Chapter 19

INTERNATIONAL TRADE, FOREIGN DIRECT INVESTMENT, AND TECHNOLOGY SPILLOVERS

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Contents

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Abstract

This chapter examines how international flows of technological knowledge affect economic performance across industries and firms across different countries. Motivated by the large share of the world's technology investments made by firms that are active across country borders, we focus on international trade and multinational enterprise activity as conduits for technological externalities, or spillovers. In addition to a review of recent empirical research on technology spillovers through trade and foreign direct investment, the discussion guided by a model of foreign direct investment, trade, and endogenous technology transfer. There is evidence for technology spillovers from both international trade and the activity of multinational enterprises. The analysis highlights challenges for future empirical research, as well as the need for additional data on technology and innovation.

Keywords

absorptive capacity, exports, gravity, horizontal foreign direct investment, imports, learning-by-exporting, multinational affiliates, multinational parents, patents, research and development expenditures, tacit knowledge, technology diffusion, technology transfer, vertical foreign direct investment

JEL classification: O3, F2, F1, O4

1. Introduction

The international trade and foreign direct investment (FDI) activity of firms is a natural starting point for thinking about the international diffusion of technology. First of all, multinational firms—those whose operations span several countries—are among the most important technology producers in the world. In the year 1999, for example, 83% of all manufacturing R&D in the United States was conducted by parent companies of US multinationals (NSF, 2005). Multinational parents will typically want to transfer the technology they have created to their affiliates abroad.[1] Second, firms that engage in international trade and FDI tend to larger and more productive than firms that only operate domestically. Thus, the latter may be able to raise their productivity by interacting with foreign firms. Moreover, trade and FDI are also strongly related. In the United States today, for example, multinational firms account for about 40% of all trade.

Why does the international diffusion of technology matter? Productivity differences explain a large part of the variation in incomes across countries, and technology plays the key role in determining productivity.[2] For most countries, foreign sources of technology are estimated to account for 90% or more of domestic productivity growth. Although the contribution of India, China, and a number of other countries is rising, most of the world's technology creation occurs in only a handful of rich countries.[3] The pattern of worldwide technical change is thus determined in large part by international technology diffusion.

International technology diffusion affects both the distribution and the growth of world incomes. First, whether countries' incomes converge over time or not turns on whether technology diffusion is global or local.[4] A better understanding of technology diffusion therefore provides insights on the likelihood that certain less developed countries will catch-up to rich countries. Second, strong cross-country diffusion of technology will generally raise the rate at which the world's technology frontier advances, so technology diffusion has not only distributional but also efficiency implications.[5]

The diffusion of technology involves both market transactions and externalities. To obtain information on the former is fairly straightforward. For instance, firms make royalty payments for their use of patents, licenses, and copyrights, and this is recorded for many countries in the international services balance (e.g., OECD). Many researchers believe that international technology diffusion occurs not only through market transactions but also, and possibly more so, through externalities.[6] These externalities are called technology spillovers. One reason is that technology is not fully codifiable. This makes, first of all, communication about the technological knowledge difficult. It may also mean that it is impossible to write contracts that cover every contingency, which may lead to a hold-up problem if the services

[1] In fact, a cornerstone of the theory of multinational firms holds that imperfection in the market for technological knowledge is a key reason why certain transfers are internalized within the firm, between a multinational parent and its affiliate.

[2] See Hall and Jones (1999) and Easterly and Levine (2001).

[3] The largest seven industrialized countries accounted for about 84% of the world's research and development (R&D) spending in 1995, for example, their share in world GDP was only 64%.

[4] See Grossman and Helpman (1991), Howitt (2000).

[5] See, for example, Aghion and Howitt (1998, Chapter 12).

[6] For example, technology externalities provided by the United States to other countries are an order of magnitude larger than US technology licensing receipts. See the US balance of payments data on trade in services, and McNeil and Fraumeni (2005) on spillovers.

provided by the supplier are specific. Another reason for market failure in the market for technology is asymmetric information: the buyer does not know the true efficiency of the technology, while the seller cannot commit to truthful claims about it.

Even though much of the international transfer of technology may thus not occur through market transactions, it will typically be associated with observable international activity. I call this activity potential channels for international technology spillovers. Among the most frequently mentioned channels are international trade and FDI, and I will present the evidence on these. A major theme will be that it is crucial to distinguish spillovers from technology diffusion, and, more generally, from other factors that influence firm productivity.[7]

To preview the results, there is evidence that imports are a significant channel of technology diffusion. The evidence for benefits associated with exporting is generally weaker, although a number of recent studies also indicate that exporting activity may transmit technological knowledge. The importance of FDI has long been emphasized in the case study literature, and recently that evidence has been complemented by some econometric findings. At the same time, despite the global reach of computer programs there is no indication that a global pool of technology yet exists. The localized character of technology suggests that an important component of it is tacit in nature, which may require face-to-face interaction. Although the relative importance of international technology diffusion appears to be increasing along with higher levels of economic integration, international diffusion of technology is neither inevitable nor automatic. Domestic technology investments are necessary.[8]

This chapter provides more details on these issues. The following section starts out by introducing a conceptual framework for analyzing trade, FDI, and technology diffusion. Section 3 discusses the available data and various approaches to do empirical work on international technology diffusion. The following three sections review the empirical evidence. Section 4 considers the relationship of international technology diffusion and geographic distance, while Sections 5 and 6 look at FDI and international trade, respectively. A concluding discussion is provided in Section 7.

2. A model of trade, FDI, and international technology transfer

Economists have studied the relation of trade, FDI, and technology diffusion using a number of different approaches. To highlight their respective advantages and disadvantages, this section introduces a model that can illustrate the major issues. For the model of international technology diffusion to be useful for thinking about these issues, it needs to satisfy two conditions. First, there should be an explicit treatment of technology in the sense of information, or knowledge required for production. This is because it is impossible to understand international technology transfer without recognizing that it requires knowledge transfer from one to another human being. Second, the firms in our model should also be able to

[7] I use the term international technology diffusion when referring to the movement of technological knowledge from firms in one to firms in other countries. This diffusion consists of arms-length market transactions and externalities, or international technology spillovers. Technology diffusion is one factor, but not the only one, that can affect productivity. In this chapter, the terms diffusion and transfer are used synonymously, even though the latter may suggest a more intentional approach than the former.

[8] Another channel, outside the scope of this chapter, is technology diffusion through international migration and networks; for recent contributions, see Agrawal and Oettl (2008), Kerr (2008), and Singh (2005).

engage in FDI and international trade. The latter point is relatively easy to address, whereas the former is relatively difficult, and in consequence, there are few attempts to formally model technology as knowledge.[9] To keep things simple, in the following framework all technology transfer is internalized by the firms. Further below the model will then be used to discuss which activities are particularly prone to generating externalities. The following discussion follows Keller and Yeaple (2008, 2009a), starting with an overview.

2.1. Overview

In this world, each country has a large number of firms that can each produce a unique variety of a differentiated final good. A firm sells its final good to foreign consumers by assembling a range of intermediate inputs, each of which can be produced at home or abroad. Production of each of these intermediate inputs, or tasks, requires mastery of its technological blueprint—the "how to"—as well as some conventional factor inputs. The costs of technological transfer come in form of communication costs: in the process of communicating the knowledge behind each task from multinational parent to affiliate, errors can occur which make affiliate production less efficient than parent production.[10]

Inputs vary in their technological complexity. More complex tasks involve higher costs of transferring the technological information needed for offshore (affiliate) production. It is difficult, for example, to transfer the knowledge about R&D on product design abroad. This may be due to noncodifiability of the technological know-how or fear of imitation in the absence of perfect property rights protection. Other tasks are easier to transfer, perhaps because the codifiability is higher or the degree of standardization is higher.

While the tasks can be completed by the multinational affiliate, alternatively the tasks can also be performed by the multinational parent in the home country, after which the assembled intermediate good is exported to the affiliate subject to shipping costs. Multinational firms thus face a trade-off between the costs of communicating disembodied technological information from parent to affiliate and the shipping cost for the intermediate that embodies the technological information.

This setting has a number of attractive features. First, technological knowledge has a well-defined meaning, and our notion of technology transfer costs is in line with Hayek (1945), Polanyi (1958), and others.[11] Second, because firms can either sell through trade or through produce in the host economy, it becomes possible to ask which of these activities is associated with greater technology transfer.

[9] To fix ideas, consider the simplest Ricardian model of trade. There are cross-country efficiency differences in production technologies, and a country tends to export final goods where it has an efficiency advantage compared to other countries. Importing a good allows to use foreign production technologies, so in some sense there is diffusion of technology. However, the production possibility frontier of a country does not shift, and it is impossible to ask whether importing a particular good has raised the importer's ability to produce similar goods at home with the same efficiency that is achieved by the exporter. As it turns out, this type of question is central to how international trade might affect international technology diffusion.

[10] The analysis builds on ideas presented in Arrow (1969). Koskinen et al. (2002) discusses the reasons why face-to-face communication has distinct advantages over all other forms of communicating technological knowledge. Teece (1977) presents direct evidence that the size of technology transfer costs in multinational enterprises is substantial.

[11] Hayek (1945) and Polanyi (1958) discuss that codifiability of information (vs. tacitness) affects its transfer cost; see also von Hippel (1994). Feldman and Lichtenberg (1997) show empirically that codifiability is associated with better transferability of information.

Moreover, even though FDI and exports are substitutes at the task level, the model implies, in line with the evidence, complementarity of trade and FDI at a more aggregated level (Blonigen, 2001).

As will be shown below, the trade-off between trade and transfer costs yields an endogenously determined level of technological knowledge that diffuses internationally. For a given foreign market, inputs with high-technology transfer costs will be produced at home and exported, while inputs with low transfer costs will be produced abroad. Conversely, across foreign markets, as trade costs rise in geographic distance, technology transfer costs rise too, and the model predicts that the inputs imported by the affiliate from its parent are becoming increasingly technologically complex.

Moreover, as trade costs are rising between the multinational firm's home and its affiliates' host countries, so will technology transfer costs, because the two are equated on the margin. As costs are increasing, firms will be forced to set higher prices in order to break even, and that reduces their sales. Thus, the result is the so-called gravity pattern for affiliate sales—FDI falling in geographic distance—that finds strong empirical support in the data.

The following section provides more details on this framework.

2.2. *The model*

Consider a world composed of $K + 1$ countries indexed by $k = \{0, 1, \ldots, K\}$. Each country is endowed with a quantity of labor, the only factor, and N_{ik} entrepreneurs each endowed with the knowledge of how to produce a variety of good i. In each country, the representative consumer has identical, homothetic preferences over I differentiated goods, indexed by i, and a single, freely traded homogenous good Y, given by

$$U = \sum_{i=1}^{I} \Phi_i \ln\left(\int_{\omega\in\Omega_i} q_i(\omega)^{(\sigma-1)/\sigma} \mathrm{d}\omega\right)^{\sigma/(\sigma-1)} + \left(1 - \sum_{i=1}^{I} \Phi_i\right) \ln Y, \tag{1}$$

where Ω_i is the set of varieties available in industry i, $q_i(\omega)$ is the quantity of output of variety ω consumed, $\sigma > 1$ is the elasticity of demand in industry i, and Y is the quantity consumed of the homogenous good. Each country produces good Y using a single unit of labor and so wages are the same in every country. Henceforth, the wage is normalized to unity. Assuming that firms are too small to affect industry-level demands, the preferences (Equation (1)) imply the following isoelastic demand for variety ω in country k:

$$q_k(\omega) = B_{ik}(p_k(\omega))^{-\sigma}, \tag{2}$$

where B_{ik} is the endogenous markup-adjusted demand level in country k and industry i, and $p_k(\omega)$ is the price of the variety ω in country k.

In industry i each variety can be costlessly assembled from a continuum of firm-specific intermediate inputs (indexed by z) according to the following production function:

$$x_i = \exp\left[\int_0^\infty \beta_i(z) \ln\left(\frac{m(z)}{\beta_i(z)}\right) \mathrm{d}z\right], \tag{3}$$

where $m(z)$ is the quantity of firm-specific intermediate of complexity used, $\beta_i(z)$ is the cost share of z for a firm producing a good in industry i. As shown below, z is an index of the technological complexity of an input. Industries that use predominantly high-z inputs have high cost shares $\beta_i(z)$ for such inputs, and consequently I refer to such industries as technologically complex industries. In the interest of simplicity, a functional form is chosen for $\beta_i(z)$ that summarizes an industry's technological complexity using a single parameter:

$$\beta_i(z) = \phi_i \exp(-\phi_i z). \tag{4}$$

This parameterization implies that the average technological complexity of intermediate inputs in industry i is $1/\phi_i$, so I refer to industries with low ϕ_i as technologically complex. Further, in the limit as $\phi_i \to \infty$ the average technological complexity goes to zero.

To produce one unit of an intermediate input z, a number of tasks, given by z, must be successfully completed. In the application of each task, problems arise that will, if unsolved, result in the destruction of that unit. A plant's management must communicate the problem to the firm's headquarters which must in turn communicate to the plant the solution to the problem. If communication is successful for each task, then one unit of the input is produced for each unit of labor employed. If the solution to any problem fails to be communicated, then the input that is produced is useless.

A firm that has chosen to assemble its product in country k must supply the local plant with intermediate inputs that are either produced in the home country or in the host country k. In making this decision, the firm must weigh two types of costs of doing business internationally: shipping costs and technology transfer costs. First, suppose that an input z is produced in the home country. It is assumed that when the plant and the headquarters are located in the same country communication is perfect and no inputs are wasted by the inability to successfully complete a task so that one unit of labor produces one unit of output. In shipping this intermediate input to its affiliate, the parent firm incurs so-called iceberg-type trade costs, that is, $\tau_{ik} > 1$ units have to be shipped in order for one unit to arrive at the destination.

If the firm produces an intermediate input z in an affiliate located in country k then it avoids shipping costs, but imperfect communication between plant and headquarters leads to a loss of productivity. As stressed by Arrow (1969), there can be large efficiency losses when communication between teachers (here the multinationals' parents) and students (here the multinationals' affiliates) fails. In particular, when the firm's headquarters and the plant are in different countries, the probability of successful communication between headquarters and affiliate is $\tilde{\lambda} \in (0, 1)$. Assuming that the success rate of communication is independent across tasks, the probability of successful communication is $(\tilde{\lambda})^z$ and so the expected number of labor units needed to produce a unit of intermediate input z is equal to the inverse of $(\tilde{\lambda})^z$:

$$\frac{1}{(\tilde{\lambda})^z} = \exp(-z \ln \tilde{\lambda}) = \exp(\lambda z), \tag{5}$$

where the parameter $\lambda \equiv -\ln \tilde{\lambda} > 0$ is inversely related to communicability and so measures the inefficiency costs of international technology transfer. Hence, a relatively high value of z is associated with relatively low productivity when production of this intermediate input takes place in the affiliate plant located offshore.

It is possible now to summarize the sense in which high-z inputs are technologically complex in our model. Inputs with high values of z require the successful completion of a relatively high number of tasks.

Because there is some difficulty in communicating technological information for each one of these tasks, a relatively high number of tasks translate into a relatively high level of technological complexity.

The following section shows how the physical cost of shipping costs and the efficiency costs of technology transfer interact to determine geography of costs across affiliates within the multinational firm.

2.3. Technical complexity and the geography of affiliate costs

Consider a firm with its headquarters in country 0 that has opened an assembly plant in country k and is minimizing the cost of supplying intermediate inputs to that affiliate. The marginal cost of supplying the affiliate with intermediate input z, $c_k(z)$, depends on where the input is produced:

$$c_{ik}(z) = \begin{cases} \tau_{ik} & \text{if imported from parent} \\ \exp(\lambda z) & \text{if produced by affiliate} \end{cases} \tag{6}$$

There exists a cutoff intermediate input $\hat{z}_{ik}$ such that all inputs with $z < \hat{z}_{ik}$ will be produced by the affiliate and all intermediates $z > \hat{z}_{ik}$ will be imported by the affiliate from the headquarters in country 0, where

$$\hat{z}_{ik} = \frac{1}{\lambda} \ln(\tau_{ik}) \tag{7}$$

One empirical implication following directly from Equation (7) concerns the technological complexity of intrafirm trade: as trade costs between the multinational parent and its affiliates increase, the average technological complexity of the affiliates' imports from their parent increases ($\mathrm{d}\hat{z}_{ik}/\mathrm{d}\tau_{ik} > 0$).

It is now shown that the trade-off between trade costs and technology transfer costs determines the multinational firms' production costs for different locations. Using Equation (3), it can be shown that the marginal cost of producing the final good i in country k is

$$C_{ik} = \exp\left(\int_0^\infty \beta_i(z) \ln c_k(z) \mathrm{d}z\right). \tag{8}$$

Substituting Equation (6) into Equation (8), using Equation (7), and integrating by parts, the marginal cost of producing final output in industry i at an affiliate located in country k is given by

$$C_{ik} = \exp\left[\frac{\lambda}{\phi_i}\left(1 - (\tau_{ik})^{-\phi_i/\lambda}\right)\right]. \tag{9}$$

Consider the effect on C_{ik} of an increase in τ_{ik}, the size of trade costs between parent and affiliate. Differentiating Equation (9) with respect to τ_{ik}, we obtain

$$\varepsilon_{\tau_{ik}}^{C_{ik}} \equiv \frac{\tau_{ik}}{C_{ik}} \frac{\partial C_{ik}}{\partial \tau_{ik}} = \exp\left(-\frac{\phi_i}{\lambda} \ln(\tau_{ik})\right) > 0. \tag{10}$$

According to Equation (10), for any industry in which technology features nonzero complexity (i.e., $1/\phi_i > 0$) an increase in the size of trade cost, τ_{ik}, between affiliate and parent results in an increase in the marginal cost of the affiliate. Further, the size of this increase is strictly increasing in the technical complexity of the industry $1/\phi_i$. Only in the limiting case of $1/\phi_i \to 0$ does an increase in trade cost *not* result in higher affiliate marginal costs. The following lemma summarizes the result.

LEMMA 1. *An affiliate's marginal cost is increasing in the size of trade cost between parent and affiliate (τ_{ik}), and the elasticity of the marginal cost of the affiliate with respect to τ_{ik}, ($\varepsilon_{\tau_{ik}}^{C_{ik}}$), is higher in technologically complex industries (low ϕ_i).*

Equation (10) has two important empirical implications.

2.4. Technological complexity and the power of gravity

Because affiliates rely on imported intermediate inputs, their marginal costs of production are rising in trade costs. The rate at which marginal costs rise depend on the firm's technological complexity: firms that require more technologically complex intermediate inputs are more exposed to changes in trade costs because they rely more heavily on inputs that are hard to offshore.

Consider the size of an affiliate's revenues generated on sales to customers in its host country market k. The isoelastic demand (Equation (2)) imply that the optimal price charged by the affiliate $p_{ik} = \sigma C_{ik}/(\sigma_i - 1)$. Using Equation (2) and substituting for the price, the affiliate's revenues are

$$R_{ik} \equiv p_{ik} x_{ik} = \left(\frac{\sigma}{\sigma - 1}\right)^{1-\sigma} B_{ik} (C_{ik})^{1-\sigma}. \tag{11}$$

Totally differentiating this expression with respect to τ_{ik} gives

$$\varepsilon_{\tau_{ik}}^{R_{ik}} \equiv \frac{\tau_{ik}}{R_{ik}} \frac{\partial R_{ik}}{\partial \tau_{ik}} = -(\sigma - 1)\varepsilon_{\tau_{ik}}^{C_{ik}}.$$

This equation combined with Lemma 1 has the following implication.

PROPOSITION 1. *Holding fixed the demand level, B_{ik}, the value of affiliate revenues generated on sales to local customers, R_{ik}, is decreasing in trade cost τ_{ik}, and the rate of this decrease is highest in technologically complex industries (low ϕ_i).*

This proposition states that there will be a gravity relationship of multinational sales with trade costs that stems from the interaction between trade costs and technical complexity. When technology is perfectly transferable internationally, as in the limiting case when $1/\phi_i \to 0$, affiliate sales display no gravity effect. As technology becomes more complex ($1/\phi_i$ increases), the power of gravity becomes increasingly pronounced.

The second important empirical implication of Equation (10) concerns the aggregate volume intra-firm imports in total affiliate costs as a function of technological complexity and the size of trade costs. By Shepard's Lemma, Equation (10) describes the cost share of intermediates imported by an affiliate from its parent firm. Letting IM_{ik} be the aggregate value of the imports of an affiliate in country k and industry i from its parent firm and letting TC_{ik} be the total costs of this affiliate, one obtains

$$\frac{\mathrm{IM}_{ik}}{\mathrm{TC}_{ik}} = \exp\left(-\frac{\phi_i}{\lambda} \ln \tau_{ik}\right). \tag{12}$$

From this expression the following proposition is immediate:

PROPOSITION 2. *The share of intermediate inputs imported from the parent firm in total costs (IM_{ik}/TC_{ik}) is strictly decreasing in transport costs (τ_{ik}) between affiliate and parent, and the rate of decline is slower in technologically complex (low ϕ_i) industries.*

For a given increase in transport costs, the cost share of intermediates imported from the parent firm in total affiliate cost is decreasing more slowly in technologically complex industries because these industries are intensive in intermediates whose production is harder to move offshore. In the limit as $1/\phi_i \rightarrow 0$ the import share $\mathrm{IM}_{ik}/\mathrm{TC}_{ik}$ goes to zero: all tasks can be costlessly off-shored and the affiliate is not exposed to the cost of importing intermediates from its parent. Controlling for other determinants of multinational activity, Keller and Yeaple (2009a) present evidence in support of both of these propositions: the gravity for multinational sales is stronger for relatively complex goods, and the share of affiliate imports tends to be high for complex goods because the technology for those is difficult to transfer.

The model also correctly predicts that trade becomes on average more technologically complex as trade costs between exporting and importing country rise. Figure 1 shows the relationship for the US exports. Here, complexity, proxied by the average R&D intensity of the exports, is on the vertical axis, while trade costs between the United States and other countries are depicted.

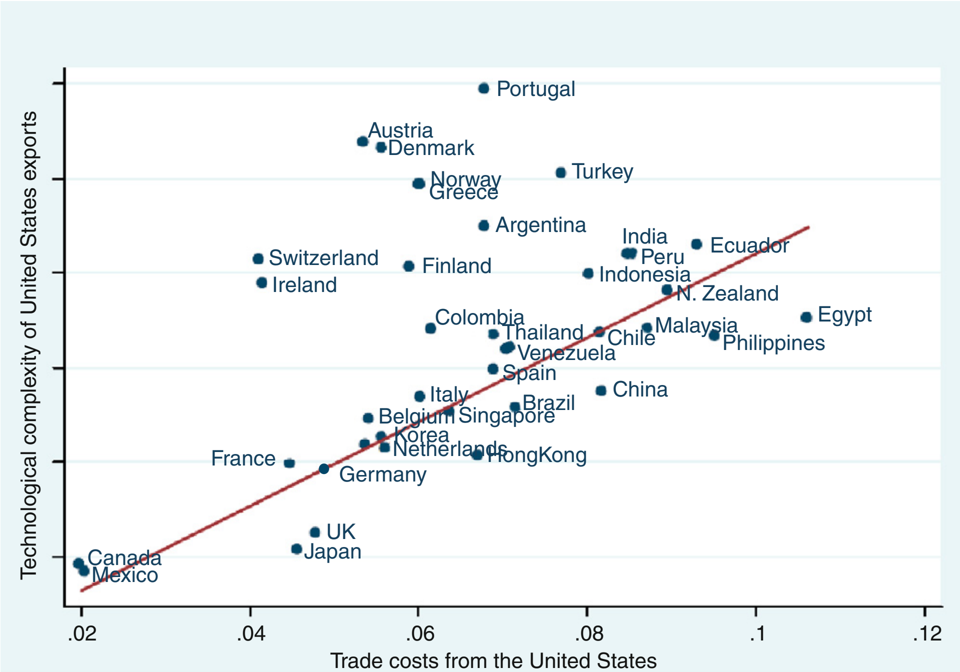


Figure 1. Complexity of exports is rising in trade costs.

There is a clear positive relationship, while trade cost differences accounting for almost half of the differences in the technological complexity of exports. Keller and Yeaple (2009a) show that the simple correlation is robust to controlling for other factors, including differences in the value-to-weight ratios of the goods that are exported.

The model can be easily closed to derive comparative static results. For example, a decline in the costs of technology transfer ($\lambda \downarrow$) is associated with lower affiliate costs and more FDI activity. These predictions describing the trade, FDI, and international technology transfer decisions of multinational firms provide a useful background for this chapter. As noted above, each firm thus far internalizes the costs and benefits from the technology transfer. At the same time, it is straightforward to extend the model so that the local production activities of the affiliate generate learning spillovers for host country firms. This would some new microfoundations for FDI technology spillovers. Similarly, the model can be extended to allow for multinational parent exports to unaffiliated host country firms. From the importer's point of view, intermediate goods from a foreign multinational parent embodying its technological knowledge are a plausible source for technology spillovers.

The model can also explain why the potential for technology spillovers are higher when interacting with a foreign multinational and exporter compared to with the average domestic firm. As shown by Keller and Yeaple (2009a), when the model is extended so that firms are heterogeneous in productivity and there are fixed costs of foreign market entry, there will a new extensive margin prediction: firms that are internationally active are more productive than purely domestic firms. In addition, there is a pecking order of foreign activity, with the most productive firms being active in most foreign markets, while the least productive internationally active firm operates in only one foreign market. Given their higher productivity, the potential for technological learning from foreign firms is thus higher than for learning from the average domestic firm.

The previous section has laid out formally the major ideas on how trade and FDI are related to international technology diffusion. The extent to which trade and FDI are systematic causes of international technology spillovers is a complex question that requires careful empirical analysis, and the evidence on it will be discussed below. The next section looks at the data, a critical element of any empirical analysis.

3. Data and what they capture

3.1. Measures of technology

Technology is an intangible that is difficult to measure directly. Three widely used indirect approaches are to measure (1) inputs (R&D), or (2) outputs (patents), or (3) the impact of technology (higher productivity). Regarding the first, internationally comparable data on R&D expenditures are published by the Organization of Economic Cooperation and Development (OECD) since about 1965. According to the OECD's definition (OECD, 1993), only about two dozen relatively rich countries report substantial amounts of R&D, because the definition captures primarily resources spent toward innovation, and not those spent on imitation and technology adoption. Technology investments of middle-income and poor countries can therefore typically not be analyzed using R&D data.[12]

[12] R&D data becomes more widely available as countries' incomes are rising. There is also increasingly information on poorer countries because surveys encompass the R&D conducted by affiliates of multinational companies located abroad; see, for example, NSF (2007) for R&D expenditures of US firms in China. Also note that the main OECD R&D statistics are on a geographic, not ownership, basis, so that R&D conducted in foreign-owned affiliates is counted as host country R&D.

A drawback of R&D as a measure of technology is that it ignores the stochastic nature of the process of innovation. The current flow of R&D expenditures is a noisy measure of technology improvements in that period. Many authors construct R&D stocks from the flows using the perpetual inventory method. Beyond year-to-year noise, the return to R&D expenditures may vary substantially. One important aspect of this is that the return to publicly funded R&D is lower than the return to privately funded R&D, and many studies focus on business research and development spending.

Turning to the second type of data on technology, a patent gives its holder a temporary legal monopoly to use an innovation in a specific market at the price of public disclosure of technical information in the patent description. An innovation must be sufficiently important to be worthy a patent, which is judged by a trained official (called patent examiner). Relative to R&D, patents have the advantage that data has been collected for longer time (more than 150 years for some countries), and also poorer countries have a substantial number of patents.

There are some issues with using patent data as well. First, a small number of patents accounts for most of the value of all patents. This means that simple patent counts may not measure well technology output. Recent work has addressed this issue in part by using citation-weighted patent data (see Jaffe and Trajtenberg, 2002). Second, the decision to patent is an act of choice on the part of the firm, and a large set of innovations is not ever patented. And third, the part of technology that is noncodifiable will necessarily be missed by patents.[13]

The third measure of technology discussed here is total factor productivity (TFP). The idea, well known since the 1950s, is that if one subtracts from output the contribution of inputs such as labor and capital, the remainder is due to the factor "technology." A simple example of TFP is the term A in the following Cobb–Douglas production function with factor capital and labor,

$$Y = A \times K^{\alpha} L^{1-\alpha} \Leftrightarrow A = \mathrm{TFP} = \frac{Y}{K^{\alpha} L^{1-\alpha}},$$

where $0 < \alpha < 1$. Other TFP measures are more general and have certain desirable properties that are important for comparability (e.g., the superlative index).

In contrast to R&D and patents, TFP is a derived measure of technology, as it is computed from data on inputs and output. This introduces measurement error and perhaps biases, because the appropriate data on inputs and outputs is rarely available. Katayama et al. (2009) emphasize that the use of (1) real sales revenues, (2) depreciated capital spending, and (3) real input expenditures; instead of (unavailable) data on the physical quantities of (1) output, (2) capital, and (3) intermediate inputs, as is frequently done, will often confound higher productivity with higher markups. Other factors might thus contaminate the use of TFP as a measure of technological efficiency, which ultimately goes back to the concern that TFP is constructed as a residual, and may potentially capture spurious influences.

Because of these difficulties in computing TFP, researchers have pursued a number of strategies. One is to consider changes in TFP as opposed to TFP levels. This will help in identifying technological change if spurious factors do not change over time, or more generally, if they change less than technology. For example, in Katayama et al. (2009) case from above, if a firm faces higher adjustment costs to changing its markup, this will reduce the mark-up variability in equilibrium. A second strategy

[13] See also Griliches (1990) who discusses the pros and cons of patent data.

has been to employ TFP measures together with data on R&D (e.g., Griliches, 1984). By establishing a relationship between TFP changes and its presumed major cause, R&D spending, the likelihood of measuring changes in technology appropriately is substantially enhanced.

There is also now survey evidence on technology and innovation activities. Some of it is even harmonized across countries; for example, the most recent wave of the European Community Innovation Survey (CIS-4) includes 101 indicators on a variety of aspects, including product and process innovation, R&D, effects of innovation, and patents. Crespi et al. (2008) and MacGarvie (2006) have employed this data. Several countries also collect more specialized information related to innovation and training parallel to their census data collection in additional programs. The ENESTyC (*Encuesta Nacional de Empleo, Salarios, Tecnología y Capacitación*) of Mexico, for example, includes information of whether plants have undergone ISO 9000 certification, which is a standard for quality management systems; see, for example, Iacovone and Keller (2009). In some cases, authors have also conducted their own interviews to obtain survey evidence on firms' use of technology (Bloom and van Reenen, 2007).

We now turn to measures of international technology spillovers.

3.2. Measurement of international technology spillovers

Naturally, data on spillovers does not exist. Measures that are related to it do exist, but typically they capture spillovers only partially, because the measures do not account for costs of acquisition (learning). For instance, if one patent application cites an earlier patent, this generally indicates that the applicant has benefited from the earlier patent, and it strongly suggests that a knowledge flow has taken place. At the same time, there is often little information on how large these benefits are net of the learning costs that the patent applicant had to incur.

Among the different methods that try to measure international spillovers, the largest set of papers employs international R&D spillover regressions. In one set of papers, if R&D of firm j is positively correlated with TFP of firm i, all else equal, this is consistent with international technology spillovers from firm j to firm i (Keller, 2002a). A variant of this approach replaces TFP by the number of patents (Branstetter, 2001) presents a hybrid approach by relating patents in region i to patents in other regions, where the latter is instrumented by R&D expenditures.

Empirical analysis using R&D spillover regressions has been extended to include particular channels for the spillovers. Coe and Helpman (1995) analyze the relationship between productivity and foreign R&D conditional on imports from that foreign country, while other authors have considered FDI as well.[14] Another strand in the literature relates a possible channel for technology spillovers directly to productivity. Aitken and Harrison (1999), for example, study the correlation of domestic firm productivity and inward FDI in so-called FDI spillover regressions.

There are two major questions that any empirical analysis needs to address. Consider an analysis at the firm level. First, if the technological capabilities of a firm have improved, can one establish that a technology transfer from another firm abroad was causal for this improvement? Causality is a key point in much of empirical analysis. In this particular setting, often the technological capability of the receiving firm is only imperfectly observed (e.g., its productivity), and there is rarely data on technology

[14] The idea of using trade or other weights in such R&D regressions goes at least back to Griliches (1979).

transfer. Establishing causality is particularly difficult under these circumstances. The second key question is which part of the transfer can be considered a technology spillover. This is crucial for assessing the case for economic policy intervention.

I will return to these issues in various contexts when discussing the evidence on technology spillovers related to trade and FDI. Before doing so, the next chapter discusses technology spillovers shaped by geography.

4. An empirical benchmark: Spillovers shaped by geography

Global technology spillovers favor income convergence, while local spillovers tend to lead to divergence, no matter through which channel technology diffuses. This is why a major strand of the literature has examined international technology diffusion in its geographic dimension (Bottazzi and Peri, 2003; Branstetter, 2001; Eaton and Kortum, 1999; Irwin and Klenow, 1994; Jaffe et al., 1993; Keller, 2002a). An advantage of this is that geography is arguably an exogenous determinant in this process.

The question has been studied in a number of ways. One question is whether technology diffusion within countries is stronger than across countries. The evidence generally supports this hypothesis, although there are exceptions. In particular, Jaffe et al. (1993) compare the geographic location of patent citations with that of the cited patents in the United States. They find that US patents are significantly more often cited by other US patents than they are cited by foreign patents. Thompson and Fox Kean (2005) have shown that the three-digit patent classification scheme employed by Jaffe et al. (1993) may be too imprecise to conduct a powerful treatment-and-control analysis. Even when the matching is based on a more disaggregated classification, it is a good idea to examine whether the patents that belong to a given patent class are technologically sufficiently homogeneous.

Branstetter (2001) uses R&D and patenting data on US and Japanese firms to compute weighted R&D spillover stocks. He confirms that patent citations are geographically localized in the sense that within-country spillovers are much stronger than between-country spillovers. More evidence for stronger diffusion within- than across countries is presented by Eaton and Kortum's (1999) study. These authors estimate that for the G-5 countries (France, Germany, Japan, the United Kingdom, and the United States), the rate of domestic technology diffusion is much higher than the typical rate of international technology diffusion between these countries.[15]

In contrast, Irwin and Klenow (1994) do not find stronger within-country spillover compared to across-country spillovers. Irwin and Klenow estimate that for eight vintages of semiconductors introduced between 1974 and 1992, the spillovers from one US firm to another US firm are not significantly stronger than those between a US firm and a foreign firm. The different results might be obtained because Irwin and Klenow's spillovers, which are identified from the effects of cumulative production on market shares, and are different from knowledge spillovers as measured in other studies. It could also

[15] Eaton and Kortum estimate a ratio of about 200 for domestic versus the average international technology diffusion rates, which may be on the high side.

have to do with the particulars of the semiconductor industry at the time. Most of the relatively small number of firms were located in the United States and in Japan, which means that the scope for identifying the within versus between country difference is limited.

The analysis has therefore been extended beyond the national versus international distinction by estimating spillovers conditional on geographic distance and the countries' locations relative to each other (Keller, 2001, 2002a). Keller (2002a) relates industry-level productivity in nine OECD countries to R&D in the G-5 countries, using a simple exponential decay function in distance

$$\ln \mathrm{TFP}_{cit} = \beta \left[S_{cit} + \sum_{j \in \text{G-5}} \exp(-\delta D_{cj}) s_{jit} \right] + X'\gamma + \varepsilon_{cit}$$

Here, D_{cj} is the geographic distance between countries c and j and $\mathbf{X}$ is a vector of control variables. If δ is estimated to be greater than zero, variation in productivity is best accounted for by giving a lower weight to R&D conducted in countries that are located relatively far away, whereas if $\delta = 0$, geographic distance and relative location do not matter. Keller (2002a) finds that δ is positive, and moreover, the decay of technology diffusion implied by the estimate is substantial: with every additional 1200 km distance there is a 50% drop of technology diffusion. Applying this estimate to Australia, for example, with its remote geographic location relative to the G-5 countries, would suggest that Australia benefits extremely little from technology created in the G-5 countries. Along the same lines, Bottazzi and Peri (2003) find a strong geographic decay in their analysis of technology diffusion between European regions. These studies suggest that technology is highly geographically localized in particular countries and regions.

A related question is whether the degree of localization has fallen in recent years. This may be expected as a consequence of transport cost improvements, information, and communication technology innovations, increased multinational activity, as well as other changes. Keller (2002a) examines this by estimating different decay parameters (δ above) for the late 1970s and the early 1990s. The estimates indicate that δ has shrunk substantially over time in absolute value, suggesting that the degree of localization has become smaller. Figure 2 illustrates the results.

According to these estimates, for the period of the 1970s and early 1980s, the degree of localization of technology diffusion was such that at a distance of 1000 km away from the technology sender, on average only about 20% of the technological knowledge was still available (see the dashed line). At 2000 km, this fraction had fallen to about 5%, and once the distance between technology sender and recipient had reached 4000 km, there was virtually no technological knowledge left. In contrast, for a later period (1986–95), the fraction of technological knowledge available according to these estimates is about 70% at 1000 km, 50% at 2000 km, and still about 25% at 4000 km (see the solid line). This provides strong evidence that the information and communication technology innovations mentioned above led to more international diffusion of technology over time.

One concern is that the estimated geography effect may be spurious, perhaps due to unobserved heterogeneity across locations. This issue is addressed in a number of studies, and while the proposed solutions are imperfect, overall the results confirm that geography, in fact, is an important determinant of technology diffusion. The key question is exactly what the geography effect captures: does this pick

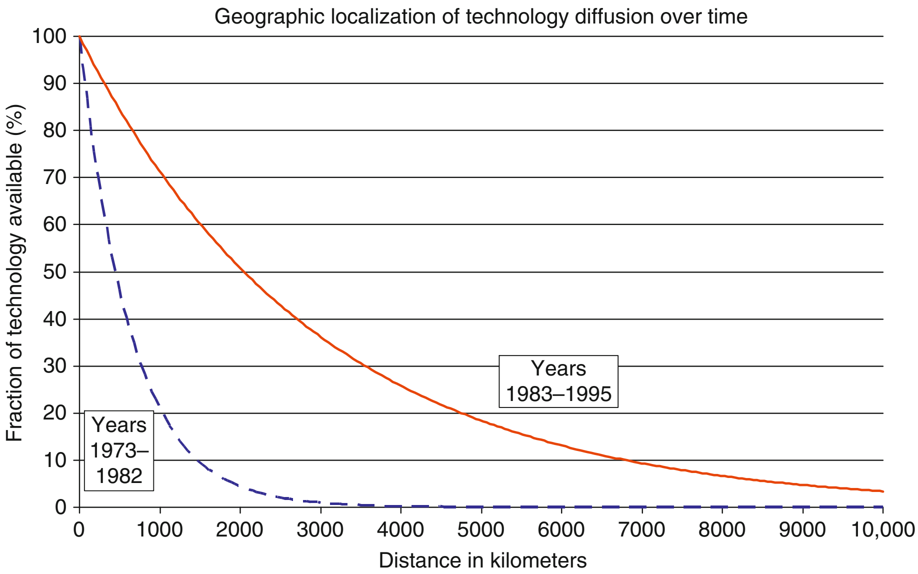


Figure 2. Geographic localization of technology diffusion over time.

up trade costs, for instance? It is well known that trade volumes are strongly declining with distance (Leamer and Levinsohn, 1995), and trade could be is associated with technology transfer (see Section 6). Moreover, FDI is also more prevalent in the geographic vicinity relative to far away destinations (Brainard, 1997). To date research has not fully accounted for the geography effect in international technology diffusion.

The following section discusses the role of FDI for international technology diffusion.

5. FDI as a channel for technology spillovers

In the model described in Section 2, multinational affiliates complete the tasks not imported from their multinational parent through local production in the host country. Local workers are hired for these purposes. If workers learn about the multinational's technology, either by on-the-job activity or formal training, then once they quit they may be able to transmit a positive learning effect to a domestic firm, or they may start their own new firm. Under the realistic assumption that job contract provisions do not fully compensate for these learning effects, the multinational affiliate generates a positive technology spillover to a domestic firm (FDI spillovers through worker turnover).[16]

[16] Fosfuri et al. (2001) provide a model.

Moreover, the multinational affiliate might generate technological learning spillovers to other firms in the industry through its business operations. The literature refers to these within-industry effects as horizontal FDI spillovers. For example, the cold chain operations that *Walmex*, Wal-Mart's affiliate in Mexico, introduced in the 1990s were soon copied by all of *Walmex* retailing competitors (Iacovone et al., 2009).[17] Because the introduction of a cold chain requires major investments, the size of the externality must be less than the value of the cold chain. At the same time, the physical proximity of the multinational affiliate will typically reduce the costs of learning about and adopting such technologies relative to what it would have otherwise been.

Instead of producing everything in-house, as in the model of Section 2, the multinational firm in the model above may also outsource certain intermediate inputs. If the affiliate buys inputs from local suppliers, there may be so-called vertical backward technology spillovers. They arise when the multinational affiliate provides technology to its supplier at a price that is below its market value. In addition, there could be additional vertical technology spillovers if the multinational's technology diffuses from its own to other suppliers. In the case of vertical forward effects, the technology would diffuse from the multinational affiliate to downstream firms.

FDI spillovers matter, not only as a possible channel of international technology diffusion, but also because governments all over the world spend large amounts of resources to attract subsidiaries of multinationals to their jurisdiction. For instance, in 1994 the United States of Alabama spent $230 million, or $ 150,000 per newly created job, to attract a new plant of Mercedes-Benz.[18] Could subsidies of this magnitude possibly be satisfied? To answer this question one requires precise estimates of the size of the positive technological externalities associated with FDI.

Researchers also need to distinguish technological externalities from pecuniary externalities. The latter arise for example if the arrival of a multinational affiliate induces local firms to produce a greater variety of inputs, which may benefit local downstream producers (Rodriguez-Clare, 1996).[19] The case is distinct, because even though there may be productivity gains for domestic firms, there is no transfer of technology. Subsidies to attract a foreign multinational can be domestic welfare-enhancing, but it may be even better for the country to simply remove domestic policy barriers that prevent domestic entry in the downstream market.

The entry of affiliates of multinational firms may also impact domestic firm productivity (as well as profits) in other ways that do not constitute evidence for technology spillovers. First, if the affiliate sells a new quality-upgraded input to domestic final goods producers, it will under realistic assumptions not be able to receive a price that compensates to 100% for the quality improvement. Even though measured productivity of local firms goes up, this is a measurement problem, not a technology spillover (see Griliches, 1995). Second, multinational entry often leads to a higher degree of competition. This increase in competition may induce firms to reduce inefficiencies, and thus increase productivity, but no technology diffusion is involved. The increase in competition through FDI may also reduce the market share of domestic firms, which could reduce productivity if there are scale economies.

[17] Alfaro and Rodriguez-Clare (2004) provide additional examples.

[18] This case is mentioned in Haskel et al. (2007).

[19] This is an example of backward linkages, a concept that goes back to Hirschman (1958). Alfaro and Rodriguez-Clare (2004) provide some discussion.

The size of positive technological externalities associated with FDI is thus difficult to obtain. In addition, the analysis relies typically only on proxies for technology variables—the exact channel is rarely identified. As a consequence, apparent technology spillovers may be spurious. There is a premium, then, for including control variables that may address omitted variables bias. Moreover, plausible exogeneous variation in FDI is needed to establish causality, and this may require instrumental-variable analysis.

I now turn to the evidence for technological externalities from inward FDI.

5.1. Evidence on inward FDI spillovers

What is the evidence on FDI spillovers? Citing primarily panel microeconometric results, observers have recently tended to conclude that there is no evidence for substantial FDI spillovers (Görg and Greenaway, 2004; Rodrik, 1999). Over the last few years, there has been a flurry of studies, and several authors have argued finding evidence for FDI spillovers. We will discuss these results below.

Moreover, there has always been relevant case study evidence on FDI spillovers, which tends to be somewhat overlooked in the economics literature. A case study of Intel's FDI into Costa Rica, for example, provides interesting information on how widespread the changes can be that FDI by a major high-technology company can trigger in a relatively small country (Larrain et al., 2000). The evidence on the impact of Wal-Mart's entry into the Mexican market is also consistent with technological learning externalities accruing to domestically owned firms (Javorcik et al., 2008). At the same time, not all the case study evidence points to technology spillovers associated with FDI. For example, a study on Latin America reports that multinational firms often do not know the technologies employed by their suppliers (Alfaro and Rodriguez-Clare, 2004). Under these circumstances the potential for substantial backward FDI spillovers will be low.

Some authors have provided econometric evidence on whether multinational affiliates raise the rate of international technology transfer as measured by patent citations (Branstetter, 2001; Globermann et al., 2000; Singh, 2003). There are two possibilities. First, affiliates could either disseminate technology to domestic firms of their host country (inward FDI technology spillovers), or they might pick up new technologies from the firms in the host country (outward FDI technology spillovers; see Section 5.2). These studies tend to find that inward technology spillovers are smaller than outward spillovers. This result, however, might be indicative of a number of problems.

The first is firm heterogeneity: multinational affiliates are larger and more technologically intensive than the average firm in the host country, and this might be the reason why they are good at sourcing technology. This interpretation seems to be confirmed by Singh's (2003) finding that patent citations between two multinational affiliates is stronger than either from affiliate to a domestic firm or the reverse. The second issue is endogeneity. It could be that one finds multinational affiliates to be sourcing more technology than they provide because the multinational parent set up the subsidiary with the explicit goal of technology sourcing, while the average host country firm, in contrast, has not made a comparable location decision. This suggests that the estimates are not fully comparable, and future research is needed to settle this issue.

In addition, the value of a patent is difficult to estimate.[20] An important issue in the patent citation studies is therefore the economic significance of the technology diffusion that has been measured in this way. In order to avoid this problem, a large literature has tried to estimate directly the extent to which FDI leads to productivity increases for domestic firms. Xu (2000) uses the US Bureau of Economic Analysis' comparable data on US outward FDI into 40 countries over almost 30 years (between 1966 and 1994). He finds generally a positive relation between FDI and domestic productivity growth, which is stronger in the richer than in the poorer countries.

There may be, however, unobserved heterogeneity across firms and sectors that affects the analysis, and for this reason, authors have recently focused on panel data analysis with micro data (Aitken and Harrison, 1999; Blalock and Gertler, 2008; Girma and Wakelin, 2001; Haskel et al., 2007; Javorcik, 2004; Javorcik and Spatareanu 2008; Keller and Yeaple, 2009b).

The typical chapter estimates a relationship between productivity growth of domestically owned firms (Δln TFP) and a measure of the change in inward FDI (ΔFDI) in order to uncover evidence for FDI spillovers:

$$\Delta \ln \mathrm{TFP}_{ijt} = \beta X' + \gamma \, \Delta \mathrm{FDI}_{jt} + u_{ijt} \tag{13}$$

Here, **X** is a vector of control variables, u is a regression error, and i, j, and t are firm (or plant), industry, and time subscripts, respectively. The parameter γ is estimated positive if productivity growth of firms in industries that have experienced large increases in FDI exceeds that of firms in industries where FDI has grown little. Under certain conditions, this approach can uncover technology spillovers to domestic firms. These spillovers can be in the same industry, as in Equation (13), which is referred to as horizontal spillovers. If the FDI is not in the same industry, but either forward (the multinational sells inputs to domestic firms) or backward (the multinational buys inputs from domestic firms), it is an analysis of vertical FDI effects. The majority of research has been on horizontal spillovers, to which I turn first.

5.1.1. Horizontal FDI spillovers

The recent view that horizontal FDI spillovers are small or do not exist at all starts with the work by Aitken and Harrison (1999). They estimate a negative relationship between inward FDI and domestic industry productivity ($\gamma < 0$), and evidence from Romania and Indonesia has confirmed this pattern (Blalock and Gertler, 2008; Javorcik and Spatareanu, 2008). Because technological learning spillovers cannot be negative, an important question is where this result comes from. One hypothesis, first proposed by Aitken and Harrison (1999), is that whatever positive FDI spillovers there are, they seem to be small compared to the negative impact of FDI on domestic productivity through increased competition.

As long as the analysis only estimates the net effect, of course the magnitude of technology spillovers through FDI is not determined. Thus, in principle, the findings are consistent with FDI spillovers justifying substantial government subsidies. However, a side effect of attracting FDI according to this argument would be lower domestic productivity through the competition effect.[21] At the same time, there is a lot of recent evidence, starting with Pavcnik (2002), that increased competition through trade

[20] See, however, Pakes (1986).

[21] The theoretical prediction for the impact of more competition on innovation is ambiguous (Aghion et al., 2005).

or FDI liberalization *increases*, not decreases domestic firm productivity. The finding of lower firm productivity due to more competition is thus puzzling. If the negative coefficient on FDI in Equation (13) is *not* the result of competition effects, then what else may be behind it?

First of all, the decision of FDI could be endogenous to the productivity of domestic firms. FDI as the mode of market entry may be primarily chosen for industries in which domestic firms are relatively unproductive, and if this is correlated with the ability to benefit from technology spillovers, the FDI coefficient will be biased downwards. The within-industry results of Aitken and Harrison (1999), Javorcik and Spatareanu (2008), and Blalock and Gertler (2008) include industry and time fixed effects to contain such effects. Endogeneity may persist, however, even after the inclusion of fixed effects. An instrumental-variable strategy may be the only way to arrive at unbiased estimates.

Second, studies often face serious data limitations, which require to employ relatively crude measures. Typically, FDI in Equation (13) is the employment or output share of foreign-owned affiliates in an industry. Because this does not capture differences in the technological capabilities flowing into the country by inward FDI across industries and over time, the estimate of γ is likely biased towards zero because of measurement error.

Haskel et al. (2007) study FDI into the United Kingdom to provide evidence on technology spillovers from horizontal FDI. In contrast to earlier work, they estimate positive FDI spillover coefficients. Haskel et al. (2007) relate productivity growth of UK-owned plants to changes in FDI employment shares to 22 manufacturing industries. It is the industry-year variation that identifies the FDI coefficient. To do this properly, it is important to distinguish the effects of FDI from other industry-year specific shocks, such as energy price shocks or new information technology, which also have an industry-specific component. For this, the industry-by-year fixed effects employed by Blalock and Gertler (2008) will be more effective than the additive industry and year dummies in Haskel et al. (2007). Moreover, if there are many plants that are affected by the same FDI inflow in a given industry-year, this will create dependence among the observations, which is equivalent to reducing the sample size. Because the estimated standard errors depend on sample size, this can affect inferences. In Haskel, Pereira, and Slaughter's study there are more than 3000 plants but only 22 industries per year. With t-statistics of around 3 without adjustment for dependence in the sample (Haskel et al., 2007, Table 3), these FDI estimates are not necessarily significant once the dependence across observations is accounted for.[22]

Keller and Yeaple (2009b) consider technology spillovers from inward FDI accruing to US firms during the period of 1987–1996. In contrast to earlier work, these authors find robust and statistically significant evidence for technology spillovers resulting from horizontal FDI, even after addressing important issues such as sample dependence and endogeneity. Moreover, Keller and Yeaple's (2009b) estimates imply an economically large impact, where FDI spillovers account for a substantial fraction—may be close to 20%—of US manufacturing productivity growth.[23]

[22] Clustering standard errors (Moulton, 1990) reduces here the effective sample size n from more than 60,000 (plant-by-year) to 440 (industry-by-year). Least-squares standard errors shrink to zero at a rate of $\sqrt{n}$ (Wooldridge, 2008), which would mean that here the dependence-adjusted standard errors may be higher by a factor of 12. Haskel et al. (2007) also present IV results to shed light on causality. For the IV results, FDI is not significant for half of them (one out of two) even when no adjustment for sample dependence is made (Haskel et al., 2007, Table 3).

[23] Keller and Yeaple's estimates range from 8% to 19%, the latter being the preferred IV estimate.

Given these differences in results, an important question is where Keller and Yeaple's (2009b) analysis differs from earlier studies. Some observers have concluded that while there are no horizontal technology spillovers from FDI in less developed countries, they do seem to exist in richer countries, such as the United States. However, this cannot be the full story, because there is much variation in FDI spillover estimates even among the set of rich countries.[24] Apart from that, why might there be no horizontal FDI spillover in less developed countries? Is the reason that the firms' capacity to benefit from FDI spillovers in less developed countries is lower? (Keller, 1996). For one, this explanation ignores firm heterogeneity in the host country. In addition, there is evidence that it is primarily the relatively small, low-productivity firms that benefit from FDI spillovers.[25] Thus, a simple technology gap explanation may not be able to explain the different findings for less developed versus rich countries.

There is evidence, however, that technology spillovers from horizontal FDI are concentrated in high-technology sectors, whereas there are no FDI spillovers in low-tech sectors (Keller and Yeaple, 2009b). High-tech sectors are where most technology creation takes place. Moreover, this suggests that FDI can have vastly different spillover potential: low-skilled assembly activities for reexport to the United States such as the Mexican maquiladoras should be expected to have lower spillovers than R&D-intensity foreign activities that are attracted to an industrial development park in Bangalore. The quality of the FDI data also makes a big difference. Keller and Yeaple (2009b) only find evidence for substantial technology spillovers from FDI when the diversification of multinational affiliates is accounted for in their FDI measure.[26] When instead using less-well-measured FDI data, they do not find evidence for technology spillovers from horizontal FDI, similar to earlier studies.

5.1.2. Vertical FDI spillovers

There have also been advances recently in estimating technology spillovers from vertical FDI relations (e.g., Blalock and Gertler, 2008; Javorcik, 2004). The focus has been primarily on backward linkages, because multinational affiliates may have an incentive to transfer knowledge to local firms in upstream sectors, as they may benefit from the improved performance of intermediate input suppliers (Javorcik and Spatareanu, 2008). However, while multinational affiliates may have an incentive to transfer technology to their suppliers as this enables them to buy high-quality inputs from them, it is not clear that multinationals would provide the technology free of charge.

More generally, the dilemma is that the more clearly identifiable the recipient of the multinational's technology transfer is, the less likely is it that any productivity effect is due to technological externalities. To arrive at an estimate of any externalities involved, the outright contractual payment for the technology transfer has to be subtracted from the supplier's revenues before computing its productivity. If in a given

[24] Comparing Haskel et al.'s (2007) study for the United Kingdom and Keller and Yeaple's (2009b) analysis for the United States, the FDI coefficients differ by a factor of about 10 (0.05 in the former and 0.5 in the latter).
[25] At least in a high-income country such as the United States (Keller and Yeaple, 2009b).
[26] These authors can keep track of changes in the composition of affiliates' activities for their top-6 industries; in contrast, most studies of FDI spillovers treat a given plant or firm as producing in only one industry.

year the supplier gains a net benefit from the technology transfer, this might be an artifact of measurement problems.[27] Thus vertical FDI spillovers may pick up a set of issues that do not arise when studying horizontal FDI, making these sets of estimates incomparable in terms of technological spillover findings.

Javorcik (2004) finds that domestic firms in Lithuania in the late 1990s that are upstream to industries which experienced a relatively strong inflow of FDI have systematically higher productivity than other domestic firms. Blalock and Gertler (2008) show a similar finding for Indonesian firms. These findings are consistent with technology spillovers through vertical FDI. At the same time, there are some reasons to be cautious. First of all, in the absence of direct evidence on buyer–seller relations, both studies employ economy-wide input–output tables to model the interaction of domestic firms with upstream multinational affiliates. This may lead to estimation bias if multinationals sourcing patterns are not the same as those of domestic firms (see Alfaro and Rodriguez-Clare, 2004 for evidence).

An interesting additional finding in Javorcik (2004) is that the correlation of productivity with FDI is strongest if the multinational is only partially, and not fully foreign owned. The result is confirmed in Javorcik and Spatareanu (2008) for a sample of Romanian firms. This is consistent with the idea that joint ownership generates more technology transfer, perhaps because wholly owned affiliates employ more sophisticated technology that is out of reach for the average domestic supplier. If the technology gap between foreign and domestic firms is the key reason for the differential effect for wholly versus partially owned affiliates, however, there should be in general a higher spillover for relatively low- compared to high-productivity domestic firms. As mentioned above, this is in line with some evidence from studies on horizontal FDI. At the same time, Javorcik and Spatareanu (2008, Table 4) report relatively high FDI coefficients for the relatively high-productivity firms. This suggests that the strong joint ownership effects are not related to the firms' differential technology gap. Future research should address this important question.

Blalock and Gertler (2008) correctly emphasize that productivity gains can only be externalities, and therefore a possible concern for policy intervention, if also domestic firms that are not the immediate supplier of the multinational affiliate experience higher productivity. This could be, for example, domestic suppliers that do not directly interact with multinational affiliates, or domestic downstream firms that "free ride" on the technology transfer from multinational affiliate to the local supplier by also buying inputs from that supplier. In order to shed light on this, Blalock and Gertler (2008) present additional results on the relationship between downstream FDI and upstream industry price, output, and profits. The results are in line with what one expects in the presence of technology spillovers—lower price, higher output, (marginally) higher profits. Blalock and Gertler (2008) do not provide IV estimation results to deal with the endogeneity of FDI location.[28]

5.1.3. FDI spillovers from labor turnover

There is also some recent work on labor mobility as a specific mechanism for FDI spillovers (Gorg and Strobl, 2005; Poole 2009). Poole (2009) estimates what may be called wage spillovers from a large matched establishment–employee dataset for Brazil. Specifically, she finds that workers in establishments with a higher proportion of workers with some experience at a multinational firm earn higher

[27] Griliches (1995) argued that such "measurement" spillovers are most prevalent when intermediate goods are being supplied; here the intermediate good is the technological knowledge.

[28] Also Javorcik (2004) and Javorcik and Spatareanu (2008) do not employ instrumental-variable estimation.

wages, consistent with the idea that there are knowledge transfers from multinational to domestic firms' workers. Her preferred estimate of the typical wage gain through former multinational workers is quite small, at 0.1% for the average worker, though this may well be only the lower bound for various reasons.[29]

Using data for about 200 Ghanaian firms, Gorg and Strobl (2005) investigate whether domestic firms which have entrepreneurs with previous training at a foreign-owned affiliate have a productivity advantage compared to other firms. The authors find that when the prior multinational training took place in a firm belonging to the same industry, there are productivity benefits, whereas there are no productivity benefits if the training occurred in a multinational that was part of a different industry. Thus, Gorg and Strobl's evidence for horizontal spillovers through labor turnover is stronger than that for interindustry spillovers.

To summarize, there has been much progress in recent studies of technology spillovers related to FDI. While few authors employing micro panel data have estimated positive horizontal spillovers, a number of crucial issues have become clear. First, one must be able to isolate spillovers from other effects, and second, the FDI data must track well changes in foreign activity to avoid attenuation bias. One study arguably provides robust evidence that inward FDI is causal in raising the productivity of domestic firms in the same industry (Keller and Yeaple, 2009b). While it suggests that technology spillovers from FDI materialize mainly in high-tech industries, they appear to be economically important, accounting for a substantial fraction of firms' overall productivity growth.

There are now several papers which suggest that there may be technology spillovers from vertical FDI. Future work should, first, confirm these results while employing credible exogenous variation in FDI, perhaps, through instrumental-variable estimation. Second, it will be crucial to separate true technology spillovers from arms-length technology transactions, linkage effects, and measurement spillovers associated with vertical FDI, because the case for public policy intervention rests with the former, not the latter.

Taken together, there is now evidence that both horizontal and vertical spillovers associated with FDI are important. In the following section, I am turning to evidence for technology spillovers from outward FDI.

5.2. *Outward foreign direct investment spillovers*

While most of the work on FDI spillovers has focused on inward FDI, researchers have also studied whether multinationals go abroad to acquire technological knowledge from other firms. The leading example of this may be a foreign firm locating an affiliate in the United States' Silicon Valley in order to "source" technology from the firms in its environment. There are some reasons to believe that this may be important. First of all, while for US multinational firms around 85% of all R&D is conducted in the parent firm, this fraction is typically higher for foreign firms that invest in the United States. The comparatively high level of R&D of these countries' affiliates in the United States is consistent with the idea that they have to develop the absorptive capacity (Cohen and Levinthal, 1990) to be able to reap technology spillovers from local firms.

Researchers have looked at the patent citations of these firms to confirm the hypothesis (Branstetter, 2006). performs a treatment-and-control group analysis of patent citations in the United States

[29] It would be desirable to have information on the establishment at the time when it hires the former multinational worker, however, Poole's (2009) otherwise remarkable dataset does not provide this.

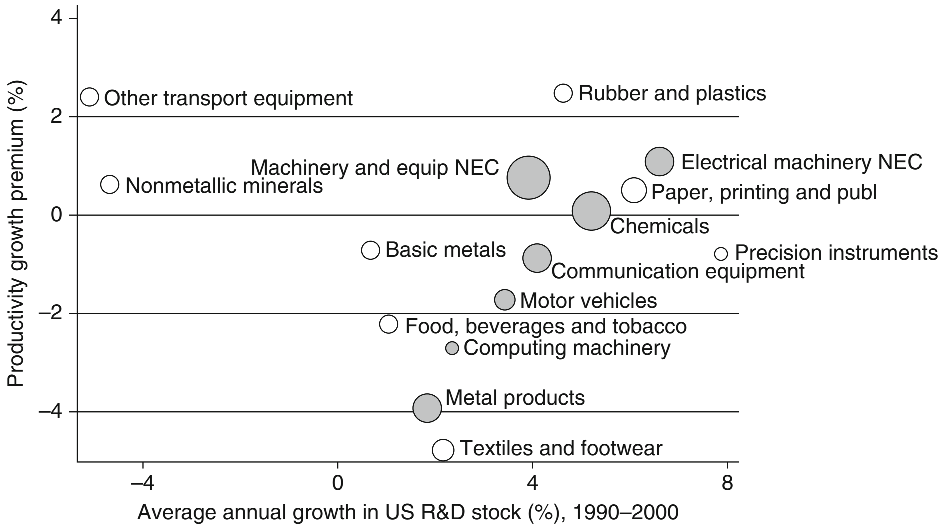


Figure 3. Productivity growth from foreign technology sourcing.

semiconductor industry similar in spirit to Jaffe et al. (1993), finding that foreign firms cite the patents of other firms in their geographic environment more strongly than the similar domestic firms. Branstetter (2006) examines the patent citation pattern of about 200 Japanese firms for the years 1980–1997. He finds that Japanese firms that have a relatively large number of affiliates in the United States cite US patents to a greater extent than Japanese firms with fewer affiliates located in the United States. This finding is strongest for Japanese R&D and product development facilities in the United States. While Branstetter (2006) does not model the reason for the location decision of Japanese firms, he controls for technological proximity, which reduces endogeneity concerns.

Researchers have also provided evidence on technology sourcing through FDI in terms of effects on firm-level productivity growth. This is shown in Figure 3.

U.S. R&D growth by industry over the period 1990–2000 against the productivity growth premium of UK firms, defined as the growth of firms with a strong versus a weak technological presence in the United States. We see that the UK productivity growth premium tends to be higher in industries for which US R&D has grown relatively strongly.[30] As the measure for technological presence, the authors compute for each UK firm the fraction of its US patent applications for which the lead inventor is located in the United States. This gives a useful combination of using patent and productivity data to study international technology diffusion. The evidence is consistent with the idea that outward FDI helps to bring foreign technology into a country.

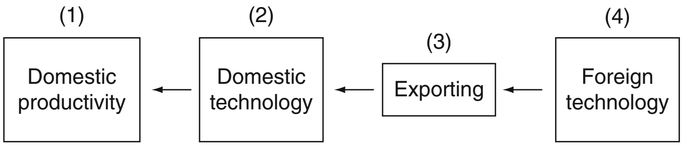
The following section discusses the evidence on international trade as a channel for technology spillovers.

[30] The gray circles are industries in which the United Kingdom lag behind the US productivity levels was particularly large in 1990, and therefore there was "the most to learn."

6. International trade

6.1. Evidence on spillovers through exporting

A major question is whether firms receive technology spillovers through their exporting experience. Ideally, one would like to see evidence on the full chain of events:



(14)

Thus, a domestic firm might through its exporting activity come into contact with foreign technology. This raises the domestic firm's technological capacity, which in turn increases the domestic firm's productivity. It turns out that there is typically no evidence on the simultaneous presence of all four elements presented above.

There is anecdotal evidence however claiming that firms do benefit from interacting with foreign customer, for instance because the latter impose higher product quality standards than domestic customer, while at the same time providing information on how to meet the higher standards. Case studies of the export success of a number of East Asian countries starting in the 1960s are particularly strong in their emphasis on learning-by-exporting effects (Rhee et al., 1984). The question is whether this evidence can be supported with econometric evidence.

There is abundant evidence that in a given cross-section, exporters are on average more productive than nonexporters (Bernard and Jensen, 1999; Clerides et al., 1998; Hallward-Driemeier et al., 2002). That does not settle the issue of causality however: Are exporting firms more productive because of learning effects associated with exporting, or is it rather the case that more firms that are more productive to start out with self-select into exporting? Currently, there is more evidence in favor of selection, however, a number of recent contributions have presented evidence that supports the learning-by-exporting view as well.

While learning-by-exporting has been emphasized primarily for low- and middle-income countries' firms, there is in principle no reason why it is limited to these countries, especially given the firms' heterogeneity in terms of productivity in any given country. Bernard and Jensen (1999) study the learning-by-exporting question using data on US firms. This has the advantage that the sample is relatively large and there is comparatively much experience with data collection and preparation, which may result in lower measurement error.

Bernard and Jensen (1999) do not model export market participation explicitly. Instead, they study the performance of different sets of firms separately.[31] Bernard and Jensen estimate that labor productivity growth for exporters is about 0.8% higher than for nonexporters.[32] This estimate is fairly small, and it becomes even smaller (and insignificant) for longer time horizons. However, the estimate of 0.8%

[31] Four types of firms can be distinguished: exporters, nonexporters, starters (plants that start exporting), and quitters (plants that stop exporting).

[32] Bernard and Jensen's estimates using TFP instead of labor productivity are lower, but the labor productivity figures are preferred in this case. The TFP measure is a simple regression residual that is fallible to a number of problems. Griliches and Mairesse (1998) provide a discussion of recent work on this.

appears to be a downward biased estimate of the learning-by-exporting effect because it comes from an analysis conditional on plant survival. Bernard and Jensen show that conditional on size, exporters are 10% more likely to survive than nonexporters.[33] It is plausible that this 10% survival probability difference is indicative of higher productivity growth for exporters than nonexporters, because plants tend to fail because their productivity growth is low. This suggests that the overall difference in productivity growth between exporters and nonexporters may be larger than 0.8%.

The paper by Clerides et al. (1998) provides evidence on learning externalities from exporting using micro data from Columbia, Morocco, and Mexico. By estimating simultaneously a dynamic discrete choice equation that determines export market participation, these authors take account that it is on average the already-productive firms that self-select into the export market. The export market participation decision is given by

$$y_{it} = \begin{cases} 1 & \text{if } 0 \leq \beta^x X_{it} + \beta^e e_t + \sum_{j=1}^{J} \beta_j^c \ln \mathrm{AVC}_{it-j} + \sum_{j=1}^{J} (F^0 - F^j) y_{ij-j} + \eta_{it} \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

and any learning-from-exporting effects are uncovered by simultaneously estimating an autoregressive cost function

$$\ln \mathrm{AVC}_{it} = \gamma_0 + \sum_{j=1}^{J} \gamma_j^k \ln K_{it-j} + \gamma^e \ln e_t + \sum_{j=1}^{J} \gamma_j^c \ln \mathrm{AVC}_{it-j} + \sum_{j=1}^{J} \gamma_j^y y_{it-j} + v_{it} \tag{16}$$

Here, y_{it} is the export indicator of plant i in period t, X_{it} is a vector of exogenous plant characteristics, e_t is the exchange rate, AVC_{it} are average costs, K_{it} is capital, and F^0 and F^J are sunk costs of export market participation.

The export equation states that one only sees a plant exporting if the profits from doing so are greater than from not exporting (the latent threshold is expressed in terms of observables). The dynamic cost equation asks whether past exporting experience reduces current cost (captured by the parameters γ_j^y), conditional on past costs and size (proxied by capital). Clerides et al. (1998) show results for the three countries separately, and also by major industry, using maximum likelihood and generalized method of moments estimation. They also discuss results for each country separately, and also by major industry. In general, they tend to show no significant effects from past exporting experience on current performance. In fact, to the extent that Clerides et al.'s estimates are significant, they go into the wrong direction (exporting raising costs). It would be surprising if indeed there would be negative learning effects, and the authors give a number of plausible reasons of why this finding may have to be discounted. Another interpretation of the generally insignificant estimates may be that the estimation framework is demanding too much of the data. However, Clerides et al.'s descriptive plots of average cost before and after export market entry support their main result of no evidence for

[33] Size is the main predictor of survival in recent industry-equilibrium models (e.g., Olley and Pakes, 1996), because a small firm might have to exit after only one bad shock, whereas, a large firm has substance enough to weather a longer succession of bad shocks.

learning-by-exporting effects. Exporters are more productive, but that is because they self-select themselves into the export market.

Some of these estimates come from a relatively small number of years, and there may be an argument that this time horizon is too short to see major learning-by-exporting effects. Alternatively, Hallward-Driemeier et al. (2002) focus on the time before entering the export market. These authors use data from five Southeast Asian countries to show that firms which eventually become exporters make more investments to raise productivity and the quality of their goods than firms that plan to stay out of the export market. This is plausible, but if these investments require—which is likely—real resources, those need to be subtracted from any learning effects the firms receive after they have entered the export market.[34] Moreover, given that the productivity increases pre-date the firm's entry into the export market, at best these are indirect learning-by-exporting effects.

Using similar methods as Clerides et al. (1998), van Biesebroeck (2005) has revisited the issue by studying productivity dynamics of firms in nine African countries. In contrast to Clerides et al., he estimates that starting to export boosts productivity by about 25% for the average firm in his sample. van Biesebroeck (2005) also estimates that the higher productivity growth of exporters versus nonexporters is sustained. By employing instrumental-variable and semiparametric techniques as alternative ways to deal with the selection issue, van Biesebroeck's analysis is more comprehensive than most. His analysis generally supports the notion that exporting leads to the transfer of technological knowledge. In trying to reconcile his findings with some of the earlier results, van Biesebroeck shows that part of the difference in productivity growth between exporters and nonexporters appears to be due to unexploited scale economies for the latter. This suggests that at least in part his results are due to constraints imposed by demand, and not due to technology transfer in the sense of an outward shift of the production possibility frontier at all levels of production. Richer data is needed to make further progress on distinguishing these hypotheses.

De Loecker (2007) uses matched sampling techniques to analyze whether firms that start exporting become more productive, using micro data of Slovenian manufacturing firms. Controlling for self-selection into exporting, De Loecker finds that export entrants indeed become more productive once they start exporting, and that the productivity gap between exporters and their domestic counterparts increases further over time.

In these papers, the evidence is primarily on elements (1) and (3) in the above diagram: the authors observe productivity and whether a firm exports or not. The analysis might be considerably strengthened by including information on elements (2) and (4), namely on the specific channel through which a firm's domestic technological capabilities have benefited from foreign technology. Utar (2009) makes progress on this by examining the impact of foreign technical service (FTS) purchases on the productivity of firms that are starting to export. The idea is that such foreign technical training and assistance or technological license purchases may give firms a better chance to access and absorb the foreign technology that they encounter while exporting their product. Because these are purchases, it is clear that they are not spillovers as such. At the same time, Utar provides evidence that learning spillovers from exporting are correlated with FTS purchases.

[34] This point is related to the fact that none of these estimates are claimed to be spillover effects; rather, they are learning effects, which could be costly to acquire. Clerides et al. (1998) do estimate spillovers to other plants; the evidence on this is mixed.

Overall, the econometric evidence for learning-from-exporting effects is mixed. The early evidence strongly supported the selection view, although recently the evidence from firm-level studies has started to tilt in favor of learning-from-exporting. There are a number of issues that still need to be addressed. First, there could be heterogeneity across industries masking strong but industry-specific learning effects, especially with respect to high-technology products.[35] Second, the analysis could be improved if we knew more on both the export destination and the exporter, instead of simply an indicator variable (exporting yes/no). For instance, to which firms, in which countries, do the exports go? Interestingly, in one study where such information is available (De Loecker, 2007), it is found that firms that export to high-income countries experience higher productivity gains than firms that export to low-income countries, consistent with technology spillovers. We need more work on these issues. Moreover, it is still not clear under which circumstances there is learning-from-exporting, and when there is none.

6.2. *Evidence on spillovers through imports*

In the model of Section 2, affiliates import intermediate goods embodying the multinational firm's technology. This amounts to the diffusion of technological knowledge from one country to another, within a given firm. Technology spillovers result when other firms learn about the multinational's technology. For example, host country firms in the same industry as the multinational affiliate might get acquainted with the characteristics of the imported good, allowing them to create a similar technology at relatively low costs.

Evidence on technology spillovers through imports will ideally cover multiple elements, as in the case of exports (see Equation (14)):

$$\overset{(1)}{\boxed{\begin{array}{c}\text{Domestic}\\ \text{productivity}\end{array}}} \longleftarrow \overset{(2)}{\boxed{\begin{array}{c}\text{Domestic}\\ \text{technology}\end{array}}} \longleftarrow \overset{(3)}{\boxed{\text{Importing}}} \longleftarrow \overset{(4)}{\boxed{\begin{array}{c}\text{Foreign}\\ \text{technology}\end{array}}} \tag{17}$$

Thus, foreign technological knowledge would augment the domestic technology stock by way of imports, and that raises domestic productivity.

One strand of evidence has employed micro data to study the productivity consequences of import liberalization. The seminal paper by Pavcnik (2002) studies the Chilean liberalizations of the late 1970s and early 1980s. She finds that the productivity of plants in industries that are most affected by import liberalization increases by more than that of plants that are less affected by liberalization. Pavcnik interprets these within-plant productivity improvements primarily as reductions in X-inefficiency, or that plants "trim their fat." This would not involve technology spillovers. Amiti and Konings (2008) show using manufacturing census data for Indonesia that it is primarily the liberalization of input tariffs, not output tariffs, that is behind the observed productivity gains. They argue that lower input tariffs may lead to gains

[35] Industry heterogeneity has recently been emphasized in the literature on inward FDI (see Section 5.1). However, Clerides et al. (1998), for example, do not estimate major differences across industries.

due to variety, quality, embodied technology, and learning. It will be crucial to employ more information on technology—elements (2) and (4) in Equation (17)—to make further progress on these questions.

Another strand of the literature has employed firm-level data to study technology learning from imports through vertical links (Blalock and Veloso, 2007). In analogy to vertical FDI spillovers (see Section 5.1), domestic firms that supply a downstream industry in which the share of imported inputs is relatively high may face a relatively high potential for technology spillovers, perhaps because the downstream firm provides relevant information on the initially superior imported inputs at low or zero costs. Blalock and Veloso (2007) show evidence consistent with this for the case of Indonesia. To go further, future research in this vein should try to incorporate the technology channel directly, both in the theory and in the empirical work. Research on international and interindustry technology spillovers at the industry level has found strong evidence for both, see Keller (2002b). An important question is whether these results hold up at the micro level.

There is also evidence on technology diffusion through trade of intermediate, or equipment, goods. In Eaton and Kortum (2001, 2002), the authors have combined the structure of technology diffusion in Eaton and Kortum (1999) with the Ricardian model of trade due to Dornbusch et al. (1977). In Eaton and Kortum's model, trade augments a country's consumption possibilities for the classic Ricardian reason: trade gives access to foreign-produced goods or, implicitly, their production technologies. By specializing in their respective comparative advantage goods, countries can gain from trade because given a country's resources, the value of output with trade is higher than without trade. There are no spillovers in this model. Importers pay the competitive price and importing has no effect on innovation. However, importing may raise the probability that technology spillovers materialize.

Eaton and Kortum (2001) assume that unit transport costs are increasing in geographic distance. This implies that the price of equipment goods in remote countries is relatively high, or, equivalently, that productivity in these countries is relatively low. These effects are shown to be quantitatively important, as differences in the relative price of equipment account for 25% of the cross-country productivity differences in a sample of 34 countries (Eaton and Kortum, 2001). However, according to Eaton and Kortum's model, equipment goods prices are relatively low in rich countries, whereas, the price data reported by Summers and Heston's International Comparison Program shows that equipment prices are relatively high in rich countries.[36] This suggests that other mechanisms are also important.

There is also evidence on the importance of imports that comes from international R&D spillover regressions. Coe and Helpman (1995) relate TFP to domestic (S_{ct}) and foreign R&D in year t:

$$\ln \mathrm{TFP}_{ct} = \alpha_c + \beta_d \ln S_{ct} + \beta_f \ln S_{ct}^f + \varepsilon_{ct}$$

where S_{ct}^f is defined as the bilateral import-share weighted R&D stocks of its trade partners, $S_{ct}^f = \sum_{c'} m_{c'c} S_{ct}$. A positive effect from the foreign R&D variable would imply that a country's productivity is increasing in the extent to which it imports from high- as opposed to low-R&D countries. This would support the hypothesis that imports are a channel of technology diffusion along the lines of the trade-and-growth models discussed in Grossman and Helpman (1991). In a sample with 22 OECD countries, Coe and Helpman (1995) estimate a positive and quantitatively large effect from

36 See Eaton and Kortum's (2001, Figure 7) and CIS (2003), respectively.

import-weighted foreign R&D. Similar effects are found for technology diffusion from highly industrialized to 77 less developed countries (Coe et al., 1997).

There are some reasons to remain skeptical here. First, the analysis of Keller (1998) has shown that the import shares in the construction of the foreign R&D variable S_{ct}^{f} are not, in fact, essential to obtain Coe and Helpman's (1995) results. Specifically, Keller (1998) uses randomly created shares, denoted by $\mu_{c'c}$, in place of the actual bilateral import shares to create the counterfactual foreign knowledge stock $\tilde{S}_{ct}^{f} = \sum_{c'} \mu_{c'c} S_{ct}$ Using this alternative foreign R&D variable yields similarly high coefficients and levels of explained variation as the regressions using the observed bilateral import shares. Given that import shares are not essential for Coe and Helpman's (1995) results, their analysis does not allow to draw strong conclusions regarding the importance of imports as a vehicle for diffusion.[37]

A number of authors have made progress by examining the international R&D spillover regressions further. Xu and Wang (1999) emphasize that technology diffusion in recent trade-and-growth models is associated specifically with differentiated capital goods trade. This is in contrast to the trade data Coe and Helpman (1995) use to construct their import shares (which come from overall trade). Xu and Wang (1999) show that this distinction matters: the capital goods–foreign R&D variable accounts for about 10% more of the variation in productivity than does Coe and Helpman's analysis, and it also performs better than Keller's (1998) counterfactual variable.

Moreover, it has been noted that the foreign R&D variable captures only current-period bilateral trade; it is clearly possible though that country A benefits from country C's technology without importing from this source, if country C exports to country B, which in turn exports to country A. Lumenga-Neso et al. (2005) use a specification that captures such indirect R&D spillovers, and show that it performs better than Coe and Helpman's (1995) and Keller's (1998) models. These results are consistent with the importance of dynamic effects from imports, but more research in an explicitly dynamic framework is needed to learn more about this.

The analysis by Acharya and Keller (2008a) extends the international R&D spillover literature in a number of dimensions. First, it encompasses more countries and a longer sample period of 30 years, and perhaps most importantly, it allows isolating major high-technology sectors—computers, information, and communication technology—that were the drivers of recent economy-wide productivity growth. Second, on the econometric side, they employ instrumental-variable and control-function approaches to estimate causal effects as opposed to correlations. Acharya and Keller (2008a) move away from the import-share weighted variable S^{f}; instead, they relate industry TFP in a sample of high-income countries to both the R&D in six large OECD countries[38] and bilateral imports from these six OECD countries:

$$\ln \mathrm{TFP}_{cit} = X\kappa + \beta_d \ln S_{ct} + \sum_{s \in \text{G-6}} \beta_{cs} \ln S_{st} + \sum_{s \in \text{G-6}} \zeta_{cs} (\tilde{m}_{csit} \ln S_{st}) + \sum_{s \in \text{G-6}} \gamma_s \tilde{m}_{csit} + \varepsilon_{cit} \tag{18}$$

where $\tilde{m}_{csit}$ is the import share of country c from one of the six large OECD, or G-6, countries, s. Thus, Equation (18) introduces the R&D of each of the G-6 countries separately, allowing for varying R&D

[37] Alternatively, Keller (1998) sets all $\mu_{c'c}$ equal to 1, which produces similar results. This confirms that the import shares do not matter for the results, whether or not they are truly random (see Coe and Hoffmaister, 1999; Keller, 1997, 2000).

[38] These are Canada, France, Germany, Japan, the United Kingdom, and the United States.

elasticities. In addition, the specification includes the R&D–import share interaction as well as imports as separate variables, while the control variables **X** are fixed effects.

The results indicate that international technology diffusion has both important components that are related to imports and others that are not related to imports, which are separately identified in Equation (18) by the parameters ζ and β, respectively. The relative magnitude of the two parameters gives information on the relative importance of imports-related technology diffusion. For example, Acharya and Keller (2008a) show that the majority of all technology transfer from the United States and the United Kingdom occurs through imports, whereas Germany and Japan transfer technology abroad primarily through nontrade channels.

The estimates also provide evidence for heterogeneity in international technology diffusion. For example, the impact of US R&D on UK productivity is twice as large as the US effect in Germany or Spain. They also find that some countries benefit more from foreign technology than other countries across the board. Canada, for example, benefits about 50% more from Japanese R&D and 33% more from French R&D than the average country, suggesting that Canada has a relatively high absorptive capacity for benefiting from international technology spillovers. Coe et al. (2008) also provide evidence on heterogeneity in international R&D spillovers by showing that they are stronger in the presence of the following institutions: doing business requires few permits, a high quality of tertiary education, strong intellectual property rights protection, and a particular origin of the legal system. These authors also find that financial development, labor market institutions, governance, and ease of trade across borders do not matter for the strength of international R&D spillovers.

Madsen (2007) employs information on domestic patent applications instead of R&D to construct the foreign knowledge stocks using bilateral import-share weights. Because patent data is available since the late nineteenth century, this allows for a considerably extended sample period. The long sample period is helpful because it increases the statistical power of the tests employed in his cointegration framework. His results are broadly supportive of the hypothesis that imports contribute to the international transmission of foreign technology.

The importance of imports for technology diffusion has also been assessed with patent citation data. Sjöholm (1996) studies citations in patent applications of Swedish firms to patents owned by foreign inventors. Controlling for a number of other correlates and also conducting an extreme-bounds analysis, Sjöholm finds a positive correlation between Swedish patent citations and bilateral imports. Another study by MacGarvie (2006) looks at patent citations of a large sample of French firms. She finds that French firms which import from another country j cite country j patents more than French firms that do not, by about 40% relative to their preimporting citation behavior. Moreover, foreign firms in country j also cite relatively strongly the patents of French firms that import from country j. Interestingly, the same is not true for exports. MacGarvie's results are robust to employing both regressions (count data) models as well as matching estimators. The results support the idea that imports contribute to international technology spillovers.

How sure can we be of quantitative results? If a firm's propensity to cite foreign technology from some country and its propensity to import from that country are positively correlated, it would be reasonable to expect a lower increase in citations for a randomly chosen new importer. Instrumental-variable estimation is one way to address these concerns.

Summarizing, the evidence points to a significant role for important in international technology diffusion. We now turn to some concluding observations.

7. Conclusions

How can the theory laid out in Section 2 be used to think about the findings that were just discussed? First, there is the finding of geographic localization of international technology diffusion. This seemingly puzzling result—after all, is technological knowledge not weightless, after all?—is easily explained if one considers the transactions costs of international commerce more broadly.[39] Yes, there are trade costs for shipping technology in embodied form, but it is also costly to communicate disembodied technological knowledge, especially if it cannot be done face-to-face. As firms equate trade and technology transfer costs at the margin, technology transfer falls with the distance between technology sender and recipient, even though technological knowledge is weightless. Technology diffusion declines with distance because in equilibrium technology transfer to remote locations is relatively costly, so there is less of it.

Moreover, in the model above multinational affiliates import intermediate goods from their parent while at the same time they produce other inputs locally. The evidence for technology spillovers associated with inward FDI discussed above is at least as strong, and may be stronger than the evidence for spillovers from importing. Thus it appears that technology learning externalities are enhanced by the physical presence of the affiliate plant, perhaps through labor turnover. Even taking account of the fact that around half of all world trade is between unaffiliated parties, technology embodied in intermediate goods may not be as accessible, and consequently technology spillovers may be lower.[40] As we have seen there is also evidence consistent with technology externalities from outward FDI. With regards to learning benefits from exporting activity, there is currently no consensus although recent evidence suggests export spillovers exist at least in specific circumstances.[41]

A perennial problem remains the appropriate measurement of technology spillovers. First of all, any costly investment has to be netted out before computing the spillover benefits. Second, it is very difficult to identify technology spillovers without information on technology indicators, as is the case for example when considering the relation between productivity and FDI or imports. Observing data on technological capabilities obviously strengthens the analysis; however, another issue is that productivity is often difficult to measure. Because of that it may be tempting to focus on evidence of technological knowledge transfers. This could be done by observing an increase in patent citations or other measures, for example the finding that an increase in imports raises the product variety of domestic firms. At the same time, without linking these variables to productivity, the results stop short of being an analysis of economic welfare.

We have seen that important findings can result from a number of different empirical methods. It is often difficult to move from showing a correlation to establishing a causal effect. Nevertheless, it is important. Researchers might also specify a model, choosing parameters to match certain data moments, and then simulate it. Such counterfactuals can help to develop intuition that may be otherwise

[39] In a weightless economy, intangible goods and in particular knowledge play the dominant role; see Quah (1999).

[40] There may of course be large productivity benefits from new intermediate goods, but only a fraction of these will be externalities.

[41] The model of Section 2 is not very well suited to explain these findings, mostly because, as is the case in almost all theory on multinational firms, all technology is generated in the headquarters of the firm (the parent). This assumption fits well the case of US multinational firms, where around 85% of all R&D is done by the parents; for multinational firms of other countries, we know much less. However, one may conjecture that parents do most of the R&D in multinationals from virtually any country.

unattainable. At the same time, it is often a challenge to agree on the relevant data moments that should be targeted, especially given that technology spillovers are hard to identify. It is difficult to believe that one can dispense with the necessity of establishing causality using regression techniques.

There are a number of issues that this chapter has not addressed very much, mostly because work in these areas is still in its infancy. For one, the trade model of Melitz (2003) explains aggregate productivity changes through market share reallocation among firms with heterogeneous but fixed firm efficiency (or productivity). While this framework rules out within-firm productivity changes, and hence technology spillovers, future work may be able to analyze productivity changes due to within- *and* between-firm effects at the same time; some initial empirical results suggest that both are important (Acharya and Keller, 2008b).

Second, firms that are heterogeneous in terms of efficiency react differently to changes in the degree of competition (Aghion et al., 2005; Iacovone et al., 2009). As discussed above, changes in the competitive environment may make it difficult to isolate technology spillovers. If there are predictions on which firm will be more affected and which firm less, however, this should be helpful in making further progress on estimating technology spillovers. Finally, an important question is whether one should think about technology spillovers as affecting production efficiency, or also affecting marketing and catering to consumer taste.[42]

In recent years we have witnessed a lot of important work on international technology diffusion, and the areas just mentioned may well be among the exciting research areas where major progress is going to take place in the years ahead.

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[42] See, for example, Foster et al.’s (2008) work on selection on productivity versus profitability.

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