Pergamon

www.elsevier.com/locate/worlddev

World Development Vol. 27, No. 7, pp. 1287–1298, 1999

0305-750X/99/$ – see front matter

PII: S0305-750X(99)00054-6

Determinants of Technological Diffusion in Mexican Manufacturing: A Plant-Level Analysis

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Summary. — Production function estimates serve to measure and compare the productive efficiency of a large panel of Mexican manufacturing firms during a period of trade liberalization (1984–90). Foreign capital is found to have a positive influence on productive efficiency at the plant level but, contrarily to crossindustry studies, it does not lead to significant spillovers at the sector level. Enlarging the analysis, it is found that technological diffusion is favored by the size of the plant and by agglomeration economies, while its correlation with international trade exposure does not appear to be robust.

1. INTRODUCTION

The importance of technological transfer through foreign direct investment (FDI) cannot be overemphasized at a time when many developing countries, notably in Latin America, have carried out drastic trade liberalization programs (e.g., Argentina, Bolivia, Mexico) that also remove discriminatory measures against FDI. The developing countries have recognized their obligations in this area by gradually implementing the agreement on TRIMs (trade-related investment measures) during the Uruguay Round. One channel through which these countries expect to gain from a closer integration in the world economy is FDI and technology transfer, especially in view of the agreement on TRIPs (trade-related intellectual property rights) which will limit more direct access to foreign technology. But even if there is wide agreement that FDI is one of the major channels of technology transfer toward developing countries, it is still unclear to what extent technological improvements in the subsidiaries of multinational corporations (MNCs) also benefit domestic producers (see Blomström and Kokko, 1998 for a recent review).

According to the "spillover" argument, the sole presence of foreign firms generates positive externalities in favor of domestic firms. MNCs introduce new products and processes in the domestic market which may be copied by domestic competitors. Another channel of transmission is the training of the domestic labor force and its turnover. Positive effects can also be expected from increased competitive pressure and reduction of (x-)inefficiencies.

Countervailing forces however are also at work. The adoption of a new process and/or product technology is generally costly and depends on the degree of technological absorption capacity of domestic firms. Labor mobility may be scarce, and limited by the wage differential between MNCs subsidiaries and their domestic competitors. Increased competitive pressure from MNC could kick local firms out of the market or force them to reduce their output, generating diseconomies of scale. It could also be that spillovers depend on the policy environment: MNCs operating in a highly regulated industry may not generate spillovers simply because sufficient "made-to-measure" protection for domestic firms insulates them from this externality.

Given these theoretical ambiguities, it is hardly surprising that the empirical testing of spillovers provides mixed evidence. Early studies, such as Caves (1974) for Australia, Globerman (1979) for Canada and Blomström and Persson (1983) for Mexico, identified a positive correlation between the productivity of

* I wish to thank Jaime de Melo for his precious suggestions, and Marcelo Olarreaga and an anonymous referee for very helpful comments. Final revision accepted: 18 December 1998.

local firms and the presence of FDI at the sector level. Blomström and Wolff (1994) also found that foreign presence contributed to the convergence of Mexican local productivity toward US levels.

A number of other studies mitigate this picture. For example, in the Mexican case, Kokko (1994, 1996) found that large technological gaps and reduced competition act against spillovers, and may lead MNC subsidiaries to work in technological enclaves isolated from local firms. Moreover, the recent availability of plant-level data has provided the opportunity to deepen the empirical research. So far, results suggest that the sectoral share of FDI has generally no significant impact on the productive efficiency of local firms, although spillovers are likelier for domestic firms working in sectors with simpler technologies (Haddad and Harrison, 1993 for Morocco) or located close to MNC subsidiaries (Aitken and Harrison, 1992 for Venezuela). Generally speaking, it appears that spillovers vary considerably across countries and sectors, and that local conditions play a fundamental role in determining their magnitude.

Useful as they are, these studies have not systematically explored the set of variables that could influence technological improvement. Apart from FDI, variations in technical efficiency are also linked to market structure, regional characteristics and government policies. In other words, FDI spillovers are part of a more global process of technological diffusion between firms. To better understand this process, it is necessary to rely on a large set of explanatory variables and to analyze more systematically their robustness.

While this study has not developed a new methodology for measuring technical efficiency, it contributes to the empirical literature on technological diffusion in several dimensions. It relies on the Mexican case, and builds up on the rich and controversial evidence gathered on this country. It is based on plant-level data, which allow a focus on plant heterogeneity. Importantly, the data cover a time period (1984–90) characterized by a substantial trade liberalization of trade and FDI policies, which makes them particularly well-suited to study the potential links between FDI and technological diffusion. As in previous studies, the data provide estimates of the correlation between local plants' efficiency and foreign presence at the sector level. The originality of the empirical framework is however to control for a larger range of industry and market indicators (including trade policy, geographic concentration and technological sophistication), and to rely on an extreme bounds analysis to check systematically the robustness of these regressors.

Section 2 develops the methodology. The selected measure of productive efficiency is the plant-specific, time-varying intercept of a value-added function estimated for each manufacturing sector. The proposition that foreign-owned firms exhibit on average a higher efficiency level than their domestic rivals is supported. Variations in efficiency levels across firms and through time are then explained using a variety of factors, whose expected and effective impact is discussed at some length in section 3, along with a detailed sensitivity analysis of results. A summary of findings and final comments follow in section 4.

Overall, once controlling for plant-level characteristics, no evidence of technological spillovers from FDI is reported. Instead, variations in productive efficiency seem to be more significantly correlated with the geographic concentration of manufacturing firms and, to a lesser extent, with the degree of technical sophistication and the exposure to international trade. Findings related to the influence of the policy environment must be mitigated since the rationalization of Mexican manufacturing sectors was not completed in the sample period. Nevertheless, this study constitutes a useful example of how plant and sector-level data, when subjected to robustness analysis, can be used to explore the patterns of technological diffusion across firms and sectors.

2. ESTIMATION OF THE TECHNOLOGICAL GAP

A production function framework is used to estimate technological diffusion between MNC subsidiaries and local firms. For a given sector, it is assumed that production possibilities are given by the following equation:

$$Y_{it} = A_{it}F(X_{it}), \tag{1}$$

where Y_{it} is the value-added of firm i,[1] in year t, X_{it} a vector of inputs and A_{it} a plant-specific, time-varying technical efficiency multiplicative term.

Estimates of A_{it} provide information of the level of multifactor productivity of the firm, a measure which is preferred to labor productivity, as it is not biased by variations in the input mix. An increase in A_{it} may be due to a reduction of resource waste, as assumed in traditional efficiency frontier analysis. But more generally, it may also reflect the acquisition of some unobservable additional input, whose impact takes the form of (Hicksian-neutral) technological progress. According to this view, the smaller the estimated dispersion of efficiency levels, the stronger the technological diffusion.

This framework may be criticized on the ground that technological differences are limited to the case of (output) technical inefficiency and/or (disembodied) neutral technological change. Although alternative methodologies to estimate productive efficiency certainly exist, their underlying assumptions are not necessarily more adequate than ours, and their data requirements often represent an important obstacle (see Färe, Grosskopf and Lovell, 1994 for an exposition of the nonparametric approach to production function and efficiency analysis, in which far more data are needed).

Following the Mexican national accounts classification, a value-added function is estimated for each one of 41 manufacturing sectors during 1984–90 (see the appendix for details on data selection). It is known that dealing with plant-level data often exacerbates the importance of left-out variables and the biases due to errors in measurement. Although the literature provides several techniques to deal with noisy data, the general lesson is one of humility: due to the imperfect nature of the data, it is often not possible to reject the simplest specification (see Griliches, 1986). Given these limitations, a simple Cobb- Douglas specification is selected, a representation of technology which has been shown to deal satisfactorily with industrial census data (see Griliches and Ringstadt, 1971).

Additional problems may come from errors in the measurement of the capital stock, which are probable, and would lead to implausibly low Ordinary Leasts Squares (OLS) estimates of the partial elasticity of capital. A rigorous solution would be to instrumentalize the true capital stock, as in the case of the Maximum Likelihood estimator developed by Tybout (1992). But as the focus of this paper is not on measurement errors and as the reliability of instruments is also uncertain, an easier way to deal with this problem has been to impose constant returns to scale (CRTS). Incidentally, on the basis of the same sample, but using a Generalized Method of Moments procedure, Tybout and Westbrook (1995) have shown that the CRTS assumption generally cannot be rejected in Mexican manufacturing.

Finally, to capture the temporal dimension of technological diffusion, the efficiency level of plant i, A_{it}, is allowed to vary with time according to a quadratic polynomial pattern (this follows the specification of Cornwell, Schmidt and Sickles, 1990). The estimated equation is thus:

$$\ln(Y_{it}/L_{it}) = \alpha_{it} + \beta_K \ln(K_{it}/L_{it}) + \varepsilon_{it} \quad \text{where } \alpha_{it} = \mathbf{t}\delta_i, \mathbf{t} = (1tt^2),\ \delta_i' = (\delta_{0i}\delta_{1i}\delta_{2i}), \tag{2}$$

where L_{it} is labor in efficiency units, K_{it} the capital stock, α_{it} the logarithm of the efficiency term ($\alpha_{it} = \ln(A_{it})$) and ε_{it} a white noise. See the appendix for a description of how variables were constructed.

Using OLS to estimate Eqn. (2) may be seen as a generalization of the within estimator used in traditional panel-data analysis. It leads to consistent estimates independently of assumptions of uncorrelatedness between primary inputs and the efficiency term. But as this estimation implies the use of $3N + 1$ variables (N is the number of plants), it has been performed in two steps to avoid dimensionality problems.[2] Although there are strong variations of $\hat{\beta}_K$ across sectors, the outcome is generally satisfactory in terms of explanatory power (R^2 is usually close to 0.8).[3] However, in nine cases, $\hat{\beta}_K$ is not statistically different from zero, suggesting problems of underutilization of installed capacity and/or measurement errors of the capital stock. All these sectors were finally kept in the sample, provided the estimated value of $\hat{\beta}_K$ was not negative.[4] The estimated value of the logarithm of the efficiency term is obtained through the estimated δ_i vector: $\hat{\alpha}_{it} = \mathbf{t}\hat{\delta}_i$.

This procedure leads to plant-level efficiency estimates, $\hat{A}_{it}$, which provide the necessary basis for analyzing the technological diffusion process. An increase in the efficiency level of a given firm would reduce its gap with respect to the most efficient firm in the sector (the "leader"). As the absolute magnitude of the leader's efficiency level is variable across sectors, however, a given reduction in the efficiency gap does not have the same meaning across sectors (the higher the leader's efficiency level, the weakest the implied technological diffusion).

To control for this "level effect" in comparisons across sectors, efficiency levels are expressed in relative terms with respect to the "leader" of each sector, e.g.:

$$\hat{E}_{it} = \frac{\hat{A}_{ijt} - \hat{A}_{jt,\max}}{\hat{A}_{jt,\max}}, \tag{3}$$

where $\hat{A}_{jt,\max}$ is the highest estimated efficiency term in sector j, year t, ($\hat{A}_{jt,\max} = \sup(\hat{A}_{ijt})$). From Eqn. (3), $\hat{E}_{it}$ is interpreted as an indicator of the technological gap, ($\hat{E}_{it}<0$) and an increase in $\hat{E}_{it}$ as a consequence of technological diffusion.

One cannot discard the possibility that part of $\hat{E}_{it}$ variations may not reflect technological diffusion but rather derive from the aggregation of heterogeneous products in the same industrial sector. Unfortunately, it is not possible to further disaggregate the data without facing serious degrees of freedom problems. Broadly speaking, $\hat{E}_{it}$ captures the effect of omitted variables, such as the degree of technological mastery of FDI spillovers, some of which will be taken into account in the next section. Finally, an indirect way to test the reliability of these efficiency estimates is to check if they reflect the technological superiority of foreign firms, a characteristic which is now widely recognized as one of the key attributes of MNC subsidiaries.

Various indicators of the technological superiority of foreign firms are provided in Table 1. The first row shows that foreign firms (defined as such when more than 50% of their equity capital is foreign-owned)[5] are relatively more frequent among the sectoral leaders than in the whole sample (roughly twice as much on average), and their pre-eminence seems to rise over time. But this crude indicator is only concerned with the upper portion of the firms' distribution. Moreover, as it relies on the identified leader of each sector, it is particularly subject to influential observations.

Therefore, the analysis is completed by a Gini index (row 2) which reflects technological differences between both categories of firms on the whole sample. Firms are sorted in 10 efficiency percentiles in each sector; then these efficiency classes are pooled together and sorted by increasing values of the ratio between foreign and domestic firms. Then a Lorenz curve is constructed on the basis of the cumulated frequency of domestic (foreign) firms on the horizontal (vertical) axis. The more unevenly distributed foreign firms are, the higher the Gini coefficient.

The Gini values suggest technological discrepancy between domestic and foreign firms. But for these figures to reflect properly a technological lead by foreign firms, the ordering of efficiency percentiles by the share of foreign firms should match their ordering by efficiency level. The Spearman rank correlation between the two classifications (last row of Table 1) varies between 0.8 and 0.9, suggesting that this is indeed the case.

In short, the evidence based on efficiency estimates suggests that foreign firms do exhibit a higher relative efficiency level than their domestic competitors in Mexican manufacturing industries. This is true not only regarding the firms at the frontier, but also all along the distribution of firms in efficiency classes. But do domestic firms benefit from the technological lead of MNC subsidiaries?

3. ESTIMATION OF THE DETERMINANTS OF TECHNOLOGICAL DIFFUSION

The general framework to identify the determinants of technological diffusion is given by the following multivariate regression:

Table 1. *Technological leadership by foreign firms*

	1984	1985	1986	1987	1988	1989	1990
Ratio of technological superiority among the leaders [a]	1.66	1.79	1.92	2.18	2.43	2.30	2.56
Gini index of technological differences [b]	0.21	0.22	0.22	0.19	0.19	0.21	0.23
Spearman rank correlation [c]	0.78	0.82	0.83	0.83	0.95	0.95	0.86

[a] (share of foreign firms among the leaders)/(share of foreign firms in the whole sample).
[b] Gini coefficient between the cumulated frequency of foreign firms and the cumulated frequency of domestic firms (grouped by efficiency percentiles).
[c] Rank correlation coefficient between classification of efficiency percentiles by efficiency level and classification by foreign share.

$$\hat{E}_{ijt} = f(\mathbf{z}_{ijt}, \mathbf{v}_{jt}, \mathbf{w}_{st}), \quad (4)$$

where $\mathbf{z}_{ijt}$ is a vector of plant-specific variables (plant i, sector j, year t), $\mathbf{v}_{jt}$ a vector of sector-specific variables and $\mathbf{w}_{st}$ a vector of location-specific variables (state s of the Mexican federation).

All variables used in the analysis are described in Table 2. Apart from the mentioned exceptions, they were all constructed on the basis of the same data base described in the appendix. When discrete values had to be attributed, they were chosen in order to make their range compatible with that of the other numeric variables.

(a) *Expected impacts*

The first plant-level variable to be taken into consideration is the percentage of equity capital attributed to foreign ownership (FORK). To the extent that increased foreign control improves managerial skills and reduces technical inefficiency, the impact of FORK should be positive. Note that this only corresponds to the direct effect of foreign ownership, reflecting the proven superiority of foreign technology, and should not be confused with technological spillovers. Another factor that could be crucial in the adoption of new technologies is the output level of the firm. Large size allows to spread out the cost of innovation, and thus influences favorably its profitability (e.g., Rodrik, 1992). To allow for crossindustry comparisons and to reduce simultaneity, I use the market share of the firm (*SHARE*) as an explanatory variable instead of output. Its correlation with E is expected to be positive, although the sense of causation is ambiguous, given that a higher efficiency level also permits the firm to gain a larger market share. Finally, as noted previously, the efficiency estimates are likely to have been affected by the underutilization of installed capacity that characterized most of the sample

Table 2. *Correlates of efficiency*

Description of variables		Availability
at the plant-level:		
$FORK_{ij}$	foreign-owned share of equity capital	1991
$SHARE_{ijt}$	market share (gross value of output over the sum of the gross value of output of all plants in the sector)	1984–90
KQ_{ijt}	capital-output ratio (capital stock over gross value of output)	1984–90
at the sector level:		
$FIND_j$	share of workers hired by foreign firms (a firm is considered as foreign if $FORK_{ij}$ >0.5)	two-digit/1991
$IMPR_{jt}$	import penetration rate (imports over apparent domestic consumption)[a]	two-digit/1984–90
$EXPR_{jt}$	export rate (exports over domestic production) [a]	two-digit/1984–90
$PROTO_{kt}$	output protection [b]	four-digit/1984–90
$PROTI_{kt}$	input protection [b]	four-digit/1984–90
$SOPH_j$	index of technological sophistication (Casar Perez, 1993) discrete values: [0.33, 0.66, 1.0]	two-digit/1985
$GEOG_j$	Gini index of (relative) geographic concentration [c]	two-digit/average 1984–90
$DENS_{js}$	index of absolute geographic concentration (based on the share of state s in total labor hired in sector j) [d] discrete values: [-1.0, -0.5, 0, 0.5, 1.0]	two-digit/average 1984–90/state of the Mexican Federation

Subscripts: i: plant, j: two-digit sector, t: year, k: four-digit sector, s: state of the Mexican Federation.

[a] Trade flows are taken from Casar Perez (1993), while domestic production is taken from INEGI (various years).
[b] Sum of the average tariff rate and the average coverage of import licenses (no better aggregation procedure was possible since elasticities are unknown).
[c] In terms of the Lorenz curve, the cumulative frequency of total manufacturing labor lies on the horizontal axis, while the cumulative share of labor hired in this particular sector lies on the other axis (see Audretsch and Feldman, 1993).
[d] A value of -1 is attributed when the state's share in total labor hired in sector j is less than half of the theoretical average share (1/32). Four other categories are defined by doubling the upper value of the previous interval and increasing the indicator by +0.5. Thus the higher value of +1 is obtained for states whose share is larger than four times the theoretical average share.

period. A crude way to control for this factor is to include the capital output ratio (*KQ*), which varies countercyclically in case of idle capacity,[6] and whose impact is therefore expected to be negative.

A first attempt to introduce the effect of the competitive and technological environment is to include a number of dummies, to capture the influence of factors that are specific to a particular sector (38 industry dummies), a particular state (29 locational dummies) or a particular year (six time dummies). Although results may be suggestive, they leave the actual sources of influences unexplained. To unveil the effects hiding behind the dummies, a second specification is estimated which includes, apart from the plant-level variables, eight more regressors.

In line with the spillover empirical literature, the first additional variable introduced is the share of workers hired by the MNC subsidiaries at the sector level (*FIND*). To the extent that positive externalities are important, *FIND* should exhibit a positive and significant correlation with *E*. But as noted previously, this is subject to controversy. For example, following Kokko (1994), if MNCs locate preferentially in industries where the technological gap with domestic firms is particularly deep, constituting "enclaves" out of which technology does not diffuse, the correlation could even be of the opposite sign.

The same kind of industrial fragmentation, where a wide range of relatively inefficient firms are excluded from the technological race, is likely to occur in markets which are particularly exposed to international competition. The import ratio (*IMPR*, imports over domestic consumption) and the export ratio (*EXPR*, exports over domestic production) could be expected to be negatively correlated with $\hat{E}_{it}$. Increased competition however may also reduce technical inefficiencies, and both trade ratios are probably linked with the economic cycle, so that their net impact is not *a priori* evident.

Another related source of influence is trade policy. The reduction in the average rate of protection on output (*PROTO*) may have stimulated domestic firms to increase their efficiency. But there again, the counterargument of Rodrik can be invoked, as output contraction following competitive pressure may reduce incentives to adopt more advanced technologies. As far as protection on inputs (*PROTI*) is concerned, as its reduction eases the access to imported inputs, its correlation with $\hat{E}_{it}$ should be negative.

Technological diffusion also depends on the capacity of domestic firms to adopt more advanced technologies, which is probably a function of technological complexity. An index of technological sophistication (*SOPH*) based on research and develpoment (R&D) expenses (see Casar Perez, 1993) is therefore included in the regression. To the extent that imitation capability decreases with sophistication, its correlation with *E* should be negative.

Finally, important sources of technical efficiency improvement may arise from economies of agglomeration. The advantages of labor market pooling, the availability of intermediate inputs and the presence of knowledge externalities are the most frequently cited reasons for industry localization (e.g., Krugman, 1991). In our context, agglomeration economies are captured by two proxies. Following Audretsch and Feldman (1993), a Gini index of geographic concentration of the labor force (*GEOG*) was elaborated for each sector. A high value of *GEOG* reflects a sector which is relatively more concentrated than the overall manufacturing industry.[7] Agglomeration economies may occur, however, in a particular sector regardless of the concentration of the other ones. Therefore, an additional indicator of absolute concentration is requested. It is represented by the density of the labor force (*DENS*), a variable which has been constructed as taking values between -1 and 1 according to the share of the state in total labor employed in the sector.

Obviously, the list of determinants of technological diffusion could still be enlarged. But this would affect the clarity of the analysis, increasing the correlation between regressors. In fact, some of the previous indicators can already be suspected to be *a priori* correlated. In particular, output protection tends to reduce imports and MNC subsidiaries are likely to use sophisticated technologies. This is why section (c) analyzes systematically the impact of each separate regressor when additional variables are included in the specification.

(b) *Results*

A first set of results appears in Table 3. Given the sample size, the explanatory power of regressions is quite satisfactory, even for model 1, which includes only plant-level variables. These three regressors, which are com-

Table 3. *Determinants of technological diffusion* [a]

	Model 1	Model 2	Model 3
$INTERCEPT_{ij}$	−0.76 ** (0.002)	−0.73 ** (0.043)	−0.86 ** (0.010)
$FORK_{ij}$	0.04 ** (0.01)	0.05 ** (0.01)	0.06 ** (0.01)
$SHARE_{ijt}$	0.36 ** (0.03)	0.42 ** (0.02)	0.36 ** (0.02)
KQ_{ijt}	−0.03 ** (0.002)	−0.03 ** (0.001)	−0.02 ** (0.002)
Industry dummies	–	[105.8]	–
Location dummies	–	[5.0]	–
Time dummies	–	[12.0]	–
$FIND_j$	–	–	−0.11 ** (0.02)
$IMPR_{jt}$	–	–	−0.06 ** (0.018)
$EXPR_{jt}$	–	–	−0.31 ** (0.02)
$PROTO_{kt}$	–	–	0.04 ** (0.007)
$PROTI_{kt}$	–	–	−0.07 ** (0.010)
$SOPH_j$			−0.003 (0.014)
$GEOG_j$	–	–	0.36 ** (0.02)
$DENS_{js}$	–	–	0.02 ** (0.003)
F-stat.	280.6	72.5	173.7
R^2	0.07	0.33	0.15
Sample size	11179	11179	11179
dep. var. mean	−0.74	−0.74	−0.74

[a] $\hat{E}_{it}$ is the dependent variable/OLS estimates/standard errors between (..)/subscripts: i stands for the plant, j for the two-digit sector, k for the four-digit sector, t for the year and s for the state/numbers between [..] refer to the F-statistic of global significance/all variables are described in Table 2.

* Significant at the 95% level.

** Significant at the 99% level.

mon to all specifications, have the expected signs and are highly significant.

As discussed previously, the negative impact of *KQ* suggests that firms can improve their efficiency by increasing their capacity utilization, while the positive influence of *FORK* reflects foreign technology superiority. These two effects being controlled for, the impact of *SHARE* is clearly positive, suggesting that the size of the firm is critical in determining the ability of the firm to adopt new technologies. It is also clear however that most of technological heterogeneity is still unexplained by this simple specification.

The inclusion of dummies (model 2) raises substantially the explanatory power of the model, which accounts for one-third of total variation. Among the three types of dummies, the most significant are the industrial ones, while the locational dummies are just globally significant (individually, only five out of 31 are significantly different from zero). This suggests that most time-invariant effects explaining the relative efficiency levels are specific to the industrial sector rather than to the geographical location.

Is it possible to be more specific? Model 3 offers some answers. Apart from *SOPH*, all regressors are highly significant. Quite surprisingly, *FIND* turns out to be negatively correlated with relative efficiency levels. This suggests that the relationship between MNC subsidiaries and the efficiency of domestic plants is far from being dominated by spillover effects. On the contrary, it appears that the larger the MNC presence, the wider the technological gap, as if technological diffusion was not favored but hampered by foreign ownership at the sector level.

A similar relationship arises regarding trade ratios. Both *IMPR* and *EXPR* exhibit a negative correlation with *E*, suggesting that the deeper the insertion in international trade, the larger the technological disparities between firms. Crossindustry variations in trade ratios may also reflect past policies of the import-substitution period.

The positive correlation exhibited by *PROTO* seems to suggest that trade liberalization has not helped to close the technological gap. But this last conclusion must be mitigated by the fact that a reduction in input protection (*PROTI*) appears to be associated with increased efficiency.

Finally, agglomeration economies appear to have been substantial, as reflected by the positive coefficient of both indicators of geographic concentration. Interestingly, the significance of the *DENS* variable, which takes five discrete values, is stronger than the significance of the continuous underlying variable (the share of the state in sectoral employment), suggesting that threshold effects characterize spillovers based on agglomeration economies.

(c) *Robustness analysis*

A first criticism that can be addressed to the previous findings is that the significance or even the sign of the estimated coefficients could be altered by a modification in the set of explanatory variables. A simple and systematic way to test the robustness of the coefficients is the extreme-bounds analysis (EBA) elaborated by Leamer (1983). This paper follows the variant of the EBA proposed by Levine and Renelt (1992).

Starting from a base specification, which in our case corresponds to model 1 plus the variable of interest (call it *M*), its principle is to report the estimated coefficient of *M* (along with its standard error) for all possible specifications obtained by adding up to three variables chosen in the "conditioning set" (in our case the eight additional regressors of model 3). A confidence interval is constructed for each specification by adding (substracting) two standard errors to the estimated coefficient. The extreme bounds correspond logically to the highest and lowest values among the bounds of the whole set of confidence intervals. If the "extreme bounds interval" so obtained remains in the positive (negative) domain, the coefficient can be considered as robust. If not, it is fragile, as its sign depends on alterations in the set of explanatory variables.

Results for the extreme bounds analysis (EBA) appear in Table 4. The first column corresponds to the *M*-variable, while the last one reports the final diagnosis (if the coefficient is fragile, the number between brackets indicates the number of additional variables necessary to provoke a sign reversal, the implicated variables being in italic in the penultimate column). Most of the variables exhibit a robust correlation with $\hat{E}_{it}$. But the robustness of *IMPR* and *FIND* does not seem firmly established, as the upper bound is particularly close to zero. In both cases, the explanation can be found in the strong correlation with one of the other regressors. The negativity of *FIND* is particularly sensitive to the inclusion of *SOPH*, suggesting that if MNCs represent an obstacle to technological diffusion, it is basically because they incorporate a more sophisticated technology (the simple correlation between both regressors is 0.44). The inclusion of *EXPR* almost cancels out the significance of *IMPR*, while the reverse is not true. Therefore, although both indicators seem to reflect the same reality (their simple correlation is 0.52), conditions for technological diffusion appear to be more adverse in export-oriented than in import-competing industries. Finally, the fragility of *SOPH* is not a surprise (it is already nonsignificant in model 3), while that of trade policy instruments is due to their high correlation between them (0.82) and with both trade ratios.

The second criticism concerns robustness with respect to time periods and efficiency grouping. For this purpose, regressions of model 3 are run on subsamples. Overall, our findings regarding plant-level variables and agglomeration economies are not affected by these subdivisions. But the correlation of the remaining indicators is sometimes affected and, although detailed results are not reported, it is worthwhile mentioning here the main changes.

When the sample is split into two periods, the first (1984–87) corresponding to the implementation of a drastic trade liberalization, results are generally not altered, except for trade-related variables. The impact of *PROTO* becomes nonsignificant in the second period, an outcome that could be due to the spatial and temporal uniformization of tariff rates and quantitative restrictions following trade liberalization. To the extent that efficiency levels adapt only progressively, their correlation with the structure of protection can be expected to be stronger in the first period, which is more representative of the import-substitution policy followed by Mexican authorities for most of the preceding decades. The same type of argument may be invoked regarding the lost significance of *IMPR* during the second period. The upsurge of imports following trade liberalization modified the distribution of imports across sectors in such a way that no longer reflects the industrial structure inherited from the import-substitution era, thus breaking its correlation with relative efficiency levels. But as exports were slower to react, their negative correlation with $\hat{E}_{it}$ remains significant.

Some differences also appear when the sample is split into two efficiency groups. These

Table 4. *Extreme bounds analysis*

Variable	Type	β	Standard error	t	R^2	Extreme bounds	Additional variables	Robust/ fragile [a]
FORK	base	0.041	0.006	7.3	0.07			R
	highest	0.066	0.006	11.4	0.10	0.08	FIND, IMPR, PROTI	
	lowest	0.038	0.006	6.7	0.07	0.03	DENS, PROTO, PROTI	
SHARE	base	0.36	0.02	20.3	0.07			R
	highest	0.40	0.02	22.6	0.10	0.44	EXPR, IMPR, SOPH	
	lowest	0.32	0.02	18.2	0.12	0.29	GEOG, SOPH, DENS	
KQ	base	−0.026	0.002	−16.4	0.07			R
	highest	−0.024	0.002	−15.5	0.11	−0.021	EXPR, DENS, IMPR	
	lowest	−0.026	0.002	−16.6	0.08	−0.030	FIND, SOPH, PROTI	
FIND	base	−0.14	0.01	−10.6	0.08			R
	highest	−0.06	0.02	−3.6	0.12	−0.02	SOPH, GEOG, PROTI	
	lowest	−0.15	0.02	−9.8	0.11	−0.19	EXPR, IMPR, SOPH	
IMPR	base	−0.24	0.01	−18.5	0.10			R
	highest	−0.04	0.02	−2.3	0.14	−0.01	EXPR, GEOG, SOPH	
	lowest	−0.27	0.02	−17.3	0.10	−0.30	FIND, SOPH, PROTI	
EXPR	base	−0.33	0.02	−17.8	0.10			R
	highest	−0.20	0.02	−9.1	0.10	−0.16	IMPR, PROTO, SOPH	
	lowest	−0.36	0.02	−19.3	0.10	−0.40	PROTI, GEOG, PROTO	
PROTO	base	0.023	0.004	5.2	0.07			F(1)
	highest	0.046	0.007	6.5	0.11	0.06	*PROTI*, GEOG, FIND	
	lowest	−0.00	0.004	−0.1	0.13	−0.01	*IMPR*, GEOG, EXPR	
PROTI	base	0.012	0.006	2.1	0.07			F(1)
	highest	0.010	0.006	1.7	0.08	0.02	*DENS*, SOPH, FIND	
	lowest	−0.073	0.010	−7.5	0.14	−0.09	*PROTO*, EXPR, GEOG	
SOPH	base	−0.09	0.01	−9.0	0.08			F(2)
	highest	0.08	0.01	6.1	0.11	0.11	*IMPR*, *FIND*, EXPR	
	lowest	−0.129	0.01	−12.5	0.12	−0.14	*GEOG*, *DENS*, PROTI	
GEOG	base	0.36	0.02	20.7	0.10			R
	highest	0.40	0.02	22.6	0.14	0.43	SOPH, PROTI, EXPR	
	lowest	0.31	0.02	17.5	0.13	0.27	IMPR, DENS, FIND	
DENS	base	0.014	0.003	4.5	0.07			R
	highest	0.020	0.003	6.6	0.11	0.026	IMPR, FIND, EXPR	
	lowest	0.013	0.003	4.2	0.11	0.007	PROTO, PROTI, GEOG	

[a] R: robust / F: fragile, with the number between brackets representing the number of additional variables necessary to provoke sign reversal (the implicated variables are in italic in the penultimate column).

groups are defined according to the estimated coefficients of industry dummies in model 3, the lowest (highest) values constituting the wide-gap (narrow-gap) group. Apart from *SOPH*, whose correlation becomes significantly negative, the results obtained for the whole sample perfectly reproduce for the wide-gap group. When turning to the narrow-gap group, however all trade-related variables, along with *FIND*, lose their significance.

A number of other empirical caveats have been addressed, such as the exclusion of outliers, the extension of the EBA conditioning set (including the Herfindahl concentration index, the geographic distance to economic centers or the share of urban population), or the estimation of a fixed effects value-added function for two subperiods and the exclusion of foreign firms from the sample. As results broadly confirm our previous findings, they are not reported here.

Generally speaking, the sensitivity analysis suggests that most of our results can be considered as robust, although the impact of trade and FDI variables at the sector level seems limited to the industrial groups characterized by wide technological gaps.

4. CONCLUSIONS

Technological diffusion in developing countries is certainly more complex than a simple, costless process. A number of factors, including market structure, institutions and government policies influence technological catch-up by national firms. The availability of plant-level data allows for a deeper understanding of this process. In particular, as it leads to an estimation of the technological distribution of firms, it provides a useful comparison with sector-level studies whose results are biased toward the influence of the biggest firms.

Relying on the Mexican case, and using a large array of local environment indicators, this paper identifies two sets of robust factors influencing the technological diffusion process. At the plant level, the efficiency of manufacturing plants is positively correlated with both the share of foreign capital and the market share of the plant. The former result most probably reflects foreign technology superiority. The latter is harder to interpret. On the one hand, it may simply mean that more efficient plants gain market shares. But on the other hand, it may also suggest that, far from occurring passively, technological improvements derive from intentional and costly learning activities whose profitability depends on the output level of the plant. In other words, technology does not diffuse freely, it needs costly catalysts to become available.

This line of reasoning is further confirmed when considering influential factors at the sector level. Indeed, once plant-level factors are controlled for, the share of labor hired by MNC subsidiaries turns out to be negatively correlated with the relative efficiency of the plant. This provides a sharp contrast with earlier studies suggesting the presence of technological spillovers. In part, this is due to the fact that MNCs preferentially locate in sectors with a high degree of technological sophistication, which means a lower degree of technological absorption capacity by domestic plants. It also reflects that plant-level analysis captures the whole spectrum of technological diversity, giving more weight to the numerous (and generally smaller) low-efficiency firms whose prospects of technological catch-up are a lot dimmer.

A similar argument may be invoked in explaining the lack of robust correlation between trade exposure and productive efficiency. A higher insertion in international trade (either through imports or exports) seems to be correlated with wider technological gaps. But, this correlation is not robust to a splitting of the sample in efficiency groups. Trade policy instruments do not exhibit a robust correlation either, which casts doubt about the impact of trade liberalization on domestic productivity. It seems premature however to draw definite conclusions about an industry rationalization process which has coincided with fiscal adjustment and certainly takes more than three years to develop all its effects.

These findings tend to mitigate the hopes placed in FDI spillovers. This does not mean however that external economies are absent from Mexican manufacturing. They simply seem to be linked with the geographic location of the firm, rather than with the presence of MNC subsidiaries. Indeed, the second set of robust factors influencing domestic productive efficiency are geographic concentration indicators. This suggests that an important role is played by agglomeration economies. In a way, this leaves us with another "spillover puzzle", but one whose nature is locational. Understanding the channels through which these effects take place certainly deserves further research.

NOTES

1. Estimates of production functions, where Y_{it} is the gross output of the firm, were also performed. However, they did not however lead to more plausible estimates of primary input elasticities. Moreover, as data on intermediates and gross output had to be corrected to account for subcontracted activities (see the appendix), the production function specification did not provide an accurate test of the nonhomotheticity of the relationship between output and intermediates.

2. In the first step, OLS is performed on the transformed variables for the whole sector, leading to the estimated value of β_K. The transformation matrix of all observations for firm i is given by $M_W (M_W = I_T - W(W'W)^{-1}W$ where W is the T observations matrix of the **t** vector and T is the number of years), which eliminates the **t** vector variables. In the second step, for each firm, the estimated errors computed from the previous regression are regressed on the transformation matrix, leading to $\hat{\delta}$ estimates. This two-step procedure is numerically equivalent to OLS applied directly on Eqn. (4). It is a straightforward extension of the usual procedure in fixed effects specifications (e.g., Hsiao, 1988).

3. As results for the value-added function are not central to our point, they are not reported in detail. They are available from the author upon request.

4. This led to the exclusion of only two sectors (21 and 26), which in fact did not affect final results.

5. An alternative threshold of 10% was also adopted, without affecting basic results.

6. I also tried to correct more directly the estimator of technological gap itself, by deflating capital stock figures with an index of capacity utilization before estimating the value-added function. But this index, taken from Casar Perez (1989), is only available at the industry level, and did not change results significantly, suggesting that most of the idle capacity variation is interfirm and must thus be captured by a variable available at the firm level.

7. This can be false for a limited number of sectors which are in fact more evenly distributed than the average but which exhibit a positive value of *GEOG* because this index is essentially sensitive to disparities in geographic distribution.

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APPENDIX — DATA SELECTION AND CONSTRUCTION OF VARIABLES

Most variables used in the analysis were elaborated on the basis of a plant-level manufacturing survey collected by Mexico's Instituto Nacional de Estadística, Geografía e Informática (INEGI, Unpublished data). Within each two-digit Mexican national accounts category, the original survey included all plants sorted by decreasing order up to a rough 80% of cumulated value-added of the group. The original sample provided annual observations on 3,218 plants during 1984–90. More than half of the plants were eliminated because they did not report values for FDI, relied for more than 10% of their total sales on subcontracting activities (*maquila*) or did not fulfill a number of other selection criteria (non-negativity of key variables, odd observations, incomplete series, plants entering/leaving the sample more than once). Fourty-one two-digit groups (for which at least 10 plants were available) were kept in the sample, which leads to a final selection of 1,637 plants. It is assumed that the missing data pattern is of the "ignorable" case, and hence does not create selectivity bias.

All monetary variables are expressed in millions of 1980 Mexican pesos, using appropriate price deflators generally available at a two or four-digit classification level. In the original survey, data on the gross value of output and on primary materials were biased by subcontracted activities in 45% of all observations. Assuming constant ratios of value added over output and of primary materials over total inputs, it was possible to correct for this bias using data on income from, and expenditure on subcontracted work (see Grether, 1996 for details). Value added is given by the gross value of output minus the value of total inputs consumed, including electricity. Labor in efficiency units is obtained by multiplying the hours of blue collar workers by $1+\omega$, where ω is the ratio between white collar and blue collar salaries. Capital stock is obtained by summing the replacement cost of its components (machinery and equipment, construction and installation, land and transportation equipment) and the capitalized value of the rent at an approximate discount rate of 10%.