Tapping Foreign Sources of Knowledge:
The Experience of Japanese Multinational Firms [1]

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Executive Summary: How can multinational firms "tap into" technological developments outside their home market? Can success in such international technology sourcing be a source of competitive advantage for firms? This paper seeks to answer these questions by drawing upon the experience of Japanese multinational firms' efforts to learn from U.S.–based technological activity over the 1981–1994 period. The paper develops an empirical methodology for tracking international knowledge spillovers at the firm level, using firm-level data on patent citations. The paper then quantifies the relative impact of technology alliances and foreign direct investment on knowledge flows to and from the initiating Japanese firms. The paper finds that both FDI and technology alliances positively enhance this knowledge flow, with the former having a more statistically robust effect. The paper also presents evidence indicating that a higher level of knowledge flow from the United States is correlated with higher levels of inventive productivity at the firm level. In other words, firms that are relatively more successful at technology sourcing are substantially more effective innovators.

[1] This is a preliminary draft prepared for submission to the 2002 HBS Strategy Conference. The current draft builds heavily on Branstetter (2000). I am grateful to Adam Jaffe for the provision of the patent citations data, to Marc Van Eckert for assistance in obtaining the CATI database, and to David Robinson for assistance with the SDC database. Masami Imai and Yoshiaki Ogura provided excellent research assistance. This paper draws on joint research with Yoshiaki Nakamura of the Japanese Ministry of Economy, Trade, and Industry, and I thank him for his input. Financial support from the National Science Foundation, Columbia Business School, and the Columbia Center on Japanese Economy and Business is gratefully acknowledged.

I. Introduction

To what extent does technological knowledge flow across national borders, and by what means are these knowledge flows mediated? These questions have received an increasing amount of attention in the international economics literature over the last decade, as some of the leading scholars in the field 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.[2] 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.[3] While less thoroughly explored in formal models, the literature also suggests the

[2] For empirical work on this possible channel of international knowledge spillovers, see Coe and Helpman (1995), and Keller (1997).

[3] 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, 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).

possibility of a "learning-by-exporting" effect in which firms learn to improve the quality of their products and production processes through contact with more advanced foreign competitors in global export markets.[4]

The flow of goods is not the only means through which technological knowledge can flow across national boundaries. An obvious alternative is foreign direct investment. In an effort to assess the effectiveness of FDI as a channel of international knowledge spillovers, Ann Harrison, Magnus Blomstrom, and others have undertaken empirical studies using various empirical approaches. The work of Harrison and her co-authors, which has been particularly influential, has used micro-level panel data drawn from Morocco and Venezuela.[5] While these papers do not explicitly model knowledge spillovers, their presence is inferred from changes in the productivity of "indigenous plants" that are associated with the "arrival" of foreign manufacturing affiliates. These studies have generally failed to find robust evidence of positive knowledge spillovers from multinational investment, although Slaughter et al. (2002) find some evidence to the contrary.[6]

In addition to the international economists, participants in the strategy literature have long been interested in the issues surrounding efforts by firms to "tap into" technology networks located outside their home countries. A number of scholars have contributed to the burgeoning literature on "asset-seeking" FDI and "technology-

[4] For empirical work on the "learning by exporting" channel, see Bernard and Jensen (1999), Clerides, Lach, and Tybout (1998), and Aw, Chen, and Roberts (1997).
[5] See Aitken and Harrison (1999) and Haddad and Harrison (1993). A number of other studies, such as Eaton and Tamura (1996), use aggregate or industry-level data to examine these and related issues.
[6] Related work by Chung, Mitchell, and Yeung (1996) casts further doubt on the role of FDI as a channel of knowledge spillovers. However, see also Blomstrom et. al. (1995), who provide evidence for a more positive view of FDI as a channel of knowledge spillovers.

sourcing" FDI.[7] Of particular interest in this literature have been the innovative activities of foreign subsidiaries. Almeida (1996) and Frost (2001), among others, have conducted studies analyzing the patenting activity of foreign subsidiaries in the United States in an effort to understand the extent to which these subsidiaries both draw upon and contribute to technological knowledge generated by economic agents physically resident in the United States. A separate strand of the strategy literature has focused not on the establishment of subsidiaries abroad but on the establishment of R&D and product development alliances between firms based in different countries. Important contributions to this fairly large literature include Mowery, Silverman, and Oxley (1996, 1998) and Gomes-Casseres, Hagedoorn, and Jaffe (2001).[8]

My paper builds on the previous work of both international economists and managerial scholars but differs from that previous work in a number of important respects. First, in contrast to much of the international economics literature, I focus on international knowledge spillovers between advanced industrial economies—in this case, between Japan and the United States. This is significant, because there is a strong presumption that foreign direct investment could lead to two-way spillovers between the investing firm and indigenous enterprises, rather than the presumed one-way flow studied by Aitken and Harrison. In fact, anecdotal evidence, manager interviews, and the results of Branstetter (2000) all suggest that Japanese FDI in the United States has enhanced flows of knowledge spillovers from American firms to the investing Japanese firms.

[7] Porter (1990) suggested the possibility of asset-seeking FDI as a useful component of firm strategy. See also Wesson (1998).

[8] The strategy literature on both of these topics is much larger than this paragraph indicates. A more complete set of references will be incorporated in subsequent drafts.

Second, I measure the impact of *both* the formation of R&D alliances between Japanese and American firms *and* increases in FDI on flows of knowledge spillovers, building upon the work of Gomes-Casseres, Hagedoorn, and Jaffe (2001) and others. This is important, because many Japanese multinationals in my sample have been quite aggressive in forming alliances with U.S. firms and universities. By integrating data on FDI with data on the formation of alliances, I hope to obtain a more complete picture of the means by which Japanese firms track and learn from technological developments outside their home country. In attempting to assess the partial impact of increases in FDI on knowledge spillovers, one would want to control for other activities undertaken by firms to enhance this flow, such as the formation of technology alliances. Likewise, in assessing the impact of technology alliances and research joint ventures on measured knowledge spillovers, one would want to control for the differential degree to which Japanese partner firms have R&D and product engineering facilities located in the United States. Interviews with firm managers suggest that there is, if anything, a complementary relationship between alliances and FDI (especially the establishment of research subsidiaries abroad), so an additional goal of this paper will be to probe the statistical relationships at the firm level between these two channels of learning.[9]

Third, this paper does not follow the earlier convention followed by the international economics literature 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 firms first enter a foreign market, their presence may erode the market power of indigenous incumbents while—at

[9] See Section IV for a more detailed discussion of this anecdotal evidence.

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." This paper presents an alternative framework for measuring the impact of both FDI and technology alliances on knowledge spillovers using patent citations data. Managerial scholars, particularly Almeida (1996) and Frost (2001), have also used patent citation data to examine knowledge spillovers, but I will argue that my framework offers a more comprehensive picture of international knowledge flow for my sample firms than that of earlier studies. I then use this framework to measure the impact of two kinds of international "connectedness"—FDI and R&D alliances—on knowledge flows *from* American firms *to* investing Japanese firms and *from* the investing Japanese firms *to* American inventors.

Fourth, this paper integrates information on the location, establishment, and technological activity of Japanese firms' U.S. subsidiaries with detailed information on the characteristics of the parent firms—including technology alliance formation. This is important because, as Belderbos (2001) has demonstrated, over most of my sample period, Japanese firms' foreign subsidiaries accounted for only a small fraction of their global R&D and patenting activity. The vast majority of R&D activity for nearly all of my firms was concentrated in Japan within the R&D operation of the parent firm, or *honsha*. Inference about knowledge spillovers based on the citation patterns found in the patents of research subsidiaries would be problematic, because these subsidiary-generated patents account for a trivial fraction of the total patents taken out in the U.S. In this paper, Japanese firms' R&D and product engineering facilities in the U.S. are viewed not as important sources of innovation in their own right—because, almost without exception, they are not—but as potential conduits through which useful technological information can flow between U.S.-based "indigenous" innovators and the firms' primary R&D operation in Japan. This approach also means that the impact of the establishment of subsidiaries on international knowledge flows can be viewed in the context of the alliance formation strategy of the parent firms—something that my interviews suggest is quite important.

II. Empirical Methodology

The methodology followed in this paper has two components. The bulk of the paper is devoted to large sample statistical evidence obtained from nonlinear regression analysis. However, these empirical results are interpreted in the context of a set of interviews conducted by the author with the R&D managers of Japanese firms. In this section, I will first describe some features of the Japanese firms in my sample which make them a particularly appropriate target for a study of international knowledge spillovers. Next, I describe the results of my interviews with Japanese R&D managers. Finally, I lay out, in some detail, the statistical methodologies employed.

Why Study Japanese Multinationals?

For decades, Japanese firms have had a reputation of aggressively learning from technology developed outside their home market. During the "catch-up" period of the late 1950s, 1960s, and early 1970s, Japanese firms signed literally thousands of technology-licensing agreements with leading Western (particularly U.S.) multinationals and invested a large fraction of their R&D dollars in adapting this foreign technology to their own needs. By the early 1980s, which is the start of my sample period, Japanese firms had, in some fields, reached the technology frontier. Japanese automobile and electronics firms spent much of the 1980s demonstrating this by forcefully wresting global market share away from their American competitors.

As the yen appreciated dramatically in the latter half of the 1980s, Japanese foreign direct investment in the United States exploded, providing the researcher with a substantial degree of time-series variation in the firm-level FDI data. Furthermore, for many firms, this FDI surge had both “asset-deploying” and “asset-seeking” components. Japanese automobile firms, for instance, shifted production to the United States as a response to exchange rate changes and American protectionism. However, these same firms also established research facilities in the United States to tap into U.S. sources of technological strength. Japanese electronics firms were particularly aggressive about establishing research subsidiaries in U.S. research centers such as Silicon Valley.

Japanese firms are also viewed as enthusiastic users of research alliances, and, over the course of the 1980s and 1990s, Japanese and American firms were increasingly linked in R&D collaboration. The growing strength of Japanese firms in applied R&D made them increasingly attractive to American firms as partners in research alliances rather than as mere licensees of technology. Likewise, the relative weakness of Japanese firms in software and certain areas of basic R&D made alliances with American firms a cost-effective way for Japanese firms to circumvent some of the shortcomings of their approach to research. The extensive degree of alliance activity as well as its variation in both the cross-section and time-series dimensions of my data make this group of firms an interesting target for study.

Finally, throughout my sample period, Japanese firms have been quite aggressive at patenting their inventions in both the U.S. and Japan. Japanese firms are by far the most important group of foreign users of the U.S. patent system. From the early 1980s through the mid-1990s, Japanese firms accounted for as much as a quarter of patents granted by the U.S. each year. This implies that the U.S. patents of Japanese firms provide an unusually complete window through which to observe their innovative activity.

This presents a marked contrast with U.S. multinationals. Because the U.S. was the technology leader in most industries for most of the postwar era, U.S. firms have engaged in relatively little "asset-seeking" or "technology-sourcing" FDI. Furthermore, many U.S. firms have a long history of operations abroad, such that the time-series variation of FDI activity within the sample of major U.S. multinationals is fairly limited over my sample period of 1981–1994. The major buildup of foreign subsidiaries—at least for many firms—occurred long before that period. European multinationals engaged in FDI and technology alliances in the U.S. over this period, but, as a group, they were less focused on the U.S. market than their Japanese counterparts and less likely to obtain patents in the U.S. as well as Europe.

Qualitative Evidence from Practitioner Interviews

In order to obtain a "practitioner's perspective" on the extent to which FDI and alliances function as channels of knowledge spillovers, I conducted a series of interviews with Japanese industry observers, government officials at the Ministry of International Trade and Industry (the government agency charged with overseeing the foreign direct investment activities of Japanese firms), and Japanese executives based in the United States. Yoshiaki Nakamura of the Japanese Ministry of Economy, Trade, and Industry, conducted additional interviews with Japanese R&D managers based in Japan, as part of an ongoing joint research project, and my remarks below draw upon our joint work.[10] These interviews were conducted in the fall of 2000, the spring of 2001, and the fall of 2001, and are therefore somewhat removed in time from my quantitative data, which currently end in 1994.[11]

All interviewees agreed with the view that foreign direct investment in the United States facilitates knowledge spillovers, as I have define that term in this paper. It was also clear from discussions with the managers of Japanese research facilities in the U.S. that a major priority of at least some of these facilities is "tracking" U.S. technological developments in universities and among the leading firms.[12] However, the interviewees also suggested that useful technology is absorbed by U.S. affiliates that are not "pure" research organizations. They agreed with the view that Japanese technology "leaks out" through their U.S. subsidiaries. In fact, this "leakage" is sometimes deliberately *fostered* by the Japanese firms. One Japanese R&D manager based in Silicon Valley described a symposium his company had recently sponsored to publicize some of the firm's more basic R&D. This was done in order to "engage" the local research community, enhance his firm's reputation among local engineers, and assist the firm in forming research partnerships with local academic experts.

Japanese firms also noted that they regard alliances with U.S. firms as an important channel of learning about U.S. technological developments. They also stressed

[10] See Branstetter and Nakamura (2002).
[11] I am currently updating my data to 1999 and re-running all major regressions on the expanded data set. The final table of the current draft draws upon updated data.
[12] A particularly effective method of "tapping into" U.S. technological developments is to hire engineers, technology managers, and research scientists away from leading American firms and universities. This is a high priority for many Japanese research facilities, but also a continuing challenge. Many traditional Japanese labor market practices, such as lifetime employment, seniority-based wages, slow promotion tracks, and consensus-style decision making, do not fit well with the more entrepreneurial culture of such U.S. technology centers as Silicon Valley.

the increasing importance of alliances with U.S. universities and individual American academic experts. The interviews suggested a strong connection between alliance activity and the establishment of research centers in the United States. Often, the location of the research subsidiary was determined by the desire to locate close to the research facilities of particular current or potential R&D alliance partners.

Japanese firms make an effort to maintain a reasonably high degree of communication and coordination between their central R&D operations and their U.S. R&D facilities. One manager of such a facility claimed to communicate on a *daily* basis with the parent company and to physically travel to Japan several times per year for conferences with central R&D managers. The same manager claimed that his firm sends large numbers of engineers from the Japanese parent company to U.S. facilities each year on short-term visits, essentially to promote knowledge spillovers. At the same time, many interviewees expressed the belief that these channels of communication could and should be made to work even more effectively.

A number of Japanese corporate interviewees expressed the view that the central R&D laboratories of Japanese firms have become bureaucratic, insular, and inefficient. Many expressed admiration for what they viewed as the much more market-oriented, dynamic “start-up” system in areas like Silicon Valley—and these expressions of admiration were voiced even after the bursting of the tech stock bubble in early 2000. Every Japanese firm I interviewed is attempting to use its research facilities in the United States as a base from which to seek out additional strategic partnerships and technology-sharing relationships with American high-tech start-ups, universities, and established enterprises in an attempt to increase the efficiency of their total R&D operation.[13] It remains to be seen whether or not these attempts will be successful. Privately, several Japanese corporate interviewees expressed concern that they would have great difficulty achieving this goal.

Nevertheless, for now, the "traditional model" of relying primarily on internal technology development efforts has been revised to emphasize greater technological integration with U.S.-based strategic partners. This seems to suggest that the U.S. subsidiaries of Japanese firms—especially the research facilities—and alliances will play an even more central role as a channel of knowledge spillovers in the future than they have in the past.

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 make a conceptual distinction between knowledge spillovers *per se* and the related processes of

[13] This pursuit of technology-sharing relationships goes beyond high-tech start-ups. Technology-sharing relationships are also cultivated with leading *established* U.S. firms, such as Hewlett-Packard, IBM, and Oracle. One firm also claims that its European research affiliates are actively involved in EU-sponsored research consortia.

"imitation" or "technology diffusion," though it is clear these phenomena overlap in practice.[14]

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 identify the "prior art" on which they build (or be open to charges of patent infringement).[15] 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.[16]

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

[14] 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.

[15] This analogy, while illustrative, is far from exact. Jaffe, Fogarty, and Banks (1998) found that some patent citations are added by either the applicant or the patent examiner for legal or procedural reasons that 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."

[16] 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, Fogarty, and Banks (1998).

outside the scope of the current patent application. As Jaffe, Trajtenberg, and Henderson (1993) put 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.

The use of patent citations to measure knowledge spillovers has been pioneered by Adam Jaffe, Manuel Trajtenberg, and Rebecca Henderson. In their 1993 paper, these three researchers used patent citations to measure the extent to which knowledge spillovers within the United States are geographically localized. In a series of working papers, Jaffe and Trajtenberg have used patent citations to compare magnitudes of knowledge flows across countries and across technological fields.[17] This paper extends the earlier empirical literature by simultaneously examining the impact of firm-level changes in FDI and alliance activity on measured international knowledge spillovers.

Estimating the Impact of FDI and International R&D Alliances on Knowledge Spillovers

Let C_{Jit} be the number of citations made by the patent applications Japanese firm *i* filed in year *t* to the cumulated stock of “indigenous” U.S.-invented patents granted as of year *t*.[18] I can then write the expectation of C_{Jit} as a function of several other observables

$$E[C_{Jit}] = (N_{Jit})^{b_1}(N_{At})^{b_2}[e^{b_3 FDI_{it}}][e^{b_4 Alliance_{it}}][e^{b_5 PROX_i}]R_{it}{}^{b_6}a_i a_t \qquad (1)$$

Let E be the expectations operator. 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 indigenous U.S. patents which exist as of year *t* (N_{At}), the level of firm *i*’s “FDI

[17] See Jaffe and Trajtenberg (1996). 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.

[18] Note that the U.S. Patent and Trademark Office only makes available data on patent applications that are eventually *granted*. In this paper, patents are dated by year of application rather than year of grant, because it takes on average two years—sometimes much longer—for the patent office to grant a patent.

presence" in the U.S. in year t (FDI_{it}), the level of firm i's alliance activity with U.S. firms in year t, and the extent to which firm i is at a point in the technology space which is "densely populated" by other indigenous U.S. patents ($PROX_i$). Some Japanese firms might cite U.S. patents more frequently simply because they happen to be working on technologies in which a large number of indigenous U.S. inventors are active.

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

$$F_i = (f_1, ..., f_k) \tag{2}$$

and each of the k elements of F represent the firm's research resources and expertise in the kth technological area.[19] 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 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:

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

[19] The k different technological clusters are constructed by aggregating the hundreds of patent classes in the U.S. Patent and Trademark Office classification system into 50 distinct categories of technology. I then count the number of patents taken out by firm i in each of these 50 categories over full length of my sample period.

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 (R_{it}) 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). 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. One may also want to assume that a firm's location in technology space relative to aggregate American inventive activity is relatively fixed over time. In that case, the effect of the *PROX* measure is absorbed into the firm fixed effects.[20] The fact that I cannot separately identify it from the firm effects is of little concern, as my primary focus is on the impact of changes in FDI on citations.

Taking the log of (1) and implementing these assumptions gives us a simple, log-linear estimation equation

$$c_{Jit} = b_0 + b_1 p_{it} + b_2 FDI_{it} + b_3 r_{it} + b_4 Alliance_{it} + \sum_t a_t T_t + a_i + e_{it} \qquad (4)$$

where c_{Jit} is the log of the number of citations made by the U.S. patent applications of Japanese firm i in year t to indigenous U.S. patents, p is the log of the count of U.S. patent applications of Japanese 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, *Alliance* measures alliance activity, the a_t's are time dummies, and a_i is a "firm effect," reflecting firm-specific research productivity and, perhaps, firm-specific but time

[20] "Industry effects" will also be absorbed into the firm effects, because firms in my sample do not change their primary industry affiliation over time.

invariant differences in the "connectedness" of the Japanese 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 to U.S. inventive activity 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. 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 me to control for the latter effect, picking up only the partial effect of an increase in FDI or alliance activity on "spillovers" as measured by citations.[21] This imposes a much more stringent statistical test of the impact of FDI (or the impact of alliance activity) on knowledge spillovers. After all, it is possible some of the movement of Japanese firms in "technology space" is *induced* by spillovers from American firms, which they receive either through their network of subsidiaries or their network of alliances. However, if a positive effect of FDI and/or alliance activity remains even after controlling for this movement, this is even stronger evidence in favor of the view that FDI and/or alliances function as a channel of knowledge spillovers. The specification suggested by this line of thinking would be

$$c_{Jit} = b_0 + b_1 p_{it} + b_2 FDI_{it} + b_3 r_{it} + b_4 Alliance_{it} + b_5 PROX_{it} + \sum_t a_t T_t + a_i + e_{it} \qquad (5)$$

[21] Suppose Fujitsu decides to become a world leader in "wireless modems." Fujitsu will need to establish distribution and, possibly, manufacturing facilities in America because it is a leading national market for this kind of product. At the same time, Fujitsu will begin to conduct more research on technologies related to wireless modems and take out more patents protecting its research in this area. Since many American firms have been active in this technology, Fujitsu's new patents will inevitably cite American patents quite frequently. In this case, a change in firm strategy generates both an increase in U.S. FDI and an increase in citations to U.S. patents, though there is no direct causal relationship between the two variables. Without controlling for the firm's movement in technology space, one could overestimate the impact of FDI on knowledge spillovers.

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 (5) 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. I note that the qualitative results on the variables of interest—FDI and alliances—do not change regardless

The focus of interest will be on the coefficients b_2 and b_4. Do firms that increase their levels of FDI in the United States experience an increased tendency to cite U.S. patents?[22] Do firms that engage in more frequent technology alliances and R&D joint ventures with U.S. experience an increased tendency to cite U.S. patents? Positive, significant coefficients would suggest the answer is yes in both cases. The reason why one might expect a positive coefficient is straightforward. To monitor and understand other firms' R&D can be a difficult task—particularly when the other firms' R&D activities are located on the opposite side of the Pacific Ocean. It may be facilitated enormously by the geographical proximity attained through FDI, through which the cost of accessing foreign firms' knowledge assets is reduced. This effect may occur regardless

[22] 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.

of whether or not the FDI by the Japanese firm takes the form of "greenfield" new investment or acquisition of existing U.S. firms. Obviously, this monitoring can also be facilitated by R&D alliances, and the alliances may foster spillover benefits that go beyond the technology targeted by the alliance and even beyond the direct alliance partners.

There are 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 in the United States may have relatively little to learn from their less technologically advanced American counterparts. On the other hand, 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.[23] In light of this, I will present results based on total FDI, "acquisition" FDI, and R&D affiliates. 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 United States, Japanese firms potentially acquire not 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.[24]

[23] Wesson (1998) also finds evidence for "asset-seeking" FDI.

[24] 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

Similarly, I am taking a slightly different view of the potential impact of alliances than Gomes-Casseres, Hagedoorn, and Jaffe (2001). These authors look at the impact of an alliance on subsequent patent citations among alliance partners. They find that the existence of an alliance leads to an increase in the incidence of citations among alliance members. In this paper, I am viewing technology alliances as one of several means by which Japanese firms are seeking to track and learn from technological developments in the U.S. The alliances could, at least potentially, inform Japanese participants about technological developments that lie beyond the explicit scope of the alliance and that involve firms other than the alliance partners. Thus, I will be looking for a statistical linkage between alliance formation and increases in citations of U.S. patents in general without explicitly distinguishing between citations to the patents of alliance partners and other firms.[25] In addition, I will be seeking to examine the impact of this alliance activity while controlling for an important alternative measure of "connectedness" to U.S. inventive activity—foreign direct investment.

Of course, for Americans, the question of greater interest may be not what the Japanese firms have learned through their investments and alliances, but what indigenous American inventors have gained from a greater Japanese "presence" in the United States, achieved through both FDI and alliances. A simple way to measure this through patent citations is to define a new dependent variable, C_{Ait}, as the number of citations made *to*

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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. I thank Jim Rauch for discussions on this point.

[25] In future versions of this paper, I hope to distinguish between increases in citations to the patents of alliance partners and increases in citations to U.S.-invented patents in general, thus providing an empirical assessment of the extent to which alliances foster spillovers beyond the exchange of knowledge among participants.

the cumulated stock of U.S. patents of Japanese firm *i* in year *t by* the universe of indigenous 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:

$$E[C_{Ait}] = (N_{Jit})^{b_1}(N_{At})^{b_2}[e^{b_3 FDI_{it}}][e^{b_4 PROX_{it}}][e^{b_5 Age_{it}}][e^{b_6 Alliance_{it}}]R_{it}^{\ b_7} a_i a_t \qquad (6)$$

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 Japanese firm *i* in year *t*, but rather the cumulative *stock* of patents of Japanese 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 in year *t*, which will be the same for all sample firms in a given year. 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 initially 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. Since, in some specifications, 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, 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*.[26]

[26] Work by Jaffe and his coauthors suggests that the frequency of citation for a given patent peaks on average four to six 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.

As in equation (4), I begin by assuming the relative technological proximity of firm *i* to aggregate American inventive activity is fixed over time, take the logs, and generate a log-linear estimating equation:

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

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 and b_4. Do U.S. inventors' citations to the patents of a Japanese firm increase as the FDI presence of that firm increases? Do they increase as that Japanese firm's level of alliance activity increases? Positive, significant coefficients would indicate the answer is yes to both questions. Relaxing the assumption of "fixed" technological proximity and controlling for changes in the age distribution of Japanese firms' patent stocks suggests a slightly more complicated specification:

$$c_{Ait} = b_0 + b_1 p_{it} + b_2 FDI_{it} + b_3 r_{it} + b_4 Age_{it} + b_5 PROX_{it} + b_6 Alliance_{it} + \sum_t a_t T_t + a_i + e_{it} \qquad (8)$$

As a statistical matter, when one attempts to estimate (4), (5), (7), or (8), one finds there are a 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, *then* take the log. 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 especially designed for count data, in which 0 is a natural outcome, such as a Poisson or Negative Binomial model. In this paper, I have taken the latter approach.

III. Empirical Results

Data on Japanese firms' sales were taken from the Japan Development Bank Corporate Finance Database. R&D data were collected from various issues of the *Kaisha Shiki Ho* series, and data on FDI were taken from the *Kaigai Shinshutsu Kigyou Souran*, 1997 edition, both published by *Toyou Keizai*. Patent data were obtained from the U.S. Patent and Trademark Office and the NBER Patent database.[27] Further details on data sources and construction are available from the author upon request. Note that data on FDI consists of *counts* of firms acquired or established in the U.S. Unfortunately, the nature of the data prevents me from weighting these counts by the size of the establishment.[28]

Data on the technology and R&D alliances between Japanese firms and U.S. firms used in this draft come from the alliances and joint ventures database maintained by the Securities Data Corporation, which has been utilized extensively by other researchers.[29] I used this database to identify cross-border technology alliances involving Japanese firms in my database, the U.S. partner firms, and the start dates. For now, these alliances are simply measured as a cumulative count, in the same way FDI establishments are measured. Because the date of termination of the alliance is not recorded consistently in the SDC database, I am forced to assume that once an alliance has been created, it stays in place indefinitely. While this is not literally true, the learning effects generated by the

[27] The NBER Patent Citations Data File is described in Hall, Jaffe, and Trajtenberg (2001).
[28] For a discussion of these measurement issues, see the Data Appendix.
[29] I thank David Robinson for help with these data. I also acknowledge learning from Robinson (2001). The flaws in this database—in particular, the sparse coverage prior to the 1990s—are well known. I have recently obtained the CATI database on R&D alliances, and, in future drafts, I plan to incorporate data from this database into my analysis. The current draft, however, uses only data from the SDC database. The appropriate caveats should be kept in mind.

alliance may be relatively long-lived, enduring after the official cessation of the alliance itself. Some sample statistics are listed in Table 1.

Results for citations by the patents of Japanese firms to the stock of U.S. patents are given in Table 2. This measures knowledge spillovers *to* Japanese firms *from* U.S. inventors. 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 database explicitly identifies it as an overseas R&D facility. Because it is plausible that there will be some lag between the establishment of a subsidiary—or the establishment of an R&D alliance—and its effect on the flow of knowledge spillovers, I lag the cumulative count by one period and run regressions on the lags. I note, though, that the results of contemporaneous measures of alliances and FDI are qualitatively similar to (though generally weaker than) those presented here.

In fixed effects Negative Binomial models, there is a statistically significant positive relationship for one measure of FDI-R&D facilities.[30] The impact of "broadly defined" FDI is positive, but not statistically significant. The same holds for "acquisition FDI." The coefficient on the FDI term has a "semi-elasticity" interpretation. For example, the number in the third column suggests that setting up an additional R&D lab in the U.S. leads to a 2.5% increase in spillovers from U.S. inventors.

[30] A specification test rejected the fixed effects Poisson regression model in favor of the more flexible fixed effects Negative Binomial model.

When entered separately as a variable, the count of alliances also has a positive, statistically significant impact on measured knowledge spillovers to Japanese firms. Interestingly, when one combines measures of FDI and the alliance count into the same econometric specification, the former generally has a statistically significant, positive coefficient, whereas the latter is statistically indistinguishable from zero, with a point estimate of impact that is much more modest in magnitude. This is the case in Table 2, where, in the fifth column, the alliance count is entered together with the measure of R&D subsidiaries.

Of course, it does not follow that FDI is necessarily more important or more effective than alliances as a channel of knowledge spillovers between the two countries. A number of interpretations of this result are possible, and my empirical work is insufficiently developed at this point to distinguish between these alternatives. One possibility, consistent with our anecdotal evidence, is that alliances are actually more productive when the firm is able to use its "research presence" in the United States to track technological trends, identify capable alliance partners, and identify useful complementarities between the technological strengths of these partners and the parent firm. A local presence may also ease the coordination problems inherent in an alliance. In the absence of a strong U.S. "research presence," alliance partners may be harder to find, harder to evaluate, and harder with which to collaborate. An alternative interpretation is that alliances are measured with more error than my counts of affiliates. The SDC "technology alliances" I have lumped together in my alliance count are a mixture of very different kinds of interfirm agreements and exchanges. Some would be quite obviously directed at enhancing knowledge spillovers, but not all. Of course, these two interpretations are not mutually exclusive.

Table 3 shows results for U.S. citations to Japanese patents, which measure knowledge spillovers *from* Japanese firms *to* U.S. inventors. As in Table 2, the results in the table are obtained using 1-period lagged measures of FDI and alliances.[31] The measured impact of total FDI on knowledge spillovers is positive and statistically significant. Counts of R&D facilities also have a statistically significant effect. The measured impact of acquisition FDI is not statistically significant at the conventional levels.

When entered separately, alliances have a positive, statistically significant measured impact on the flow of knowledge from Japanese firms to the aggregate of U.S. inventors, suggesting that the flow of knowledge within alliances is also not one-way. However, when entered together with the measures of FDI that have a consistently significant effect on knowledge spillovers, the measured impact of alliances on knowledge flows is less robust. In Table 3, the alliance count is statistically insignificant when entered into a specification with the total count of U.S. subsidiaries. When entered together with the count of R&D subsidiaries only, it is significant whereas the R&D subsidiary count falls below the conventional levels of statistical significance. As will be apparent later in the paper, this pattern of results is not robust to the inclusion of additional controls.

Tables 4 and 5 provide a robustness check on the earlier results by incorporating a time-varying measure of the technological proximity of Japanese firms with respect to

[31] Contemporaneous FDI tends to have limited, generally statistically insignificant effects on spillovers from Japanese firms to U.S. inventors.

U.S. invention. Table 4 measures spillovers *to* Japanese firms using a fixed effects Negative Binomial estimate of equation (5). The results are broadly similar to those presented in Table 2—in fact they are a bit stronger. Now, both the total count of subsidiaries *and* the count of R&D facilities have a positive, statistically significant impact on measured knowledge spillovers.[32] The alliance count only has a statistically significant impact on measured knowledge flows when it is entered separately into the empirical specification.

Table 5 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. In introducing these additional controls, I lose observations. Nevertheless, the results clearly indicate that "total" FDI and the establishment of research facilities have a positive and statistically significant effect on spillovers to the U.S.[33] The measure of alliance activity is also positively and significantly correlated with measures of spillovers to the U.S., but the significance of this measure falls below the conventional threshold levels when one also includes either a measure of total FDI or a measure of research subsidiaries.

To briefly summarize these results, the establishment of U.S. R&D facilities tends to have a robust positive impact on spillovers both to and from investing Japanese firms. The "total" measure of FDI also tends to have a positive impact on knowledge spillovers in *both* directions. Acquisition FDI tends not to have a statistically significant impact on measured knowledge flows in either direction. This may be because my current measure

[32] Note that the inclusion of the additional controls cuts down the sample size—I lose about one quarter of the observations. A similar problem affects the results of Table 5.

[33] As in Table 3, measures of FDI are lagged by two periods. However, results with contemporaneous measures of FDI are qualitatively very similar to those presented here.

of acquisition fails to distinguish between firms acquired for their “knowledge assets” (i.e., Kubota’s 1987 acquisition of a Silicon Valley disk drive manufacturer) and firms acquired for other reasons (i.e., Kirin’s 1988 acquisition of a winery in the California Napa Valley), thus generating a fair amount of “noise” in the data.

According to my regression results, the estimated marginal impact of an additional U.S. affiliate on spillover flows ranges from approximately .3% to 2.5%. This sounds like a small effect, but the cumulative impact of a large increase in a firm’s U.S. “FDI presence” could be substantial. Many sample firms establish and/or acquire *dozens* of U.S. affiliates over the course of the sample period. Multiplying this level of increase in a firm’s FDI stock by my estimated marginal effects implies a relatively large increase in knowledge spillover flows. If one takes seriously the estimated impact of alliances in specifications where the alliance count variable is entered separately, the estimated coefficients imply a similarly large increase in total knowledge spillover flows as a consequence of the observed increase in alliance activity over the sample period.

IV. Has It Worked?

The finding that the establishment of overseas R&D facilities and research alliances enhance knowledge flows is of limited interest unless it is the case that firms that receive greater knowledge flows from the U.S. are able to translate that into greater innovative productivity. Of course, firmly establishing a causal linkage between enhanced knowledge flows and greater innovative productivity is difficult, but in the Table 6, I present evidence that is at least consistent with this view. The first column of the table reports the results of a fixed effects negative binomial regression. In this case, the dependent variable is a measure of U.S. patent output generated by my Japanese firms, adjusted for the quality of the underlying inventions. This quality adjustment is based on the number of times each patent is cited by subsequent patents over a four-year window beginning with the grant date. I regress this quality-adjusted measure of innovative output on firm-level R&D spending and two separate measures of knowledge flows from the U.S. The first measure is the count of citations to U.S. patents—the dependent variable from our previous set of regression results. One sees clearly that U.S. knowledge flows are positively associated with higher quality patent output, and that this association is robust to the inclusion of a control for patent counts.[34] The coefficient is very small, but the reader should recall that the statistical interpretation of this coefficient is the increase in patent quality associated with an additional citation. Because some firms make hundreds of such citations in a single year's cohort of patent applications, the cumulative effects of a substantial increase in such citations could be quite substantial.

This point is demonstrated by the results in the second column of Table 6. The measure of knowledge flow used in this column is a simple dummy variable equal to 1 if the firm in question receives higher than the median level of citations over the sample period. A random effects negative binomial regression shows that this variable is highly significant and large in magnitude, suggesting that there is a strong correlation in the cross-section between high levels of knowledge flow and high levels of quality-adjusted patent output. Frequently-citing firms generate patents that are nearly 90% "better," as measured by their *ex-post* citations. I cannot interpret this as strong *causal* evidence of a linkage between knowledge flows from the U.S. and invention quality, because there are likely to be important unmeasured differences in the research quality of firms which may

[34] The obvious relationship between counts of citations to prior U.S. patents and the number of successful Japanese patent applications requires the use of this control. This implies that our innovative output

be correlated with the frequency with which they cite U.S. patents. Nevertheless, these results offer large sample statistical evidence consistent with the view expressed by my interviewees that "tapping into U.S. technology networks" can be a useful component of a global R&D strategy.

V. Conclusions and Extensions

In this paper, I have used patent citations data to measure the importance of foreign direct investment and interfirm alliances in mediating flows of knowledge spillovers across national borders. In contrast to other recent micro-level studies, I find evidence that FDI is a significant channel of knowledge spillovers, both *from* investing firms *to* indigenous firms and *from* indigenous firms *to* investing firms. This evidence is broadly consistent with the perceptions of market participants, as discussed in Section II. It is also robust to the inclusion of a firm-specific, time-varying measure of the incidence of interfirm R&D alliances with U.S. firms. The evidence presented in Table 6 is consistent with the notion that higher levels of knowledge flows from the U.S. are linked to higher levels of innovative productivity on the part of the receiving Japanese firms.

Strategy experts have long asserted that investing abroad can be a useful way of tapping into foreign technology networks. My study upholds this belief with quantitative data, emphasizing the potential importance of multinational corporations as channels of knowledge spillovers between advanced economies. While one needs to exercise caution in drawing general policy implications from these findings, my results suggest national restrictions on FDI could *hamper* rather than promote a domestic industry's technological development.

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measure is, in effect, measuring the *average* quality of patents in a given cohort.

Extending the framework presented in this paper to analyze the impact of Japanese *exports* to the United States 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 exports to the U.S. market into equation (1). Export data broken down by destination market are available for many Japanese firms. In principle, it should be feasible to place measures of exports and FDI into the same estimating equation, allowing the researcher to compare the impact of these two measures of international "connectedness" on knowledge spillovers. Likewise, the framework could be extended to measure the impact of Japanese exports to the United States (that is, *imports* of Japanese goods by American inventors) on the propensity of *U.S.* innovators to cite Japanese inventions.[35]

While the average impact of interfirm alliances on measured knowledge spillovers seems less robust than the impact of FDI, it would obviously be of interest to explore the heterogeneity of outcomes across alliances of different types and to examine further how alliance activity interacts with the establishment of research subsidiaries abroad. What determines the benefits received by Japanese firms in an R&D alliance with U.S. partners? What alliance characteristics are systematically correlated with better outcomes? This latter question has been the focus of much recent research. Branstetter and Sakakibara (forthcoming) have examined the determinants of success in a large cross-section of Japanese government-supported research consortia. The work of Sampson (2000), Lerner and Tsai (2000), and Robinson and Stuart (2000) explores these

[35] A specification that could measure "learning by exporting" would be something along the lines of $E[C_{Jit}] = (N_{Jit})^{b_1}(N_{At})^{b_2}[e^{b_3 FDI_{it}}][e^{b_4 EXPORTS_{it}}]R_{it}^{\,b_5}a_i a_t$. Likewise, a specification measuring "learning by importing" would be $E(C_{Ait}) = (N_{Jit})^{b_1}(N_{At})^{b_2}[e^{b_3 FDI_{it}}][e^{b_4 EXPORTS_{it}}]R_{it}^{\,b_5}a_i a_t$.

issues using U.S. data in various industry contexts. A further extension of the present paper would be to examine the international alliances of Japanese firms in this more detailed manner.

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Table 1 Sample Statistics for Japanese Firms

Variable	Mean	St. dev.	Min.	Max.
Patents	26.37	105.28	0	2006
R&D	22,869.82	53,793.95	50	445,212.3
Citations to U.S.-invented patents	50.7	233.90	0	4,465
Citations by U.S.-invented patents	53.77	283.35	0	7,321
Sales	351,525.6	741,148.2	2,720.623	9,025,592
U.S. affiliates	1.16	3.05	0	51
Alliances	.279	1.78	0	36

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

Table 2 Spillovers *to* Japanese Firms
Negative Binomial Regressions
Dependent Variable: Citations Obs.=2,233

	Fixed effects(1)	*Fixed effects(2)*	*Fixed effects(3)*	*Fixed effects*	*Fixed effects(3)*
Log R&D	.072 (.020)	.073 (.020)	.074 (.020)	.074 (.020)	.074 (.020)
Log U.S. patents	.744 (.020)	.745 (.020)	.743 (.020)	.744 (.020)	.742 (.020)
U.S. FDI	**.003** **(.003)**	**.018** **(.022)**	**.025** **(.006)**		**.023** **(.007)**
U.S. alliances				**.007** **(.003)**	**.002** **(.004)**
Time dummies	Yes	Yes	Yes	Yes	Yes
Log likelihood	-7311.5	-13075.7	-13056.3	-6519.8	-6514.4

(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* Japanese Firms
Negative Binomial Regressions
Dependent Variable: Citations Obs.=2,207

	Fixed effects(1)	***Fixed effects(2)***	***Fixed effects(3)***	***Fixed effects***	***Fixed effects(1)***	***Fixed effects(3)***
Log R&D	-.011 (.014)	-.006 (.014)	-.010 (.014)	-.007 (.014)	-.010 (.014)	-.009 (.014)
Log U.S. patents	.650 (.022)	.662 (.023)	.651 (.023)	.658 (.022)	.651 (.022)	.654 (.023)
U.S. FDI	**.011 (.002)**	**-.015 (.016)**	**.011 (.004)**		**.010 (.002)**	**.006 (.004)**
U.S. alliances				**.007 (.002)**	**.004 (.002)**	**.006 (.002)**
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-6154.7	-6169.7	-6166.3	-6163.7	-6153.2	-6162.7

(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
Negative Binomial Regressions,
Using a Time-Varying Measure of Technological Proximity
Dependent Variable: Citations Obs.=1,857

	Fixed effects(1)	***Fixed effects(2)***	***Fixed effects(3)***	***Fixed effects***	***Fixed effects(1)***	***Fixed effects(3)***
Log R&D	-.020 (.014)	.029 (.021)	-.017 (.014)	-.020 (.014)	-.017 (.014)	-.017 (.014)
Log U.S. patents	.846 (.016)	.510 (.024)	.840 (.016)	.847 (.016)	.840 (.016)	.840 (.016)
Time-varying proximity	.574 (.084)	1.02 (.119)	.543 (.085)	.579 (.085)	.543 (.085)	.543 (.085)
U.S. FDI	**.005 (.002)**	**.034 (.025)**	**.017 (.004)**		**.0035 (.002)**	**.015 (.004)**
U.S. alliances				**.004 (.002)**	**.0032 (.002)**	**.0016 (.002)**
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-6440.5	-6895.2	-6433.7	-6440.5	-6433.4	-6433.4

(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,
Using a Time-Varying Measure of Technological Proximity and a Summary Statistic of the Age Distribution
Dependent Variable: Citations Obs.=1,847

	Fixed effects(1)	*Fixed effects(2)*	*Fixed effects(3)*	*Fixed effects*	*Fixed effects(1)*	*Fixed effects(3)*
Log R&D	.012 (.014)	.014 (.014)	.005 (.020)	.014 (.014)	.012 (.014)	.013 (.014)
Log U.S. patents	.621 (.025)	.631 (.026)	.621 (.026)	.629 (.025)	.621 (.025)	.622 (.026)
Time-varying proximity	.249 (.085)	.292 (.085)	.255 (.086)	.272 (.085)	.245 (.085)	.250 (.086)
Age	1.10 (.091)	1.05 (.092)	1.08 (.092)	1.04 (.092)	1.10 (.091)	1.07 (.093)
U.S. FDI	**.012 (.002)**	**.005 (.015)**	**.012 (.004)**		**.012 (.002)**	**.009 (.004)**
U.S. alliances				**.005 (.002)**	**.001 (.002)**	**.004 (.002)**
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-5702.2	-5721.3	-5716.6	-5717.1	-5701.9	-5714.9

(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 Do Increased Knowledge Flows Raise Innovative Productivity?
Negative Binomial Regressions
Dependent Variable: Citation-adjusted patent output

	Fixed effects(1)	***Random effects(2)***
Log R&D	.031 (.021)	.023 (.027)
Log real sales	.011 (.034)	.101 (.036)
Log U.S. patents	.956 (.016)	.822 (.021)
Log citations to U.S. Patents	**.0001** **(.00002)**	
Dummy for citation greater than median		**.899** **(.096)**
Time dummies	Yes	Yes
Log likelihood	-6119.5	-7884.8

Data Appendix

In order to keep the text of the paper reasonably short, I have omitted a number of details about data sources, data construction, and the empirical methodology. This Data Appendix describes the basic data sources in greater detail and offers a sketch derivation of the count data models employed in the paper.

Data Sources and Measurement Issues

The primary source of data on the U.S. FDI of Japanese firms is *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. Japanese FDI in the U.S. (as opposed to FDI from other 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. The unit of analysis in the *Kaigai Shinshutsu Kigyou Souran* 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.

Data on parent firms' sales and industry affiliation were taken from the Japan Development Bank Corporate Finance database. 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. 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 the subsidiaries of Japanese firms. These inventors are specifically excluded from the sample of "American" patents in the specifications reported in Tables 4 and 5, as is indicated in the text. "American" inventors working for non-U.S. multinationals are considered "American" for the purposes of this study.[36] 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 *physically located in that country*. It is also worth noting that the vast majority of R&D activity conducted by U.S. multinationals is undertaken within 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.

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 (1984). 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

[36] To be more precise, "American" inventors who produce patents assigned to the investing Japanese parent company are always considered to be "Japanese." Americans working for "native" enterprises that are subsequently acquired by Japanese firms are considered "American" in Tables 2 and 3 of the paper. However, all patents produced by these firms are excluded from the analysis presented in Tables 4 and 5 of the paper.

$$pr(n_{it}) = f(n_{it}) = \frac{e^{-l_{it}} l^{nit}{}_{it}}{n_{it}!} \tag{1}$$

where $l_{it} = e^{X_{it}b}$ (2)

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

$$l_{it} = e^{X_{it}b} + e_i \tag{3}$$

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

$$\Pr[N_{it} = n_{it}] = \int \Pr[N_{it} = n_{it} | l_{it}] f(l_{it}) dl_{it} \tag{4}$$

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

$$l_{it} = \Gamma(a_{it} j_{it}) \tag{5}$$

where

$$a_{it} = e^{X_{it}b} \tag{6}$$

then

$$\Pr(n) = \int_0^\infty \frac{e^{-l_{it}} l_{it}}{n_{it}!} \frac{l_{it}{}^{-1}}{\Gamma(j_{it})} [\frac{j_{it} l_{it}}{a_{it}}]^{f_{it}} e^{f_{it} l_{it} \int a_{it}} dl_{it} \tag{7}$$

where

$$E(l_{it}) = a_{it} V(l_{it}) = \frac{a_{it}{}^2}{f_{it}} \tag{8}$$

Integrating by parts and using the fact that

$$\Gamma(a) = a\Gamma(a-1) = (a-1)! \tag{9}$$

yields the following distribution:

$$\Pr(n_{it}) = \frac{\Gamma(n_{it} + f_{it})}{\Gamma(n_{it}+1)\Gamma(f_{it})}[\frac{f_i}{a_{it} + f_{it}}]^{f_{it}}[\frac{a_{it}}{f_{it} + a_{it}}]^{n_{it}} \tag{10}$$

with

$$E(n_{it}) = a_{it} \tag{11}$$

and

$$V(n_{it}) = a_{it} + a_{it}^{2} / f_{it} \tag{12}$$

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

$$L(b) = \sum_i \sum_t \log\Gamma(l_{it} + n_{it}) - \log\Gamma(l_{it}) - \log\Gamma(n_{it}+1) + l_{it}\log(d) - (l_{it} + n_{it})\log(1+d) \tag{13}$$

with

$$V(n_{it}) = e^{X_{it}b}(1+d)/d \tag{14}$$

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

From here, we can proceed to a sketch derivation of the “conditional” or “fixed-effects” negative binomial estimator. The derivation and the notation closely follow Hausman, Hall, and Griliches (84), and the presentation here is meant only to summarize their work. For more details, the reader is referred to their paper.

Let the moment generating function for the negative binomial distribution be

$$m(t) = \left(\frac{1+d+e^{l}}{d}\right)^{-g} \tag{15}$$

Now consider a simple case with two observations. If g 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 $(g_1 + g_2, d)$. 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.

$$pr(w_1 | z = w_1 + w_2) = \frac{pr(w_1)\,pr(z - w_1)}{pr(z)} \tag{16}$$

$$= \frac{\frac{\Gamma(g_1 + w_1)}{\Gamma(g_1)\Gamma(w_1+1)}(1+d)^{-(w_1+w_2)}\left(\frac{d}{1+d}\right)^{g_1+g_2}\frac{\Gamma(g_2+w_2)}{\Gamma(g_2)\Gamma(w_2+1)}}{\frac{\Gamma(g_1+g_2+z)}{\Gamma(g_1+g_2)\Gamma(z+1)}(1+d)^{-z}\left(\frac{d}{1+d}\right)^{g_1+g_2}}$$

$$= \frac{\Gamma(g_1+w_1)\Gamma(g_1+w_2)\Gamma(g_1+g_2)\Gamma(w_1+w_2+1)}{\Gamma(g_1+g_2+z)\Gamma(g_1)\Gamma(g_2)\Gamma(w_1+1)\Gamma(w_2+1)}$$

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

$$pr(n_{i1},\ldots,n_{iT}\left|\sum n_{it}\right.) = \left(\prod_t t\frac{\Gamma(g_{it}+n_{it})}{\Gamma(g_{it})\Gamma(n_{it}+1)}\right)\left(\frac{\Gamma(\sum_t g_{it})\Gamma(\sum_t n_{it}+1)}{\Gamma(\sum_t g_{it}+\sum_t n_{it}}\right) \tag{17}$$

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

$$\log L = \sum_i \sum_t \log\Gamma(l_{it}+n_{it}) - \log\Gamma(l_{it}) - \log\Gamma(n_{it}+1) + \log\Gamma(\sum_t l_{it}) + \tag{18}$$

$$\log\Gamma(\sum_t n_{it}+1) - \log\Gamma(\sum_t l_{it}+\sum_t n_{it})$$

where

$$l_{it} = e^{X_{it}b} \tag{19}$$