Is Foreign Direct Investment a Channel of Knowledge Spillovers? Evidence from Japan's FDI in the U.S.*

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Abstract

Recent empirical work has examined the extent to which international trade fosters international "spillovers" of technological information. FDI is an alternate, potentially equally important channel for the mediation of such knowledge spillovers. I introduce a framework for measuring international knowledge spillovers at the *firm* level, and I use this framework to directly test the hypothesis that FDI is a channel of knowledge spillovers for Japanese multinationals undertaking direct investments in the United States. Using an original firm-level data set on Japanese firms' FDI and innovative activity, I find evidence that FDI increases the flow of knowledge spillovers *both from and to* the investing Japanese firms.

I. Introduction

"To what extent does technological knowledge flow across national borders?"

"By what means are these knowledge flows mediated?"

These questions have received an increasing amount of attention over the last decade, as some of the leading scholars in international economics have focused considerable research effort on the broad topic of knowledge spillovers. Ethier (1982), Rivera-Batiz and Romer (1991), Feenstra (1996), and, perhaps most notably, Grossman and Helpman (1990, 1991), among others, helped place this general subject in the forefront of international economic research with their pathbreaking work on models of endogenous innovation-driven growth and trade.

Incorporating technological progress into trade models can make a real difference, at least in theory. Technological considerations can expand the gains from trade. Liberal trade policies provide domestic entrepreneurs with the possibility of exploiting global markets rather than merely national ones; inducing more R&D (or greater specialization); and generating higher levels of economic growth or welfare. Moreover, imported manufactured goods can -- in some of these models -- serve as channels of knowledge spillovers. Domestic firms can "learn from" the foreign goods they purchase by reverse-engineering the technological innovations embodied in these goods. In this way, the "knowledge stock" on which domestic innovators can build is enlarged through liberal trade.[1] While less thoroughly explored in formal models, the literature also suggests the possibility of a "learning-by-exporting" effect in which firms learn to improve the quality

[1] Technological considerations can also complicate the gains from trade. If knowledge spillovers are national rather than international in scope, then comparative advantage itself can become path dependent,

of their products and production processes through contact with more advanced foreign competitors in global export markets.

These ideas have been enthusiastically received by the international economics research community, in part because they seem to considerably strengthen the case for open trade policies by introducing potential *dynamic* gains from trade to complement the traditional static gains from trade. However, the empirical evidence on the degree that international knowledge spillovers are mediated by the flow of goods has been, at best, mixed.[2] Furthermore, a number of carefully executed microeconometric studies have failed to find convincing empirical evidence for "learning by exporting."[3]

Of course, the flow of goods across countries constitutes only one channel through which technological knowledge can flow across national boundaries. An obvious alternative channel is foreign direct investment. A number of countries have policies that encourage or even subsidize multinational investment. Often, as is the case in Singapore, Malaysia, and China, these policies are deliberately biased in favor of multinational firms in "technology intensive" industries. These preferential policies are based at least partly on the view that production and/or research activities undertaken by multinational affiliates within national borders confer greater "spillover" benefits than imports. This view receives some support from the managerial literature. A series of research reports undertaken by the McKinsey Global Institute has consistently

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and an "accident of history" or a temporary policy that provides one country with a temporary advantage in an R&D-intensive sector can have long-lasting implications for trade. See Grossman and Helpman (1991).

[2] The recent study by Keller (1998) calls this into question using industry-level data from several OECD countries. Work at the aggregate level by Funk (1998) has cast doubt on the original work of Coe and Helpman (1995). Work at the firm level by Branstetter (forthcoming) and at the patent level by Jaffe and Trajtenberg (1996) have emphasized the degree to which knowledge spillovers across national boundaries are limited, despite the presence of high levels of trade in goods.

[3] See Clerides, Lach, and Tybout (1998), Bernard and Jensen (1998), and Aw, Chen, and Roberts (1997) for examples.

emphasized the importance of FDI as a channel for the international diffusion of "best practice" technology and management practices.[4] In his widely cited work, Michael Porter has also emphasized the importance of this channel.[5]

In an effort to submit these views to careful statistical tests, Ann Harrison, Magnus Blomstrom, and others have undertaken empirical studies of "spillover" benefits from FDI. The work of Harrison and her co-authors, which has been particularly influential, has used micro-level panel data drawn from developing countries such as Morocco and Venezuela.[6] While these papers do not explicitly model knowledge spillovers, their presence is inferred from changes in the productivity levels and growth rates of "indigenous plants" that are associated with the "arrival" of foreign manufacturing affiliates. Like the "learning from exporting" studies, these studies fail to find robust evidence of positive knowledge "spillovers" from multinational investment.[7]

This paper also examines the role FDI plays in mediating knowledge spillovers, but does so in a very different economic context and takes a completely different methodological approach.

First, I examine Japanese FDI in the U.S., rather than in a developing country. The motivations for this kind of FDI as well as its economic effects could be quite different from FDI in Morocco or Venezuela.[8] In that sense, this paper provides a useful complement to earlier studies. Japanese FDI in the U.S. (as opposed to FDI from other

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[4] See, for example, McKinsey Global Institute (1993).

[5] See Porter (1990). Walter Kuemmerle (1997) has undertaken extensive case studies of multinationals' foreign R&D facilities and how they fit into the overall R&D strategy of the firm.

[6] See Aitken and Harrison (1999) and Haddad and Harrison (1993). For reasons of brevity, I will omit mention of papers such as Eaton and Tamura (1996) which use aggregate or industry-level data to examine these and related issues.

[7] Related work by Chung, Mitchell, and Yeung (1996) also casts doubt on the role of FDI as a channel of knowledge spillovers.

significant source countries) is of particular interest, because it changed so dramatically over the course of the 1980s. A large number of Japanese multinationals shifted from a position of very limited direct investment (or no direct investment) in the U.S. at the beginning of my sample period to a position of "substantial" direct investment by the end. This large change may help identify the parameters of interest.

Second, I do not follow the earlier convention of using measured changes in TFP or other revenue-based measures to infer the presence or absence of knowledge spillovers. As is well known, conventional measures of productivity can reflect market power as well as technical efficiency. When technologically more advanced foreign affiliates first enter a market, their presence may erode the market power of indigenous incumbents while -- at the same time -- introducing new production techniques and technologies from which these same incumbents learn. Real knowledge spillovers can take place, yet their effects can be masked in the data by changes in "appropriability conditions."

In contrast, this paper presents an alternative framework for measuring the impact of foreign direct investment on knowledge spillovers using detailed patent data. I then use this framework to measure the impact of foreign direct investment in the United States by a group of Japanese manufacturing firms on knowledge flows *from* American firms *to* these investing Japanese firms and *from* the investing Japanese firms *to* American inventors. I find evidence foreign direct investment enhances knowledge flows in both directions. I also show how this framework could be extended to measure the

[8] Note that most FDI consists of investment *from* advanced industrial economies *to* other advanced industrial economies.

effects of exports and imports on knowledge spillovers, and I offer some observations on the implications of my findings for the theoretical literature and for policy.

II. Empirical Methodology

Using Patent Citations Data to Infer Knowledge Spillovers

In describing the approach taken in this paper, I need to carefully define what I mean by the term "knowledge spillovers." When I use this term, I refer to the process by which one inventor learns from the research outcomes of others' research projects and is able to enhance her own research productivity with this knowledge without compensating the other inventors. In other words, I am referring to the kinds of classic technological externalities that are at the core of the endogenous growth literature. A true knowledge spillover, by my definition, is something that generates further innovation. I am, therefore, making a conceptual distinction between knowledge spillovers *per se* and the related processes of "imitation" or "technology diffusion," though it is clear these phenomena overlap in practice.[9]

Patent documents provide a potentially rich source of information on knowledge spillovers. Every U.S. patent applicant is required to include appropriate citations to the "prior art" in his or her application. By explicitly identifying the "prior art" on which the inventor builds, these citations serve the important legal function of bounding the innovation protected by the patent document. Just as academic researchers are expected to explicitly acknowledge the ideas and findings of others that they use in their own research (or be open to charges of plagiarism), so patent applicants are expected to

[9] By restricting the focus of my paper to knowledge spillovers, I am necessarily taking a narrower approach than have some other papers in this literature, and I freely acknowledge that this narrower approach excludes much which is of economic interest.

identify the prior art on which they build (or be open to charges of patent infringement).[10] By examining the citations in corporate patent documents, one can see the innovations the inventors consider to be the "technological antecedents" of their own inventions.[11]

The legal function citations play in delineating the scope of the intellectual property rights conferred by a patent creates strong incentives for inventors to get the number and nature of citations right. The cost of citing a friend in a scientific paper is minimal, so it may frequently take place even when little or no knowledge spillover has taken place. The cost of extraneous citations in a patent document can be substantial, because they narrow the scope of the patent by explicitly placing related inventions *outside* the scope of the current patent application. As Jaffe et al. (1993) puts it, including extraneous citations is "leaving money on the table." Likewise, not including appropriate citations can expose a patent applicant to patent infringement lawsuits or to sanctions by the U.S. Patent and Trademark Office.

Patent citations provide as direct a measure of "knowledge spillovers" as researchers are ever likely to get. They are perhaps the best answer to the challenge posed by Paul Krugman. In his 1991 book, *Geography and Trade*, Krugman opined "Knowledge flows … are invisible; they leave no paper trail by which they may be measured or tracked, and there is nothing to prevent the theorist from assuming anything about them that she likes." In fact, knowledge spillovers *do* leave a paper trail in the form of patent citations -- and this information is provided *at the level of the individual*

[10] This analogy, while illustrative, is far from exact. Jaffe, Fogarty, and Banks (1998) find that some patent citations are added by either the applicant or the patent examiner for legal or procedural reasons which have nothing to do with "knowledge spillovers." Nevertheless, they also found strong evidence that patent citations do indeed reflect patterns of knowledge spillovers, albeit with some "noise."

[11] The points in this paragraph have been made and substantiated by Jaffe and his various co-authors, and some of the language here closely follows Jaffe et. al. (1998).

innovation.[12] The use of patent citations to measure knowledge spillovers has been pioneered by Adam Jaffe and a set of co-authors.[13] Jaffe, Trajtenberg, and Henderson (1993) used patent citations to measure the extent to which knowledge spillovers within the United States are geographically localized. Hall, Jaffe, and Trajtenberg (1998) used patent citations to measure *the ex-post* economic value of corporate patents. Henderson, Jaffe and Trajtenberg (1998) analyzed changes in university patenting over time. In a series of working papers, Jaffe and Trajtenberg used patent citations to compare magnitudes of knowledge flows across countries and across technological fields.[14]

Until now, no one has used patent citations to investigate whether trade or FDI aids or abets flows of knowledge across national borders.[15] This paper takes such an approach. It also differs from much of the existing literature in that it links data on citations with the firm-level characteristics of the cited and citing firms. Jaffe and his co-researchers have recently set up a comprehensive database that provides a complete "citation mapping" of U.S. patent documents from 1963-1996. The empirical results presented in this paper use these data to measure knowledge flows *from* Japanese firms investing in the U.S. as well as knowledge flows *to* Japanese firms investing in the U.S.

[12] Jaffe, Trajtenberg, and Henderson (1993) make this very point, also in response to Krugman.
[13] See Caballero and Jaffe (1993), Jaffe, Trajtenberg, and Henderson (1993), and Jaffe and Trajtenberg (1996) for examples.
[14] The contributors to this literature have also pointed out a number of problems with patent citation data. Among these is the simple fact that not all important innovations are patented.
[15] This statement needs qualification, in that two papers examine closely related topics. Almeida (1996) examines the citations in patents generated by a small number of foreign semiconductor affiliates. Frost (1995) examines the patent citations generated by a larger number of multinational affiliates across a broader range of industries. However, neither paper examines the impact of foreign direct investment on the R&D of the parent firm or the extent to which increases in FDI lead to increases in knowledge spillovers, as I do in this paper. This distinction is quite important because, as Rene Belderbos (1999) has shown, only a *tiny* fraction of Japanese firms' total R&D and patenting is conducted through their overseas subsidiaries. These subsidiaries may nevertheless play an important role in fostering knowledge spillovers if *they affect the nature of R&D conducted by the parent company*. This paper directly assesses the magnitude of that effect.

I examine whether the patents of Japanese firms with a substantial FDI presence in the U.S. are more frequently cited by U.S. inventors than those of firms without such networks. The existence of data in both the time series and cross-section dimensions allows us to look at changes in the propensity of U.S. inventors to cite the patents of specific Japanese firms as those firms increase or decrease their level of FDI in the U.S. Likewise, I examine whether the patents of Japanese firms show an increased propensity to cite the patents of U.S. firms when these firms increase their level of foreign direct investment in the U.S.[16]

Estimating the Impact of FDI on Knowledge Spillovers

This simple description of the approach ignores a number of conceptual and practical difficulties, some of which are outlined below. First, however, I establish some notation to guide the discussion. Let C_{Jit} be the number of citations made by the patents of Japanese firm i filed in year t to the cumulated stock of U.S.-invented patents granted as of year t. I can then write the expectation of C_{Jit} as a function of several other observables

$$E[C_{Jit}] = (N_{Jit})^{b_1} (N_{At})^{b_2} [e^{b_3 FDI_{it}}][e^{b_4 PROX_i}] R_{it}^{b_5} a_i a_t \qquad (1)$$

Here E[C_{Jit}] is a function of the number of patents Japanese firm i has taken out in the U.S. in year t (N_{Jit}), the number of potentially cited U.S. patents which exist as of year t (N_{At}), the level of firm i's "FDI presence" in the U.S. in year t (FDI_{it}), and the extent to which firm i is at a point in the technology space which is "densely populated" by other U.S. patents ($PROX_i$). Some Japanese firms might cite U.S. patents more frequently

[16] Note that all inference will be based on citations from and to the U.S. patents of Japanese firms. For a discussion on why this is appropriate, see the Data Appendix. The Data Appendix also describes how the U.S. patents of Japanese firms are distinguished from the U.S. patents of "indigenous" American inventors. I emphasize here that Japanese firms tend to patent their best ideas in both Japan and the U.S.

simply because they happen to be working on technologies in which a large number of "indigenous" U.S. inventors are active. Therefore, spillovers arise from "proximity" in technology space rather than through establishing and maintaining FDI networks.

If one wishes to control for this "technological proximity," the existing literature suggests a way in which it could be done. The typical Japanese firm in this data set conducts R&D in a number of technological fields simultaneously. One 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 firm *i*'s R&D program be described by the vector *F*, where

$$F_i = (f_1, \ldots, f_k) \qquad (2)$$

and each of the *k* elements of *F* represent the firm's research resources and expertise in the *k*th technological area.[17] From the number of patents taken out in different technological areas, I can infer 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, I can obtain a quantitative measure of the firm's level of technological expertise in that field.[18]

In the same way, I can also compute a vector of location in technology space for the aggregate of all U.S. inventors, treating them as though they belonged to a single giant enterprise, and denoting that F_{US}. This suggests that $PROX_i$ might be measured as:

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

[18] 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"

$$PROX_i = \frac{F_i F_{US}'}{[(F_i F_i')(F_{US} F_{US}')]^{1/2}} \tag{3}$$

This is a "technological proximity" coefficient in the spirit of Jaffe (1986).

One may also wish to allow citations to be influenced by the firms' R&D spending and by vectors of multiplicative "fixed effects" associated with the citing firm (a_i) and the (application) year in which the citation takes place (a_t).[19] Including these fixed effects actually simplifies the equation, provided one is willing to make some assumptions. The stock of cumulated potentially citable "indigenous" U.S. patents will be the same for all Japanese citing firms in each year, so that the N_{At} terms are effectively absorbed into the time dummies. I am not able to separately identify the effects of time and cumulated patent stock on citation probabilities, but since my primary focus is on the partial impact of changes in FDI presence on citations, this is not a concern. One may also want to assume that a firm's location vis-à-vis the set of U.S.-invented patents is relatively fixed over time, which is implied by my specification of (3). In that case, the effect of the PROX measure is absorbed by the firm fixed effect. Again, the fact that I cannot separately identify it from the firm effect is of little concern, as my primary focus is on the impact of changes in FDI on citations.

Taking the logs of (1) gives us a simple, linear estimation equation

$$c_{Jit} = b_0 + b_1 p_{it} + b_2 FDI_{it} + b_3 r_{it} + \sum_c d_c D_c + \sum_t a_t T_t + a_i + e_{it} \tag{4}$$

position in technology space as long as the "ease of codification" varies across fields in a common way across firms.

[19] Patents are dated by year of application rather than year of grant. This is important, because it can take two to three years (sometimes much longer) for the U.S. Patent Office to grant or reject a patent application.

where c_{Jit} is the log of the number of citations made by Japanese firms' U.S. patent applications to "indigenous" U.S. patents, p is the log of the count of U.S. patent applications of firm i in year t, FDI is one of a number of alternative measures of the FDI stock of firm i in year t, r is the log of R&D spending of firm i in year t, the a_t's are time dummies, the d's are industry effects, and I consider the a_i to be a firm effect, reflecting firm-specific research productivity and, perhaps, firm-specific but time invariant differences in the "connectedness" of the firm's research team to current developments in U.S. research that might affect its tendency to cite U.S. patents.

The assumption that the technological proximity of a Japanese firm with respect to U.S. inventors stays fixed over a long period is a strong one. The data permit me to allow this proximity measure to vary within firms over time, although I lack sufficiently rich patent data to do this for all firms or all years. Allowing for a time-varying measure of technology proximity imposes a much more stringent statistical test of the impact of FDI on knowledge spillovers. After all, it is possible some of the movement of Japanese firms in "technology space" is *induced* by the spillovers from American firms, which they receive through their network of subsidiaries. Controlling for this movement might underestimate the total impact of these spillovers. However, if a positive effect remains even after controlling for this movement, this is even stronger evidence in favor of the view that FDI is a channel of knowledge spillovers.[20] The specification suggested by this line of thinking would be:

$$c_{Jit} = b_0 + b_1 p_{it} + b_2 FDI_{it} + b_3 r_{it} + b_4 PROX_{it} + \sum_c d_c D_c + \sum_t a_t T_t + a_i + e_{it} \qquad (5)$$

[20] If firms are simultaneously increasing their FDI in the U.S. and moving "closer" to U.S. firms in technology space, this new specification allows us to control for the latter effect, picking up only the partial effect of an increase in FDI on "spillovers" as measured by citations.

A potential econometric problem arises due to the possible dependence of the level of Japanese patenting in the U.S. on the level of citations. If citations measure spillovers, and if spillovers increase the research productivity of the firm, then one might think some of that increased research productivity would show up in increased levels of U.S. patenting. This implies p_{it} depends on lagged and, perhaps, current values of c_{Jit}. If the spillover effects are sufficiently strong and the spillover lags are sufficiently short, this could create an identification problem. The appropriate solution to this problem is to formally model the dependence of p_{it} on c_{Jit} and estimate that equation as well as (4) as a system. I have not taken that step, largely due to the lack of sufficient information on the "reverse" relationship between the two variables. As an expedient partial remedy, I substitute one-period lagged patents, which I (plausibly) assume not be influenced by future spillovers, into my empirical specifications in place of contemporaneous patents.

The focus of interest will be on the coefficient b_2. Do firms that increase their levels of FDI in the U.S. experience an increased tendency to cite U.S. patents?[21] A positive, significant coefficient would suggest the answer is yes. The reason why one might expect a positive coefficient is straightforward: spillovers are not automatic. To monitor and understand other firms' R&D can be a difficult task. It may be facilitated enormously by the geographical proximity attained through FDI, through which the cost of accessing foreign firms' knowledge assets is reduced.

To put this another way, I hypothesize that the possession of U.S. subsidiaries provides Japanese firms with a level of direct contact with leading firms in the U.S. market that they could not otherwise obtain. This heightened level of contact may occur

[21] It may be that an acquisition or greenfield investment might not have an immediate impact on the research of the Japanese parent firm, so various lags of the FDI "stock" will be considered.

regardless of whether the subsidiary is set up explicitly or entirely for the purposes of following research trends in the U.S. It may occur regardless of whether or not the FDI by the Japanese firm takes the form of "greenfield" new investment or acquisition of existing U.S. firms.

However, there are also both theoretical and empirical reasons for thinking the spillover-enhancing effects of acquisition FDI and "greenfield" FDI are different. The "internalization" theory of FDI suggests firms establishing greenfield investments abroad may be exploiting firm-specific technological (and other) assets not possessed by their foreign competitors. Thus, Japanese firms establishing new production facilities abroad may have relatively little to learn from their U.S. counterparts, being more technologically advanced than these counterpart firms at the time they undertake the actual investment. On the other hand, empirical work by a number of authors suggests that "acquisition FDI" is at least partially motivated by the desire to obtain the technological assets of the purchased firms. In fact, Kogut and Chang (1991, 1996), Yamawaki (1993), and Blonigen (1997) have all found evidence suggesting that *Japanese acquisitions in the United States* are motivated -- at least in part -- by the desire to "access" American technological strengths.[22] In light of this, I will later break down Japanese FDI into "acquisition" FDI and "greenfield" FDI and present results based on total FDI as well as "acquisition" FDI only.[23] Note that I am taking a broader view of the potential spillover benefits of acquisition than others have taken in this literature. I hypothesize that by purchasing a firm in the U.S., Japanese firms potentially acquire not

[22] Wesson (1998) also finds evidence for "asset-seeking" FDI.
[23] Because of the richness of my FDI data, I also can (and do) separately examine the impact of Japanese firms' U.S. R&D and product engineering facilities on spillovers. For a more "case-study" based approach to the impact of foreign R&D facilities on firm innovation, see Kuemmerle (1997).

only the proprietary knowledge assets of the acquired firm but also entrée into the informal technological networks and knowledge sharing relationships possessed by the research personnel of the acquired firm.

This discussion raises the question of how I should treat Japanese firms' citations of the U.S. patents of their acquired subsidiaries and, conversely, the citations by the acquired subsidiaries to the U.S. patents of the Japanese parents. It would hardly be surprising to see such citations – in both directions – increase after an acquisition. However, this would *not* be evidence of a "spillover" in the sense that unaffiliated U.S. firms are receiving and providing greater technological externalities vis-à-vis the Japanese parent firms as a consequence of an increase in the "FDI presence" of those parent firms. In recognition of this, I will present results both with and without citations to and from acquired subsidiaries. This does not change the qualitative nature of my conclusions. [24]

Of course, for Americans, the question of greater interest may be not what the Japanese firms have learned through their investments, but what "indigenous" American inventors have gained from a greater Japanese "presence" in the United States. A simple way to measure this through patent citations is to define C_{Ait} as the number of citations made *to* the cumulated stock of U.S. patents of Japanese firm *i* in year *t* *by* the universe of U.S.-invented patents applied for in year *t*. I can then consider C_{Ait} to be a function of observables and unobserved firm characteristics:

$$E[C_{Ait}] = (N_{Jit})^{b_1}(N_{At})^{b_2}[e^{b_3 FDI_{it}}][e^{b_4 PROX_{it}}][e^{b_5 Age_{it}}]R_{it}^{\ b_6} a_i a_t \tag{6}$$

[24] I thank Jim Rauch for discussions on this point.

where the variables have the same definitions as in (1), except for N_{Jit} and N_{At}. Here N_{Jit} stands, not for the number of patents applied for by firm *i* in year *t*, but rather the cumulative stock of patents of firm *i* as of year *t*. This is because the number of citations a Japanese firm receives in a given year is likely to be a function of its cumulative stock of U.S. patents rather than the number of applications taken out in a particular year. N_{At} stands for the number of potentially citing U.S. patents as of year t. I have also added a variable, *Age,* which is described below.

In their detailed studies of patent citations, Adam Jaffe and his co-authors have found that it takes time for the knowledge contained in patents to diffuse, such that patent citations increase over time. As time passes, the knowledge contained within patents becomes obsolete, so that patent citations have a tendency to decrease over longer lengths of time. Because they are interested in the parameters describing the time path of diffusion and obsolescence, Jaffe and his co-authors estimate a double exponential function of the lag between the granting of the cited patent and the grant date of the citing patent. My aim here is more modest. I do *not* wish to recover the underlying parameters describing the processes of diffusion or obsolescence. Rather, I want to control for differences in the "citedness" of different Japanese firms that are driven by differences in the age distribution of their patent stocks rather than FDI. In some specifications, I will include for each Japanese firm in each year for which I have sufficient data a summary statistic of the age distribution of their U.S. patent stocks, denoted *Age*.[25]

As in equation (4), I begin by assuming the relative proximity of firm *i* to the set of U.S. patents is fixed over time, take the logs, and produce a linear estimating equation:

$$c_{Ait} = b_0 + b_1 p_{it} + b_2 FDI_{it} + b_3 r_{it} + b_4 Age_{it} + \sum_c d_c D_c + \sum_t a_t T_t + a_i + e_{it} \qquad (7)$$

where the variables have the same definitions as in (4), with the exception that p_{it} now stands for the cumulative stock of patents of firm *i* as of year *t*. Again, my interest will focus on b_2. Do U.S. inventor's citations to the patents of Japanese firms increase as the FDI presence of those firms increases? A positive, significant b_2 would indicate this.[26] Relaxing the assumption of "fixed" technological proximity suggests a slightly more complicated specification:

$$c_{Ait} = b_0 + b_1 p_{it} + b_2 FDI_{it} + b_3 r_{it} + b_4 Age_{it} + b_5 PROX_{it} + \sum_c d_c D_c + \sum_t a_t T_t + a_i + e_{it}$$

(8)

As a statistical matter, there are a nontrivial number of observations for which the dependent variable is 0, and hence, the log of the dependent variable is undefined. There are two ways to address this problem. The first and simplest, which is standard in the older "R&D/productivity" literature, is to add 1 to each observation. This raises the concern that this arbitrary transformation of the dependent variable could somehow bias the results. The alternative is to use an econometric model where 0 is a natural outcome, such as a Poisson or Negative Binomial model. I take both approaches, obtaining broadly similar results.[27]

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[25] Work by Jaffe and his coauthors suggests that the frequency of citation for a given patent peaks on average 4-6 years after the granting of the patent. This summary statistic measures the fraction of the U.S. patent stock for Japanese firm *i* in year *t* which is at this "prime" age.

[26] Note that, in this case, the potential "endogeneity problem" of equation (4) does not arise, at least not in the same way. There is no reason to think that Japanese patenting in the U.S. is directly increased by spillovers from Japan to the U.S.

[27] The basic framework of the Poisson and Negative Binomial models is laid out in the technical appendix.

Extending the Framework to Analyze the Impact of Trade on Knowledge Spillovers

Extending this framework to analyze the impact of Japanese *exports* to the U.S. on the ability of the exporting firms to "learn from" U.S. technological developments (the focus of the "learning by exporting" literature) is straightforward. One can simply insert measures of export intensity – the fraction of total revenue derived from exports to the U.S. market – into equation (4). Such data exist for many Japanese firms and have been exploited by Rene Belderbos and his co-authors.[28] In principle, it should be feasible to place measures of export-intensity and FDI presence into the same estimating equation, allowing the researcher to compare the impact of the two measures on citations. Thus, the expectations function for citations by Japanese firms to the cumulated stock of U.S. patents becomes:

$$E[C_{Jit}] = (N_{Jit})^{b_1}(N_{At})^{b_2}[e^{b_3 FDI_{it}}][e^{b_4 EXPORTS_{it}}]R_{it}{}^{b_5}a_i a_t \tag{9}$$

Likewise, the framework could be extended to measure the impact of Japanese exports to the U.S. (that is, imports of Japanese goods by American inventors) on the propensity of U.S. innovators to cite Japanese inventions. This, "learning from imports," is the traditional focus of the "international spillovers" literature. Thus I could estimate:

$$E[C_{Ait}] = (N_{Jit})^{b_1}(N_{At})^{b_2}[e^{b_3 FDI_{it}}][e^{b_4 EXPORTS_{it}}]R_{it}{}^{b_5}a_i a_t \tag{10}$$

In one sense, I am measuring these spillovers at the "micro level," in that I can relate them to the characteristics of the spillover "source." However, equation (10) does not take into account the characteristics of the individual U.S. "spillover recipient" firms or the American inventors from whom the citations come.

[28] See, for example, Belderbos and Sleuwaegen (1996).

III. Estimates and Results

I collected data from a number of sources to estimate the specifications described in the preceding sections. An abbreviated description of this process is presented in the Data Appendix. Further details are available from the author upon request.

Some sample statistics are given in Table 1. Data on FDI give counts of firms acquired or established in the U.S. The unit of analysis in the *Kaigai Kigyou Shihon Shinshutsu* data source is that of the enterprise or business. Some of these acquired or established enterprises contain several plants and large numbers of employees. Other acquired or established firms are smaller. In principle, one might want to weight counts of acquired or established enterprises by the size of these enterprises. In practice that is difficult, as the data on employment or sales of U.S. affiliates of Japanese firms are not recorded with consistency. Branstetter (2000) uses an alternative data source on Japanese FDI that has more consistent measures of size, although this source looks only at manufacturing establishments – distribution centers and R&D facilities are not included. Empirical results suggest size-weighted counts of affiliates or counts of employees yield results that are no better than those obtained using simple counts of affiliates.

In Table 2, I present linear results with a transformed dependent variable. The estimating equation is thus:

$$c_{Jit} = b_0 + b_1 p_{it-1} + b_2 FDI_{it} + b_3 r_{it} + \sum_c d_c D_c + \sum_t a_t T_t + a_i + e_{it} \qquad (11)$$

In all specifications, real sales is added as an additional control variable.

In the fixed effects results, the impact of “acquisition” FDI is positive and significant. The impact of FDI by other measures is generally not statistically significant. The designation of specifications as (1), (2), and (3) refers to three alternative measures of FDI. (1) counts the cumulative sum of total affiliates, regardless of the means of establishment or the purpose of the affiliate. (2) counts only the cumulative sum of affiliates obtained through acquisition. (3) counts only the cumulative sum of affiliates whose "statement of business purpose" in the FDI data base explicitly identifies it as an overseas R&D facility. Although not shown in the table, I experimented with various lags of the FDI variables. I found the results of the lags were qualitatively similar to, but statistically weaker than the results of contemporaneous count measures. This may indicate that spillovers occur almost immediately after the acquisition or "greenfield" establishment takes place.

The interpretation of the coefficient on the FDI terms is the percentage increase in "spillovers" (as measured by citations) that results from an additional affiliate. Thus, even small coefficients can be indicative of fairly large effects. The coefficient in the fifth column, for instance, suggests that a firm that made three acquisitions would increase the flow of spillovers by more than 30%.[29]

In Table 3, where I look at citations *by* U.S. inventors *to* the Japanese investing firms, I find in all specifications a positive relationship between FDI and spillovers from the Japanese firms to U.S. inventors. Recall that the estimating equation is:

$$c_{Ait} = b_0 + b_1 p_{it} + b_2 FDI_{it} + b_3 r_{it} + \sum_c d_c D_c + \sum_t a_t T_t + a_i + e_{it} \qquad (12)$$

In all specifications, sales is used as an additional control.[30] The positive relationship between citations and FDI holds regardless of the exact measure of FDI used. The table shows only the results of regressions with contemporaneous measures of FDI, but the

[29] Of course, this discussion of interpretation begs the question of whether the impact of additional affiliates is really constant. This is a question which can be investigated with the available data. Such investigation is the subject of ongoing research.

results tend to be qualitatively similar and statistically *stronger* if the measures of FDI are lagged by one or two periods. Again, the coefficients suggest the cumulative effect of a large increase in the number of affiliates could be quite substantial. There is no support in this specification for the notion that greenfield investment should be encouraged while acquisition should be shunned because it leads to a one-way flow of spillovers back to Japan. If anything, the fixed effects results suggest acquired firms are a more effective channel of spillover *to* the U.S. than newly established enterprises or even R&D facilities.

However, these linear results need to be viewed with some caution. For a large number of observations, the realization of the dependent variable is zero. The effects of the transformation required to make these observations "work" in a log-linear framework may lead to bias. Fortunately, the econometrics of "count data" is now fairly well developed. It is possible to estimate fixed-effects versions of the Poisson and Negative Binomial models. Results from these models are presented in Tables 4 and 5.

Results for citations by the patents of Japanese firms to the stock of U.S. patents are given in Table 4. Although some of the regression coefficients are smaller than in the linear case, the relationship between FDI and spillovers as measured in this framework remains relatively robust. In fixed effects Poisson and Negative Binomial models, there is a statistically significant positive relationship for two measures of FDI – acquisition FDI and R&D facilities.[31] I remind the reader the interpretation of the coefficient on the FDI term continues to have a "semi-elasticity" interpretation. For example, the number in the sixth column suggests that setting up an additional R&D lab in the U.S. leads to a

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[30] Recall that here, p_{it} refers to the cumulated *stock* rather than the contemporaneous *flow* of patents of firm i in year t.

[31] Acquisition FDI is only significant at the 10% level in the Negative Binomial fixed effects regressions. R&D facilities continue to be significant at the traditional 5% level.

2.3% increase in spillovers from U.S. inventors. The number of observations is smaller here than in the earlier sets of regression results, because the fixed-effects Poisson estimation routine automatically excludes firms for which the dependent variable never varies from zero.[32]

Table 5 shows results for U.S. citations to Japanese patents. The results in the table are obtained using 2-period lagged rather than contemporaneous measures of FDI. Contemporaneous FDI tends to have limited, generally statistically insignificant effects on spillovers from the Japanese firms to U.S. inventors. However, lagged FDI measured by total counts of affiliates is positively (and significantly) correlated with citations. Counts of (lagged) Japanese R&D facilities, on the other hand, are not statistically significant. Although, in keeping with earlier results, the measured impact of acquisition FDI is larger than total FDI in terms of its absolute magnitude, it is also not statistically significant at the conventional levels.

Surveying all of the results in Tables 2-5, it is clear that the exact magnitudes of the key coefficients and the exact levels of statistical significance vary across specifications, as one might expect. Nevertheless, the preponderance of the evidence seems to support the view that FDI is important as a channel of knowledge spillovers.

Tables 6 and 7 provide a robustness check on the earlier results by incorporating a time-varying measure of technological proximity of Japanese firms with respect to U.S. invention. Furthermore, in these regressions, all citations to and from *acquired U.S. subsidiaries* are deleted from the total counts. Table 6 measures spillovers *to* Japanese

[32] A full explanation of why this happens would require a formal derivation of the "fixed-effects" version of the Poisson estimator. For reasons of space, I do not include such a derivation in this paper. The reader is referred to the study by Hausman, Hall, and Griliches (1984). I note that all regression results in this paper were run using the program STATA 6.0.

firms using a fixed effects Negative Binomial estimate of equation (6). The results are both smaller and statistically weaker than those presented elsewhere in the paper. This may be driven largely by the fact that the inclusion of the additional controls cuts down the sample size – I lose about one quarter of the observations.[33] Nevertheless, the reader will note that FDI does have a positive and statistically significant effect on spillovers, as evidenced by the *FDI* coefficients presented in columns (1) and (3). In keeping with the pattern of my earlier results, the magnitude of the coefficient for "acquisition" FDI is the largest, but in this case the coefficient falls below the conventional level of statistical significance.

Table 7 measures spillovers *from* Japanese firms using controls for both time-varying technological proximity and the changing age distribution of these Japanese firms' U.S. patent stocks. Again, the results are both smaller and weaker than in some of the earlier tables. In introducing both of these additional controls, I lose a number of observations. Nevertheless, column (1) clearly shows that (total) FDI has a positive and statistically significant effect on spillovers to the U.S. The impact of "acquisition" FDI is statistically indistinguishable from zero in these regressions, as is the impact of R&D facilities only.[34] Though I do not include these results for reasons of space, I note that when I include a measure of "age" of the patent stocks but no time-varying measure of technological proximity (which increases the number of observations by several

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[33] Simply excluding citations to and from the U.S. subsidiaries of Japanese firms has almost no effect on the results. The differences in Tables 6-7 seem to be driven by the inclusion of the additional control variables and the corresponding loss of observations.

[34] The reader may note that, in the columns of Table 7, the estimated coefficients on firm-level R&D spending and sales are *negative*. While these results run counter to what one might suspect, it is probably the case that, controlling for the firms' technological positions and total level of patenting, information on R&D spending and sales adds little in terms of explaining how much the firms' patents are cited year by year. Furthermore, it is worth noting that there are large, R&D-intensive firms in Japan actively producing

hundred), the impact of all FDI measures becomes positive, of approximately the same magnitude, and both total FDI and establishment of R&D facilities have effects that are statistically significant at conventional levels.

IV. Conclusions and Further Extensions

Knowledge spillovers *do* leave a paper trail -- in the form of patent citations. In this paper, I exploit this source of data to measure the importance of one form of international "contact" – foreign direct investment – in mediating flows of knowledge spillovers across national borders. I find evidence supporting the proposition that FDI is indeed a significant channel of knowledge spillovers, both *from* investing firms *to* indigenous firms and *from* indigenous firms *to* investing firms. These results are quite different from the results reported by other micro-level studies. In my view, the differences in results arise both from a difference of economic context (I look at FDI in an "advanced" country) and a difference in methodology. If the establishment of foreign-affiliated rivals in one's domestic market increases the opportunity for knowledge spillovers but also reduces the domestic firms' ability to appropriate the benefits of these knowledge spillovers through higher prices or higher sales volumes, then a TFP-based approach may fail to measure positive knowledge spillovers.

Some interesting policy implications emerge from these results. Strategy experts have asserted and case studies have demonstrated that investing abroad, particularly through acquisition, can be a useful way of tapping into foreign technology networks. This study upholds this belief with quantitative data drawn from nearly 200 Japanese multinationals in a wide range of industries. My findings emphasize the importance of

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in industries which have long since declined in the United States. The presence of these firms could account for the negative sign of the R&D and sales coefficients.

multinational corporations as channels of knowledge spillovers between advanced countries and suggest that international M&A activity is an important component of that spillover process. The results also suggest that the establishment of R&D facilities abroad can increase a firm's ability to track foreign technological developments.

Moreover, some of the evidence in this paper also suggests the concerns expressed by many American policy analysts over the acquisition of U.S. "high-tech" firms by Japanese multinationals may be misplaced. FDI generally leads to increased knowledge flows in *both* directions, and in some specifications, the impact of *acquisition* on knowledge flows from the Japanese parent to American firms is actually larger than the corresponding impact of greenfield investment.[35] While one needs to exercise caution in extrapolating from these results to other contexts, this could suggest that national restrictions on FDI and, in particular, on foreign acquisition of domestic firms in "high-tech" industries, could hamper rather than protect a domestic industry's technological development.

In the text, I have shown how my framework could be extended to examine the importance of exports and imports, that is, the flow of *goods*, as a channel of knowledge spillovers. Ongoing research with Ryuhei Wakasugi seeks to estimate such an extended model, using Japanese firm-level data on exports to the United States. I hope the framework presented in this paper will find application beyond an examination of *Japanese* foreign direct investment and exports. Although Japanese firms are the most important foreign users of the U.S. patent system, large numbers of British, French, and

[35] Of course, one needs to exercise caution here. While the magnitude of the "acquisition FDI" coefficient is often larger than that of the "total" coefficient, it tends to lose statistical significance when one shifts to count data models and includes controls for time-varying technological proximity and the age distribution

German firms patent in the U.S. This study could be replicated for multiple OECD countries, provided micro-level data could be assembled. Finally, the citations-based framework used in this paper could potentially serve as the nucleus for a more complete empirical model of the R&D-intensive multinational firm that links information on knowledge spillovers derived from patent citations to other "innovative output" measures of the firm. Creating such a model is the focus of current research.

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of Japanese firms' U.S. patent stocks. Because of this, it is difficult to estimate *statistically significant* differences in the impact of different kinds of FDI on knowledge spillovers in most specifications.

Bibliography

Aitken, Brian and Ann Harrison, (1999) "Do Domestic Firms Benefit from Foreign Direct Investment? Evidence from Venezuela" *American Economic Review*, Vol. 89 (3), pp. 605-618.

Aitken, Brian, Gordon Hansen, and Ann Harrison (1997), "Spillovers, Foreign Investment, and Export Behavior" Journal of International Economics, Vol. 43 (1-2), pp. 103-32.

Almeida, Paul (1996), "Knowledge Sourcing by Foreign Multinationals: Patent Citation Analysis in the U.S. Semiconductor Industry," *Strategic Management Journal*, Vol. 17, pp. 155-165.

Aw, Bee, Xiaomin Chen, and Mark Roberts (1997), "Firm-level Evidence on Productivity Differentials, Turnover, and Exports in Taiwanese Manufacturing," NBER working paper no. 6235.

Belderbos, Rene (1999), "Overseas innovations by Japanese firms: A micro-econometrical analysis of patent and subsidiary data," working paper 99-1, Hitotsubashi University, Institute of Innovation Research.

Belderbos, Rene and Leo Sleuwaegen (1996) "Japanese Firms and the Decision to Invest Abroad: Business Groups and Regional Core Networks," *Review of Economics and Statistics*, Vol. 78, pp. 214-220.

Bernard, Andrew and J. Bradford Jensen (1998), "Exceptional Exporter Performance: Cause, Effect, or Both?" *Journal of International Economics*, Vol. 47 (1), pp. 1-25.

Blomstrom, Magnus and Ari Kokko (1996), "Multinational Corporations and Spillovers," NBER Working Paper.

Blonigen, Bruce (1997), "Firm-Specific Assets and the Link Between Exchange Rates and Foreign Direct Investment," *American Economic Review*, Vol. 87 (3), pp. 447-465.

Branstetter, Lee (forthcoming), "Are Knowledge Spillovers Intranational or International in Scope: Microeconometric Evidence from the United States and Japan" forthcoming in the *Journal of International Economics*.

Branstetter, Lee (2000), "Foreign Direct Investment and R&D Spillovers: Is there a Connection?" forthcoming in Takatoshi Ito and Anne Krueger, (eds), *The Role of Foreign Direct Investment in Economic Development*, University of Chicago Press.

Branstetter, Lee (1996), "Innovation, Knowledge Spillovers, and Dynamic Comparative Advantage: Evidence from Japan and the United States," Ph.D. Thesis, Harvard University.

Branstetter, Lee and Mariko Sakakibara (1998), "Japanese Research Consortia: A Microeconometric Analysis of Industrial Policy," *Journal of Industrial Economics*, Vol. 46 (2), pp. 207-233.

Caballero, Ricardo, and Adam Jaffe, (1993), "How High are the Giants' Shoulders?" In: Blanchard, O. and S. Fischer, eds., *1993 Macroeconomics Annual*, MIT Press and National Bureau of Economic Research, Cambridge.

Caves, Richard (1993), "Japanese Investment in the United States: Lessons for the Economic Analysis of Foreign Investment," *The World Economy*, Vol. 16, pp. 279-300.

Chung, Wilbur, Will Mitchell, and Bernard Yeung (1996), "Foreign Direct Investment and Host Country Productivity: The Case of the American Automotive Components Industry," manuscript, University of Michigan, School of Business Administration.

Clerides, Sofronis, Saul Lach, and James Tybout (1998), “Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco,” *Quarterly Journal of Economics*, Vol. 113 (3), pp. 903-948.

Coe, David and Elhanan Helpman, (1995), “International R&D spillovers,” *European Economic Review* Vol. 39, pp. 859-887.

Coe, David and A. Hoffmaister, (1998) “Are There International R&D Spillovers Among Randomly Matched Trade Partners? A Response to Keller,” working paper.

Cohen, Wesley and Daniel Levinthal (1989), “The Two Faces of R&D,” *Economic Journal*, Vol. 99 (September), pp. 569-610.

Eaton, Jonathan and Samuel Kortum (1996), “Trade in Ideas: Patenting and Productivity in the OECD,” *Journal of International Economics*, Vol. 40, pp. 251-278.

Eaton, Jonathan and Samuel Kortum (1998), “Technology, Geography, and Trade,” working paper.

Eaton, Jonathan and Akiko Tamura (1996), “Japanese and U.S. Exports and Investment as Conduits of Growth," *Financial Deregulation and Integration in East Asia*, edited by Anne O. Krueger and Takatoshi Ito. University of Chicago Press.

Ethier, Wilfred, (1982), “National and International Returns to Scale in the Modern Theory of International Trade,” *American Economic Review*, Vol. 72 (3), pp. 389-405.

Feenstra, Robert, (1996), “Trade and Uneven Growth,” *Journal of Development Economics*, Vol. 49 (1), pp. 229-256.

Funk, Mark, (1998), “Productivity, R&D, and the International Diffusion of Knowledge,” Unpublished Ph.D. dissertation, University of California, Davis.

Frost, Tony (1995), “Multinationals and Spillovers of Technical Knowledge: A Comparative Institutional Analysis,” working paper, MIT.

Griliches, Zvi and Jerry Hausman (1986), "Errors in Variables in Panel Data" *Journal of Econometrics*, Vol. 31 (1), pp. 93 - 118.

Grossman, Gene and Elchanan Helpman, (1991), *Innovation and Growth in the Global Economy*. The MIT Press, Cambridge.

Grossman, Gene and Elchanan Helpman, (1990), “Comparative Advantage and Long-run Growth,” *American Economic Review*, Vol. 80 (4), pp. 796-815.

Haddad, Mona and Ann Harrison (1993), “Are There Positive Spillovers from Direct Foreign Investment? Evidence from Panel Data for Morocco,” *Journal of Development Economics*, Vol. 42 (1), pp. 51-74.

Hausman, Jerry, Bronwyn Hall, and Zvi Griliches (1984), "Econometric Models for Count Data with an Application to the Patents-R&D Relationship," *Econometrica*, Vol. 52 (4), pp. 909-938.

Head, Keith, John Ries, and Deborah Swenson (1995), “Agglomeration Benefits and Location Choice: Evidence from Japanese Manufacturing Investments in the United States,” *Journal of International Economics*, Vol. 38, pp. 223-247.

Henderson, R., A. Jaffe, and M. Trajtenberg (1998), “Universities as a Source of Commercial Technology: A Detailed Analysis of University Patenting, 1965-1988,” *Review of Economics and Statistics*, Vol. 80 (1), pp. 119-127.

Jaffe, Adam (1986), "Technological Opportunity and Spillover of R&D: Evidence from Firms' Patents, Profits, and Market Value," *American Economic Review*, Vol. 76 (5), pp. 984-1001.

Jaffe, A., M. Trajtenberg, and R. Henderson (1993), “Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations,” *Quarterly Journal of Economics*, Vol. 108 (3), pp. 577-598.

Jaffe, Adam, and Manuel Trajtenberg (1996), “Flows of Knowledge Spillovers From Universities and Federal Labs: Modeling the Flow of Patent Citations Across Institutional and Geographic Boundaries,” NBER Working Paper 5712.

Jaffe, Adam, Michael Fogarty, and Bruce Banks, (1998), “Evidence from Patents and Patent Citations on the Impact of NASA and Other Federal Labs on Commercial Innovation,” *Journal of Industrial Economics*, Vol. 46 (2), pp. 183-205.

Keller, Wolfgang, (1998), “Are International R&D Spillovers Trade-related? Analyzing Spillovers among Randomly Matched Trade Partners,” *European Economic Review*, Vol. 42, pp. 1469-81.

Kogut, Bruce and Sea Jin Chang (1991), “Technological Capabilities and Japanese Foreign Direct Investment in the United States,” *Review of Economics and Statistics*, Vol. 73, pp. 401-413.

Kuemmerle, Walter (1997), “Building Effective R&D Capabilities Abroad,” *Harvard Business Review*, March-April issue, pp. 61-70.

MacKnight, Susan (1987-1991), *Japan’s Expanding U.S. Manufacturing Presence* (Washington, D.C.: Japan Economic Institute).

McKinsey Global Institute (1993), “Manufacturing Productivity,” McKinsey & Company, Washington, D.C.

Montalvo, Jose and Yishay Yafeh (1994), “A Micro-Econometric Analysis of Technology Transfer: The Case of Licensing Agreements of Japanese Firms,” *International Journal of Industrial Organization*, Vol. 12 (2), pp. 227-244.

Porter, Michael E. (1990), *The Competitive Advantage of Nations*, The Free Press, New York.

Rivera-Batiz, Luiz and Paul Romer, (1991) “Economic Integration and Endogenous Growth,” *Quarterly Journal of Economics*, Vol. 106 (2), pp. 531-555.

Scherer, F.M. (1984), “Using Linked Patent and R&D Data to Measure Interindustry Technology Flows,” in Griliches, ed., *R&D, Patents, and Productivity*, University of Chicago Press.

Sakakibara, Mariko, and Lee Branstetter (1999), “Do Stronger Patents Induce More Innovation? Evidence from the 1988 Japanese Patent Law Reforms,” NBER working paper no. 7066.

Toyou Keizai Publishing Co., *Kaigai Shinshutsu Kigyou Souran*, 1997, Tokyo, Japan.

Toyou Keizai Publishing Co., *Kaisha Shiki Ho*, various issues, Tokyo, Japan.

Wesson, Tom (1998), “Asset-Seeking Foreign Direct Investment,” working paper, York University.

Data Appendix

The primary source of data on the U.S. FDI of Japanese firms was *Kaigai Shinshutsu Kigyou Souran*, published in Japanese by the *Toyou Keizai* publishing company of Japan. This source provides comprehensive data on FDI activity at the firm level. Data on parent firms' sales and industry affiliation were taken from the Japan Development Bank Corporate Finance database. Data on the U.S. patenting of Japanese firms were taken from the CASSIS CD-ROM published by the U.S. patent office and later matched to patent data in the REI database at Case-Western Reserve University. This amounted to hundreds of thousands of patents and even larger numbers of citations. The years of my sample period are 1981 through 1994.

This study uses data on the U.S. patents of 187 Japanese firms (an unbalanced panel) and the universe of "American" inventors, as determined by the address of the first listed inventor. Of course, some "American" inventors work for Japanese firms or subsidiaries of Japanese firms. These inventors are specifically excluded from the sample of "American" patents in the specifications reported in Tables 6 and 7, as is indicated in the text. "American" inventors working for non-U.S. multinationals are considered "American" for the purposes of this study. Conversely, foreign inventors (that is, inventors with a non-U.S. address) working for U.S. firms are not counted as part of the body of "American" inventors. This is intentional, in that the purpose of this study is to examine the impact of the geographic proximity conferred by FDI *in the U.S.* on spillovers to and from inventive activity in that country. It is also worth noting that the vast majority of R&D activity conducted by U.S. multinationals is undertaken with the boundaries of the United States.

For this study, there was really no alternative to the use of data on Japanese firms' U.S. patents, as it has proven impossible to date to obtain reliable information on the citations in Japanese patent applications. This, in part, stems from the very different set of legal requirements for citation that firms have faced under Japanese patent law. Nevertheless, interviews with leading Japanese firm executives and empirical studies such as Branstetter and Sakakibara (1998) and Sakakibara and Branstetter (1999) suggest that Japanese firms seek to patent all their valuable ideas in both the U.S. and Japan, so that trends in their U.S. patents should be reflective of their total innovative activity. Note that Japanese firms are by far the most important foreign users of the U.S. patent system, accounting for roughly one quarter of all patents granted by the U.S. during the latter 1980s and early 1990s. Data on the R&D spending of Japanese firms were taken primarily from survey data published (in Japanese) in the *Kaisha Shiki Ho* quarterly series of reports on Japanese publicly traded firms.

Technical Appendix

Sketch Derivation of Poisson and Negative Binomial Regression Models

Here, I summarize the results of the derivation of count data estimators by Hausman, Hall, and Griliches. The notation below borrows extensively from the presentation of these basic results found in Montalvo and Yafeh (1994).

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

$$pr(n_{it}) = f(n_{it}) = \frac{e^{-l_{it}} \, l^{nit}{}_{it}}{n_{it}!} \tag{13}$$

where $l_{it} = e^{X_{it}b}$ (14)

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. I allow the Poisson parameter lambda to be randomly distributed according to a gamma distribution. Thus defining lambda as before

$$l_{it} = e^{X_{it}b} + e_i \tag{15}$$

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

$$\Pr[N_{it} = n_{it}] = \int \Pr[N_{it} = n_{it} \,|\, l_{it}] f(l_{it}) d l_{it} \tag{16}$$

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

$$l_{it} = \Gamma(a_{it} j_{it}) \tag{17}$$

where

$$a_{it} = e^{X_{it}b} \tag{18}$$

then

$$\Pr(n) = \int_{0}^{\infty} \frac{e^{-l_{it}}\, l_{it}}{n_{it}!} \frac{l_{it}^{-1}}{\Gamma(j_{it})} [\frac{j_{it}\, l_{it}}{a_{it}}]^{f_{it}} e^{f_{it} l_{it} \int a_{it}} d\, l_{it} \qquad (19)$$

where

$$E(l_{it}) = a_{it} V(l_{it}) = \frac{a_{it}^{2}}{f_{it}} \qquad (20)$$

Integrating by parts and using the fact that

$$\Gamma(a) = a\Gamma(a-1) = (a-1)! \qquad (21)$$

yields the following distribution

$$\Pr(n_{it}) = \frac{\Gamma(n_{it} + f_{it})}{\Gamma(n_{it}+1)\Gamma(f_{it})} [\frac{f_{i}}{a_{it} + f_{it}}]^{f_{it}} [\frac{a_{it}}{f_{it} + a_{it}}]^{n_{it}} \qquad (22)$$

with

$$E(n_{it}) = a_{it} \qquad (23)$$

and

$$V(n_{it}) = a_{it} + a_{it}^{2} / f_{it} \qquad (24)$$

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

$$L(b) = \sum_{i} \sum_{t} \log\Gamma(l_{it} + n_{it}) - \log\Gamma(l_{it}) - \log\Gamma(n_{it}+1) + l_{it}\log(d) - (l_{it} + n_{it})\log(1+d) \qquad (25)$$

with

$$V(n_{it}) = e^{X_{it} b}(1+d)/d \qquad (26)$$

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

In the interests of space, I will not reproduce here the derivation of *fixed-effects* versions of the Poisson and Negative Binomial models. The reader is referred to Hausman, Hall, and Griliches (1984).

Table 1 Sample Statistics for Japanese Firms

Variable	Mean	St. Dev.	Min	Max
Patents	49.57	140.69	0	1178
R&D	22,869.82	53,793.95	50	445,212.3
Citations to U.S.-invented patents	106.45	325.38	0	2820
Citations by U.S.-invented patents	89.28	312.91	0	4348
Sales	351,525.6	741,148.2	2,720.623	9,025,592
U.S. affiliates	1.44	2.68	0	35

Units of sales and R&D figures are millions of 1990 Japanese yen.

Table 2 Spillovers *to* Investing Japanese Firms
Linear Regressions
Dependent Variable: Log(citations) Obs=2120

	Random Effects (1)	***Random Effects(2)***	***Random Effects(3)***	***Fixed Effects(1)***	***Fixed Effects(2)***	***Fixed Effects(3)***
log R&D	.0394 (.0319)	.0412 (.0321)	.0406 (.0319)	.1187 (.0461)	.1188 (.0460)	.1190 (.0461)
log sales	.1042 (.0428)	.0941 (.0423)	.0949 (.0424)	.1879 (.1030)	.1981 (.1029)	.1877 (.1042)
log U.S. patents	.9572 (.0166)	.9518 (.0167)	.9541 (.0167)	.6012 (.0285)	.5911 (.0286)	.5997 (.0285)
U.S. FDI	**-.0119 (.0086)**	**.0175 (.0388)**	**-.0035 (.0192)**	**-.0081 (.0107)**	**.1057 (.0048)**	**-.0070 (.0225)**
Industry Dummies	Yes	Yes	Yes	N.A.	N.A.	N.A.
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

(1) Indicates FDI measured as cumulative counts of all U.S. subsidiaries.
(2) Indicates FDI measured as cumulative counts of acquired U.S. subsidiaries.
(3) Indicates FDI measured as cumulative counts of U.S. R&D/product development facilities.

Table 3 Spillovers *from* Investing Japanese Firms
Linear Regressions
Dependent Variable: Log(citations) Obs=2120

	Random Effects (1)	***Random Effects(2)***	***Random Effects(3)***	***Fixed Effects(1)***	***Fixed Effects(2)***	***Fixed Effects(3)***
log R&D	.0593 (.0254)	.0556 (.0257)	.0617 (.0255)	.0332 (.0274)	.0277 (.0276)	.0341 (.0275)
log sales	.1885 (.0399)	.2260 (.0398)	.1847 (.0400)	.0573 (.0610)	.1012 (.0615)	.0358 (.0621)
log U.S. patents	.6066 (.0151)	.6096 (.0152)	.6154 (.0149)	.4769 (.0205)	.4740 (.0182)	.4879 (.0206)
U.S. FDI	**.0397** **(.0062)**	**.0623** **(.0279)**	**.0733** **(.0132)**	**.0421** **(.0063)**	**.0839** **(.0287)**	**.0644** **(.0134)**
Industry Dummies	Yes	Yes	Yes	N.A.	N.A.	N.A.
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

(1) Indicates FDI measured as cumulative counts of all U.S. subsidiaries.
(2) Indicates FDI measured as cumulative counts of acquired U.S. subsidiaries.
(3) Indicates FDI measured as cumulative counts of U.S. R&D/product development facilities.

Table 4 Spillovers *to* Japanese Firms
Poisson and Negative Binomial Regressions
Dependent Variable: Citations Obs=2093

	Fixed Effects(1)	***Fixed Effects(2)***	***Fixed Effects(3)***	***Fixed Effects(1)***	***Fixed Effects(2)***	***Fixed Effects(3)***
	Poisson	Poisson	Poisson	NB	NB	NB
log R&D	.0446 (.0098)	.0452 (.0098)	.0450 (.0098)	.1143 (.0327)	.1160 (.0328)	.1215 (.0329)
log sales	.3220 (.0178)	.3102 (.0176)	.2624 (.0187)	-.1842 (.0238)	-.1851 (.0238)	-.1871 (.0238)
log U.S. patents	.6754 (.0067)	.6728 (.0067)	.6762 (.0067)	.8096 (.0208)	.8084 (.0208)	.8079 (.0207)
U.S. FDI	**.0006 (.0008)**	**.0351 (.0053)**	**.0136 (.0015)**	**.0031 (.0035)**	**.0427 (.0246)**	**.0227 (.0065)**
Industry Dummies	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

(1) Indicates FDI measured as cumulative counts of all U.S. subsidiaries.
(2) Indicates FDI measured as cumulative counts of acquired U.S. subsidiaries.
(3) Indicates FDI measured as cumulative counts of U.S. R&D/product development facilities.

Table 5 Spillovers *from* Japanese Firms
Negative Binomial Regressions
Dependent Variable: Citations Obs=2006

	Fixed Effects(1)	***Fixed Effects(2)***	***Fixed Effects(3)***
log R&D	-.0306 (.0197)	-.0286 (.0197)	-.0287 (.0197)
log sales	-.1294 (.0193)	-.1243 (.0193)	-.1247 (.0193)
log U.S. patents	.8827 (.0283)	.8754 (.0285)	.8772 (.0285)
U.S. FDI	**.0103 (.0021)**	**.0201 (.0151)**	**.0029 (.0040)**
Industry Dummies	N.A.	N.A.	N.A.
Time Dummies	Yes	Yes	Yes

(1) Indicates FDI measured as cumulative counts of all U.S. subsidiaries.
(2) Indicates FDI measured as cumulative counts of acquired U.S. subsidiaries.
(3) Indicates FDI measured as cumulative counts of U.S. R&D/product development facilities.

Table 6 Spillovers *to* Japanese Firms
Negative Binomial Regressions,
Using a Time-Varying Measure of Technological Proximity
Dependent Variable: Citations Obs=1,492

	Fixed Effects(1)	***Fixed Effects(2)***	***Fixed Effects(3)***
log R&D	.095 (.040)	.094 (.039)	.104 (.040)
log sales	-.188 (.030)	-.187 (.030)	-.195 (.030)
log U.S. patents	.655 (.029)	.657 (.029)	.660 (.028)
Time-varying Proximity	1.91 (.323)	1.91 (.325)	1.77 (.322)
U.S. FDI	**.008 (.004)**	**.046 (.029)**	**.030 (.008)**
Industry Dummies	N.A.	N.A.	N.A.
Time Dummies	Yes	Yes	Yes

(1) Indicates FDI measured as cumulative counts of all U.S. subsidiaries.
(2) Indicates FDI measured as cumulative counts of acquired U.S. subsidiaries.
(3) Indicates FDI measured as cumulative counts of U.S. R&D/product development facilities.

Table 7 Spillovers *from* Japanese Firms
Negative Binomial Regressions,
Using a Time-Varying Measure of Technological Proximity and a Summary Statistic of the Age Distribution
Dependent Variable: Citations Obs=1,492

	Fixed Effects(1)	***Fixed Effects(2)***	***Fixed Effects(3)***
log R&D	-.009 (.020)	-.004 (.020)	-.005 (.020)
log sales	-.155 (.023)	-.210 (.023)	-.209 (.023)
log U.S. patents	.826 (.034)	.830 (.040)	.833 (.037)
Time-varying Proximity	1.31 (.323)	1.38 (.334)	1.32 (.333)
Age	.903 (.109)	.814 (.109)	.842 (.110)
U.S. FDI	**.009** **(.002)**	**.019** **(.015)**	**.006** **(.004)**
Time Dummies	Yes	Yes	Yes
Log Likelihood	-3843.1	-3856.6	-3856.2

(1) Indicates FDI measured as cumulative counts of all U.S. subsidiaries.
(2) Indicates FDI measured as cumulative counts of acquired U.S. subsidiaries.
(3) Indicates FDI measured as cumulative counts of U.S. R&D/product development facilities.