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

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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 (1991-2002). We use two alternative approaches. In the first, we estimate TFP 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 capacit y to absorb technology, measured by the proportion of skilled labor.

JEL classification numbers: F2, O1, O2
Keywords: Productivity, TFP, imports, Olley-Pakes, Ackerberg-Caves-Frazer, absorptive capacity

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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. These findings, which suggested a potential causal chain from trade to technology diffusion to productivity growth, were confirmed by Acharya and Keller (2007) who showed, however, that the link (which was largely a black box) was heterogeneous across countries and sectors.

Opening the black box requires a firm-level analysis, with several possible linkages between trade and productivity. First, better access to imported intermediates can raise productivity because either foreign intermediates are better, or through the production equivalent of a "love-of-variety" argument (Ethier 1982). We will call this a "vertical" (upstream-downstream) linkage. Second, a number of "horizontal" linkages (within final-good markets) can be at play. Foreign competition in the final-goods market can whip up the productivity of domestic producers (Horn and al. 1995), force markups down (Krugman 1979, Helpman and Krugman 1985, Bernard and al. 2003), or raise the speed of technology adoption because there are fewer domestic firms (Ederington and McCalman 2008).[1] Conversely, foreign competition in the final-goods market can slow down the rate of technology adoption by reducing the domestic firms' market share and hence reducing the return to process innovation (Rodrik 1992, Miyagiwa and Ohno 1999, Ederington and McCalman 2008). Finally, foreign competition can also raise *aggregate* productivity through a reallocation of market shares from less productive firms to more productive ones, as in Melitz (2003).

Empirically, with better access to micro data, the literature has naturally turned to firm-level analysis, but results are, so far, fairly heterogenous. Two strands 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) find a positive overall impact of imports on TFP. The second strand, which distinguishes vertical linkages from horizontal ones, includes Van Biesebroeck (2003), Muendler (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). They find that firm imports and input-tariff reductions have widely varying effects 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

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

[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).

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.

Thus, it is fair to say that some more empirical work may be in point to ascertain the magnitude and significance of the various channels discussed earlier. In this paper, we use a very rich panel of Spanish manufacturing firms to explore the extent to which the strength of the "vertical" linkage (from foreign inputs to productivity) depends on firm characteristics. In doing so, we fully use the firm-level nature of the dataset. Our basic conjecture is that the impact of imported inputs (intermediates and capital equipment) on TFP is mediated by the firm's "absorptive capacity" (Cohen and Levinthal, 1990). Specifically, we conjecture that firms with insufficiently skilled labor may fail to take advantage of the technology embodied in imported inputs. Failing to take this interaction into account biases the estimated effect downward, potentially explaining the weakness of the measured vertical-linkage effect in the literature.

When estimating the effect of import decisions on firm-level TFP, a number of methodological issues must be taken into account. First, productivity shocks known to the firm but not to the econometrician may affect input choices and generate a simultaneity bias between inputs and TFP. Second, there is a potential twofold selection bias due to the fact that (i) more productive firms are more likely to source intermediates and capital goods abroad; and (ii) estimation at t is carried out for firms that have not exited at $t - 1$, which may lead to overestimating TFP if exiters are the least productive firms. We deal with these issues through a combination of approaches. The first approach goes in two stages. In stage 1, we estimate TFP à la Olley and Pakes (1996, henceforth OP) and Ackerberg, Caves and Frazer (2007, henceforth ACF). In stage 2, we use a matching-difference in differences (DID) regression of the estimated TFP on the firm's import status. As argued by Blundell and Costa Dias (2000) matching-DID is the best way of estimating treatment effects. So far, it has been used in a TFP-and-imports context only by Vogel and Wagner (2008). Usually 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. The second, direct approach goes in one stage and extends the OP and ACF methods by including the share of imported inputs in the production function. In addition to a strong control for the endogeneity of imports, this approach has the advantage of using all the information contained in importing decisions (not just status, but also share).

Our results are strong, especially under the direct approach. 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 nearly 8% for firms with a proportion of skilled labor of 30% and by 19,1% to 21,4% for highly skill-intensive firms (i.e. with a proportion of skilled labor of 60%). 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 when import share is interacted with skilled labor. We find effects largely in accordance with the preceding when we use other firm characteristics as proxies of absorptive capacity (like the share of foreign capital, mean wage, R&D intensity, or export share). 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, as in Keller (1996).

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 presents baseline estimation results under the two-stage and direct approaches. Section 5 presents discusses extensions and robustness. Section 6 concludes.

2. Estimation issues

As discussed in the introduction, we use two distinct estimation procedures, a two-stage one and a direct one.

In the first (two-stage) approach, we first estimate Total Factor Productivity (TFP) at the firm level using the method of Ackerberg, Caves and Frazer (2007)—we also report results using the Olley-Pakes (1996) method for robustness—and then apply a treatment-effect approach using propensity-score matching to the estimation of the effect of import status. This allows us to capture the import market entry. 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 methods 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 automatically adjusted at period *t*. In 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 approach, we estimate directly the effect of importing on TFP by introducing the share of imports in intermediates and capital equipment in the production function and treating it as endogenous, like investment. Contrary to the preceding, this approach uses the information of the import decision irrespective of when firms have started importing. We now turn to a fuller discussion of both methods.

2.1 Indirect (two-stage) approach

The first stage consists of estimating a “universal” TFP equation for the whole sample, irrespective of import status. Under the ACF method, the estimation equation is

$$\ln(y_{it}) = \alpha_m m_{it} + \phi_t(i_{it}, k_{it}, l_{it}) + \delta_i + \nu_{it} \qquad (1)$$

where i indexes firms and t time, m_{it} is intermediate-good purchases (whether domestically-purchased or imported), i_{it} is investment, k_{it} is the capital stock, ℓ_{it} is labor, and δ_i denotes a vector of firm-level fixed effects. The function $\phi(.)$ is approximated by a 4th-order polynomial in all of its arguments and their interactions. Under OP, the corresponding equation is

$$\ln\left(y_{it}\right)=\alpha_l \ell_{it}+\alpha_m m_{it}+\phi_t\left(i_{it},k_{it}\right)+\delta_i+v_{it}. \quad (2)$$

That is, the OP procedure treats labor as a free input whereas ACF treats it as a state variable, alongside capital.

The second stage is the treatment-effect estimation. Let

$$\theta_{it}=\begin{cases}1 & \text{if firm } i \text{ imports inputs at } t\\ 0 & \text{otherwise.}\end{cases} \quad (3)$$

We run, year by year, a probit regression

$$\Pr\left(\theta_{it}=1\middle|\theta_{i,t-1}=0\right)=\Phi\left(\mathbf{x}_{i,t-1},\delta_j\right) \quad (4)$$

where $\mathbf{x}_{it-1}$ is a vector of lagged firm characteristics and δ_j are industry (two digits level) effects affecting both the decision to import and the level of TFP[3]. Firm characteristics include lagged profit, which controls for "Ashenfelter's dip"[4], lagged TFP, lagged export status, lagged size, lagged capital intensity, and lagged average wage. Estimation of (4) by probit on the whole sample (importing and non-importing firms) yields an estimated propensity score $\hat{p}_{it}$. We use kernel matching on the common support and run a number of "balancing score" tests (see Smith and Todd 2005a, 2005b), described in the appendix.

Let q_{it} be TFP estimated in the first stage and s_{it} the proportion of skilled workers in the labor forced; let also $\Theta_{it}=1$ mark the event that firm *i* switches import status at *t* (from $\theta_{i,t-1}=0$ to $\theta_{it}=1$); that is,

$$\Theta_{it}=\begin{cases}1 & \text{if firm } i \text{ switches import status at } t\\ 0 & \text{otherwise.}\end{cases} \quad (5)$$

Let also δ_t and δ_L be respectively time and location effects, and $\mathbf{x}_{it}$ and $\mathbf{z}_{jt}$ two vectors of firm and industry characteristics. Our second-stage regression equation, run on the common support, is

$$\ln\left(q_{it}\right)=\delta_t+\delta_L+\beta_1\Theta_{it}+\beta_2 s_{it}+\beta_3\Theta_{it}\times s_{it}+\mathbf{x}_{it}\boldsymbol{\gamma}_1+\mathbf{z}_{jt}\boldsymbol{\gamma}_2+\varepsilon_{it}. \quad (6)$$

The interaction term between the proportion of skilled workers in the labor force and the entry status is introduced to test the hypothesis that the effect of importing on TFP depends on the firm's absorptive capacity, proxied by its skill intensity (we explore alternative effects in Section 4 below). Given this

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[3] We have refrained from doing the matching by sector because sectors are too small, so the trade-off would be unfavorable on other dimensions of the matching. Given that we have firm fixed effects (in the TFP estimation) the potential for confounding influences at the sector level is limited. We also have sector fixed effects throughout, as some firms switch sectors in the sample period.

[4] Ashenfelter's dip is 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. Here, firms may turn to imported intermediates at t because they experienced a drop in profits at t-1. Conversely, they could turn to more expensive foreign inputs because a rise in profits made them more optimistic. Including lagged profits as a determinant of the treatment decision controls for either effect.

interaction and the binary nature of Θ_{it}, the effect of import status on TFP at a level of skills $\bar{s}_{it}$ is

$$\begin{aligned}\Delta \ln\left[q_{it}\left(\Theta_{it}, \bar{s}_{it}\right)\right] &= \ln\left[q_{it}\left(\Theta_{it}=1, \bar{s}_{it}\right)\right] - \ln\left[q_{it}\left(\Theta_{it}=0, \bar{s}_{it}\right)\right] \\ &= \beta_1 + \beta_3 \bar{s}_{it}\end{aligned} \tag{7}$$

or

$$\frac{\Delta q_{it}\left(\Theta_{it}, \bar{s}_{it}\right)}{q_{it}\left(\Theta_{it}, \bar{s}_{it}\right)} = e^{\left[\beta_1 + \beta_3 \bar{s}_{it}\right]} - 1 \tag{1}$$

2.2 Direct approach

Here we modify the ACF approach by assuming that firms anticipate the effect of importing on their productivity. Thus we include the share of imports in intermediates and capital-equipment purchases directly as a regressor in the production function and treat them as a function of contemporaneous productivity, like investment. Our procedure is somewhat similar 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, define a cutoff level s_0 in terms of skill intensity and an indicator function h_{it} such that

$$h_{it} = \begin{cases} 1 & \text{if } \mathrm{s}_{it} \geq s_0 \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

Thus h_{it} partitions the set of firms into skill-intensive ones (h_{it} = 1) and non-skill intensive ones (h_{it} = 0). Let $\mu_{i,t-1}$ be firm *i*'s share of imports in total intermediates and capital-equipment consumption at *t-1*. Our production function becomes

$$\ln\left(y_{it}\right) = \beta_m m_{it} + \beta_s s_{it} + \phi_t\left[i_{it}, k_{it}, \ell_{it}, h_{it}\mu_{it-1}, \left(1-h_{it}\right)\mu_{it-1}\right] + \delta_i + v_{it} \tag{9}$$

for the ACF method and

$$\ln\left(y_{it}\right) = \beta_l \ell_{it} + \beta_m m_{it} + \beta_s s_{it} + \phi_t\left[i_{it}, k_{it}, h_{it}\mu_{it-1}, \left(1-h_{it}\right)\mu_{it-1}\right] + \delta_i + v_{it} \tag{10}$$

for OP, where δ_i denotes a vector of firm-level fixed effects. As the terms $h_{it}\mu_{it-1}$ and $\left(1-h_{it}\right)\mu_{it-1}$ add up to $\mu_{i,t-1}$, the latter has to be excluded from the regression equation to avoid perfect collinearity. We lag the share of imported inputs by one period in order to allow for technology upgrading to affect TFP (our conjecture).

3. Data

3.1 Data sources

Our 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 (1'071 observations)[5]. 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 of 9% based on the average rate 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* (i.e. 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

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

	All	Non-importing firms	Importing Firms	Switchers
# of firms	2'354	715	880	759
Output a/	5'989.26 (28500.00)	331.72 (1370.18)	10'900.00 (36900.00)	5'521.95 (265000.00)
Capital a/	3'060.90 (15800.00)	143.2 (581.47)	5'432.32 (22100.00)	2'580.22 (12000.00)
Labor b/	263 (860)	31 (60)	453 (1'119)	237 (687)
Intermediates a/	3'749.46 (20900.00)	165.83 (801.40)	6'466.63 (27700.00)	3'164.62 (18900.00)
Skilled-labor share	0.102 (0.119)	0.051 (0.090)	0.132 (0.122)	0.101 (0.120)
Capital-labor ratio	6'278.12 (7'013.40)	3'073.81 (4'155.97)	8'529.33 (8'001.36)	5'958.96 (6'464.18)
<u>Export/output ratio</u>				
Whole sample	0.166 (0.243)	0.028 (0.115)	0.267 (0.266)	0.145 (0.229)
Exporters	0.272 (0.261)	0.178 (0.237)	0.305 (0.263)	0.237 (0.253)
<u>Import ratio</u> c/				
Whole sample	0.153 (0.254)	-	0.297 (0.247)	0.094 (0.171)
Importers	0.25 (0.240)	-	0.297 (0.247)	0.159 (0.198)
<u>Share of foreign capital</u>				
Whole sample	0.187 (0.372)	0.009 (0.086)	0.346 (0.451)	0.131 (0.320)
Firms with foreign capital	0.839 (0.273)	0.697 (0.289)	0.853 (0.263)	0.807 (0.295)
Markup d/	0.223 (0.138)	0.208 (0.141)	0.23 (0.131)	0.225 (0.142)
R&D ratio c/	0.016 (0.058)	0.004 (0.023)	0.025 (0.072)	0.014 (0.056)
Firm age	24 (22)	14 (14)	30 (24)	24 (22)

Standard deviations are in parentheses.
a/ Millions of constant Pesetas.
b/ Number of employees.
c/ Relative to investment and intermediate consumption.
d/ Calculated as [(sales – average costs)/sales] which is an approximation of the Lerner index.

Table 1 shows that, before matching, importing firms are significantly larger in terms of sales and capital than non-importing ones. They are also more capital-intensive. 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 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 domesticallyowned 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 average firm characteristics across groups defined by importing status highlight the need for a careful construction of the control group. Propensity-score matching ensures that treated and control firms are comparable, whereas raw categories are obviously too heterogeneous to be compared.

4. Estimation results

4.1 Two-stage approach: TFP estimation

As a first pass at the data, Table 2 reports baseline parameter estimates for aggregate production functions based on the ACF and OP approaches respectively for the whole sample. These results are only illustrative; results by industry are used to generate the TFP used in the second stage. They are relegated to Appendix 2 to avoid cluttering the paper. Note that in the estimation of TFP, we include not only firm fixed effects, but also sector ones, as some firms switch sectors in the sample period. The two are thus not collinear.

Table 2
Production function parameter estimates

Dependent variable : ln (y_{it})			
Estimator		ACF	OP
Capital	*(k)*	0.220***	0.261***
		(0.008)	(0.008)
Labor	*(ℓ)*	0.417***	0.365***
		(0.006)	(0.011)
Intermediates	*(m)*	0.474***	0.476***
		(0.012)	(0.012)
Fixed effects			
Firm		yes	yes
Sector		yes	yes
Number of obs.		11'770	11'770

Robust standard errors are in parentheses * significant at 10%, ** at 5%; *** at 1%.

Results under ACF and OP are very similar, and this observation will remain true throughout the paper. Point estimates are similar to current estimates in the literature.

4.2 Two-stage approach: Treatment effect

Table 3 reports three balancing-score tests to verify that the matching procedure performs correctly. The first column is a standardized-difference test, based on formula (A1) in Appendix 1. As discussed in the appendix, Rosenbaum and Rubin (1985) suggest a maximum value of 20. The second column reports p-values for a regression-based test (also explained in Appendix 1) where the value of firm characteristic x is regressed on a polynomial in the estimated propensity scores and their interaction with the treatment-group dummy. The null of joint insignificance of the interaction terms should not be rejected. The third column reports simple paired t-tests of equality between the two groups. Again, the null should not be rejected.

Test results reported in Table 3 concern the TFP variable. They all fail to reject the null of equality between the treatment and control groups. We ran the same tests on all of the first-stage probit's explanatory variable (results are omitted for brevity but are available from the authors) and found that, in all cases, conditions for the validity of the control group were satisfied.

Table 3
Balancing score tests by year, TFP

Year	Average Standardized difference (%)	p-values: Regression-based test	p-values: 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	0.95
2000	11.81	0.509	0.378
2001	8.79	0.783	0.602
2002	8.08	0.952	0.924

Table 4, which summarizes the characteristics of matched importers and non-importers, shows that, indeed, matching largely eliminates systematic differences between the treatment and control group in terms of average TFP, profit, capital intensity and wage rate.[6]

Table 4
Characteristics of matched importers and non-importers

	Importers	Non importers
TFP (OP)	3.13	3.12
TFP (ACF)	3.43	3.42
Profit	0.216	0.21
Capital intensity	3'723.745	3'130.112
Average wage	2'957.896	2'786.527

Table 5 shows baseline estimation results for equation (6). The sample size is reduced compared to Table 2 because not all firms document the skill composition of their labor force. The effect of switching to imported intermediates is, by itself, insignificant in the barebones version of the equation. When we interact with skills, the interaction term has a large and significant effect on TFP.

[6] We constrained the matching to be year by year, but refrained from constraining it to be within industries as sample sizes are too small at the industry level.

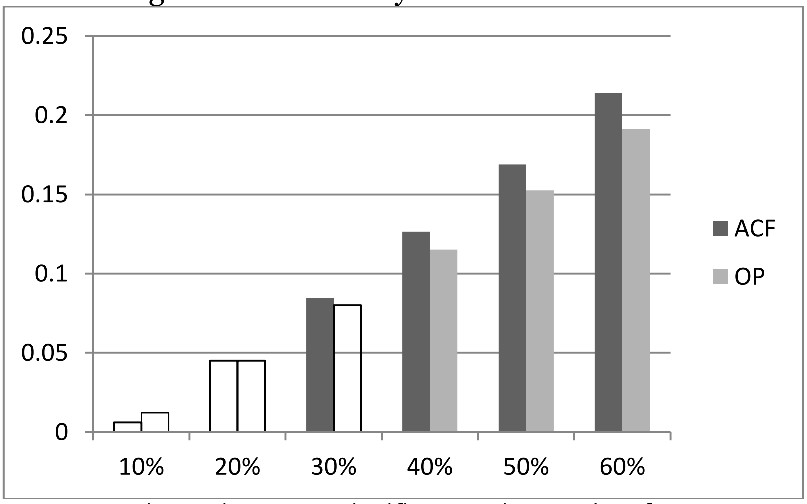
Table 5
Import status, skills, and TFP

Estimator:	ACF		OP	
Dependent variable: ln(TFP_{it})	(1)	(2)	(3)	(4)
Entry	0.020	-0.031	0.025	-0.021
	(0.020)	(0.025)	(0.020)	(0.025)
Skills		0.716***		0.713***
		(0.128)		(0.140)
Skills × Entry		0.375**		0.326*
		(0.181)		(0.190)
Constant	2.848***	3.531***	2.690***	3.268***
	(0.091)	(0.082)	(0.110)	(0.081)
Control variables	yes	yes	yes	yes
Fixed effects				
Location	yes	yes	yes	yes
Year	yes	yes	yes	yes
Observations	5 812	5 095	5 812	5 095
R^2	0,10	0,12	0,11	0,13

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, export status, market share, Herfindahl index and industry output growth as controls. Omitted estimates are available upon request. They are significant and bear the expected coefficient sign, with the exception of foreign capital.

Figure 1 shows graphically our estimates of the marginal effect of entry on TFP, taking into account the interaction between entry and labor-force skills. The estimates use equation (8), evaluated at different levels of the proportion of skilled labor, s_{it}. The marginal effect of entry rises monotonically with the proportion of skilled labor—a direct consequence of the functional form—and the productivity increase, when significant, ranges roughly between 8.4% and 21.4%, a sizable boost.

Figure 1
Marginal effect of entry at different skill levels



Bar heights represent point estimates. Insignificant estimates (p-values over 10%) are shown without color. The horizontal axis measures the proportion of skilled labor (s_{it}) at which expression (7) is evaluated. Standard errors are computed using the delta method.

4.3 Direct estimation

We now turn to the direct approach where the share of imported intermediates is included directly in the ACF (or OP) equation, as in (10). In columns (1) and (3), we introduce the share or imported inputs linearly in the regression equation, which is equivalent to constraining the coefficient on this share to the homogenous across firms. In columns (2) and (4), by contrast, we interact it with our high-skill and low-skill dummies. We fix the cutoff between "high" and "low" at the 75^{th} percentile of the firm distribution. We tried other cutoffs (i.e. 60^{th}, 70^{th}, 80^{th}) and results are largely robust because the coefficients remain stable across specifications

Each firm is either a high-skill one (h_{it} = 1), in which case $h_{it}\mu_{it-1} = \mu_{it-1}$, or a low-skill one ($h_{it}$ = 0), in which case $(1-h_{it})\,\mu_{it-1} = \mu_{it-1}$. Thus, $\mu_{i,t-1}$ must be excluded. By contrast, s_{it} is included linearly, so the firm's level of skills is controlled for. If our conjecture is true, i.e. if imported inputs generate a stronger boost on TFP for firms with relatively skilled labor, the coefficient on $h_{it}\mu_{it-1}$ should be higher than that on $(1-h_{it})\,\mu_{it-1}$. Results are shown in Table 6.

Table 6
Direct estimation results, labor skills

Estimator		ACF		OP	
Dependent variable : ln (y_{it})		(1)	(2)	(3)	(4)
Capital	*(k)*	0.219***	0.191***	0.242***	0.236***
		(0.009)	(0.005)	(0.010)	(0.010)
Labor	*(ℓ)*	0.370***	0.069***	0.354***	0.354***
		(0.006)	(0.027)	(0.015)	(0.015)
Intermediates	*(m)*	0.481***	0.480***	0.483***	0.483***
		(0.017)	(0.17)	(0.017)	(0.017)
Share of skilled labor	*(s)*	0.103***	0.109***	0.098***	0.100***
		(0.035)	(0.035)	(0.035)	(0.036)
Share of imported interm.	(μ_{t-1})	0.134***		0.135***	
		(0,018)		(0.019)	
Import share × high skills	$(\mu_{t-1} \times h_t)$		0.321***		0.305***
			(0.009)		(0.027)
Import share × low skills	$[\mu_{t-1} \times (1-h_t)]$		0.052***		0.028
			(0.018)		(0.021)
Equality tests of "high" and "low" coeff. a/			0.00		0.00
Fixed effects					
Firm		yes	yes	yes	yes
Sector		yes	yes	yes	yes
Number of obs.		10'419	10'419	10'419	10'419

Robust standard errors are in parentheses * significant at 10%, ** at 5%; *** at 1%.
a/ Chi-square test *p*-values.

Coefficients on capital, labor and intermediates are largely stable across specifications and estimation methods in terms of significance and magnitude, with the exception of the coefficient on labor under ACF in column (2), which is lower. Columns (1) and (3) suggest that the share of imported inputs has a strong and significant effect on TFP even after controlling for skills and even when one constrains the coefficient to be same for all firms. Thus, the impact of import status comes out stronger (i.e. more precisely estimated) under the direct approach than under the two-step one, suggesting that direct estimation yields efficiency gains. At a constant overall level of intermediates consumption, a ten percentage-point rise in the share of imported inputs raises TFP by 1.34% under ACF and 1.35% under OP. This result is close to that found by Halpern et al. (2005) for Hungarian exporting firms, but lower than that found by Kasahara and Rodrigue (2008) for Chilean manufacturing firms, although their estimation procedures are different.

Columns (2) and (4) test our conjecture by splitting the sample into high-skill and low-skill firms, as per equation (9). As expected, the effect of the share of imported intermediates on TFP is substantially stronger for high-skill firms (we use a 75% cutoff) and insignificant for low-skill ones. Again, this effect is after controlling for the autonomous effect of skills. A test of equality of coefficients rejects the null at 1%.

5. The role of other firm characteristics

Here we extend to firm characteristics other than labor skills our exploration of the role of those characteristics in mediating the impact of import status, using the direct approach which was shown in section 4 to generate the strongest results. Our rich dataset allows us to explore the effect of a number of firm characteristics, shown in Table 7. We show results under ACF only in order to save space. In all cases, the cutoff between “high” and “low” levels of the characteristic under consideration is set at the 75th percentile of the firm distribution.

Effects are largely in accordance with intuition. The effect of the share of imported inputs on TFP is twice larger for firms with a high share of foreign capital. It is three times higher for firms with a high average wage level, which is fully consistent with our results in the previous section since average wages correlate with the share of skilled labor, although far from perfectly (the coefficient of correlation is 0.48, suggesting that average wages pick up many influences other than skills, including possibly unionization etc.). In the case of R&D intensity, the difference in the impact of imported inputs is much smaller quantitatively (26%) although the null hypothesis of equality of coefficients is still rejected at the 5% level (*p*-value 0.024).

Only in the case of export intensity is the ranking of impacts reversed, with more impact for firms that have a low export intensity (0.326 for low-export intensity firms vs. 0.276 for high-export intensity ones). It may be the case that export-oriented firms (the quarter of firms exporting the highest share of their production) are already close to the efficiency frontier, as they should in a Melitz model, so that they do not register large efficiency gains by importing more inputs, having already access to state-of-the-art technology.

Table 7
Direct estimation results: Other firm characteristics

Estimator: ACF				
Dependent variable : ln(y'_{it})				
Factors				
Labor	0.185***	0.517***	0.198***	0.055**
	(0.013)	(0.022)	(0.016)	(0.022)
Capital	0.244***	0.226***	0.244***	0.216***
	(0.008)	(0.010)	(0.008)	(0.006)
Intermediates	0.478***	0.452***	0.474***	0.478***
	(0.015)	(0.015)	(0.016)	(0.015)
Absorption capacity proxies				
Foreign share in firm capital a/	0.039***			
	(0.012)			
Average wage		0.315***		
		(0.015)		
R&D intensity b/			0.071	
			(0.748)	
Export intensity c/				0.002
				(0.018)
Interactions				
Import share × high foreign share	0.291***			
	(0.008)			
Import share × low foreign share	0.152***			
	(0.025)			
Import share × high average wage		0.448***		
		(0.012)		
Import share × low average wage		0.155***		
		(0.024)		
Import share × high R&D intensity			0.302***	
			(0.008)	
Import share × low R&D intensity			0.240***	
			(0.027)	
Import share × high export intensity				0.276***
				(0.010)
Import share × low export intensity				0.326***
				(0.027)
Equality tests of "high" and "low" coefficients d/	0.000	0.000	0.024	0.077
Fixed effects				
Firm	yes	yes	yes	yes
Sector	yes	yes	yes	yes
Number of obs.	7'965	7'965	8'038	7'962

a/ Foreign share of equity capital as reported by firms in the survey.
b/ Share of R&D expenses in the sum of intermediates purchases and investment.
c/ Export/output ratio
d/ Chi-square p-values

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. Our data being about firms in an advanced industrial country

(Spain), the productivity boost generated by imported intermediates and capital equipment should not be interpreted as reflecting adoption of radically different technology. Rather, it is likely to come from higher-quality intermediates and better machinery, in which case the effect is likely to be felt almost immediately.

Our results also show that this effect is heterogeneous across firms, and this is our key message. Superior intermediates and machinery purchased abroad will give a stronger boost to productivity if workers understand how to use them, which is likely to depend on their skills. For instance, a firm in the upper quartile of the skills distribution stands to benefit twice as much from imported intermediates and capital, in terms of TFP, than one in the first three quartiles.

Other characteristics seem also to play a role. Firms with foreign capital stand to benefit more than others from importing intermediates and capital, suggesting that learning takes place through familiarity with foreign equipment, training programs or foreign management (more likely in firms with foreign capital, where the parent company may even 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 if accompanied by training programs or specific aids for the hiring of skilled personnel, like 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.

Cohen, W.M., Levinthal, D.A., 1989. Innovation and Learning: Two faces of R&D. Economic Journal 99, 569-596.

Cohen, W.M., Levinthal, D.A., 1990. Absorptive Capacity: A new Perspective on Learning and Innovation. Administrative Science Quaterly 35, 128-152.

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.

Appendix 1

This appendix gives some detail on the construction of balancing score tests reported in Table 3. Let $\bar{x}_i$ be the average value, over the sample period, of some attribute of firm *i* (say, its size). For the control group to be valid, the average value of that attribute should not differ "too much" between the treatment and control group. Three approaches are available to test whether this condition holds.

The first is based on the average standardized difference, i.e. 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 attribute x over the treatment (T) and control (C) groups respectively, N_T is the size of the treatment group, and $w_{ij} = w(x_i, x_j)$ is the weight given to control firm *j* in the matching. Although there is no unique criterion on the maximum acceptable difference, Rosenbaum and Rubin (1985) suggest that it should not exceed 20.

The second consists of estimating, for each firm attribute *x*, a 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.

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

Appendix 2

This appendix provides TFP estimation results by industry, which are used to generate the estimates used in the second stage of the two-stage approach.

Table A1
First-stage TFP estimation, by industry

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