Asymmetry of Knowledge Spillovers between MNCs and Host Country Firms

(Forthcoming, *Journal of International Business Studies*)

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Original Submission: April 22, 2004
Last Revised: Nov 16, 2006

Suggested running title: "MNCs and Knowledge Diffusion"

An earlier version of this paper was titled "Multinational Firms and Knowledge Diffusion: Evidence using Patent Citation Data", and was awarded the 2004 William H. Newman Award by the Academy of Management. This paper is based on Chapter 2 of my PhD dissertation, and I am grateful to my advisors Tarun Khanna, Josh Lerner and Richard Caves for their guidance. I thank Bharat Anand, Wilbur Chung, Ken Corts, James Costantini, Mihir Desai, Lee Fleming, Bronwyn Hall, Elhanan Helpman, Rebecca Henderson, Adam Jaffe, Wolfgang Keller, Walter Kuemmerle, Megan MacGarvie, Anita McGahan, Marc Melitz, Jan Rivkin, Jordan Siegel, Olav Sorenson, Catherine Thomas, Peter Thompson and Manuel Trajtenberg for comments. This paper has also gained from feedback during seminars at CMU, Columbia, Emory, GWU, Harvard, HEC, IESE, INSEAD, Instituto de Empresa, LBS, Maryland, Minnesota, MIT, NBER, NUS, NYU, Rutgers, SMU, UNC, Vanderbilt, Wharton and the 2004 meetings of American Economic Association, Academy of International Business and Academy of Management. I also thank the *JIBS* Departmental Editor, J. Myles Shaver, and two anonymous referees for detailed suggestions. Finally, I am grateful to Harvard Business School and INSEAD for funding. Errors remain my own.

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Abstract

We use patent citation data to examine knowledge flows between foreign MNCs and host country organizations in 30 countries. We find not just significant knowledge inflows from foreign MNCs to host country organizations, but also significant outflows back from the host country to foreign MNCs. In fact, in technologically advanced countries, knowledge outflows to foreign MNCs greatly outweigh knowledge inflows. Even in technologically less advanced countries, knowledge outflows are only slightly weaker than inflows. Additional analysis shows that the exact pattern varies across sectors within a country, depending on the country's expertise in individual sectors. Finally, knowledge inflows and outflows appear to track personnel flows between foreign MNCs and host country organizations.

Keywords: Technology Diffusion, Knowledge Spillovers, Multinational Firms, R&D, Personnel Mobility, Networks
JEL Codes: F2, L2, M2, O3

1. Introduction

The primary goal of this paper is to examine both knowledge inflows and knowledge outflows resulting from foreign multinational companies (MNCs) investing in a country. To achieve this, we address three related questions: First, how much do foreign MNCs contribute in terms of knowledge inflows to host country organizations? Second, how does the extent of these inflows compare with knowledge outflows back from the host country to foreign MNCs? Third, what drives the direction of net knowledge flow, and the variation in knowledge flow patterns across countries and sectors? Such an empirical examination of bi-directional knowledge flows between foreign MNCs and host country organizations is important for several reasons. First, it helps rigorously establish "stylized facts" of general interest to anyone doing research on MNCs. Second, the findings can be a useful starting point for policy debates regarding knowledge spillover effects related to MNCs. Third, the results should also be of interest to managers involved in cross-border knowledge management in MNCs.

Foreign sources of technology typically account for over 90 percent of a country's domestic productivity growth, with most technologies originating from just a few technologically advanced countries (Keller, 2004).[1] In fact, about 84% of all worldwide research and development (R&D) funding and 92% of all innovations registered with the U.S. Patent and Trademark Office (USPTO) are concentrated in the seven most industrialized countries. This makes economic growth worldwide highly dependent on international diffusion of knowledge (Romer, 1990; Grossman and Helpman, 1991). However, knowledge is often tacit and not easy to transmit as blueprints (Polanyi, 1967; Nelson and Winter, 1982). This can cause knowledge diffusion to be geographically localized, an argument supported by

[1] Although concentration of technology has been declining somewhat since regions such as South Korea, Taiwan, Ireland and Israel have also rapidly built innovative capabilities (Mahmood and Singh, 2003; Furman and Hayes, 2005), it is still likely to remain relatively high at least in the near future.

numerous empirical studies (Jaffe *et al.*, 1993; Audretsch and Feldman, 1996; Branstetter, 2001; Keller, 2002). However, it has also been suggested that foreign direct investment (FDI) is a mechanism that helps a country overcome this geographic localization of knowledge diffusion. As a result, a motivation behind many FDI-friendly government policies is the prospect of acquiring modern technology and know-how, including product and process technology as well as management, distribution and marketing skills.[2]

However, the evidence on exactly how much MNCs really contribute to host country knowledge still remains inconclusive.[3] In addition, in industrialized countries, there is also a debate regarding potential "leakage" of domestic technology through local subsidiaries of foreign MNCs. The concern is that, in addition to being a source of valuable knowledge, these subsidiaries might also be a channel through which domestic technology falls into the hands of foreign competitors. To the extent that unique access to such technology might be crucial for competitive advantage of a country's firms, some people worry that these knowledge outflows could reduce the competitiveness of host country firms in global markets. For example, Dalton and Serapio (1995) summarize this debate in the context of U.S.: "*Rapid growth of foreign R&D in the U.S. has led to concerns about an erosion of U.S. technology leadership… Some observers have questioned the quality of the research effort by foreign companies. They have argued that U.S. research centers of foreign companies are merely 'listening posts' that focus on technology scanning*." Reid and Schriesheim (1996) echo these

[2] Indeed, governments around the world continue to spend enormous resources as subsidies and tax breaks to attract MNCs. This is true not just for developing countries (such as the widely cited case of Intel in Costa Rica) but also for the more industrialized countries. For instance, the 2001 mission statement of Industrial Development Authority of Ireland said "We will win for Ireland, its people and its regions, the best in international innovation and investment so as to contribute to the continued transformation of Ireland to a world-leading society which is rich in creativity, learning and social well-being". Even in the U.S., the state of Alabama in 1994 spent $230 million, or about $150,000 per newly created job, to attract a new plant of Mercedes-Benz (Haskel *et al.*, 2002).

[3] See Caves (1996) and Keller (2004) for surveys. As Dani Rodrik puts it, "Today's policy literature is filled with extravagant claims about positive spillovers from FDI, but the hard evidence is sobering" (Rodrik, 1999, p. 37).

concerns: "*U.S.-based affiliates of foreign-owned firms increased their share of total private R&D spending from 6.6 percent (in 1980) to 14.5 percent (in 1992)… foreign-owned companies and their stakeholders abroad may be extracting more intellectual property and associated value from the United States than they contribute to it*" (p. 39). In this paper, we take a first step at investigating the extent to which such concerns might be justified. Specifically, we focus on rigorously measuring and comparing the extent of knowledge inflows versus outflows resulting from foreign MNCs investing locally in 30 countries. We then discuss implications of our findings, while being cautious in pointing out that further research would be needed for conclusively establishing the exact welfare effects.

Knowledge spillovers are hard to measure directly. Therefore, the conventional approach has been to infer them indirectly by estimating change in productivity of domestic firms as a result of investment by foreign MNCs (Caves, 1974, 1996). A challenge in doing so, however, is separating knowledge diffusion effects of FDI from its effect on market structure (Aitken and Harrison, 1999; Haskel *et al.*, 2002; Chung *et al.*, 2003). An alternate approach used in related literature is to trace knowledge flows directly using citations between patents (Jaffe *et al.*, 1993; Almeida, 1996; Frost, 2001). This approach exploits the fact that, since existing innovations provide ideas and inspiration for further innovation, patent citations help capture knowledge flows across organizations. In fact, since an organization rarely captures all rents associated with an innovation, these knowledge flows at least in part represent unintended externalities or "knowledge spillovers". Following this approach, we also use patent citations to measure two-way knowledge flows between MNCs and their host countries.

Existing studies on knowledge diffusion effects of MNCs typically focus on a single country, making it difficult to reach general conclusions. An important contribution of this paper is therefore examining data across a large number of countries in order to explore cross-sectional similarities as well as differences in patterns of knowledge diffusion. Since knowledge outflows are a real concern only in countries that do have advanced technology to start with, the analysis focuses on the 30 technologically advanced countries that together represent 99.5% of all patents filed with USPTO. The findings suggest that there are indeed not just knowledge inflows from foreign MNCs to host country organizations but also significant knowledge outflows back from host country organizations to foreign MNCs. In fact, on an average, MNCs appear to contribute less to host country knowledge than they gain from it. This asymmetry in knowledge flows exists not only in the aggregate but also in a large majority of the individual countries. However, there are also several exceptions. There are countries, such as the U.K. and Belgium, for which the two-way knowledge flows between MNC subsidiaries and host country firms are almost symmetric. There are others, such as Taiwan, South Korea, Sweden, Israel, Finland, Austria, Spain and Hong Kong, for which the asymmetry turns in the other direction, i.e., knowledge inflows from foreign MNCs exceed knowledge outflows. Further investigation reveals that greater knowledge outflows are more typical in countries where domestic organizations are technologically advanced. Digging deeper, cross-sector differences within countries reveal an analogous pattern: knowledge outflows are greater in sectors where the host country is relatively stronger in its technological capabilities.

This paper also takes a first look at micro-level mechanisms that could drive observed knowledge diffusion patterns. Specifically, we use data on career histories of patent inventors as a window into inter-organizational personnel movement. Preliminary analysis suggests that knowledge flows mirror the underlying patterns of personnel mobility: personnel flows from domestic organizations to MNC subsidiaries exceed personnel flows in the opposite direction.

Further, countries where MNC subsidiaries hire significantly more personnel from domestic players than they lose to them are typically also those most likely to exhibit greater knowledge outflows than inflows from MNCs. Thus, inter-organizational mobility of personnel appears to be an important determinant of cross-country differences in patterns of knowledge diffusion.

The rest of the paper is organized as follows. Section 2 discusses theoretical issues related to knowledge diffusion effects of MNCs, and motivates our key hypotheses. Section 3 describes our patent data and parent-subsidiary matching for MNCs. Section 4 applies a novel citation-level regression framework for measuring and comparing knowledge flows to and from foreign MNCs. Section 5 investigates cross-country and cross-sector differences in knowledge flow patterns. Section 6 examines inter-organizational personnel flows as one possible mechanism behind the observed knowledge diffusion patterns. Section 7 discusses methodological issues in using patent citation data for measuring knowledge flows. Section 8 offers tentative implications from our findings, while highlighting caveats in trying to link the direction of knowledge flows to overall welfare effects for the host country.

2. Knowledge Flows between MNCs and Host Country Organizations

Knowledge is not always codifiable in a way that enables easy transmission in the form of blueprints. Instead, it is often ‘tacit’, making diffusion of knowledge across large distances difficult (Polanyi, 1967; Nelson and Winter, 1982). Not surprisingly, empirical research has also found knowledge diffusion to be constrained by geographic distance (Jaffe *et al.*, 1993; Audretsch and Feldman, 1996; Branstetter, 2001; Keller, 2002). However, MNCs might be a vehicle that facilitates global diffusion of knowledge by combining intra-firm mechanisms for long-distance knowledge transfer with localized knowledge exchange with organizations in different parts of the world. In fact, one of the reasons for the very existence of MNCs is considered to be their ability to transfer and integrate knowledge globally (Hymer, 1976; Buckley and Casson, 1976). Several theoretical mechanisms have been proposed for this. The knowledge-based view argues that firms facilitate interpersonal networks and a social context that enable transmission of tacit knowledge over large distances (Hedlund, 1986; Bartlett and Ghoshal, 1989; Kogut and Zander, 1993; Nohria and Ghoshal, 1997). The transaction cost literature argues that knowledge transfer is also facilitated through decreased opportunism within a firm (Williamson, 1985; Ethier, 1986; Teece, 1986).

Two streams of literature are relevant for studying the extent and direction of knowledge flows between MNCs and their host countries. On the one hand, literature in International Economics focuses on the role of MNCs in enabling technology transfer *to* host countries, and finds mixed evidence for the same (Aitken and Harrison, 1999; Haskel *et al.*, 2002). On the other hand, literature on International Business and Strategy highlights that MNCs themselves can use foreign subsidiaries as a means of accessing knowledge *from* host countries (Hedlund, 1986; Bartlett and Ghoshal, 1989; Almeida, 1996; Frost, 2001). To study the overall knowledge-related effect from MNCs needs combining insights from both these literatures to simultaneously examine knowledge inflows and outflows. To the extent that imitation of technology by foreign MNCs may erode technology-related competitive advantage of domestic firms, knowledge outflows could negatively impact the profitability of domestic firms and ultimately hurt the welfare of the host country. However, as discussed at length in the final section of this paper, even a simultaneous exploration of knowledge inflows and outflows may not be conclusive in establishing precise welfare effects. Nevertheless, this exploration is still a step closer to determining overall welfare implications than would be possible via a focus only on *uni-directional* knowledge flows typically emphasized in International Economics.

There are several reasons why knowledge outflows from host country organizations to MNC subsidiaries might be greater than knowledge inflows from MNC subsidiaries to the host country organizations. If MNC subsidiaries were involved in cutting-edge research or innovative product development, high degree of knowledge spillover benefits might result for the host country. However, while the number of MNC subsidiaries performing advanced research has been increasing over time, such cases still comprise only a small fraction of all cases of FDI (Kuemmerle, 1999 and Frost *et al.*, 2002). A majority of MNC subsidiaries, including those engaging in any form of R&D, continue to have one of the following mandates. First, even today, they often focus on incremental adaptation of their parent firm's products for the local markets just as it was reported years ago in surveys like Mansfield *et al.* (1979). Second, many subsidiaries act as "listening posts" to monitor technological developments in the host country (Almeida, 1996; Florida, 1997; Frost; 2001). In either of these cases, an MNC subsidiary is less likely to be a source of advanced technological knowledge than it could have been if its main charter were doing original R&D. In fact, as Cantwell and Janne (1999) report, foreign subsidiaries of even technologically advanced firms typically focus on peripheral technologies where these firms lag behind other countries rather than cutting-edge R&D in core technologies of the firm. Further, MNCs often restrict leakage of their core technologies by leveraging their globally innovation network and complementary capabilities, which ensures that access to knowledge from just their local subsidiary would not be very valuable for a potential competitor in the host country (Zhao, 2006; Alcacer and Zhao, 2006). Similarly highlighting the importance of an MNC's global innovation network, Singh (2006) shows that innovations resulting from integration of knowledge across MNC subsidiaries in different locations are more valuable than those arising only from knowledge from one subsidiary.

Raising further concerns about knowledge spillover benefits from FDI is an adverse selection in technological capabilities of MNC subsidiaries that do locate close to host country organizations. In particular, both the decision to set up a subsidiary overseas and the choice of where to locate it take into account not only the potential gains from tapping into external know-how but also the potential risk that the firm's own technology will fall into the hands of its competitors (Sanna-Randaccio and Veugelers, 2006). This has two implications: First, in order to minimize the risk of having their technology imitated, foreign MNCs that are technologically most advanced often decide not to set up a subsidiary in a country. Consistent with this argument, Kogut and Chang (1991) find that a disproportionately large fraction of Japanese FDI in the U.S. is limited to industries where the Japanese MNCs lag behind their U.S. counterparts in technological competence. Second, a technologically advanced MNC that does set up a subsidiary overseas often locates it far away from host country organizations perceived as potential competitors (Shaver and Flyer, 2000; Chung and Alcacer, 2002; Alcacer and Chung, 2006). As a result, MNC subsidiaries that locate close to host country firms are relative laggards, with relatively less to lose from knowledge exchange with domestic organizations. On the other hand, location decisions of host country organizations are typically determined not by such strategic considerations but by historical factors such as the region where an entrepreneur already lived and the region where the original resources conducive to an industry were located (Sorenson and Audia, 2000; Stuart and Sorenson, 2003; Klepper, 2005). These differences in drivers of location choice between MNC subsidiaries and domestic organizations accentuate the possibility that host countries would lose more in terms of knowledge outflows to MNC subsidiaries than they could gain as inflows. This leads to the following hypothesis:

Hypothesis 1. *On an average, knowledge outflows from host country organizations to MNC subsidiaries exceed knowledge inflows from MNC subsidiaries to host country organizations.*

It is worth emphasizing that the above hypothesis is not theoretically unambiguous. In particular, MNC subsidiaries might be at a disadvantage compared with domestic players in terms of access to local information networks and knowledge base. To borrow the term from Zaheer (1995), MNC's might suffer from a "liability of foreignness" in operating in another country. As Hymer (1976) explains: "National firms have the general advantage of better information about their country: its economy, its law and its politics. To a foreigner the cost of acquiring this information might be considerable" (p 34-35). Several empirical studies have demonstrated that such a liability of foreignness can translate into an asymmetry in relative performance of foreign and local players (Zaheer, 1995; Zaheer and Mosakowski, 1997; Mezias, 2002; Miller and Parkhe, 2002), even though MNCs might be more susceptible to liability of foreignness in some settings compared with others (Nachum, 2003). In the specific context of knowledge diffusion, a liability of foreignness could arise from an MNC's inability to get access to tacit knowledge embedded in the regional interpersonal networks. However, reversing the asymmetry of knowledge hypothesized above would require not just that an MNC is unable to tap into the regional networks but also that it simultaneously fails to prevent leakage of its own knowledge into these networks. Whether or not this actually happens is an empirical question.

We now sharpen the above hypothesis regarding aggregate patterns by examining conditions under which the asymmetry of knowledge flow is likely to be most pronounced in a cross-country comparison. Although the above discussion argues that knowledge flows from MNCs are weak because R&D activities being done in MNC subsidiaries are not as advanced as R&D in the home bases of MNCs, it really is the quality of these activities relative to the technological capabilities of host country organizations that should determine the potential for knowledge outflows versus inflows. In particular, we should expect knowledge inflows from MNC subsidiaries to domestic firms to be stronger in countries whose domestic organizations are technologically not very advanced. In such countries, the knowledge that domestic organizations possess is far behind the world technology frontier, making knowledge diffusion from MNCs particularly likely (Findlay, 1978; Sjöholm, 1999; Haskel *et al.*, 2002).

In contrast to laggard countries, countries already at or close to the technology frontier have domestic organization with little to gain in terms of knowledge from MNC subsidiaries. Instead, they are likely to possess valuable knowledge foreign MNCs do not have, making them vulnerable to MNC "listening posts" that monitor domestic developments. A similar argument can be made not just at the level of a country but also at the level of individual sectors within a country, since different sectors within the same host country often differ in the extent to which domestic organizations possess world-class knowledge and cutting-edge R&D capabilities. Therefore, extending the above logic, the relative extent of knowledge outflows from the host country to MNCs should also be most intense in sectors where the domestic organizations are technological leaders. These arguments lead to the following hypothesis:

Hypothesis 2. *Knowledge outflows from domestic organizations to MNC subsidiaries exceed knowledge inflows from MNC subsidiaries to domestic organizations in countries as well as in sectors within a given country where domestic organizations are more advanced technologically.*

While the last hypothesis may seem intuitive, there are theoretical arguments for why it need not always hold in real data. As the difference in level of technological sophistication between an advanced MNC and a lagging home country increases, the domestic firms might actually have less rather than more to gain as knowledge because the MNC's technology might become too advanced to have direct applicability for these firms (Lapan and Bardhan, 1973). In addition, the literature of absorptive capacity of firms (Cohen and Levinthal, 1989) suggests that domestic firms that lag far behind might not even have the minimum knowledge needed to absorb further knowledge. Such an argument is consistent with Cantwell's (1989) finding that domestic firms in European markets during 1955-1975 gained most from entry of US MNCs in industries where Europe already had a strong technological tradition. Once more, whether or not this effect overshadows the effect hypothesized above becomes an empirical question.

3. Data

3.1. Patent Data

Patent citations leave behind a trail of how a new innovation builds upon existing knowledge. An inventor is legally bound to report relevant "prior art", with the patent examiner serving as an objective check to ensure that all relevant patents are cited. There are, however, two factors that add noise to citations as a measure of knowledge flows. First, citations might be included by the inventor for strategic reasons like avoiding litigation. Second, a patent examiner might add citations to innovations that the original inventor did not know about. Nevertheless, recent studies show that the correlation between patent citations and actually reported knowledge flows is high, justifying use of citations at least in large samples (Jaffe and Trajtenberg, 2002, Chapter 12; Duguet and MacGarvie, 2005). [4]

Since patents from different patent offices are not comparable to each other, it is common practice to use data from a single patent granting country like the U.S. (Jaffe and Trajtenberg, 2002) or the U.K. (Lerner, 2002) to standardize the measure of innovation. Likewise, we use a

[4] It is worth emphasizing that we use patent citations as a measure correlated with actual knowledge flows without assuming that citations are the actual mechanism behind these flows. Consider the analogy that a student's citation to his advisor's research paper may tell us that she built upon knowledge that her advisor created, even if most of the actual knowledge transfer happened not through her reading the paper but by working closely with the advisor.

dataset on patents registered with the U.S. Patent Office (USPTO) during 1986-1995. The dataset was created by merging raw data from USPTO with additional data fields from Jaffe and Trajtenberg (2002). As Table 1 summarizes, the number of USPTO patents for 1986-1995 is about 1.01 million, with 83% owned by organizations. This paper focuses on patents from the top 30 countries, each of which gave rise to at least 200 USPTO patents during 1986-1995. Together, these countries account for 99.5% of all USPTO patents for this period.

3.2. MNC Parent-Subsidiary Data

In order to ascertain whether a specific innovation should be considered as originating from a domestic organization or from an MNC subsidiary operating in the country, we need to know what its assignee's home country is. However, since USPTO data includes about 175,000 assignees, it is impossible to manually verify the home country for each assignee. For example, a patent arising from a German subsidiary of IBM could appear as being owned by the parent company "IBM" or under a separate assignee name like "IBM Germany" or something else from which its affiliation to IBM is not even obvious. To construct our parent-subsidiary database, we therefore manually inspected about 10,000 major assignees as follows.[5] First, Compustat-based parent firm identifiers from Jaffe and Trajtenberg (2002) were used to match approximately 4,600 assignees to 2,500 parent firms. Second, Stopford's *Directory of Multinationals* was used to match 2,800 additional assignees to about 200 parent firms. Third, about 400 major government-affiliated bodies, 550 research institutes and 450 universities worldwide were identified. Finally, the ownership of 1,000 of the largest remaining assignees was determined using *Who Owns Who* directories and company web sites. These steps account for about 0.59 million patents, or about 73% of all assigned patents. The home country for the remaining

[5] To ensure a unique definition of the parent, we define an assignee to be an MNC subsidiary when a foreign firm has a *majority* stake in it. For cases with a 50-50 stake, we simply broke the tie in favor of the first firm. See Mowery, Oxley and Silverman (1996) or Gomes-Casseres *et al.* (2005) for a closer look at the issue of alliances.

assigned patents was calculated as the country where most of any given assignee's patents originate, though all results are robust to simply dropping these patents from further analysis.

4. Citation-Level Regression Analysis

Since only a fraction of innovations ends up as patents (Levin *et al.*, 1987), measures based on raw counts of patents and patent citations can be misleading. To circumvent this issue, we econometrically estimate the probability of citation between random pairs of patents without making an assumption that these patents comprise all the innovations.

4.1. Conceptual Framework for Estimating Probability of Citation

Suppose that the probability of any patent *K* citing another patent *k* is given by a "citation function" P(*K*, *k*). By assuming that the citation function takes a logistic functional form, one could potentially carry out an econometric estimation of this function if one were given a large enough random sample of patent pairs. In such a sample, an observation *i* would capture relevant characteristics of the potentially citing patent *K* and cited patent *k*, and the binary dependent variable *y* would be defined as being 1 if and only if a citation actually exists between the given pair of patents. Formally, *y* would be taken as a Bernoulli outcome that is 1 for observation *i* with a probability given by

$$\Pr(y = 1 \mid x = x_i) = \Lambda(x_i \beta) = \frac{1}{1 + e^{-x_i \beta}}$$

where $\mathbf{x_i}$ is the vector of covariates corresponding to the pair of patents and $\boldsymbol{\beta}$ is the vector of parameters to be estimated. Specifically, this framework can allow us to test whether the probability that a random patent from an MNC subsidiary cites a random patent from a domestic player is systematically different from a citation in the opposite direction. As Figure 1 shows, the covariates should include indicator variables for cases where the potential citation implied by any given observation represents a within-country knowledge flow from domestic entities to MNC subsidiaries (D→M), from MNC subsidiaries to domestic entities (M→D), between domestic entities (D→D) or between MNC subsidiaries (M→M).[6] Similarly, to capture within-MNC knowledge flow across borders, the covariates should include dummy variables for cases where the citation represents a within-MNC knowledge flow from a foreign subsidiary of an MNC to its home base (S→H) or vice-versa (H→S). Table 2 summarizes these indicator variables. Since all observations representing an intra-national self-citation from an assignee to itself are dropped, the omitted (reference) category for interpreting regression coefficients is cross-border knowledge flow among different firms.

4.2. Choice-Based Sampling and WESML Estimation

Since the number of patents is almost a million, the population of all potential citations (K, k) is almost a trillion. However, the fraction of actual citations or "ones" in this population is extremely small: only about seven in a million. This makes estimation using the usual random sampling impractical. From an informational point of view, it would be desirable to have a greater fraction of observations with $y = 1$. This can be achieved by a "choice-based" sampling procedure that over-samples the patent pairs for which a citation actually exists. In other words, the sample consists of a fraction α of all possible patent pairs with $y = 0$, and a fraction γ of the pairs with $y = 1$, where α is much smaller than γ. However, this difference in sampling rate causes the usual logistic estimates to be biased. This can be overcome using the *weighted exogenous sampling maximum likelihood* (WESML) estimator, which explicitly recognizes the difference in sampling of the "zeroes" and "ones" by weighting each term in the log likelihood

[6] This approach of studying intra-national knowledge flows between different kinds of firms (domestic versus foreign) echoes the views expressed by Baldwin *et al.* (1998): "The connection between productivity measurement and a geographic basis for economic accounting is strong if the only important inputs are land, labor, physical capital, and possibly human capital… If, however, technology, organizational skills, patents, or brand name are major determinants of output and productivity, the advantage of the geographic measure disappears because these types of intangible capital reside not in locations but in organizations that may span state and national borders" (p.3).

function by the inverse of the ex ante probability of inclusion of an observation in the sample (Manski and Lerman, 1977).[7] Mathematically, the WESML estimator is obtained by maximizing the following weighted "pseudo-likelihood" function:

$$\ln L_w = \frac{1}{\gamma}\sum_{\{y_i=1\}}\ln(\Lambda_i)+\frac{1}{\alpha}\sum_{\{y_i=0\}}\ln(1-\Lambda_i) = -\sum_{i=1}^{n} w_i \ln(1+e^{(1-2y_i)x_i\beta})$$

where $w_i = (1/\gamma)\, y_i + (1/\alpha)(1-y_i)$. The appropriate estimator of the asymptotic covariance matrix is White's robust "sandwich" estimator. Further, the standard errors should be calculated without assuming independence across observations with the same citing patent. Since technological similarity of patents is a strong determinant of the probability of citation, estimation efficiency of WESML can be further improved by drawing "zeroes" more often from the sub-population of patent dyads where the citing and cited patents share the same technology class. As Singh (2005) shows, the WESML weights should now be adjusted to take this differential sampling frequency into account.

4.3. Control Variables Affecting Probability of Citation

Firms active in similar technologies tend to locate near each other, often for reasons such as availability of specialized labor or intermediate goods rather than just expected knowledge spillovers (Marshall, 1920; Krugman, 1991; Jaffe *et al.*, 1993). Therefore, in studying knowledge spillovers, it is important to rule out if frequent citation between co-located patents is just an artifact of them being technologically related rather than a genuine outcome of geographic co-location. To do so, the conventional "matching" approach defines the appropriate benchmark as being frequency of citation from the citing patents to a set of potentially cited patents that are technologically similar to the actually cited patents from the

[7] See Amemiya (1985), Greene (2003) or King and Zeng (2001) for more discussion on WESML. Sorenson and Fleming (2004) and Singh (2005) have also used WESML specifically for predicting patent citations.

same time period (Jaffe *et al.*, 1993). While we discuss the details of matching in the context of cross-country comparison in the next section, it is worth mentioning two issues raised by Thompson and Fox-Kean (2005). First, the technological match involves a trade-off: the commonly used 3-digit classification over-estimates spillovers because of coarse matching, while finding a close match using a more detailed 9-digit classification is often impractical. Second, since a patent is often associated with multiple technological classes but matching can only captures the "primary" class, technological relatedness manifesting as overlapping "secondary" classes gets ignored. Our regression framework resolves both these issues by using multiple indicator variables to capture relatedness appearing as the same technological category (1 out of 6), same technological subcategory (1 out of 36), same 3-digit primary class (1 out of 418), same 9-digit primary sub-class (1 out of 150,000), or an overlap of secondary subclasses. These variables are formally defined in Table 2.

Since frequency of citation differs across sectors, the set of controls in our regressions includes fixed effects for the broad technological category of the citing patent. In addition, since innovators in different countries may differ in their likelihood of citing patents registered with the USPTO, all regressions also include citing country fixed effects. Finally, since the impact of time lag between the citing and cited patents on the probability of citation cannot be captured simply using a linear or even a quadratic functional form (Jaffe and Trajtenberg, 2002, Chapter 13), we use a set of dummy variables to capture different time lags as measured in years. All results reported here are robust to adding citing year fixed effects.

4.4. Results from Citation-Level Regression Analysis

The sample used here had 1,867,579 actual citations ("ones") and 5,049,445 control citations ("zeroes"), giving an overall sample size of 6,917,024 patent dyads. The WESML results appear in Table 3. Column (1) shows that patent citations are particularly frequent within the same country, and also within the same MNC. As column (2) shows, including control for technological relatedness at the 3-digit class level significantly reduces the estimated effects for *within same country* and *within same MNC*, implying that column (1) results are partly driven by technological specialization of regions and firms. By accounting for similarity along 9-digit primary and secondary subclass, column (3) addresses the concern that technological controls at the 3-digit class level are inadequate. This further lowers the knowledge flow estimates for *within same country* and *within same MNC*. Nevertheless, the estimates remain significant, implying that knowledge flows are indeed concentrated within countries and MNCs even after controlling for technological specialization.

We now analyze the economic significance of these results. Table 3 reports not just the coefficient estimates, but also the corresponding marginal effects (in square brackets, after multiplying them by a million for readability).[8] The predicted citation rate between two random patents is approximately 5.0 in a million, implying that the reported marginal effect of 2.88 for *within same country* in Column (3) of Table 3 corresponds to patents arising from firms located in the same country being 58% more likely to have a citation than are otherwise similar patents from different countries.[9] Similarly, the marginal effect of 9.03 for *within same MNC* suggests that patents from different international divisions of the same MNC are almost 3 times as likely to have a citation as are those from different firms across borders.

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[8] The marginal effect of a variable j is given by $\beta_j\,\Lambda'(\boldsymbol{x\beta})$. From the logit formula, it is easy to show that this equals $\beta_j\,\Lambda(\boldsymbol{x\beta})[1-\Lambda(\boldsymbol{x\beta})]$. One can then substitute either the mean predicted probability or the population mean for $\Lambda(\boldsymbol{x\beta})$ for getting an estimate of the marginal effect. We report the former. The latter is typically slightly greater in value.

[9] Because citations are rare events, $\Lambda(\boldsymbol{x\beta})$ is typically several orders of magnitude smaller than 1, so the marginal effect $\beta_j\,\Lambda(\boldsymbol{x\beta})[1-\Lambda(\boldsymbol{x\beta})] \approx \beta_j\,\Lambda(\boldsymbol{x\beta})$. Therefore, in this setting, β_j can actually be interpreted as the percentage change in the probability of citation when the corresponding dummy variable goes from 0 to 1.

Table 4 breaks up the *within same country* knowledge flows into 4 types: diffusion between domestic entities (D→D), from domestic entities to MNC subsidiaries (D→M), from MNC subsidiaries to domestic entities (M→D) and between MNC subsidiaries (M→M). The results from the entire sample are reported in column (1). Note that the reference category is again the cross-border inter-firm citation probability of approximately 5.0 in a million. Compared with this baseline, D→D citation probability is greater by 59% (2.9 in a million), D→M citation probability is greater by 48% (2.4 in a million), M→D citation probability is greater by 37% (1.8 in a million), and M→M citation probability is greater by 69% (3.4 in a million). Therefore, all four kinds of intra-national knowledge flows are large not just in statistical significance but also in relative magnitude. While M→D and D→M knowledge flows are thus both positive and significant, the latter exceeds the former by about 33%.[10] A statistical test rejects the hypothesis that the two coefficients are equal. Thus, although there are significant knowledge flows both from the MNC subsidiaries to the host country players and vice versa, the former seem to exceed the latter.[11]

Table 4 also breaks down the knowledge flows *within same MNC* category into two sub-categories: those from an MNC subsidiary to its home base (S→H), and those from its home base to the foreign subsidiary (H→S). The comparable and statistically indistinguishable estimates in column (1) suggest that, on an average, the knowledge flows between an MNC's foreign subsidiary and its home base are quite comparable in the two directions. This is consistent with a view of MNCs as a "learning organization", where

[10] Note that we have not modeled endogeneity of an MNC's decision of whether and where to locate overseas. Therefore, our results represent knowledge flow patterns resulting from *existing* location choices by MNCs and not necessarily what would result if MNCs faced incentives to make a different set of location choices.

[11] In order to rule out the possibility that the results are driven just by greater knowledge spillovers from domestic universities or research labs to MNC subsidiaries, analysis not reported here separated out the effect of universities and research labs. The result on asymmetry in knowledge flows still persisted.

subsidiaries not only build upon the knowledge of the home base but also contribute to further learning (Kogut and Zander, 1993; Dunning, 1992b).[12]

It is also interesting to note that MNC subsidiaries are particularly good at learning from each other, as indicated by the M→M estimate being significantly greater than other estimates. This is consistent with previous findings on knowledge diffusion between MNC subsidiaries (Head *et al.*, 1995; Feinberg and Majumdar, 2001; Feinberg and Gupta, 2004). In analysis not reported here, we found the M→M knowledge flow to be particularly strong between foreign subsidiaries of MNCs from the same home country. An explanation could be closely integrated interpersonal or ethnic networks for MNCs from the same home country.

The above analysis does not account for systematic differences between intra-national citations within the U.S. versus abroad. A concern is that results for patents originating in the U.S. might be different when using USPTO data, and that heavy representation of U.S. patents could affect the overall results. To address this, columns (2) and (3) in Table 4 separately report results for citations made by patents originating in the U.S. versus those arising elsewhere. The main findings still hold: both sub-samples find D→M knowledge flows to be greater than M→D flows. Thus the observed asymmetry is not just a U.S.-only phenomenon.

What causes the observed asymmetry in knowledge diffusion? Discussion leading up to Hypothesis 2 suggests that the asymmetry might depend on a country's level of technological competence, with countries whose domestic firms are already at the technological frontier being most likely to exhibit this asymmetry. To examine if this is the case, we split the sample along the lines of whether the observation pertains to a technologically leading country or not. In particular, column (4) reports the results of an

[12] These findings could be driven by the fact that patent data only include subsidiaries active in R&D. It seems plausible that knowledge flows involving subsidiaries not doing R&D are much less symmetric.

analysis based on the 6 leading countries in terms of patenting volume, while column (5) reports findings for the remaining 24 countries. For the former, there is clear evidence of knowledge outflows to MNC subsidiaries being greater than knowledge inflows back to domestic organizations. For the latter, knowledge outflows to MNCs appear to instead be somewhat smaller than knowledge inflows from them, though the relatively large standard errors make it impossible to reject equality of knowledge flow in the two directions.

5. A Closer Look at Individual Countries and Sectors

In results not reported here, we tried to extend the aggregate WESML-based analysis to the country level. Among the top six countries, we found D→M knowledge flows to be stronger than M→D flows in the U.S., Japan, Germany and Canada, though the equality could not be rejected for France and the U.K. When this analysis was repeated for the remaining countries individually, the coefficient estimates were found to be unstable and highly sensitive to the exact sample that got drawn. This is probably the result of the fact that sample sizes are relatively small (in terms of number of "ones") for these countries, and even medium sized samples can be insufficient for WESML estimation when there are some strong determinants (such as technological relatedness in our setting) of the probability of getting a "one". Therefore, despite its limitations discussed earlier, we resort back to the "matching approach" for analyzing knowledge flow patterns in individual countries.

5.1. The Matching Methodology

Analogous to the regression framework above, the goal of matching is to determine if the frequency of patent citations among a group of firms is "abnormally high" when compared with an appropriate reference. The reference is now defined as the citation frequency among patent pairs with technological and temporal characteristics that are comparable to the original citations.

To clarify how this is computed, let us study knowledge flows from MNC subsidiaries to domestic firms (M→D flows) using matching. Let *D* be the set of all citations made by domestic firms in a country. For comparison, we construct a set *D'* by replacing each actual citation in the set *D* by a set of up to five "control citations" obtained by replacing each cited patent by up to five "control patents" with the same technology and application year as the cited patent.[13] Since the *3-digit* technological classification typically used in such matching studies is not detailed enough, we try to get a finer match using the 9-digit technological subclass whenever possible.[14] Next, to test for M→D knowledge flows, we examine if the fraction of citations to patents originating from MNC subsidiaries is statistically different between the set of actual citations *D* made by the domestic firms and the corresponding set of control citations *D'* defined above.

In order to understand illustrate the exact procedure, let us take Germany as a specific example. The number of actual citations made by German domestic entities (N_D) is 61,098, and the number of control citations (N'_D) resulting from the matching described above is 295,231. It turns out that 2.09% of the former set of patents cite patents of MNC subsidiaries located in Germany ($p_{M\rightarrow D} = 2.09\%$), while only 1.52% of the latter cite patents of MNC subsidiaries located in Germany ($p'_{M\rightarrow D} = 1.52\%$). We would like to examine if the observed difference between $p_{M\rightarrow D}$ and $p'_{M\rightarrow D}$ is enough to statistically reject equality of the two proportions in the population. Analogous to the test used by Jaffe *et al.* (1993) for detecting localized knowledge flows, the t-statistic that allows us to formally carry out this test is

[13] Like Jaffe *et al.* (1993), all citations for which either the original or the control citation involved a self-citation from a firm to itself were excluded from the sample. In addition, there were a few observations for which a match could not be found. This caused the average number of control citations to be less than five for some actual citations.

[14] If we cannot get enough 9-digit matches for some cited patent, we resort to a 3-digit match. However, the main results are largely robust to an alternate approach where observations with no 9-digit match are simply excluded.

$$t_{M \to D} = \frac{p_{M \to D} - p'_{M \to D}}{\sqrt{\frac{p_{M \to D}(1 - p_{M \to D})}{N_D} + \frac{p'_{M \to D}(1 - p'_{M \to D})}{N'_D}}}$$

Doing this calculation based on the above values for Germany gives a t-statistic of 9.18, which easily rejects the null hypothesis of equality of the two proportions. In other words, the extent to which domestic entities in Germany cite local patents is statistically greater than what we would have expected in terms of citation frequency between random patent pairs with comparable technological and temporal characteristics. Thus there are indeed localized knowledge flows from MNC subsidiaries to domestic entities in Germany. We can similarly compute the t-statistic for D→M knowledge flow by constructing a control set *M'* for the set of citations *M* made by multinational subsidiaries, and switching the role of "M" and "D" in the above formula.

5.2. Cross-Country Differences in Knowledge Flows

Following the above sequence of steps for each of the 30 countries in our sample, Table 5(a) calculates the results on localized knowledge diffusion from MNC subsidiaries to domestic organizations (M→D flows) while Table 5(b) reports the results on knowledge diffusion from domestic organizations to MNC subsidiaries (D→M flows). Column (7) in Table 5(a) reports the t-statistic calculated as above in order to test the equality of the two proportions $p_{M \to D}$ and $p'_{M \to D}$ reported in columns (3) and (6) respectively. Column (9) gives the ratio of these two proportions, which we define as the "M→D flow intensity" and use as a measure of the extent to which localized knowledge diffusion exists from MNC subsidiaries to domestic firms in any given country. For example, the M→D intensity of 1.37 for Germany indicates that the probability of knowledge flow from a patent by an MNC subsidiary to a domestic patent is 1.37 times as likely as for two otherwise random patents with similar technological and temporal characteristics. An analogous calculation in Table 5(b) shows that the "D→M flow intensity" as reported in column

(9) is 1.53. This is greater than the M→D intensity calculated above, suggesting that the knowledge flows from domestic entities to MNC subsidiaries are somewhat stronger than those from MNC subsidiaries back to domestic entities.[15]

While Tables 5(a) and 5(b) carry out the above calculation for each of the 30 countries individually, the number of citations between domestic entities and MNC subsidiaries is too small to be statistically meaningful for many of these countries. For countries that do have a non-trivial number of such citations, we again find significant localized knowledge diffusion in both directions: D→M and M→D. Further, of the 20 countries with enough citations that the two-way knowledge flow intensities to be reported in column 9 of Tables 5(a) and 5(b) can be calculated, 11 have a greater value for D→M intensity than for M→D intensity. Of these, eight are among the top ten technologically most active countries and only three among the rest. This is again consistent with Hypothesis 2, which states that the asymmetry in favor of D→M knowledge flow should be greatest among countries that are technologically advanced.

5.3. Cross-Sector Differences in Knowledge Flows

We now analyze patents from the top six countries to study differences in the pattern of knowledge diffusion across six broad technology sectors. The reason for focusing just on the six largest countries is that the number of citations between MNC subsidiaries and host country organizations in any individual sector is typically quite small for the remaining countries, seriously limiting statistical validity of any finding regarding direction of net

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[15] To check for consistency and robustness of the aggregate results obtained from WESML in the previous section, the last row in Tables 5(a) and 5(b) repeats the matching analysis for all countries aggregated together. Consistent with Table 4, we find evidence for bi-directional knowledge spillovers, with the D→M intensity again being greater than the M→D intensity. Note that the D→M and M→D intensity definitions for matching are not directly comparable in magnitude to the corresponding coefficients with the same name in WESML.

knowledge flow. The analysis involves, in effect, "zooming into" the first six rows of Tables 5(a) and 5(b) and conducting the analysis for each of these rows at the sector level.

The results are reported in Table 6. Column (1) reports the M→D flow intensity analogous to column (9) of Table 5(a), but at the sector level within a country. Similarly, column (2) reports the corresponding D→M intensity. Most of the values in columns (1) and (2) are greater than 1, consistent with the aggregate results that there are two-way knowledge flows in all these countries. Further, the ratio of the M→D intensity to the D→M intensity, as reported in column (3), is less than one in 25 of the 36 cases reported. This is also consistent with the earlier finding that M→D knowledge flows are, on an average, weaker than D→M knowledge flows. But the fact that the ratio does exceed one in 11 of the cases also highlights that the aggregate findings mask important sector-level heterogeneity since the pattern of knowledge flows often differs across sectors even within the same country. For example, for Japan, the M→D knowledge flows exceed D→M flows for the "Drugs & Medical" sector, while the situation is just the opposite in the "Mechanical" sector.

We now check if the cross-sector variation is consistent with Hypothesis 2 that the ratio of M→D intensity to D→M intensity is lower in sectors where the host country is technologically more superior. Since comparing raw patent counts across countries can be misleading because of differences in size and propensity to patent, we follow previous research in constructing a "relative technological advantage" (RTA) index that measures the *relative* distribution of a country's inventive activity in each sector (Soete, 1987; Dunning, 1992a). Formally, the RTA index for country i in sector j is defined as the ratio of country i's share of total world patents in sector j to country i's share of total world patents, i.e.,

$$RTA_{ij} \equiv \left(n_{ij} / \sum_{i} n_{ij} \right) \Big/ \left(\sum_{j} n_{ij} / \sum_{i} \sum_{j} n_{ij} \right)$$

where n_{ij} is the number of patents of country *i* in sector j. This index is 1 if the country holds the same share of worldwide patents in a given technology as in the aggregate, and is below (above) 1 if there is a relative weakness (strength). The RTA values are reported in column (4) of Table 6. In computing these RTA values, we use patents arising from each country during the 5 years immediately preceding the period for which knowledge flows are analyzed, since that mitigates a concern that increased knowledge inflow into a particular sector can itself boost innovation and increase RTA for that sector.

The correlation between the values reported in columns (3) and (4) is negative and significant at -0.19. If we calculate the correlation for values within each country separately, the correlation is found to be negative for five of the six countries included in the analysis (the only exception being France). This is again consistent with Hypothesis 2 that net outflows are largest in sectors where a country is a technological leader. While one could argue that the correlation is not very large, that could be the result of our measures being quite crude. In particular, recall that column (3) is a ratio of sample proportions, which is very sensitive to the exact sample selected during the matching process. Therefore, we interpret our sector-level findings as being suggestive rather than statistically conclusive, leaving more in-depth analysis of sector-level knowledge flows for future research.

6. Potential Mechanisms behind Knowledge Flow Patterns

While differences in the level of technological sophistication of MNC subsidiaries versus domestic players suggest a potential for asymmetry in knowledge flow, we now investigate the actual mechanisms behind these knowledge flows. There can be a wide range of potential mechanisms, such as reverse engineering of products, alliances and joint ventures, vertical relationships with suppliers and customers, etc. However, investigating these comprehensively is beyond the scope of this paper, especially given our data constraints. Instead, we only consider underlying patterns of inter-firm mobility of personnel as one possible driver of knowledge flow patterns. Previous research has established that personnel mobility can play an important role in diffusion of knowledge. For example, differences in extent of localized knowledge diffusion across regions is influenced by inter-regional differences in cross-firm personnel mobility (Almeida and Kogut, 1999) as well as the effect this mobility has in shaping interpersonal networks (Singh, 2005).[16] Specific to the context of MNCs, Fosfuri *et al.* (2001) present a theoretical model exploring technology diffusion from MNC subsidiaries to their host countries through mobility of employees. A stream of empirical studies also shows that employees leaving MNCs to join host country organizations help diffuse knowledge from MNCs to their host countries (Katz, 1987; Gerschenberg, 1987). However, this literature focuses on inter-firm mobility in a single direction: that from the MNCs to the domestic firms.

Extending the above arguments, it is plausible that the extent and direction of two-way knowledge flows between domestic organizations and MNC subsidiaries is significantly influenced by patterns of personnel movement between the two groups. Patent data makes an investigation of this feasible, since individual patents include information regarding both the individual inventors and their employers. By studying innovation data for an inventor over time, one can therefore infer if he or she has moved from one organization to another. The dataset used here was obtained by merging inventor data from Singh (2005) with data already described.

[16] Co-employment is not the only means through which strong interpersonal relationships develop. For example, a growing literature shows the importance of co-ethnicity as another mechanism promoting interpersonal ties (Kerr, 2005; Agrawal *et al.*, 2006; Kalnins and Chung, 2006). However, data constraints prevent us from exploring these alternative sources of interpersonal ties.

Table 7 reports our analysis of inter-organizational inventor movements in different countries. As the last row indicates, we observe a total of about 1.25 million inventors, each of whom is involved in an average of 2.21 patents (with there often being multiple inventors per patent). The total number of inter-organizational moves we observe during 1986-1995 is about 0.176 million, or about 0.14 per inventor. Since detecting a move requires the inventor to successfully patent both in the original employer and the new employer, this figure definitely underestimates the actual inter-organizational mobility. Nevertheless, it provides some interesting insights. In particular, it is interesting to note that the overall number of moves from domestic players to MNC subsidiaries (12,742) significantly exceeds the number of moves in the other direction (10,892). In other words, the asymmetry of inter-firm labor movements appears to mimic the pattern of knowledge flows discussed earlier.

Needless to say, looking just at the aggregate numbers is far from conclusive. Therefore, we also take a closer look at the individual countries in our sample. Of the 30 countries, the only eight where the direction of net flow of researchers is the opposite of the aggregate pattern (i.e., where more researchers move from MNC subsidiaries to domestic players than in the opposite direction) are Taiwan, South Korea, Israel, Spain, Hong Kong, Ireland, Mexico and Venezuela. Interestingly, as reported in Tables 5(a) and 5(b), almost all of these countries also violate the aggregate pattern of asymmetry of knowledge flow by exhibiting a lower value of D$\rightarrow$M intensity than M$\rightarrow$D intensity. The only exceptions are Mexico and Venezuela, for which we do not have enough citations to make a conclusive statement about any asymmetry in knowledge flows. Thus, country-level evidence is also consistent with a view that the asymmetry of knowledge flows follows the pattern of inter-firm mobility of personnel. In related projects, we are more systematically examining mechanisms such as cross-firm and cross-regional personnel mobility and interpersonal networks in shaping the worldwide fabric of innovation and knowledge diffusion (Singh, 2005; Sorenson and Singh, 2006; Singh, 2006).

7. Methodological Issues in Using Patent Citation Data

One challenge in using patent citation data is that it is highly noisy in capturing real knowledge flows. Just having large samples might not get around this, since the noise is not always random. A specific issue is that patent examiners insert a significant fraction of citations, with these examiner-added citations being systematically less likely to represent true knowledge flows (Alcacer and Gittelman, 2006; Thompson, 2006). In our setting, inclusion of country fixed effects ensures that any systematic cross-country difference in extent of examiner-added citations would not affect our results. But, if patent examiners also differ in the extent to which they add citations to patents from domestic entities versus MNC subsidiaries within a given country, the findings could be affected. To the best of our knowledge, there is no documented evidence of such systematic bias in citations. Nevertheless, one might worry that citations added by examiners (who are based in the U.S.) might be biased towards patents originating in the U.S. or filed by U.S. MNCs. However, the fact that our findings hold separately for sub-samples from the U.S. as well as other leading countries gives some confidence that just examiner-added citations do not drive our results. While we would still have liked to directly check the robustness of our findings to dropping examiner-added citations from the analysis, data constraints made that impractical.

Another potential source of bias is that domestic organizations versus foreign MNCs may differ in the extent to which they cite USPTO patents versus cite the same innovations as embodied in a patent registered with another country's patent office. Since our analysis only included citations to USPTO patents, these differences could erroneously get interpreted as genuine differences in knowledge flows. To look into this possibility, we examined citations made to patents registered with USPTO as well as European Patent Office (EPO) by a sample of 1,612 random USPTO patents, about half drawn from domestic organizations and the remaining from MNC subsidiaries. For each cited EPO patent, we checked if there existed an equivalent USPTO patent that could instead have been cited. The determination of equivalent USPTO patents was done using the "OECD Triadic Patent Families" database, which has information on patents filed with both USPTO and EPO for the same innovation.

The results are summarized in Table 8. The mean number of citations from a random patent to USPTO patents was 5.85, and to EPO patents was 1.13. The mean number of citations to EPO patents that do have equivalent USPTO patents, which represents the "missing citations" that could bias any analysis based only on USPTO data, was 0.32 per patent. Further, as Table 8 shows, the average number of "missing" citations per patent for MNC subsidiaries (0.43) is a little greater than that for domestic organizations (0.22). This holds both for patents originating in the U.S. (0.39 for MNC subsidiaries and 0.24 for domestic organizations) and originating elsewhere (0.46 for MNC subsidiaries and 0.21 for domestic organizations). In either sub-sample, the bias therefore is slightly in the direction of underestimating knowledge outflows to foreign MNCs rather than inflows to domestic organizations. In other words, if we could correct for this bias, it would only strengthen our result that D→M knowledge flows exceed M→D knowledge flows.

8. Implications and Caveats

This study uses patent citation data from 1986-1995 to examine bi-directional knowledge flows between MNC subsidiaries and host country organizations in 30 countries. The analysis reveals that, while local subsidiaries of foreign MNCs are a significant source of knowledge for the host country, they are also very effective as a channel through which foreign MNCs gain access to host country technology. In fact, in technologically advanced countries, subsidiaries of foreign MNCs gain significantly more than they contribute in terms of knowledge. Even for the remaining countries in our sample, knowledge outflows to foreign MNCs are almost as large as knowledge inflows.

Our findings give some justification to concerns that gains from inward FDI, particularly in countries that possess valuable technology of their own, may not be free. Even if the host country gains in terms of knowledge spillovers or other externalities from foreign MNCs, these MNCs could also be a channel through which indigenous technologies fall into the hands of foreign competitors. To the extent that such knowledge outflows represent a "cost" to the host country, this has to be taken into consideration rather than only looking at expected benefits like knowledge spillovers, job creation, etc. when setting FDI policy. However, one should exercise caution in not taking a literal interpretation of our findings too far. While patent citations help measure knowledge inflows and outflows, they do not directly measure the actual externalities and welfare effects. Below, we describe two sets of caveats to bear in mind in any attempt to link observed knowledge flow patterns to welfare effects for the host country.

The first caveat is that knowledge outflows to MNCs are not necessarily bad even for the host country firms. For example, transfer of technology to MNCs is desirable in scenarios where it represents not unintended externalities but actual market transactions for which domestic organizations get compensated in the form of contractual payments, royalties or license fees. In fact, as Acs *et al.* (1997) point out, global application of domestic knowledge through MNCs can be an important vehicle for host country organizations, particularly small and medium size enterprises, to tap into foreign markets. Absent this channel, such host country firms might not be able to tap into foreign markets at all due to limited resources for overcoming entry barriers overseas or for dealing with lack of intellectual property right protection in foreign countries. Likewise, in cases where knowledge outflows facilitate development of new technologies and products that are complements to rather than direct competitors of host country technologies, domestic firms might again be better off as a result of knowledge outflows. Finally, even if greater knowledge outflows represent a direct cost to the host country firms, these firms might still be better off since more citations to their patents and more widespread application of their technologies can also enhance their reputation among employees, investors or customers.

A second set of caveats in judging welfare effects arises from an observation that, even if net knowledge outflows were bad for host country firms, indirect effects from such outflows might improve the welfare of the host country as a whole. For example, if outward diffusion of technology leads to development of new products, the residents of host country might be better off because of a broader choice of products that result from application of this knowledge. Further, there might be a *quid pro quo* in FDI policy that makes all countries better off: allowing firms of country X to tap into local knowledge in country Y may be a pre-condition for firms of country Y to be allowed access to knowledge, resources and markets in country X.[17] Finally, even if the knowledge dimension of welfare effects is unfavorable, MNCs may have positive effects along other dimensions such as lower prices, more job creation, development of related industries, and higher wages. Such considerations would have to be taken into account in determining net welfare effects and ultimately the optimal FDI policy in any given situation.

Despite the above caveats, our study emphasizes a few broad issues that a policy maker should bear in mind. It shows that FDI might have potential costs in situations where knowledge

[17] For example, analysis not reported here revealed that, though Japanese MNCs benefit from knowledge spillovers in the U.S., U.S. MNCs enjoy similar gains when investing in Japan: we find no evidence that Japanese firms are worse at sharing knowledge, a conclusion consistent with Spencer (2000).

outflows do represent true negative externalities for which the host country does not get compensated either directly (e.g., in the form of profits for its firms) or indirectly (e.g., in the form of new products for its consumers or higher wages for its workers). Further, to the extent that inflow of knowledge might be welfare improving for the host country, any incentives to encourage FDI should be tied not just to the magnitude of FDI but also to its content. In addition, there might be gains from facilitating mechanisms to ensure that knowledge spillovers to the host country actually do take place. Such mechanisms could include training of workers, participation by MNCs in local consortia and conferences, technology transfer agreements, tie-ups of MNCs with domestic schools and universities, etc. Our findings also suggest that, since outward FDI appears to be quite effective for acquiring foreign knowledge, a country might sometimes gain from encouraging its own firms to expand overseas in search of new knowledge rather than discouraging outward FDI for fear of loss of local jobs or leakage of technology.

The extent of bi-directional knowledge spillovers between MNC subsidiaries and host country firms is also interesting for MNC strategy. Imagine a firm trying to acquire technology developed overseas. An issue is whether it would really gain from opening a "listening post" in a foreign country or whether "liability of foreignness" would make it difficult to tap domestic sources of knowledge. Our study finds that knowledge flows from the domestic economy to MNC subsidiaries are only slightly smaller than knowledge flows even between domestic organizations, and are significantly larger than knowledge flow back from MNC subsidiaries to domestic firms. In other words, the constraints imposed by liability of foreignness appear to be rather limited as far as acquisition of technological knowledge is concerned. In particular, our findings on personnel mobility suggest that hiring skilled and well-connected personnel might be a way that MNCs overcome liability of foreignness and get access to local knowledge networks.

While the present study focuses on issues of most concern to industrialized countries, at least two general points made above apply to developing countries as well. First, not just the magnitude but also the content of MNC investments affects the extent of knowledge spillovers. Different kinds of MNC activity, like state-of-the-art R&D and production facilities versus simple assembly operations, might have very different implications for knowledge spillovers. Second, the extent of inter-firm personnel mobility and resulting interpersonal networks could be a significant mediating factor in knowledge spillover outcomes from FDI. For example, an MNC subsidiary located in one of India's "Export Processing Zones" but cut-off from the domestic economy may be no better as a source of knowledge spillovers than a firm based in a foreign country. In such situations, a key policy issue might be how to facilitate interpersonal networks and other mechanisms enabling knowledge diffusion between the MNC subsidiary and the domestic firms. Examination of such issues forms a promising agenda for future research.

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Table 1: Summary of patent data from USPTO (1986-1995)

Country	Successful patents arising from the country during 1986-1995	Number of patents assigned to firms or organizations	Fraction of assigned patents arising from MNC subsidiaries
	(1)	(2)	(3)
United States	546,824	418,045	6.14%
Japan	217,313	212,427	1.99%
Germany	74,041	67,154	14.42%
France	29,791	27,120	14.23%
United Kingdom	26,631	23,968	28.45%
Canada	20,700	13,015	25.23%
Italy	12,457	10,877	17.87%
Switzerland	12,287	10,854	16.25%
Taiwan	11,178	3,531	5.47%
Netherlands	9,053	8,425	16.36%
Sweden	7,956	6,579	12.69%
South Korea	7,774	7,017	1.10%
Australia	4,679	3,209	16.83%
Belgium	3,850	3,589	60.63%
Israel	3,798	2,813	20.12%
Austria	3,623	2,915	25.04%
Finland	3,431	3,013	4.38%
Denmark	2,278	1,930	11.97%
Spain	1,499	1,026	22.61%
Norway	1,290	946	10.99%
South Africa	1,099	601	14.14%
Hong Kong	649	447	23.04%
Ireland	595	465	51.61%
New Zealand	537	322	17.70%
Brazil	522	378	20.63%
Mexico	413	212	20.28%
Singapore	409	353	63.17%
India	286	231	49.35%
Argentina	251	76	22.37%
Venezuela	250	190	8.95%
Other countries	4,760	3,116	30.01%
Total worldwide	1,010,224	834,844	7.95%

Table 2: Definition of variables

Within same country	Indicator variable that is 1 if the citing and cited patents originate from inventors located in the same country, 0 otherwise
Within same MNC	Indicator variable that is 1 if the citing and cited patents are from the same MNC, 0 otherwise. (Since self-citations from a firm to itself in the same country are not included in the sample, a value of 1 refers to *cross-border* citation within an MNC.)
Indicator variables for different kinds of knowledge flow within the same country:	
D→D	Indicator variable that is 1 if both the citing and potentially cited patent originate in the same country, with assignees for both being domestic players in the country
D→M	Indicator variable that is 1 if both the citing and potentially cited patent originate in the same country, with assignee for the former being a local subsidiary of a foreign MNC and for the latter being a domestic player
M→D	Indicator variable that is 1 if both the citing and potentially cited patent originate in the same country, with assignee for the former being a domestic player and for the latter being a local subsidiary of a foreign MNC
M→M	Indicator variable that is 1 if both the citing and potentially cited patent originate in the same country, with assignees for both being local subsidiaries of foreign MNCs
Indicator variables for different kinds of knowledge flow within the same MNC:	
S→H	Indicator variable that is 1 if citing patent is from the home base of an MNC and the cited patent is from a foreign subsidiary (located abroad) of the same MNC
H→S	Indicator variable that is 1 if citing patent is from the local subsidiary of a foreign MNC and the cited patent is from the home base (located abroad) of the same MNC
Control variables for technological relatedness:	
Same tech category	Indicator variable that is 1 if both the citing and the potentially cited patent belong to the same broad industry category (one of 6) as defined in the Jaffe and Trajtenberg (2002) database
Same tech subcategory	Indicator variable that is 1 if both the citing and the potentially cited patent belong to the same broad technical subcategory (one of 36) as defined in the Jaffe and Trajtenberg (2002) database
Same primary tech class	Indicator variable that is 1 if both the citing and the potentially cited patent belong to the same 3-digit primary technology class (one of about 450) as defined in the US Patent classification system
Same primary subclass	Indicator variable that is 1 if both the citing and the potentially cited patent belong to the same 9-digit primary technology subclass (one of about 150,000) as defined in the US Patent classification system
Secondary subclass overlap	Indicator variable that is 1 if at least one of the secondary 9-digit subclasses of one patent is the same as a primary or secondary subclass of the other patent in the dyad

Table 3: Analysis of intra-national and intra-MNC knowledge flows

	(1)	(2)	(3)
Within same country	0.748**	0.656**	0.575**
	(0.008)	(0.004)	(0.011)
	[3.74]	[3.28]	[2.88]
Within same MNC	3.742**	2.266**	1.805**
	(0.075)	(0.024)	(0.087)
	[18.71]	[11.33]	[9.03]
Technological relatedness:			
Same tech category		1.181**	1.154**
		(0.009)	(0.009)
Same tech subcategory		1.317**	1.264**
		(0.011)	(0.015)
Same primary tech class		3.291**	1.891**
		(0.009)	(0.018)
Same primary tech subclass			2.305**
			(0.031)
Subclass overlap			4.253**
			(0.014)
Number of observations	6,917,024	6,917,024	6,917,024

The dependent variable is 1 if there is a citation between the pair of patents, 0 otherwise
A weighted logit regression is used, with weights depending on sampling frequency
Robust standard errors in parentheses, with clustering on citing patent
Marginal effects in square brackets after multiplication with 1,000,000
Fixed effects used for technological category of cited patent, citing country and time lag between patents
** significant at 1%; * significant at 5%

Table 4: Detailed break-up of intra-national and intra-MNC knowledge flows

	Entire sample	US versus Non-US		Technology leaders versus the rest	
	(1)	(2)	(3)	(4)	(5)
Within same country	**All 30 Countries**	**US**	**Non-US**	**Top 6 Countries**	**Other 24 Countries**
D→D	0.590**	0.571**	0.601**	0.582**	1.595**
	(0.011)	(0.013)	(0.020)	(0.011)	(0.081)
	[2.95]	[2.86]	[3.01]	[2.91]	[7.98]
D→M	0.482**	0.416**	0.779**	0.472**	1.148**
	(0.042)	(0.047)	(0.061)	(0.043)	(0.202)
	[2.41]	[2.08]	[3.90]	[2.36]	[5.74]
M→D	0.368**	0.326**	0.560**	0.356**	1.216**
	(0.036)	(0.040)	(0.055)	(0.037)	(0.191)
	[1.84]	[1.63]	[2.80]	[1.78]	[6.08]
M→M	0.689**	0.531**	1.127**	0.644**	1.851**
	(0.091)	(0.109)	(0.100)	(0.093)	(0.232)
	[3.45]	[2.66]	[5.64]	[3.22]	[9.26]
Within same MNC					
S→H	1.889**	2.178**	1.467**	1.927**	1.667**
	(0.104)	(0.142)	(0.145)	(0.107)	(0.279)
	[9.45]	[10.89]	[7.34]	[9.64]	[8.34]
H→S	1.746**	1.606**	1.739**	1.696**	1.843**
	(0.127)	(0.182)	(0.167)	(0.155)	(0.117)
	[8.73]	[8.03]	[8.70]	[8.48]	[9.22]
Observations	6,917,024	2,596,206	4,320,818	5,216,717	1,700,307

The dependent variable is 1 if there is a citation between the pair of patents, 0 otherwise
A weighted logit regression is used, with weights depending on sampling frequency
Marginal effects in square brackets after multiplication with 1,000,000
Controls for technological similarity of citing and cited patent included in regression, but not shown here to enhance readability
Fixed effects used for technological category of citing patent, citing country and time lag between patents
** significant at 1%; * significant at 5% (In case of ratios, whether statistically different from 1 is tested)

Table 5(a): Knowledge flows from MNC subsidiaries to domestic organizations (M→D)

	Actual Citations			Control Citations			Comparison		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Country	Cites by domestic	Cites by domestic to MNC subs	%Cites by domestic to MNC subs	Cites by domestic	Cites by domestic to MNC subs	%Cites by domestic to MNC subs	(3) - (6)	t-ratio	(3)/(6) M→D Intensity
United States	968,962	28,581	2.95%	4,694,439	128,451	2.74%	0.21%	11.37	1.08
Japan	338,741	2,712	0.80%	1,622,646	10,825	0.67%	0.13%	8.05	1.20
Germany	61,098	1,280	2.09%	295,231	4,500	1.52%	0.57%	9.18	1.37
France	28,233	235	0.83%	136,396	754	0.55%	0.28%	4.85	1.51
United Kingdom	21,541	462	2.14%	104,372	1,216	1.17%	0.98%	9.41	1.84
Canada	18,750	179	0.95%	91,463	385	0.42%	0.53%	7.20	2.27
Taiwan	8,344	9	0.11%	40,258	14	0.03%	0.07%	1.97	3.10
South Korea	18,276	14	0.08%	87,458	9	0.01%	0.07%	3.20	7.44
Italy	9,303	68	0.73%	45,129	118	0.26%	0.47%	5.13	2.80
Switzerland	8,744	46	0.53%	42,320	96	0.23%	0.30%	3.71	2.32
Netherlands	8,431	22	0.26%	40,753	68	0.17%	0.09%	1.59	1.56
Sweden	9,507	52	0.55%	45,863	43	0.09%	0.45%	5.89	5.83
Australia	3,217	7	0.22%	15,659	18	0.11%	0.10%	1.19	1.89
Israel	5,229	26	0.50%	25,379	15	0.06%	0.44%	4.45	8.41
Belgium	1,407	16	1.14%	6,772	30	0.44%	0.69%	2.36	2.57
Finland	4,278	18	0.42%	20,586	2	0.01%	0.41%	4.14	43.31
Austria	2,118	35	1.65%	10,263	59	0.57%	1.08%	3.76	2.87
Denmark	1,874	2	0.11%	9,141	3	0.03%	0.07%	0.95	3.25
Spain	952	3	0.32%	4,622	1	0.02%	0.29%	1.60	14.57
Norway	996	1	0.10%	4,819	0	0.00%	0.10%	1.00	Infinite
South Africa	509	7	1.38%	2,467	0	0.00%	1.38%	2.66	Infinite
Hong Kong	583	4	0.69%	2,845	5	0.18%	0.51%	1.45	3.90
Singapore	420	0	0.00%	2,027	0	0.00%			
Ireland	430	7	1.63%	2,103	2	0.10%	1.53%	2.50	17.12
New Zealand	280	0	0.00%	1,380	0	0.00%			
Brazil	315	0	0.00%	1,543	0	0.00%			
India	192	1	0.52%	927	0	0.00%	0.52%	1.00	Infinite
Mexico	275	2	0.73%	1,335	0	0.00%	0.73%	1.42	Infinite
Argentina	63	0	0.00%	308	0	0.00%			
Venezuela	192	4	2.08%	935	0	0.00%	2.08%	2.02	Infinite
Total	1,523,260	33,793	2.22%	7,359,439	146,614	1.99%	0.23%	17.41	1.11

Table 5(b): Knowledge flows from domestic organizations to MNC subsidiaries (D→M)

	Actual Citations			Control Citations			Comparison		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Country	Cites by MNC subs	Cites by MNC subs to domestic	%Cites by MNC subs to domestic	Cites by MNC subs	Cites by MNC subs to domestic	%Cites by MNC subs to domestic	(3) - (6)	t-ratio	(3)/(6) D→M Intensity
United States	61,029	35,044	57.42%	294,649	139,225	47.25%	10.17%	46.17	1.22
Japan	7,297	3,095	42.41%	35,022	11,351	32.41%	10.00%	15.87	1.31
Germany	15,546	2,006	12.90%	74,481	6,296	8.45%	4.45%	15.48	1.53
France	6,133	395	6.44%	29,663	1,018	3.43%	3.01%	9.10	1.88
United Kingdom	14,286	620	4.34%	69,065	1,562	2.26%	2.08%	11.57	1.92
Canada	6,352	238	3.75%	30,626	440	1.44%	2.31%	9.32	2.61
Taiwan	471	12	2.55%	2,251	26	1.16%	1.39%	1.83	2.21
South Korea	174	2	1.15%	847	4	0.47%	0.68%	0.80	2.43
Italy	3,282	143	4.36%	15,734	191	1.21%	3.14%	8.57	3.59
Switzerland	2,630	128	4.87%	12,778	186	1.46%	3.41%	7.88	3.34
Netherlands	2,276	55	2.42%	11,038	104	0.94%	1.47%	4.40	2.56
Sweden	1,148	38	3.31%	5,538	55	0.99%	2.32%	4.25	3.33
Australia	844	19	2.25%	4,089	20	0.49%	1.76%	3.37	4.60
Israel	1,837	18	0.98%	8,889	17	0.19%	0.79%	3.36	5.12
Belgium	3,078	22	0.71%	14,731	44	0.30%	0.42%	2.63	2.39
Finland	217	24	11.06%	1,062	16	1.51%	9.55%	4.42	7.34
Austria	845	6	0.71%	4,070	20	0.49%	0.22%	0.71	1.44
Denmark	663	16	2.41%	3,228	12	0.37%	2.04%	3.37	6.49
Spain	295	1	0.34%	1,421	6	0.42%	-0.08%	-0.22	0.80
Norway	123	2	1.63%	596	1	0.17%	1.46%	1.27	9.69
South Africa	152	1	0.66%	736	3	0.41%	0.25%	0.36	1.61
Hong Kong	243	1	0.41%	1,170	4	0.34%	0.07%	0.16	1.20
Singapore	566	0	0.00%	2,718	0	0.00%			
Ireland	623	14	2.25%	3,030	0	0.00%	2.25%	3.78	Infinite
New Zealand	52	2	3.85%	259	0	0.00%	3.85%	1.44	Infinite
Brazil	135	0	0.00%	641	0	0.00%			
India	158	0	0.00%	765	0	0.00%			
Mexico	80	1	1.25%	386	0	0.00%	1.25%	1.01	Infinite
Argentina	35	0	0.00%	170	0	0.00%			
Venezuela	41	0	0.00%	200	0	0.00%			
Total	130,611	41,903	32.08%	629,853	160,601	25.50%	6.58%	46.91	1.26

Table 6: Asymmetry of knowledge flows at the country-sector level of analysis

Country	Industry	(1) M➡D Intensity	(2) D➡M Intensity	(3) (1)/(2)	(4) RTA
United States	Chemical	1.12	1.17	0.96	1.00
United States	Computers & Communication	1.04	1.30	0.80	0.93
United States	Drugs & Medical	0.97	1.17	0.82	1.07
United States	Electrical & Electronics	1.02	1.21	0.84	0.96
United States	Mechanical	1.29	1.19	1.08	0.91
United States	Others	1.16	1.24	0.93	1.13
Japan	Chemical	1.44	1.59	0.90	0.91
Japan	Computers & Communication	1.05	1.08	0.97	1.53
Japan	Drugs & Medical	2.22	1.30	1.70	0.68
Japan	Electrical & Electronics	1.32	1.36	0.97	1.18
Japan	Mechanical	1.06	1.35	0.79	1.19
Japan	Others	1.19	1.46	0.82	0.63
Germany	Chemical	1.43	1.78	0.81	1.25
Germany	Computers & Communication	1.26	1.31	0.97	0.50
Germany	Drugs & Medical	1.03	1.67	0.61	0.94
Germany	Electrical & Electronics	1.63	1.45	1.12	0.88
Germany	Mechanical	1.34	1.44	0.93	1.17
Germany	Others	1.26	1.84	0.68	0.89
France	Chemical	2.37	2.17	1.10	0.94
France	Computers & Communication	1.27	1.95	0.65	1.11
France	Drugs & Medical	1.15	0.94	1.22	1.20
France	Electrical & Electronics	1.53	2.44	0.63	1.13
France	Mechanical	1.35	1.84	0.74	0.99
France	Others	1.43	2.06	0.70	0.87
United Kingdom	Chemical	1.50	2.05	0.73	1.01
United Kingdom	Computers & Communication	2.46	1.93	1.27	0.87
United Kingdom	Drugs & Medical	1.59	1.47	1.08	1.53
United Kingdom	Electrical & Electronics	1.74	2.74	0.64	1.02
United Kingdom	Mechanical	2.11	1.81	1.17	0.96
United Kingdom	Others	1.76	1.65	1.07	0.90
Canada	Chemical	3.72	2.01	1.85	0.81
Canada	Computers & Communication	1.46	2.84	0.51	0.84
Canada	Drugs & Medical	2.07	2.97	0.70	0.82
Canada	Electrical & Electronics	2.98	2.05	1.46	0.76
Canada	Mechanical	0.93	3.95	0.23	1.08
Canada	Others	2.08	2.32	0.90	1.42

Table 7: Inventor mobility between MNC subsidiaries and host country organizations

Country	**(1) Number of inventors**	**(2) Average number of patents per inventor**	**(3) Number of moves from MNC subsidiaries to domestic players**	**(4) Number of moves from domestic players to MNC subsidiaries**	**(5) (3)/(4)**
United States	556,709	2.46	5,678	6,636	0.86
Japan	338,963	2.21	1,321	1,426	0.93
Germany	112,489	1.98	1,043	1,174	0.89
France	44,923	1.75	382	518	0.74
United Kingdom	32,848	1.97	778	918	0.85
Canada	28,978	1.67	370	380	0.97
Taiwan	16,900	1.58	37	14	2.64
South Korea	15,586	1.68	59	49	1.20
Italy	16,316	1.92	245	412	0.59
Switzerland	14,007	1.96	187	237	0.79
Netherlands	12,208	1.87	139	197	0.71
Sweden	11,452	1.59	99	143	0.69
Australia	6,694	1.53	80	88	0.91
Israel	6,553	1.61	99	72	1.38
Belgium	5,733	2.11	83	89	0.93
Finland	5,469	1.69	44	81	0.54
Austria	4,997	1.81	79	101	0.78
Denmark	3,452	1.83	48	59	0.81
Spain	2,731	1.42	17	16	1.06
Norway	2,087	1.45	29	40	0.73
South Africa	1,472	1.46	18	20	0.90
Hong Kong	966	1.48	8	6	1.33
Singapore	957	1.48	4	9	0.44
Ireland	1,022	1.48	20	10	2.00
New Zealand	931	1.45	16	28	0.57
Brazil	939	1.35	0	2	0.00
India	1,116	1.50	4	13	0.31
Mexico	838	1.35	2	1	2.00
Argentina	381	1.40	0	2	0.00
Venezuela	472	1.75	3	1	3.00
Total	1,248,189	2.21	10,892	12,742	0.85

Table 8: Citations by USPTO patents to other USPTO and EPO patents

	Citing patents from any country			Citing patent from U.S.		Citing patent not from U.S.	
	(1) All assignees (N=1,612)	(2) Domestic (N=810)	(3) MNC (N=802)	(4) Domestic (N=436)	(5) MNC (N=369)	(6) Domestic (N=374)	(7) MNC (N=433)
Mean number of citations to USPTO patents	5.84	5.68	6.00	6.75	6.95	4.42	5.19
Mean number of citations to EPO patents	1.12	0.83	1.41	0.77	1.42	0.89	1.41
Mean number of citations to EPO patents with "equivalent" US patents in the OECD triadic database	0.32	0.22	0.43	0.24	0.39	0.21	0.46

Figure 1: Six kinds of knowledge flows

This figure illustrates the six kinds of knowledge flows studied in this paper. Four of these are knowledge flows within the same country but across different firms and organizations: D→M, M→D, D→D and M→M (where "D" refers to "Domestic firm or organization" like Intel and IBM in the U.S., and "M" refers to "MNC subsidiary" like subsidiaries of foreign MNCs Sony and NEC in the U.S.). The remaining two knowledge flows are those within the same MNC but across different countries: S→H and H→S (where "S" refers to "Subsidiary" and "H" refers to the "Home Base" of an MNC). The reference category (i.e., knowledge flows not included in any of these six groups) is the cross-border inter-organizational knowledge flows.