Imports and TFP at the Firm Level: The Role of Absorptive Capacity§

Patricia Augier+
Olivier Cadot∗
Marion Dovis±

March 2010

Abstract

This paper estimates the effect of the decision to import intermediate goods and capital equipment on Total Factor Productivity (TFP) at the firm level on a panel of Spanish firms covering the period between 1991 and 2002. We use two alternative approaches. In the first, we estimate TFP using the Olley-Pakes semi-parametric method and apply a diff-in-diff estimator with a control group constructed by propensity-score matching. In the second, direct method, we estimate TFP with imported inputs as a state variable in one stage. Both approaches show that the effect of a firm's decision to source intermediates and capital equipment abroad on its TFP depends critically on its capacity to absorb technology, measured by the proportion of skilled labor. This provides indirect evidence that imported capital equipment may embody new or different technologies that require adaptation at which some firms are better than others. If skilled labor proxies for adaptability, it is how firms adapt their production processes to the foreign inputs that seems to determine whether or not they benefit from them.

JEL classification numbers: F2, O1, O2

Keywords: Productivity, TFP, imports, Olley-Pakes, Ackerberg-Caves-Frazer, absorptive capacity

The authors would like to thank Ana Fernandes and Josh Ederington for their very useful comments and suggestions.

§ The autors would like to thank Ana Fernandes and Josh Ederington for their very useful comments and suggestions. This paper benefited from financial support from CEPREMAP's international trade program. Cadot also gratefully acknowledges the hospitality of DEFI in May 2008.
+ DEFI, University of Aix-Marseilles.
∗ University of Lausanne, CEPR, CEPREMAP and CERDI.
± Euromed Management and DEFI, University of Aix-Marseilles.

1. Introduction

The notion that international trade acts as a vehicle for productivity-enhancing technology diffusion has been a subject of intense scrutiny in recent years. Seminal contributions include Coe and Helpman (1995) paper, Xu and Wang (1999) and Eaton and Kortum (2001, 2002), who showed that international trade (in capital goods in the case of Xu and Wang 1999 and Eaton and Kortum 2001) spreads technology, with a traceable effect on productivity. Lumengo-Neso et al. (2001) showed that this technology diffusion could even work through *indirect* trade links (country *A* gets country *C*'s technology by trading with country *B* which trades with country *C*). Acharya and Keller (2007) confirmed these findings but showed that the linkage between trade and productivity was largely heterogeneous across countries and sectors. These findings were suggestive of a potential causal chain from trade to technology diffusion to productivity growth.

However, as long as the unit of observation was defined at the aggregate level, the channels through which foreign technology, mediated by international trade, would translate into domestic productivity growth remained a black box. Understanding these channels would require firm-level analysis. At the firm level, there can be four possible linkages between trade and productivity, one "vertical" and three "horizontal". First, better access to imported intermediates can raise productivity because either (ia) foreign intermediates are of better quality, or (ib) through the production equivalent of a "love-of-variety" argument (Ethier 1982). It has also been emphasized, in endogenous growth models, that importing new varieties leads to productivity gains in the short and medium terms (Romer 1987, River-Batiz and Romer 1991). Second, foreign competition in the final-goods market can whip up the productivity of domestic producers thanks to an X-inefficiency effect (Horn and al. 1995) and/or to a decrease in markup (due to a decline in the prices of intermediate inputs) accompanied by a scale effect (Krugman 1979, Helpman and Krugman 1985, Bernard and al. 2003) and/or thanks to an increase in the speed of technology adoption through the reduction in the number of domestic firms (Ederington and McCalman 2008[1]). Third, by contrast, foreign competition in the final-goods market can reduce firm productivity by slowing the rate at which new technology is adopted (by reducing the domestic firm's market share) (Rodrik 1992, Miyagiwa and Ohno 1999 and also Ederington and McCalman 2008, as a direct impact of a decrease in domestic tariffs). Fourth, foreign competition in the final-goods market can also leave productivity at firm-level unchanged, while increasing average productivity through a reallocation effect (the least productive domestic firms exit and the more

[1] This is what the authors call the indirect effect of a decrease in domestic tariffs.

productive domestic firms increase their market shares), as in Melitz (2003). Verifiying empirically the existence and magnitude of these channels requires firm-level analysis.

With better access to micro data, the empirical literature naturally turned to firm-level analysis. Two strands of papers can be distinguished in this rapidly growing literature. The first looks at the overall impact of imports on TFP without disentangling vertical linkages from horizontal ones.[2] In this strand, Djankov and Hoekman (2000), Bottasso and Sembenelli (2001), Halpern and Korosi (2001), Pavnick (2002), Muendler (2004), Schor (2004), and Fernandes (2007) found a positive overall impact of imports on TFP. In the second strand, by contrast, vertical linkages are distinguished from horizontal ones. This strand, which includes Van Biesebroeck (2003), Muendler[3] (2004), Halpern, Koren and Szeidl (2005), Amiti and Konings (2007), Kasahara and Rodrigue (2008), Lööf and Andersson (2008), Vogel and Wagner (2008), and Goldberg, Khandelwal, Pavcnik and Topalova (2008) found widely varying effects of firm imports or of declines in input tariffs on productivity. For instance, on the basis of a panel of large Hungarian exporting firms, Halpern et al. found that a 10 percentage point increase in the share of imports raised firm productivity by 1.8% with GMM but had no impact with a fixed-effect estimator. Amity and Konings found that a 10 percentage points reduction in input tariffs raised the TFP of importing Indonesian firms by 12%, which is consistent with the results of Goldberg et al. for Indian data. In the Chilean case, Kasahara and Rodrigue found that importing intermediates raised TFP by anything between 2.6% and 22%, depending on the estimator. While for Muendler the use of foreign inputs plays a minor role in productivity gains, Vogel and Wagner found no evidence of import status affecting labor productivity on the basis of German data. In Van Biesebroeck's paper, importing inputs was found to have a negative impact on the productivity growth of Columbian firms; by contrast, Lööf and Anderson found a positive impact on the basis of Swedish data. Moreover, they found that imports from industrial countries had a stronger effect, giving support to the Coe-Helpman hypothesis. This paper focuses on this vertical linkage in order to see what occurs in the case of Spanish manufacturing firms in a context where the input tariffs on intermediate and capital goods remain nearly unchanged[4] but where imports increase.

---

[2] Exportations at firm level being easier to obtain, a long-standing literature, reviewed in Wagner (2007), has explored the link between export status and productivity and found support for the self-selection hypothesis (according to which only the most productive firms can export, a direct implication of the existence of fixed export costs in Melitz's model).

[3] In his paper, Muendler tests both vertical and horizontal linkages.

[4] The tariffs on intermediates and capital goods have decreased and were aligned with the Common European External Tariff before our period of analysis.

By and large, the balance of findings so far is in favor of a positive overall effect, in line with the discussion above. But the heterogeneity of these findings is disturbing, and there is lingering uncertainty about which channel matters most. This paper starts from the idea that the effect of trade on productivity depends not only on firm involvement in trade, but also on other firm characteristics. Empirical studies find that firms using imported intermediates are fairly different (across a broad range of individual characteristics) from firms that don't[5]. TFP comparisons that do not properly account for firm heterogeneity across groups may end up comparing apples and oranges. In addition, most of the empirical literature has focused on the effect of importing *intermediates* (through decreasing inputs prices). But firms may also import capital equipment, and foreign capital equipment may embody new or different technologies. The effect of the decision to import on TFP may then depend not just on where firms import their inputs from (as in Lööf and Andersson) but also on the firms' ability to "absorb" the technology embodied in foreign capital equipment.

To test the effect of firms' imports or decisions to import on TFP, certain methodological issues must be taken into account: (i) the simultaneity bias between inputs and TFP (the level of productivity known by the firm, but not by the econometrician, has an impact on the choice of inputs); (ii) the twofold selection bias since, first, the tests at period t are carried out for firms that have not exited at period t-1 (and hence the risk of overestimating TFP) and, finally, due to the fixed costs of importing, only highly productive firms can import intermediates and/or capital goods. We attempt to overcome these econometrical issues with a combination of approaches. The first one is in two stages. In stage 1, we estimate TFP using two alternative approaches: Olley and Pakes (1996) (Henceforth, OP) and Ackerberg, Caves and Frazer (2007) (Henceforte, ACF). In stage 2, we regress estimated TFP on the firm's decision to import. Stage 2 combines a difference-in-differences estimator with propensity-score matching in order to be as sure as possible that the superior performance of importers (treatment group) compared to non-importers (control group) is indeed due to importing. As argued by Blundell and Costa Dias (2000) this combination is the most reliable way of estimating treatment effects and has so far been used only by Vogel and Wagner (2008) in the TFP-and-imports context[6].

The second approach is direct (one stage). We extend both the OP and ACF methods to control for possible correlation between firm imports and

[5] For instance, Kasahara and Lapham (2008), Andersson et al. (2008), and Muuls and Pisu (2007) show that firms that import and export (two-way traders) tend to be more productive than those that only import or only export.
[6] Matching methods have been used by Girma et al. (2004), Girma et al. (2007) and De Loecker (2007) to analyze the effect of exporting status on firm-level TFP.

unobserved productivity shocks by including the importing share of intermediates and capital goods purchases directly in the production function. In addition to a stronger control for endogeneity of imports, this approach has the advantage of using all the information contained in importing decisions (not just status, but also share).

We are able to control for the absorptive capacity of firms thanks to a particularly rich panel of Spanish firms[7] (covering the period between 1991 and 2002). In addition to data on foreign firm purchases, it includes the proportion of skilled labor as well as R&D expenditures, which we use to proxy absorptive capacity. Our identification strategy consists in interacting these firm characteristics with the decision to import or, alternatively, the impact of the share of imports to differenciate groups of firms by skilled employment, R&D intensity, and other characteristics. We also control, albeit imperfectly, for possible markup effects using market-share data (also in the database).

Our results are strong and telling. Without controlling for interaction with firm characteristics, the effect of the decision to import on TFP is only weakly identified. By contrast, once importing decision is interacted with the proportion of skilled labor, the effect is very significant and robust across a variety of specifications. With this two-stage approach, we find that starting to import intermediates and capital equipment raises productivity by 8 percentage points the first year, by 9 percentage points the second year and by 9.5 percentage points the third year for skill-intensive firms. With the direct approach, we find that a ten-percentage point increase in the share of imports in total intermediates and capital-goods purchases raises TFP by 1.5% on average for the whole sample. But we also find that this effect is greatest for "skill-intensive" firms. Our results lend support to the hypothesis that, over and above any contestability effect, imports raise TFP by giving access to more and possibly better inputs; the importance of absorptive capacity providing indirect support to the notion that foreign capital equipment brings in better technology.[8]

The paper is organized as follows. Section 2 reviews estimation issues for our two approaches (two-step and direct). Section 3 presents the data. Sections 4 and 5 present estimation results and discuss a variety of robustness issues. Section 6 concludes.

---

[7] Most studies on Spanish firms (e.g. Delgado et al. 2002, Campa 2004, Fariñas and Martin-Marcos 2007) have focused on the relationship between exports and productivity. Others studies, including Castellani and Zanfei (2003), Jabbour and Mucchielli (2007) and Sembenelli and Siotis (2008), looked at foreign indirect investments. Lastly, some papers examined innovations (Huergo, 2006, Diaz-Diaz, Aguiar-Diaz et De Saa-Perez, 2008, Vega-Jurado et al. 2008).

[8] This idea of complementarity between international technological diffusion and domestic human formation has been formalized by Keller (1996).

2. Estimation issues

As discussed in the introduction, our first procedure involves two stages. In the first, we obtain consistent estimates of Total Factor Productivity (TFP) at the firm level using two alternative semi-parametric methods, one developed by Olley and Pakes (1996), and the other by Ackerberg, Caves and Frazer (2007). The OP and ACF methods provide consistent estimates in the presence of endogenous input choices and selection issues using investment as a proxy for unobservable firm-specific shocks. The main difference between these two metholodogies is in the treatment of labor. In OP, capital alone is considered as a state variable and is chosen at period t-1 by the firm. Labor is automatiquely adjusted at period t. With ACF, labor is no longer a free variable and is assumed to be chosen before period t. This can be justified, for instance, by constraints or rigidities in lay-off or hiring procedures on the labor market.

In the second stage of our procedure, described in section 2.1, we apply a treatment-effects methodology to assess the impact of import decision on TFP, using propensity-score matching to construct a control group of non-importing firms with characteristics similar to those of importing firms. Our alternative, direct approach is discussed in section 2.2.

2.1 Stage 2: TFP and import decision

The second part of our procedure consists of analyzing how a firm's decision to start importing affects its estimated TFP. This is a "treatment-effect" problem where, as in most treatment-effect problems in economics, difficulties come from the definition of the control group and the proper way of addressing the treatment's endogeneity. We do this by combining a difference-in-differences estimator with construction of the control group by propensity-score matching, following Rosenbaum and Rubin (1983). The diff-in-diff estimator compares the change in the TFP of importing firms when they start importing with the change in the TFP, over the same years, of similar firms that never imported. The propensity-score matching serves to identify the "similar" firms. The second stage goes, like the first, in several steps.

Step 1. We start with the definition and selection of the treatment and control groups. The *treatment group* is the set of firms that start importing at some t in the sample period. Because the treatment is a voluntary decision instead of being randomly assigned, the decision to take it has to be modeled as a function of firm observables. This requires the estimation of probit regressions to explain the probability of starting to import year by year. That is, letting:

$$\theta_{it} = \begin{cases} 1 & \text{if firm } i \text{ imports inputs at } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

we run an equation of the type

$$\Pr\left(\theta_{it} = 1 \middle| \theta_{i,t-1} = 0\right) = \Phi\left(\mathbf{x}_{i,t-1}, \delta_j\right) \tag{2}$$

Where $\mathbf{x}_{it-1}$ is a vector of lagged firm characteristics (profit,[9] estimated TFP, export status, size, capital-labor ratio, and average wage) and δ_j are industry effects affecting both the decision to import and the level of TFP.

Estimation of (2) by probit on the whole sample (importing and non-importing firms) yields an estimated propensity score which, by abuse of notation, we will denote again by $\hat{p}_{it}$.

The *control group* is constructed by propensity-score matching using scores estimated from (2). For each importing firm *i*, in general the matching procedure[10] selects the non-importing firms *j* whose propensity score $\hat{p}_{jt}$ lies within a predetermined distance λ (we take $\lambda = 0.01$, which means that "matchable" firms must differ in their probability of taking the treatment by no more than 1%). When several firms fall within this distance, weights $w_{ij} = w\left(\hat{p}_i, \hat{p}_j\right)$ are attributed to each of them.[11] We use the caliper matching method, i.e. we take the non-treated firm whose propensity score falls within a pre specified radius with the treated. We also impose a "common support" constraint; that is, if no firm *j* such that $\left|\hat{p}_{jt} - \hat{p}_{it}\right| < \lambda$ can be found, we throw *i* out of the sample.

The validity of the control group constructed this way is assessed on the basis of "balancing score" tests (see Smith and Todd 2005a, 2005b), whose logic is detailed in annex.

Step 2. Letting q_{it} (without the hat) denote TFP estimated in the first stage, the baseline diff-in-diff equation is

$$q_{it} = \boldsymbol{\alpha}_t + \boldsymbol{\alpha}_\ell + \alpha_1 \Theta_{it} + \boldsymbol{\alpha}' U_{it} + \gamma' V_{it} + \varepsilon_{it} \tag{3}$$

---

[9] Lagged profits control for something like "Ashenfelter's dip", i.e. firms turning to imports at t because they experienced a drop in profits at t-1 (the original Ashenfelter dip was the observation that individuals tend to enrol in training programs after a temporary earnings dip; ignoring the dip would bias estimates by attributing to the training program the effect of the recovery from the dip). We could also find an opposite effect, insofar as more profits at t-1 could allow for the purchase of more capital goods from abroad at t.

[10] This procedure is implemented by Stata's psmatch2 command, due to Leuven and Sianesi (2003).

[11] The choice of a weighting scheme is, again, the experimenter's decision.

where $\Theta_{it} = 1$ marks the event that firm *i* switches import status at *t* (from $\theta_{i,t-1} = 0$ to $\theta_{it} = 1$):

$$\Theta_{it} = \begin{cases} 1 & \text{if firm } i \text{ switches import status at } t \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

In the regression we include control variables where U_{it} is a vector of firm characteristics (foreign capital share, market share) and V_{it} a vector of industry characteristics (Herfindahl index, output growth), and $\boldsymbol{\alpha}_{\ell}$ and $\boldsymbol{\alpha}_{t}$ are vectors of location and time dummies respectively. We run several variants of (3), discussed in the course of the paper. We include lagged values of Θ_{it} to allow for dynamic (learning) effects. One variant distinguishes between one-time and repeated switchers and another one uses the interaction between the binary status and the skilled labor share.

2.2 The direct approach

The preceding subsection presented a two-stage methodology to evaluate the impact of starting to import on productivity. To assess the robustness of our findings, we use an alternative specification and method. To this end, we modify the OP and ACF methodologies assuming that firms anticipate the effect of their imports on their productivity. We address this issue by estimating a production function that includes the share of imports in intermediates and capital equipment purchases directly as a regressor and treated as endogenous like investment. Using the share of imported intermediates and capital (rather than the binary import status), our production function equation for the extended OP method becomes

$$y_{it} = \beta_l \ell_{it} + \beta_m m_{it} + \phi_t \left(i_{it}, k_{it}, Mshare_{it-1} \right) + v_{it} \tag{5}$$

with $Mshare_{it-1} = \ln\left[\left(M + I \right)^{*}_{it-1} / \left(M + I \right)_{it-1} \right]$ where * denotes foreign variables, *M* purchases of intermediates and *I* investment.

And for the extended ACF method, our production function equation becomes:

$$y_{it} = \beta_m m_{it} + \phi_t \left(i_{it}, k_{it}, \ell_{it}, Mshare_{it-1} \right) + v_{it} \tag{6}$$

This alternative procedure has some similarity to the one used, *inter alia*, by Kasahara & Rodrigue (2008), but we modify it in order to explore the central hypothesis of this paper, namely that the effect of imports on productivity depends on the firm's absorptive capacity. In order to do so, for each firm characteristic z_{it}^{k} of interest to us (R&D intensity, skill intensity, profit growth, etc.) we define a cutoff level z_{0}^{k} and an indicator function $High_{it}^{k}$ such that

$$High_{it}^{k} = \begin{cases} 1 & \text{if } z_{it}^{k} \geq z_{0}^{k} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

For example, suppose that z_{it}^{k} is the share of skilled manpower in the firm's labor force. Then $High_{it}^{k} = 1$ characterizes skill-intensive firms (those we presume have a high absorptive capacity for foreign technology embodied in imported inputs). Using characteristic *k* to determine the "high" and "low" groups, we then have a production function (in logs) of the form for the extended OP method:

$$y_{it} = \beta_{l}\ell_{it} + \beta_{m}m_{it} + \phi_{t}\left(i_{it}, k_{it}, Mshare_{it-1} * High_{it}^{k}, Mshare_{it-1} * \left(1 - High_{it}^{k}\right)\right) + v_{it} \tag{8}$$

And for the extended ACF method:

$$y_{it} = \beta_{m}m_{it} + \phi_{t}\left(i_{it}, k_{it}, \ell_{it}, Mshare_{it-1} * High_{it}^{k}, Mshare_{it-1} * \left(1 - High_{it}^{k}\right)\right) + v_{it} \tag{9}$$

We estimate (8) and (9) for the entire sample, and repeat the estimation exercise for various groupings (some of which multiple-category generalizations of (7)), each defined by an individual characteristic *k*. If a high value of z_{it}^{k} denotes a high absorptive capacity, we hypothesize that $\beta_{Mshare*High} > \beta_{Mshare*(1-High)}$, with $\beta_{Mshare*High}$ and $\beta_{Mshare*(1-High)}$, the respective coefficients of $Mshare_{it-1} * High_{it}^{k}$ and $Mshare_{it-1} * \left(1 - High_{it}^{k}\right)$.

3. Data

3.1 Data sources

Our firm data is an unbalanced panel of 3'462 firms covered by Spain's *Encuesta Sobre Estrategias Empresariales* (ESEE), a very detailed annual manufacturing survey covering 70% of all firms above 200 employees and 5% of firms below 200 employees between 1991 and 2002. The initial number of observations was 24'139. Our method for cleaning the data is largely inspired by Hall and Mairesse (1995). We interpolated missing data only for single unreported years (131 observations). We excluded firms never reporting any value added (322) or intermediate consumptions (12), as well as those reporting more exports than their turnover (2 observations). We also threw out the top and bottom 1% of the sample in terms of value added per employee, output per employee and capital per employee[12] (1'071 observations). Finally we threw out observations where value added or output grew by more than 300% or dropped by more than 90% over one year, and those whose employment or capital stock grew by more than 200% or dropped by more than 50% (376 observations). The cleaning job reduced our sample to 2'722 firms tracked between 1991 and 2002, or 19'589 observations.

Output, capital, investment and intermediate consumptions are all measured in constant pesetas using the *Instituto Nacional de Estadistica*'s 2-digit sectoral price indices as deflators. Labor is the number of employees. The capital stock was constructed from investment data using the Perpetual Inventory Method (PIM) with the sum of corporate fixed assets as initial values and a rate of depreciation taken from Mas, Perez and Uriel (2003).

Data on foreign purchases does not distinguish between intermediates and capital equipment. This does not matter when using a binary classification of firms between importing and non-importing ones. We gain added precision by using actual amounts purchased, but then those must be compared to total purchases of intermediates *and capital goods* (ie investment) to be meaningful.

3.2 Descriptive statistics

Table 1 shows descriptive statistics for the firms in our sample, averaged over the whole sample period. Because the distinction between firms that import intermediates and firms that do not at the core of our analysis, the table distinguishes between three categories: (i) firms that never used imported intermediates (30.4% of the sample), (ii) firms that always used imported intermediates (37.4% of the sample), and (iii) firms that switched status once or more (the remaining 32.2%).

Table 1:Descriptive statistics for the entire sample of Spanish firms

It can be seen from Table 1 that there is a huge difference in the average size of importing firms relative to non-importing ones (the former are thirty-three times larger than the latter in terms of output and thirty-eight times larger in terms of capital). Because they are also 2.8 times more capital-intensive, importing firms are only fifteen times larger than non-importing ones in terms of employment. Importing firms are slightly more intensive in their use of intermediates (59% of output value against 50% for non-importing firms), tend to export more (27% of their output against 3% for non-importing ones), and have R&D ratios six times higher. Finally, the least surprising observation

[12] This step is necessary to eliminate aberrant values due to typing errors during data entry.

is that the share of foreign capital is much higher (35%) for importing firms than for non-importing ones (1%), suggesting that foreign-owned firms tend to buy intermediates abroad –possibly in parent companies— more than domestically-owned ones. In all dimensions, the average characteristics of switching firms are, unsurprisingly, convex combinations of those of importing and non-importing ones.

These large differences in individual characteristics across groups defined by importing status highlight the need for a careful construction of the control group. Using a propensity-score matching approach ensures that we compare firms that are comparable instead of raw categories that are obviously too heterogeneous to be compared.

4. Two-stage estimation results

4.1 TFP estimation

Table 2 reports the parameter estimates for industry production functions based on the OP and ACF methodologies.

Table 2: Production function parameter estimates, by industry

Figure 1 shows the evolution of estimated TFP[13] over the sample period for our three firm types as defined by import status: always importing, never importing and switching. In order to control for industry effects, the curves correspond to yearly averages of residuals obtained by regressing TFP on industry dummies.

Figure 1: Unweighted average TFP by import status controlling for industry effect

It can be seen that (i) firms that import either regularly or sporadically have an unweighted average productivity which is slightly lower than that of non-importing firms (ii) TFP for importers and switcher importers have increased throughout the period, whereas firm productivity for non-importers has been relatively stagnant. Moreover, importers have increased their average TFP more significantly. In order to assess whether these different trends observed can be “explained” by firm imports, we now turn to the econometric analysis with in first the treatment effect.

[13] Figure 1 is constructed with TFP issued from OP methodology. With ACF we obtain very similar graphs. The coefficient for the correlation between OP-estimated TFP and ACF-estimated TFP is high (0.91).

4.2 Treatment effect

Table 3 reports balancing score tests for the TFP variable. The same tests are applied to all variables of the probit specification but not reported for brevity. In all cases, conditions for the validity of the control group are satisfied. Table 3: Balancing score tests, TFP

Following our PSM, in table 4 we summarize the firm characteristics of the matched importers and non-importers by industry for the entire sample. For TFP, profit, capital intensity and average wage, major similarities are observed between the treatment group (importers) and the control group (non-importers).

Table 4: Characteristics of matched importers and non-importers by industry

Tables 5a and 5b show OLS with robust standard errors and outlier-robust[14] estimation results[15] for (3) with lagged values of what we call "entry", by which we mean switching from non-importing to importing status. In the first column, the treatment group is the set of all firms that start importing at least once over the sample period. In the second, the treatment group is split between two sub-groups: one is made of firms that switch from non-importing to importing status only once in the sample period ("single switchers"), and the other is made of firms that switch several times ("multiple switchers"). Here we compare each sub-group with the control group constructed in the preceding step of PSM. The idea behind this subdivision of the treatment group is as follows. When a firm starts importing intermediates or capital equipment, either it observes an improvement in its operations or it does not. In the first case, it will either keep on importing or convince its domestic suppliers to match the foreign specifications (for a discussion of this, see Blalock and Veloso 2007), in which case it will cease *permanently* to import. This is our first sub-group. In the second case, it will stop and retry with other foreign suppliers, incurring multiple spells. This is our second sub-group. Thus, we would expect to see an effect on TFP in the first case but not in the second: these are like two different treatments for which we have different priors.

Table 5a: Effect of import status on TFP (Olley and Pakes, 1996)
Table 5b: Effect of import status on TFP (Ackerberg, Caves and Frazer, 2007)

[14] See Rousseeuw and Leroy (1987) or Hamilton (1991).
[15] The matching estimate is very sensitive to the choice of the algorithm. For this reason Dehejia and Wahba (2002) recommend a sensitivity analysis, consisting in re-estimate the propensity score matching with a different algorithm. We run the estimation with the nearest neighbour. Results are similar and available upon request.

Tables 5a and 5b show that the effect of switching to imported intermediates is insignificant in the barebones version of the equation (columns (1) and (4) in each table). However, when importing status is interacted with the single vs. multiple-switcher dummy, the effect of switching becomes significant for the first category that we can see in columns (2) and (5) in the two tables. The impact effect is a 12-13%[16] boost in TFP (significant at 10% and 5%), with a long-run effect (after two years) in the 11-15% range. This is a large effect, although in table 5b where TFP is estimated using the ACF method, the coefficients are lower and less significant (only at the 10% level for the outlier robust regression, column (5)).

In order to shed more light on the mechanisms determining the impact of becoming importer, we have estimated an equation interacting import status with firm characteristics (other than single/multiple switcher). Columns (3) and (6) in tables 5a and 5b show that interacting the importing status of firms with the proportion of skilled labor changes radically the results compared to the equation's barebones version. Firms which both start importing and increase their share of skilled labor get a very high productivity gain, but not necessarily in the first year of importing. The significant and large coefficient for the following years shows that this productivity-enhancing effect of imports is persistent. A 10% increase in the share of skilled labor could produce a differential gain of about 26% three years after taking up importing. Other interaction terms with a set of firm characteristics (export share, share of R&D expenses in the sum of intermediates purchases and investment, market share, share of foreign capital, average profit growth rate, average production growth rate during the first three years after imports begin), by contrast, are insignificant. These results have not been reported[17].

5. Direct estimation results

If the decision to purchase foreign intermediates is a short-run one, it may be correlated with the unobserved idiosyncratic shock, TFP. If that is true, the OP approach should be applied to purchases of foreign as well as domestic inputs. In order to verify that our results are not biased by inadequate treatment of this endogeneity, we re-estimate the production function with import share as one of the regressors. To verify the robustness of our estimates, we also extend the ACF approach as was done for the OP approach. Estimation results, by industry, are shown in Table 6 for the two approaches.

Table 6: Direct approach production function parameter estimates, by industry

---

[16] We obtain this percentage by calculating [exp(coefficient of the dummy variable) – 1]*100.
[17] Results available upon request.

The share of imported inputs has a positive and significant effect on TFP in 8 out of 12 industries for the extended OP method, the four exceptions being leather products, wood and paper, rubber and plastics, and other non-metallic mineral products. All four of these industries transform imported raw materials (leather, rubber, timber, and ores) and it is reassuring that our measure of TFP does not pick up anything for them. This could thus indicate that import share only has an impact on TFP when imported inputs integrate a certain amount of technology. Results for the extended ACF method are in line with the preceding results, except for the rubber and plastics and other non-metallic mineral products sectors, which display a significant coefficient for import share at the 10 percent level. The highest coefficients are obtained for printing products (0.426), machinery and equipment (0.281) and office equipment and precision (0.201) for both approaches.

Table 7 shows the potential effect of intermediates and/or equipment imports on firm productivity for the whole sample. In the first column we can see that a 10 percentage points increase in import share[18] raises TFP by 1.5% for the extended OP approach and 1.4% for the extended ACF approach. This result is close to that found by Halpern et al. for Hungarian exporting firms, but significantly lower than the findings of Kasahara and Rodrigue for Chilean manufacturing firms (although their estimation procedures are different). In the following columns we test whether firm imports could have differenciated effects on TFP by taking into account firm heterogeneity. The other columns in Table 7 show estimation results by groups defined on individual firm characteristics. For each characteristic z_{it}^{k}, coefficients on labor (ℓ), capital (k), and total materials (m), are the same for "high-value" and "low-value" groups. For the coefficients on *Mshare*, we interact the import share with a "High" dummy indicator using the seventy-fifth percentile as the switchpoint for each characteristic.

In the first regression, we return to absorptive capacity by using skill intensity, foreign capital and R&D intensity in columns (2), (3) and (4). The importance of skilled employment in explaining the import-induced productivity gains which were highlighted using the preceding methodology (PSM associated with diff-in-diff) is clearly checked. For the "low-skill" group of firms, the import share coefficient is either significant but very low (with the extended ACF method) or not significant (with the extended OP method). By contrast, for the "high-skill" group (ie for the twenty-five percent of firms having higher skilled employment shares), the coefficient is significant and very high, indicating that a 10 percentage points increase in the share of

[18] To check for a potential « learning-by-importing » effect, it seems more logical to use lagged firm import share instead of current share.

imports raises TFP by 3.4% (with ACF) and 3.6% (with OP approach). Surprisingly, however, the differenciated effect of using foreign inputs (column (4)) goes in different direction between groups defined on R&D intensity depending on the approach used. These results do not allow us to make conclusions.

The effect of imports on TFP is also stronger for firms with a high share of foreign capital. This may be due in part to foreign-owned firms purchasing intermediates from the parent company, in which case they are likely to get technical assistance as well.

In columns (6) and (7), we define the firm groups based on profit growth and market share. The idea is to look at whether or not firms' choices to purchase intermediates and equipment abroad are motivated by the search for cheaper inputs. If importing leads to cost decreases, firms could either lower their prices (and their markups) in order to enlarge market share, or increase their profitability. The results show that the effect is also a bit stronger for firms with a high market share or a high growth in profitability, but by a small margin. The margin's smallness, incidentally, suggests that our productivity effects are *not* driven by differences in markups. This result is not surprising, since Spanish firms have intensified their European market integration by increasing their imports from these countries. This choice does not correspond to a price strategy.

The purpose of the test in column (8), is to verify the role of scale effect by using production growth, ie the firm average for production growth rate. Descriptive statistics have highlighted that importing firms tend to be larger. This may mean that when firms grow, they increase their probability to import. Consequently, we could hypothesize that productivity gains are linked to increasing return to scale and not due to becoming an importer of inputs. The results show a slightly stronger effect for firms with high production growth (both with extended OP and ACF methods), but this effect is too weak to validate this assumption.

Finally, and surprisingly, the productivity-enhancing effect of imports appears *smaller* for firms that export more. Thus, our sample does not seem to confirm the complementarity between imports and exports found by other authors.

Table 7: Direct approach production function parameter estimates, by group

In total, our results suggest that firms with a substantial share of skilled manpower or foreign capital benefit more from imported inputs than others. This is consistent with Acemoglu and Zilibotti's model (2001). At the country level, they show that discrepancies between domestic skill and imported technologies are a source of productivity differences. To improve productivity through importing, a country needs to have an appropriate local skill level. Our results lead us to a similar conclusion at the firm level. Firms that employ many engineers, scientists and technical workers obtain higher productivity gains when they use foreign intermediate and/or equipment goods.

6. Concluding remarks

Whether based on a direct approach (in which foreign intermediates are included directly in the production function) or on a diff-in-diff estimator with a control group constructed by propensity-score matching, our results suggest, in accordance with the recent literature, that importing foreign intermediates and capital raises total factor productivity at the firm level, pointing to a learning by importing effect.

But they also show that this effect is not the same across firms. Using a rich dataset of Spanish firms, we find that absorptive capacity, proxied by the firm's skill intensity, significantly enhances this effect. For instance, a firm with a proportion of skilled personnel above the seventy-fifth percentile stands to benefit *twice more* from imported intermediates and capital, in terms of TFP, than one below that cutoff.

We also find that firms with foreign capital stand to benefit more than others from importing intermediates and capital. This can be interpreted as suggesting that learning effects are important, whether through familiarity with foreign equipment or, possibly, through the presence of training programs and foreign management (more likely in firms with foreign capital, where the parent company may happen to be the provider of foreign equipment).

These results suggest that average correlations between TFP and various measures of exposure to international trade should be interpreted cautiously, as the benefits that exposure can bring about depend in large part on absorptive capacity, which cannot be assessed without detailed data on the firm's activities and characteristics. In terms of economic policy, our results also suggest that trade-liberalization reforms could be made more effective in terms of raising an economy's productive efficiency (putting aside allocative-efficiency issues) if accompanied by training programs or specific aids for the hiring of skilled personnel (engineers and technicians) aimed at potential *importers*, not just exporters (the usual target for assistance).

References

Acemoglu, D. and Zilibotti, F., 2001. Productivity Differences. Quaterly Journal of Economics 116(2), 563-606.

Acharya, R.C., Keller, W., 2007. Technology Transfer through Imports. NBER Working Paper 13086.

Ackerberg, D., Caves, K., Frazer, G., 2007. Structural identification of production functions. UCLA mimeo.

Amiti, M., Konings, J., 2007. Trade Liberalization, Intermediate Inputs and Productivity: Evidence from Indonesia. American Economic Review 97(5), 1611-1638.

Anderson, M., Lööf , H., Johansson, S., 2008. Productivity and international trade: Firm level evidence from a small open economy. Review of World Economics 144(4), 774-801.

Bernard, A., Eaton, J., Jensen, B. and Kortum, S., 2003. Plants and Productivity in International Trade, The American Economic Review, 93(4), 1268-1290.

Blalock, G., Veloso, F.M., 2007. Imports, Productivity Growth and Supply Chain Learning. World Development 35, 1134-1151.

Blundell, R., Costa Dias, M., 2000. Evaluation Methods For Non-Experimental Data. Fiscal Studies 21, 427-468.

Bottasso, A., Sembenelli, A., 2001. Market Power, Productivity and the EU Single Market Program: Evidence from a Panel of Italian Firms. European Economic Review 45, 167-186.

Campa, J.M., 2004. Exchange Rates and Trade: How Important is Hysteresis in Trade? European Economic Review 48, 527-548.

Castellani, D., Zanfei, A., 2003. Technology Gaps, Absorptive Capacity and the Impact of Inward Investments on Productivity of European Firms. Economics of Innovation and New Technology 12(6), 555-576.

Coe, D., Helpman, E., 1995. International R&D Spillovers. European Economic Review 39, 859-887.

Dehejia, R., Wahba, S., 2002. Propensity Score Matching Methods for Non Experimental Causal Studies. Review of Economics and Statistics 84, 151-161.

Delgado, M.A., Fariñas, J.C., Ruano, S., 2002. Firm Productivity and Exports Markets: A Non Parametric Approach. Journal of International Economics 57, 397-422.

De Loecker, J., 2007. Do Exporter Generate Higher Productivity? Evidence From Slovenia. Journal of International Economics 73, 69-98.

Diaz-Diaz, N.L., Aguiar-Diaz, I., De Saa-Perez, P., 2008. The Effect of Technological Knowledge Assets on Performance: The Innovative Choice in Spanish Firms. Research Policy 37, 1515-1529.

Djankov, S., Hoekman, B., 2000. Market Discipline and Corporate Efficiency: Evidence From Bulgaria. Canadian Journal of Economics 33, 190-212.

Eaton, J., Bernard, S., Kortum, S., 2001. Trade in Capital Goods. European Economic Review 45(5), 1195-1235.

Eaton, J., Bernard, S., Kortum, S., 2002. Technology, Geography and Trade. Econometrica 70(5), 1741-1780.

Ederington J., McCalman P., 2008. Endogenous Firm Heterogeneity and the Dynamics of Trade Liberalization. Journal of International Economics 74, 422-440.

Ethier, W., 1982. National And International Returns to Scale in the Model Theory of International Trade. American Economic Review 72(3), 389-405.

Fariñas, J.C., Martin-Marcos, A., 2007. Exporting and Economic Performance: Firm-Level Evidence For Spanish Manufacturing. The World Economy 30(4), 618-646.

Fernandes, A.M., 2007. Trade Policy, Trade Volumes and Plant-Level Productivity in Colombian Manufacturing Industries. Journal of International Economics 71, 52-71.

Girma, S., Greenaway, D., Kneller, R., 2004. Does Exporting Increase Productivity? A Microeconometric Analysis of Matched Firms. Review of International Economics 12, 855-866.

Girma, S., Kneller, R., Pisu, M., 2007. Do Exporters Have Anything to Learn From Foreign Multinationals? European Economic Review 51, 981-998.

Goldberg, P., Khandelwal, A., Pavcnik, N., Topalova, P., 2008. Imported Intermediate Inputs and Domestic Product Growth: Evidence from India. NBER Working Paper 14416.

Hall, B. H., Mairesse, J., 1995. Exploring The Relationship Between R&D and Productivity In French Manufacturing Firms. Journal of Econometrics 65, 263-293.

Halpern, L., Koren, M., Szeidl, A., 2005. Imports and Productivity. CEPR DP 5139.

Halpern, L., Korosi, G., 2001. Efficiency And Market Share In The Hungarian Corporate Sector. Economics of Transition 9(3), 559-592.

Hamilton, L.C., 1991. How Robust Is Robust Regression?. Stata Technical Bulletin 2, 21-26.

Helpman, E., Krugman, P., 1985. Market Structure and Foreign Trade: Increasing Returns, Impecfect Competition and the International Economy, MIT Press, Cambridge, MA.

Horn, H., Lang H. and Lundgren, S., 1995. Managerial Effort Incentives, X-Inefficiency and intenational trade, European Economic Review*,* 39(1)*, 117-38.*

Huergo, E., 2006. The Role of Technological Management As a Source of Innovation: Evidence From Spanish Manufacturing Firms. Research Policy 35, 1377-1388.

Jabbour, L., Mucchielli, J.L., 2007. Technology Transfer Through Vertical Linkages: The Case of The Spanish Manufacturing Industry. Journal of Applied Economics 10, 115-116.

Kasahara, H., Lapham, B., 2008. Productivity and the Decision to Import and Export: Theory and Evidence. Forthcoming, Journal of International Economics.

Kasahara, H., Rodrigue, J., 2008. Does The Use of Imported Intermediates Increase Productivity? Plant-Level Evidence. Journal of Development Economics 87, 106-118.

Keller, W., 1996. Absortive Capacity: On the Creation and Acquisition of Technology in Development. Journal of Development Economics 49, 199-227.Krugman, P., 1979. Increasing Returns, Monopolistic Competition and International Trade, Journal of International economics, 9, 469-79.

Leuven, E., Sianesi, B., 2003. PSMATCH2: Stata Module to Perform Full Mahalanobis And Propensity Score Matching, Common Support, Graphing, and Covariate Imbalance Testing Http://Ideas.Repec.Org/C/Boc/Bocode/S432001.Html.

Lööf, H., Anderson, M., 2008. Imports, Productivity and the Origin Markets: The Role of Knowledge-Intensive Economies. The Royal Institute of Technology CESIS, Electronic WP 146.

Lumenga-Neso, O., Olarreaga, M., Schiff, M., 2001. On 'Indirect' Trade-Related R&D Spilloversy. Mimeo, World Bank.

Mas, M., Pèrez, F., Uriel, E., 2003. Stock De Capital En España Y Su Distribucion Territorial (1964-2000). Fundacion BBVA, Bilbao, http://Www.Fbbva.Es.

Melitz, M., 2003. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. Econometrica 71, 1695–1725.

Miyagiwa, K., Ohnon, Y., 1995. Closing the technology gap under protection. American Economic Review 85, 755-770.

Muendler, M., 2004. Trade, Technology, and Productivity: A Study of Brazilian Manufacturers, 1986-1998. Department of Economics, UC San Diego, University of California At San Diego, Economics Working Paper.

Muûls, M., Pisu, M., 2007. Imports And Exports at the Level of the Firm: Evidence From Belgium. LSE, Center For Economic Performance, DP 801.

Olley, S., Pakes, A., 1996. The Dynamics Of Productivity in The Telecommunications Equipment Industry. Econometrica 64, 1263-1297.

Pavcnik, N., 2002. Trade Liberalisation, Exit, and Productivity Improvements: Evidence From Chilean Plants. Review of Economic Studies 69, 245-276.

Rivera-Batiz, L., P. Romer P., 1991. Economic Integration and Endogenous Growth. Quarterly Journal of Economics, 531-555.

Rodrik D., 1992. Closing technology gap: does trade liberalization really help? In: Helleiner, G. (Ed.), Trade Policy, Industrialization and Development: New Perspectives. Claredon Press.

Romer, P., 1987. Growth Based on Increasing Returns Due to Specialization. American Economic Review, 77(2), 56-62.

Rosenbaum, P., Rubin, D.B., 1983. The Central Role of The Propensity Score in Observational Studies For Causal Effects. Biometrika 70, 41-55.

Rosenbaum, P., Rubin, D.B., 1985. Constructing a Control Group Using a Multivariate Matched Sampling Method that Incorporates the Propensity Score. The American Statistician 39, 33-38.

Rousseeuw, P.J., Leroy, A.M., 1987. Robust Regression And Outlier Detection. New York: John Wiley & Sons.

Schor, A., 2004. Heterogeneous Productivity Response To Tariff Reduction. Evidence From Brazilian Manufacturing Firms. Journal of Development Economics 75, 373-396.

Sembenelli, A., Siotis, G., 2008. Foreign Direct Investment And Mark-Up Dynamics: Evidence From Spanish Firms. Journal of International Economics 76, 107-115.

Smith, J., Todd, P., 2005a. Does Matching Overcome Ladonde's Critique of Nonexperimental Estimators? Journal of Econometrics 125, 305-353.

Smith, J., Todd, P., 2005b. Rejoinder. Journal of Econometrics 125, 365-375.

Van Biesebroeck, J., 2003. Revisiting some productivity debates, NBER Working Paper 10065.

Vega-Jurado, J., Gutiérrez-Gracia, P., Fernandez-De-Lucio, I., Manjarrés-Henriquez, L., 2008. The Effect of External and Internal Factors On Firms'product Innovation. Research Policy 37, 616-632.

Vogel, A., Wagner, J., 2008. Higher Productivity in Importing German Manufacturing Firms: Self-Selection, Learning From Importing, or Both? University of Lüneburg, WP 106.

Wagner, J., 2007. Exports and Productivity: A Survey of The Evidence From Firm Level Data. The World Economy 30, 60-82.

Xu, B., Wang, J., 1999. Capital Goods Trade and R&D Spillovers in the OECD. Canadian Journal of Economics 32, 1258-1274.

Annex 1 - The Balancing Score Tests

Let $\bar{x}_i$ be the average value over the sample period of some individual characteristic of firm *i* (say, its productivity). For the control group to be valid, the average value of that individual characteristic should not differ "too much" between the treatment and control group. Two approaches are available to test whether this condition holds. The first is based on the following test statistic:

$$SDIFF(x) = \frac{(100/N_T)\left[\sum_{i \in T}\left(\bar{x}_i - w_{ij}\bar{x}_j\right)\right]}{\sqrt{\left(\sigma_x^T + \sigma_x^C\right)/2}} \tag{A1}$$

where σ_x^T and σ_x^C are the sample variances of individual characteristic x over the treatment (*T*) and control (*C*) groups respectively, N_T is the size of the treatment group, and $w_{ij} = w\left(x_i, x_j\right)$ is the weight given to control firm *j* in the matching. Although there are no real criteria on the maximum difference which we can accept in an unquestionable way, Rosenbaum and Rubin (1985) suggest that this difference should not exceed 20.

The second test consists of running, for each variable entering the propensity score model, a formal paired t-test between the two groups to satisfy that no significant differences exist.

In the third test we estimate for each variables regression of the form

$$x = \beta_0 + \sum_{k=1}^{3}\beta_k \hat{p}(\Theta)^k + \sum_{k=1}^{3}\gamma_k \theta \hat{p}(\Theta)^k + \varepsilon \tag{A2}$$

where $\hat{p}(\Theta)$ denotes the estimated propensity score and θ is a dummy variable equal to 1 if the firm switches import status. As explained by Smith and Todd (2005b), the balancing condition requires the γ's to be jointly insignificant.

Annex 2 - Tables and figure

Table 1
Descriptive statistics for Spanish firms throughout the sample

	All	**Non-importing firms**	**Importing Firms**	**Switchers importing firms**
# of firms	2'354	715	880	759
(Percent of total)		(0.304)	(0.374)	(322)
Output (Y)	5'989.26	331.72	10'900.00	5'521.95
	(28500.00)	(1370.18)	(36900.00)	(265000.00)
Capital (K)	3'060.90	143.20	5'432.32	2'580.22
	(15800.00)	(581.47)	(22100.00)	(12000.00)
Labor (L)	263	31	453	237
	(860)	(60)	(1'119)	(687)
Intermediates (M)	3'749.46	165.83	6'466.63	3'164.62
	(20900.00)	(801.40)	(27700.00)	(18900.00)
Markup	0.223	0.208	0.230	0.225
	(0.138)	(0.141)	(0.131)	(0.142)
Capital-labor ratio	6'278.12	3'073.81	8'529.33	5'958.96
	(7'013.40)	(4'155.97)	(8'001.36)	(6'464.18)
Export ratio (X/Y)	0.166	0.028	0.267	0.145
	(0.243)	(0.115)	(0.266)	(0.229)
Export ratio for exporting firms	0.272	0.178	0.305	0.237
	(0.261)	(0.237)	(0.263)	(0.253)
Import ratio [(M+I)*/(M+I)], whole sample	0.153	-	0.297	0.094
	(0.254)		(0.247)	(0.171)
Import ratio, importing firms only	0.250	-	0.297	0.159
	(0.240)		(0.247)	(0.198)
R&D ratio [R&D/(M+I)]	0.016	0.004	0.025	0.014
	(0.058)	(0.023)	(0.072)	(0.056)
Foreign capital share (K*/K)	0.187	0.009	0.346	0.131
	(0.372)	(0.086)	(0.451)	(0.320)
Foreign capital share if foreign capital > 0	0.839	0.697	0.853	0.807
	(0.273)	(0.289)	(0.263)	(0.295)
Age	24	14	30	24
	(22)	(14)	(24)	(22)
Skilled-labor share	0.102	0.051	0.132	0.101
	(0.119)	(0.090)	(0.122)	(0.120)

Notes: Standard deviations are in parentheses. Output, capital and intermediate purchases are measured in millions of constant Pesetas. Labor is the number of employees. Markups are calculated as [(sales – average costs)/sales] which is an approximation of the Lerner index. Export ratios are relative to firm output. Import and R&D ratios are relative to the sum total intermediates and total investment by firm (M+I). (M+I) are the imported intermediates and investment goods.*

Table 2
Production function parameter estimates, by industry

			Olley and Pakes (1996) approach			Ackerberg, Caves and Frazer (2007) approach		
Industry		Variable	Coef.	S.E.	Nb obs.	Coef.	S.E.	Nb obs.
Food & tobacco	1	*l*	0.250***	(0.024)	2388	0.276***	(0.015)	2388
		k	0.322***	(0.023)		0.283***	(0.023)	
		m	0.513***	(0.032)		0.510***	(0.030)	
Textiles & textile prod.	2	*l*	0.426***	(0.033)	1444	0.361***	(0.024)	1444
		k	0.220***	(0.029)		0.247***	(0.030)	
		m	0.417***	(0.024)		0.408***	(0.024)	
Leather & leather prod.	3	*l*	0.124***	(0.036)	382	0.227***	(0.020)	382
		k	0.152***	(0.020)		0.142***	(0.013)	
		m	0.581***	(0.029)		0.582***	(0.026)	
Wood and Paper	4	*l*	0.282***	(0.028)	857	0.285***	(0.024)	857
		k	0.176***	(0.017)		0.178***	(0.028)	
		m	0.583***	(0.027)		0.563***	(0.024)	
Printing prod.	5	*l*	0.410***	(0.048)	868	0.681***	(0.035)	868
		k	0.274***	(0.038)		0.181***	(0.050)	
		m	0.372***	(0.030)		0.360***	(0.028)	
Rubber & plastic prod.	6	*l*	0.425***	(0.069)	949	0.393***	(0.027)	949
		k	0.232***	(0.018)		0.248***	(0.029)	
		m	0.414***	(0.081)		0.396***	(0.090)	
Other non- metall. mineral prod.	7	*l*	0.605***	(0.043)	1140	0.481***	(0.035)	1140
		k	0.267***	(0.035)		0.284***	(0.038)	
		m	0.317***	(0.041)		0.291***	(0.040)	
Basic metals & fab. metal prod.	8	*l*	0.409***	(0.025)	2030	0.302***	(0.021)	2030
		k	0.205***	(0.018)		0.236***	(0.021)	
		m	0.470***	(0.025)		0.470***	(0.025)	
Machinary & equipment	9	*l*	0.398***	(0.039)	1241	0.434***	(0.024)	1241
		k	0.266***	(0.034)		0.213***	(0.036)	
		m	0.429***	(0.036)		0.435***	(0.032)	
Office equip. & precision inst.	10	*l*	0.236***	(0.050)	283	0.371***	(0.035)	283
		k	0.257***	(0.046)		0.172***	(0.048)	
		m	0.567***	(0.034)		0.527***	(0.045)	
Transport equip.	11	*l*	0.342***	(0.032)	1181	0.284***	(0.021)	1181
		k	0.137***	(0.016)		0.169***	(0.024)	
		m	0.571***	(0.023)		0.566***	(0.023)	
Other manuf. Prod.	12	*l*	0.263***	(0.029)	1070	0.474***	(0.016)	1070
		k	0.255***	(0.008)		0.111***	(0.020)	
		m	0.481***	(0.043)		0.497***	(0.029)	

*Source: authors' calculations. Robust standard errors are in parentheses * significant at 10%, ** at 5%; *** at 1%.*

Table 3
Balancing score tests, TFP

Year	***Average*** ***Standardized difference (%)***	***p-values*** ***Regression-based test***	***t-test***
1993	8.69	0.979	0.812
1994	7.03	0.231	0.571
1995	10.36	0.844	0.559
1996	9.36	0.877	0.845
1997	7.19	0.715	0.729
1998	7.03	0.891	0.909
1999	9.25	0.919	0.950
2000	11.81	0.509	0.378
2001	8.79	0.783	0.602
2002	8.08	0.952	0.924

Notes: Standardized differences are calculated for each of the matching variables using the equation (A1) in annex. Regression-based tests are conducted for all explanatory variables included in the probit specification. We test for the joint significance of the γ coefficients. A p-value greater than the specified significance level (say 5%) is evidence in favour of balancing. Formal paired t-tests are conducted for all explanatory variables included in the probit regression.

Table 4
Characteristics of matched importers and non-importers by industry

Variables	***Inds.***	***Importers***	***Non-importers***	***Inds.***	***Importers***	***Non-importers***
TFP (O&P)		1.98	2.01		3.79	3.69
TFP (ACF)		2.37	2.38		4.26	4.28
Profit	1	0.214	0.209	7	0.283	0.251
Capital intensity		4'786.91	3'800.46		6'350.03	4'939.22
Average wage		2'768.50	2'53		3'251.07	2'907.48
TFP (O&P)		3.74	3.75		3.42	3.42
TFP (ACF)		3.76	3.77	8	3.43	3.42
Profit	2	0.213	0.185		0.212	0.204
Capital intensity		2'212.52	1'404.16		3'379.11	2'809.69
Average wage		2'333.52	2'177.66		3'291.33	3'112.65
TFP (O&P)		3.52	3.49		3.31	3.33
TFP (ACF)		3.29	3.30		3.69	3.70
Profit	3	0.157	0.159	9	0.204	0.207
Capital intensity		1'391.09	1'162.17		2'589.24	2'136.40
Average wage		2'123.54	2'113.55		3'520.10	3'363.73
TFP (O&P)		2.72	2.75		2.55	2.54
TFP (ACF)		2.92	2.94		3.41	3.61
Profit	4	0.193	0.190	10	0.155	0.093
Capital intensity		2'748.36	2'579.79		858.314	695.345
Average wage		2'465.24	2'442.21		3'251.32	2'730.41
TFP (O&P)		3.62	3.62		3.14	3.29
TFP (ACF)		4.14	4.16		3.06	3.20
Profit	5	0.262	0.257	11	0.158	0.201
Capital intensity		4'301.59	4'172.22		3'541.52	2'239.65
Average wage		3'526.90	3'270.95		3'277.61	3'179.56
TFP (O&P)		3.62	3.61		3.09	3.05
TFP (ACF)		3.75	3.73		3.75	3.72
Profit	6	0.233	0.236	12	0.192	0.160
Capital intensity		4'637.43	3'728.15		2'044.21	1'930.93
Average wage		2'993.29	2'813.43		2'503.63	2'412.96
All sample :						
TFP (O&P)					3.13	3.12
TFP (ACF)					3.43	3.42
Profit					0.216	0.210
Capital intensity					3'723.745	3'130.112
Average wage					2'957.896	2'786.527

Table 5a
Effect of import status on TFP (Olley and Pakes, 1996)

	Dependent variable: ln(TFP_{it})					
	OLS			**Outlier robust regression**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
No interaction :						
Entry year	0.052		0.013	0.047		0.007
	(0.035)		(0.040)	(0.037)		(0.043)
1 year after entry	0.038		-0.009	0.040		-0.005
	(0.036)		(0.040)	(0.038)		(0.043)
2 years after entry	0.022		-0.025	0.023		-0.024
	(0.039)		(0.044)	(0.041)		(0.046)
Interaction variable :						
Single switchers						
Entry year		0.124**			0.124**	
		(0.054)			(0.057)	
1 year after entry		0.154***			0.146***	
		(0.049)			(0.055)	
2 years after entry		0.153***			0.136**	
		(0.053)			(0.061)	
Multiple switchers						
Entry year		0.011			0.002	
		(0.044)			(0.048)	
1 year after entry		-0.057			-0.054	
		(0.049)			(0.050)	
2 years after entry		-0.072			-0.064	
		(0.053)			(0.054)	
Skills						
Entry year			0.826***			0.784*
			(0.278)			(0.429)
1 year after entry			0.972***			0.889**
			(0.271)			(0.402)
2 years after entry			1.051***			0.952**
			(0.257)			(0.425)
Constant	2.676***	2.676***	2.682***	2.413***	2.408***	2.416***
	(0.133)	(0.133)	(0.134)	(0.096)	(0.096)	(0.096)
Control variables	yes	yes	yes	yes	yes	yes
Loca. dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
Observations	4806	4760	4806	4806	4760	4806
R^2	0.12	0.12	0.12	0.13	0.14	0.13

*Source: authors' calculations. Standard errors are in parentheses. * Significant at 10%, ** at 5%; *** at 1%. OLS regressions are estimated using robust standard errors. All regressions include foreign capital share, market share, Herfindahl index and industry output growth as controls. For the sake of simplicity, we do not present their coefficients. They are, however, significant and bear the expected coefficient sign, with the exception of foreign capital.*

Table 5b
Effect of import status on TFP (Ackerberg, Caves and Frazer, 2007)

	Dependent variable: $\ln(TFP_{it})$					
	OLS			**Outlier robust regression**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
No interaction :						
Entry year	0.059*		0.024	0.058		0.022
	(0.034)		(0.039)	(0.038)		(0.044)
1 year after entry	0.029		-0.015	0.034		-0.009
	(0.035)		(0.039)	(0.039)		(0.044)
2 years after entry	0.032		-0.012	0.039		-0.007
	(0.038)		(0.043)	(0.042)		(0.047)
Interaction variable :						
Single switchers						
Entry year		0.107**			0.110*	
		(0.052)			(0.058)	
1 year after entry		0.093**			0.096*	
		(0.047)			(0.056)	
2 years after entry		0.102*			0.103*	
		(0.053)			(0.062)	
Multiple switchers						
Entry year		0.03			0.026	
		(0.044)			(0.049)	
1 year after entry		-0.022			-0.020	
		(0.048)			(0.052)	
2 years after entry		-0.013			-0.005	
		(0.053)			(0.056)	
Skills						
Entry year			0.750***			0.711
			(0.285)			(0.440)
1 year after entry			0.903***			0.834**
			(0.250)			(0.412)
2 years after entry			1.002***			0.951**
			(0.276)			(0.437)
Constant	3.000***	2.999***	3.005***	2.743***	2.741***	2.741***
	(0.137)	(0.137)	(0.137)	(0.099)	(0.099)	(0.099)
Control variables	yes	yes	yes	yes	yes	yes
Loca.dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
Observations	4806	4760	4806	4806	4760	4806
R^2	0.13	0.13	0.13	0.15	0.15	0.15

*Source: authors' calculations. Standard errors are in parentheses. * Significant at 10%, ** at 5%; *** at 1%. OLS regressions are estimated using robust standard errors. All regressions include foreign capital share, market share, Herfindahl index and industry output growth as controls. For the sake of simplicity, we do not present their coefficients. They are, however, significant and bear the expected coefficient sign, with the exception of foreign capital.*

Table 6
Direct approach production function parameter estimates, by industry

			Olley and Pakes (1996) approach			Ackerberg, Caves and Frazer (2007) approach		
Industry		Variable	Coef.	S.E.	Nb obs.	Coef.	S.E.	Nb obs.
Food & tobacco	1	*l*	0.250***	(0.023)	2039	-0.068***	(0.011)	2039
		k	0.346***	(0.028)		0.059*	(0.031)	
		m	0.524***	(0.027)		0.522***	(0.025)	
		$Mshare_{t-1}$	0.116*	(0.060)		0.176***	(0.055)	
Textiles & textile prod.	2	*l*	0.408***	(0.041)	1229	0.325***	(0.025)	1229
		k	0.178***	(0.016)		0.249***	(0.030)	
		m	0.434***	(0.029)		0.432***	(0.029)	
		$Mshare_{t-1}$	0.201***	(0.060)		0.198***	(0.051)	
Leather & leather prod.	3	*l*	0.103**	(0.041)	320	0.237***	(0.022)	320
		k	0.180***	(0.018)		0.134***	(0.015)	
		m	0.612***	(0.036)		0.568***	(0.038)	
		$Mshare_{t-1}$	-0.037	(0.060)		0.119	(0.097)	
Wood and Paper	4	*l*	0.271***	(0.031)	709	0.313***	(0.024)	709
		k	0.169***	(0.016)		0.122***	(0.029)	
		m	0.580***	(0.026)		0.575***	(0.028)	
		$Mshare_{t-1}$	0.027	(0.047)		0.064	(0.039)	
Printing prod.	5	*l*	0.399***	(0.062)	733	0.650***	(0.037)	1061
		k	0.168***	(0.015)		0.107**	(0.054)	
		m	0.356***	(0.034)		0.344***	(0.034)	
		$Mshare_{t-1}$	0.426***	(0.071)		0.514***	(0.082)	
Rubber & plastic prod.	6	*l*	0.396***	(0.094)	804	0.404***	(0.028)	804
		k	0.278***	(0.023)		0.279***	(0.034)	
		m	0.408***	(0.123)		0.369***	(0.129)	
		$Mshare_{t-1}$	0.035	(0.061)		0.099*	(0.051)	
Other non- metall. mineral prod.	7	*l*	0.586***	(0.052)	985	0.485***	(0.040)	985
		k	0.301***	(0.042)		0.287***	(0.041)	
		m	0.314	(0.056)		0.282***	(0.055)	
		$Mshare_{t-1}$	0.011	(0.095)		0.127*	(0.076)	
Basic metals & fab. metal prod.	8	*l*	0.380***	(0.026)	1731	0.294***	(0.022)	1731
		k	0.193***	(0.020)		0.204***	(0.022)	
		m	0.500***	(0.018)		0.502***	(0.019)	
		$Mshare_{t-1}$	0.156***	(0.046)		0.130***	(0.032)	
Machinary & equipment	9	*l*	0.410***	(0.045)	1062	0.407***	(0.024)	1062
		k	0.236***	(0.034)		0.229***	(0.036)	
		m	0.443***	(0.045)		0.447***	(0.039)	
		$Mshare_{t-1}$	0.281***	(0.069)		0.351***	(0.056)	
Office equip. & precision inst.	10	*l*	0.160***	(0.081)	227	0.349***	(0.030)	227
		k	0.394***	(0.071)		0.113***	(0.023)	
		m	0.581***	(0.052)		0.534***	(0.000)	
		$Mshare_{t-1}$	0.201**	(0.086)		0.348***	(0.068)	
Transport equip.	11	*l*	0.353**	(0.036)	1010	0.283***	(0.021)	1010
		k	0.142***	(0.015)		0.173***	(0.025)	
		m	0.553***	(0.028)		0.557***	(0.028)	
		$Mshare_{t-1}$	0.173***	(0.042)		0.194***	(0.037)	
Other manuf. Prod.	12	*l*	0.260***	(0.031)	921	0.484***	(0.016)	921
		k	0.254***	(0.008)		0.094***	(0.021)	
		m	0.470***	(0.033)		0.486***	(0.029)	
		$Mshare_{t-1}$	0.089**	(0.045)		0.197***	(0.045)	

*Source : autors' calculation. Robust standard errors are in parenthesis * significant at 10%, ** at 5%; *** at 1%.*

Table 7
Direct approach production function parameter estimates, by group

		No interaction		Interaction						
				Skill intensity	**R&D Intensity**	**Foreign capital**	**Export intensity**	**Profit growth**	**Market share**	**Production growth**
		(1)		**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Olley and Pakes (1996) approach	*l*	0.363***								
		(0.014)								
	k	0.251***	*Mshare*$_{t-1}$**High*	0.361***	0.130***	0.168***	0.071***	0.221***	0.179***	0.213***
		(0.010)		(0.028)	(0.021)	(0.022)	(0.021)	(0.030)	(0.021)	(0.031)
	m	0.476***								
		(0.015)	*Mshare* $_{t-1}$*(1-High)*	0.012	0.214***	0.071***	0.284***	0.131***	0.074**	0.129***
	Mshare$_{t-1}$	0.153***		(0.021)	(0.028)	(0.027)	(0.029)	(0.021)	(0.030)	(0.020)
		(0.019)								
Equality tests of *Mshare*$_{t-1}$ coefficients [a]				0.000	0.009	0.002	0.000	0.006	0.001	0.011
Ackerberg, Caves and Frazer (2007) approach	*l*	0.344***								
		(0.008)								
	k	0.219***	*Mshare* $_{t-1}$**High*	0.344***	0.283***	0.288***	0.271***	0.312***	0.290***	0.318***
		(0.011)		(0.008)	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)
	m	0.474***								
		(0.015)	*Mshare* $_{t-1}$*(1-High)*	0.037**	0.225***	0.135***	0.323***	0.143***	0.103***	0.145***
	Mshare$_{t-1}$	0.138***		(0.017)	(0.024)	(0.023)	(0.026)	(0.017)	(0.026)	(0.017)
		(0.014)								
Equality tests of *Mshare*$_{t-1}$ coefficients [a]				0.000	0.019	0.000	0.063	0.000	0.000	0.000
Inds. dummies		yes		yes	yes	yes	yes	yes	yes	yes
Number of obs.		11770		11519	11770	11770	11770	11755	11706	11770

*Notes: [a] p-value is reported. For example, the first value of column 2 reports the test for the equality of the coefficients of Mshare*High and Mshare*(1-High).*
*Source: authors' calculations. Robust standard errors are in parentheses * significant at 10%, ** at 5%; *** at 1%. Concerning the regressions with interacted variables, for the sake of simplicity, we do not present the coefficients for labor, capital and intermediary consumption. They are, however, significant. They bear the expected coefficient sign and remain stable, except for the labor coefficient in the extended ACF approach, which varies from one specification to another and is insignificant in the estimation in column (8).*

Figure 1
Unweighted average TFP by import status controlling for industry effects