Strategic Management Journal
Strat. Mgmt. J., 29: 1207–1224 (2008)
Published online in Wiley InterScience (www.interscience.wiley.com) DOI: 10.1002/smj.706
Received 20 December 2004; Final revision received 31 March 2008

INTERNATIONAL KNOWLEDGE SOURCING: EVIDENCE FROM U.S. FIRMS EXPANDING ABROAD

WILBUR CHUNG[1]* and STEPHEN YEAPLE[2]
[1] R.H. Smith School of Business, University of Maryland, College Park, Maryland, U.S.A.
[2] Department of Economics, University of Colorado-Boulder, Boulder, Colorado, U.S.A.

Recent research demonstrates that firms, motivated by national differences in technical activity, expand abroad to source unique knowledge. Extant research suggests that firms use a knowledge sourcing strategy to 'catch up' with competitors and to obtain 'technical diversity.' We widen the investigation by suggesting that firms also use knowledge sourcing as a springboard to reduce their next generation R&D costs–that firms would seek out similar R&D activity to combine with their own. Using unique data that encompasses the multitude of countries where U.S. firms invest, we test the importance of these explanations. Measuring knowledge via patent stocks, we find that country-industries with larger stocks and greater technical similarity to the United States are more attractive. These findings suggest that an important explanation for firms investing abroad is not catching up or technologically diversifying, but is using similar R&D efforts of others to overcome fixed R&D cost hurdles.

INTRODUCTION

The central role of knowledge for firms' competitive advantage has heightened interest in how firms identify, acquire, and use knowledge external to them. While firms strive to develop internal stocks, they also use acquisitions and alliances to access unique external knowledge. Coupled with such formal arrangements, firms might also source externally generated knowledge through indirect means of spillovers—by sharing common buyers and suppliers, through informal meetings of scientists and engineers across firms, by hiring competitors' employees, and other channels. For example, Song, Almeida, and Wu (2003) show that mobility of engineers and scientists across firms alters receiving firms' technology portfolio.

Firm sourcing technology from abroad is the subject of a large and growing literature in international business. Cantwell (1989) notes that technology differs across locations since technology depends on location-specific factors, such as innovations previously established, the education system, and the linkages between educational institutions and firms. As a consequence, firms may supplement their existing technologies by expanding internationally to access new knowledge. Consistent with 'sourcing of the U.S. locational advantages in technology,' Kogut and Chang (1991: 403) look across manufacturing industries in the United States and show that more Japanese investment occurs in industries that have greater research and development (R&D) differences. Extending Kogut and Chang (1991), Neven and Siotis (1996) explore Japanese, U.S., and EU (European Union) investment into four EU nations and find evidence

Keywords: knowledge spillovers; international expansion; location choice
*Correspondence to: Wilbur Chung, R.H. Smith School of Business, University of Maryland, 3417 Van Munching Hall, College Park, MD 20742, U.S.A. E-mail: wchung@rhsmith.umd.edu

for technological sourcing by the Japanese and U.S. investment.

Formalizing from prior literature, we define international knowledge sourcing as firms investing abroad in order to obtain access to knowledge developed there. This behavior is premised on two underlying assumptions. First, knowledge varies across countries; Furman, Porter, and Stern (2002) provide an excellent quantification of such differences by comparing patent output, patents filed by industry sector, R&D funding sources, and other elements of national innovation systems for 17 Organisation for Economic Co-operation and Development (OECD) nations. Second, gaining proximity by establishing a foreign affiliate in another country facilitates access to that country's knowledge; Kogut and Zander (1992) argue that some portion of knowledge is tacit, which proximity assists in transferring via more frequent interpersonal contact.

Prior research raises two reasons for firms to use a knowledge sourcing strategy. A basic reason is that a nation's firms are somehow behind in developing new knowledge or technology; accordingly, knowledge can be thought of as a stock and a greater stock of knowledge abroad suggests that firms will use a knowledge sourcing strategy internationally to 'catch up' Cantwell (1989), Wesson (1993), Kuemmerle (1999). Alternatively instead of just a stock, knowledge can be thought of as heterogeneous and multidimensional. Useful knowledge of one sort may be developed in one country while useful knowledge of another sort might be developed in another.[1] That different types of knowledge might be combined advantageously, gives rise to the argument of knowledge sourcing abroad to obtain 'technical diversity' Cantwell and Janne (1999).

To these two reasons, we add a third; that firms use knowledge sourcing as an 'R&D springboard' to reduce their fixed R&D costs. Future technological improvement often requires substantial incremental R&D spending. For example, Pisano, Russo, and Teece (1988) note that initial development costs in high-tech industries increase with each subsequent generation of technology, which represent escalating fixed cost hurdles. Instead of facing these hurdle costs alone, firms might combine their internal R&D efforts with knowledge sourced externally, which allows them to more easily surmount these fixed cost R&D hurdles. In this case, instead of technical diversity, the firm would be interested in sourcing knowledge more similar to its own upon which the firm then could more readily build.

While establishing the existence of knowledge sourcing, prior research has been limited in understanding the reasons why firms use this strategy. In this study, we separate and assess the relative importance of these three reasons for firms to knowledge source in order to provide a fuller sense of firms' use of this strategic behavior in two ways. First, such an assessment builds upon and integrates the prior nascent literature to provide a more comprehensive, top-down perspective of the phenomena; we take motives that were raised separately, add an additional one, and then evaluate these multiple motives simultaneously. Second, better understanding 'why' firms knowledge source further clarifies the difference from 'how' they knowledge source.[2] A substantial literature explores 'how' firms knowledge source using channels such as acquisition, alliance, and knowledge spillovers to pursue targeted knowledge. The magnitude of this literature can lead to related but separate questions being subsumed and overlooked; for example, the question of 'why' firms knowledge source. With a better understanding of 'why,' we can clarify similarities and differences and thus improve our understanding of both how and why.

Aiding us in this assessment is our empirical context. Most prior research in knowledge sourcing has been constrained by examining a single country pair—such as Japan and the United States—or select countries—such as Japan, the United States, and the European Union. While examining countries or country pairs where knowledge sourcing is likely helps demonstrate its existence, such selection of usual suspect countries likely provides an incomplete perspective of how firms employ this strategy and limits identification of important theoretical motivations. Therefore, we conduct a broader empirical test using a multitude

[1] For example, in the automotive industry, the United States focused on efficient, large displacement engines, European companies on diesel engines, and the Japanese makers on smaller displacement engines with variable, valve timing.

[2] For example, 'knowledge sourcing' is different from 'knowledge spillovers.' Knowledge sourcing helps explain why firms go abroad; while knowledge spillovers are one of several channels through which firms might obtain targeted knowledge.

of country-pairs emanating from a specific focal country—the 35 countries where U.S. firms invest around the world.[3] We examine what country-industry attributes attract more investment: why certain industries in certain countries receive more investment. To do so, we make use of a comprehensive dataset from the U.S. Department of Commerce, Bureau of Economic Analysis that tracks the count of investment transactions made by U.S. firms abroad.

Recognizing that firms invest abroad for reasons besides knowledge sourcing—most notably to follow an internalization (market seeking) strategy—we account for these other reasons by including several control variables; for example, to control for obtaining low cost factors as a motivation, we include measures to reflect factor costs (for a review of motivations for conducting foreign investment, see Caves,1996).

To isolate knowledge sourcing versus other strategies, we make use of the fact that firms motivated by technology or knowledge sourcing will be attracted to locations with technical activity. In contrast, firms pursuing an internalization (market seeking) strategy, or other strategies, will be attracted to other attributes such as market size or factor costs. As such, we include several measures to indicate the size and type of knowledge present across country-industries as well as other measures to reflect market attractiveness and other potentially important traits.

Using data for 1989–1999, we examine the influence of technical similarity between country pairs and the size of knowledge stocks in the home and host countries. Measuring knowledge stocks using patent counts, we use the composition of patents across patent classes to measure technical similarity. We find that country-industries with larger stocks that are more technically similar to the United States are more attractive. From among several explanations for why firms source knowledge, this finding highlights U.S. firms investing abroad as a springboard to reduce their fixed R&D costs.

We proceed as follows. In the next section, we review and develop motives for firms to use a knowledge-seeking strategy. We then argue that certain attributes would make a country more attractive for knowledge sourcing. Next is methodology, followed by data, and results. Finally, we highlight several findings, discuss future research, and conclude.

INTERNATIONAL KNOWLEDGE SOURCING

Countries vary in the type and nature of their innovations and intellectual activity due to differences in their innovation systems, such as intellectual property and trade policies, educational systems, and agencies promoting R&D. For example Furman *et al*. (2002) show that scale of R&D (R&D workforce, R&D spending) and productivity of R&D (intellectual property protection, openness to trade, sources of R&D funding) lead to differences in patenting rates.

Because of these differences, Cantwell (1989), Wesson (1993), and Kuemmerle (1999) argue that firms may supplement their existing technical capabilities by expanding internationally. Such expansion would allow them to access new technology, skills, or knowledge; which might be product, process, and/or managerial in nature. As such, the literature in international strategy raises two explanations for sourcing knowledge abroad: *catching up* and *sourcing technical diversity*.

A third possibility, that of an *R&D springboard*, comes from applying findings in technology strategy regarding investment cost for new generations of technology. More advanced technologies require substantial fixed costs to be invested before output in the form of viable commercial innovations result. For high-tech industries, Pisano *et al*. (1988) note that initial development costs increase with each subsequent generation of technology; market participation for new generations requires greater initial investment. As a result, firms would seek out R&D activity similar to their own to build upon.

These rising investment hurdles lead firms to look externally for complementary knowledge in order to reduce their own internal investment costs. Ahuja and Katila (2001) argue that instead of making their own series of investments, firms can grow their knowledge base by acquiring other firms and the other firms' knowledge stocks. Similarly, looking at the motivations for alliances, Sampson (2004) argues that these increasing development costs are a significant motivation for firms

[3] While we started with the 60 countries where U.S. firms invested during this time period, missing data for key control variables limited our subsequent empirical investigation to 35 countries.

to engage in R&D alliances and share the initial fixed costs with others, instead of covering them alone. Besides such formal arrangements, firms might also reduce the incremental fixed costs they face by sourcing externally generated knowledge through indirect means of spillovers.

We expect these increasing fixed costs to be an important motivation for international expansion. This is because the escalating costs affect the competitors that a firm faces and, as a result, who the firm looks to as a source for complementary external knowledge. Thinking about domestic competitors, for a given domestic market size, there will be fewer participants as fixed costs increase; this rising entry barrier limits the players since there will be reduced hopes of covering the initial investment costs. Among these fewer participants, concerns about sharing knowledge with such immediate competitors may dissuade alliances. Similarly, with fewer participants, acquisitions of domestic competitors are more likely to encounter antitrust constraints. In contrast, foreign competitors become increasingly important because these rising fixed costs drive globalization; fewer firms in each country will be able to afford the rising investment hurdles and firms that can overcome these hurdles will increasingly compete beyond their own home markets to recoup fixed costs as their domestic markets alone become increasingly insufficient. This growing importance of foreign competitors makes them increasingly attractive sources for external knowledge. As a result, firms will increasingly consider acquiring, allying with, or setting up greenfield facilities near foreign firms to tap into complementary knowledge in other countries.

What attributes would attract firms expanding abroad to access technical and innovative activity? Each of the three explanations highlights different attributes. Catching up emphasizes relative position in knowledge stocks—firms from country-industries that are further behind will be drawn to other country-industries with greater stocks. Sourcing greater technical diversity suggests the nature of knowledge stocks is important—how similar or different stocks are across countries. R&D springboard focuses on the size of similar knowledge stock—how firms might use other countries' activities to build upon their own R&D activities.

Catching up suggests that firms in industries whose country is further behind will expand abroad to those countries that are further ahead. This focuses on relative knowledge stocks between the focal country-industry and target country-industries suggesting that larger stocks in target country-industries are more attractive.

This catching up perspective is coupled with a competitive consideration. Larger knowledge stocks may be the result of a location with more competitors, stronger competitors, or both. Such competitors are likely aware that trying to borrow others' knowledge is a possible strategy. As a result, participants in highly competitive markets are likely to actively protect their knowledge base. They will be careful to consider partners' incentives before entering alliances, focus on retaining key scientists and engineers, and have tight relationships with critical suppliers; all of which will decrease the potential for knowledge sourcing. Therefore, if markets with more patents are also more competitive, then while the amount of knowledge for knowledge sourcing may be large, the success of accessing the knowledge may actually be low due to these protective mechanisms. Even with this competitive consideration, we expect potential for knowledge sourcing to dominate, especially in knowledge-intensive industries, though the empirical tests will determine whether catching up or the competitive effect dominates.[4]

Hypothesis 1: The larger the host country-industry's knowledge stock relative to the home country-industry, the more attractive the host.

Turning to the nature of knowledge, the logic behind sourcing technical diversity suggests an interest in different technical activity: the more different the activity, the more attractive. This desire for technical diversity is likely tempered by a firm's ability to absorb knowledge. A firm's absorption is affected by how similar or different the desired knowledge is, with absorption likely becoming increasingly difficult as knowledge becomes more dissimilar. Essentially a firm will need some preexisting related knowledge stock to identify, acquire, and employ additional new information. When such overlap between what the firm already knows and what it wants to learn doesn't exist, then absorbing the new target knowledge will be difficult. This suggests that:

[4] If firms' managers believe the benefits of knowledge spillovers outweigh the costs of competitive considerations for a particular market, then firms will invest and we will observe significant results in the empirical tests.

Hypothesis 2: A host country-industry's attractiveness first increases with dissimilarity of home and host country-industry knowledge stocks, and then decreases after dissimilarity crosses a threshold.

For the third motivation, R&D springboard, the objective is to supplement R&D activities at home with knowledge sourced abroad to surmount investment cost hurdles for new generations of products. This suggests two components. First is the magnitude of target country-industry technical activity with greater activity being more attractive. The second component is the type of knowledge sought. The technical activity in the target country-industry has to be similar to that being conducted at home or the aggregate of home and host activity will not grow; large stocks different from existing home activity will not help surmount the fixed cost hurdle for succeeding generations' products and technology. The technical activity in the target location has to be similar to that being conducted by firms from the focal country. Putting these two components of R&D springboard together suggests:

Hypothesis 3: The larger and more similar the host country-industry knowledge stock relative to the home country-industry, the more attractive the host country-industry.

This is somewhat of an opposite expectation than that of Hypothesis 2, where sourcing technical diversity led to preferring differences. The empirical tests will determine whether the technical diversity or R&D springboard perspective receive support.

Overall, the three explanations suggest the importance of potential host country-industries' knowledge stock size, the home country-industry's knowledge stock size, and the host country-industry stock's technical similarity relative to the home country-industry.

METHOD

We test the attractiveness of these country-industry attributes using a count-based measure of foreign investment—how many incremental investments are made a year in each of a multitude of different countries and their industries. The empirical model must accommodate the nature of these counts: nonnegative, integer values with a high frequency of zero and small integer values. As such we use a count-based model: the negative binomial. Zero and small values of the dependent variable are naturally incorporated into the model. The negative binomial model is:

$$\Pr[investment = p] = \frac{e^{-\lambda}\lambda^{p}}{p!} \qquad (1)$$

Where:

- investment is the count of investment transactions in a country-industry-year;
- λ is $e^{\beta' X+\varepsilon}$
- X is a vector of country-industry attributes; and
- β is a vector of parameters

The focal attributes will be host country-industries' knowledge stock size, the host country-industry stock's technical similarity relative to the home country-industry, and an interaction between the two. Summarizing the focal attributes, we have a vector of attributes:

$$\beta_0 \text{Host\_stock} + \beta_1 \text{Technical\_similarity} + \beta_2 \text{Host\_stock} \times \text{Technical\_similarity} \qquad (2)$$

Linking this set of parameters back to our theoretic expectations, we can summarize our expectations with the following relationships:

$\beta_0 > 0$ Hypothesis 1 catching up receives support
$\beta_0 < 0$ competitive effect supercedes catching up
$\beta_1 < 0$ Hypothesis 2 sourcing technical diversity receives support
$\beta_2 > 0$ Hypothesis 3 R&D springboard receives support

In addition to country-industry attributes we also include country, industry, and year fixed effects. Estimating fixed effects for nonlinear models with maximum likelihood has the potential for the 'incidental parameter problem'—with panel data of fixed T observations per individual; the slope parameters (individual effects) are inconsistent on the order of 1/T. While our interest is not with these slope parameters, Greene (2002) recently notes that for certain models while slope parameters are consistent, estimated disturbance variance

DOI: 10.1002/smj

is biased, which would influence marginal effects. Greene also notes that for a wide variety of models, when T increases above 5, slope parameter and disturbance variance bias is minimal, which is the case here: we use data from 1989–1999: T = 11. Alternately in the robustness section we relax the number of effects to be estimated by substituting country attributes for fixed effects; when doing so we obtain similar results for our focal variables. We discuss these and other control variables below in the data section.

DATA

Our empirical context is U.S. firms expanding abroad from 1989–1999. As such we need data on U.S. investment abroad as well as country-industry attributes for a comprehensive range of destination locations. In particular we require measures for countries' knowledge stock size as well as technical similarity relative to the United States by industry for a wide swath of countries.

For the U.S. investment data we turn to the Bureau of Economic Analysis (BEA) of the Department of Commerce. One of the BEA's congressional mandates is tracking investment both into and out of the United States via the Benchmark and Annual Surveys of U.S. Foreign Direct Investment. While the aggregated data—such as whether any U.S. firms invested in a particular country or the total dollar value of investment in a country is readily available, the BEA is required to protect the identities of the U.S. firms that disaggregated data might reveal. As such, more disaggregated data requires the additional assistance of the BEA. With such assistance, we were able to obtain data on the count of investments in each country-year, disaggregated by industry (a mix of two- and three-digit standard industrial classification [SIC] codes) and by investment mode (greenfield or acquisition).[5] While further disaggregation is possible, it requires substantial further assistance by the BEA and is accompanied by commensurate restrictions on how the data can be used.

Figure 1 illustrates the most popular destinations for outgoing U.S. foreign investment for the years 1989 through 1999. The top seven countries account for one-half of the total transactions. The bulk of transactions are via acquisition, though greenfield investments seem more numerous for some developing countries.

We match this country-industry-year investment count data to information on host country-industry-year knowledge stock size and technical similarity. To reflect the size and type of knowledge present across country-industries, we use patents from the National Bureau of Economic Research (NBER) Patent Database. Patents allow us to readily quantify these two dimensions due to the detailed information regarding the nature of the technology. Other potential measures such as R&D spending are simply not available across many countries disaggregated by industry, year, and technical specialty. While likely the only viable measurement option, one possible shortcoming is whether a foreign country's U.S. patents accurately reflects the country's technical activity; do U.S. patents originating from Argentina reflect Argentina's technical activity? While such a concern exists, the U.S. patent system is certainly the most important in the world for establishing intellectual property rights (even outside of the United States); therefore any significant innovations, regardless of where they originate, tend to have U.S. patents.[6]

To indicate knowledge stock, we use patent counts; more patents indicate greater knowledge stock size. To link patent to industries we rely on the *'Concordance Between the Standard Industrial Classification (SIC) Code System and the United States Patent Classification (USPC) System'* issued in January 2002 by the U.S. Patent and Trademark Office (USPTO). This concordance maps USPTO technological classes into 41 product fields that are a mix of two-digit and three-digit SIC industries with finer three-digit gradation in select high-tech sectors.[7] With this data we know the flow of

[5] Industry definitions may be based on either the parent or the subsidiary. In situations where these are different, we use the parent's industry definition since it is the parent who is involved in knowledge sourcing.

[6] Eaton and Kortum (1999) develop a model of world economic growth: countries grow by both innovating themselves and adopting other countries' inventions. A focal decision criterion for a country's growth is choosing between a national and an international patent system—which affects other countries' ability to adopt a nation's innovations. Examining country-level determinants of international patents, Furman *et al.* (2002) operationalize international patents as those filed in the United States by foreigners, which they argue accounts for significant innovations at the world's technical frontier because filing for a U.S. patent is a costly undertaking and therefore foreign filers obtain U.S. patents only for those innovations that they know are or they expect to be important.

[7] An alternate method for linking SIC industries and USPTO patent classes is pioneered by Silverman (1999) who takes

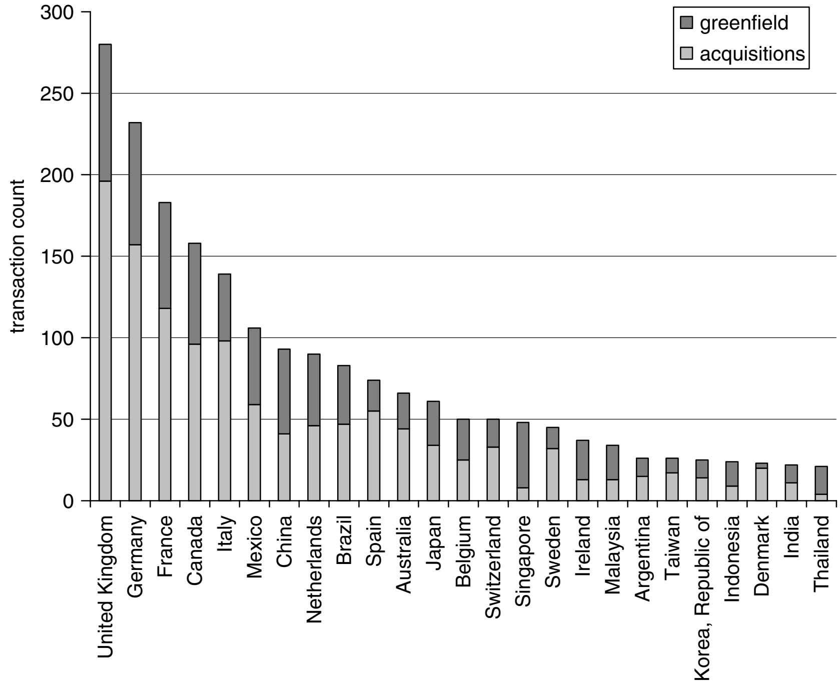

Figure 1. Top 25 destinations for U.S. outward foreign investment 1989–1999 Count of transactions by acquisition and greenfield investment

patents for each country-industry-year. For year, we use the filing date of a patent application rather than the grant date of the patent since the filing date is more indicative of when the knowledge was created. For number of patents, instead of using the yearly flow that can fluctuate dramatically across years, we construct a moving stock using the perpetual inventory method; we use the yearly flow in 1976 as our starting point and depreciate the existing stock by 20 percent while adding additional patents each year.[8]

Using the country-industry-year patent data we can construct host location knowledge stock relative to home location. Relative position would be a linear combination of the host patent count and the home patent count—specifically the host count less the home count scaled by the home count. Instead of the linear combination, we simply include both of the component terms: *'patent count–host'* and *'patent count–U.S.'* *'patent count–host'* is country-industry-year varying while *'patent count–U.S.'* is industry-year varying.

To indicate technical similarity between the knowledge stock of a host country-industry and the U.S.-industry, we use their overlap in distribution of patent stocks across patent classes. We replicate the measure used by Jaffe (1986) but at a

advantage of the Canadian Patent Office's (CPO) practice of assigning granted patents both an International Patent Class (IPC) and an International Standard Industry Code (ISIC). Silverman then links these international identifiers to the U.S. equivalents: IPC is linked to U.S. patent class and ISIC is linked to U.S. SIC. This concordance was the only option available to researchers prior to 2002 when the USPTO published their direct U.S. tech class to U.S. industry mapping. In other work, we compare the USPTO concordance to the Canadian-based concordance and find a very high correlation: for patents awarded to industry, academic, and government assignees the correlations were 0.95, 0.94, and 0.95 respectively. We chose the USPTO concordance because the one degree of separation method (U.S. patent class–to–U.S. SIC) used by U.S. government officials should have less noise or systematic bias than the three degrees of separation method used by international trade and Canadian officials.

[8] The choice of this depreciation rate is based upon Hall (1993) and Hall, Jaffe, and Trajtenberg (2001). Hall uses a 15 percent depreciation rate when building a stock of R&D based upon R&D spending. We follow Hall's (1993) 'perpetual inventory method' but recognize that we are building a stock of patents rather than an R&D stock. We choose a depreciation rate for patents based upon patents' timing of citations from Hall *et al.* (2001) who show that patent citations peak after five years, plateau briefly, and then decline quickly afterward. We use this timing of citations as the basis for the 20 percent depreciation rate. Lowering this rate of depreciation to 15 percent does not affect our results.

DOI: 10.1002/smj

country-industry-year level—we compare similarity by industry-year between two countries. This measure has been used extensively in the innovation and R&D productivity literature. Comparing several possible archival measures of technical similarity contributing to knowledge spillovers to innovation survey data, Kaiser (2002) recently finds that Jaffe's (1986) uncentered correlation to be the best predictor for knowledge spillovers. The measure (*'technical similarity'*) is shown below:

$$\text{technical similarity} = \frac{F_i F_{i'}{}'}{\sqrt{(F_i F_i{}')(F_{i'} F_{i'}{}')}} \times \text{where } i \neq i' \tag{3}$$

F_i and F_i' are multidimensional vectors representing the distribution of a country-industry's patents across multiple patent classes. $F_i = (F_i{}^1 \ldots F_i^s)$, where F_i^s represents the number of patents assigned to country i in patent class s. Technical similarity is then the extent that two countries' industry vectors overlap—the uncentered correlation between a pair of countries' industry technical stocks. Technical similarity varies by country-industry-year. For example, the technical focus of the Japanese, European, and North American automotive industries may differ in a given year, and the technical focus of the Japanese automotive industry may change over time. This country-industry-year variation is constructed using within industry variation as follows.

To reflect the multiple dimensions of each country-industry-year, we use 313 separate patent classification categories; each country-industry-year vector has 313 dimensions, though each industry uses only a subset of the possible 313 categories (some of the 313 categories are consistently zero within a given industry).[9] We construct the technical similarity measure for each country-industry-year relative to the corresponding U.S.-industry-year. Technical similarity varies from zero to one, with a value of one indicating that the two vectors are completely overlapped—that the two country-industries have the greatest possible technological similarity.

Figure 2 shows two distributions: (1) the technical similarity between the United States and all other country-industry-years that U.S. firms could have invested—12,969 in total and (2) the technical similarity between the United States and other country-industry-years where U.S. firms did invest—1,769 U.S. investment transactions were made in 1,262 country-industry-years. Looking at the upper distribution, two aspects appear: there are numerous country-industry-years with zero overlap in technical similarity; and excepting these zero overlap cases, the number of country-industry-years tends to increase with similarity—country-industry-years with greater similarity are more numerous. This suggests, simply by how numerous the cases, that U.S. firms have a good chance of randomly choosing both locations with zero overlap and high overlap. At question is whether U.S. firm location choices are higher or lower than the base rates shown in the upper distribution. Looking at the lower distribution: while country-industry-years with high technical similarity generally seems to have a greater number of investment transactions (potentially at a higher rate than in the upper distribution), a small but distinct number of investment transactions are made in country-industries-years that have no technical overlap at all with the United States (potentially at a lower rate than in the upper distribution). Conscious that this zero overlap discontinuity might affect the coefficient estimate for '*technical similarity*'—a linear estimate would have difficulty reflecting both high similarity/many investments and zero similarity/many investments—we also include a dummy variable '*technical similarity equal zero*' to account for this zero similarity/many investments possibility.

Recognizing that firms invest abroad for a variety of reasons besides sourcing knowledge, we also include several control variables. For example, in addition to locations' technical activity, Henisz and Macher (2004) show that locations' political hazards interact with locations' technical activity to determine firms' location decisions. Instead of including numerous other variables to account for a multitude of other explanations, we include several sets of fixed effects. For the 11 years of data: 1989–1999, we include 10 year dummies; for the 41 product fields/industries, we include 40 industry dummies. For the 35 countries where U.S. firms invest, we included 34 country effects. This complete set of country, industry, and year effects accounts for many alternate explanations.

[9] To do so, we needed to supplement the NBER Patent Database with raw patent data. The NBER Patent Database provides a patent's class, but not the more detailed subclass that is needed to construct the vectors.

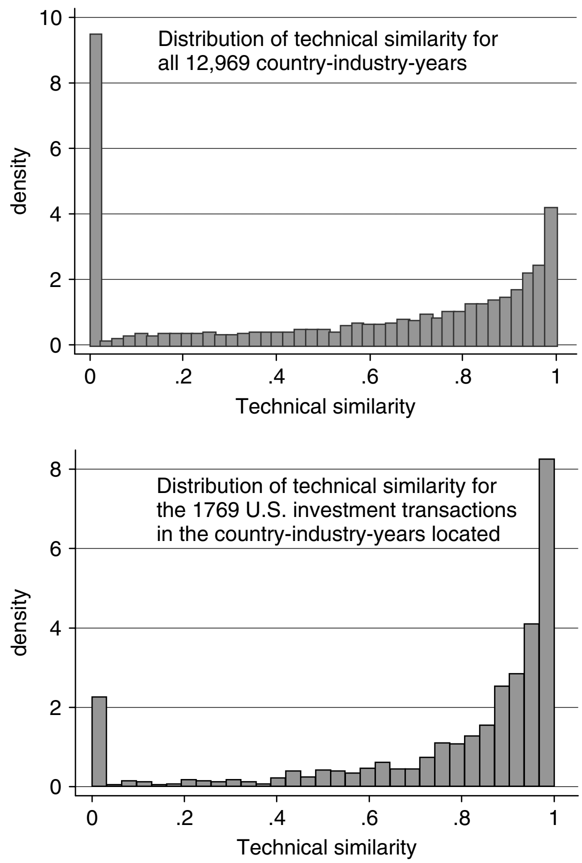

Figure 2. Distribution of technical similarity. Technical similarity between U.S. and host countries for those country-industry-years that U.S. firms invest. Above: all country-industry-years; Below: 1769 U.S. investment transactions in 1262 country-industry-years

For example, country effects account for attractiveness of large markets, access to inexpensive inputs such as labor, and other relatively constant country attributes. Industry effects account for greater international competition, lower fixed costs for investment abroad, or similar explanations.

Beyond these three sets of fixed effects that account for many alternate explanations, we also pay careful attention to the main alternate explanation of why firms expand abroad—to access new markets (via internalization). While country fixed effects account for market size and similarity, we also recognize that markets may be becoming more or less similar to the United States, and those markets that are becoming more similar are likely to be more attractive to U.S. firms for two reasons. First, consumer preference becoming more similar allows U.S. firms to sell existing products and services with little modification. For example, while Mexico and Canada have roughly the same gross domestic product (GDP)—924.4 billion in 2002 versus 934.1 billion respectively—the Canadian market is more similar to the U.S. market and is likely to move in a similar fashion to the U.S. market, thus making Canada more attractive. Second, U.S. firms may use the host country as an export platform that would require a comparable richness of factor inputs and dynamic shifts in factor input stocks for the firms' production processes. Similarly, relocating production to Canada would require firms to modify their existing production processes less than relocating to Mexico would.[10] To assess customer and factor input

[10] Of note, if attracted to relocate production to Mexico for cheap labor, firms are unlikely to open their own subsidiary. Relocation of activity to less expensive locations is likely to be outsourced. Dissimilarity in revealed comparative advantage suggests a country-industry may be attractive for outsourcing, but not for foreign investment.

DOI: 10.1002/smj

similarity we make use of comparative advantage: that a country's exports intensively use factor inputs that the country is most rich. For example, the United States tends to export capital intensive products while developing nations tend to export labor intensive products. Using data from the NBER International Trade Database[11], we construct the revealed comparative advantage (RCA) for each country-industry-year. Revealed comparative advantage is the country's share of world exports of an industry divided by the country's share of total world exports. The index for country i industry j is $RCA_{ij} = 100(X_{ij}/X_{wj})/(X_{it}/X_{wt})$. We then scale each country-industry-year's RCA by the corresponding U.S.-industry-year RCA to give a relative measure to the United States (*'revealed comp. adv. ratio'*).

Descriptive statistics for the above variables and several additional country control variables discussed in the robustness section as alternatives to country fixed effects are shown below as Table 1.

In the subsequent empirical tests we take the logs of several of the independent variables before regressing count of U.S. investment transactions on them.[12] We do so to facilitate assessing economic significance (with independent variables in logs, the associated coefficient estimates are to be interpreted as elasticities) and to reduce the weight accorded to outlying observations. We take the logs of *'patent count–host,' 'patent count–U.S.,'* and '*revealed comp. adv. ratio.*'

RESULTS

The results of exploring the relationship between host country-industry attributes and count of U.S. investments into those countries-industries are shown below in Table 2. The first column is a benchmark specification that includes the three sets of fixed effects and the ratio of host to U.S. revealed comparative advantage (*'revealed comp. adv. ratio'*). Subsequent columns introduce other focal independent variables, notably technical similarity.

Looking across the columns '*revealed comp. adv. ratio*' is consistently positive and significant. The more a country-industry's share of world exports relative to the corresponding U.S.-industry, the more attractive the country-industry is for U.S. investment.

Turning to the focal independent variables, Columns 2 through 6 incrementally introduce the focal independent variables. Columns 2 and 3 separately introduce the two components for the 'catching up' explanation. We see in Column 2 that '*patent count–U.S.*' via both individual t-test and incremental log likelihood test (0.03 difference in LogL from Column 1 versus Column 2 for 1 degree of freedom (d.o.f.) has a probability value of 0.874) is not significant. In Column 3, '*patent coun—host*' has is positive and significant t-test (0.3640 coefficient estimate with a 0.187 standard error is significant at the 10% level for a two-tailed test), but a nonsignificant incremental LogL (1.88 difference in LogL for 1 d.o.f. has a probability value of 0.171). If '*patent count–host*' was significant via both t-test and incremental LogL test, the results would suggest that the host country's position was an important determinant of U.S. investment abroad. And since the coefficient for '*patent count–U.S.*' is not significant, it would be the absolute position (only '*patent count–host*' matters) rather than the relative position (both '*patent count–U.S.*' and '*patent count–host*' matter). But since both are not significant, the catching up expectation is not supported in this context, which is not that surprising since U.S. industries are likely leaders on average and therefore would not need to catch up.

Columns 4 and 5 introduce the uncentered correlation '*technical similarity*' and '*technical similarity equal zero*' to explore the 'sourcing technical diversity' expectation. Initially in Column 4, the coefficient estimate for '*technical similarity*' is negative, which is consistent with a sourcing technical diversity argument, but is far from significant. Once '*technical similarity equal zero*' is accounted for in Column 5, the coefficient for '*technical similarity*' becomes positive but remains far from significant. Investigating the second part of *Hypothesis 2,* whether high levels of dissimilarity make a host country-industry unattractive, we find introducing a quadratic term does not significantly improve model fit.[13]

[11] See Feenstra (1996, 1997) for more details.

[12] When doing so, if an independent variable's minimum value is 0, we add 1 since log of 0 is undefined.

[13] Versus the model in Column 5, the additional quadratic term decreases log likelihood by only 2.32, which for 1 d.o.f. has a probability value of 0.13.

Table 1. Descriptive statistics
U.S. FDI transaction 1989–1999 and attributes of host countries

variable	source	availability	varies by	n*	mean	std dev	minimum	maximum
count outward U.S. FDI	Bureau of Econ Analysis	1989–99	ctry-ind-yr	12 969	0.125	0.489	0.000	11.000
those by acquisition		1989–99	ctry-ind-yr	12 969	0.079	0.374	0.000	10.000
those by greenfield		1989–99	ctry-ind-yr	12 969	0.047	0.248	0.000	6.000
patent count—U.S.**	NBER Patent Data	1989–99	ctry-ind-yr	12 969	0.104	0.546	0.000	17.949
patent count -host**	NBER Patent Data	1989–99	ctry-ind-yr	12 969	4.431	5.509	0.234	28.952
technical similarity	NBER Patent Data	1989–99	ctry-ind-yr	12 969	0.553	0.380	0.000	1.000
revealed comp. adv. ratio (RCA)	NBER Feenstra Trade Data	1989–99	ctry-ind-yr	12 969	0.889	1.012	0.000	15.235
population (millions)	Penn World Tables	1989–99	ctry-yr	12 969	0.056	0.151	0.003	0.998
real GDP (thousands)	Penn World Tables	1989–99	ctry-yr	12 969	14.849	7.476	1.635	26.607
openness	Penn World Tables	1989–99	ctry-yr	12 969	0.066	0.045	0.014	0.305
physical dist. (to host)	Hall and Jones QJE 1999		ctry	12 969	7673.419	3520.203	734.000	15 958.000
english speakers (fraction)	Hall and Jones QJE 1999		ctry	12 969	0.120	0.298	0.000	0.974
K/L ratio (industry)	Hall and Jones QJE 1999		ctry	12 969	10.585	0.852	8.236	11.589
intellectual protect	Ginarte Park 1997	1995	ctry	12 969	3.257	0.852	1.080	4.240

* 35 countries × 34 industries × 11 years = 13,090 − 121 (missing data for RCA) = 12,969
** annual stock constructed from annual flows using perpetual inventory method (making fraction of patents possible)

Table 2. Effect of foreign country technical activity on U.S. foreign investment negative binomial regression–count of U.S. subsidiaries abroad by country-industry-year

	baseline	*attractiveness of target country technical activity*				
	(1)	(2)	(3)	(4)	(5)	(6)
country effects	included***	included***	included***	included***	included***	included***
industry effects	included***	included***	included***	included***	included***	included***
year effects	included***	included***	included***	included***	included***	included***
revealed comp. adv. ratio	0.2239***	0.2239***	0.2135***	0.2157***	0.2206***	0.2129***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
patent count–U.S.		−0.0733	−0.1269	−0.1237	−0.1097	−0.1417
		(0.328)	(0.329)	(0.330)	(0.329)	(0.330)
patent count -host [H1]			0.3640*	0.3440*	0.2792	−2.1583***
			(0.187)	(0.188)	(0.191)	(0.782)
technical similarity (U.S.-host) [H2]				−0.1576	0.1904	−0.0673
				(0.178)	(0.224)	(0.231)
technical similarity equal zero					0.5547***	0.3977*
					(0.209)	(0.210)
patents(host)* tech sim. [H3]						3.0105***
						(0.897)
Observations	12 969	12 969	12 969	12 969	12 969	12 969
Log likelihood	−3520.11	−3520.08	−3518.21	−3517.81	−3514.28	−3507.22
compare model		(1) vs (2)	(2) vs (3)	(3) vs (4)	(4) vs (5)	(5) vs (6)
difference LogL		0.03	1.88	0.39	3.54	7.05
additional d.o.f.		1	1	1	1	1
chi-squared test		0.874	0.171	0.532	0.060*	0.008***
compare model			(2) vs (3)	(2) vs (4)	(2) vs (5)	(2) vs (6)
difference LogL			1.88	2.27	5.80	12.86
additional d.o.f.			1	2	3	4
chi-squared test			0.171	0.322	0.121	0.012**
Pseudo r-squared	0.277	0.277	0.277	0.277	0.278	0.280

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1% for two-tailed test

Focusing on '*technical similarity equal zero*' in Column 5, the coefficient estimate is positive and significant (a significant t-test at least a 0.01 level and a chi-squared test for change in log likelihood value of 3.54 that for 1 d.o.f. is significant at a 0.06 level). This shows that after using a multivariate test to account for other possible correlates that a relationship suggested in Figure 2—the attractiveness of no technical overlap country-industries—persists. While this relationship may simply reflect the high underlying count of zero overlap choices—since they are more numerous, U.S. firms may by chance select zero overlap choices significantly more often—another possible explanation is a desire of some U.S. firms investing abroad to avoid any possible competitors that would benefit from the U.S. firms' presence; U.S. firms' technical capabilities might spillover thereby assisting competitors. For example, Shaver and Flyer (2000) argue that stronger firms generate externalities that assist weaker ones and show for foreign firms entering the United States that stronger foreign entrants prefer to locate away from places densely populated by U.S. firms. The finding for '*technical similarity equal zero*' would be similar but at an international level: recognizing that their technical capabilities might spillover thereby assisting competitors, some U.S. firms choose zero technical similarity locations. To further explore this possibility, we later examine differences across modes of entry.

Column 6 investigates the 'R&D springboard' explanation and introduces '*patent count–host*' interacted with '*technical similarity*'; larger and more similar technical activity within the host country being more attractive. The interaction term of '*patent count–host* × *technical similarity*' is positive with both a very significant t-test and increase in log-likelihood. Comparing Column 5 to Column 6, the incremental change in log-likelihood for the one additional d.o.f. is a 7.05 decrease that is significant at a 0.008 level indicating that even though the interaction term is highly correlated with the individual component terms by construction, which might inflate the t-test, that including the interaction term is a very important explanatory factor. Also comparing Column 5 to 6, the coefficient for '*patent count–host*' becomes strongly negative. The coefficient on '*patent count–host*' is −2.1583 and the coefficient on the interaction term of '*patent count–host* × *technical similarity*' is 3.0105. Thinking about the overall effect, '*technical similarity*' ranges from 0 to 1 which indicates that country-industries with technical similarity values of greater than 0.7169 are attractive to U.S. investment. Of course for a given level of technical similarity of greater than 0.7169, a country-industry with a larger patent count is also more attractive. But if technical similarity is less than 0.7169 a country-industry is unattractive, which suggests that a competitive effect may dominate and discourage investment when there is insufficient technical similarity to encourage investment. The results in Column 6 support the 'R&D springboard' expectation of Hypothesis 3.

Overall for outward U.S. foreign direct investment, we find that country-industries with similar technical profiles and with larger knowledge stocks are increasingly attractive. These results are mainly consistent with an explanation of firms investing abroad to springboard their R&D activities.

ROBUSTNESS TESTS AND ADDITIONAL HETEROGENEITY

Before settling on the above results, we conduct several alternate tests. First is verifying that our set of fixed effects and '*revealed comp. adv. ratio*' act as adequate controls. To do so, we introduce several other independent variables to represent other common explanations for why a country might be attractive for investment. We include population ('*population*') and real GDP per capita ('*real GDP*') to represent how attractive a country is as a target market. As investment may also be spurred by favorable exchange rates, which makes acquisitions relatively less expensive, or the cost of erecting new facilities less costly, we included the real exchange rate ('*exchange rate*'). Also a country's stance ('*openness*') toward international economic flows will affect whether firms are likely to invest, which is the sum of imports and exports scaled by real GDP. Related to openness is what types of laws a country has in place to enforce patents ('*intellectual protect*'); weak enforcement would dissuade investment.[14] Also to reflect gravity trade models—that more physically distant markets are less attractive—we include the distance between countries' capital cities ('*distance*'). We also include countries' fraction of English- speaking population ('*English* speakers').[15] Table 1 lists these variables sources. As these measures are only country or country-year varying, when including them we omit country fixed effects, which would be perfectly colinear. Introducing these measures also assesses the potential incidental parameter problem; if results stay similar when substituting country measures for country effects, then the potential problem is not a substantial issue. While the coefficient estimates for '*population,*' '*openness,*' and fraction of '*English speakers*' have significant t-tests, the log-likelihood for this model is less than even the baseline model in Column 1 (−3583.93 versus −3520.11), which indicates that sets of fixed effects account for numerous alternate explanations. With this list of controls, the results for the focal variables testing Hypotheses 1, 2, and 3 stay the same in sign and significance as reported in Column 6 of Table 2.

Besides empirical robustness, another important conceptual consideration is the managerial logic leading firms to pursue international knowledge sourcing. An antecedent is that firm managers realize the potential benefits from differences in countries' knowledge stocks; but some managers may be more aware than others. To assess this possibility, we make use of the level of import competition an industry faces. U.S. firms in those industries that face more import competition should be more aware of knowledge sourcing benefits. For each industry, we use the value of import sales divided by domestic value added: a larger ratio indicates

[14] We use the measure developed by Ginarte and Park (1997), which reflects four categories of patent law: extent of coverage, membership in international patent agreements, provisions for loss of protection, and duration of protection. This measure is constructed every five years from 1960 through 1990; we use the measure from 1995, which is in the middle of our investigation period.

[15] '*Distance*' and '*English speakers*' are drawn from Hall and Jones (1999).

DOI: 10.1002/smj

more import competition (to avoid any yearly fluctuation in calculating these ratios, we use the average ratio for five years from 1989–1993). We split our full sample into above and below median imports and repeat focal specifications; the results appear as Table 3 below.

Table 3 has six columns. The first two columns are for the full sample (the same as in Table 2, Columns 5 and 6) and act as benchmark specifications. Recall that the specification in Table 2, Column 5 tests Hypotheses 1 and 2; the specification in Table 2, Column 6 tests Hypothesis 3 with an interaction term. Interpreting Hypotheses1 and 2 is easier in Column 5 without the interaction term. The four subsequent columns (two sets of two specifications) represent the industries split by above or below median imports.

While the full sample has no evidence for catching up, splitting the sample reveals that behavior consistent with catching up occurs in lower import competition industries. 'Patent count-host' is positive and significant in Column 5, but not in Columns 1 and 3.[16] Hypothesis 1 is supported for lower import industries: firms in U.S. industries exposed to less international competition expand abroad to catch up, which is counter to expectations. An additional finding, from Column 4, is that support for Hypothesis 3 (R&D springboard: firms boosting their ongoing R&D activities) emanates mostly from higher import competition industries. Putting these two results together, a possible explanation is that all U.S. firms eventually expect to experience high international competition in this 1990s era of increasing globalization. Firms in those U.S. industries with higher

[16] We interpret the results in Column 5 instead of Column 6 because the incremental log-likelihood test comparing the two specifications indicates that Column 6 does not significantly improve over Column 5: introducing the interaction term in Column 6 does not explain more variation (a decrease of 2.26 for 1 d.o.f. has a probability value of 13.2%).

Table 3. Effect of foreign country technical activity on U.S. foreign investment (split by import competition) negative binomial regression—count of U.S. subsidiaries abroad by country-industry-year

			split by import competition			
	full sample baseline		*higher imports*		*lower imports*	
	(1)	(2)	(3)	(4)	(5)	(6)
country effects	included***	included***	included***	included***	included***	included***
industry effects	included***	included***	included***	included***	included***	included***
year effects	included***	included***	included***	included***	included***	included***
revealed comp. adv. ratio	0.2206***	0.2129***	0.2355***	0.2431***	0.1792***	0.1608***
	(0.041)	(0.041)	(0.069)	(0.069)	(0.055)	(0.056)
patent count–U.S.	−0.1097	−0.1417	0.2162	0.2200	−0.4629	−0.4919
	(0.329)	(0.330)	(0.495)	(0.496)	(0.434)	(0.435)
patent count -host [H1]	0.2792	−2.1583***	−0.2595	−3.1545**	0.8632***	−1.1164
	(0.191)	(0.782)	(0.282)	(1.568)	(0.278)	(1.006)
technical similarity (U.S.-host) [H2]	0.1904	−0.0673	0.2483	−0.0738	0.1459	−0.0342
	(0.224)	(0.231)	(0.388)	(0.406)	(0.277)	(0.287)
technical similarity equal zero	0.5547***	0.3977*	0.8584**	0.6490*	0.3780	0.2835
	(0.209)	(0.210)	(0.352)	(0.356)	(0.260)	(0.261)
patents(host)*tech sim. [H3]		3.0105***		3.5409**		2.3333**
		(0.897)		(1.774)		(1.134)
Observations	12 969	12 969	6501	6501	6468	6468
Log likelihood	−3514.28	−3507.22	−1452.64	−1449.57	−2024.08	−2021.82
compare model		(1) vs (2)		(3) vs (4)		(5) vs (6)
difference LogL		7.05		3.07		2.26
additional d.o.f.		1		1		1
chi-squared test		0.008***		0.080*		0.132
Pseudo r-squared	0.278	0.280	0.295	0.297	0.273	0.274

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1% for two-tailed test

imports already need to coordinate domestic and international efforts to be competitive, which leads to investing abroad to springboard R&D activity. Firms in those industries with lower imports can look to other industries already experiencing increased globalization pressure and, rather than wait for the international competitors to arrive and then think about a catching-up strategy, some managers in these industries may proactively invest abroad in the important competing countries.

Exploring potentially important dimensions of heterogeneity, we also make use of entry mode—whether investment transactions were made via greenfield or acquisition. Our data from the BEA separates the count of outward U.S. investment transactions into these two categories.[17] For each of these two entry modes we repeat the five focal specifications from Table 2. Table 4 reports the results for count of acquisitions and greenfield investments respectively.

Results for acquisitions are in Columns 1 through 5 while greenfield investments are in Columns 6 through 10. The attractiveness of countries with large patent stocks and similar technical profiles to the United States appears for both acquisitions and greenfield investments; the '*patent count–host* × *technical similarity*' interaction term is significant (Columns 5 and 10) and improves model fit (Column 4 versus 5 and Column 9 versus 10, respectively). This suggests that when seeking to springboard R&D activities, firms use both entry modes. One difference is that the improvement in model fit of Column 9 versus 10 for greenfield investments (2.79) is not as large as the improvement for acquisitions in Column 4 versus 5 (4.34), which suggests that the use of greenfield investments for knowledge sourcing may be more limited. Another difference appears in Column 9—the coefficient estimate for '*technical similarity equal zero*' is positive and significant via the individual t-test and incremental log likelihood (a 2.82 decrease for 1 d.o.f. chi-squared test is significant at a 0.093 level): '*technical similarity equal zero*' affects greenfield investments but not acquisitions. This suggests that U.S. firms prefer to establish greenfield investments for other reasons besides as a springboard for their R&D activities. Since greenfield investments are typically preferred to acquisition when the investing firm has proprietary technical capabilities versus managerial capabilities, U.S. firms may use greenfield investments to protect their preexisting technical knowledge. This difference between greenfield investments and acquisitions is consistent with U.S. firms protecting their technical assets by making greenfield investments in locations where the local firms have no technical overlap—where the local firms have little or no capability to absorb technical knowledge from U.S. firms.

Another potentially important dimension of heterogeneity is a country's level of economic development. A low level of economic develop makes a country substantially less attractive for firms intent on knowledge sourcing. As such, we split our sample based on level of development into developed versus emerging countries using a US$10,000 per capita GDP cutoff and repeat the focal specifications from Table 2. As we would expect, these tests show that all statistical evidence of knowledge sourcing behavior is limited to the developed country sample; among emerging countries, knowledge stock size and overlap measures are uniformly insignificant. Excluding emerging countries from our sample would tend to strengthen our results reported above.

CONCLUSIONS

The central role of knowledge for firms' competitive advantage has heightened interest in how firms identify, acquire, and use knowledge external to them. Several authors have recently highlighted the strategy of firms expanding internationally to source knowledge motivated by firms' need to 'catch up' with others or to broaden their knowledge portfolio by 'sourcing technical diversity' from other geographic locations.

We raise an additional motivation by applying findings from technology strategy: that of an 'R&D springboard' with firms looking to reduce their fixed R&D costs by supplementing their internal R&D activity with knowledge sourced externally via acquisitions, alliances, or spillovers. To identify the several motives for international knowledge sourcing, we use a comprehensive dataset of outward U.S. investment to examine what technology attributes of country-industries attract more investment. This broader empirical context allows us to simultaneously test these different

[17] Joint ventures are reported in the appropriate category depending upon whether joint ventures were formed by acquiring existing entities or establishing new ones.

DOI: 10.1002/smj

Table 4. Effect of foreign country technical activity on U.S. foreign investment (acquisition vs greenfield entry mode) negative binomial regression–count of U.S. subsidiaries abroad by country-industry-year

	acquisition					*greenfield*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
country effects	included***	included***	included***	included***	included***	included***	included***	included***	included***	included***
industry effects	included***	included***	included***	included***	included***	included***	included***	included***	included***	included***
year effects	included***	included***	included***	included***	included***	included***	included***	included***	included***	included***
revealed comp. adv. ratio	0.2535***	0.2369***	0.2387***	0.2399***	0.2328***	0.1813***	0.1767***	0.1788***	0.1896***	0.1802***
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
patent count–U.S.	−0.1665	−0.2415	−0.2396	−0.2324	−0.2625	−0.0288	−0.0563	−0.0538	−0.0356	−0.0671
	(0.410)	(0.411)	(0.412)	(0.412)	(0.413)	(0.525)	(0.526)	(0.527)	(0.526)	(0.526)
patent count -host [H1]		0.5072**	0.4884**	0.4537*	−1.9713**		0.1880	0.1709	0.0659	−2.2516*
		(0.241)	(0.242)	(0.245)	(0.993)		(0.283)	(0.286)	(0.293)	(1.183)
technical similarity (U.S.-host) [H2]			−0.1688	0.0465	−0.2223			−0.1187	0.3914	0.1395
			(0.236)	(0.288)	(0.298)			(0.263)	(0.347)	(0.359)
technical similarity equal zero				0.3976	0.2271				0.7051**	0.5541*
				(0.295)	(0.295)				(0.301)	(0.302)
patents(host)* tech sim. [H3]					2.9872***					2.8822**
					(1.137)					(1.362)
Observations	12 969	12 969	12 969	12 969	12 969	12 969	12 969	12 969	12 969	12 969
Log likelihood	−2510.77	−2508.58	−2508.32	−2507.42	−2503.08	−1844.25	−1844.03	−1843.93	−1841.11	−1838.32
compare model		(1) vs (2)	(2) vs (3)	(3) vs (4)	(4) vs (5)		(6) vs (7)	(7) vs (8)	(8) vs (9)	(9) vs (10)
difference LogL		2.19	0.25	0.90	4.34		0.22	0.10	2.82	2.79
additional d.o.f.		1	1	1	1		1	1	1	1
chi-squared test		0.139	0.615	0.341	0.037**		0.640	0.750	0.093*	0.095*
compare model			(1) vs (3)	(1) vs (4)	(1) vs (5)			(6) vs (8)	(6) vs (9)	(6) vs (10)
difference LogL			2.44	3.35	7.69			0.32	3.14	5.93
additional d.o.f.			2	3	4			2	3	4
chi-squared test			0.295	0.341	0.104			0.852	0.371	0.204
Pseudo r-squared	0.277	0.277	0.278	0.278	0.279	0.240	0.240	0.240	0.241	0.242

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1% for two-tailed test

motives and assess their relative importance. For outward U.S. foreign direct investment, we find that (1) country-industries with large knowledge stocks of similar technical profiles are increasingly attractive, (2) firms from industries experiencing high versus low import competition view potential host country-industries differently, and (3) the use of greenfield investments for knowledge sourcing may be more limited than acquisitions. The results don't support 'sourcing technical diversity' or 'catching up' (except in industries experiencing low import competition), but are mainly consistent with an 'R&D springboard' explanation—that firms would reduce their fixed R&D costs by seeking out similar technical activity to combine with their own. For firms expanding abroad, our results highlight the importance of firms acquiring others to springboard their R&D activities when a country-industry has a larger amount of technical activity and when this activity is similar to U.S.-industry activity.

These results provide a more complete representation for how firms use international knowledge sourcing as a strategy. They highlight a previously unidentified motivation of firms boosting their ongoing R&D activities and suggest the greater importance of this R&D springboard motivation rather than for catching up or for sourcing technological diversity.

The results also highlight the two-way nature of knowledge sourcing: a firm going abroad to obtain knowledge from local technical activity simultaneously becomes a potential knowledge source for local competitors. Recognizing this potential hazard, some firms choose to locate where the local firms have no technical overlap. This result complements Shaver and Flyer (2000) and Alcácer and Chung (2007) who show that stronger firms may want to prevent helping weaker ones by avoiding their locations. Our results refine this argument by suggesting that the extent of technical overlap is another important determinant for whether firms avoid one another.

Our investigation of knowledge sourcing based upon attributes of potential host countries compliments other recent findings by Feinberg and Gupta (2004) who focus on the attributes of the U.S. multinationals themselves. Feinberg and Gupta examine likelihood of existing subsidiaries of U.S. multinationals beginning to conduct R&D abroad and find that more R&D activity in the country, especially by other multinationals, is likely to lead to multinationals seeking knowledge spillovers by assigning R&D responsibility to that location. Taken together, these studies—focusing on attributes of the choices (countries) and of the choosers (firms)—create an opening to further improve our understanding of knowledge sourcing strategy.

Several caveats for our results exist. While examining a multitude of country pairs—one of the countries in our pairs is always the United States. This context likely contributes to our results differing from the findings of Cantwell and Janne (1999). Cantwell and Janne find that firms from leading European countries source technical diversity (they tend to patent in different technology classes when abroad than they did at home), and that firms from lagging European locations catch up (these firms patent in the same classes abroad and at home). These differences are likely driven by our U.S. study context, which we see as a complement to prior research. That U.S. industries are less likely to need to catch up helps identify this additional motivation of firms using knowledge seeking as a springboard to reduce their fixed R&D costs. Another possibility for why we don't find evidence of catching up could be the nature of our dependent variable—the count of investments in each country-industry-year—which can be noisy. Two other caveats relate to our data. We use a country-industry-year level of analysis; technical similarity is U.S.-industry versus potential host country-industries. If better data were available, technical similarity could be made firm specific from the U.S. side; the technical profile of the individual investing firms might be introduced rather than the profile for the U.S.-industry-year. At the subsidiary level, being able to differentiate between subsidiaries' activities—whether they are manufacturing and/or R&D focused—would also be desirable. If such better data were available, we would be able to further assess the robustness of our results.

While further improvements exist, as far as we know, ours is the first study that looks widely across numerous countries to provide a richer sense of how firms use knowledge sourcing as a strategy. Theoretically, we broaden the set of motivations for using knowledge sourcing. Empirically, we show the relative importance of these motivations and also make use of entry mode and industry import competition to tease out additional

DOI: 10.1002/smj

heterogeneity. Further improvements should similarly broaden and deepen our understanding of this strategic behavior.

REFERENCES

Ahuja G, Katila R. 2001. Technological acquisitions and the innovation performance of acquiring firms: a longitudinal study. *Strategic Management Journal* **22**(3): 197–220.

Alcácer J, Chung W. 2007. Location strategies and knowledge spillovers. *Management Science* **53**(5): 760–776.

Cantwell J. 1989. *Technological Innovation and Multinational Corporations*. Basil Blackwell: Oxford, UK.

Cantwell J, Janne O. 1999. Technological globalisation and innovative centres: the role of corporate technological leadership and locational hierarchy. *Research Policy* **28**(2–3): 119–144.

Caves RE. 1996. *Multinational Enterprise and Economic Analysis*. Cambridge University Press: New York.

Eaton J, Kortum S. 1999. International technology diffusion: theory and measurement. *International Economic Review* **40**(3): 537–570.

Feinberg SE, Gupta AK. 2004. Knowledge spillovers and the assignment of R&D responsibilities to foreign subsidiaries. *Strategic Management Journal* August–September Special Issue **25**: 823–845.

Feenstra RC. 1996. U.S. imports, 1972–1994: data and concordances. NBER working paper 515. National Bureau of Economic Research: Cambridge, MA.

Feenstra RC. 1997. U.S. exports, 1972–1994: with state exports and other U.S. data. NBER working paper 5990, National Bureau of Economic Research: Cambridge, MA.

Furman J, Porter ME, Stern S. 2002. The determinants of national innovative capacity. *Research Policy* **31**(6): 899–933.

Ginarte JC, Park WC. 1997. Determinants of patent rights: a cross-national study.' *Research Policy* **26**(3): 283–301.

Greene W. 2002. The bias of the fixed effects estimator in nonlinear models. Department of Economics, Stern School of Business, New York University working paper. Available at http://pages.stern.nyu.edu/∼wgreene (1 November 2004).

Hall BH. 1993. Industrial research during the 1980s: did the rate of return fall? In *Brookings Papers on Economic Activity: Microeconomics*, Bailey MN, Reiss PC (eds). Brookings Institution Press: Washington, D.C.; 289–343.

Hall BH, Jaffe AB, Trajtenberg M. 2001. The NBER patent citations data file: lessons, insights and methodological tools. National Bureau of Economic Research working paper 8498. NBER: Cambridge, MA.

Hall RE, Jones CI. 1999. Why do some countries produce so much more output per worker than others? *Quarterly Journal of Economics* **114**(1): 83–116.

Henisz WJ, Macher JT. 2004. Firm- and country-level tradeoffs and contingencies in the evaluation of foreign investment: the semiconductor industry, 1994–2002. *Organization Science* **15**(5): 537–554.

Jaffe AB. 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. *The American Economic Review* **76**(5): 984–1001.

Kaiser U. 2002. Measuring knowledge spillovers in manufacturing and services: an empirical assessment of alternative approaches. *Research Policy* **31**(1): 125–144.

Kogut B, Chang SJ. 1991. Technological capabilities and Japanese foreign direct investment in the United States. *The Review of Economics and Statistics* **73**(3): 401–413.

Kogut B, Zander U. 1992. Knowledge of the firm, combinative capabilities and the replication of technology. *Organization Science* **3**: 383–397.

Kuemmerle W. 1999. Foreign direct investment in industrial research in the pharmaceutical and electronics industries—results from a survey of multinational firms. *Research Policy* **28**(3): 179–193.

Neven D, Siotis G. 1996. Technology sourcing and FDI in the EC: an empirical evaluation. *International Journal of Industrial Organization* **14**: 543–560.

Pisano G, Russo MV, Teece DJ. 1988. Joint ventures and collaborative arrangements in the telecommunications equipment industry. In *International Collaborative Ventures in U.S. Manufacturing*, Mowery DC (ed). Ballinger: Cambridge, MA; 183–222.

Sampson RC. 2004. The cost of misaligned governance in R&D alliances. *Journal of Law, Economics and Organization* **20**(2): 484–526.

Shaver JM, Flyer F. 2000. Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States. *Strategic Management Journal* **21**(12): 1175–1193.

Silverman BS. 1999. Technological resources and the direction of corporate diversification: toward an integration of the resource-based view and transaction cost economics. *Management Science* **45**(8): 1109–1124.

Song J, Almeida P, Wu G. 2003. Learning-by-hiring: when is mobility more likely to facilitate interfirm knowledge transfer? *Management Science* **49**(4): 351–365.

Wesson TJ. 1993. An alternative motivation for foreign direct investment. PhD diss. Harvard University, Cambridge, MA.

DOI: 10.1002/smj