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

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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 substantial productivity gains for domestic firms. The size of FDI spillovers is economically important, accounting for about 14% of productivity growth in U.S. firms between 1987 and 1996. FDI spillovers are particularly strong in high-tech sectors, whereas they are largely absent in low-tech sectors. Small firms with low productivity benefit more from FDI spillovers than larger and more productivity firms. The evidence for import spillovers is much weaker.

JEL: F1, F2, O3
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1. Introduction

There are many reasons to believe that the local affiliates of foreign multinationals provide positive externalities for host country firms. Multinational companies are well-known to be more productive and to do more R&D than purely domestic firms, and the knowledge transferred from parent to its foreign affiliates may spillover to host country firms. Host country firms may also obtain access to foreign knowledge by hiring away the employees of the foreign affiliates of multinationals. Other mechanisms that could give rise to positive externalities can arise through vertical linkages and the provision of specialized inputs. Given these strong conceptual arguments, it is not surprising that many policymakers and academics tout the benefits to a country of attracting multinational companies.

As plausible as these arguments are, the empirical literature has not found large positive externalities from the affiliates of multinational companies to host country firms. This paper shows that these externalities are strong. With data on about 1,300 U.S. manufacturing firms for the years 1987-1996, we show that spillovers from foreign multinationals to U.S. firms can explain a substantial part, about 14 percent, of U.S. manufacturing productivity growth. The estimates range from 8 to 19 percent depending on the empirical specification.

Our analysis examines spillovers from multinationals to local firms in the same industry (horizontal spillovers). To the best of our knowledge, this paper is the first to show that multinationals can cause economically important productivity benefits to domestically-owned firms.[1] We attribute our strong results to several methodological features of our analysis. First, we properly compute total factor productivity using the

[1] See Keller (2007) for a recent review of the literature.

Olley-Pakes (1996) method. Second, we use instrumental variable techniques in estimating the effect of FDI, being careful to choose instruments motivated by theory. The resulting estimates imply much larger technology spillovers from multinationals to local firms than found in previous studies. Third, we show that large FDI spillovers are only estimated with high-quality data on foreign employment across industries. If we employ FDI data similar to that more commonly available in other studies of FDI spillovers, we too estimate only a small or zero effect of FDI on US productivity growth.

Our study is also unique in several other dimensions. First, we investigate heterogeneity within industries and across industries in the strength of spillovers. FDI spillovers are shown to be strongest in high-technology industries and have a bigger impact within industries on the productivity growth of those firms most distant from the productivity frontier. This systematic variation in the strength of FDI spillovers should be of interest to both policymakers and theorists. Second, our statistical inferences with respect to the significance of parameter estimates are based on the most stringent of assumptions. Finally, we also consider the possibility that there are externalities associated with imports activity. While we find some evidence for imports spillovers, the results are far less robust than for foreign direct investment.[2]

The remainder of this paper is as follows. The following section briefly lays out our empirical approach. Section three describes our data. Estimation results are presented in section four, and section five provides some concluding discussion. Additional information on the estimation technique and the data is presented in the appendix.

[2] Within the literature on FDI spillovers, Haskel, Pereira, and Slaughter (2007) is closest to our own. The authors estimate positive, but relatively small spillovers from foreign multinationals to plants located in the United Kingdom. While they do employ instrumental variable estimation (with mixed results), their study differs from our own along the other dimensions discussed in the text above.

2. Estimation framework

Since 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 modeling a particular mechanism, our approach is to ask whether there is evidence that the productivity of domestic firms grows faster in industries in which foreign activity in terms of FDI and imports is expanding. More formally, let tfp_{ijt} denote the total factor productivity of firm i in period t. The following regression equation is estimated:

$$(1) \qquad \Delta tfp_{ijt} = \beta X + \gamma_1 \Delta FDI_{jt} + \gamma_2 \Delta IMP_{jt} + \varepsilon_{ijt}.$$

Here, FDI_{jt} is a measure of foreign direct investment in the industry to which firm i belongs at time t, and analogously for imports, IMP_{jt} measures firm i's exposure to industry imports. Also included is a vector of control variables, X, and ε_{ijt} is a mean-zero error term. The Δ indicates time differencing. By considering a time differenced specification, we remove any time-invariant heterogeneity across firms.

It is critical that TFP, FDI, and IMP are carefully measured. To properly measure TFP, we rely on work by Olley and Pakes (1996). These authors develop a framework for dynamic industry equilibrium analysis where firms optimally choose sales and investment, as well as entry and exit. One advantage of this approach is that the firm-specific productivity can change over time. Since firms will optimally demand more inputs when productivity is high, the Olley-Pakes approach can address the problem of the simultaneity of input choice in productivity calculations.

Let y_{it} denote 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. Total factor productivity is computed in the usual way,

$$(2) \qquad tfp_{it} = y_{it} - \beta_k^{OP} k_{it} - \beta_l^{OP} l_{it} - \beta_m^{OP} m_{it},$$

for all i and t, where $\beta_k^{OP}, \beta_l^{OP}$, and β_m^{OP} are the Olley-Pakes estimates of the capital, labor, and materials production function elasticities. More details on this can be found in Appendix I.[3]

Second, our measures for imports and foreign direct investment, IMP_{jt} and FDI_{jt}, are defined as follows: IMP_{jt} is the share of U.S. imports (denoted *m*) in imports plus total shipments (denoted *d*) of the industry to which the firm belongs:

$$IMP_{jt} = \frac{m_{jt}}{m_{jt} + d_{jt}},$$

for each period t, industry j and firm i belonging to industry j.[4]

Correspondingly, FDI_{jt} is the share of the foreign-owned affiliates' employment (denoted *f*) in foreign affiliates employment plus employment of U.S.-owned firms (denoted by *e*) by industry j to which firm i belongs (source: Bureau of Economic Analysis):

[3] We have also considered alternative methods of productivity calculations, including allowing for industry-specific elasticities; see the discussion below.
[4] A list of these industries can be found in Table 1.

$$FDI_{jt} = \frac{f_{jt}}{f_{jt} + e_{jt}} \quad .$$

These measures of imports and FDI capture the prevalence of foreign economic activity in a particular U.S. industry. If specialized imports trigger technology spillovers, or if foreign affiliates of MNEs generate positive externalities for U.S. firms by building up more efficient supplier chains or a pool of highly skilled technicians, then we would expect that TFP would be correlated with measures of foreign presence in that industry. A positive correlation between TFP and our measures of foreign presence need not be evidence of a causal effect, however. For example, 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 that does not provide evidence for FDI spillovers. Instrumental-variable estimation will be employed below to address these concerns.

We also employ a vector of control variables, denoted X in equation (1), to better isolate spillover effects (see Appendix II for variable construction). First, we include a variable that picks up the degree of capacity utilization (denoted as CU). If changes in capacity utilization are not controlled for, they will be part of the error and thus cause inconsistent estimates as long as they are correlated with the FDI and import measures. Second, it is important to control for changes in the degree of market competition that might be associated with changes in foreign activity. We follow Nickell (1996) and others and use the firm's market share in the industry as well as the firm's mark-up and the industry mark-up to capture these effects (denoted by MS, FM, and SM, respectively, and entering lagged). 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. A firm's (log) R&D expenditures, *r*, may also impart a major influence on productivity growth and it included as control variable.

There is a substantial degree of unobserved heterogeneity across firms in different industries in our sample. Productivity growth in some industries is higher than in others due to factors unrelated to imports and FDI, 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 the specifications below. We also include time fixed effects, α_t, in all regressions, in part because our sample period covers the 1990/91 U.S. recession.

The next section reviews the main characteristics of the data.

3. Data

This study is based on data on an unbalanced sample of manufacturing firms in the United States from Standard and Poor's *Compustat* database. *Compustat* includes only publicly traded companies and publishes data from the companies' balance sheets according to legal reporting requirements. Because this might be not as good for our purposes as manufacturing census data, we have extensively cleaned the data in order to avoid biases, and the cross-industry variation in our productivity figures resembles closely that of U.S. manufacturing as a whole. Unlike census data, the *Compustat* database has the advantage of being publicly available. It also includes most of the larger

U.S. firms, which means that- as in Griliches and Mairesse (1984), as well as Jovanovic and Rousseau (2002), e.g.- we cover a major portion of all U.S. economic activity.

From *Compustat*, we obtain data on the firms' (log) output y, as well as (log) labor, materials, and capital inputs (l, m, and k), where our output measure is net sales.[5] 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 *Compustat* comes data on the firms' R&D expenditures, on firms' market share, firms' mark-up, and industry mark-up. Not all information is available for all firms, and we have had to fill in small amounts of missing data, typically for the firms' capital stocks. After extensive data cleaning, our sample consists of 1,277 U.S.-owned firms that were active between the years 1987 to 1996, covering about 40% percent of U.S.-owned manufacturing employment and roughly 55% of U.S.-owned manufacturing research and development expenditures in the United States. [6]

Our primary interest is whether productivity is related to the importance of imports and foreign-owned affiliates in the firm's relevant economic environment. The analysis is at the relatively detailed two to three-digit SIC, industry 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

[5] Data on materials is estimated netting out capital depreciation and labor costs from cost of goods sold and administrative and selling expenses; for this and other details of the variables' definition and construction, see Appendix II.

[6] Because large firms often span several industries, our matching of firms to industries is imperfect and introduces measurement error in our dependent variable. A different part of *Compustat* contains more detailed (line of business) data for sales, but unfortunately not for all inputs. Analyzing productivity at the plant instead of the firm level might help; not infrequently though, plants are operating in several industries as well. To address measurement error concerns, we conduct a robustness analysis.

list of the industries. For our sample period we choose the years 1987 to 1996, because before and after this period there have been changes in the BEA's industry classification. Data on foreign employment 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 based on the industry classification of the activity of individual affiliate employees rather than the industry classification of the affiliate as a whole, by its mainline of business rather than the mainline of business of the affiliate as a whole.[7] 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 for the entire affiliate if the affiliate's mainline of business 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).

Table 2 shows how FDI employment and import penetration varied by broad industry classification over the sample period. For all of manufacturing, the fraction of imports increased by 3.5 percentage points, from 12.9 to 16.5 percent, while FDI increased by 4.0 percentage points, from 7.7 to 11.7 percent. The table indicates that for both FDI and imports, there is a substantial amount of variation across industries. For example, FDI employment in the motor vehicles industry increased by 8 percentage points (6.6 to 14.6 percent), while in the wood & furniture industry FDI employment hardly changed at all.

We now turn to the empirical results.

[7] An affiliate's mainline of business is the industry in which the affiliate has the majority of its sales. 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 employment was largest; other affiliates had to specify their employment (and sales) in the three industries in which their employment were largest.

4. Results

This section presents the results of the paper. First, we present the Olley-Pakes estimates underlying our total factor productivity calculation. Second, we lay out the main results of estimating the spillover equation. Third, we discuss the magnitude of the coefficients and provide two explanations for why they are larger than those found in other studies.

Table 3 reports the production elasticities for capital, labor, and materials that we estimate using the Olley-Pakes (O-P) 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 some indication of the range of estimates that is obtained.[8] 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, because the computer industry has experienced exceptionally high productivity growth over this period. The elasticities are estimated to be 0.188, 0.301, and 0.594 for capital, labor, and materials, respectively. Without the trends, the capital elasticity rises to 0.213 (see O-P (2)).

For comparison purposes, we also show the OLS estimates (in first-differences) of the elasticities. These lead to capital and materials, with 0.041 and 0.467, respectively. These results are consistent with simultaneity and exit leading to an important downward bias on the capital coefficient. Looking at the implied scale elasticities, it is 1.083 for O-P(1) and 0.926 for OLS, respectively. For this sample of industries and firms, increasing

[8] 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.

returns is a more plausible deviation from constant returns than decreasing returns to scale. Thus, the Olley-Pakes estimates are preferable to the OLS coefficients, both conceptually as well as empirically, and we use the O-P(1) estimates to compute our main firm TFP measures according to equation (2) above.[9]

In Table 4, results from our initial specification are shown. Since it is not known over which time horizon FDI- and imports-related spillovers operate—if they exist--, we consider contemporary, one-year as well as two-year lagged variables in our analysis. The regression equation is given by

$$\begin{aligned} \Delta tfp_{ijt} &= \alpha_j + \alpha_t + \beta_1 CU_{jt} + \beta_2 \Delta MS_{ijt-2} + \beta_3 FM_{it-2} + \beta_4 SM_{jt-2} + \beta_5 r_{ijt} + \\ &\quad \gamma_{1q} \sum_{q=0}^{2} \Delta FDI_{jt-q} + \gamma_{2q} \sum_{q=0}^{2} \Delta IMP_{jt-q} + \varepsilon_{ijt} . \end{aligned} \tag{3}$$

Specification (4.1) in column 1 shows OLS results for the full sample of firms. Standard errors clustered by industry-year combination are shown in parentheses. These are the preferred standard errors since firms in the same industry j are experiencing the same FDI_{jt} and IMP_{jt} innovation in a given year. The clustered standard errors are also relatively large; failing to account for the dependence of FDI_{jt} and IMP_{jt} shocks across firms may substantially overstate the evidence for spillovers.

We estimate a coefficient on contemporaneous FDI of 0.213 and a coefficient on one-year lagged FDI of 0.303. The sum of the significant coefficients of 0.516 provides an estimate of the total effect of FDI. As indicated by the F-Test statistic at the bottom of the table this estimate of the total effect is statistically significant at the standard five

[9] Below we also discuss results from a number of alternative productivity measures.

percent level. Our finding that only the contemporaneous and one-period lagged FDI variables enter significantly suggests that spillovers from FDI materialize relatively quickly—within two years.[10]

The contemporaneous and one-year lagged imports point estimates are positive, but the standard errors are large so that overall the imports effect is not significant (p-value of F-test of 13.9%). Turning to the control variables, their signs come in as expected, but they are not always statistically significant. For the mark-up variables, we find that high industry mark-ups but low firm mark-ups are associated with higher productivity growth, all else equal.

Table 4 also shows results for longer differences. The focus on longer differences relative to one-year differences has the advantage of picking up less noisy movements in the data but at the expense of a reduced number of observations. To avoid eliminating too many observations, we include now only the contemporaneous FDI and imports variables. Specification (4.2) shows results for two-year and specification (4.3) for three-year differences.[11] In both cases, the FDI estimate is around 0.4, significant at the 5% (two-year) and 10% (three-year) level of significance. These coefficients are not much lower than the one-year differences estimate of 0.51, the sum of significant coefficients in specification (4.1). In addition, we estimate a positive, albeit insignificant effect from imports, and the control variable estimates are qualitatively similar as well.

[10] That foreign technology may leak to domestic competitors in a relatively short period of time is consistent with findings by Mansfield and Romeo (1980). These authors find that in more than 40% of the cases, technology transferred from a multinational parent to its affiliate was available to competitors within one and a half years.

[11] The sample size goes down moving from one-year to longer differences because we employ non-overlapping periods (the overall sample period of 1987-96 consists of nine one-year differences, four two-year differences, and three three-year differences). Also the inclusion of lagged FDI and imports terms affects sample size.

An important question is whether FDI affects equally the weak and strong domestic firms. It may be that relatively weak firms benefit more since they have most to learn technologically. Alternatively, the relatively strong firms benefit more since only the capabilities of these firms are sufficiently high to absorb the incoming technology. Compared to the Table 4 specifications, we include now interactions of FDI and imports with an indicator of the firm's size or productivity.[12]

The first column of Table 5 shows results for the one-year differences specification, where we have dropped the two-period lagged FDI and imports variables since they were not significant before (see (4.1) in Table 4). We estimate positive coefficients for contemporaneous and one-period lagged FDI, with the latter being significant at standard levels. The FDI-size interactions are negative, and the one-year lagged estimate is significant. This suggests that smaller firms benefit more from FDI spillovers than larger firms. The mean estimate in (4.1) is about 0.5, while (5.1) suggests that for the smallest firms the FDI coefficient is about 0.8. In contrast, the largest firms do not benefit from FDI spillovers, since the direct and interaction-cofficients are roughly equal in absolute value.

This pattern is generally confirmed using alternative specifications. According to the two-year differences specification, the smallest firms benefit about two and a half times as much as the average firm, with estimates of 0.984 in (5.2), versus 0.379 in (4.2). Again, the largest firms do not benefit at all from inward FDI spillovers. We obtain similar results with a three-year differences estimation, finding that the smallest firms

[12] Size is measured in terms of the rank in the distribution of log sales at the beginning of the period, normalized by the total number of firms, for each industry and each year. Hence, the variable is defined on (0,1], with a value of 1 for the largest firm. Productivity is measured analogously using our estimated TFP levels.

benefit almost three times as much as the average firm from FDI spillovers (see (5.3) and (4.3)).

These findings also hold if we stratify firms by productivity instead of size.[13] Column four in Table 5 shows the results for productivity in the three-year differences specification. They suggest that firms at the lower end of the productivity distribution benefit about three times as much form FDI spillovers as the average firm (coefficient of 1.19 versus 0.41 in (4.3)). In contrast, for imports, we do not estimate significant spillover effects for any firm size or productivity level.

The next step is to interpret the direction of causation in the correlation of FDI with productivity. This correlation could reflect spillovers from foreign multinationals to U.S. firms or it could be instead that productivity growth affects the propensity of foreign multinationals to invest in the United States. An industry's productivity growth could bias downward our spillover estimate if FDI is concentrated where 'weak' (low-productivity) firms make easy targets to expand market share or it could bias upward our spillover estimate if foreign multinationals are attracted to high productivity growth industries. To account for the possibility of endogeneity of both FDI and imports, we employ instrumental variable (IV) estimation using variables suggested by the theory of the multinational firm. These variables include contemporaneous changes in shipping costs and tariffs (see Brainard 1997) and lagged levels of the real exchange rate interacted with industry dummies (see Froot and Stein 1991).[14]

Table 6 shows in column 1 the IV results for the one-year differences specification. The instruments are valid: the over-identification test statistic cannot reject

[13] Coefficients are somewhat less precisely estimated using productivity instead of size. We attribute this to measurement error in the constructed TFP measures.
[14] We also include lagged values of FDI_{jt} and IMP_{jt} as additional instruments.

the null hypothesis of orthogonality (p-value of 0.849). They are also relevant as the partial R-squared (obtained by regressing each endogenous variable on the excluded instruments) is 0.33 in the FDI equation and 0.22 in the import equation. We find no evidence for contemporaneous or two-year lagged spillovers, but the coefficient on the one-year lagged FDI variable is positive at 0.885, and the p-value of the overall FDI test is 6.4%. Relative to the corresponding OLS specification (Table 4), now the FDI spillovers are predominantly operating with a one-year lag. For imports, our IV estimates confirms the OLS results of no significant overall effect at standard levels (p-value of F-test of 16.1%).

Specification (6.2) in Table 6 provides IV results for the two-year differences, analogous to the OLS results of (4.2) in Table 4. Again, the instruments are valid: the over-identification test cannot reject the hypothesis of orthogonality (p-value of 0.46). Further, the fit of the first-stage regression is stronger than in the one-year difference equations: the partial R-squared is 0.75 in the FDI equation and 0.77 in the imports equation.[15] The FDI coefficient is positive and significant at 0.645, while the imports point estimate is positive but not significant at standard levels.[16]

Both IV specifications suggest that FDI indeed has positive spillover effects for the domestic economy. Interestingly, the coefficient estimates in the IV specifications imply larger effects than the corresponding OLS regressions: 0.885 versus 0.516 for one-year differences, and 0.645 versus 0.379 for two-year differences estimation.

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[15] Given the relatively small number of independent observations on FDI and imports due to industry-year clustering, the first stage F-statistics are somewhat low. Based on the high partial R^2, we think the instruments are strong. If one believed otherwise, the IV estimates would be biased towards the OLS estimates (see Bound, Jaeger, and Baker 1995), and consequently, one should view the estimates of 0.885 (in 6.1) and 0.645 (in 6.2) as lower bounds.

[16] The full first stage results are available upon request from the authors.

There are at least two explanations for the relatively large estimates in the IV regression relative to those in the OLS regressions. First, if the employment share of multinational enterprises is an imperfect proxy for the R&D or knowledge that is moved to the U.S. by multinationals, there is measurement error. Nevertheless, we stick with the foreign employment share as our key FDI variable in part because it should be correlated with a very broad range of mechanisms of spillovers, and because this variable has been extensively employed in the previous literature. Second, if there is heterogeneity in FDI spillover effects, the point estimate in the IV estimation will depend on the observations that drive identification. For instance, only those FDI movements most associated with real exchange rate movements and transport cost changes are featured in the IV regression and these FDI movements might be most associated with FDI spillovers.[17]

The finding of significant FDI spillovers also emerges from a number of robustness checks we have conducted. This includes separating the FDI variable into two variables, foreign employment and total employment (numerator and denominator of FDI_{it}, respectively) in order to see that the estimated effect is not solely due to changes in total industry employment; we find this to be the case. In addition, we have employed cost shares from the Bureau of Labor Statistics as alternative estimates of the production function elasticities β_k, β_l, and β_m in the computation of total factor productivity. With these figures varying by industry, this relaxes the constraint imposed by our Olley-Pakes estimation of identical elasticities; our FDI spillover results for this case are similar.[18]

[17] Card (2001) discusses such heterogeneous treatment effects in another context.
[18] Analogous to the OLS results for equation (3), the sum of significant coefficients with productivity based on BLS cost shares is 0.533 (versus 0.516 in specification 4.1).

We now discuss the magnitude of the economic impact of foreign spillovers on productivity growth in the U.S. that is suggested by our estimates. For FDI, the share of foreign employment in U.S. manufacturing rose between 1987 and 1996 from 7.7% to 11.7%, or by 4.0 percentage points (Table 2). Based on our Olley-Pakes input elasticity estimates (O-P (1) in Table 3), we estimate an average productivity growth in our sample of 0.19 over the sample period of 1987-96.[19] The mean spillover estimates in Tables 4 to 6 range, depending on the exact method, from 0.379 (specification 4.2) to 0.885 (specification 6.1). This means the FDI spillovers account for between 8% and 19% of US manufacturing productivity growth during 1987-96.[20] With a mid-point estimate of 13.5% of US manufacturing productivity growth, these estimates are quite large, certainly relative to the earlier literature (see discussion in section 1). In the following, we therefore address the question of what factors explain our relatively large estimate of technology spillovers.

A first reason may lie in the fact that relative to much of the existing literature, our analysis is based on productivity figures derived using the Olley-Pakes (O-P) method, with its advantages described above. This turns out to be the case only in a limited sense. If instead of O-P one simply runs an OLS regression of output on inputs and FDI, imports, and all controls, analogous to specification (4.1), the coefficients on the FDI variables are very similar.[21] Using O-P makes a difference only for the calculation of the importance of FDI spillovers in accounting for productivity growth. Using OLS with

[19] This number is a weighted-average of the individual firm level TFP estimates, where the weights are the average real sales by firm over the sample period.
[20] Calculated as 0.379*0.04/0.19 = 0.08, and 0.885*0.04/0.19 = 0.19, respectively.
[21] The significant coefficients are for contemporaneous FDI, with 0.246, and for one-year lagged FDI, with 0.318; this sums to 0.564, versus 0.516 in the O-P specification (4.1).

inputs on the right-hand side, one estimates considerably higher productivity growth in the sample, so the share accounted for by FDI spillovers is lower.[22]

More important are two other factors. The first lies in the precise way in which the FDI data we use is collected. As mentioned earlier, the FDI variable is constructed by aggregating up to the industry level the number of employees engaged in particular activities, which is below the affiliate level. Frequently, however, it is only possible to allocate all of a particular affiliate's labor force to one industry, the affiliate's 'mainline of business'. Because foreign affiliates are often diversified and have employees in several industries, our approach avoids the mismeasurement of industry FDI associated with changes in the affiliates' mainline of business that causes large year-to-year jumps in measured foreign employment.

To assess the quantitative importance of this for FDI spillover estimates, we have re-done our estimations using the more commonly available 'mainline of business' data. In Table 7, we compare results from estimation with 'activity' FDI versus 'mainline of business' FDI data for one-year and two-year difference estimation. On the left, specifications 7.1 and 7.2 repeat the earlier results (4.1 and 4.2) with the preferred activity data. The corresponding FDI spillover results when 'mainline of business' FDI data is employed are shown in the two columns on the right. With one-year differences, only the contemporaneous FDI coefficient is positive and significant at the 10% level. However, with a value of 0.074, it is much smaller than the sum of significant coefficients of 0.516 for the preferred FDI data in (7.1), and neither is the overall FDI

[22] Table 3 shows that the scale elasticity using an OLS regression of output on inputs is about 0.93, versus 1.08 using O-P. In consequence, the average productivity growth using OLS is 35% over the sample period, not the O-P estimate of 19%. The share of productivity growth accounted for by FDI spillovers would be only 0.564*0.04/0.35 = 6.4%, not 13.5%.

effect significant when 'mainline of business' FDI data is employed (p-value of 0.352 in 7.3). Using two-year difference estimation, the comparison between the two sets of results yields the same conclusion: detailed information on industry FDI activity is crucial for estimating spillovers.

Second, we may estimate relatively large FDI spillovers because of the composition of our sample. Our sample contains firms that tend to be technologically very active and disproportionately in "high-tech" sectors relative to the U.S. economy. We explore this possibility further by dividing the sample into two groups, referred to as high- and low-tech industries. To define these groups, we sort industries by their average R&D intensity (defined as R&D over sales) and then choose a cutoff level of R&D intensity to yield two categories with roughly similar numbers of firms. We choose R&D 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. 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.[23]

Table 8 shows results for the high- and low-tech samples separately. With one-year differences, we estimate significant FDI spillovers for the high-tech industries, and the p-value for the FDI F-test is lower than the standard 5% level (specification 8.1). In contrast, there are no significant spillovers from FDI into low-tech industries, with an FDI p-value of 97.2% (specification 8.2). The results for the two-year differences specifications are similar: for high-tech industries, the FDI coefficient is 0.680, significant at the 10% level, whereas for low-tech industries, the estimate is 0.133 and not

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

significant (specifications 8.3 and 8.4, respectively). Our results suggest that to the extent that spillovers occur, they occur in the high-tech sector.

We now turn to a concluding summary and discussion.

5. Summary and discussion

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. In contrast, the econometric evidence on this from micro-level panel data studies is thin. In this paper, we estimate international technology spillovers to U.S.-owned manufacturing firms via imports and FDI between the years of 1987 and 1996. These firms make up about half of US manufacturing during this period. Our results suggest that FDI leads to significant productivity gains for domestic firms. The size of FDI spillovers is economically important: we estimate that they accounted for between 8% and 19% of productivity growth of U.S. firms. The evidence on imports-related spillovers is much weaker.

A number of reasons for why our spillover estimates are larger than usually found are discussed, ranging from econometric method over data quality to the economics involved. We find that the latter needs particular emphasis. The estimated FDI spillovers are much larger in the relatively high-technology industries than in the relatively low-technology industries. Given that our sample includes high technology firms more than proportionately, this clearly explains in part our high spillover point estimates, though it does not necessarily imply a larger contribution of FDI spillovers to productivity growth, because high technology firms' productivity was growing particularly fast. That FDI spillovers in high-tech sectors are relatively large is intuitively plausible. First, most of the TFP growth in the sample is in the high-tech sector. Second, one would expect that it is precisely these industries where there is likely to be knowledge that foreign affiliates impart on domestic firms. In the low-tech sector, market competition or other effects are more likely to dominate any potential spillovers from foreign firms.

Our research suggests examining whether strong FDI spillovers in high-tech sectors are also found in other contexts. Another important question is whether our results extend to other countries, in particular to middle- and low-income countries. We have emphasized two dimensions that affect how strong FDI spillovers are: the sectoral dimension and the firm dimension. First, to the extent that FDI is not in high-technology sectors, it suggests that spillovers in poorer countries will be limited. At the same time, we find that firms with lower productivity tend to benefit stronger from FDI spillovers, and to the extent that poorer countries have relatively more of those firms, they should benefit more. In addition, there could be country characteristics, such as intellectual property rights protection, that have an important influence on spillover strength across countries. More research needs to be done to better understand how the firm, industry, and country dimensions together affect how technological knowledge moves between countries.

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Appendix I: Productivity Estimation

Two aspects of the Olley and Pakes (1996) approach are most important for our purposes: 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 productivity calculations for a long time: simultaneity of input choice and selection biases.

To see this, consider the following equation:

(A1) $$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + u_{it},$$

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.[1] The last term, u_{it}, is an error representing all disturbances that prevent (A1) from holding exactly. Let this term be composed of two parts,

(A2) $$u_{it} = \omega_{it} + \eta_{it}.$$

Consider the case when neither ω_{it} and η_{it} are observed by the econometrician, whereas the firm cannot observe η_{it}, but it does know ω_{it}. The term η_{it} could be capturing 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 will be a function of ω_{it}, and simple OLS estimation will suffer from a simultaneity bias because $E[u_{it} \mid l_{it}] \neq 0$.[2] If the term ω_{it}

[1] We drop the industry subscript j in the following discussion.
[2] 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

is constant over time, $\omega_{it} = \omega_i$, all t, taking time- or within-firm differences of (A1) 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 imports and FDI is exactly the question we are asking. This strategy is therefore ruled out. As shown below, we will identify ω_{it} from the firms' investment choices. Once ω_{it} is known, the simultaneity of input choices can be modeled and the bias avoided.

We now turn 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 of current productivity, so that it will remain in operation at lower realizations of ω_{it}. Relatively small firms exit at productivity draws for which relatively large firms would have continued to operate, so 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

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correlated, and labor is more strongly correlated with ω_{it} than capital, then OLS will tend to overestimate β_l and underestimate β_k.

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 (A1), (A2), 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.[3] This means that the investment function can be inverted to yield

(A3) $\omega_t = h_t(i_t, k_t).$

Substituting (A3) and (A2) into (A1) gives

(A4) $y_t = \beta_l l_t + \beta_m m_t + \phi_t(i_t, k_t) + \eta_t,$

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 (A4) can be estimated to obtain consistent estimates β_l and β_m on the variable inputs, labor and materials. Equation (A4) is a partially linear regression model of the type analyzed by Robinson (1988), and we use a fourth-order polynomial in investment and capital to capture the unknown function $\phi_t(.)$.[4]

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[3] A generalization of the Olley-Pakes (1996) approach, along the lines of Criscuolo and Martin (2005) and De Loecker (2007), would allow for a first-round effect of FDI and imports on investment. In our case, the capacity utilization and mark-up variables control in part for this effect.

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

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 (A4) 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). Substituting this into (A4) gives

$$\text{(A5)} \quad y_t - \hat{\beta}_l l_t - \hat{\beta}_m m_t = \beta_k k_t + \hat{\phi}_{t-1} - \beta_k k_{t-1} + \xi_t + \eta_t,$$

where $\hat{\phi}_{t-1}$ comes from estimating (A4), 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 depend only 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); the estimated survival probability is denoted by $\hat{P}_t$. The final step is to estimate β_k from the resulting equation:

$$\text{(A6)} \quad y_t - \hat{\beta}_l l_t - \hat{\beta}_m m_t = \beta_k k_t + g(\hat{\phi}_{t-1} - \beta_k k_{t-1}, \hat{P}_t) + \xi_t + \eta_t.$$

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.

Using the estimates of coefficients of labor, materials, and capital, we estimate log total factor productivity as $tfp_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} - \hat{\beta}_k k_{it}$, which is equation (2) in the text.

Appendix II: Variable definitions, sources, and data construction

- 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 8); deflators are from the BEA satellite accounts.
- Materials (M): defined as cost of goods sold from Compustat (data item 41) plus administrative and selling expenses from Compustat (data item 189) less depreciation, from Compustat (data item 14), and wage expenditures. Wage expenditures were calculated L multipled by average industry wage, where the former is defined above and the average industry wage is from Bartelsman and Gray (2001). Deflators from Bartelsman and Gray (2001).
- R&D (denoted by R): Research and development expense, from *Compustat* (data item 46); 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).
- Firm mark-up (FM): Defined as firm's sales over sales minus profits; profits is measured by net income, *Compustat* data item 172.

- Industry mark-up (SM): Analogous to firm mark-up, at the industry level.
- 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.
- Investment: Capital expenditures, from *Compustat* (data item 128); investment deflators by 4-digit SIC industry are from Bartelsman and Gray (2001).
- Transport cost measures are derived from U.S. import data as reported in Feenstra, Romalis, and Schott (2002). Free on board (FOB) and cost, insurance, freight (CIF) import data were aggregated to the BEA industry code for each year for the countries: Canada, United Kingdom, Japan, Germany, France, the Netherlands and Switzerland. Transport costs were calculated as (CIF imports-FOB imports)/FOB imports.
- Tariffs were calculated for the same countries and from the same data source as that for Transport cost measures. The definition of tariffs is duties collected/FOB imports.

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); these give similar results. To obtain our sample, we have started out with all manufacturing firms that were active between 1987 and 1996. We first removed the foreign-owned firms from the sample, and cleaned the data from obvious errors. This left 2,648 firms for which we had sales, capital, and employment data for at least two consecutive years, which is necessary for our dynamic estimation framework.

For these 2,648 firms, we have plotted each individual time series on sales as well as on capital stock, employment, materials, and R&D. Firms for which any time series exhibited implausibly large year-to-year changes were removed. We have also dropped firms that displayed large changes in inputs while output was flat, or vice versa. Moreover, we have adopted a conservative stance on including firms where output and inputs do not seem to reflect a reasonably stable relationship to estimate production function parameters; this is particularly true for upstart firms where the recording of inputs and outputs does not always seemed to be well synchronized, and likewise for failing firms. When in doubt on any of these criteria, we have dropped the firm from the sample. This procedure led to 1,277 firms that report output and inputs including R&D expenditures.`

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

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

TABLE 2: Exposure to Imports and FDI by Aggregated BEA Industries

	Import Share* in %				FDI Share** in %			
	1987	1992	1996	Change 1996/87	1987	1992	1996	Change 1996/87
Manufacturing	12.9	14.0	16.5	3.6	7.7	11.5	11.7	4.0
Food and Kindred Products	3.7	3.7	4.1	0.4	8.4	11.9	9.9	1.5
Textile Mill Products	8.1	8.8	10.1	2.0	3.7	6.7	7.3	3.6
Apparel and Oth. Textile	24.7	29.1	33.4	8.7	1.1	3.2	4.5	3.4
Wood and Furniture	7.6	8.5	11.2	3.6	1.9	2.6	2.1	0.2
Paper	8.4	8.0	9.0	0.6	6.9	7.5	8.8	1.9
Printing and Publishing	1.1	1.2	1.5	0.4	5.4	6.6	7.3	1.9
Chemicals	7.6	9.2	11.4	3.8	26.2	32.1	31.2	5.0
Rubber and Plastic	5.7	7.5	8.6	2.9	6.6	14.8	15.4	8.8
Stone, Glass, and Mineral	8.1	9.5	10.5	2.4	14.5	20.9	21.6	7.1
Primary metals	14.8	15.0	18.1	3.3	12.2	15.9	14.4	2.2
Fabricated Metals	4.6	5.6	6.6	2.0	4.1	8.3	9.4	5.3
Industrial Machines	17.9	22.9	24.5	6.6	5.9	11.3	11.2	5.3
Electronics	20.6	25.2	27.3	6.7	12.0	17.2	18.6	6.6
Motor Vehicles	29.3	26.0	26.7	-2.6	6.6	11.0	14.6	8.0
Other Transport	7.4	9.2	12.9	5.5	1.0	4.9	4.2	3.2
Instruments	11.7	12.5	15.6	3.9	7.4	11.9	13.3	5.9

* Imports over imports plus shipments; based on Feenstra (2002), Bartelsman and Gray (2001)
** Employment in foreign-owned subsidiaries over total employment; based on Survey of Current Business, various issues, and Bartelsman and Gray (2001)

TABLE 3: Olley-Pakes Input Elasticity Estimates

			for comparison
	O-P (1) *	**O-P (2)**	OLS first differences *
Capital	0.188	0.213	0.041
	(0.026)	(0.029)	(0.018)
Labor	0.301	0.295	0.418
	(0.011)	(0.012)	(0.016)
Materials	0.594	0.607	0.467
	(0.010)	(0.012)	(0.017)
Scale elasticity	1.083	1.115	0.926

* includes trend, trend*SIC357
Standard errors in parentheses

Table 4: OLS Results With One-, Two-, and Three-year Differences

	(4.1)	(4.2) Δ^2	(4.3) Δ^3
R&D	0.001 (0.001)	0.003 (0.002)	0.005 (0.003)
Cap. Utilization	-0.030 (0.057)	-0.067 (0.075)	-0.163 (0.316)
Mkt Share	-0.089 (0.102)	-0.292 (0.210)	-0.269 (0.316)
Firm Mark-up	-0.009 (0.004)	-0.005 (0.005)	-0.089 (0.041)
Industry Mark-up	0.367 (0.177)	0.998 (0.417)	1.034 (0.453)
FDI			
Current	0.213 (0.122)	0.379 (0.196)	0.411 (0.233)
Lagged One	0.303 (0.112)		
Lagged Two	-0.049 (0.097)		
Imports			
Current	0.480 (0.407)	0.341 (0.480)	0.210 (0.392)
Lagged One	0.754 (0.323)		
Lagged Two	-0.236 (0.291)		
F-test FDI	4.58 (0.033)		
F-test Imports	2.20 (0.139)		
Obs R-squared	5,895 0.110	3,175 0.169	2,226 0.217

Figures in parentheses are standard errors clustered by industry-year combination.
The null hypothesis of the F-test is that the sum of coefficients equals zero.

Table 5: Differential Spillover Estimates by Size and Productivity

	(5.1) Δ (Size)	(5.2) Δ^2 (Size)	(5.3) Δ^3 (Size)	(5.4) Δ^3 (TFP)
R&D	0.005 (0.002)	0.013 (0.004)	0.023 (0.006)	-0.002 (0.009)
Cap. Utilization	-0.034 (0.058)	-0.076 (0.077)	-0.180 (0.122)	-0.161 (0.116)
Mkt Share	-0.050 (0.109)	-0.290 (0.215)	-0.198 (0.339)	-0.371 (0.297)
Firm Mark-up	-0.009 (0.004)	-0.005 (0.005)	-0.080 (0.036)	-0.071 (0.040)
Industry Mark-up	0.359 (0.177)	0.987 (0.419)	0.984 (0.464)	1.047 (0.446)
FDI				
Current	0.338 (0.275)	0.986 (0.345)	1.184 (0.498)	1.192 (0.500)
Current*Size	-0.181 (0.360)	-1.022 (0.364)	-1.349 (0.590)	-1.785 (0.885)
Lagged1	0.802 (0.266)			
Lagged1* SizeLagged1	-0.832 (0.348)			
Imports				
Current	0.698 (0.462)	-0.194 (0.873)	0.729 (0.656)	-0.719 (0.822)
Current*Size	-0.361 (0.774)	0.908 (1.036)	-0.804 (0.824)	2.201 (1.946)
Lagged1	0.606 (0.507)			
Lagged1* SizeLagged1	0.256 (0.703)			
Size	-0.045 (0.067)	-0.087 (0.027)	-0.125 (0.045)	-0.093 (0.084)
SizeLagged1	0.023 (0.064)			
F-test FDI	3.50 (0.008)	4.34 (0.014)	2.87 (0.060)	2.90 (0.058)
F-test Imports	1.61 (0.170)	0.83 (0.439)	0.63 (0.534)	0.70 (0.500)
Obs R-squared	5,895 0.112	3,175 0.177	2,226 0.232	2,226 0.233

Figures in parentheses are standard errors clustered by industry-year combination.
The null hypothesis of the F-test is that the sum of coefficients equals zero.

Table 6: Instrumental Variable Estimation

	(6.1) Δ	(6.2) Δ^2
R&D	0.003 (0.001)	0.004 (0.003)
Cap. Utilization	0.032 (0.064)	-0.022 (0.071)
Mkt Share	-0.107 (0.116)	-0.520 (0.202)
Firm Mark-up	-0.010 (0.005)	-0.004 (0.006)
Industry Mark-up	0.395 (0.187)	1.094 (0.375)
FDI		
Current	0.028 (0.366)	0.645 (0.232)
Lagged One	0.885 (0.383)	
Lagged Two	0.034 (0.271)	
Imports		
Current	1.618 (0.686)	0.784 (0.455)
Lagged One	-1.804 (0.916)	
Lagged Two	1.380 (0.857)	
F-test FDI	3.47 (0.064)	
F-test Imports	1.98 (0.161)	
First-stage FDI Partial R-sq F-statistic	 0.33 3.1	 0.75 5.1
First-stage Imports Partial R-sq F-statistic	 0.22 1.8	 0.77 5.8
Obs	3,746	2,407
R-squared	0.135	0.200

Figures in parentheses are standard errors clustered by industry-year combination.
The null hypothesis of the F-test is that the sum of coefficients equals zero.

Table 7: FDI Activity versus Mainline of Business Data

	FDI Activity Data		FDI Mainline of Business Data	
	(7.1) Δ	(7.2) Δ^2	(7.3) Δ	(7.4) Δ^2
R&D	0.001 (0.001)	0.003 (0.002)	0.001 (0.001)	0.003 (0.002)
Cap. Utilization	-0.030 (0.057)	-0.067 (0.075)	-0.035 (0.060)	-0.100 (0.080)
Mkt Share	-0.089 (0.102)	-0.292 (0.210)	-0.081 (0.105)	-0.217 (0.221)
Firm Mark-up	-0.009 (0.004)	-0.005 (0.005)	-0.009 (0.004)	-0.005 (0.005)
Industry Mark-up	0.367 (0.177)	0.998 (0.417)	0.402 (0.184)	1.062 (0.434)
FDI				
Current	0.213 (0.122)	0.379 (0.196)	0.074 (0.041)	0.035 (0.095)
Lagged One	0.303 (0.112)		0.020 (0.040)	
Lagged Two	-0.049 (0.097)		-0.017 (0.036)	
Imports				
Current	0.480 (0.407)	0.341 (0.480)	0.478 (0.416)	0.367 (0.512)
Lagged One	0.754 (0.323)		0.783 (0.347)	
Lagged Two	-0.236 (0.291)		-0.192 (0.305)	
F-test FDI	4.58 (0.033)		0.870 (0.352)	
F-test Imports	2.20 (0.139)		2.20 (0.139)	
# of Obs.	5895	3175	5895	3175
R-squared	0.110	0.169	0.108	0.152

Figures in parentheses are standard errors clustered by industry-year combination.
The null hypothesis of the F-test is that the sum of coefficients equals zero.

Table 8: FDI Spillovers in High-Technology versus Low-Technology Industries

	(8.1) Hi-Tech; Δ	(8.2) Low-Tech; Δ	(8.3) Hi-Tech; $Δ^2$	(8.4) Low-Tech; $Δ^2$
R&D	0.003 (0.002)	0.000 (0.001)	0.005 (0.003)	0.000 (0.002)
Cap. Utilization	0.051 (0.068)	-0.083 (0.048)	-0.020 (0.114)	-0.007 (0.075)
Mkt Share	0.282 (0.286)	-0.139 (0.111)	-0.019 (0.618)	-0.318 (0.222)
Firm Mark-up	-0.016 (0.003)	-0.004 (0.001)	0.030 (0.076)	-0.008 (0.003)
Industry Mark-up	0.831 (0.220)	0.058 (0.079)	1.403 (0.409)	0.388 (0.153)
FDI				
Current	0.257 (0.173)	-0.012 (0.098)	0.680 (0.390)	0.133 (0.153)
Lagged One	0.412 (0.202)	0.173 (0.107)		
Lagged Two	0.241 (0.225)	-0.135 (0.085)		
Imports				
Current	0.185 (0.487)	0.175 (0.161)	-0.340 (0.901)	0.235 (0.158)
Lagged One	0.738 (0.541)	0.318 (0.144)		
Lagged Two	-1.415 (0.773)	-0.101 (0.146)		
F-test FDI	5.23 (0.026)	0.00 (0.972)		
F-test Imports	0.170 (0.683)	1.87 (0.173)		
Obs R-squared	2,794 0.133	3,101 0.048	1,506 0.208	1,669 0.068

Figures in parentheses are standard errors clustered by industry-year combination.
The null hypothesis of the F-test is that the sum of coefficients equals zero.