DO FIRMS LEARN FROM INTERNATIONAL TRADE?

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Abstract—Using patent citations as a proxy for the influence of foreign technology on French firms' patents, this paper finds that the inventions of importers are significantly more likely to be influenced by foreign technology than are the inventions of firms that do not import. Furthermore, importers' citations increase relative to similar firms after they start importing. Exporting, in contrast, is not significantly associated with citations to foreign patents. These results persist after controlling for foreign ownership linkages and joint ventures and alliances, and after correcting for selection bias using propensity-score matching.

I. Introduction

DO firms gain information about foreign technology when they sell or buy in foreign markets? A publication of the Institute for International Economics suggests that "exports are a conduit for information—competitively valuable information about innovation, rivals, and regulation."[1] The empirical evidence on whether international trade is a conduit for the diffusion of technological knowledge, however, remains somewhat ambiguous. Previous efforts to answer this question have been limited by the difficulty of measuring knowledge flows. This paper measures knowledge diffusion more directly, using patent citations and a new and uniquely detailed firm-level trade data set. Listed in the patent application, citations refer to the precedents to the technology for which protection is sought. As Jaffe, Trajtenberg, and Henderson (1993) put it, "in principle, a citation of Patent X by Patent Y means that X represents a piece of previously existing knowledge upon which Y builds." This paper investigates how this measure of influence is related to exports and imports observed at the firm level. This fine level of detail permits a more specific focus on how knowledge about technological innovation is transmitted across borders. This paper finds that importing firms' patents are significantly more likely to be influenced by technology in the exporting country than are the patents of firms that do not import from that country. Firms that export do not cite significantly more patents from their destination countries. The estimated effect of importing on firms' citation patterns is robust to controls for the firms' foreign ownership linkages and joint ventures or alliances, as well as correction for selection bias.

Additional evidence from a survey of innovating firms sheds light on the specific activities associated with foreign technology acquisition. This paper argues that the findings based on patent citations stem in part from differences in the channels through which exporters and importers gain access to foreign technology, and the extent to which these channels are correlated with patent citations. More specifically, importers acquire and disseminate technology through collaborative research and development (R&D) and joint ventures with foreign firms, and these activities tend to be associated with citations to foreign patents as well as foreign citations to the firms' patents. Exporters gain access to foreign technology by analyzing foreign competitors' products and by communicating with foreign buyers, but knowledge diffusion through these channels is not well measured by patent citations.

II. Trade and Knowledge Diffusion

This paper draws on and contributes to three streams of literature: research on R&D spillovers at the aggregate level, studies of firm-level exports and productivity, and the literature on patent citations as a proxy for the diffusion of technological knowledge. Many of these papers are inspired by models of endogenous growth (for example, Romer, 1990; Grossman & Helpman, 1991) that emphasize the *nonrival* nature of technology that allows the benefits of technological progress to be shared. These models emphasize the potential for externalities to technological progress that benefit firms not directly involved in the development of the technology in question through *knowledge spillovers.* The effects of these externalities may be to increase productivity (as new, more efficient technologies are adopted) or the pace of technological progress (as inventors build on the achievements of other inventors). Econometric research on international R&D spillovers was spurred by Coe and Helpman (1995), who found large spillover effects from foreign R&D capital stocks to domestic total factor productivity (TFP). Interpretations of this finding grew more cautious after Keller (1998) obtained results similar to Coe and Helpman's after replacing actual trade weights with randomly chosen numbers. Keller (2001), extending the analysis of R&D-productivity spillovers at the industry level to include the influence of foreign direct investment (FDI), language barriers, and geographic distance, finds that trade patterns account for most of the differences in R&D spillovers across countries and industries. Eaton and Kortum (1996) find that, after controlling for geographic distance and other influences, bilateral imports do not help to predict international patent applications (which they interpret as a measure of technology flows). The focus of this prior literature is much broader than that of the analysis presented here, which of necessity is restricted to measuring the influence of patented inventions on each other.

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[1] Richardson and Rindal (1995, p. 20).

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The second literature to which this paper contributes is characterized by empirical research on international trade that examines how exporting firms differ from other firms in an industry.[2] Among the central findings of this literature are that exporters tend to be larger, be more productive, and supply higher-quality products than nonexporting firms. These findings have led researchers to ask whether firms export because they are more productive, or whether they learn something in the export market that confers a productivity advantage. Conducting a battery of tests on productivity and export data from Mexico, Colombia, and Morocco, Clerides, Lach, and Tybout (1998) find no evidence that exporting improves productivity, nor do Bernard and Jensen (1999) with respect to American manufacturing plants. In contrast, similar tests on data from Chinese (Kraay, 1997) and African (Bigsten et al., 1999) firms do find evidence that exporting causes productivity improvements. Hallward-Driemeier, Iarossi, and Sokoloff (2002) test the hypothesis that firms self-select to compete in export markets. After looking at firms' export status in the first year of their existence, they conclude that it is in aiming for export markets that firms make decisions about investment, training, technology, and other factors that enhance productivity.

The literature on FDI emphasizes three mechanisms for knowledge diffusion through FDI: demonstration effects, labor mobility, and linkages with buyers and suppliers.[3] Demonstration effects, which operate when firms observe and imitate the products or practices of foreign firms, seem likely to be affected by trade—for example, when foreign firms copy or modify aspects of exporters' products, or when the exporter's analysis of the foreign market yields information about foreign innovations. An example of this type of learning is the evolution of Fuji Film Co. during the 1970s and 1980s, when its market share in the United States expanded substantially due to technical improvements in its product that brought it in line with Kodak, the market leader. Another example is the case of Ellis Agricultural Equipment of Australia, which imports American-made harvesters and distributes them to Australian farmers. When Ellis noticed that the American harvesters lacked features that would make them more compatible with the unique Australian soil, they invented a new harvester based on the American version and applied for a patent to protect the invention.[4]

This paper presents evidence that labor mobility may be a channel for technology diffusion through trade. Appendix C shows that exporters tend to transfer new technology abroad through the departure of skilled workers.

Linkages with buyers and suppliers seem likely to be an important source of learning for exporters and importers. As an example of learning through communication with foreign suppliers and buyers, consider Usinor, a French manufacturer of steel products and the largest supplier of auto body components in Europe. Usinor emphasizes "close technical partnerships with customers," communicating with buyers' technical departments, tailoring products to buyers' specifications, and providing technical assistance. Usinor's U.S. Patent 6,398,286 is a reinforced lightweight automobile engine hood. It cites patents assigned to Mazda, Chrysler, Suzuki Motor, and DaimlerChrysler, as well as another metals producer (Alcoa) and a producer of coatings for auto bodies (Akzo).[5] These citations could reflect information obtained through communication with buyers about product specifications, or information obtained from suppliers in the process of incorporating intermediate goods (for example, a coating for the engine hood) in the product. Another example is the case of Fluid Management, a small Illinois manufacturer of paint-mixing equipment, which after entering international markets discovered a foreign supplier of "revolutionary" machinery now used in its production process.[6] Evidence of how firms learn by exporting is offered by Rhee, Ross-Larsen, and Pursell (1984), who found that almost half the Korean exporters they surveyed claimed to have directly benefited from technical information provided by foreign buyers, and that approximately 40% said that contacts with foreign buyers had improved their techniques of quality control and production.[7]

In the last decade, patent citations have increasingly come to be used as a way of tracking the influence of past inventions across time and geographic boundaries.[8] Jaffe and Trajtenberg (1999) find that patents whose inventors reside in the same country are typically 30% to 80% more likely to cite each other than inventors from other countries, and that these citations are made sooner than citations in other countries. Using citation data from the United States Patent and Trademark Office (USPTO), Branstetter (2004)[9] finds evidence that Japanese firms conducting FDI in the United States cite and are cited by American patents more

[2] See Tybout (2003).

[3] See Blomström and Kokko (1997) and Görg and Greenaway (2002) for reviews of the literature on knowledge diffusion and FDI.

[4] See http://www.ipaustralia.au, the Australian Patent Office Web site.

[5] The information reported here was obtained from Usinor's 2001 Annual Report and the European Patent Office Web site: http://www.european-patent-office.org.

[6] Richardson and Rindal (1995, p. 20).

[7] These benefits were created through visits both by foreign engineers to Korean plants, and by Korean engineers to the foreign buyers. The exchange of blueprints and specifications, and feedback on design, quality, and technical performance, were also cited as means by which Korean exporters benefited from their relationships with foreign buyers. In a related study, Pack and Westphal (1986) found a common pattern. Starting from technological capability used or acquired in previous production, a firm would reverse-engineer a new product. The firm would then agree to supply the product to a foreign buyer, but would be unable to supply the product according to the buyer's expectations without some form of technology transfer from the export buyer. With the collaboration of the firm's R&D staff, these transfers would cumulate over time, and the firm would begin to diversify and upgrade its product varieties.

[8] For a comprehensive discussion of the use of patent citations as a measure of international knowledge flows, see Keller (2003).

[9] Branstetter (2004) is an updated version of a paper that originally appeared in 2000.

often than similar firms, and that an additional U.S. subsidiary is associated with an increase of 1%–4% in U.S. citations. Almeida (1996) uses patent citations to analyze knowledge flows within multinational firms in the semiconductor industry. Frost (2001) uses USPTO citations to characterize the extent to which multinationals learn from foreign subsidiaries. Singh (2004) performs a multicountry analysis of multinationals' citation patterns, and finds evidence of cross-border knowledge flows within multinationals. Sjöholm (1996) finds that Swedish firms' citations of patents from a country are positively correlated with Sweden's aggregate trade with that country (unlike this paper, Sjöholm does not compare citations with firm-level trade data).

The focus of this paper is on the type of technological knowledge diffusion that can be measured with patent citations. Although patent citations are a rare source of insight into the influence of one invention on another, they are subject to certain limitations. Knowledge diffusion measured by patent citations is not synonymous with R&D spillovers. The latter term refers to the broader form of diffusion in which technological progress initiated by one organization can, due to its nonrival nature, benefit many others. Patents are only granted for inventions that are novel, and as a result, patent citations capture the contribution or similarity of other patented technologies to the invention—they do not capture technology transfer that does not culminate in new patented inventions. As a result, the normative implications of productivity-enhancing R&D spillovers can be quite different from those associated with the type of knowledge flows measured by patent citations, which, it could be argued, mainly benefit the firm holding the patent. Analysis based on patent citations assesses whether trading firms' inventions owe more to patented technologies from abroad than do the inventions of purely domestic firms, but it cannot assess whether exporters are more likely to, for example, reverse-engineer or exactly replicate a product or process common in an foreign market, or incorporate imported productivity-enhancing equipment in its production process. In this paper's analysis of citations, that type of noninventive activity will only be captured to the extent that it contributes to learning that results in a patent. Furthermore, the substantial number of novel inventions that are not patented but are protected through trade secrets and other informal mechanisms will also be excluded from this analysis. The results presented here should thus be considered a lower bound on the amount of knowledge diffusion taking place through trade.

Is there any economically significant benefit to firms whose patents make more citations to foreign patents? It is well established that patents *receiving* more forward citations are more valuable.[10] Harhoff et al. (1999) found that an additional U.S. citation was associated with an increase of $1 million in the value of a patent, and it stands to reason that patents reaching an international audience may have attained a higher threshold of value. Harhoff et al. also show that *backward* citations are positively and significantly related to patent value. One might conclude that firms citing more foreign patents show evidence of gaining access to more important or more valuable technological knowledge. However, little evidence currently exists on this point. At the aggregate level, Coe and Helpman (1995) and Keller (2001) identify significant productivity enhancements associated with international R&D spillovers (Keller's industry-level analysis of the G-7 countries plus Sweden shows that 20% of domestic productivity growth is explained by spillovers from foreign R&D investment). However, Peri (2004) finds no evidence that increased rates of interregional knowledge diffusion as measured by patent citations have a positive effect on invention. Peri argues that the negative effects associated with higher rates of patent citations—the realization of decreasing returns to innovation—offset whatever positive knowledge externalities may be at work. He also suggests that knowledge externalities may enhance productivity even if they do not encourage innovation.

III. Data

This paper uses a new data source compiled by researchers at INSEE and based on information collected by French customs during 1986–1992. The data cover all transactions in manufactured goods taking place between French and foreign firms in manufacturing, trade, and services. This data set facilitates analysis at a level of detail previously unavailable in studies of exporting and importing at the firm level, because it includes information on the origin or destination of the traded good, the total value in francs, and the type of good (by two-digit product class) exchanged by each importing or exporting firm.[11] Eaton, Kortum, and Kramarz (2004) provide more information on the features of this database.

The customs database is linked, by firm identification numbers, to a patent database that makes it possible to identify the individual European Patent Office documents associated with French firms' patents.[12] To this database one can add information on the citations made by the French firms' patents. The customs data is also linked to comprehensive balance-sheet and employment data and the firms' responses to a survey on innovation. The former is constructed from the mandatory reports of French firms to the fiscal administration. The data include total labor costs,

[10] Trajtenberg (1990); Harhoff et al. (1999); Hall, Jaffe, and Trajtenberg (2004).

[11] The industrial classification system used is the NAP (*nomenclature anuelle de production*).

[12] This database covers all European patents with at least one French inventor granted between 1987 and November 1994. It contains 27,924 observations and includes information on the firm's identification number, the applicant's name and country, the number of French coapplicants, the number of French inventors, the inventor's country, designated countries, the number and origin of any oppositions, the application date, the date of issue, and the date of first opposition, among other things.

TABLE 1.—SUMMARY STATISTICS

Statistic	Nonexporters Mean	Nonexporters Std. Dev.	Exporters Mean	Exporters Std. Dev.	Nonimporters Mean	Nonimporters Std. Dev.	Importers Mean	Importers Std. Dev.
Number of firms	1,116		1,641		1,269		1,487	
p_{it}	0.291	1.649	1.351	7.183	0.261	0.959	1.487	7.615
Backward citations	0.012	0.200	0.057	0.553	0.007	0.094	0.066	0.600
Forward citations	0.017	0.232	0.072	0.801	0.010	0.122	0.084	0.857
No. of export destinations	2.389	2.191	6.374	1.793	3.472	2.724	5.859	2.299
No. of import origins	2.850	2.208	5.309	2.161	2.631	1.995	5.752	1.905
No. of years exporting	1.134	1.635	6.227	1.456	2.676	2.838	5.430	2.360
No. of years importing	2.078	2.546	4.919	2.552	1.156	1.609	6.009	1.611
$Prox_{ist}$	0.103	0.312	0.198	0.399	0.106	0.312	0.205	0.406
Cites to France	0.045	0.374	0.237	1.543	0.039	0.296	0.262	1.628
$Soph_i$	0.065	0.479	0.309	2.040	0.055	0.401	0.075	0.966
Employment	250.7	1,695.0	867.6	4,151.5	173.3	666.5	997.4	4,544.2
Labor productivity†	6.396	1.155	6.613	0.870	6.421	1.070	6.614	0.929
Capital/labor ratio†	5.975	2.194	6.034	2.228	5.925	2.155	6.083	2.263
Average wage†	4.632	0.963	4.837	0.602	4.665	0.907	4.832	0.629

†In logs.
$Soph_i$ = Firm's proximity to the technological frontier (absorptive capacity) in year t. *Cites to France* = number of backward citations to French patents by firm i in year t. $Prox_{ist}$ = technological similarity between country s and firm i in year t. The unit of observation is a firm-country-year. "Nonexporters" may export to other countries or in other years.

sales, value added, total purchases, total assets, full-time employment, and the dates of firm creation and termination. Further information on these data sets and their construction can be found in appendix A.

After merging the customs data with the patent and balance-sheet data and retaining only manufacturers and firms for which information was available in every year of the sample period, 2,757 firms remained.[13] Firms that began or ended operations during the sample period are omitted from the sample. The unit of observation in the data set on which this paper is based consists of a firm-country-year combination. I focus on eight countries or regions (Germany, Benelux, Spain and Portugal, Italy, Japan, Switzerland, the United Kingdom and Ireland, and the United States) and seven years (1986–1992). Table 1 contains some summary statistics of this data set. For an average year and country, there are 1,641 exporters and 1,116 nonexporters, 1,487 importers and 1,269 nonimporters. Exporters are likely to be importers, and if a firm exports at all, it is likely to export to more than one market (the average number of export markets for a firm exporting to a given country in a given year is 6.37). Because attention has been restricted to patenting firms, the average size of the firms is large—on average nonimporters have 173.29 employees, and importers have 997.14. Firms that export or import are more productive, are more capital-intensive, and pay higher wages. They also patent more frequently and have more citations.

Another data source (described in more detail in appendix A) is an innovation survey in which firms were asked whether or not they acquired technology from abroad through a list of possible channels (analyzing foreign products, communicating with foreign buyers, and so on). They were also asked about their transfers of new technology to foreign firms. I combine these survey data with trade data for the 498 firms that are both in the patents database and covered by the innovation survey. The results offer insight into the differences in the types of technology diffusion associated with exports and imports, and help explain the results obtained with the citation data.

IV. Empirical Approach

The following sections ask whether firms that export or import cite more foreign patents than firms that do not engage in international trade, after controlling for other factors associated with citations. It also asks whether the patents of exporters and importers are cited more often by foreign patents. The key variables of interest in this study are:

1. b_{ist}, the number of *backward citations* made by firm i to country s in year t. A backward citation occurs when French firm i's patent cites a patent from country s.[14] Because backward citations refer to a patent's technological antecedents, the number of backward citations to foreign patents can be interpreted as an indicator of the influence of foreign technology on the patent in question. In this study, backward citations are used to measure how much exporters and importers learn about foreign technology through trade.
2. f_{ist}, the number of *forward citations* to firm i by country s in year t. A forward citation of firm i's patent occurs when the patent application of a firm from country s cites i's patent. In this paper, I use forward citations to measure of the extent to which a firm's patents influence the inventions of foreign firms. Forward citations have been shown to be correlated with

[13] Preliminary analysis of an unbalanced sample yielded results similar to the ones obtained from the balanced sample.

[14] Citations to or from foreign patents held by firm i are not included in either b_{ist} or f_{ist}.

patent value, and it will be important to take this into account when interpreting the analyses described in this paper.[15]

The data on the average number of foreign citations per patent listed in table 1 provides preliminary support for the hypothesis that exporters and importers cite more patents from the countries with which they trade. However, a number of other factors are likely to influence citation behavior, and in the following I describe these factors.

Consider a model in which innovative firm i learns about ideas from country s at rate λ_{ist} per year. b_{ist}, a proxy for the number of ideas from country s that influence firm i in year t, comes from a Poisson distribution with intensity λ_{ist}:

$$b_{ist}|\lambda_{ist} \sim \text{Poisson}(\lambda_{ist}).$$

Thus the rate of knowledge acquisition is $E(b_{ist}|\lambda_{ist}) = \lambda_{ist}$. Although I will use b_{ist} to refer to the dependent variable here, this description can also be applied to the model in which the dependent variable is f_{ist}. This rate depends on observable factors x_{ist} through the functional form $\exp(\beta' x_{ist})$. We might expect $\beta' x_{ist}$, the observable factors that affect learning, to depend on the following:

1. Firm i's exposure to ideas from country s. Because the focus of this study is on whether firms are exposed to foreign inventions through their activities in foreign markets, b_{ist} is expressed as a function of variables that indicate the firm's status as an exporter or importer. $Export_{ist}$ is a dummy variable equal to 1 if firm i exports to country s in year t, and $Import_{ist}$ is a dummy variable equal to 1 if firm i imports from country s in year t.
2. The relevance of the average technology in country s to firm i. One measure of relevance is the degree of technological similarity (*proximity*) between firm i's technology and country s's technology, denoted $Prox_{ist}$. If there is a lot of innovation in country s in a technical field in which firm i specializes, the firm is likely to learn more from that country's technology than from a country with little innovation in the area. Another factor affecting the relevance of innovation in country s is the average value or importance to firm i of patents from country s, $Value_{ist}$.
3. The firm's ability to assimilate or make use of ideas external to the firm. This *absorptive capacity* depends on the firm's research effort, proxied here by the number of ideas generated by the firm, p_{it}. To test the hypothesis that firms with more cutting-edge research efforts have higher absorptive capacity, learning is also modeled as a function of the average quality or sophistication of firm i's ideas, $Soph_i$,
4. The number of ideas produced by the firm, P_{it}, and the number of ideas in country s, P_{st}.[16]

Thus,

$$\begin{aligned}\beta' x_{ist} = {} & \beta_E Export_{ist} + \beta_M Import_{ist} + \beta_P Prox_{ist} \\ & + \beta_{So} Soph_i + \beta_V Value_{ist} + \beta_s P_{st} \\ & + \beta_i p_{it} + \beta_C C_{ist},\end{aligned}$$

where C_{ist} is a matrix of additional controls likely to affect citations, including the firm's citations to French patents; firm characteristics like employment, productivity, and wages; and country, industry, and year dummies.[17] The number of forward citations, f_{ist}, can be modeled in a symmetric fashion, by treating $Soph_i$ as a measure of the average value of firm i's patents and $Value_{ist}$ as a measure of the sophistication of the foreign research effort in country s. This specification closely resembles that of Branstetter (2004), which models the backward and forward citations of Japanese firms as a function of their investment in the United States.[18]

The rate of knowledge acquisition, λ_{ist}, depends on the observable variable $\exp(\beta' x_{ist})$ and on unobserved firm-specific factors. Following Hausman, Hall, and Griliches (1984), I summarize the unobserved factors by the firm-specific variable μ_i, and model λ_{ist} as drawn from a Gamma distribution where $E[\lambda_{ist}|\mu_i] = \exp(\beta' x_{ist} + \mu_i)$, so firms with higher unobserved μ_i have a higher expected rate of knowledge acquisition.

I use the random-effects model of Hausman et al. (1984) to handle the unobserved factor μ_i. The observed effects are assumed independent of x_{ist}, and $1/(1 + \mu_i)$ is modeled as a draw from a $\beta(r, s)$ distribution. By integrating over the unobserved μ_i, we obtain a joint density for the data in terms of β, r, and s. Here β summarizes the effect of the observed variables, and (r, s) describe the distribution of the unobserved factor among firms. A formula for the joint density appears in Hausman et al. (1984, p. 927). The tables contain estimates from the random-effects model alongside those from Hausman et al.'s fixed-effects estimator. In the fixed-effects model, the fixed effect is introduced by conditioning on the sum of the dependent variable (citations) in the conditional joint density for the i firm.[19]

[15] See, for example, Trajtenberg (1990), Harhoff et al. (1999), and Lanjouw and Schankerman (1999) for documentation of the relationship between forward citations and patent value.

[16] When f_{ist} is the dependent variable, as in table 3, P_{it} is the *cumulative* number of patents held by the firm.

[17] I have included the log of the firm's patents and the log of the country's patents as regressors, rather than treating them as the "exposure." I also include a dummy equal to 1 when the firm has zero patents. The latter approach constrains the coefficients on P_{st} and P_{it} to be 1, whereas the approach I adopt allows for the possibility that the relationship between citations and patents is not one-to-one. I also tried estimating the model with the potential number of citations, $P_{st}P_{it}$, constrained to be 1, and the results were substantially the same.

[18] Branstetter's main estimating equation regresses citations on the number of patents held by the firm, the firm's FDI in the United States, the firm's R&D spending and the log of its sales, and time dummies.

[19] The log likelihood function for the conditional fixed-effects negative binomial model is

It is important to control for technological similarities between the citing firm and the cited country, because a firm with a majority of its patents in chemicals, for example, would be more likely to cite and be cited by patents from countries with larger numbers of chemicals patents. The European Patent Office uses the International Patent Classification (IPC) system to describe the technological orientation of the patents it grants. This system consists of eight broad categories, and whenever a patent is granted, it is assigned to one or more categories based on the technology represented by the patent application.[20] Patents in the same IPC class can be considered closer in technology space than patents in different classes. The measure of technological proximity should allow for the fact that firms and countries have patents in a number of classes. Jaffe (1986) proposes a measure of technological proximity that measures the extent to which the distribution of patents across firms and countries overlaps. To control for technological similarities between firms and countries, I include $Prox_{ist}$, a version of Jaffe's technological proximity variable, as a control variable (see appendix A for the formula used to calculate this variable).[21]

The measure of the firm's technological sophistication used in the regressions presented here, $Soph_i$, consists of the average across patent classes of the ratio of the number of forward citations received by the firm's patents to the number of forward citations received by the average patent in the class. This variable can also be interpreted as an indicator of firm i's closeness to the technological frontier. Firms with more cutting-edge technology may be less likely to make citations to other firms, because they themselves are the technological leaders and are more likely to be cited by follower firms. A similar variable, $Value_{ist}$, controls for the importance or value of the foreign citing or cited industries' patents relative to France. It is calculated as the ratio of the average number of citations received by patents in country s to the average number of citations received by French patents in the same class, averaged over classes within the industry in which firm i lies. Appendix A contains a more detailed description of how $Prox_{ist}$, $Soph_i$, and $Value_{ist}$ were constructed. Other variables that are used to control for the firm's absorptive capacity include productivity, size, the average wage (as a proxy for labor quality) and capital intensity. Because these variables are included as controls, and their coefficients are not of independent interest, they have been omitted from tables 2 and 3 to conserve space. They will be made available upon request. The same is true of the coefficients on the country, year, and industry dummies that are also included as controls for overall differences in citations across countries and industries and over time.

Other controls include the number of citations made by the firm to French patents in year t and the number of citations to the firm's patents by other French patents. The former is included in regressions where the dependent variable is the firm's backward citations, to control for the possibility that exporting or importing firms simply cite more patents—both foreign and domestic. The latter variable, included when the dependent variable is the firm's forward citations, proxies for patent quality or importance. The number of forward citations received by a patent can be thought of as a measure of the patent's importance or value as well as a measure of the extent to which information was gleaned by other firms.

A. *Negative-Binomial Regressions*

Tables 2 and 3 list results from negative-binomial regressions on a balanced panel of all French firms with EPO patents for which data were available in every year between 1986 and 1992. In columns 1–3 of table 2, the number of the firm's citations to patents from country s in year t is modeled as a function of export and import dummies equal to 1 if the firm exported to (or imported from) country s in year t, the set of controls described above, and country and industry fixed effects. Column 1 shows that, whereas exporting to a country is not associated with a significant increase the number of citations made to that country's patents, importing from a country is associated with making approximately 43% more citations to that country's patents. As predicted, the coefficient on the firm's patent count is positive and significant at the 5% level, as are those associated with the importance of the firm's patents ($Soph_i$) and the technological proximity variable ($Prox_{ist}$). The finding that firms with more valuable or important patents cite more foreign patents can be interpreted as evidence that more technically advanced firms are better able to absorb innovation originating outside the firm. It is not just how *many* inventions a firm produces that matters (this is captured by

$$\ln L = \sum_{i=1}^{n}\left\{\ln \Gamma\left(\sum_{t=1}^{n_i}\lambda_{it}\right) + \ln \Gamma\left(\sum_{t=1}^{n_i} y_{it}+1\right) - \ln \Gamma\left(\sum_{t=1}^{n_i}\lambda_{it} + \sum_{t=1}^{n_i} y_{it}\right)\right\} + \sum_{t=1}^{n_i}\left\{\ln \Gamma\left(\sum_{t=1}^{n_i}\lambda_{it} + \sum_{t=1}^{n_i} y_{it}\right) - \ln \Gamma\left(\sum_{t=1}^{n_i}\lambda_{it}\right) - \ln \Gamma\left(\sum_{t=1}^{n_i} y_{it}+1\right)\right\},$$

where n_i is the number of observations per firm (the subscript s has been dropped for the sake of simplicity). Note that when $\Sigma_{t=1}^{n_i} y_{it} = 0$, the maximum likelihood procedure chooses a value for the fixed effect μ_i equal to $-\infty$ and drops all observations of firm i from the data. I deal with this problem by adding 0.01 to the dependent variable, so that its distribution is not materially affected, but the sum of the dependent variables is not 0. The results are very similar to those obtained when the observations are dropped.

[20] The eight main categories, labeled A through H, are: human necessities, performing operations/transporting, chemistry/metallurgy, textiles/paper, fixed constructions, mechanical engineering/lighting/heating/ etc, physics, and electricity. These categories are then divided into numbered subclasses.

[21] $Prox_{ist}$ is calculated using IPC classes at the *class-subclass* level (A01, B64, and the like).

TABLE 2.—BACKWARD-CITATION REGRESSIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$D(Exports_{ist})$	0.022	0.053	0.042	0.006			
	(0.052)	(0.057)	(0.051)	(0.060)			
$D(Imports_{ist})$	0.365***	0.357***	0.312***	0.264***			
	(0.062)	(0.068)	(0.060)	(0.069)			
$\ln(Exports_{ist})$					−0.012***	−0.009	−0.010
					(0.004)	(0.006)	(0.007)
$\ln(Imports_{ist})$					0.059***	0.056***	0.058***
					(0.008)	(0.012)	(0.013)
$D(Parent_{ist})$			0.223**	0.308***	0.335***	0.121	0.278*
			(0.099)	(0.103)	(0.103)	(0.154)	(0.158)
$D(Subsidiary_{ist})$						−0.019	−0.009
						(0.080)	(0.077)
$D(JV_{ist})$						0.051	−0.101
						(0.069)	(0.093)
$\ln(P_{st})$	−0.323	−0.012	−0.374***	−0.373***	−0.358***	−0.010	−0.048
	(0.199)	(0.220)	(0.004)	(0.004)	(0.004)	(0.553)	(0.523)
$\ln(p_{it})$	1.183***	1.174***	1.217***	1.274***	1.271***	1.156***	1.028***
	(0.030)	(0.034)	(0.031)	(0.052)	(0.053)	(0.055)	(0.106)
$Prox_{ist}$	0.764***	0.739***	0.809***	0.994***	0.910***	0.763***	0.907***
	(0.130)	(0.143)	(0.124)	(0.167)	(0.167)	(0.223)	(0.273)
$Cites\ to\ France_{it}$	−0.015***	−0.341***	−0.014	−0.008	−0.008	−0.007*	−0.003
	(0.004)	(0.004)	(0.188)	(0.192)	(0.191)	(0.005)	(0.008)
$Value_{ist}$	0.157***	0.161***	0.155***	0.155***	0.133***	0.112***	0.098**
	(0.019)	(0.021)	(0.019)	(0.025)	(0.025)	(0.037)	(0.045)
$Soph_i$	0.302***	0.270***	0.249***			0.007	
	(0.076)	(0.085)	(0.078)			(0.143)	
Constant	0.286	0.370	16.322	17.074	18.338	0.137	20.763***
	(1.820)	(2.008)	(12.196)	(15.983)	(37.226)	(5.242)	(6.554)
Observations	149,472	125,376	127,656	127,656	127,656	12,208	12,208
Log likelihood	−9,958.04	−8,044.33	−9,611.902	−7,276.170	−7,254.352	−2,446.539	−2,434.221

Dependent variable = number of citations to patents from country s by firm i in year t. (1) Random effects (RE), full sample. (2) RE, firms with foreign parents and subsidiaries dropped (does not include minority stakes for firms with employment <500). (3) RE, all firms. (4) Fixed effects (FE), all firms. (5) FE, all firms. (6) RE, firms with employment <500 dropped and years <1990 not included (restricted sample—parent and subsidiary variables include minority stakes for all firms). (7) FE, restricted sample. Notes: Standard errors in parentheses. *, **, ***: significantly different from 0 at the 10%, 5%, 1% level. $D(Export)$ = 1 if firm i exports to country s in year t. $D(Import)$ = 1 if firm i exports to country s in year t. $D(Parent)$ = 1 if the firm has a parent in country s in year t. $D(Subsidiary)$ = 1 if the firm has a subsidiary in country s in year t. $D(JV)$ = 1 if the firm has a joint venture or alliance in country s in year t. p_{it} = firm's patents in year t. P_{st} = country's patents in year t. $Value_{ist}$ = foreign industry's proximity to the technological frontier (value of foreign patents) in year t. Controls for the firms' employment, capital intensity, average wage, labor and productivity, as well as country, industry (except in FE model), and year dummies, are included.

the firm's patent count), but also the *importance* of the firm's patents.

Firms that export and import are likely to be also involved in FDI. Other work has established a link between FDI and foreign patent citations (see Branstetter, 2004). Does the estimated effect associated with importing apply only to firms with foreign parents or subsidiaries? In the results reported in columns 3 through 7, information on foreign ownership linkages has been included. Data on foreign parents and subsidiaries comes from the LIFI (a financial linkages data set), which contains information on the ownership of all public and private French firms majority-owned by a foreign firm, and all French firms that hold controlling interests of more than 8 million francs. The LIFI also contains information on smaller (below 50%) stakes for all French firms that have sales of at least 400 million francs or employment of at least 500 people.[22] In column 2, firms classified by the LIFI as having foreign parents or affiliates have been dropped from the sample, which results in a slight decline in the coefficient on $D(Import)$. In columns 3 (a random-effects specification) and 4 (a fixed-effects specification), a dummy variable is included that equals 1 if the firm has a foreign parent, and the coefficient on this variable is positive and significant at the 5% level, implying that firms with foreign parents make approximately 25%–36% more citations to foreign patents. However, the import coefficient remains positive and significant at the 1% level. Similar results are found in columns 5 through 7, which include the log of imports and exports on the right-hand side to obtain estimates of the elasticity of citations with respect to imports. A 10% increase in imports is associated with a roughly 0.6% increase in citations per patent.

The specifications in columns 6 and 7 introduce the foreign subsidiary dummy[23] $D(Subsidiary_{ist})$ and a dummy, $D(JV_{ist})$, that indicates whether the firm has joint ventures or alliances in country s in year t. The latter variable comes from the Securities Data Company (SDC) database. For more information on this data, see Anand and Khanna (2000). The authors note that the information on joint ventures in this database is not reliable before 1990; therefore, the specifications that incorporate $D(JV_{ist})$ are esti-

[22] Ownership data are not available for 1988, and that year is dropped from the sample in the regressions incorporating foreign ownership. See appendix A for more information on the data set used to create the foreign-parent and -subsidiary variables.

[23] Note that $D(Subsidiary)$ equals 1 even when the firm owns less than 50% of the foreign affiliate.

TABLE 3.—FORWARD-CITATION REGRESSIONS

	(1)	(2)	(3)	(4)	(5)	(6)
$D(Exports_{ist})$	0.134**	0.124**	0.180*		0.237**	
	(0.054)	(0.057)	(0.100)		(0.106)	
$D(Imports_{ist})$	0.445***	0.464***	0.388***		0.224*	
	(0.061)	(0.065)	(0.146)		(0.130)	
$\ln(Exports_{ist})$				0.001		0.003
				(0.006)		(0.007)
$\ln(Imports_{ist})$				0.037***		0.045***
				(0.012)		(0.012)
$D(JV_{ist})$			−0.012	−0.011	0.106	0.087
			(0.080)	(0.080)	(0.083)	(0.088)
$D(Parent_{ist})$			0.223	0.221	0.170	0.137
			(0.138)	(0.138)	(0.152)	(0.149)
$D(Subsidiary_{ist})$			0.216***	0.196**	0.261***	0.202***
			(0.088)	(0.089)	(0.089)	(0.099)
$\ln(P_{st})$	0.508**	0.354	−0.079	−0.058	−0.072	−0.030
	(0.202)	(0.216)	(0.533)	(0.532)	(0.507)	(0.516)
$\ln(p_{it})$	0.417***	0.545***	0.702***	0.704***	−0.018	−0.153**
	(0.033)	(0.037)	(0.054)	(0.054)	(0.080)	(0.067)
$Prox_{ist}$	0.660***	0.801***	0.938***	0.883***	0.801***	0.828***
	(0.148)	(0.161)	(0.226)	(0.229)	(0.255)	(0.260)
Cites from France$_{it}$	−0.008**	−0.013***	0.004	0.003	0.011	0.006
	(0.003)	(0.004)	(0.005)	(0.005)	(0.007)	(0.006)
$Value_{ist}$	0.235***	0.214***	0.240***	0.231***	0.316***	0.306***
	(0.020)	(0.020)	(0.031)	(0.031)	(0.038)	(0.041)
$Soph_i$	1.188***	1.248***	0.956***	0.949***		
	(0.089)	(0.085)	(0.176)	(0.178)		
Constant	−9.079***	−8.212***	−3.610	−3.348	6.450	6.654
	(1.847)	(1.973)	(5.079)	(5.054)	(5.394)	(5.393)
Observations	149,472	125,376	12,208	12,208	12,208	12,208
Log likelihood	−11,009.003	−10,716.863	−3,442.099	−3,441.205	−2,922.619	−2,918.937

Dependent variable = number of citations by patents from country *s* to firm *i* in year *t*. (1) Random effects (RE), full sample. (2) RE, firms with foreign parents and subsidiaries dropped (does not include minority stakes for firms with employment <500). (3) RE, firms with employment <500 dropped and years <1990 not included (restricted sample—parent and subsidiary variables include minority stakes for all firms). (4) RE, restricted sample. (5) Fixed effects (FE), restricted sample. (6) FE, restricted sample.

Notes: Standard errors in parentheses. *, **, ***: significantly different from zero at the 10%, 5%, 1% level. *D*(*Export*) = 1 if firm *i* exports to country *s* in year *t*. *D*(*Import*) = 1 if firm *i* exports to country *s* in year *t*. *D*(*Parent*) = 1 if the firm has a parent in country *s* in year *t*. *D*(*Subsidiary*) = 1 if the firm has a subsidiary in country *s* in year *t*. *D*(*JV*) = 1 if the firm has a joint venture or alliance in country *s* in year *t*. $Value_{st}$ = foreign industry's proximity to the technological frontier (value of foreign patents) in year *t*. *Cites from France* = number of forward citations by French patents to firm *i* in year *t*. Controls for the firms' employment, capital intensity, average wage, labor, and productivity, as well as country, industry (except in FE model), and year dummies, were included.

mated on a restricted data set that omits years before 1990. Because complete foreign holdings data (that is, including minority stakes) are only available for firms with more than 500 employees, the data set is also censored by firm size. This explains the large reduction in sample size in columns 6 and 7. The results in these columns continue to demonstrate a robust positive relationship between imports and citations of foreign patents. After controlling for imports, exports, and foreign ownership linkages including foreign parents or affiliates in which the stake is below 50%, however, there does not seem to be an independent relationship between foreign joint ventures or alliances and backward citations.[24] This corroborates the finding of Branstetter (2004), who shows that technology alliances are insignificantly correlated with backward citations after controlling for FDI.[25]

In table 3, the dependent variable is forward citations to firm *i* by country *s* in year *t*. Whereas the export coefficients in table 2 can be thought of as measuring learning by exporting among French firms, the import coefficients in table 3 measure the relationship between a firm's imports and its influence on foreign patents, and the coefficient on $Export_{ist}$ in table 3 tells us how much foreign inventors are influenced by French exporters. There is an important caveat to be mentioned here, that forward citations are also indicators of a patent's value or importance. As a result, the estimates may be biased by a correlation between the value of the firm's patents and its propensity to engage in international trade. The number of forward citations received from domestic patents is included in an attempt to control for this bias.

The results displayed in the first column of table 3 suggest that foreign inventors learn about French firms' patents when those firms export, but also when they import. In the random-effects specification in column 1, exporters are found to be cited 14% more often by foreign patents, and importers 57% more often. When the model controls for foreign ownership linkages and joint ventures and alliances in column 3, the coefficient on *D*(*Imports*) falls to 0.39 (suggesting that imports were partly picking up the effect of foreign subsidiaries in columns 1 and 2), and the coefficient on *D*(*Exports*) rises to 0.18. Other coefficients are as expected, with both $Value_{ist}$ and $Soph_i$ implying that foreign

[24] The measure of joint ventures and alliances includes all types of ventures and alliances included in SDC. I also tried restricting this variable to include only R&D collaboration or technology alliances, but the results did not change in a meaningful way.

[25] Branstetter (2004, p. 39).

industries closer to the technological frontier make more citations to French firms' patents, and that firms with higher-quality patents are cited more often by foreign firms. In the fixed-effects specification presented in column 5, which controls for foreign ownership and joint ventures, the coefficient on *D*(*Imports*) falls further to 0.22, which is significant only at the 10% level, while the coefficient on *D*(*Exports*) increases to a statistically significant (at the 5% level) 0.24. However, in the fixed-effects regression of forward citations on the log of exports in column 6, the coefficient on ln(*Exports*) is insignificantly different from 0, but the coefficient on the log of imports is significant. Thus, it seems that whereas the *act* of exporting is significantly associated with forward citations, increases in the *volume* of exports are not associated with more citations. It is interesting to note that, just as table 2 presents evidence that French firms learn significantly more about foreign technology when they have foreign parents, table 3 shows that French firms disseminate more knowledge when they have foreign subsidiaries.

A potential explanation for the magnitude of the import coefficient in the forward-citation regressions comes from the innovation survey. It shows that importers transfer new technology abroad through joint ventures and alliances. This is one of the types of knowledge transfer most closely associated with forward citations. In our analysis of the relationship between citations and technology flows as measured by the innovation survey, Duguet and MacGarvie (2005) show that outward technology flows through equipment sales, mergers, and joint ventures and alliances are significantly associated with forward citations. Backward citations are correlated with acquisitions of new technology through R&D collaboration, patents and licenses, and mergers. Appendix C demonstrates that imports (but not exports) are associated with technology acquisition through all of the latter three mechanisms, and they are associated with outward transfers to foreign firms through joint ventures and alliances. Clearly, importers both acquire *and transfer* technology as a result of their engagement in joint ventures and collaboration with foreign firms. This could explain why importers are cited by foreign patents more often than nonimporters. And indeed, once joint ventures and alliances are controlled for in the fixed-effects specification in column 5, the import coefficient becomes insignificant at conventional levels. However, the significance of the log of imports (and insignificance of the log of exports) in column 6 remains a puzzle that does not seem to be explained by the relationship between joint ventures and imports.

Appendix C also shows that exporting is associated with types of knowledge diffusion not well captured by patent citations. For example, exporters are significantly more likely to gain access to foreign innovation by analyzing the products of foreign competitors or by communicating with foreign buyers. Thus, though table 2 shows that exporting is not significantly associated with knowledge flows of the type that culminate in patent citations, Appendix C provides evidence for other forms of learning by exporting.

Whereas U.S. patent law states that inventors who are aware of the existence of prior art but do not cite it may see their patents declared invalid or be charged with fraud, European patent law does not have an equivalent provision. To assuage any resulting concern that EPO citations do not measure knowledge flows as well as USPTO citations, I test whether the results obtained using EPO citations as the dependent variable are also obtained when USPTO citations are the dependent variable. The French firms' EPO patents were matched to their equivalents in the USPTO, and the number of USPTO citations to foreign patents was calculated.[26] Appendix B contains results of an analysis of USPTO citations that replicates the regressions described above, and the findings with respect to the trade variables are quite similar to those obtained with EPO citation data.

B. *Propensity-Score Matching and Differences in Differences*

The preceding section established that there is a positive and statistically significant relationship between firms' citations of foreign patents and their activities in international markets. It is possible, however, that this relationship is characterized by selection bias. Innovative firms with the ability to absorb and make use of technology from sources outside the firm are likely to select into exporting and importing because their profits from doing so are higher than those of firms without those capabilities. Furthermore, firms may enter markets *because* of an invention similar to foreign inventions that allows them to compete abroad. It may be the case that citations increase *before* trade begins because the firm has invented a new product that is similar to products in demand in country *s,* where much of the production of similar goods and the intermediate products that go into them is located. An invention that cites or is cited by a country's patents may the factor that causes firms to begin trading with that country. Because one does not necessarily know the correct functional form that will eliminate selection bias in the relationship between trade and citations, this section uses matching methods, which provide an alternative functional form and a robustness check. Angrist (1998) shows that regression and matching both estimate a weighted average effect, but use different weights. In the case studied by Angrist, regression estimates exceeded matching estimates by 25%.[27]

[26] I was able to match equivalents for 1,042 firms. Information on equivalents can be found at http://ep.espacenet.com.

[27] Whereas matching weights observations on the probability of observing treatment at that value of the covariates, regression weights observations by the *variance* of treatment at that value of the covariates. As a

This section compares exporters with nonexporters and importers with nonimporters that are as similar as possible and examines the differences in their citation patterns. In this approach, a *treatment* group is matched to *controls*. Matching methods seek to replicate a randomized experiment in which the matched treated and control observations do not differ systematically from each other. In this paper, exporting (importing) and nonexporting (nonimporting) firms are matched on an index (the propensity score) of the characteristics most relevant to the decision to seek treatment. The propensity score, or the estimated probability of exporting or importing, is calculated from the fitted values of a probit model of the firm's decision to export to (import from) country *s* as a function of size, productivity, patents, wages, dummies, sector-specific foreign demand shocks, exchange rates, and so on.[28] After matching market entrants with the nonentrants that have the closest probability of exporting, I report in table 4 the observed difference in citations to patents from country *s* between the firm that trades and the firm that does not, conditional on the two firms' having the same predicted probability of trading with country *s*. Table 4 also contains estimates of the difference in differences of the treatment and control groups. These estimates allow us to determine whether firms that begin trading with foreign countries see an increase in citations following the initiation of trade, relative to similar firms that do not begin trading. The difference-in-differences estimates are calculated for pairs of trading and nontrading firms matched on the propensity score, and as a result constitute a strict test of the effect of trade on foreign citations.

The firm characteristics used for matching include firm productivity, employment, capital intensity, wages, and the number of the firm's patents. In accordance with previous research on the determinants of the firm's export decision, I expect firms that are more productive, larger, or more capital-intensive or that pay higher wages to be more likely to export. Less research has been done on the determinants of firm-level imports (and in this sense the results found in table 5 are one of the contributions of the paper), though Biscourp and Kramarz (2002) find that importers are more capital-intensive and have lower employment. Several papers have shown that exporters tend to be more innovative than nonexporters (for example, Shaver and Salomon, 2001), and so I use the number of patents as an explanatory variable for the export or import decision. Country-specific variables include real GDP per capita, population, and the importance of the foreign industry's patents. I expect real income per capita and population be positively correlated with demand for exports and supply of imports, and so I expect these variables to be positively associated with both $Export_{ist}$ and $Import_{ist}$. Variables specific to the firm-country relationship include a dummy variable equal to 1 if the firm's headquarters are located in a *département* that borders country *s*, the distance of the foreign country's capital from Paris (both $Border_{is}$ and $Distance_{is}$ are proxies for trade costs), and the real exchange rate.

Two separate probit models are used to estimate the firms' propensity to trade: (1) Pr($Export_{ist}$ = 1), and (2) Pr($Import_{ist}$ = 1). Table 5 lists parameter estimates from these models in which the dependent variable equals 1 when the firm exports (in column I) or imports (in column II), and 0 when it does not. Statistically significant coefficients of

TABLE 4.—PROBIT MODELS USED TO CALCULATE PROPENSITY SCORES

Dependent Variable	I Export	II Import
$Import_{ist}$	0.666***	
	(0.009)	
$Export_{ist}$		0.670***
		(0.009)
P_{it}†	0.149***	0.118***
	(0.011)	(0.010)
Cites to France	−0.025***	0.015
	(0.005)	(0.009)
$Soph_{it}$	0.014	0.068***
	(0.011)	(0.010)
$Value_{st}$	0.050***	0.097***
	(0.005)	(0.005)
Employment†	0.303***	0.360***
	(0.003)	(0.003)
Capital intensity†	0.027***	0.041***
	(0.002)	(0.002)
Average wage†	−0.026***	−0.118***
	(0.006)	(0.007)
Productivity†	0.119***	0.094***
	(0.006)	(0.006)
RGDP per capita†	1.259***	−0.009
	(0.158)	(0.159)
Population†	0.570***	0.056
	(0.112)	(0.117)
Distance†	−0.543***	−0.579***
	(0.025)	(0.027)
RXR†	0.592***	0.453***
	(0.084)	(0.084)
$Border_{is}$	0.473***	0.503***
	(0.032)	(0.029)
Constant	−22.053***	−1.456
	(2.229)	(2.265)
Observations	154,392	154,392
Log likelihood	−71,664	−72,403
Pseudo-R^2	0.2879	0.2984

Standard errors in parentheses. *, **, ***: significantly different from 0 at the 10%, 5%, 1% level.
†In logs.
Robust standard errors correct for heteroskedasticity. Country, industry, and year fixed effects included. *Export* = 1 if firm *i* exports to country *s* in year *t*. *Import* = 1 if firm *i* exports to country *s* in year *t*. P_{it} = firm's patents in year *t*. $Soph_{it}$ = Firm's proximity to the technological frontier (absorptive capacity) in year *t*. $Value_{st}$ = Foreign industry's proximity to the technological frontier (value of foreign patents) in year *t*. *Cites to France* = number of backward citations to French patents by firm *i* in year *t*. *Prox* = technological similarity between country *s* and firm *i* in year *t*. *RXR* = real exchange rate in country *s* in year *t*.

result, regression can overstate the effect of a treatment by disproportionately weighting individuals or firms most likely to benefit from it.

[28] Roberts and Tybout (1994) find that plant size, plant age, and the structure of ownership are related to the propensity to export. Aitken, Hanson, and Harrison (1995) find that plant size, wages, and foreign ownership are determinants of export participation. Bernard and Jensen (1999) find almost no role for geographic spillovers, externalities from market participation by other firms, or state government export promotion. They confirm prior findings that exporters tend to pay their workers more. They find that the major issue in estimating their model of the decision to export is unobserved heterogeneity across firms.

TABLE 5.—DIFFERENCES BETWEEN TRADING AND NONTRADING FIRMS MATCHED ON THE PROPENSITY SCORE

	Obs.	Backward Citations	Forward Citations
Matched on Pr(*Import*)			
Importers versus nonimporters	70,397	0.013*** (0.001)	0.028*** (0.002)
({*Import* = 1} − {*Import* = 0} *Export* = 1)	55,083	0.012*** (0.001)	0.022*** (0.003)
({*Import* = 1} − {*Import* = 0} *Export* = 0)	15,314	0.017*** (0.002)	0.030*** (0.003)
({*Import* = 1} − {*Import* = 0} *Export* = 0), restricted sample	1,068	0.095*** (0.023)	0.167*** (0.053)
({*Import* = 1} − {*Import* = 0} *Export* = 0), restricted sample, no foreign parent, subsidiary, or joint venture	968	0.084*** (0.025)	0.159*** (0.058)
Difference in differences	3,002	0.027*** (0.006)	0.033*** (0.006)
Matched on Pr(*Export*)			
Exporters versus nonexporters	80,253	0.006*** (0.002)	0.018*** (0.002)
({Export = 1} − {Export = 0} Import = 1)	57,102	0.008*** (0.003)	0.024*** (0.003)
({Export = 1} − {Export = 0} Import = 0)	23,151	0.000 (0.001)	0.001 (0.001)
({Export = 1} − {Export = 0} Import = 0), restricted sample	838	−0.010 (0.006)	0.018* (0.011)
({Export = 1} − {Export = 0} Import = 0), restricted sample, no foreign parent or subsidiary or joint venture	799	−0.009 (0.006)	0.023** (0.011)
Difference in differences	3,203	0.017 (0.014)	0.007 (0.008)

0.666 on *Import* in the column I and 0.670 on *Export* in II reveal a strong correlation between exporting and importing. Firms with more patents, higher productivity, a higher capital-labor ratio, and a larger workforce are more likely to export and import. In contrast to the findings of previous studies, the coefficient on the firm's average wage is negative in the export regression. As expected, the country's distance from France and real exchange rate (*RXR*) enter negatively. The coefficient on GDP per capita is positive and significant in column I and negative and significant in column II. The coefficient on $Border_{ist}$ is equal to 0.473 in I and 0.503 in II, implying that firms located near a border are more likely to engage in trade with the neighboring country.

Using the probabilities of exporting and importing predicted by the probit models, the trading (or "treated") firms were then matched to the nontrading firm with the closest propensity score.[29] Table 4 reports estimates of the differences in citations between trading and nontrading firms matched on the propensity score. On average, importers cite 0.013 more patents (with a standard error of 0.001) from their import markets than do nonimporters with the nearest probability of exporting. Firms that import *and* export actually make fewer citations to foreign patents than do firms that do not import, whereas firms that only import make 0.017 (with a standard error of 0.002) more citations than nonimporters matched on the propensity to import. Firms in the restricted sample (with more than 500 employees) that import and do not have ownership links (including minority stakes) with foreign affiliates also make 0.084 (with a standard error of 0.025) more citations than similar nonimporters. Firms that export make 0.006 more citations than nonexporters matched on the propensity score. However, when one excludes exporters that also import, there is no statistically significant difference in backward citations between exporters and matched nonexporters.

The mean differences in forward citations of firms matched on the propensity score reveal that, again, firms that import exhibit more citations than similar nonimporters. Importers that also export are not cited significantly more often abroad. The difference in citations between exporters and nonexporters matched on the propensity score is statistically significant only among those exporters that also import and in the estimates based on firms in the restricted sample with no foreign ventures or ownership linkages.

To control for unobserved but time-invariant firm-specific characteristics, table 4 also reports estimates of the difference in differences between exporters (importers) and nonexporters (nonimporters). A firm that enters the export or import market is compared with the firm with the closest propensity score that did not enter the market. The results show again that the effect of exporting on backward citations is not significantly different from 0, whereas entering an import market does have a significant positive effect on backward citations *and* forward citations. Firms that began importing from a country in 1988, 1989, or 1990 and continued until the end of the sample period saw an increase of 0.027 citations to patents from that country after they began importing, relative to nonimporting firms over the same period. Though this number may seem small, it should be noted that the average change in citations made by the nonimporting firms during this period was 0.019, so this represents an increase in citations of 42% relative to nonimporters. Estimates of the difference in differences

[29] This nearest-neighbor matching was performed using an algorithm written by Barbara Sianesi. More information on this algorithm is available at http://ideas.uqam.ca/ideas/data/Softwares/bocbocodes418602.html. I also estimated the differences between treated and untreated firms matched on the propensity score using Angrist's methodology (which was used to compare export and import entrants matched on preentry citations), and the results obtained from this methodology did not yield different conclusions.

for forward citations are also positive and statistically significant for importers, but not for exporters. Thus, firms that start importing cite more foreign patents, and firms that start exporting are not cited more often abroad.

Thus, importing appears to have a significant causal effect on both backward and forward citations. There is no evidence of a causal effect of exporting on technological knowledge diffusion as measured by patent citations. Thus, though a policy designed to encourage firms to export in order to learn about foreign technology would be likely to fail, a policy encouraging firms to import seems likely to increase international knowledge flows both to and from domestic firms. Because the inventions engendered by these knowledge flows are protected by patents, the increment to social welfare associated with an increase in patent citations is likely to be more circumscribed than that usually associated with the type of R&D and productivity spillovers discussed by Coe and Helpman (1995) and others. However, if it is the case that patent citations are the "tip of the iceberg," and that trade is actually associated with many more types of knowledge diffusion than are measured by citations (as suggested by the innovation survey), the latter conclusion may be too conservative.

V. Conclusion

This paper finds that, after controlling for factors that affect citation behavior, the inventions of importers are more likely to be influenced by foreign patents than those of similar nonimporters. Exporters' patents are cited abroad more often than those of nonexporters, and foreign inventors cite patents held by French importers more often than patents held by nonimporters. The results suggest that firms with more important or more valuable patents make more citations to foreign patents and are cited more often abroad, highlighting the role of the firm's existing knowledge base in learning about foreign technology. The estimated effect of importing is robust to correction for selection bias using propensity-score matching. Furthermore, though firms do not see an increase in citations relative to similar firms after entering export markets, they do cite more foreign patents after beginning to import.

REFERENCES

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

Anand, B., and T. Khanna, "The Structure of Licensing Contracts," *Journal of Industrial Economics* 48:1 (2000), 103–135.

Angrist, J., "Estimating the Labor Market Impact of Voluntary Military Service Using Social Security Data on Military Applicants," *Econometrica* 66 (1998), 249–288.

Bernard, A., and J.B. Jensen, "Exceptional Exporter Performance: Cause, Effect, or Both?" *Journal of International Economics* 47 (1999), 1–25.

Biscourp, P., and F. Kramarz, "The Impact of Imports on the Firm's Production Process: A Firm-level Analysis for France," CREST mimeograph (2002).

Blomström, Magnus, and Ari Kokko, "How Foreign Investment Affects Host Countries," World Bank International Economics Dept., International Trade Division, Washington (1997).

Branstetter, L., "Is Foreign Direct Investment a Channel of Knowledge Spillovers? Evidence from Japan's FDI in the United States," NBER working paper no. W8015 (2004).

Coe, D., and E. Helpman, "International R&D Spillovers," *European Economic Review* 39:5 (1995), 859–887.

Duguet, E., and M. MacGarvie, "How Well Do Patent Citations Measure Flows of Technology?" *Economics of Innovation and New Technology,* vol. 14:5 (2005).

Eaton, J., and S. Kortum, "Trade in Ideas: Patenting and Productivity in the OECD," *Journal of International Economics* 40:3/4 (1996), 251–278.

Eaton, J., S. Kortum, and F. Kramarz, "Dissecting Trade: Firms, Industries, and Export Destinations," *American Economic Review Papers and Proceedings* 93 (2004).

Frost, T., "The Geographic Sources of Foreign Subsidiaries' Innovations," *Strategic Management Journal* 21:2 (2001), 101–123.

Görg, H., and D. Greenaway, "Much Ado about Nothing? Do Domestic Firms Really Benefit from Foreign Direct Investment?" CEPR discussion paper no. DP3485 (2002).

Grossman, G., and E. Helpman, "Quality Ladders in the Theory of Growth," *Quarterly Journal of Economics* 106 (1991), 557–586.

Hall, B., A. Jaffe, and M. Trajtenberg, "Market Value and Patent Citations: A First Look," NBER working paper no. W7741 (2000).

Hallward-Driemeier, M., G. Iarossi, and K. L. Sokoloff, "Exports and Manufacturing Productivity in East Asia: A Comparative Analysis Using Firm-level Data," NBER working paper no. w8894 (2002).

Harhoff, D., F. Narin, F. M. Scherer, and K. Vopel, "Citation Frequency and the Value of Patented Innovations," this REVIEW, 81 (1999), 511–515.

Hausman, J., B. Hall, and Z. Griliches, "Econometric Models for Count Data with an Application to the Patents-R&D Relationship," *Econometrica* 52:4 (1984), 909–938.

Jaffe, A., "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value," *American Economic Review* 76:5 (1986), 984–1001.

Jaffe, A., and M. Trajtenberg, "International Knowledge Flows: Evidence from Patent Citations," *Economics of Innovation and New Technology* 8 (1999), 105–136.

Jaffe, A., M. Trajtenberg, and R. Henderson, "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations," *The Quarterly Journal of Economics* 108:3 (1993), 577–598.

Keller, W., "Are International R&D Spillovers Trade-Related? Analyzing Spillovers among Randomly Matched Trade Partners," *European Economic Review* 42 (1998), 1469–1481.

——— "Trade and the Transmission of Technology," *Journal of Economic Growth* 7 (2001), 5–24.

——— "The Geography and Channels of Diffusion at the World's Technology Frontier," NBER working paper no. W8150 (2003).

Peri, G., "Determinants of Knowledge Flows and Their Effect on Innovation," working paper (2004).

Rhee, Yung Whee, Bruce Ross-Larsen, and Gary Pursell, *Korea's Competitive Edge: Managing the Entry into World Markets* (Baltimore: The Johns Hopkins University Press, 1984).

Richardson, D., and Rindal, K., "Why Exports Really Matter!" Institute for International Economics (1995).

Singh, J., "Multinational Firms and Knowledge Diffusion: Evidence Using Patent Citation Data," working paper (2004).

Sjöholm, F., "International Transfer of Knowledge: The Role of International Trade and Geographic Proximity," *Weltwirtschaftliches Archiv* 132, 97–115 (1996).

Trajtenberg, M., "A Penny for Your Quotes: Patent Citations and the Value of Innovations," *RAND Journal of Economics* 21 (1990), 172–187.

Tybout, J., "Plant- and Firm-Level Evidence on 'New' Trade Theories," in E. Kwan Choi and James Harrigan (Eds.), *Handbook of International Trade* (Oxford: Basil Blackwell, 2003).

APPENDIX A

Data Appendix

The data set on which this paper's analysis is based is a compilation from several sources. These sources are described below. The data collected by the French government are confidential, and analysis of these data was conducted on the premises of the Institut National de Statistique et Etudes Economiques (INSEE). For further information on gaining access to these data, researchers should contact Francis Kramarz (kramarz@ensae.fr).

1. Patent Data from the European Patent Office

In the analysis described in this paper, I restrict myself to firms that have applied for at least one European patent during 1986–1992 (the sample period over which the trade data are available). INSEE maintains a list of all the European patents applied for by French firms. I merged these patent numbers with the numbers contained in patent citation data provided by Dietmar Harhoff. The citation data list the numbers of the citing and cited patents. I used information on the location of firms to which the cited patents were assigned to identify the nationality of the cited patents. Information on the technology classes and application dates of these patents was also drawn from the patent data provided by Dietmar Harhoff. Because all French firms are assigned SIREN identification numbers, the patent data can be easily merged with the trade and balance-sheet data.

2. Firm-Level Trade Data

Whenever a firm ships goods into or out of France, it is required to declare the shipment to French customs. This paper uses a database, compiled by researchers at INSEE, which lists the annual shipments by country and NAP600 two-digit industrial classification of all French firms. The original transactions are recorded in francs and measure the amount paid or received by the firm. In the data set I use, the amounts are deflated by two-digit industrial price indices. Also, certain regions are grouped together, and the resulting eight regions covered by my data are the following: Germany, Benelux, Spain and Portugal, Italy, Japan, Switzerland, the United Kingdom and Ireland, and the United States.

3. Other Firm-Level Information

Other information on firms comes from the BAL-SUSE database, which is constructed from the mandatory reports of French firms to the fiscal administration. This data set covers all French firms with sales of more than 3,000,000 FF in 1990 (which results in the data set containing information on the firms responsible for 94% of total sales in the French economy). It contains detailed balance-sheet information on firms' total sales, labor costs, wage bills, value added, purchases, assets, full-time employment, and dates of firm creation and termination. Information on foreign parents and subsidiaries is taken from the Liens Financiaires (LIFI) database.

4. Constructed Variables

The measure of technological proximity should allow for the fact that firms and countries have patents in a number of classes. Jaffe (1986) proposes a measure of technological proximity similar to the following:

$$Prox_{ist} = \frac{\sum_{k=1}^{K} P_{ikt} P_{skt}}{\sqrt{\left(\sum_{k=1}^{K} P_{ikt}^2\right)\left(\sum_{k=1}^{K} P_{skt}^2\right)}},$$

where P_{ikt} is the number of patents held by firm i in class k in year t, and P_{skt} is the number of patents held by country s in class k in year t. Thus $Prox_{ist}$ is a measure of the extent to which the distribution of patents across firms and countries overlaps. If the share of the firm's patents in each class is equal to the share of the country's patents in those classes, $Prox_{ist}$ will be equal to 1. If none of their patents fall in the same classes, $Prox_{ist}$ will equal 0.

The measure of the firm's distance from the technological frontier used in the regressions presented here consists of the average across patent classes of the ratio of the forward citations received by the firm's patents to the number of forward citations received by the average patent in the class. This variable is calculated as

$$Soph_i = T \sum_{t=1}^{T} \left(K_{it}^{-1} \sum_{k=1}^{K} \overline{f_{ikt}} / \overline{f_{kt}} \right),$$

where $\overline{f_{itk}}$ is the average number of forward citations to i's patents in class k in year t, $\overline{f_{kt}}$ is the average number of forward citations received by patents in class k, and K_{it} is the number of classes in which firm i patents in year t. This last variable provides a measure of how important the firm's patents are relative to an average, taking into account differences in citation frequencies across classes. A value of $Soph_i$ greater than 1 suggests that the firm is a technological leader, and a value less than 1 suggests the firm is a technological follower.

A similar variable controls for the foreign citing and cited industries' proximity to the frontier of France. It is calculated as the ratio of the average number of citations received by patents in country s, $\overline{f_{skt}}$, to the average number of citations received by French patents in the same class f_{Fkt} averaged over classes within an industry j:

$$Value_{ist} = K_{jt}^{-1} \sum_{\mathrm{k}} \overline{f_{skt}} / \overline{f_{Fkt}},$$

where K_{jt} is the number of classes in which firms in industry j (the industry to which firm i belongs) patents in year t. This variable provides a measure of the level of technological development of the citing or cited country relative to France. It can be expected to be positively correlated with the firm's backward citations to country s. It may be positively correlated with forward citations (because the frontier countries have greater absorptive capacity) or negatively correlated (because the technological laggards have more to learn from French firms).

5. The Innovation Survey

France's *Ministère de l'industrie et du commerce extérieur* conducted a survey in 1993 in which roughly 4,000 firms were asked whether they had obtained new technologies via a number of specified sources in France, the European Community, non-E.C. Europe, the United States, Japan, or another country. The specified sources were: personnel exchanges, joint ventures, mergers and acquisitions, communication with clients, communication with suppliers, recruiting, equipment purchases, consulting, analysis of competing products, licensing, R&D collaboration, and R&D outsourcing. Another section of the survey asked whether the firms had themselves transferred new technologies to third parties via a similar set of channels: R&D outsourcing or subcontracting, patent licensing, providing expert consultation for other firms, equipment sales, departure of qualified workers, communication with other firms, mergers, and joint ventures or strategic alliances.

Appendix B

Results Based on USPTO Citations

APPENDIX C

Results from the Innovation Survey

The innovation survey asked firms "Did you acquire new technology via the following channel from the following region during 1990–1992?" If the firm answered "yes" to the question about R&D outsourcing, for example, that variable is set equal to 1. This variable, indicating whether or not the firm obtained new technology from region s, is regressed on exports to and imports from region s, so the coefficients listed in table C1 reflect the relationship between trade with a given region and the probability of obtaining technology from that region through the specified channel.

The innovation survey also asked firms "Did you transfer new technology via the following channel to the following region during 1990–1992?" The coefficients listed in table C2 reflect the relationship between trade with a given region and the probability of transferring technology to that region through the specified channel.

TABLE B1.—USPTO BACKWARD CITATIONS

	(1)	(2)	(3)	(4)
$D(Exports_{ist})$	−0.128 (0.232)	0.084 (0.323)		
$D(Imports_{ist})$	0.941*** (0.332)	0.705** (0.324)		
$\ln(Exports_{ist})$			0.013 (0.022)	0.032 (0.053)
$\ln(Imports_{ist})$			0.091** (0.040)	0.024 (0.086)
$D(Parent_{ist})$			0.105 (0.268)	0.229 (0.477)
$D(Subsidiary_{ist})$				−0.263 (0.562)
$D(JV_{ist})$				0.189 (0.488)
$\ln(p_{it})$	0.199*** (0.048)	0.050 (0.097)	0.100 (0.081)	−0.049 (0.145)
$\ln(P_{st})$	0.410 (1.078)	−0.491 (1.131)	0.136 (1.045)	−0.352 (4.532)
$Prox_{ist}$	1.989*** (0.482)	0.198 (0.347)	1.218 (0.623)	0.772 (1.419)
Cites to France	−0.092*** (0.020)	−0.042 (0.049)	−0.065 (0.037)	−0.033 (0.073)
$Value_{ist}$	0.124 (0.090)	0.365*** (0.109)	0.331 (0.284)	0.540 (0.174)**
$Soph_i$	1.179** (0.476)			
Constant	4.809 (217.126)	17.376 (117.983)	9.857 (153.883)	−1.114 (0.000)
Observations	60,578	45,590	45,584	6,472
	−909.569	−384.1329	−477.84169	−110.086

Dependent variable: number of citations by firm i to country s in year t. (1) Random effects (RE), all firms. (2) Fixed effects (FE), all firms. (3) FE, all firms. (6) FE, firms with employment <500 dropped and years <1990 not included (restricted sample—parent and subsidiary variables include minority stakes for all firms).

Notes: Standard errors in parentheses. *, **, ***: significantly different from zero at the 10%, 5%, 1% level. $D(Export)$ = 1 if firm i exports to country s in year t. $D(Import)$ = 1 if firm i exports to country s in year t. $D(Parent)$ = 1 if the firm has a parent in country s in year t. $D(Subsidiary)$ = 1 if the firm has a subsidiary in country s in year t. $D(JV)$ = 1 if the firm has a joint venture or alliance in country s in year t. p_{it} = firm's patents in year t. P_{st} = country's patents in year t. $Value_{ist}$ = foreign industry's proximity to the technological frontier (value of foreign patents) in year t. Controls for the firms' employment, capital intensity, average wage, labor, and productivity, as well as country, industry (except in FE model), and year dummies, are included.

TABLE B2.—USPTO FORWARD CITATIONS

	(1)	(2)	(3)	(4)
$D(Exports_{ist})$	0.275*** (0.058)	0.322*** (0.061)	0.201*** (0.073)	
$D(Imports_{ist})$	0.379*** (0.068)	0.358*** (0.069)	0.094 (0.075)	
$\ln(Exports_{ist})$				−0.019 (0.010)
$\ln(Imports_{ist})$				0.036** (0.017)
$D(Parent_{ist})$				0.362* (0.201)
$D(Subsidiary_{ist})$				−0.201 (0.125)
$D(JV_{ist})$				0.211 (0.134)
$\ln(p_{it})$	0.086*** (0.016)	0.056*** (0.019)	0.020 (0.021)	0.007 (0.039)
$\ln(P_{st})$	2.158*** (0.362)	2.593*** (0.391)	1.948*** (0.414)	12.068** (1.109)
$Prox_{ist}$	−0.258* (0.141)	0.012 (0.152)	−0.288 (0.192)	−0.007 (0.184)
Cites from France	−0.009*** (0.001)	−0.011*** (0.001)	0.007* (0.004)	−0.002 (0.004)
$Value_{ist}$	0.093*** (0.025)	0.086*** (0.027)	0.081*** (0.031)	0.113** (0.055)
$Soph_i$	0.306*** (0.097)	0.338*** (0.100)		
Constant	−23.306*** (3.150)	−27.210*** (3.404)	−20.902*** (3.613)	−107.109*** (9.885)
Observations	58,312	48,520	35,979	6,520
Log likelihood	−137,720.7	−118,310.4	−7,025.8232	−1,881.317

Dependent variable = number of citations by country s to firm i in year t. (1) Random effects (RE), all firms. (2) RE, firms with foreign parents and subsidiaries dropped (does not include minority stakes for firms with employment < 500). (3) Fixed effects (FE), firms with foreign parents, subsidiaries, or joint ventures dropped (does not include minority stakes for small firms). (4) FE, firms with employment <500 dropped and years <1990 not included (restricted sample—parent and subsidiary variables include minority stakes for all firms).

Notes: Standard errors in parentheses. *, **, ***: significantly different from zero at the 10%, 5%, 1% level. $D(Export)$ = 1 if firm i exports to country s in year t. $D(Import)$ = 1 if firm i exports to country s in year t. $D(Parent)$ = 1 if the firm has a parent in country s in year t. $D(Subsidiary)$ = 1 if the firm has a subsidiary in country s in year t. $D(JV)$ = 1 if the firm has a joint venture or alliance in country s in year t. p_{it} = firm's patents in year t. P_{st} = country's patents in year t. $Value_{ist}$ = foreign industry's proximity to the technological frontier (value of foreign patents) in year t. Controls for the firms' employment, capital intensity, average wage, labor, and productivity, as well as country, industry (except in FE model), and year dummies, are included.

Table C1.—Acquisitions of Foreign Technology, by Source

Channel	log(*Exports*)	log(*Imports*)
R&D outsourcing	0.058 (0.041)	0.263*** (0.074)
Collaborative R&D	0.015 (0.036)	0.130** (0.055)
Patents and licenses	0.017 (0.029)	0.249*** (0.053)
Analyzing competing products	0.047** (0.022)	0.086*** (0.028)
Equipment purchases	0.037 (0.038)	0.187*** (0.066)
Hiring employees	0.000 (0.052)	0.025 (0.076)
Foreign suppliers	0.055 (0.037)	0.338*** (0.065)
Foreign buyers	0.226*** (0.071)	0.042 (0.027)
Mergers and acquisitions	−0.027 (0.049)	0.251*** (0.098)
Joint ventures and alliances	0.068 (0.061)	0.139** (0.070)

Dependent variable = 1 if firm obtained new technology via specified channel to region *s*. Robust standard errors in parentheses. ***, **, *: significant at the 1%, 5%, 10% level. Each set of export and import parameters comes from a separate regression. Region (European Union, Europe outside European Union, Japan, United States, other) and industry fixed effects included, as well as log(*Employment*) and log(*Sales*).

Table C2.—Transfers of Foreign Technology, by Source

Channel	log(*Exports*)	log(*Imports*)
Contract R&D	0.016 (0.050)	0.033 (0.053)
Licensing patents	0.098** (0.039)	0.031 (0.031)
Consulting	−0.019 (0.042)	0.106* (0.055)
Equipment sales	0.097** (0.045)	−0.049 (0.036)
Departure of employees	0.279** (0.120)	0.141 (0.100)
Communication with other firms	0.031 (0.051)	0.068 (0.043)
Mergers and acquisitions	0.351 (0.403)	−0.202 (0.182)
Joint ventures and alliances	0.071 (0.071)	0.102** (0.051)

Dependent variable = 1 if firm transferred new technology via specified channel to region *s*. Robust standard errors in parentheses. ***, **, *: significant at the 1%, 5%, 10% level. Each set of export and import parameters comes from a separate regression. Region (European Union, Europe outside European Union, Japan, United States, other) and industry fixed effects included, as well as log(*Employment*) and log(*Sales*).