense.

[10]Obviously, advances in some technological fields are more easily codified into and protected by patents than advances in others. However, the $F$ vector can still function as a reasonable measure of ''relative'' position in technology space as long as the ''ease of codification'' varies across fields in a common way across firms.

entire sample period. By construction, I am assuming that firms remain in that position for the duration of my sample period.

Griliches and Jaffe have reasoned that ''R&D spillovers'' between firms should be proportional to the similarity and intensity of their research programs. We can measure the ''technological proximity'' between two firms by measuring the degree of similarity in their patent portfolios. To be more precise, 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

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

The total potential pool of intranational 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. Thus, the potential intranational, or ''domestic'' spillover pool for the $i$th firm is $K_{dit}$, where $K_{dit}$ is

$$K_{dit} = \sum_{i \neq j} T_{ij} R_{jt} \tag{3}$$

Here $R_{jt}$ is the R&D spending of the $j$th firm ($j$ not equal to $i$) in the $t$th year and $T_{ij}$ is the ''similarity coefficient.'' Recall that the $T_{ij}$s are time-invariant, by construction, but $K_{dit}$ varies over time because the R&D spending of the other domestically-based firms is changing over time.

In the same way, we can calculate the potential international, or ''foreign,'' spillover pool as

$$K_{fit} = \sum_{i \neq j} T_{ij} R_{jt} \tag{4}$$

Where $R_{jt}$ represents the R&D spending of individual firms based in a foreign country, again weighted by the $T_{ij}$'s. If we postulate that innovation at the firm level is a function of own R&D and external knowledge, then we can let the ''innovation production function'' for the $i$th firm be

$$N_{it} = {}^{\beta}_{it} K_{dit}^{\gamma_1} K_{fit}^{\gamma_2} \Phi_{it} \tag{5}$$

where

$$\Phi_{it} = \mathrm{e}^{\sum_c \delta_c D_{ic}} \, \mathrm{e}^{\varepsilon_{ti}} \tag{6}$$

Here the $\delta$'s can be thought of as exogenous differences in ''technological opportunity'' across $c$ different industries.

Taking the logs of both sides of (5) yields the following log-linear equation

$$n_{it} = \beta r_{it} + \gamma_1 k_{dit} + \gamma_2 k_{fit} + \sum_c \delta_c D_{ic} + \varepsilon_{it} \tag{7}$$

In (7), $n_{it}$ is innovation, $r_{it}$ is the firm's own R&D investment, $k_{dit}$ is the domestic spillover pool, $k_{fit}$ is the international spillover pool, the $D$'s are dummy variables to control for differences in technological opportunity across industries (indicated by the subscript $c$), and $\varepsilon$ is an error term. In this specification, the $\gamma$ coefficients are interpreted as measuring the ''innovative output elasticity'' of our domestic and international spillover pools.

One might suppose that external R&D only enters into the knowledge production function with a long and variable lag. However, empirical research suggests that the time required for new innovation to ''leak out'' is quite short. Mansfield (1985) finds that 70% of new product innovations ''leak out'' within one year and only 17% take more than 18 months.[11] Recent survey evidence obtained by Cohen et al. (1998) suggests that some 71% of Japanese firms and 69% of U.S. firms receive useful information about the R&D activities of their competitors on a *monthly* basis.

There is an immediate practical challenge to estimating an equation like (7): there are no *direct* measures of innovation. In order to operationalize (7), we assume that some fraction of new knowledge is patented, such that the number of new patents generated by the $i$th firm is an exponential function of its new knowledge,

$$P_{it} = \mathrm{e}^{\sum_c \alpha_c D_{ic}}\, \mathrm{e}^{\xi_i} N_{it} \tag{8}$$

If this assumption is approximately correct, then the production of new knowledge can be proxied by examining the generation of new patents.[12] We take the logs of both sides of (8) and substituting into (7), we get

$$p_{it} = \beta r_{it} + \gamma_1 k_{dit} + \gamma_2 k_{fit} + \sum_c \delta_c D_{ic} + \mu_{it} \tag{9}$$

where $p_{it}$ is the log of the number of new patents and the other variables are as

[11] Caballero and Jaffe (1993) also find evidence consistent with rapid diffusion of new innovations.

[12] Note that this formulation allows for both industry and firm differences in the propensity to patent. This flexibility is important given the observed differences in patenting behavior across firms and industries.

before, except for the error term which is defined below. With this substitution, the interpretation of the coefficients on the $D$'s has changed. They now represent industry-level differences in the propensity to patent, which are a function of both the level of ''technological opportunity'' of the $c$th industry, as in (6), and the usefulness of patents as a tool of appropriation in the $c$th industry. It is known that strong differences in both factors exist across industries.

The interpretation of the $\gamma$'s also changes in an important way which merits immediate comment. We do not observe the ''pure effects'' of knowledge spillovers on firm innovation, which constitute an unambiguously positive externality. We instead observe the effects of knowledge spillovers on economic manifestations of the firms' innovation, patents. Clearly, patents are a tool of appropriation. If technological rivalry with other firms is intense enough and the scope of intellectual property rights conferred by patents is broad enough, then firms may sometimes find themselves competing in a limited range of the intellectual product space for a limited pool of available patents — a patent race. For this reason, the positive technological externality is potentially confounded with a negative effect of other firms' research due to competition.[13] Because of this, if actual flows of knowledge are weak and rivalry is strong, our estimates of the $\gamma$'s may be negative even though the underlying knowledge externality is positive. Unfortunately, it is not possible to disentangle these two effects in the data, though my empirical results suggest that both are present.[14]

We allow the error term in (9) to contain a firm-specific component such that

$$\mu_{it} = \xi_i + u_{it} \tag{10}$$

where the latter term is assumed to be a normal ''iid'' disturbance. If $\xi_i$ is uncorrelated with the right hand side regressors, then this effect can be estimated using the ''random effects'' framework. However, this firm-specific component in the error term may be quite plausibly correlated with a firm's own research levels. If we assume unobservable but permanent differences in the productivity of firm's research, owing perhaps to the unequal distribution of high quality research personnel across firms, we can easily imagine that firms with high quality research personnel will do more research, and that this will lead to more patents. In this case, estimates are biased unless we correct for the correlation between firm-specific research productivity and R&D levels. We can do this using a ''fixed

[13] Adam Jaffe (1986) and others have also made this point, and some of my language here closely follows Jaffe (1986). The recent survey evidence presented by Cohen et al. (1998) suggests that *81% of U.S. firms and 95% of Japanese firms* regard this ''competitive effect'' as relevant to their own patenting experience.

[14] See Jaffe (1986), who finds direct evidence of negative ''competitive'' externalities in a framework similar to the one used in this paper.

effect'' estimator.[15] Results from both a random effects specification and a fixed effects specification are provided. Unfortunately, I am unable to allow the propensity to patent to vary according to the strength of the spillover term, as that would preclude identification.

The use of patents as indicators of economic activity has a number of disadvantages. Perhaps the most important of these is the fact that the ultimate economic value of firms' patents varies widely, with some patents leading to no commercial products and others leading to billions of dollars in revenues. Because of this, the link between patent counts and the economic effects of innovation that economists tend to care about is less than straightforward. For this reason, it would be useful to have an alternative index of innovation by the firm, and I provide one.

Real technological spillovers should lead not only to more patents but also higher levels of revenue for the innovating firm, by increasing product quality, and thus product demand, or lowering production costs. To measure this effect, I estimate a standard Cobb–Douglas production function in its ''growth rate'' (difference) form, using the spillover terms as regressors. Thus, output can be described as

$$Q_{it} = C_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\phi} K_{dit}^{\varphi} K_{fit}^{\rho}\, \mathrm{e}^{\epsilon_i} \tag{11}$$

taking the logs of both sides gives us

$$q_{it} = \alpha c_{it} + \beta l_{it} + \phi r_{it} + \varphi k_{dit} + \rho k_{fit} + \epsilon_{it} \tag{12}$$

Here $q$ is output, $c$ is capital, $l$ is labor input, $r$ is the firms' own R&D stock, and the $k$'s are the domestic and foreign spillover stocks respectively. In this case, firm's own R&D and the spillover terms are calculated as stocks, following Griliches (1984).[16] Again, we allow for the existence of individual effects which are potentially correlated with the right hand side regressors, such that

$$\epsilon_{it} = \lambda_{it} + u_i \tag{13}$$

The standard procedure is, of course, to use a ''within'' panel estimator to eliminate the individual effect. However, if there is measurement error in the

[15]The obvious alternative would be some sort of instrumental variables approach. Unfortunately, the only instrumental variables available at the firm level are lagged values of the included variables. If research quality evolves slowly over time, these lagged values are likely to be no less endogenous than the variables for which we instrument. As for GMM ''dynamic'' panel estimators which use lagged levels as instruments for current differences, Blundell and Bond (1995), among others, have found that in short, moderately sized panels with autoregressive explanatory variables (such as my data set), these estimators can behave quite poorly.

[16]A full discussion of why the use of stock measures is appropriate here is given in Section 5.

variables of interest, the ''within'' estimate may have a serious bias of its own.[17] Following Griliches and Hausman (1986), we use a ''within'' estimator that is less likely to suffer from this second source of bias than either using the first-differences estimator or transforming the data by calculating deviations from firms' ''time means.'' 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.

$$q_{iT} - q_{i0} = \alpha(c_{iT} - c_{i0}) + \beta(l_{iT} - l_{i0}) + \phi(r_{iT} - r_{i0}) + \varphi(k_{diT} - k_{di0}) + \rho(k_{fiT} - k_{fi0}) + (\lambda_i - \lambda_i) + u_{iT} - u_{i0} \tag{14}$$

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

Since we do not directly observe output growth, per se, we will use revenue growth as our proxy for output growth.[18] This raises problems of inference, because revenue growth is subject to idiosyncratic and systematic demand and input supply shocks. In particular, unmeasured growth in the effective demand for a firm's products, the level of capacity utilization, or the quality of capital and labor inputs can all show up in the ''residual'' as productivity growth.[19] 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.

Revenues of firms are subject to the same mix of positive technological externalities and negative competitive externalities as are patents, because successful imitation can deplete monopoly rents. Where knowledge flows are strong, we

[17] Here, serious measurement error is a virtual certainty. Research by Pakes and Griliches (1984) has shown that accounting rates of depreciation physical capital are wildly inaccurate measures of the true depreciation of capital services. Even less is known about the true rate of depreciation of ''knowledge capital,'' whether internal or external to the firm.

[18] See Griliches (1984). This is, of course, problematic to the extent that there are large stocks of unsold goods or to the extent that price indices fail to reflect industry or firm-specific price and quality changes. The available data provide us with little leverage on either issue.

[19] In addition, there is the problem of the potential endogeneity of the right hand side variables, which my ''fixed effects'' model may not completely fix. On this issue (which effects most empirical work in the micro R&D/productivity literature) and the difficulty of doing much about it, see Griliches and Mairesse (1997).

can expect a net positive effect of external R&D on own firm productivity growth. Where flows of knowledge are weak and rivalry in the product market is strong, we can anticipate a zero or even negative estimate.

## 4. A note on data

I use microdata on publicly traded high-technology manufacturing firms in the United States and Japan. This choice was motivated by data availability, but also by the intrinsic importance of the two countries. Japan and the United States are the leading technological superpowers in the OECD.[20] They are also highly integrated economically. Finally, there is considerable anecdotal evidence to suggest that Japanese firms are particularly good at monitoring R&D developments abroad. If one is going to find international knowledge spillovers anywhere, one should find them here. Fortunately, there also exists broadly comparable, publicly available data at the micro-level on the innovative activities of publicly traded firms in both countries.[21]

I chose to examine the five industries in the U.S. and Japan in which the average R&D/sales ratio is highest, for the simple reason that one is less likely to identify the sources and effects of spillovers in industries with little technological innovation. Since I rely on patents both as indicators of innovative activity and as a means of locating firms in technology space, I restricted my sample to U.S. and Japanese firms with more than ten patents granted in the U.S. during my initial sample period, 1977–1989. I later shortened this sample period to 1983–1989 because of limitations on the availability of micro-level data on R&D spending by Japanese firms. Prior to 1985, the publicly available data on firm-level R&D spending is of uneven quality, with gaps in the time series of individual firms.

[20]The two countries account for over 60% of the world's scientists and engineers. See Eaton and Kortum (1996) for more evidence on the skewness of innovative activity.

[21]Public sector R&D in either the U.S. or Japan is excluded from this study, as this study focuses on the extent to which private R&D spills over domestically and internationally. For Japan, this is not necessarily an important omission, since the private sector accounts for more than 80% of the national total during the years of my sample period. It is true that, in contrast, U.S. government R&D accounted for a substantial percentage of total expenditures over the sample period. However, much of this R&D effort was concentrated in health care, space, defense, or academic science, and could be seen as much less relevant to the majority of firms in my sample than R&D undertaken in the private sector. Furthermore, it is difficult to place much of this research into the same ''technology space'' as the private sector R&D. Finally, in principle, our measures of firm-level patenting capture the benefits of international and intranational spillovers from the public sector. To the extent that public sector R&D positively effects foreign firms' R&D, we might expect its omission to bias the coefficient on international spillovers upward rather than downward. This suggests that the central conclusion of this paper may not be affected by the omission of public sector R&D.

Table 1
Sample statistics for Japanese data[a]

| Variable | Obs | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Patents | 1025 | 41.47 | 117.17 | 0 | 966 |
| R&D | 1025 | 15369.33 | 39020.69 | 0 | 316147 |
| Dom. Pool | 1025 | 605,780.6 | 294,972.7 | 50326.07 | 1,742,435 |
| Foreign Pool | 1025 | 1,441,850 | | 136,659.1 | 3,462,034 |

[a] Units are millions of 1985 Japanese yen.

Thus, in most of my regressions, I am forced to further restrict the sample period to the years 1985–1989.

The Japanese panel consists of 205 firms from the chemicals, machinery, electronics, transportation, and precision instruments manufacturing industries. For each firm, we have data by year for the years 1985–1989. For each year, I have the number of patents granted to these firms in the U.S. (classified by date of application), their R&D expenditures in that year, a ''domestic spillover'' term consisting of the weighted sum of ''external'' R&D performed by technologically related Japanese firms computed for each year, and a foreign spillover term consisting of ''external'' R&D performed by technologically related U.S. firms.[22] Table 1 gives some summary statistics for the Japanese sample.[23]

Similar data was gathered for American firms from the same industries.[24] The final U.S. panel consists of 209 firms. Firms were required to be listed on the stock exchange continuously during the sample period, and firm with large jumps in recorded capital stock (generally the result of large mergers or divestitures) were

[22]Here I use the U.S. patents of Japanese firms to locate them in technology space and to measure their innovation. The patent classification schemes and the patent screening processes used in the two countries are different enough that, to insure the comparability of patents for both sets of firms, I decided to use U.S. patents. It should be noted that Japanese firms have been extremely aggressive about patenting their inventions in the U.S. as well as Japan. In the late 1980s and early 1990s, Japanese firms accounted for about 25% of new patents in the U.S., making them by far the most important foreign users of the American patent system. Finally, it is also true that detailed data on the *Japanese* patents held by these firms is difficult to obtain and extraordinarily expensive.

[23]The use of U.S. patents to infer the R&D activities of Japanese firms raises the possibility that I am systematically undermeasuring Japanese research productivity. To the extent that Japanese patent only a fraction of their inventions in the U.S., but that this fraction is constant across firms and across time, it will fall into the constant term (since I estimate separate knowledge production functions for U.S. and Japanese firms). To the extent that it is constant across firms but not across time, it will fall out in the time dummies. To the extent that it is not constant across firms, but is constant across time, this differential will be absorbed into the fixed effect. In the absence of more detailed information about the *Japanese* patents of Japanese firms and how they vary with these firms' U.S. patents, little more can be said on this issue, though I acknowledge that it may cloud my interpretation of the empirical results.

[24]The U.S. sample is based on the NBER Productivity Data Base produced by Bronwyn Hall.

Table 2
Sample statistics for U.S. data[a]

| Variable | Obs | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Patents | 1045 | 58.11 | 107.5 | 0 | 750 |
| R&D | 1045 | 189.58 | 495.15 | 0.6939 | 4885.939 |
| Dom. Pool | 1045 | 9532.2 | 3669.64 | 1806.36 | 21841.21 |
| Foreign Pool | 1045 | 3872.14 | | 419.36 | 10328.73 |

[a] Units are millions of 1987 U.S. dollars.

removed in the interest of avoiding large outliers. Table 2 gives sample statistics for the U.S. sample.[25]

## 5. Empirical analysis

### 5.1. Empirical results using linear models

This section presents results from a linear regression framework. The estimating equation is

$$p_{it} = \alpha + \beta r_{it} + \gamma_1 k_{dit} + \gamma_2 k_{fit} + \sum_c \delta_c D_{ic} + \mu_{it} \tag{9}$$

where $p$ is the log of patents for firm $i$ in the $t$th year, $\alpha$ is an overall constant term, $r$ is the log of firm's own R&D, the $k$'s represent the logs of ''domestic'' and ''foreign'' spillover terms, and the $D$'s are dummy variables for the five industries represented. In some firm-years in the sample, the number of patents is zero. Since the log of zero is undefined, this issue was dealt with by adding one to all observations of the dependent variable, then taking the log. This is the ''standard'' procedure for dealing with this problem in the older micro R&D/productivity literature. Concerns that this transformation might bias the results motivated the estimation of alternative nonlinear models, described below.

Investments in R&D, particularly basic R&D, may take some time to bear fruit. Accordingly, when estimating the impact of R&D on some measure of innovation, one can make an argument for including lagged values of past R&D investment or, alternatively, constructing an R&D ''stock'' by assuming that past R&D investments do contribute to current innovation, albeit with decreasing effectiveness over time due to technological obsolescence. However, empirical research on patenting indicates that the temporal linkage between R&D and patenting is quite close. Survey evidence from the U.S. and the former West Germany suggests that the time lag between the initial conception of an invention and filing for a patent

[25] Further details on data construction can be found in Branstetter (1996).

application is only 9 months. Econometric studies also show that the relationship between patenting and R&D is apparently largely contemporaneous.[26] It seems to be the case that firms tend to take out patents at a relatively early stage in the research and development process. Based on these results, my specification of Eq. (9) relates patents applied for in period $t$ with firm R&D spending in period $t$. Thus, I use a contemporaneous ''flow'' measure of R&D.

The same issues of timing exist with regard to the spillover terms. As mentioned before there is a fair amount of evidence based on U.S. data suggesting that new innovation spills over fairly quickly.[27] The short length of the time series dimension of my panel and the multicollinearity in the data effectively preclude the estimation of intricate lag structures on the spillover term. In the regressions below, I treated ''domestic spillovers'' as contemporaneous whereas ''foreign spillovers'' were lagged by one year. This was done, in part, to allow ''foreign'' innovations longer to diffuse. It was also done to partly control for differences in accounting conventions in the two countries, as the fiscal years of most of the U.S. firms and those of the Japanese firms do not perfectly overlap. However, experiments with contemporaneous ''foreign spillovers'' and lagged ''domestic spillovers'' yielded results that are qualitatively similar to the ones reported in this paper. In results that I do not report, I constructed stock-based measures of own firm R&D and domestic and foreign spillover terms and reestimated (9) using these stocks rather than flows. This yielded results very similar to the ones reported in the tables.[28] Note also that lagging foreign spillovers by one year means that we lose 205 observations in the Japanese sample and 209 observations in the U.S. sample in our reported regressions.

In Table 3, the first and fourth columns present coefficients and standard errors for OLS versions of (9) in which domestic and foreign spillovers are entered along with own R&D using Japanese and U.S. data, respectively. The second and fifth columns give results from using the ''random-effects'' panel estimator on Japanese and U.S. data, respectively. The third and sixth columns give results from using the ''fixed-effects'' or ''within'' panel estimator using both terms on Japanese and U.S. data, respectively. *A Hausman test rejects the random effects estimator in*

[26]For more on this survey evidence, see Scherer (1984). Hausman et al. (1986) found essentially no effect of past R&D investments on current patenting. Blundell et al. (1995) found similar results of lagged R&D on current patenting using a GMM-based multiplicative distributive lag model.

[27]See Mansfield (1985) and Caballero and Jaffe (1993).

[28]While the similarity is heartening, it is driven by the fact that most of the variability in firms' R&D spending is in the cross-section dimension, with individual firms showing relatively little variation in their R&D spending over time (which also explains why the introduction of simple lags has little effect on my empirical results). In addition, due to data limitations for Japanese firms, construction of the stock variables required me to extrapolate R&D spending into the past based on firm behavior in the sample period. Finally, very little is known about the rate at which knowledge depreciates. I make the standard assumption of 15% annual depreciation, which is ultimately nothing more than an educated guess. See Griliches (1984).

Table 3
Linear regressions[a]

| | Results for Japanese firms | | | Results for U.S. firms | | |
|---|---|---|---|---|---|---|
| | OLS | Random effects | Fixed effects | OLS | Random effects | Fixed effects |
| Log R&D | 0.7294 | 0.5941 | 0.0711 | 0.7223 | 0.6295 | 0.1952 |
| | (0.0270) | (0.0443) | (0.0912) | (0.0217) | (0.0373) | (0.0821) |
| Log domestic spillovers | 0.9091 | 1.108 | 1.084 | 0.7967 | 0.9658 | 0.9994 |
| | (0.1881) | (0.2800) | (0.6166) | (0.1768) | (0.3244) | (1.081) |
| Log foreign spillovers | −0.5449 | −0.4930 | −1.113 | −0.7003 | −0.6694 | −1.872 |
| | (0.2091) | (0.2976) | (1.222) | (0.1646) | (0.2876) | (0.6978) |
| Test of equality | $F=14.28$ | $\text{Chi}^2=8.46$ | $F=2.89$ | $F=20.79$ | $\text{Chi}^2=7.73$ | $F=3.74$ |
| | $P=0.0002$ | $P=0.0036$ | $P=0.0896$ | $P=0.0000$ | $P=0.0054$ | $P=0.0536$ |
| Chemicals | −0.4144 | −0.2950 | n.a. | 0.1574 | 0.3270 | n.a. |
| | (0.1742) | (0.2964) | | (0.1111) | (0.2213) | |
| Machinery | −0.1196 | −0.1236 | n.a. | 0.2223 | 0.2504 | n.a. |
| | (0.1764) | (0.2968) | | (0.0994) | (0.2149) | |
| Electronics | −0.5538 | −0.5542 | n.a. | −0.1440 | −0.0908 | n.a. |
| | (0.1650) | (0.2847) | | (0.0969) | (0.1950) | |
| Transportation | −0.5146 | −0.4891 | n.a. | 0.1628 | 0.2503 | n.a. |
| | (0.1822) | (0.2948) | | (0.1282) | (0.2420) | |
| Year 2 | −0.0414 | −0.0196 | −0.2128 | 0.1086 | 0.1263 | −0.1835 |
| | (0.0984) | (0.0590) | (0.2476) | (0.0897) | (0.0514) | (0.1772) |
| Year 3 | 0.0601 | 0.0939 | −0.0113 | 0.2218 | 0.2353 | 0.0810 |
| | (0.0962) | (0.0636) | (0.1863) | (0.0878) | (0.0465) | (0.1241) |
| Year 4 | 0.0707 | 0.0829 | 0.0148 | 0.1120 | 0.1219 | −0.0310 |
| | (0.0965) | (0.0538) | (0.1070) | (0.0904) | (0.0472) | (0.0916) |

[a] Dependent variable: Log (Patents + 1). Standard errors in parentheses.

*favor of a fixed effects estimator*, and firm-level heterogeneity in patenting and R&D spending suggests that firm effects are important.

On this basis, fixed effects specifications are preferred. However, the fixed effects approach requires us to throw away the cross-sectional variance, which is most of the variance in the data. Furthermore, as I have noted, fixed effects estimators can exacerbate the problem of measurement error bias, which is likely to be a significant issue with this data set. Adding a full set of time dummies removes all common time variance, leaving only firm-specific variance over time from which to estimate the parameters of interest. This reduces the signal-to-noise ratio even further. The predictable result is that our estimates lose precision. Nevertheless, the qualitative results are consistent with those of our other linear specifications.[29]

[29]In these and other regressions, we hold the elasticities of ''innovative output'' with respect to own R&D and the spillover terms constant, though we do allow for industry, time, and firm effects. Attempts to allow these elasticities to vary across industries for the Japanese data were severely constrained by the small cross-section of firms in a particular industry. Estimates of intra- and international spillovers based on data from 20 firms tend to be quite imprecise!

In all models but the fixed effects models, we can reject the hypothesis of equality of the coefficients of domestic and foreign spillovers at the 5% level using the standard *F*-test (or Chi-squared test, in the case of the random effects model). Even in the fixed effects case, we can reject the hypothesis of equality at levels close to the standard 5% level (note the *P*-values given in the tables) and below the 10% level.

### 5.2. Results from the negative binomial model

Patent data are ''count data'' — non-negative integers — and in any given year a number of firms perform R&D but generate no patents. Over the past decade a set of regression models have been developed expressly for the purpose of handling this kind of data. The technique used here is a generalization of the Poisson model known as the ''negative binomial'' estimator. For a formal development of this model, please consult Hausman et al. (1984). This model has the advantage of being able to accommodate ''zero'' outcomes for the dependent variable in a natural way. Unfortunately, this benefit is achieved at the cost of imposing a number of strong assumptions on the data.[30]

Estimates from the negative binomial models are given in Table 4. Again, the coefficients of domestic and foreign spillovers are clearly not equal. The formal null hypothesis of equality of the two coefficients can be rejected at conventional levels in all specifications, for both the Japanese and U.S. data sets.[31] Also, there is no evidence of a positive effect of foreign spillovers on domestic innovation. Hausman, Hall, and Griliches have also developed a ''fixed effect'' version of the negative binomial estimator. Results from this specification are provided in the second and fourth columns of Table 4 for regressions using the Japanese and U.S. data, respectively. Again, the hypothesis of equality of the coefficients for domestic and foreign spillovers can be rejected at well below the conventional levels of significance in both the U.S. and the Japanese data.

### 5.3. Results from a ''productivity growth'' equation

As an alternative to the results based on patents, I also present empirical evidence based on the ''long difference'' form of the Cobb–Douglas production function derived in Eq. (14). Unlike the relationship between patents and R&D, the relationship between R&D and revenues is subject to fairly long, variable lags.

[30] If the error term does *not* follow the assumed negative binomial distribution, there is no guarantee, even asymptotically, that the results are consistent. The results are robust only to certain forms of heteroskedasticity, and the omission of relevant variables, even those *not* correlated with the included variables, can also lead to biased results.

[31] One can easily conduct a Wald test of the equality of the coefficients on the domestic and foreign spillover terms. In all cases, the test statistics easily exceeded the critical values at well below the 1% significance level.

Table 4
Negative binomial regressions[a]

| | Japanese firms | | U.S. firms | |
|---|---|---|---|---|
| | n.b. totals | Fixed effects | n.b. totals | Fixed effects |
| Log R&D | 0.7987 | 0.8483 | 0.8107 | 0.8056 |
| | (0.0273) | (0.02110)) | (0.0203) | (0.0329) |
| Log domestic spillovers | 1.246 | 1.275 | 0.7267 | 0.8123 |
| | (0.1591) | (0.1347) | (0.1710) | (0.2278) |
| Log foreign spillovers | −0.7970 | −1.518 | −0.8152 | −0.8926 |
| | (0.1533) | (0.1245) | (0.1924) | (0.2589) |
| Test of equality | $\text{Chi}^2=46.04$ | $\text{Chi}^2=116.4$ | $\text{Chi}^2=18.06$ | $\text{Chi}^2=12.3$ |
| | $P=0.0000$ | $P=0.0000$ | $P=0.0000$ | $P=0.0005$ |
| Chemicals | −0.5487 | n.a. | 0.1541 | n.a. |
| | (0.1621) | | (0.1438) | |
| Machinery | −0.1710 | n.a. | 0.2950 | n.a. |
| | (0.1539) | | (0.1338) | |
| Electronics | −0.8230 | n.a. | −0.0194 | n.a. |
| | (0.1435) | | (0.1283) | |
| Transportation | −0.5256 | n.a. | 0.4027 | n.a. |
| | (0.1482) | | (0.1379) | |
| Time trend | −0.08331 | −0.0104 | −0.0081 | −0.0023 |
| | (0.0236) | (0.0311) | (0.0284) | (0.0525) |
| Log likelihood | −2965.91 | −3004.80 | −3468.8 | −3561.23 |

[a] Dependent variable: Patents.

Bringing an idea from the ''patent'' stage to the ''product'' stage requires several steps, each of which generates a lag between the time the initial R&D is performed and the period in which it has an impact on a firm's sales. Because of this, I estimate (14) using ''stock'' measures of a firm's own R&D and the spillover terms. Unfortunately, because of the limited time series dimension of the Japanese micro R&D data, the construction of these stocks is quite problematic and the resulting stock numbers likely contain a substantial degree of measurement error.[32]

Because revenue growth is affected by changes in demand and in the quality and price of factors of production other than technology, I attempt to eliminate the effect of these irrelevant fluctuations by ''averaging them out.'' Thus data preparation differs from that used with the patent equations. I use a longer sample period, 1983–1989. In my specification of (14), the variables consist of the differences in the logs of data averaged over the first 3 years of the sample and the

[32] Reliable R&D data prior to the early 1980s do not exist for most Japanese firms. In order to create an R&D stock series, I had to ''backcast'' R&D expenditures based on the time path of R&D spending during the sample period. Unfortunately, this means that the R&D stock numbers for Japanese firms are, to a large extent, *imputed*. This may introduce considerable measurement errors into the R&D stock measures. The implausibly small estimated coefficients for the own R&D stock term suggest that these measurement errors are leading to regression estimates which are biased toward zero.

data averaged over the last 4 years of this extended sample. In the U.S. panel, capital stock data are calculated using the perpetual inventory method. Data limitations in the Japanese panel require me to use the ''book value'' of a firm's capital stock, taken directly from the firm's accounts and deflated by the capital goods price deflator.[33] This introduces an additional source of measurement error, as accounting adjustments in the capital stock often have little basis in economic reality. Finally, data on raw materials expenditures are available at the firm level for Japanese firms but such data are not available for the U.S. sample. Because of all these caveats, the results from the production function are offered in the spirit of a ''reality check'' for the patent equation results.

Table 5, based on Japanese data, yields results that differ in some respects from the patent equation results. The coefficients on capital stock and own R&D stock are implausibly small and insignificant, suggesting that measurement error in these two variables is leading to a downward bias in the coefficients.[34] The presence of the bias clearly limits the inference we can make. The coefficients on the spillover terms are also estimated with less precision than is the case in the patent equations, and the foreign spillover term enters with a positive sign, providing some evidence that Japanese firms do benefit from U.S. research. However, while these coefficients are of reasonably large magnitude, the domestic spillover term is only

Table 5
Production function regression (Japanese data)[a]

| | |
|---|---|
| $\Delta$ Log (Capital) | 0.083 |
| | (0.057) |
| $\Delta$ Log (Labor) | 0.293 |
| | (0.083) |
| $\Delta$ Log (Materials) | 0.351 |
| | (0.087) |
| $\Delta$ Log (Own firm R&D) | 0.007 |
| | (0.051) |
| $\Delta$ Log (Dom. Pool) | 0.503 |
| | (0.322) |
| $\Delta$ Log (Foreign Pool) | 0.396 |
| | (0.314) |

[a] Dependent Variable: $\Delta$ Log (Deflated sales), Obs = 205.

[33] A full description of the Japanese capital stock data used in this paper is given in Branstetter (1996). The use of a capital stock measure computed using the perpetual inventory method would have been preferable to the deflated ''book value'' measures used here. Unfortunately, given the data limitations I confronted, this alternative was not feasible.

[34] I should note that attempts to estimate production functions using the ''within'' dimension of similar micro-level panels often produce estimates implying decreasing returns to scale. The micro ''R&D/productivity'' literature is full of such results. See Griliches and Hausman (1986) and Griliches (1984) for some examples and references.

marginally significant[35] and foreign spillovers are statistically indistinguishable from zero. The general qualitative pattern of the greater impact of domestic spillovers (both in terms of magnitude and significance) holds here as well, but it is difficult to interpret this result given the obvious data problems.

Finally, I offer results based on a ''production function'' approach for the U.S. data in Table 6. The production function results seem more plausible than those for the Japanese sample, reflecting the higher quality of the U.S. data, and, in particular, the much longer time series dimension of the U.S. micro R&D data, which allows for more accurate construction of R&D and spillover ''stocks.'' These results are broadly consistent with the results from the patent equations.

### *5.4. Comments on results*

One of the striking features of the results is the frequency with which foreign spillovers are estimated to have a negative impact on innovative output, though I should point out that in many cases the coefficients are not statistically distinguishable from zero. There are two potential explanations for this finding. The first refers back to points raised in Footnotes 12 and 13. For clarity, I repeat some of the points already made in the text. We do not observe the ''pure effects'' of knowledge spillovers on firm innovation, which constitute an unambiguously positive externality. We instead observe the effects of knowledge spillovers on economic manifestations of the firms' innovation, such as patents or revenues. For this reason, the positive technological externality is possibly confounded with a negative effect of other firms' research due to competition. Because of this, if

Table 6
Production function regression (U.S. data)[a]

| | |
|---|---|
| $\Delta$ Log (Capital) | 0.302 |
| | (0.010) |
| $\Delta$ Log (Labor) | 0.512 |
| | (0.094) |
| $\Delta$ Log (Own firm R&D) | 0.366 |
| | (0.119) |
| $\Delta$ Log (Dom. Pool) | 0.829 |
| | (0.439) |
| $\Delta$ Log (Foreign Pool) | $-0.244$ |
| | (0.180) |

[a] Dependent variable: $\Delta$ Log (Deflated sales), Obs = 209.

[35] A one sided test would find domestic spillovers to be significant at the 10% level. The foreign spillovers term does not meet even this unusually generous threshold.

actual flows of knowledge are weak — or nonexistent — and rivalry is strong, our estimates of the $\gamma$'s may be negative.[36]

In other words, firms can be engaged in a patent race, in which the successful research outcomes of competing firms can ''block'' the firm's own patenting efforts. If one is learning a great deal from domestic competitors, than this negative effect due to competition is outweighed by the positive effect of knowledge spillovers. A similar pattern could be observed in the production function regressions. Competition in the product market can lower revenues earned from new products, leading to a negative effect of others' research on ones own revenues. If the underlying knowledge spillover is strong enough, then the net effect estimated will be a positive one.

For this interpretation to be correct, one would need strong reasons to think that there is a substantial difference in the underlying knowledge spillovers within countries versus the spillovers that flow between them. Recent survey evidence and econometric evidence suggests that this is in fact the case. Econometric analysis of U.S. patent citations data and bibliometric studies of the biological sciences literature both show that innovators are far more likely to cite other innovators in the same country than would be expected given the distribution of research resources across time, fields, and countries. This statistical evidence of the localization of knowledge spillovers is confirmed by the survey evidence presented by Goto and Nagata (1997). These authors conducted a survey which directly asked Japanese and U.S. corporate R&D managers where they perceived their ''spillover'' benefits to be coming from. The survey results indicate that knowledge spillovers are perceived by industry participants to be largely intranational in scope, further corroborating the central finding of this paper.

An alternative explanation of the finding of a ''negative'' effect of knowledge spillovers is that this finding is an artifact of the data, driven by multicollinearity problems. In fact, the domestic and foreign spillover terms are highly correlated with one another.[37] Because there is little independent variation in the two series, regressions could, in principle, produce coefficients with the ''wrong'' sign, as often happens in the case of severe multicollinearity. In results not reported here, I ran a number of regressions in which the foreign spillover term was entered without the domestic spillover term. What I found was that, even when entered independently into the regression equation, the foreign spillover term often has a negative coefficient.[38] This suggests that the results reported herein are not purely

[36] The language used in this paragraph closely follows Jaffe (1986), who describes a similar issue in his paper.

[37] This is illustrated in Branstetter (1996). The simple correlation coefficient of (log) domestic spillover and foreign spillover terms is 0.855 in the Japanese data and .906 in the U.S. data.

[38] For instance, when entered by itself into a fixed effects model with time dummies, the foreign spillover term has a negative (but statistically insignificant) coefficient in the Japanese data. In the U.S. data, foreign spillovers enter with a negative coefficient in every specification tried.

driven by multicollinearity, and that the first explanation is likely to be the correct one.

Taking the results at face value, we can briefly discuss their economic implications. The coefficients are expressed in terms of elasticities. For instance, the coefficients estimated by the random effects model with the Japanese data imply that a 100% increase in the level of own R&D spending generates a 59% increase in the level of patenting. On the other hand, a 100% increase in the level of the R&D spending of domestic firms implies an increase in patenting of approximately 111%. Finally, an increase in the R&D spending of foreign firms generates, all other things equal, a decrease in own patenting, though the negative coefficient on the foreign spillover term is statistically indistinguishable from zero at conventional levels. Results using U.S. data and results obtained through the use of a negative binomial model are broadly similar in magnitude. At first glance, these results seem to imply implausibly large intranational spillover effects. However, they are quite consistent with the view of R&D as having the attributes of a local public good. They are also consistent with knowledge spillovers playing the role of ‘‘engine of endogenous growth’’ as has been stressed in recent theory. Finally, these results are broadly consistent with those obtained using U.S. data and a slightly different specification by Jaffe (1986), who found an elasticity with respect to the (domestic) spillover term of approximately 1.1.

To give the reader a sense of the economic magnitudes involved, I have calculated the number of patents generated by one billion yen of ‘‘internal’’ and ‘‘external’’ R&D. Evaluated in terms of marginal products at the mean of the Japanese data, the random effects coefficients imply that one billion yen of own R&D spending generates 1.6 patents and one billion yen of other (domestic) firms’ R&D spending generates 0.076 patents. Because any one firm’s own R&D investment is small relative to the potential spillover pool, the impact of other firms’ R&D spending is a very important factor in explaining innovative performance at the firm level. I note that these figures should be interpreted with some caution. Recall from the definition of $T_{ij}$ that the proximity coefficients, with which the spillover pools are calculated, are not normalized.[39] The implications of this for interpretation of my empirical results can perhaps be best summarized as follows. The ‘‘true’’ technologically relevant spillover pools could be one tenth as large as my calculated spillover pools suggest. If so, that would not effect my estimated elasticities, but it would affect the implied marginal products.

Finally, I wish to comment on the variations in the results across the different specifications. One consistently finds quite pronounced differences in the measured impact of domestic and foreign spillovers in the patent regressions using both

[39] See Eq. (2). Jaffe (1986) encounters a similar problem.

linear and negative binomial models on both U.S. and Japanese data. In the case of the U.S. production function regression, given in Table 6, while we cannot reject the null hypothesis of equality of the coefficients, this is primarily because the foreign spillover term is estimated with very little precision. It is worth noting, however, that the qualitative pattern of a positive, significant impact of domestic spillovers and a negative, but insignificant impact of foreign spillovers is quite consistent with our findings from the patent regressions. On the other hand, in the Japan production function regression, given in Table 5, there is little qualitative difference in the measured impact of the two spillover terms, and neither is statistically significant at conventional levels. Given the evident downward biases in the other regression coefficients, however, it is difficult to argue that these results are very informative. The lack of much of a time series on R&D data with which to construct an R&D stock and the obvious measurement problems in the capital stock data make it difficult to draw strong conclusions from these results. I take some assurance from the fact that the qualitative pattern of relatively stronger intranational knowledge spillovers is reflected in these data as well.

## 6. Conclusions and extensions

In general, the data support the following conclusions:

*1. There is strong evidence of intranational knowledge spillovers.*

*2. There is limited evidence that Japanese companies benefit positively from research undertaken by American firms. However, there are no specifications in which the estimated impact of foreign spillovers is positive and significant once domestic spillovers are controlled for.*

*3. There is no evidence that American companies benefit positively from research undertaken by Japanese firms. In fact where the effect is statistically distinguishable from zero, it is negative.*

The implications of these findings for the theoretical and empirical literature are potentially quite significant. They clearly lend credence to a number of models that generate multiple equilibria in trade flows, allow comparative advantage to be determined endogenously, and allow temporary government policies to have a lasting (perhaps even permanent) impact on trade. They also lead to a whole nexus of research questions. What are the barriers to the flow of knowledge spillovers across countries? Will they become less important over time as multinational firms conduct more R&D abroad and become more aggressive and proficient in transferring their existing knowledge capital abroad?

The implications for policy are also potentially significant, and lead to some natural extensions of the paper. My results certainly support the view that private R&D has public good aspects and that the private marginal product of investment in R&D may be considerably lower than the social marginal product. In addition, because these effects are intranational in scope, they lend some support to the view that there may be strategic reasons for supporting private R&D.

The potential benefits of such policies have not been lost on the Japanese. Since Spence (1984), numerous economists have explored the possibility of using research consortia to ‘‘internalize’’ the externalities created by R&D. No nation has utilized this policy instrument more intensely than Japan. Surprisingly little serious empirical research has been done on these consortia.[40] Ongoing research with Mariko Sakakibara of the Anderson Graduate School of Management at UCLA is using the data developed here to estimate the impact of participation in a joint venture on Japanese firms' ex-post R&D spending, patenting in Japan and the U.S., and measures of intranational spillovers. We present evidence in Branstetter and Sakakibara (1998) and Branstetter and Sakakibara (2000) that participation in consortia has had a positive impact on the innovative activities of participating firms.

It is also well-known that Japanese firms frequently collaborate with their suppliers or customers in the development of new products even without the inducements of government-organized consortia. This kind of collaboration is often concentrated in the vertical *keiretsu* groups. To what extent is Japanese industrial organization responsible for the high estimates of intranational spillovers in these data?[41] Using micro-level data on affiliation to vertical keiretsu groups, I have investigated this potential linkage in Branstetter (2000a), comparing the spillovers of affiliated firms to non-affiliated firms, and examining the intra-group correlation of productivity residuals. This paper documents evidence of a relationship between *keiretsu* affiliation and spillovers of process technology.

While this paper has found little evidence of a strong impact of international spillovers on the ‘‘average’’ Japanese firm in the sample, it is likely that these effects confer greater benefits on some firms than others. Does the impact of international spillovers correlate in any way with measures of exports to the U.S. market or FDI in the U.S.? For decades, observers have attributed some component of Japan's success to its focus on exports to advanced country markets. Might this have augmented Japan's ability to effectively absorb new technological knowledge embodied in the products of U.S. competitors? Alternatively, given the degree to which knowledge spillovers seem to flow within countries but not between them, might setting up subsidiaries in the U.S. provide Japanese firms with a channel through which to more effectively absorb these knowledge

[40]See Wakasugi (1986) for an excellent summary of the issues involved and some ‘‘case study’’ evidence on the effectiveness of the consortia.

[41]See Suzuki (1993) for another analysis of the effects of vertical keiretsu ties on innovation.

spillovers? Preliminary evidence on these points is provided in Branstetter (2000b). In that paper, I allow the international spillover elasticity to vary across firms depending on the fraction of their total sales that is exported to the U.S. market. In a separate specification, I allow the international spillover elasticity to vary according to the firm's stock of FDI in the U.S. The preliminary results suggest that the impact of knowledge spillovers *is* positively correlated with both firm-level measures of ''exposure'' to the U.S. market.[42]

Finally, it is my hope that this paper will stimulate additional research in international economics at the firm level employing the types of data used here. Knowledge capital and innovation are not only at the core of the ''new'' models of trade and growth, but they also figure prominently in existing theories of foreign direct investment and in the theory of the multinational firm. Detailed, publicly available data at the producer level exists on these assets, and the econometric techniques developed by the micro productivity literature should find fruitful application in testing a number of the hypotheses generated by these theories. Intellectual arbitrage between these two fields (or, exploiting the spillovers between them) should increase the research productivity of both.

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[42]This point is being further investigated in Branstetter (2000c), with a more direct measure of knowledge spillovers-patent citations. This study finds evidence that Japanese firms' FDI in the U.S. functions as a channel of knowledge spillovers from the U.S. to Japan *and* from the investing Japanese firms to ''local'' U.S inventors.

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