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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 a number of theoretical models, it has been shown that technological externalities can generate multiple equilibria in the global pattern of specialization and trade, with different consequences for the relative welfare of the trading countries. In such models, temporary government policies can have lasting effects by pushing the global economy into a particular equilibrium. However, the prediction of multiple equilibria generally hinges on the assumption that the technological externalities are *intranational* rather than international in scope.

In this paper, I point out important shortcomings in previous attempts to estimate the effects of intranational and international knowledge spillovers. Then, 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 which provide a rich description of the firms' technological activities and allow for potentially much more accurate measurement of spillover effects.

My estimates indicate that knowledge spillovers are primarily *intranational* in scope, providing empirical confirmation of a crucial assumption in much of the theoretical literature. This finding has important implications for the theoretical literature and the public debate on "strategic trade policy."

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I. 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. Krugman (87) and Young (91) examined learning-by-doing, and Grossman and Helpman (90, 91) have looked at knowledge externalities. 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 the traditional Heckscher-Ohlin framework, this equilibrium is unique, and is determined by exogenous factor endowments.[2] In the new models, there are multiple equilibria with different consequences for the relative welfare of the trading countries. Comparative advantage itself is endogenously determined, and can be permanently affected by temporary government policies. These theories have been seized on by industrial policy advocates as providing a theoretical rationale for the protection or promotion of domestic producers in high-technology sectors.[3]

However, in order to obtain such multiple equilibria, one must generally assume that technological externalities are *intranational* in scope. As Grossman and Helpman have explicitly shown, even in a model with innovation and technological change, trade patterns can still be ultimately determined by factor endowments if technological externalities are global in scope. Thus the policy implications, even the policy relevance, of many of these models depend on technological externalities being to some extent, local in scope. Are they? Given the central importance of this issue in the theoretical literature, surprisingly little work has been done to answer this question.

This paper 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 intranational spillovers are stronger than international spillovers. This finding is consistent across alternate econometric specifications as well as data from

[2] To be precise, the equilibrium of trade in goods is unique only when there are as many goods as there are factors. With more goods than factors, the equilibrium becomes indeterminate. However, the implicit trade in factor services can still be predicted from factor endowments. See Krugman and Helpman (84) for an explanation and comparison with alternative models.

[3] See the recent book *Who's Bashing Whom: Trade Conflict in High-Technology Industries*, by Laura Tyson, for a particularly thorough exposition of this kind of argument.

different countries. The implications of this finding for the theoretical literature and for policy are quite significant, and are discussed in the conclusion.

Before going any further, I wish to be precise about exactly what sort of externality I am attempting to measure and why I chose it. My work is most closely related to the theoretical contributions of Grossman and Helpman (90, 91), who 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.[4] 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 endogenous engine of economic growth.

Do the results of traditional models, where the pattern of trade is determined by comparative advantage, still hold in a world of innovating countries? 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.[5]

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[4] In a typical formulation, $\dot{n}_i = \dfrac{L_{ni} K_i}{a_{L_{ni}}}$

where "n dot" is the rate of new product introduction, L is the level of research employment, a is the productivity of research labor, and K is the stock of general knowledge. Here the "knowledge stock" enters directly into the firm's "knowledge production function."

[5] With two countries, the total stock of general knowledge becomes

$$K_{it} = \lambda_h \int e^{\lambda_h(\tau - t)} n_i(\tau) d\tau + \lambda_f \int e^{\lambda_h(\tau - t)} n_j(\tau) d\tau$$

where λ_h is the rate of knowledge spillover within country i, λ_f is the rate of spillover between countries, n_i is the number of innovations at home by time τ, and n_j is the number of innovations abroad. If $\lambda_h = \lambda_f$, then firms in both countries will have access to the same level of knowledge even if knowledge generation occurs more rapidly in one of the countries. If they are different, then firms in the country with a higher initial level of innovation will have a greater stock of

On the other hand, if the rate of knowledge spillover is much stronger within nations than across them, then patterns of trade are no longer necessarily determined by factor endowments. Instead, they can exhibit path dependence. For example, a country that 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. It is possible that by limiting trade temporarily or subsidizing industry R&D, a country could "build up" an R&D-intensive sector, resulting in the establishment of a comparative advantage in that sector, arising not from exogenous factor endowments but endogenous innovation. Here, temporary policies can have permanent effects on the pattern of trade.[6]

There may be welfare consequences as well. Under certain conditions, economic growth and wages can be higher in the country with the comparative advantage in the "high-technology" (i.e., R&D-performing) sectors. This happens, for instance, in Grossman and Helpman's work in cases in which the steady-state equilibrium is outside the factor price equalization set.

This theoretical framework is not without its critics.[7] Furthermore, a general test of the model's full implications for policy could be extremely difficult given its complicated structure and the extreme assumptions the authors make to derive a closed form general equilibrium solution, and is beyond the scope of the present paper.[8] My goal is not to justify this framework so much as to test one of its key assumptions.

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knowledge on which to draw, and will, by the previous equation, become more productive in subsequent innovation.

[6] See also Krugman (87) for an earlier model which generates similar results.
[7] The most serious problem is their assumption that past knowledge is never rendered obsolete by new innovation. This assumption leads to the unrealistic empirical implication that an increase in the resources devoted to R&D leads to an increase in the growth rate of the economy. In reality, the stock of knowledge does depreciate over time due to technological obsolescence. See the critique by Charles Jones (1995) and the work by Caballero and Jaffe (1994).
[8] See work by Charles Jones (95) which tests the relationship between changes in R&D spending and changes in macroeconomic growth rates implied by these models.

For multiple equilibria in trade to exist, it must be the case that intranational spillovers are relatively stronger than international spillovers. Following the spirit of this model, I derive an empirical framework that allows us to estimate the steady state relationship of new increments to the general knowledge stock, or "flows" of spillovers, from foreign and domestic sources, on the innovative performance of the average firm in Japan and the United States.

II. 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 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 they spill over internationally.[9] They find that learning-by-doing spillovers do exist, but that they are much less important than the effects of own-firm production experience.[10] Furthermore, they cannot distinguish empirically between intranational spillovers and international spillovers in the data. Finally, they find little evidence that production experience in one generation of DRAM chips has a significantly positive effect on firm productivity in the production of the next generation.

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. These assumptions make a firm's marginal cost a

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[9] They estimate

$$c_i = \nu * E^{\beta_i} * e^{ui}$$

where c is marginal cost and E is the cumulative production experience of the firm.

[10] Here experience also includes production external to the firm, such that $E_i = Q_i + \alpha(Q_c - Q_i) + \gamma(Q_w - Q_c)$ where Q_c is the production experience of all other domestic producers and Q_w the production experience of all world producers. Thus α captures the effect of intranational spillovers and γ the effect of international spillovers.

linear function of its market share and the market price. To the extent that this assumption fails to hold, the dependent variable is mismeasured.[11]

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. Given their focus on learning-by-doing spillovers, this is understandable. Nevertheless, the semiconductor industry is one of the most R&D-intensive sectors in manufacturing, and has been characterized by a great deal of product innovation as well as cost reduction. It is reasonable to suppose that "knowledge spillovers" of the kind modeled by Romer, Grossman and Helpman, and Aghion and Howitt may also be important in this sector and are worth exploring.

Looking more generally at the R&D-intensive sectors, it is difficult to identify industries with learning curves as steep and pervasive as those in semiconductors. However, knowledge spillovers may be quite pervasive and important in a number of sectors. Furthermore, knowledge spillovers may ultimately be more significant as an engine of endogenous growth. While learning-by-doing is certainly important, the economic gains from the refinement of production techniques are probably product-specific (a result supported by Irwin and Klenow's results). Over time, the R&D-intensive sectors of the economy may create more producer and consumer surplus through the introduction of new and better goods and services, rather than the ever more efficient production of existing goods and services. It is difficult to imagine this kind of fundamental innovation being driven by learning-by-doing. Finally, one of the central arguments offered for the promotion of the semiconductor industry is based on the spillovers it provides to *related* industries like downstream computer manufacturers and upstream semiconductor manufacturing equipment producers. Irwin and Klenow's empirical framework does not measure these intersectoral spillovers. Thus, this paper complements the work of Irwin and Klenow by examining knowledge spillovers in five R&D-intensive sectors.

This paper is not the first to attempt to measure international "knowledge spillovers." Coe and Helpman (95) and Mohnen and Bernstein (94) have done so, using country-level data to assess the

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[11] To be precise, they assume that $p * (1 + \frac{s_i}{\eta}) = c_i$ where s_i is the market share of firm i, η is the price elasticity of demand for semiconductors, p is the market price and c_i is the marginal cost of firm i.

statistical relationship between aggregate R&D capital accumulation abroad and own country growth in total factor productivity. Keller (95) has taken a similar approach using 2-digit industry data from 8 countries. In both cases, taking the country or industry as the unit of observation, a pool of external R&D is constructed using data on bilateral trade flows.[12] Coe and Helpman, in particular, find evidence of extremely potent international R&D spillovers. Their results suggest that the "output elasticity" of international spillovers is virtually identical to that of intranational spillovers.

The problem with econometric work at this level of aggregation is that 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. The impact of true knowledge spillovers must be proportional to proximity in "technology space." 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. We are more likely observing common demand or input price shocks or a common time trend than actual spillovers. This problem has been underscored by recent research conducted by Wolfgang Keller (96). He finds, using the Coe-Helpman data set, that when one weights "foreign" aggregate R&D by randomly created "trade matrices" rather than the actual measures of bilateral trade, one typically gets even *higher* coefficients on the "foreign" R&D term than those reported by Coe and Helpman.

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

[12] These models typically posit aggregate (or industry-level) total factor productivity growth as being a function of own R&D and the R&D of trading partners j not equal to i, so that $TFP_i = F(R_i, S_i)$ where S_i, the spillover term, is a weighted sum of external R&D, and where the weights are measures of bilateral trade, T_j, such that $S_i = \sum_{i \neq j} R_j T_j$

as "mismeasurement spillovers" -- correlations resulting from the misclassification of R&D data at the industry level.[13]

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.

III. Empirical Methodology

This paper builds on the methodologies suggested by Zvi Griliches (1979) and first implemented by Adam Jaffe (1985). 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

$$F_i = (f_1 \dots f_k) \tag{1}$$

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.

I 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, I calculate for each firm in my sample a single location vector based on its patenting behavior over the entire sample period. By construction, I am assuming that firms remain in that position over the entire period.

13 Personal communication with author.

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. 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 P_{ij} where P_{ij} is the uncentered correlation coefficient of the F vectors of the two firms, or

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

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 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, P_{ij}, used as weights. More simply, suppressing time subscripts here and in the equations below for expositional convenience, the intranational, or "domestic" spillover pool for the ith is K_{di}, where K_{di} is

$$K_{di} = \sum_{i \neq j} P_{ij} R_j \tag{3}$$

Here R_j is the R&D spending of the jth firm (j not equal to i) and P_{ij} is the "similarity coefficient." Similar, the potential international, or "foreign," spillover pool is computed as

$$K_{fi} = \sum_{i \neq j} P_{ij} R_j \tag{4}$$

Where R_j is the R&D of firms based in a foreign country, again weighted by the P_{ij} 's. Assume that innovation is a function of own R&D and external knowledge. Then, the "innovation production function" for the ith firm is

$$N_i = R_i^{\beta} K_{di}^{\gamma_1} K_{fi}^{\gamma_2} \Phi_i \tag{5}$$

where

$$\Phi_i = e^{\sum_c \delta_c D_{ic}} e^{\varepsilon_i} \tag{6}$$

Here the δ's can be thought of as exogenous differences in the "technological fecundity" of c different technological fields.

Taking the logs of both sides of (5) and adding time subscripts 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 the propensity to generate new knowledge across technological fields (indicated by the subscript c), and ε is an error term.[14]

Our understanding of the way spillovers combine with own firm R&D to generate innovation is sufficiently limited that the choice of functional form here is somewhat arbitrary. My choice reflects the influence of Jaffe's approach and the belief that external knowledge is more likely to enter the knowledge production function as a complement than as a substitute to the R&D of the firm.[15]

Now we come to a pivotal question: how do we measure innovation? In fact, there are no direct measures of innovation, so tracking "innovation" will require the use of indirect and noisy empirical proxies. If some fraction of new knowledge is patented, such that the number of new patents generated by the ith firm is an exponential function of its new knowledge,

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[14] One might suppose that external R&D only enters into the knowledge production function with a long and variable lag. Empirical research suggests that the time required for new innovation to "leak out" is actually quite short, with the precise lag structure being difficult to identify. See work by Mansfield (85) and Caballero and Jaffe (94). I will return to this question in the discussion of empirical results.

[15] An alternative specification would be one in which innovation is a function of total R&D, both internal and external, such that $N_i = T_i^{\alpha}$ where $T_i = (R_i + \theta K_i + \vartheta K_i)$. Taking the logs of both sides yields the following nonlinear relationship: $n_i = \alpha \ln(R_i + \theta K_i + \vartheta K_{Ai})$. At this stage of research, the choice of functional form is somewhat arbitrary. My specification yields an estimating equation in which the treatment of random and fixed effects is straightforward. Furthermore, it is true to the spirit of the models of Grossman and Helpman in that an increase in external R&D increases the innovation-maximizing level of internal R&D effort. Finally, the use of nonlinear functional forms yielded estimates which are qualitatively similar to the ones reported for the linear case. I thank Sam Kortum for discussions which clarified my thinking on these points.

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

then the production of new knowledge can be proxied by examining the generation of new patents. 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 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 "technological fecundity" of the cth industry, as in (6), and the usefulness of patents as a tool of appropriation in the cth industry. It is known that strong differences in both factors exist across industries.

In some sense, the interpretation of the γ 's changes as well. 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. 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, firms may sometimes find themselves competing 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.[16] Because of this, if actual flows of knowledge are weak and rivalry is strong, our estimates of the γ 's may be negative even though the underlying knowledge externality is positive.

[16] To make this explicit, we can decompose the γ 's in the following fashion:

$$\gamma = \left(\frac{\partial n}{\partial k}\frac{k}{n} - \frac{\partial p}{\partial k}\frac{k}{p}\right)$$

In other words, the γ 's that we observe are the net result of two opposite effects -- the "true" positive technological externality of external knowledge on firm i's innovation $\frac{\partial n}{\partial k}$, and a negative "patent race effect," $\frac{\partial p}{\partial k}$ in which the ith firms ability to patent new innovation is crowded out by the previous patenting of competitive firms. Adam Jaffe (86) and others have also made this point.

Some attention needs to be devoted to the assumed properties of the new error term. Allowing the propensity to patent to vary across firms in a way not correlated with the other regressors creates a systematic component to the error - an individual effect such that

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

where the latter term is assumed to be a normal "iid" disturbance. If ξ_i is uncorrelated with the right hand side regressors, then this effect can be estimated using the "random effects" framework developed by Maddala.

One can imagine, though, that this individual effect in the propensity to patent may be 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 firm's 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 effect" estimator. 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 propensity to patent does vary widely across industries. I can control for this to some extent with industry dummy variables. I make the assumption that an individual firm's propensity to patent does not change over time -- a reasonable assumption given the short time dimension in my data, but still not necessarily true. There are other problems with using patents as indicators of innovative activity. 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. For these reasons, 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, 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, suppressing time subscripts, output can be described as

$$Q_i = C_i^{\alpha} L_i^{\beta} R_i^{\phi} K_{di}^{\varphi} K_{fi}^{\rho} e^{\varepsilon_i} \tag{11}$$

taking the logs of both sides gives us

$$q_i = \alpha c_i + \beta l_i + \phi r_i + \varphi k_{di} + \rho k_{fi} + \varepsilon_i \tag{12}$$

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 via the perpetual inventory method.[17] Again, we allow for the existence of individual effects which are potentially correlated with the right hand side regressors, such that

$$\varepsilon_i = \lambda_i + u_i \tag{13}$$

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 variables of interest, the "within" estimate may have a serious bias of its own.[18] Following Hausman and Griliches (86), 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.

$$q_{iT} - q_{i0} = \alpha(c_{iT} - c_{i0}) + \beta(l_{iT} - l_{i0}) + \phi(r_{iT} - r_{i0}) + \varphi(k_{iT} - k_{i0}) + \rho(k_{AiT} - k_{Ai0}) + (\lambda_i - \lambda_i) + u_{iT} - u_{i0} \tag{14}$$

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.

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. As a result of this additional noise, it may be considerably more difficult to distill a relationship between

[17] A full discussion of why the use of stock measures is appropriate here is given in section V.

[18] Here, serious measurement error is a virtual certainty. Research by Griliches and Pakes (84) 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.

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 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.

IV. 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. They are also highly integrated economically. Japan is disproportionately dependent on the United States both as a market for its exports and a source of its imports, particularly high-technology imports. Likewise, the United States trades more with Japan than with any other country with which it does not share a border. 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.

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 as indicators of both 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 and large jumps in the time series of individual firms. 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.[19] Table A gives some summary statistics for the Japanese sample.

Similar data was gathered for American firms from the same industries. 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 removed in the interest of avoiding large outliers. Table B gives sample statistics for the U.S. sample.

V. Empirical Analysis

Empirical Results for Japan

This section presents results from a linear regression framework. Suppressing time subscripts, the estimating equation is

$$p_i = \beta r_i + \gamma_1 k_{di} + \gamma_2 k_{fi} + \sum_c \delta_c D_{ic} + \mu_i \tag{9}$$

where p is the log of patents for firm i in the j year, 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.

[19] Here I use the U.S. patents of Japanese firms to locate them in technology space and to measure their innovation. I also have data, not used in this draft, on the Japanese patents of these firms. 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 are extremely aggressive about patenting their inventions in the U.S. as well as Japan. Japanese firms now account for about 25% of new patents in the U.S., by far the most important foreign users of the American patent system.

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, a long tradition of empirical research on patenting by U.S. firms has failed to identify the lag structure of past R&D investment on current patenting. Most research indicates that the relationship between patenting and R&D is largely contemporaneous.[20] Inventions must represent some advance in the state of the art to qualify for patent protection. In R&D-intensive industries, where the state of the art is rapidly advancing, it may be the case that only the firm's most recent R&D is associated with inventions that meet that test. It also seems to be the case that firms tend to take out patents at a relatively early stage in the research and development process to preempt the competing claims of other firms in the product development stage. Based on these results, my specification of equation (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.[21] 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.

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[20] Hausman, Hall, and Griliches (86) found essentially no effect of past R&D investments on current patenting.

[21] See Mansfield (85) and Caballero and Jaffe (93).

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.[22] My final defense for the use of "flow" spillover measures is this: given my data limitations, I purport to measure only the long-run steady-state relationships between the variables of interest. A full-blown study of the dynamics would require richer data and substantially longer time series.

In Table 3, the first column and second columns present coefficients and "White" standard errors for OLS versions of (9) in which domestic and foreign spillovers are entered along with own R&D into separate equations. The third column presents results for an OLS regression with White standard errors for both spillover terms. The fourth column is the "random-effects" panel estimator proposed by Maddala using both terms, and the fifth column is the "fixed-effects" or "within" panel estimator using both terms. The sixth column reestimates the fixed-effects model using time dummies. *A Hausman test rejects the random effects estimator in favor of a fixed effects estimator*, and firm-level heterogeneity in patenting and R&D spending suggests that firm effects are important.[23]

In all models but the fixed effects specification without time dummies, 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, there are clear qualitative differences in the estimated impact of the two kinds of spillovers, and although the domestic term is significant, the international term is statistically indistinguishable from zero.

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[22] 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 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 and Mairesse (84).

[23] A frequent problem encountered in this type of this specification is that, for a non-negligible number of firm-years, there are no patents generated. To fit that outcome into the log-linear model, I set the log of patents for those observations equal to zero. This is the standard adjustment used in this literature. A better approach may be to use a statistical model formulated specifically to handle count data. Such a model is derived in the appendix and estimated in the following table, with results similar to those of the log-linear model.

When time dummies are used in the fixed effects specification, the sign of foreign spillovers changes and we are again able to reject the hypothesis of equality at the 5% level.

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. 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 (84). Here, I summarize their results, borrowing extensively from the presentation of these basic results found in Montalvo and Yafeh (94).

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

$$pr(n_{it}) = f(n_{it}) = \frac{e^{-\lambda_{it}} \lambda^{nit}{}_{it}}{n_{it}!} \tag{15}$$

where $\lambda_{it} = e^{X_{it}\beta}$ (16)

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

$$\lambda_{it} = e^{X_{it}\beta} + \varepsilon_i \tag{17}$$

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

$$\Pr[N_{it} = n_{it}] = \int \Pr[N_{it} = n_{it} | \lambda_{it}] f(\lambda_{it}) d\lambda_{it} \tag{18}$$

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

$$\lambda_{it} = \Gamma(\alpha_{it} \varphi_{it}) \tag{19}$$

where

$$\alpha_{it} = e^{X_{it}\beta} \tag{20}$$

then

$$\Pr(n) = \int_0^\infty \frac{e^{-\lambda_{it}}\lambda_{it}}{n_{it}!}\frac{\lambda_{it}^{-1}}{\Gamma(\varphi_{it})}[\frac{\varphi_{it}\lambda_{it}}{\alpha_{it}}]^{\phi_{it}} e^{\phi_{it}\lambda_{it}\int\alpha_{it}} d\lambda_{it} \tag{21}$$

where

$$E(\lambda_{it}) = \alpha_{it} V(\lambda_{it}) = \frac{\alpha_{it}^{2}}{\phi_{it}} \tag{22}$$

Integrating by parts and using the fact that

$$\Gamma(\alpha) = \alpha\Gamma(\alpha-1) = (\alpha-1)! \tag{23}$$

yields the following distribution

$$\Pr(n_{it}) = \frac{\Gamma(n_{it}+\phi_{it})}{\Gamma(n_{it}+1)\Gamma(\phi_{it})}[\frac{\phi_i}{\alpha_{it}+\phi_{it}}]^{\phi_{it}}[\frac{\alpha_{it}}{\phi_{it}+\alpha_{it}}]^{n_{it}} \tag{24}$$

with

$$E(n_{it}) = \alpha_{it} \tag{25}$$

and

$$V(n_{it}) = \alpha_{it} + \alpha_{it}^{2} / \phi_{it} \tag{26}$$

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

$$L(\beta) = \sum_i \sum_t \log\Gamma(\lambda_{it}+n_{it}) - \log\Gamma(\lambda_{it}) - \log\Gamma(n_{it}+1) + \lambda_{it}\log(\delta) - (\lambda_{it}+n_{it})\log(1+\delta) \tag{27}$$

with

$$V(n_{it}) = e^{X_{it}\beta}(1+\delta)/\delta \tag{28}$$

Thus, the coefficients are estimated using standard maximum likelihood techniques. Estimates from a simple negative binomial model 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. Hausman, Hall, and Griliches have also developed a "fixed effect" version of the negative binomial estimator. The derivation of this estimator is given in the technical appendix. Results are provided in the third column of Table 4.

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 equation (14). Unlike the relationship between patents and R&D, the relationship between R&D and revenues is subject to fairly long lags. 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.

Because revenue growth is affected by changes in demand and in the quality and price of factors of production other than technology, we 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 log differences in the data averaged over the first 3 years of the sample and the 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. This introduces an additional source of measurement error, as accounting adjustments in the capital stock often have little basis in economic reality. Furthermore, the shorter time series available on Japanese firms' R&D spending means that a relatively higher degree of imputation is necessary to construct the R&D stock variables. 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 are very consistent with 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. The presence of the bias limits the inference we can make, but the coefficients on the spillover terms are very consistent with the results from the patent equations. Domestic spillovers are strongly positive and significant at conventional levels. Foreign spillovers are statistically indistinguishable from zero.

Results from U.S. Data.

A U.S. panel of 209 high-technology manufacturing firms was prepared along the same lines as the Japanese panel. Empirical results from this sample were broadly consistent with those obtained for Japan. Table 6 gives results for regressions based on a linear model.

There are a few differences with the Japanese results that I wish to comment on here. The domestic spillover effect is generally weaker and less robust in the U.S. data, depending on the specification. This is consistent with considerable anecdotal evidence suggesting that U.S. corporate R&D laboratories suffer from a "not-invented-here" syndrome, giving insufficient attention to technological developments outside the firm.

Table 7 gives results from a negative binomial model. Again, the negative binomial estimator results indicate the impact of the two types of spillovers is not equal.

Finally, I offer results based on a "production function" approach for the U.S. data in Table 8. The production function results seem more plausible than those for the Japanese sample, reflecting the higher quality of the U.S. data. They, too, are consistent with the results from the patent equations.

The empirical results are presented in terms of elasticities. In order to provide the reader with a sense of the economic magnitudes involved, I calculated the patents generated per one billion yen of "internal" and "external" R&D. Evaluated at the mean of the data for the Japanese sample, the coefficients from the "fixed effects linear model" in Table 3 imply that one billion yen of "own" R&D generated 2.1 patents in the U.S. (a figured quite similar to that of the U.S. firms, adjusted for exchange rate differences), whereas one billion yen of "domestic spillovers" yielded .06 patents and the same amount of foreign spillovers yielded .01 patents. This calculation, however, should be taken with a large grain of salt. The reason is that, with no obvious means of normalizing the P_{ij} matrices, the units of the spillover terms are arbitrary. Adam Jaffe explains this problem in greater detail in his paper (Jaffe, 86).

Comments on Results

Are these results plausible? The results for Japan seem plausible enough. The frequency with which foreign spillovers are negative, especially in the U.S. data, is certainly surprising. Of course, one can never rule out the possibility that these results are an artifact of the data. The use of diagnostic techniques to identify influential outliers seems to indicate that they are not driving these results. The data *are* characterized by a fairly high level of multicollinearity. In particular, the spillover terms are generally more highly correlated with one another than they are with the dependent variable or the other regressors.[24]

This multicollinearity is less pronounced in the "within" dimension of the data, which seem to produce the more plausible estimates (for instance, in the production function estimates, the two terms have a correlation of only .2668 in the Japanese data). Two of the fixed-effects models show the effect of foreign spillovers on Japanese innovation to be substantially positive, though estimated with little statistical precision. Even in these "within" estimates, though, substantial differences can be seen in the impact of intranational and international spillovers. Moreover, when domestic and foreign spillover terms are entered into the knowledge production function separately, they have very different elasticities. This differential is quite consistent across specifications and countries.[25]

It is important to recall that I am estimating a net effect of unobservable technological externalities, which are positive, and competitive externalities, which are negative. A consistently net negative result in the case of the U.S. is not so surprising given considerable anecdotal evidence of a "not-invented-here"

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[24] The Data Appendix illustrates this problem with tables showing simple correlations among the dependent variable and the regressors.

[25] An alternative interpretation of these coefficients is that they represent the competitive reaction of the *i*th firm to an increase in the R&D spending of its domestic (and foreign) rivals. There are several problems with this hypothesis. First, the "external R&D" is not just the weighted sum of that firm's rivals in the product market. Instead, it is the weighted sum of external R&D performed by all technologically proximate firms, including firms in upstream and downstream industries. Given that product market rivals' R&D constitutes only a small fraction of total external R&D, the "reaction" interpretation is problematic. Second, this interpretation requires us to impose some assumptions on the nature of competition, namely that increases in R&D spending are "strategic complements" rather than "strategic substitutes." Empirical evidence on this presented by Scherer and Kuh (1992) suggests that such an assumption is unwarranted. Finally, there is no obvious reason why such a reaction should differ so markedly for domestic versus foreign rivals. I thank Aloysius Siow for raising these points.

syndrome among technologically active U.S. firms.[26] If U.S. firms devote little effort to tracking research activities abroad, as they are accused of doing, than the weak technological externalities will have less effect on my estimates than the negative "competitive" externalities. In some industries, such as electronics, these competitive effects are obviously quite strong and may be driving my results. Even in the case of Japanese firms, a result in which foreign spillovers are statistically indistinguishable from zero is not inconceivable. The ability of firms to track technological developments abroad probably requires a substantial investment in an international industrial intelligence network that only the larger, more capable, and more international companies in Japan's more competitive industries are capable of making. The firms in my data set are quite diverse in their size, R&D-intensity, and involvement in international markets. It must be true that the average company is considerably less plugged in to the American R&D networks than Fujitsu or Toshiba.

The central conclusion of this paper, namely that knowledge spillovers are primarily an intranational phenomenon, receives support from other recent studies using very different methods. Francis Narin (95) has recently conducted a study of knowledge spillovers in pharmacological science research community. Using data on citations in scientific papers, Narin finds that scientists tend to cite other scientists in the same country far more frequently than one would expect given the geographic distribution of scientists and research resources. Jaffe and Trajtenberg (95) find similar patterns in their preliminary work on patent citations: patent citations also seem to indicate that knowledge spillovers have a strong intranational component. I have one final piece of confirming evidence: the subjective opinion of Japanese R&D managers themselves. Goto and Cohen have recently created surveys on the appropriability of R&D along the lines of the survey used by Levin, Cohen, et. al. These surveys were distributed to R&D managers in the U.S., Japan, and the EC to allow for an international comparison. When asked whether foreign or domestic "spillovers" were more important, the Japanese respondents' answers indicate that domestic spillovers are overwhelmingly more important.[27]

[26] I thank Dr. David Kahaner of the Asian Technology Transfer Project and Miles Wakayama of Hitachi Central Research and Development for sharing their stories and insights on this topic.
[27] Based on personal communication between Professor Goto and the author concerning contemporary research of the National Institute for Science and Technology Policy, Science and Technology Agency, Japan.

VI. Conclusions and Extensions

In general, the data support the following three conclusions:

1. Intranational spillovers are stronger than international spillovers.

2. There is some evidence that Japanese companies benefit positively from research undertaken by American firms, although this effect is smaller and less robust than the effect of intranational spillovers.

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 significant. First, these results provide empirical backing for the assumption that knowledge spillovers are primarily intranational in scope. This clearly lends credence to a number of models that generate multiple equilibria in trade flows, allow comparative advantage to be determined endogenously, and allow government policy to have a lasting impact on trade. It also leads 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.

I hesitate to say that this provides justification for "strategic trade policy." There is nothing in my empirical results to suggest that it is in the national interest to subsidize the production of any particular commodity or to deny foreign producers the right to export to or make direct investments in the United States. However, the idea that promotion of private R&D can have an impact on comparative advantage is one that trade economists should take more seriously. At the very least, the promotion of research consortia along the lines advocated by Spence (84) may be an option worth considering, since it seeks to "internalize" the externality created by new technological innovation.[28]

The potential benefits of such policies have not been lost on the Japanese. The celebrated research consortia organized by MITI have been lauded and feared as a potent policy instrument by which Japan built comparative advantage. Surprisingly little serious empirical research has been done on these consortia.[29] Ongoing research with Mariko Sakibara of Anderson Graduate School of Management 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. Are they responsible for the measurably higher levels of spillovers in Japan? Perhaps policy lessons for the U.S. could be drawn from the Japanese experience.

It is also well-known that Japanese firms are more apt to collaborate with their suppliers or customers in the development of new products even without the carrots and sticks of government-organized consortia. This kind of collaboration is concentrated in the vertical keiretsu groups. To what extent is Japanese industrial organization responsible for the high and robust estimates of intranational spillovers in this data?[30] Using micro-level data on affiliation to vertical keiretsu groups, I investigated this potential linkage in the fourth chapter of my Ph.D. dissertation, comparing the spillovers of affiliated firms to non-affiliated firms, and examining the intra-group correlation of productivity residuals. I have found strong evidence of a relationship between keiretsu affiliation and spillovers of process technology, but further work is needed to clarify the nature of this relationship and its interpretation.

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

[28] Spence (84) was the first to draw attention to the potential role of research joint ventures in correcting the externality problem. More recently, Paul Romer (93) and Paul Krugman (90) have also advocated subsidized research joint ventures.

[29] See Wakasugi (86) for an excellent summary of the issues involved and some "case study" evidence on the effectiveness of the consortia.

[30] See Suzuki (93) for another analysis of the effects of vertical keiretsu ties on innovation.

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.

Data Appendix

Firm-level data on Japanese R&D spending are taken from Japanese language primary sources, namely the *Kaisha Shiki Ho*, published by Toyo Keizai, and the *Nikkei Kaisha Joho*, published by the Nihon Keizai Shimbunsha. Data on Japanese firm output and other inputs was drawn from the Japan Development Bank Corporate Finance Data Base. Data on the U.S. patents of Japanese firms was obtained from the U.S. patent office. These data had to be matched to the other micro data on a firm by firm basis, since patents are classified by the English name of the Japanese firm while my other data are classified by the Tokyo Stock Exchange code, which is the Japanese equivalent of the Compustat code. Data on the Japanese patents of Japanese firms and additional information on the R&D activities of Japanese firms was taken from the Japanese language records of the Ministry of International Trade and Industry. The full data construction process required over six months, four of which were spent in Japan. It would not have been completed without the generous assistance of the staff at the Japan Development Bank's Research Institute of Capital Formation and the Research Institute of the Ministry of International Trade and Industry.

The U.S. data comes from the NBER R&D/Productivity data base compiled by Bronwyn Hall and others. Data on subsidiaries was taken from the Directory of Corporate Affiliations, various issues.

The following tables illustrates the multicollinearity in levels in the data:

Table A Japanese Data

Variables	log(patents)	log(R&D)	log(domestic)	log(foreign)
log(patents)	1			
log(R&D)	.7536	1		
log(domestic pool)	.4751	.4847	1	
log(foreign pool)	.4372	.5217	.8549	1

Table B U.S. Data

Variables	log(patents)	log(R&D)	log(domestic)	log(foreign)
log(patents)	1			
log(R&D)	.8238	1		
log(domestic pool)	.4226	.5326	1	
log(foreign pool)	.3262	.4849	.9056	1

Technical Appendix

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 (84) 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

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

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.

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

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

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

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.

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

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

$$\log L = \sum_{i} \sum_{t} \log\Gamma(\lambda_{it} + n_{it}) - \log\Gamma(\lambda_{it}) - \log\Gamma(n_{it} + 1) + \log\Gamma(\sum_{t} \lambda_{it}) +$$

$$\log\Gamma(\sum_{t} n_{it} + 1) - \log\Gamma(\sum_{t} \lambda_{it} + \sum_{t} n_{it})$$

where

$$\lambda_{it} = e^{X_{it}\beta}$$

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Table 1 **Sample Statistics for Japanese Data**

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

Units are millions of 1985 Japanese yen.

Table 2 **Sample Statistics for U.S. data**

Variable	Obs	Mean	St. Dev.	Min	Max
patents	1045	58.11	107.5	0	750
R&D	1045	189.58	495.15	.6939	4885.939
Dom. Pool	1045	9532.2	3669.64	1806.36	21841.21
Foreign Pool	1045	3872.14		419.36	10328.73

Units are millions of 1987 U.S. dollars.

Table 3 Linear Regressions Based on Japanese Data

Dependent Variable: Log(Patents), Obs=820 Standard Errors in Parentheses

	OLS (dom)	*OLS (foreign)*	*OLS (both)*	*Random Effects*	*Fixed Effects*	*Fixed Effects*
log R&D	.7698 (.0255)	.8169 (.0298)	.7855 (.0284)	.6377 (.0477)	.0953 (.0977)	.0793 (.0974)
log domestic spillovers	.5011 (.0944)		.9642 (.2055)	1.245 (.3017)	.9268 (.3557)	1.249 (.6591)
log foreign spillovers		.2752 (.1190)	-.5837 (.2284)	-.5981 (.3208)	.3727 (5022)	-2.033 (1.306))
test of equality	n.a.	n.a.	F=13.53 p=0.0003	Chi2=9.67 p=0.0019	F=.47 p=.49	F=5.65 p=0.018
chemicals	-.5631 (.1645)	-.7815 (.1805)	-.4270 (.18324)	-.2735 (.3201)	n.a.	n.a.
machinery	-.0795 (.1720)	-.1702 (.1971)	-.0914 (.1849)	-.0926 (.3207)	n.a.	n.a.
transportation	-.5399 (.1599)	-.5362 (.1831)	-.5848 (.1721)	-.5862 (.3076)	n.a.	n.a.
precision instruments	-.5084 (.1752)	-.5828 (.2003)	-.5156 (.1906)	-.4816 (.3185)	n.a.	n.a.
year 2	-.0238 (.1128)	-.0821 (.1071)	- 0534 (.1054)	-.0299 (.0632)		-.3579 (.2647)
year 3	.0155 (.1095)	-.0765 (.1022)	.0365 (.1028)	.0797 (.0682)		-.0984 (.1991)
year 4	.0781 (.1132)	.0345 (.1043)	.0648 (.1025)	.0794 (.0575)		-.0360 (.1143)

Results from the Negative Binomial Model

Table 4 Negative Binomial Model (Japanese Data)
Dependent Variable: Patents, Obs=820

	n.b. totals	*fixed effects*
log R&D	.6753 (.0245)	.8483 (.02110))
log domestic spillovers	.4131 (.1414)	1.275 (.1347)
log foreign spillovers	-.1353 (.1414)	....-1.518 (.1245)
test of equality	Reject*	Reject*
chemicals	-.9168 (.1220)	n.a.
machinery	-.5319 (.1184)	n.a.
transportation	-.6789 (.1056)	n.a.
precision instruments	-.9690 (.1165)	n.a.
time trend	-.08331 (.0236)	-.0104 (.0311)
Log likelihood	-3173.84	-3004.80

The negative binomial regressions follow Hausman, Hall, and Griliches (84). Standard errors are computed from the analytic second derivatives.

Table 5
Production Function Regression (Japanese Data)
Dependent Variable: Δ Log (Deflated sales), Obs=205

Δ Log (Capital)	.0864 (.0566)
Δ Log (Labor)	.2829 (.0816)
Δ Log (Materials)	.3803 (.0854)
Δ Log (Own firm R&D)	.0132 (.0493)
Δ Log (Dom. Pool)	.7034 (.3464)
Δ Log (Foreign Pool)	.3787 (.3056)

Table 6
Linear Regressions Based on U.S. Data
Dependent Variable: Log(Patents) Obs=836

	Domestic	*Foreign*	*OLS Both*	*Random Effects*	*Fixed Effects*	*Fixed Effects*
log R&D	.7575 (.0194)	.7873 (.0234)	.7791 (.0230)	.6841 (.0401)	.2461 (.0907)	.2225 (.0901)
log domestic spillovers	.1551 (.0881)		.9869 (.1900)	1.1467 (.3487)	.3638 (.5320)	1.303 (1.186)
log foreign spillovers		-.0791 (.0958)	-.8475 (.1781)	-.7990 (.3094)	-.6568 (.4020)	-1.937 (.7656)
test of equality			F=26.92 p=0	Chi2=9.45 p=0.002	F=1.3 p=.25	F=3.96 p=0.05
machinery	.5061 (.0947)	.4681 (.1081)	.4195 (.1069)	.3975 (.1962)	n.a.	n.a.
chemicals	.6314 (.0892)	.5147 (.1174)	.3232 (.1251)	.4489 (.2060)	n.a.	n.a.
transportation	.3920 (.1114)	.4248 (.1271)	.3387 (.1312)	.3741 (.2222)	n.a.	n.a.
precision instruments	.2257 (.0903)	.2075 (.1010)	.1375 (.1043)	.0849 (.2090)	n.a.	n.a.
year 2	.0795 (.0812)	.1241 (.0968)	.1124 (.0957)	.1319 (.0560)		-.1504 (.1944)
year 3	.1312 (.0814)	.1883 (.0956)	.2267 (.0946)	.2406 (.0507)		.1039 (.1361)
year 4	.1021 (.0829)	.1650 (.0968)	.1296 (.0962)	.1410 (.0514)		.0015 (.1005)

Table 7
Negative Binomial Model (U.S. Data)
Dependent Variable: Patents, Obs=836

	n. b. totals	*fixed-effects*
log R&D	.8106 (.0203)	.8056 (.0329)
log domestic spillovers	.7284 (.1706)	.8123 (.2278)
log foreign spillovers	-.8178 (.1930)	-.8923 (.2589)
test of equality	Reject*	Reject*
machinery	.3013 (.0919)	n.a.
chemicals	.1602 (.1055)	n.a.
transportation	.4101 (.0957)	n.a.
precision instruments	-.0218 (.1256)	n.a.
time trend	-.0081 (.0284)	-.0226 (.0525)
log likelihood	-3468.8	-3561.23

Table 8
Production Function Regression (U.S. Data)
Dependent Variable: Δ Log (Deflated sales), Obs=209

Δ Log(Capital)	.2842 (.0992)
Δ Log(Labor)	.5292 (.0962)
Δ Log(Own firm R&D)	.3619 (.1298)
Δ Log(Dom. Pool)	.8307 (.4431)
Δ Log(Foreign Pool)	-.4828 (.5089)