Multinational Enterprises, International Trade, and Productivity Growth: Firm-Level Evidence from the United States[1]

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Abstract

We estimate international technology spillovers to U.S. manufacturing firms via imports and foreign direct investment (FDI) between the years of 1987 and 1996. In contrast to earlier work, our results suggest that FDI leads to significant productivity gains for domestic firms. There is also some evidence for imports-related spillovers, but it is weaker than for FDI. The size of FDI spillovers is economically important: we estimate that they accounted for about 13% of productivity growth in U.S. firms between 1987 and 1996. We also trace out the effects that differences in our study relative to previous work have, showing that our results are likely to generalize to other countries and periods.

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1. Introduction

Productivity increases are critical for output and economic welfare to rise over time. If growth is instead due to more inputs, welfare typically rises by less, because work generates less utility than taking leisure. The absence of productivity growth would also impose more narrow limits to growth, as inputs such as the work time in a day cannot be augmented indefinitely. These considerations are consistent with recent cross-country evidence. Differences in productivity growth are found to be a major determinant of differences in income growth (Easterly and Levine 2001), and differences in income levels across countries can be to a large extent traced back to differences in productivity levels (Prescott 1998, Hall and Jones 1999).

Why do these differences in productivity exist? Instead of the view that this is simply due to technological change occurring at different rates in isolated countries, some authors have argued that the international diffusion of technological knowledge between--more or less--open economies is key to understanding cross-country productivity differences. Recent estimates that domestic productivity growth is derived ultimately from foreign sources in most countries of the world supports this view (Eaton and Kortum 1999, Keller 2002a).

When an economy liberalizes to become more open, broadly speaking, there might be market- as well as non-market mechanisms through which the technological knowledge of foreign firms can affect domestic productivity. First, foreign firms might exert competitive pressures that force domestic firms to change their pricing behavior, eliminate inefficiencies and become thus more productive. Market mechanisms can also operate even with fully competitive markets: the change in relative prices associated with trade liberalization, e.g., can lead to productivity gains through a more efficient pattern of specialization. Foreign firms might also be the source of a particular set of externalities--sometimes called technology spillovers--that raise the productivity of domestic firms through non-market channels. It is these externalities that we will try to quantify in this paper for the United States between the years of 1987 and 1996.

Our focus will be on externalities associated with U.S. imports and the activities of multinational enterprise (MNE) subsidiaries associated with foreign direct investment (FDI) into the United States. These two channels have been most emphasized by theoretical and empirical work.[5] Importing a technologically advanced commodity might trigger learning that allows producing a similar good at lower costs domestically. Another possibility is that the price does not fully reflect the quality of imported good, due to issues associated with market power of the buyer and problems of appropriability for the seller.

FDI might be associated with spillovers for domestic firms because workers that 'embody' the firm-specific knowledge asset of the MNE subsidiary can be attracted to domestic firms (Fosfuri, Motta, and Rønde 2001), because multinationals give access to new specialized intermediate inputs (Rodriguez-Clare' 1996), or because domestic firms use local intermediate goods supplier chains whose productivity has been raised through the know-how of the MNE. In these and other instances, it is *a priori* plausible that market prices do not necessarily reflect the full value of the transaction to all parties, and there is at least some, albeit often anecdotal evidence to which we turn briefly in section 2 that this might be empirically important.

[5] Also externalities associated with export activity ('learning-by-exporting'), as well as other channels have been analyzed; see Keller (2001) for a broader discussion.

We use data on a sample of about 1,100 large U.S. firms between the years of 1987 and 1996 to examine whether technology spillovers arising from U.S. imports and the activity of foreign-owned subsidiaries are important in affecting the productivity of U.S. firms. We estimate the impact of differences in imports and FDI activity across fairly disaggregated U.S. manufacturing industries on the productivity of the firms in our sample. We also take into account the U.S. firms' own technological investments in form of their R&D spending, which is well-known to be positively correlated with productivity (Griliches and Mairesse 1984).

Our results are consistent with substantial technology spillovers from foreign-owned subsidiaries to U.S. firms. The estimates that we obtain are large, especially relative to results obtained in the existing literature. According to our preferred estimates, the extent to which technology spillovers from FDI account for U.S. productivity growth between the years 1987 and 1996 is 13.4%. There is also some evidence consistent with imports-related technology spillovers, although it is weaker. We conclude the paper with an account of possible reasons for why we estimate relatively large FDI spillovers. It appears to result primarily from having access to data that measures the activity of multinational enterprises in the host economy especially well. On this basis, we argue that our results are likely to generalize once such data is available in other circumstances as well.

The following section briefly reviews the available evidence, before we present our model and the estimation framework in section 3. Section 4 gives an overview of the data, with more detail provided in the appendix. All estimation results can be found in section 5, while section 6 contains some concluding discussion.

2. Technology spillovers through imports and FDI

The empirical literature on technological externalities associated with trade and FDI activity has grown rapidly in recent years but from a relatively small base. Given its relatively short history, dating back to only about the mid-1990s, the literature has established few truly robust results to date.[6]

A first set of papers has looked for trade-related international R&D spillovers. In an influential paper, Coe and Helpman (1995) have related productivity to the import-share weighted R&D of the countries' trade partners, estimating a positive coefficient. Xu and Wang (1999) have strengthened these results by focusing on machinery imports instead of all imports. At the same time, Keller (1998) generates almost as strong results with counterfactual instead of observed import data. This underlines that the evidence for imports-related technology spillovers on the basis of these regressions is not strong. More recent research has sought to provide a more powerful empirical framework by employing more disaggregated data and allowing for alternative spillover channels in addition to imports. This has produced mixed results so far: for instance, Keller's (2002b) industry-level analysis of technology spillovers among the G-7 countries finds evidence in support of imports-related effects, while Kraay, Isoalaga, and Tybout (2001) in their study of firm productivity dynamics in three less developed countries do not.

[6] See Keller (2001) for more details on the following.

As for foreign direct investment, the focus in recent work is on multinational enterprises owning firm-specific technological knowledge assets that are internationally transferred between parent and subsidiaries (Markusen and Maskus 2001). This asset could be the basis for technology spillovers from inward FDI. However, the evidence that this occurs at all, and moreover, that this is quantitatively important for domestic productivity growth, is quite weak so far.

Among the recent studies using micro data, Aitken and Harrison (1999) find that an increase in the presence of foreign-owned subsidiaries at the industry-level is associated with lower productivity in a sample of Venezuelan plants in the late 1970s and 1980s. The authors attribute this result to strong competition and average cost effects—e.g., incoming foreign-owned subsidiaries hire the most highly skilled workers away from domestic plants—that far outweigh any positive FDI spillovers that might exist.

Girma and Wakelin (2001) as well as Haskel, Pereira, and Slaughter (2001) have recently studied inward FDI for the United Kingdom; these authors have tried to control for changes in the degree of competition to isolate FDI spillovers. Both studies find evidence for positive FDI spillovers, although the estimated productivity effects for U.K. plants are small: according to Haskel, Pereira, and Slaughter, e.g., the roughly 50% increase in the share of foreign employment—the measure of FDI--accounts for only about 5% of the TFP growth in British manufacturing in the two decades from 1973 to 1992.

Finally, Kinoshita (2001) has studied FDI spillovers with a panel of firms in the Czech Republic. Arguably, firm-level data is best suited for studying international technology transfer and FDI spillovers, because the MNE's knowledge asset operates at the firm- and not the plant-level. Kinoshita finds evidence for FDI spillovers for Czech firms that invest heavily into R&D, consistent with the notion of absorptive capacity. One reason why she does not find a general FDI spillover effect might be her very short sample period (1995-98).[7]

Summarizing, there is some evidence for imports-related technology spillovers, but this evidence is far from ubiquitous, and in particular, it becomes weaker when micro data and relatively structural econometrics is being employed. Regarding FDI, there too is stronger evidence for spillovers when more aggregated data is employed. Among the recent studies that have employed micro data, only two find statistically significant positive productivity effects. Even here, the estimated effects are small in an economic sense, and they are obtained by abstracting from all other mechanisms through which technology spillovers might operate.[8] This is the background for our empirical analysis of imports- and FDI-related technology spillovers that follows.

3. Model and estimation framework

At this stage when there is no consensus on the existence of strong spillovers, we take a broad view on how FDI and imports might affect the productivity of domestic firms. Instead of estimating a model that incorporates a particular way of how FDI leads to spillovers—for instance the labor turnover model of Fosfuri, Motta, and Rønde (2001) from above--, we simply ask whether there is evidence for higher productivity of

[7] Among the other studies are Baldwin, Braconier and Forslid (1999), Keller (2002b), and Xu (2000) who find some evidence consistent with FDI spillovers using industry-level data, as well as Branstetter (2000) who shows that FDI between the U.S. and Japan is associated with higher knowledge flows as measured by patent citations of U.S. and Japanese firms.

[8] We are not alone in our assessment that there is no evidence for strong FDI spillovers in studies using micro data; Hanson (2001) in his recent survey, e.g., writes that "on average, the presence of multinationals appears to depress the productivity of domestic plants", p.15; see also Görg and Greenaway (2002) for a comprehensive study of recent work on FDI spillovers.

domestic firms in industries where there is more foreign penetration in terms of inward FDI and imports. By and large, this is the question that has been asked so far, with the answer being non-affirmative (see section 2 above).

Our analysis relies on correctly measuring firm productivity. To this end we build on recent work by Ericson and Pakes (1995) and Olley and Pakes (1996).[9] These authors develop a framework for dynamic industry equilibrium analysis where firms choose optimally investment, exit, and entry into the market.[10] For our purposes, two aspects of the Olley and Pakes approach are most important: first, it allows for firm-specific productivity differences that exhibit idiosyncratic changes over time, and second, the model endogenizes the firm's liquidation decision by generating an exit rule. These features address two major concerns that have afflicted production function estimates, crucial input into productivity calculations, for a long time: simultaneity and selection biases. To see this, consider the following equation:

(1) $$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + u_{it},$$

where y_{it} is the logarithm of output of firm i at time t, and correspondingly, l_{it}, m_{it} , and k_{it} are the firm's (log of) labor, materials, and capital inputs. The last term, u_{it}, is an error term representing all disturbances that prevent (1) from holding exactly. Let this term be composed of two parts,

(2) $$u_{it} = \omega_{it} + \eta_{it}.$$

Consider the case when neither ω_{it} and η_{it} are observed to the econometrician, whereas the firm cannot observe η_{it}, but it does know ω_{it}. The term η_{it} could be capturing

[9] The following introduces only the most salient features of their approach, and we refer to these papers for a full description of this approach. See also Griliches and Mairesse (1995) for more discussion.
[10] The equilibrium concept in these models is Markov perfect Nash in the sense of Maskin and Tirole (1988): in equilibrium, firms' perceptions of the distribution of future market structures are consistent with the objective distribution of market structures that the firms' optimal choices generate.

unpredictable demand shocks while ω_{it} could be firm productivity, for instance. If ω_{it} is known to the firm, the optimal labor input choice, for example, will be a function of ω_{it}, and simple OLS estimation will suffer from a simultaneity bias because $E[u_{it} \mid l_{it}] \neq 0$.[11] If the term ω_{it} is constant over time, $\omega_{it} = \omega_i$, all t, taking time- or within-firm differences of (1) and proceeding with OLS on the transformed data can lead to consistent parameter estimates. But in our framework, ω_{it} is firm productivity, and how this changes in relation to foreign penetration is exactly the question we are asking. This strategy is therefore ruled out. As shown below, we will identify ω_{it}, following Olley and Pakes, from the firms' investment choices. Knowing ω_{it} allows controlling for the simultaneity of input choices, and thus to avoid this bias.

We turn now to the selection problem. The firm maximizes the expected discounted value of its future net cash flows. At the beginning of the period, the firm learns its productivity ω_{it}, which is assumed to evolve according to an exogenous Markov process. Then, the firm makes three choices. It decides whether to exit or not, it chooses variable factors (labor and materials), and how much to invest in capital. For a sufficiently low value of ω_{it}, a firm's value of continuing in operation will be less than some (exogenous) liquidation value, and it will exit; call the threshold level at which a firm is indifferent between exiting and staying $\underline{\omega}_t$.

One can show that if the firm's per-period profit function is increasing in k, the value function must be increasing in k as well, while $\underline{\omega}_t$ is decreasing in k. The reason is that a firm with a larger capital stock can expect larger future returns for any given level

[11] The existence of this bias depends on the possibility that input choice can be varied; this explains why we use the example of labor as an input, which is generally considered to be not subject to large adjustment costs. In the multivariate case, the OLS bias can usually not be unambiguously signed. However, if labor and capital are positively correlated, and labor is more strongly correlated with ω_{it} than capital, then OLS will tend to overestimate β_l and often underestimate β_k.

of current productivity, which means that it will remain in operation at lower realizations of ω_{it}. Relatively small firms self-select into exit at productivity draws ω_{it} for which relatively large firms would have continued to operate, which implies that the relatively small firms that stay in the market tend to be those that received unusually favorable productivity draws. The correlation between ω_{it} and k_{it} is negative, and failing to account for the self-selection induced by exit behavior will lead to a negative bias in the capital coefficient. The Olley and Pakes approach generates an exit rule, so that we can account for this self-selection and avoid the associated bias.

In terms of estimation, we take the following steps. In equations (1), (2), we assume that labor and materials are variable inputs so that their choice is affected by ω_{it}, whereas capital k_{it} is only determined by past values of ω, not the current one. Dropping the firm subscript for ease of notation, let i_t be the firm's optimal investment choice at time t. Provided that $i_t > 0,$ it is possible to show that investment is strictly increasing in ω_t for any k_t.[12] This means that we can invert the investment function to yield

(3) $\omega_t = h_t(i_t, k_t).$

Substituting (3) and (2) into (1) gives

(4) $y_t = \beta_l l_t + \beta_m m_t + \phi_t(i_t, k_t) + \eta_t,$

with $\phi_t(i_t, k_t) = \beta_0 + \beta_k k_t + h_t(i_t, k_t)$. Because $\phi_t(.)$ contains the productivity term $\omega_t = h_t(.)$ that is the source of the simultaneity bias, equation (4) can be estimated to obtain consistent estimates β_l and β_m on the variable inputs, labor and materials. Equation (4) is a partially linear regression model of the type analyzed by Robinson (1988), and we

[12] The requirement that investment must be positive may be limiting for some applications. Levinsohn and Petrin (2001) propose therefore a variant of Olley and Pakes' approach in which productivity is identified from materials inputs (which is usually greater than zero). In our sample, the zero-investment problem is negligible, so that the Olley and Pakes approach works fine.

use a fourth-order polynomial in investment and capital to capture the unknown function $\phi_t(.)$.[13]

With consistent estimates of β_l and β_m in hand, we proceed to estimating the effect of capital on output, β_k, which is not identified in (4) because it is combined with capital's effect on investment. We assume for simplicity that k_t is uncorrelated with the innovation in ω_t, $\xi_t = \omega_t - \omega_{t-1}$, or, ω_t is a random walk (this can be generalized). Then we can substitute into (4) to get

(5) $$y_t - \hat{\beta}_l l_t - \hat{\beta}_m m_t = \beta_k k_t + \hat{\phi}_{t-1} - \beta_k k_{t-1} + \xi_t + \eta_t,$$

where $\hat{\phi}_{t-1}$ comes from estimating (4), and $\hat{\phi}_{t-1} - \beta_k k_{t-1}$ is an estimate of ω_{t-1}.

The probability of survival to period t depends on ω_{t-1} and $\underline{\omega}_{t-1}$, the unobserved level of productivity that would make a firm shut down its operations, which can be shown to only depend on capital and investment at time t-1. We generate an estimate of the survival probability by running a probit regression on a fourth-order polynomial in capital and investment (lagged by one period); we denote the estimated survival probability by $\hat{P}_t$. The final estimation step is given by estimating β_k from the following equation:

(6) $$y_t - \hat{\beta}_l l_t - \hat{\beta}_m m_t = \beta_k k_t + g(\hat{\phi}_{t-1} - \beta_k k_{t-1}, \hat{P}_t) + \xi_t + \eta_t.$$

Here we approximate the unknown function g(.) by a fourth-order polynomial in $\hat{\phi}_{t-1} - \beta_k k_{t-1}$ and $\hat{P}_t$; β_k is then estimated non-linearly across all terms that contain it.

[13] This includes all cross terms, and we also allow this function to vary over time for the subperiods 1987-90, 1991-1993, and 1994-1996.

Using the estimates of coefficients of labor, materials, and capital, we estimate log total factor productivity as $tfp_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} - \hat{\beta}_k k_{it}$. Our empirical analysis relates firms' TFP growth, Δtfp_{it}, to changes in the degree of foreign penetration through imports (ΔIM_{it}) and FDI (ΔFI_{it}) at the industry level:

(7) $$\Delta tfp_{it} = X'_{it} + \Delta IM_{it} + \Delta FI_{it} + \varepsilon_{it},$$

where X'_{it} is a vector of control variables, and ε_{it} is a Gaussian error term; the exact definitions of ΔIM_{it}, ΔFI_{it}, and X'_{it} are discussed in the data section, to which we turn now.

4. Data

The results of this study are based on an unbalanced sample of relatively large and publicly traded manufacturing firms in the U.S. from Standard and Poor's *Compustat* database. Our sample covers the years from 1987 to 1996 and a total of about 1,100 firms. The analysis encompasses the majority of U.S. manufacturing during this period in terms of employment and R&D (about 58% and 70%, respectively).

The productivity of firms in the U.S. during this period has on average been relatively high, and perhaps higher than in any other country of the world. It might therefore be at first somewhat surprising that we try to identify technology spillovers to these already productive firms. Two points are worth noting in this respect. First, as we have discussed above, so far the evidence for technology spillovers is at least as strong for more- relative to less developed countries, which is consistent with the idea that a certain minimum, or threshold level of productivity is in fact needed for spillovers to materialize. When analyzing large, publicly listed U.S. firms, one can be fairly sure that this possible threshold level of productivity has been surpassed.

Second, and more importantly, we know from many recent studies that there is a lot of heterogeneity in terms of productivity across firms within one country. It is well established that MNE subsidiaries tend to be relatively productive compared to the average firm, even in the United States (e.g. Doms and Jensen 1998). Thus, even if foreign spillovers to the relatively productive U.S.-owned firms were too small for us to identify, we should still be able to estimate those to U.S.-owned firms at the bottom of the productivity ranking in the United States, if there are any.[14] We are also able to distinguish U.S.-owned from foreign-owned firms that are located in the United States, as the *Compustat* data base has an identifier for foreign incorporated firms. This means that we can focus on spillovers to domestically owned firms in the United States.

From the *Compustat* data base, we obtain data on the firms' (log) output y, as well as (log) labor, materials, and capital inputs (l, m, and k), with our measure of output is net sales.[15] Firm sales are deflated by a common deflator at the three-digit SIC level that we have constructed from the Bartelsman and Gray (2001) NBER Productivity data base, while the deflators for the capital stock come from the Bureau of Labor Statistics. Also from the *Compustat* data base comes data on the firms' R&D expenditures, which is a likely another determinant of productivity; log R&D expenditures are denoted by r_{it}. Not all data is available for all firms; for instance, a significant number of firms (about 15%)

[14] Note that our foreign spillover estimates are up and beyond the externalities that one U.S.-owned firm might generate for another U.S.-owned firm.
[15] Firm data on the flow of materials usage is estimated from the change in the firm's stock of materials; for this and other details of the variables' definitions, see the Appendix A.

do not report material input usage. In some cases we have had to fill in small amounts of missing data, typically for the firms' capital stocks.[16]

Our primary interest is whether productivity, conditional on the firm's R&D investments, is related to the importance of imports and foreign-owned subsidiaries in the firm's relevant economic environment. We measure the importance of imports for a given firm by the share of U.S. imports in imports plus total shipments in the industry to which the firm belongs; this variable is denoted by IM_{it}. Correspondingly, the importance of FDI is measured by the share of foreign subsidiary employment in total employment in the industry to which the firm belongs (this share is denoted by FI_{it}). For both imports and FDI, our analysis is at a relatively detailed industry level (two to three-digit SIC level). This is determined by the roughly 50 industries in which the U.S. Bureau of Economic Analysis (BEA), responsible for reporting U.S. FDI data, is classifying total manufacturing activity; see Table 1 for a list of the industries.

Data on employment by foreign subsidiaries comes from confidential affiliate level data collected by the BEA in its annual surveys. This data is aggregated from the affiliate level to the level of the industry classification that we use. The employment figures are by the industry classification corresponding to the activity of the employee rather than the industry classification of the affiliate.[17] The former is preferred, because it avoids the sudden shifts of a large number of employees from one industry to another industry that is associated with data on employment by affiliate if the affiliate's primary industry of

[16] The data is cleaned from obvious errors, and we have further developed a data quality classification system, with four main categories. The results are based on the sample of domestically owned firms that report materials usage and whose data is relatively good (primarily based on year-to-year noise).
[17] In BEA's annual surveys of foreign direct investment in the United States for the years covered in this study, large affiliates were required to specify their employment (as well as sales) in the eight industries in which their sales were largest; other affiliates had to specify their employment (and sales) in the three industries in which their sales were largest.

sale changes. The imports data is obtained from Feenstra (2002), and the values for total shipments and employment by industry come from Bartelsman and Gray (2001).

These measures of imports and FDI are broadly capturing the prevalence, and more precisely the intensity, of foreign economic activity in a particular U.S. industry. If specialized imports are important in triggering technology spillovers, or if foreign subsidiaries generate positive externalities for U.S. firms by building up more efficient supplier chains or a pool of highly skilled technicians, it is plausible that this is correlated with the intensity of foreign presence in that industry.[18]

The Olley and Pakes method of computing firm productivity addresses the problem of simultaneity in input choices, but the endogeneity of imports and FDI could be an issue as well. For instance, FDI could be attracted to industries in which productivity is growing relatively fast on average. This would lead to a positive correlation of FDI and productivity, but it would not be evidence in favor of positive FDI-related technology spillovers.[19] Endogeneity issues of this kind are here primarily addressed by considering not only the contemporaneous relationship between productivity and foreign penetration, but also that of current productivity with lagged imports and FDI.[20]

A number of other variables will be employed in our attempt to isolate the possible externalities associated with imports and FDI. First, we include a variable that picks up

[18] Our measures will not be able to pick up externalities that are generated between major industries (vertical production specialization); however, many important buyer-supplier relationships will be within our still relatively broadly defined industry classification.
[19] Alternatively, it could be that FDI is attracted to weak domestic industries to capture these markets. In that case, the correlation of cross-industry productivity growth and inward FDI might well be negative.
[20] To develop a structural framework that incorporates also the choice of firms to import or interact with foreign-owned subsidiaries is left for future work.

the degree of capacity utilization (denoted as CU), for instance hours worked in the case of labor. The number of workers a firm hires is likely to be positively related to both hours worked as well as sales, which means that we might be overestimating the coefficient on labor if capacity utilization is not controlled for.

Second, in discussing the existing literature, we have noted above that it is important to control for changes in the degree of market competition associated with changes in foreign penetration if one's goal is to isolate any technology spillover effects. We follow Nickell (1996) and others and use the firm's market share in the industry (denoted by MS) as well as the firm's mark-up (denoted by FM) and the industry mark-up (SM) to capture these effects.[21] To the extent that a higher market share or a higher firm mark-up, conditional on the industry's overall mark-up indicate less competitive pressures, we expect that a firm's productivity growth slows down, all else equal.

There is a substantial degree of heterogeneity across firms in different industries in our sample that we cannot observe. Productivity growth in some industries is higher than in others due to factors that we do not fully capture, an example being the advances in the information technology and communications industry during our sample period. We therefore allow for exogenous differences in productivity growth across industries by including industry fixed effects, α_j in some of the specifications below. We also include time fixed effects, α_t, in all regressions, because our sample period covers the 1990/91 U.S. recession. The baseline estimation equation is therefore given by

$$\begin{aligned}\Delta tfp_{it} &= \alpha_j + \alpha_t + \beta_1 \Delta r_{it} + \beta_2 \Delta CU_{it} + \beta_3 \Delta ms_{it-2} + \beta_4 FM_{it-2} + \beta_5 SM_{it-2} \\ &\quad + \gamma_1 \Delta IM_{it} + \gamma_2 \Delta FI_{it} + \varepsilon_{it},\end{aligned} \tag{8}$$

[21] Firm mark-up is computed as sales over sales minus profits, where the profits data comes also from *Compustat*, see Appendix A. The industry mark-up is computed analogously.

Here, Δ indicates a one-year difference, so that ΔFI_{it}, for example, is the change in the share of foreign-subsidiary employment in total employment in consecutive years.

We now turn to the estimation results.

5. Results

It is useful to analyze the main trends in imports and FDI by industry before discussing the regression results. There are large differences across industries. For instance, there are three industries for which in our sample, the firms' labor input is declining on average by more than 5% annually (SIC 204, SIC 208, and SIC 230), while at the same time there are four industries for which employment is growing annually by more than 5% per year on average (these are SIC 283, SIC 341, SIC 352 and SIC 355). Our sample period also covers the year of 1991, which witnessed the most recent recession before the current one in the United States.

The U.S. firms in our sample have increasingly been exposed to import competition; see Table 2 for some major trends in imports and FDI over the sample period. In 1987, the average (median) ratio of imports to shipments (which we will refer to as import share) was 18.5% (11.6%), while by 1996, the average (median) import share had risen to 25.8% (18.1%). The annual growth of imports these firms were facing was almost twice as high as the growth in industry shipments. In addition, this increase in the import share over time is more or less monotonic.

Also the share of U.S. manufacturing employment accounted for by foreign-owned U.S. affiliates has been growing over time, from 7.7% in 1987 to 11.4% in 1996.

However, in this case, we can distinguish two separate phases of FDI dynamics into the United States. Between 1987 and 1993, FDI grew particularly strongly, from 7.7% to 12.3%. In the aftermath of the 1991 recession, however, foreign investors receded somewhat from the U.S. market.[22]

Figure 1 compares the average sales shares in our sample with the sales shares in the NBER Productivity Data Base, Bartelsman and Gray (2001), each by BEA industry. [23] Clearly, our sample does not exactly reflect the relative industry sizes of the U.S. manufacturing as a whole. For instance, the figure shows that we have a substantially larger share of computer industry firms (SIC 357) in our sample than exists in the U.S. economy as a whole, while other industries such as motor vehicles (SIC 371), appear to be somewhat underrepresented in our sample. While we note that the rank correlation of BEA industry sales shares in the two samples is positive (and significant), we will need to take the composition of our sample into account when interpreting our results.

5.1 Olley-Pakes Elasticities

Table 3 reports the production elasticities for capital, labor, and materials that we estimate using the Olley-Pakes method described above. We have tried several specifications that differ in the set of variables that is included as right-hand side variables in stage one, equation (4) from above, and columns 1 and 2 in Table 3 give

[22] The trend towards greater internationalization has continued also in terms of FDI, however. According to the latest available figures from the BEA and the Bureau of Labor Statistics (BLS), in 1999, the share of foreign employment in U.S. manufacturing was 14.1%.

[23] Note that one difference between the NBER Productivity Data Base and our sample is that the former includes affiliates of foreign multinationals, whereas the latter focuses on U.S.-owned firms; this difference is small relative to the sampling difference though.

some indication of the range of estimates that is obtained.[24] In specification O-P (1), we follow Griliches and Mairesse (1995) by including a general trend and a differential trend for computers as regressors in the first stage. This corresponds to the fact that the computer industry has experienced exceptionally high productivity growth over this period, and the computer industry constitutes an important part of our sample. The elasticities are estimated to be 0.300, 0.466, and 0.256 for capital, labor, and materials, respectively. Without the trends, the capital elasticity falls to 0.251 (see O-P (2)). For comparison purposes, we also show the OLS estimates of the elasticities. These lead to significantly lower capital and materials estimates, with 0.200 and 0.164, respectively; these results are consistent with simultaneity and exit leading to an important downward bias on the capital coefficient. Also on the basis of the estimated scale elasticities (between 0.98 and 1.02 for Olley-Pakes, and 0.83 for OLS), the Olley-Pakes estimates seem to be preferred. We therefore compute firm TFP using the elasticity estimates of the preferred specification O-P (1), and use these TFP estimates in the following analysis.

5.2 Baseline Results

We now turn to our regression results. We begin by estimating equation (8) using one-year differences. The benefit of using one-year differences is that we can make maximum use of the time variation in our data. One aspect of this variation that is of critical interest in our analysis is the time span over which spillovers might occur. To this end, we use measures of the change in import and multinational activity that are contemporaneous and lagged one and two years. Because we may exacerbate problems

[24] These specifications differ in (1) whether we allow the investment function to vary over time or not; (2) whether we use capital investment, or capital investment plus acquisitions minus divestitures; and (3) whether we include R&D expenditures as a regressor or not.

of error-in-variables by relying on short-run movements, we experiment with longer time differences below.

The results are shown in Table 4. The columns correspond to different specifications that vary in the timing of import and MNE activity relative to subsequent TFP growth and to different industry controls. The first four columns correspond to specifications in which we include a full set of industry indicators variables (coefficients suppressed). Allowing for industry controls is crucial if there are unobserved industry characteristics not captured by our controls that might affect both TFP growth rates and the extent of foreign activity as measured by both imports and FDI. In the fifth column we report estimates obtained by estimating equation (8) without industry dummies. In the final column, we report estimates obtained by estimating equation (8) allowing for both industry specific intercepts and time trends. In all cases, the standard errors reported in parentheses under coefficient estimates are both heteroskedascity consistent and adjusted for clustering at the level of the firm.

There is data on 839 firms for the specification with a full set of contemporaneous and lagged foreign activity variables and industry fixed effects shown in column one. We first consider the controls. In the first row is the coefficient corresponding to contemporaneous levels of R&D expenditure. The coefficient is positive and statistically significant, indicating that firms that conduct greater research and development efforts do experience faster TFP growth. This result is consistent with the literature as reported by Griliches (1995). In the second row is the coefficient estimate for our proxy for contemporaneous changes in capacity utilization as captured by the ratio of industry capital stock to industry hours worked. The negative coefficient is consistent with our hypothesis that measured TFP rises during periods of intense capital usage. In the third row is our measure of two-year lagged change in firms' market share, included as a control for changing product market competition. The coefficient is negative but not statistically significant. In the forth row is our measure of firm specific markup over costs lagged two years, another control the strength of product market competition. This coefficient is negative and marginally statistically significant. The coefficients on these two measures of product market competition seem to suggest that firms enjoying a strong position in the product market show less TFP growth as would be consistent with non-pecuniary slack enjoyed by monopolists. Our final control is industry average markups, again lagged two years, as shown in the fifth row. Interestingly, the coefficient on industry mark ups is positive and statistically significant suggesting that industries enjoying growing (falling) markups are associated with rising (falling) rates of TFP growth. This variable may again reflect cyclical, industry effects that are not captured by our measure of capacity utilization.

Turning to the foreign activity variables, rows six through eight show the coefficients for FDI activity; this is defined as the change in the share of MNE employment in total industry employment, both contemporaneous as well as lagged. The results reveal that current and one-year lagged FDI growth are associated with faster TFP growth on average while two-year lagged FDI growth is associated with slower TFP growth. Of these three coefficients only the current and one-year lagged variables are statistically significant. The F-test reported at the bottom of the table reveals that as a whole the three coefficients are statistically significant at a high level of confidence. The general impression created by these coefficient estimates is that to the extent that there are spillovers from FDI, they have been fully reflected in domestic TFP within two years.

Now consider the coefficients on imports shown in rows nine through eleven. A similar pattern emerges in these coefficients: the current and one-year lagged measures are positive while the two-year lagged measure is negative. Another similarity is that the three coefficients are jointly significant at high levels of confidence as indicated by the F-test at the bottom of the table. Like the two-year lagged FDI measure, the coefficient on two-year lagged imports is not statistically significant on its own. Again, the results are consistent with technology spillovers through imports that occur fairly rapidly.

To confirm our hypothesis on the timing on potential spillovers in the data, we show the results in columns two through four of estimating a single measure of foreign penetration at different lags. In each of these specifications, the time span of the sample varies so that the number of firms in the sample also varies across columns. The results reported in columns two through four are highly consistent with those reported in column one despite the slight change in sample size. Some of the sample composition change is captured in the controls such as R&D and Market Share, which change substantially across samples. We also note that the absolute size of coefficients on our foreign penetration variables are slightly smaller in magnitude, but whose relative size and statistical significance is comparable to the results in column one.[25]

In column five, we report the estimates obtained by dropping the industry fixed effects to gauge the potential importance of unmeasured industry characteristics in

[25] This seems in part due to the fact that the additional firms that enter the sample are primarily smaller, poorly performing firms that subsequently disappear from the sample; see more on the effects of sample composition below.

driving both foreign activity and TFP growth. In the interest of space, we focus our discussion of these results on the FDI and imports variables.

The coefficients on the current and lag-one FDI variables are small in size, and the two-year lag variable becomes negative and statistically significant. This would suggest that the net effect of FDI as measured by the sum of the three coefficients on FDI is negative, as some earlier studies have found. In contrast, the coefficients on the import variables move in exactly the opposite direction. All three coefficients are larger now than in column one, and all coefficients are now individually statistically significant. These results would suggest even a larger role for imports in observed TFP growth in the United States. In fact, we think that these results primarily suggest that unobserved industry characteristic play an important role in both the extent of foreign activity and TFP growth, and that industry fixed effects should therefore be included.

Speficially, the result that including industry fixed effects affects the coefficients on FDI and imports in opposite direction is consistent with much of the theoretical literature on trade and FDI in which these two mechanisms for serving a distant market are generally modeled as substitutes. If this substitution were at work in our data, then we might expect FDI and imports to respond to unobserved industry characteristics in opposite directions. That unobserved industry characteristics are important in explaining cross industry TFP growth rates is clearly seen by comparing the R-squared of the two regressions. Adding the fixed effects doubles the R-squared suggesting that at a minimum, fixed effects explain half the variance in the total specification.

By including fixed effects by industry, we control for time invariant determinants of TFP growth across industries that are also potentially correlated with our measures of interest: the foreign penetration measures. There may also be time varying determinants of FDI and imports, such as changing factor prices and transportation costs to name two, that are not controlled in the intercept fixed effect specification. Hence, we explore the effect of estimating a model with both industry fixed effects and industry time trends. The results of this are shown in column six.

Including industry specific trends has several interesting consequences for the magnitudes of the estimated coefficients. Among the controls, the effect of estimating industry specific trends is to drive the coefficient on industry markups to zero from its large value in the intercept fixed effect specification (column one). Among the import and FDI variables, including an industry specific trend in addition to industry specific intercepts eliminates the negative coefficient on lagged imports and FDI respectively.

Overall, our results so far suggest that there are technology spillovers associated with both imports and FDI. Only in the specification without industry specific fixed effects is there no evidence for positive FDI spillovers, but as we have discussed above, our results strongly suggest that industry fixed effects should be part of the specification, due to unobserved heterogeneity in TFP growth across industries that are correlated with changes in foreign activity. We think that column one gives the preferred specification, with the sum of the significant point estimates of about 1.09 and 1.13 for FDI and imports, respectively. In the following, we discuss some robustness analysis.

5.3 Robustness

5.3.1 Longer Differences

Here we consider estimations with longer time differences. The benefit of considering longer differences is that doing so will give relatively more weight to more persistent changes in the variables of interest and hence reduce the influence of noise. The cost of the exercise is that longer time differences reduce the number of observations and the size of the sample in terms of the number of firms observed. As a compromise, we experiment with two and three-year differences but consider only the relationship between contemporaneous change of FDI and imports on imports and firm level TFP growth since adding lags would seriously strain the time span of the data.

Table 5 shows the results. The first two columns correspond to the 2-year specifications while the last two correspond to the three-year specification. We also here consider specifications with and without industry fixed effects. We now focus on the coefficients on FDI and imports. A glance across the relevant rows suggests that the story that emerged in the one-year difference specification also appears in the longer differences. When industry dummies are not included, imports appear to be strongly associated with TFP growth while FDI has apparently no effect. When industry dummies are included, the coefficients on imports fall substantially while the coefficients on FDI rise. An important difference in this specification is that imports are not statistically significant while FDI is. We conclude from this that in general, the baseline results do not seem to be driven by short-term noise in the data, while at the same time noting that the evidence for FDI related spillovers is stronger than for spillovers associated with imports.

5.3.2 Alternative Measures of Foreign Activity

In this section we consider a very different robustness check on our results. An important consideration in our analysis so far is that our measures of foreign activity with respect to both FDI and imports are changes in ratios of foreign activity to total activity. At one extreme, it is thus possible that all of the variance in our measures of exposure to foreign activity comes purely from changes in total activity.

To rule out the possibility that TFP growth is related only to total activity and not to foreign activity, we consider a specification in which both foreign and total activity by industry is allowed to have its own effect. Our new measure of changes in multinational activity is the absolute yearly change in employment at foreign multinationals normalized by lagged total employment by industry. To gauge the effect of the change in total employment on TFP growth, we define a new variable Total Employment. This variable is the absolute yearly change in total employment by industry normalized by lagged total employment. In effect, including this variable allows the denominator of our measure of FDI penetration in the baseline specification to have an independent effect on TFP growth. Variables for real import growth and real sales growth by industry are defined analogously.

The results of this analysis are shown in Table 6. We report two sets of results in table six, corresponding to the case with and without industry specific trends. Both sets of results are estimated with a full set of industry indicator variables. In discussing these results, we will exclude mention of our standard controls in the interest of space.

The results shown in columns one and two of Table 6 are highly consistent with the baseline results shown in Table 4. Both FDI and import growth appear to be associated with TFP growth but the effect appears to occur within two years. Note that increases in total employment are generally associated with slower TFP growth. This result is sensible when one considers that producing output using fewer resources is the nature of productivity growth. The coefficients on real sales growth are negative and not statistically significant. The reason that real sales growth appears to have no effect is that it's effect is captured entirely by the industry indicators and time trends.[26]

While the actual magnitudes of the coefficients reported in Table 6 are not directly comparable to those reported in Table 4, the signs and statistical significance is comparable and turns out to be very similar. We conclude from this analysis that our baseline results are not an artifact of the manner of construction of our measures.

5.3.3 Temporal variation in FDI and imports effects

We are also interested in the extent to which the FDI and imports effects that we estimate might be depending on the particular time period that we cover. First, TFP growth in the United States appears to have been particularly strong relative to other years in the mid 1990s, which correspond to almost half of our sample. Another feature is that our sample period contains the descent into the 1990 recession, with the subsequent recovery. In the following analysis, we investigate whether these factors seem to have a major influence on our FDI and imports spillover estimates.

While we cannot compare our results to those that would obtain over other time periods, we can ask whether there are significant differences between the coefficients that we would obtain in the early, recessionary 1990s to those coefficients that obtain in the boom years of the mid-1990s. To firmly distinguish between the two time periods we

[26] Dropping industry dummies and time trends yield coefficients on real sales growth which are both positive and statistically significant.

omit the middle year 1993. Table 8 presents these results, with the estimates that correspond to the years 1990-1992 in column one, the results for the years 1994-1996 in column two, and for comparison purposes, we repeat the results that obtain for the full sample period in column three.

There are several differences in the estimated coefficients for the two time periods. With respect to FDI, the coefficients for 1994-96 are all larger than the corresponding coefficients for the period of 1990-92, and in the later period also the two-years lagged FDI coefficient is positive and significant, which is not the case during 1990-92. At the same time, the joint effect of FDI is still significantly positive at a 10% level also in the years of 1990-92. These results suggest that while the partial correlation between FDI and TFP growth is more substantial in periods of rapid TFP growth, our qualitative finding on FDI spillovers is robust across two periods that are very different in terms of cyclical economic activity.

Turning to the estimated coefficients on the imports variables, we see that the differences between the coefficients for the two sample periods are more pronounced. In the relatively slow TFP growth period of the early 1990s, imports are not associated with TFP growth at all, while in the more rapid TFP growth period of the later 1990s, the positive relationship between imports and TFP growth emerges for the contemporaneous and one-year lagged variables. The results suggest that the time period appears to matter substantially for the relationship between import activity and TFP growth.

We conclude from this analysis that the correlation of imports and FDI with TFP varies to some extent across the years within our sample. Primarily, this has to do with a strongly time-varying imports effect. This finding confirms the impression given in Table

5 (Longer Differences) that the evidence for spillovers associated with FDI activity is stronger than that for imports related spillovers.

In the following, we turn to a brief discussion of the economic significance of our spillover findings.

5.4 Importance of spillovers in accounting for U.S. productivity growth

This section tries to shed some light on the economic impact of imports and FDI in the U.S. that is suggested by our spillover estimates. We first consider FDI. The share of foreign employment in U.S. manufacturing rose between 1987 and 1996 from 7.7% to 11.4%, or by 3.7 percentage points. Our preferred estimate of the FDI spillover effect on productivity is based on the first specification in Table 4. In this specification, the significant coefficients are 0.547 (for current FDI) and 0.543 (for one-year lagged FDI), which sums to a total effect of 1.090. Based on our Olley-Pakes input elasticity estimates (O-P (1) in Table 3), we estimate an average productivity growth in our sample of 0.301 over the sample period of 1987-96. This means that an estimate of the share of productivity growth that is associated with FDI spillovers according to our estimates is 1.090*0.037/0.301, or about 13.4%. In our view, this means that technology spillovers associated with FDI activity could be large enough to matter substantially in economic terms, that is, for productivity growth and welfare.[27]

[27] An analogous calculation for the effect of imports, based on the results of specification one in Table 4, would suggest that imports account for a share of about 27.5% of productivity growth in the U.S. over the sample period. However, as noted above, the imports estimates are less robust than our FDI estimates, and we believe that more work is needed to establish the magnitude of imports related spillovers.

Recall that much of the earlier literature estimating FDI spillovers with micro data found no or economically quite small effects. An important question therefore is why our estimates are considerably larger. We turn to this issue in what follows.

5.5 What explains the relatively strong FDI spillovers estimated in this paper?

A number of factors could explain why we estimate larger FDI spillover effects than those that have been obtained in earlier studies. While our analysis cannot be complete, it is important to discuss at least some of the major issues, because this will allow understanding whether our results are likely to generalize to other settings.

5.5.1 FDI spillovers in the United States

First, we analyze technology spillovers to U.S.-owned firms, which are among the most productive firms in the world. It might seem surprising at first that we find evidence consistent with U.S. firms benefiting from foreign technology. However, as noted above, the relatively high average productivity of U.S. firms masks a large amount of heterogeneity across U.S. firms, and the typical foreign-owned affiliate in the U.S. is likely to have a higher productivity than the average U.S.-owned firm in this industry (see Doms and Jensen 1998). But what if we estimate strong FDI spillovers not despite, but because U.S. firms are relatively productive compared to the domestic firms in other countries? That is, perhaps a relatively high productivity is required for a firm to acquire FDI related spillovers; in the U.S., there are relatively many such firms, and consequently, we estimate relatively high FDI spillover effects. There might be threshold effects in benefiting from FDI spillovers, but the evidence provided by Haskel, Pereira, and Slaughter (2001), for instance, suggests that it cannot be the whole story.[28]

5.5.2 Sample composition: Many high-tech firms

Another reason of why we estimate a relatively strong relationship between FDI and TFP might lie in the composition of our sample. We have already noted that our sample contains firms that are disproportionately in "high tech" sectors relative to the U.S. economy. The composition of the sample matters if in fact spillovers vary in strength from one industry to another. In particular, if spillovers are more likely in high-tech industries, then our results will tend to overstate the value of FDI and imports in generating TFP growth in the economy as a whole.

To explore this possibility, we divide our sample into two groups, which we will refer to as high and low tech industries. To define these groups, we sorted industries by their average R&D intensity and then chose a cutoff level of R&D intensity to yield two categories with roughly similar number of firms. We choose R&D intensity as our metric for dividing the sample because we conjecture that spillovers are more likely to occur in industries in which firms are likely to develop proprietary knowledge.

We find that roughly half the firms in the sample are in eight "high-tech" industries. These industries are the four chemical industries, computers and office equipment, electronic components, scientific instruments, and medical instruments.[29] To

[28] In their broad sample of firms, Haskel, Pereira, and Slaughter (2001) estimate that less productive (and smaller) firms receive on average stronger FDI spillovers than more productive (and larger) firms. Moreover, these authors study FDI spillovers to U.K. firms, whose productivity is not much below that of U.S. firms. Nevertheless, these authors estimate spillover effects that are only about one third of what we estimate.

[29] In terms of BEA codes of Table 1, these are industries 281, 283, 284, 289, 357, 367, 381 and 384.

expand the number of low-tech firms, we drop R&D as an explanatory variable at this point because it is missing for a large number of those firms. This expands the number of firms in our sample from roughly 839 to 1115. The results of this analysis are reported in Table 8.

The first column in Table 8 is the preferred specification (Table 4, column 1) estimated on the pooled sample of both high and low-tech industries without R&D as a regressor. The results in the expanded sample are remarkably similar to those shown in Table 4. One noticeable difference is that the coefficients on the foreign activity variables are moderately smaller, a change that suggests that there may be systematic differences between low and high tech firms.

This hypothesis is confirmed in columns two and three, which correspond to the high-tech and low-tech samples, respectively. Looking down the two columns, it is clear that there are substantial differences in the results for the two samples of industries. Most importantly, in the high tech sample, all three measures of FDI enter positive, and both the current and one-year lagged variable are statistically significant. In the low-tech sample, none of the FDI variables enter with a significantly positive sign, and two-year lagged coefficient is negative and significant. Turning to the import measures, similar differences appear. In the high-tech sample, we find that the one-year lagged import share is statistically significant and positive while in the low-tech sample, none of the import variables is statistically significant.[30]

[30] Moreover, virtually none of the coefficients of the control variables is precisely estimated in the low-tech sample, while CAPACITY and both Firm and Industry Markups are statistically significant in the high-tech sample.

These results are highly informative because they suggest that to the extent that spillovers occur, they occur in the fast growing high-tech sector. These results are intuitively plausible. First, most of the TFP growth in the sample is in the high-tech sector. Second, one would expect that it precisely these high-tech industries where there is likely to be knowledge that can be imparted on domestic firms. In the low-tech sector, market competition effects are more likely to dominate any potential spillovers from foreign firms.

The heterogeneity in the response of TFP to imports and FDI activity across industries is important to recognize in interpreting our aggregate results. Our sample features disproportionately firms that pursue R&D and hence are more likely to show evidence of spillovers in the aggregate than samples more reflective of the composition of U.S. industry. This means that it would be inappropriate to use our FDI spillover estimates—specifically, the preferred estimate of 1.09 based on Table 4, column 1—to compute the contribution of FDI spillovers to productivity growth in U.S. manufacturing as a whole.

Instead, our estimate from section 5.4 above-- that FDI spillovers are responsible for 13.4% of TFP growth over the period 1987-96-- takes this sample composition effect into account. We compute the importance of FDI spillover effects by comparing the FDI spillover estimates to the TFP growth in our sample, not to productivity growth in U.S. manufacturing as a whole. The composition of our sample therefore affects both FDI spillover elasticities and TFP growth—both is relatively high in our sample--, so that our analysis of the extent to which FDI spillovers account for TFP growth is meaningful.[31]

Overall, this suggests that the fact that our sample consists of relatively many high-tech firms can explain in part our relatively high FDI spillover coefficients. At the same time, the composition of our sample does not necessarily affect our estimate of the extent to which FDI spillovers account for productivity growth. If FDI spillovers are primarily found in high-tech industries, however, as our results seem to indicate, then this suggests that empirical studies should focus on these high-tech industries, because there does not seem to be something like an 'average' FDI spillover effect that can be found across high and low-tech industries. There could be FDI spillovers in low-tech industries, but given our results, it seems more plausible that they take the form of inter-industry spillovers—spillovers to low-tech industries from FDI in high-tech industries.

5.5.3 Data measurement error: FDI by mainline of business versus by activity

Another feature of our analysis that might explain why we estimate relatively strong FDI spillover effects lies in different procedures for measuring the extent of FDI. As mentioned earlier, we measure FDI by aggregating from the firm level the number of employees engaged in particular industrial activities while many studies aggregate the number of employees by the mainline of business of the enterprise in which they are employed. Our measure thus avoids mismeasurement associated with changes in mainline of business of enterprises that causes large jumps in measured employment by industry.

[31] According to the Bureau of Labor Statistics, multi-factor productivity growth in U.S. manufacturing as a whole for the period of 1987-96 was 6.7% (BLS 2002), versus an Olley-Pakes estimated average TFP growth of 30.1% in our sample.

To assess the extent to which our relatively strong results on FDI employment spillovers are due to the better measurement of employment, we compare these results with those obtained by measuring FDI employment by an enterprise's mainline of business. This comparison is done in Table 9. In the first column of Table 9 we repeat the results from the preferred specification, Table 4, column 1. In the second column are the results corresponding to the alternative, and we would argue flawed, measure of FDI based on enterprise mainline of business.

A comparison of the coefficients on the contemporaneous and lagged measures of foreign multinational activity confirms our hypothesis that measurement matters. While the sign pattern and relative magnitudes across time periods are similar for the two different measures of FDI, the mainline of business coefficients are much smaller—only about one seventh of the coefficients in the preferred FDI-by-activity specification in column 1.[32] This result is consistent with the standard intuition that mismeasurement of an explanatory variable will tend to bias downward the coefficient estimate.

We conclude that a major source of the difference in the magnitudes of estimated FDI spillovers in this versus earlier work is likely to be due to proper measurement of the extent of foreign multinational activity into the domestic market. This means that there is reason to believe that our results will generalize to other countries and time periods, because to the extent that our estimates of FDI spillovers depend simply on the foreign activity being measured accurately, it should be possible to revise FDI spillover estimates upward in other settings as soon as better data becomes available.

We now turn to a concluding summary.

[32] The sum of the significant FDI coefficients in column 1 is equal to 1.09, and it is 0.147 in column 2.

6. Summary

Governments all over the world spend large amounts of resources in order to attract multinational companies to their region or country, often based on the assumption that such companies generate various types of positive externalities, or spillovers, to domestic firms. This stands in sharp contrast to the influential recent literature that has used micro-level data to provide econometric evidence for such FDI spillovers—without finding much. In this paper, we estimate international technology spillovers to U.S. manufacturing firms via imports and foreign direct investment (FDI) between the years of 1987 and 1996. In contrast to earlier work, our results suggest that FDI leads to significant productivity gains for domestic firms. There is also some evidence for imports-related spillovers, but it is weaker than for FDI. The size of FDI spillovers is economically important: we estimate that they accounted for about 13% of productivity growth in U.S. firms between 1987 and 1996.

We also trace out the effects that a number of differences in our study relative to previous work have. The single biggest effect appears to result from using data that measures the activity of multinational enterprises in the host economy especially well. We argue that therefore our results are likely to generalize to other countries and periods once FDI activity can be properly measured.

In general, our results provide the strongest evidence that we are aware of that could support the provision of subsidies to attract FDI from a viewpoint of social welfare. The next question, of course, is whether a socially optimal policy is indeed implemented, given the political-economic realities of local electoral competition.

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Appendix A: Variable definitions and sources

- Sales (denoted Y): Net sales, from Compustat's Industrial data file (data item 12); deflated by industry-level price index aggregated up from Bartelsman and Gray (2001).
- Labor (L): Number of employees, from Compustat (data item 29).
- Capital (K): value of property, plant and equipment, net of depreciation, from Compustat (data item 42); deflators are from the BEA satellite accounts.
- Materials (M): Estimated from Compustat's firm-level data on year-end raw materials inventory (data item 76), and the correlation of raw materials inventory and raw materials usage across 4-digit SIC industries, from Bartelsman and Gray (2001) and Manufacturing Census data kindly provided by Wayne Gray; deflators from Bartelsman and Gray (2001).
- R&D (denoted by R): Research and development expense, from Compustat (data item 46); R&D stocks are constructed from the R&D expenditure data using the perpetual inventory method (R&D depreciation rate is assumed to be 10%). The initial R&D capital stock is estimated from R&D expenditures between 1972-82 whenever data was available; for the remainder of firm's, we have made the assumption that in 1982, firms were in steady-state, and used the perpetual inventory method from there; deflators are from the BEA satellite accounts until 1992; beyond that, we have estimated them using the variation across industries and over time of the deflators for capital.
- Capacity utilization (CU): is defined as the ratio of capital stock over total hours of production workers, at the BEA industry level; aggregated up from the 4-digit SIC data in Bartelsman and Gray (2001).
- Rents (PI): Defined as firm's net income, from Compustat (data item 172), over sales.
- Market share (MS): Defined as firm sales over total BEA industry sales (constructed from Bartelsman and Gray 2001).
- Import share (IM): U.S. imports by industry, from Feenstra (2002), over U.S. imports plus total shipments by industry; the latter from Bartelsman and Gray (2001).
- FDI share (FI): Foreign affiliate employment by industry of activity, aggregated from the affiliate level to the BEA industry level, over total U.S. employment by BEA industry; source: confidential affiliate level FDI data at the BEA.

In addition, for the Olley and Pakes (1996) productivity estimates, we have used

- Investment: Capital expenditures, from Compustat (data item 128); investment deflators by 4-digit SIC industry are from Bartelsman and Gray (2001).

Following Jovanovic and Rousseau (2002), we have also computed and used an alternative investment series that takes into account acquisitions (Compustat data item 129) and divestitures (Compustat data item 107).

Table 1: Industry Classification of the Bureau of Economic Analysis (BEA)

BEA Code	BEA Name	BEA Code	BEA Name
	Food and kindred products		**Textile and Apparel**
208	Beverages	220	Textile mill products
201	Meat products	230	Apparel and other textile products
203	Preserved fruits and vegetables		
204	Grain mill products		**Wood and Furniture**
209	Other food and kindred products	240	Lumber and wood products
		250	Furniture and fixtures
	Chemicals and allied products		
281	Industrial chemicals and synthetics		**Paper**
283	Drugs	262	Pulp, paper, and board mills
284	Soap, cleaners, and toilet goods	265	Other paper and allied products
287	Agricultural chemicals		
289	Chemical products, nec	270	**Printing and publishing**
	Primary metal industries		**Rubber and Plastic**
331	Ferrous	305	Rubber products
335	Nonferrous	308	Miscellaneous plastics products
	Fabricated metal products		**Glass, Stone, and Mineral**
341	Metal cans, forgings, and stampings	321	Glass products
342	Cutlery, hardware, and screw products	329	Stone, clay, concrete, etc
343	Heating equip., plumbing and structural		
349	Metal services, ordnance, and nec		**Transport Equipiment**
		371	Motor vehicles
	Machinery	379	Other transportation
357	Computer and office equip.		
351	Engines and turbines		**Instruments**
352	Farm and garden	381	Measuring, scientific, and optical
353	Construction, mining, and material handling	384	Medical and ophthalmic
354	Metalworking	386	Photographic equipment
355	Special industry		
356	General industrial		**Other Manufacturing**
358	Refrigeration and service industry	210	Tobacco
359	Industrial machinery, nec	310	Leather
		390	Miscellaneous
	Electronic		
363	Household appliances		
366	Audio, video, and communications		
367	Electronic components and accessories		
369	Electronic, nec		

TABLE 2: Foreign Activity in the U.S. by Aggregated BEA Industries

	FDI Share			Import Share		
	1988	1992	1996	1988	1992	1996
Food and Kindred Products	10.8	11.9	9.3	3.6	3.7	4.1
Textile Mill Products	4.6	6.7	7.5	7.4	8.8	10.1
Apparel and Oth. Textile	1.5	3.2	4.6	23.9	29.1	33.4
Wood and Furniture	2.2	2.6	2.1	7.4	8.5	11.2
Paper	6.8	7.5	8.5	8.8	8.0	9.0
Printing and Publishing	6	6.6	7.2	1.2	1.2	1.5
Chemicals	27.2	32.1	30.7	7.9	9.2	11.4
Rubber and Plastic	10.8	14.8	14.7	6.7	7.5	8.6
Stone, Glass, and Mineral	15.7	20.8	21	8.7	9.5	10.5
Primary metals	10.6	15.9	14.1	14.3	15.0	18.1
Fabricated Metals	5.9	8.3	8.6	4.9	5.6	6.6
Industrial Machines	7.5	11.2	11	18.9	22.9	24.5
Electronics	13.7	17.2	18	20.8	25.2	27.3
Motor Vehicles	7.4	11	14.2	27.6	26.0	26.7
Other Transport	2.3	4.9	3.6	7.6	9.2	12.9
Instruments	8.2	11.9	12.8	11.6	12.5	15.6
Other Manufacturing	6.3	10.2	7.6	30.3	31.9	37.1

Source: *Survey of Current Business* , various years

TABLE 3: Olley-Pakes Input Elasticity Estimates

			for comparison
	O-P (1)	**O-P (2)**	OLS
Capital	0.300	0.251	0.200
	(0.037)	(0.036)	(0.035)
Labor	0.466	0.456	0.463
	(0.022)	(0.021)	(0.031)
Materials	0.256	0.276	0.164
	(0.025)	(0.026)	(0.032)
Scale elasticity	1.022	0.983	0.827

O-P (1) includes trend, trend*SIC357 in first stage
Standard errors in parentheses

TABLE 4: Baseline Results

One-year differences

	(1)	(2)	(3)	(4)	(5)	(9)
R&D	0.004	0.002	0.002	0.004	0.003	0.004
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Capacity	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market Share	-0.052	-0.195	-0.114	-0.071	0.001	-0.096
	(0.091)	(0.123)	(0.103)	(0.091)	(0.129)	(0.079)
Firm Markup	-0.005	-0.009	-0.007	-0.005	-0.006	-0.005
	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Industry Markup	0.408	0.428	0.404	0.463	0.333	0.005
	(0.134)	(0.121)	(0.130)	(0.138)	(0.084)	(0.151)
FDI						
Current	0.547	0.352			0.375	0.894
	(0.169)	(0.149)			(0.152)	(0.226)
Lagged One	0.543		0.339		0.238	0.550
	(0.161)		(0.163)		(0.151)	(0.202)
Lagged Two	-0.227			-0.157	-0.839	0.073
	(0.163)			(0.160)	(0.162)	(0.208)
Imports						
Current	0.431	0.134			0.780	0.349
	(0.329)	(0.279)			(0.298)	(0.385)
Lagged One	1.133		0.781		2.803	1.108
	(0.309)		(0.279)		(0.296)	(0.356)
Lagged Two	-0.154			-0.307	1.317	0.297
	(0.323)			(0.322)	(0.286)	(0.367)
Fixed Effects						
Industry	YES	YES	YES	YES	NO	YES
Year	YES	YES	YES	YES	YES	YES
Industry Trends	NO	NO	NO	NO	NO	YES
Obs	4202	5395	4792	4202	4202	4202
Firms	839	938	880	839	839	839
F-Test (FDI)	7.36	5.6	4.35	0.96	11.16	6.8
(P-value)	(0.0001)	(0.018)	(0.037)	(0.328)	(0.000)	(0.0002)
F-Test (Imports)	4.84	0.23	7.85	0.91	45	3.27
(P-value)	(0.002)	(0.632)	(0.005)	(0.340)	(0.000)	(0.021)
R-Squared	0.134	0.089	0.109	0.127	0.066	0.148

Standard errors are hetero-skedasticity consistent and allow for clustering by firm
The calculation of TFP uses the coefficients from the preferred specification O-P (1)

TABLE 5: Robustness - Longer Differences

	Two-year differences		Three-year differences	
	(1)	(2)	(3)	(4)
R&D	0.008	0.007	0.018	0.016
	(0.002)	(0.003)	(0.004)	(0.004)
Capacity	-0.002	0	-0.003	0
	(0.001)	(0.001)	(0.002)	(0.001)
Market Share	-0.586	-0.293	-0.218	-0.4
	(0.194)	(0.246)	(0.191)	(0.159)
Firm Markup	-0.009	-0.011	-0.434	-0.432
	(0.004)	(0.004)	(0.110)	(0.107)
Industry Markup	0.824	0.717	1.485	0.153
	(0.235)	(0.175)	(0.307)	(0.178)
FDI - Current	0.514	0.003	0.502	-0.042
	(0.226)	(0.201)	(0.257)	(0.225)
Import - Current	0.504	2.754	0.552	2.827
	(0454)	(0.394)	(0.586)	(0.483)
Fixed Effects				
Industry	YES	NO	YES	NO
Year	YES	YES	YES	YES
Industry Trends	NO	NO	NO	NO
Obs	2254	2254	1572	1572
Firms	762	762	685	685
F-Test (FDI)	5.15	0	3.8	0.04
(P-value)	(0.024)	(0.989)	(0.052)	(0.850)
F-Test (Imports)	1.23	48.9	0.89	34.27
(P-value)	(0.268)	(0.000)	(0.346)	(0.000)
R-Squared	0.207	0.062	0.272	0.096

Standard errors are hetero-skedasticity consistent and allow for clustering by firm
The calculation of TFP uses the coefficients from the preferred specification O-P (1)

TABLE 6: Robustness - Controlling for Changes in Total Sales and Employment

	(1)	(2)
R&D	0.004	0.004
	(0.002)	(0.002)
Capacity	0.000	-0.001
	(0.001)	(0.001)
Market Share	-0.064	-0.129
	(0.082)	(0.085)
Firm Markup	-0.004	-0.004
	(0.003)	(0.003)
Industry Markup	0.400	0.157
	(0.133)	(0.152)
Change FDI EMP		
Current	0.621	0.952
	(0.166)	(0.225)
Lagged One	0.408	0.612
	(0.163)	(0.209)
Lagged Two	-0.094	0.154
	(0.167)	(0.204)
Change Total EMP		
Current	-0.084	-0.154
	(0.115)	(0.134)
Lagged One	-0.357	-0.246
	(0.137)	(0.161)
Lagged Two	-0.133	-0.245
	(0.138)	(0.174)
Change Imports		
Current	0.421	0.303
	(0.227)	(0.252)
Lagged One	0.693	0.743
	(0.249)	(0.287)
Lagged Two	-0.238	-0.054
	(0.264)	(0.304)
Change Total Sales		
Current	0.117	0.038
	(0.085)	(0.092)
Lagged One	-0.017	-0.154
	(0.104)	(0.124)
Lagged Two	-0.096	-0.004
	(0.082)	(0.090)
Fixed Effects		
Industry	YES	YES
Year	YES	YES
Industry Trends	NO	YES
Obs	4040	4040
Firms	797	797
F-Test (FDI)	6.15	6.72
(P-value)	(0.0004)	(0.0002)
F-Test (Imports)	3.88	2.69
(P-value)	(0.009)	(0.045)
R-Squared	0.147	0.158

Standard errors are hetero-skedasticity consistent and allow for clustering by firm
The calculation of TFP uses the coefficients from the preferred specification O-P (1)
Change in FDI-EMP is absolute change in FDI employment divided by lagged total employment
Change in Total-EMP is absolute change in total employment divided by lagged total employment
Change in Imports is absolute change in real imports divided by lagged real imports + local production
Change in Total Sales is absolute change in real local sales + imports divided by lagged real imports + local production

Table 7: Robustness - Sample Split By Period

	1990-1992	1994-1996	Full Sample
R&D	0.003	0.004	0.004
	(0.002)	(0.002)	(0.002)
Capacity	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)
Market Share	-0.140	0.027	-0.052
	(0.204)	(0.081)	(0.091)
Firm Markup	-0.004	-0.008	-0.005
	(0.001)	(0.011)	(0.003)
Industry Markup	0.213	0.119	0.408
	(0.345)	(0.188)	(0.134)
FDI			
Current	0.548	1.087	0.547
	(0.363)	(0.334)	(0.169)
Lagged One	0.711	0.703	0.543
	(0.387)	(0.294)	(0.161)
Lagged Two	-0.126	0.732	-0.227
	(0.317)	(0.339)	(0.163)
Imports			
Current	-1.202	0.934	0.431
	(0.690)	(0.657)	(0.329)
Lagged One	-0.111	1.221	1.133
	(0.759)	(0.294)	(0.309)
Lagged Two	0.140	-1.187	-0.154
	(0.589)	(0.678)	(0.323)
Fixed Effects			
Industry	YES	YES	YES
Year	YES	YES	YES
Obs	1774	1865	4202
Firms	634	717	839
F-Test (FDI)	2.14	4.38	7.36
(P-value)	(0.093)	(0.005)	(0.0001)
F-Test (Imports)	1.91	2.6	4.84
(P-value)	(0.126)	(0.051)	(0.002)
R-Squared	0.089	0.198	0.134

Standard errors are hetero-skedasticity consistent and allow for clustering by firm
The calculation of TFP uses the coefficients from the preferred specification O-P (1)

TABLE 8: Sample Split into Low & High Tech Industries

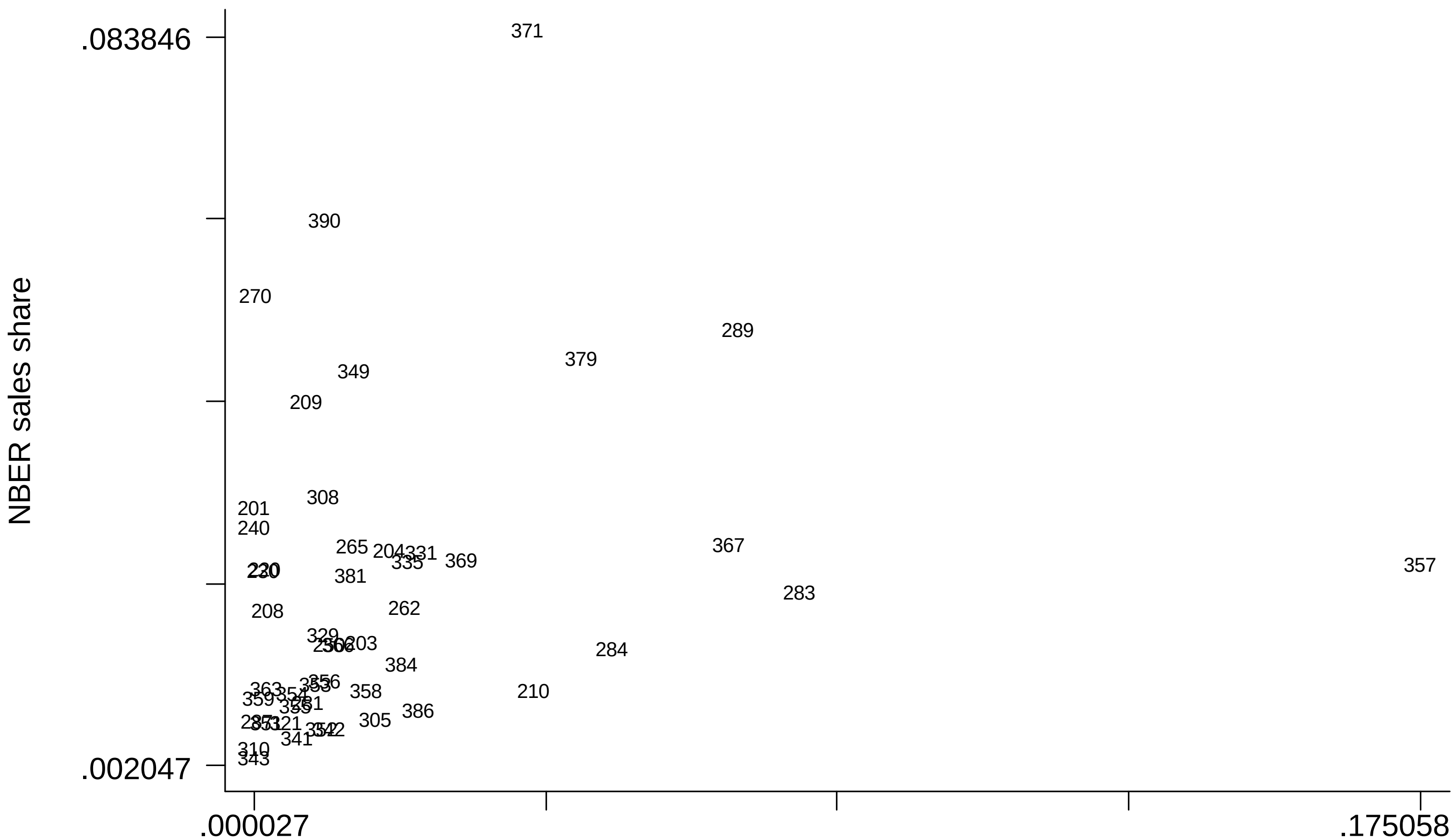
	Full Sample	High Tech Only	Low Tech Only
Capacity	-0.003	-0.002	-0.001
	(0.001)	(0.001)	(0.001)
Market Share	-0.055	0.852	-0.133
	(0.080)	(0.993)	(0.067)
Firm Markup	-0.005	-0.091	-0.002
	(0.003)	(0.028)	(0.001)
Industry Markup	0.272	0.801	-0.166
	(0.111)	(0.207)	(0.127)
FDI			
Current	0.537	0.999	-0.171
	(0.145)	(0.212)	(0.180)
Lagged One	0.436	0.567	0.086
	(0.141)	(0.239)	(0.182)
Lagged Two	-0.21	0.092	-0.291
	(0.143)	(0.275)	(0.167)
Imports			
Current	0.495	0.421	-0.394
	(0.297)	(0.496)	(0.345)
Lagged One	0.943	1.001	0.489
	(0.297)	(0.543)	(0.362)
Lagged Two	0.306	-0.931	0.47
	(0.303)	(0.583)	(0.360)
Fixed Effects			
Industry	YES	YES	YES
Year	YES	YES	YES
Obs	5614	2686	2928
Firms	1115	525	590
F-Test (FDI)	8.17	9.47	1.38
(P-value)	(0.000)	(0.000)	(0.249)
F-Test (Imports)	4.11	2.43	1.77
(P-value)	(0.007)	(0.065)	(0.153)
R-Squared	0.101	0.157	0.15

Standard errors are hetero-skedasticity consistent and allow for clustering by firm
The calculation of TFP uses the coefficients from the preferred specification O-P (1)
Hitech industries are 281, 283, 284, 289, 357, 367, 381, 384

TABLE 9: Industry of Affiliate vs Industry of Employment Activity FDI Data

	FDI employment data by …	
	by activity of employment	by entire affiliate
FDI		
Current	0.547	0.089
	(0.169)	(0.079)
Lagged One	0.543	0.147
	(0.161)	(0.068)
Lagged Two	-0.227	-0.023
	(0.163)	(0.067)
Imports		
Current	0.431	0.460
	(0.329)	(0.334)
Lagged One	1.133	1.061
	(0.309)	(0.320)
Lagged Two	-0.154	-0.072
	(0.323)	(0.318)
Fixed Effects		
Industry	YES	YES
Year	YES	YES
Industry Trends	NO	NO
Obs	4202	4202
Firms	839	839
F-Test (FDI)	7.36	2.23
(P-value)	(0.0001)	(0.083)
F-Test (Imports)	4.84	3.95
(P-value)	(0.002)	(0.008)

Standard errors are hetero-skedasticity consistent and allow for clustering by firm
The calculation of TFP uses the coefficients from the preferred specification O-P (1)



Sales Shares in Sample and NBER Productivity Database