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EXPLORING THE IMPORT-EXPORT NEXUS AT FIRM LEVEL USING A GENERALIZED PROPENSITY SCORE APPROACH

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Abstract

We use a dose-response function to investigate how the level of imports of intermediate inputs affects the level of exports using the universe of Spanish two-way trading manufacturers in the year 2004. First, we find a positive but non-linear import-export nexus. Second, low levels of imports don't significantly boost exports—but as import levels reach the median range, the positive impact becomes much more pronounced. Third, the impact varies by the level of income of the country-of-origin of imports; the larger effect on total exports is linked to imports coming mainly but not exclusively from high-income countries. Finally, higher imports from high-income countries lead firms to export more to these countries relative to low-income countries while the opposite is not observed.
Keywords: Exports performance, Imports of intermediate inputs, Dose-Response function, Spanish firms.
JEL codes: F14, F23, L25, C14

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Abstract

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1. Introduction

In this paper we investigate empirically the heterogeneity of the effects of imports of intermediates on exports at the firm level using a generalized propensity score (GPS) approach.[1] Is import activity a truly causal factor for exports? If so, do imports affect exports linearly? Is there a threshold of imports to affect exports? Is it possible to find an optimal level of imports that maximizes

[1] The empirical literature using micro-level trade data establishes three stylized facts on the import-export connection among manufacturing firms. First, most companies simultaneously import and export (Aristei et al., 2013). Second, companies that directly buy foreign inputs are more productive than those that do not (Kasahara and Lapham, 2013; Halpern et al., 2015; Forlani, 2017). Third, companies that import exhibit a better export performance (Bas and Strauss-Kahn, 2014; Feng et al., 2016; Requena et al, 2023). This literature, however, still leaves some relevant questions unanswered:

the level of exports? Are all imports, whatever their origin, equally effective on their impact on exports?

An experimental approach to answer these questions would involve randomly assigning different amounts of imports to firms with similar observable characteristics and then analyze their response in terms of their export performance. If import doses cannot be administrated under experimental conditions, the estimation of the dose-response function is still possible by using the generalized propensity score methodology (GPS) developed by Imbens (2000) and Imai and van Dyk (2004). This method relies on three main ideas: that import levels can be treated as random once we account for firm characteristics (unconfoundedness), that there are similar firms across all import levels (common support), and that firms with the same GPS score are alike in all relevant ways (balancing property). Thus, this quasi-experiment approach consists in applying different levels of imports (the treatment) to otherwise identical firms, allowing us to observe how their export performance (the response) changes. Thus, the dose–response function describes the relationship between the level of imports and the average potential response of exports. To estimate it, we account for the universe of Spanish manufacturing firms simultaneously importing and exporting in year 2004; this provides a more comprehensive understanding of how different levels of imports affect firm's exports, rather than just estimating an average effect of imports. Since adjusting by GPS removes the bias in the level of exports associated with any differences in the covariates across firms, we also graph the corresponding treatment effect function, that is, the change in the response of exports driven by a change in the level of imports across its range.[2]

A novel feature of the paper is to build a GPS from two continuous treatments by considering two groups of sourcing countries of imports. If access

[2] By mimicking aspects of randomized experiments, GPS methods can strengthen causal inference in observational studies about treatment effects. GPS methods offer a powerful alternative to regression analysis in observational studies, particularly when dealing with continuous or multi-level treatments.

to improved imported inputs enables firms to upgrade the quality or technology of their export products, we expect that high-technological (or high-quality) imported inputs will provide the strongest benefits to exports -for example, accessing to the most difficult or quality-demanding markets (the so-called technology channel). Opposed to this technological conjecture, we consider a low-price conjecture in which cheaper imports reduce costs leading to an increase in firm's exports revenues (the so-called price channel). As we do not have specific information on the technology or quality level embedded in the inputs imported by Spanish firms, we use the level of income of the sourcing country as a proxy for input quality, in line with previous research (Lo Turco and Maggioni, 2013; Bass and Strauss-Khan, 2014; Feng et al. 2016). We assume that imports from high-income sourcing countries provide high-technology or quality inputs than imports from low-income countries, while low-income sourcing countries provide cheaper inputs to firms seeking to reduce costs.

Connected with these ideas, we can also investigate whether market knowledge embedded in import activity would play any role in enhancing exports to that market. Studies linking a firm's inward- and outward-internationalization activities finds that its inward activities (e.g., international sourcing) facilitates and stimulates the outward part of its internationalization process (Meinen, 2015; Bas and Strauss-Kahn, 2014; Di Gregorio, et al., 2009; Welch and Luostarinen, 1993). Through their import experience, firms develop capabilities and legitimacy, stablish network connections and increase firm's market specific knowledge to deal with business and institutional environments of foreign specific markets which may help them when establishing export relationships in these markets (Karlsen et al., 2003; Johanson & Vahlne, 2009; Stirbat et al., 2015; Choquette, 2019). So, another research question emerges: does firm's imports composition affect the destination composition of firm's exports?

Our results suggest that, for the case of Spain, the technology channel is stronger than the price channel. The marginal effect of a one percent increase in (log) imports from a high-income country, given the level of imports from a low-income country, is always greater than the marginal effect of imports from low-income countries given the level of rich-origin imports. Thus, the relationship between imports and exports is non-linear—modest import levels yield little export benefit, but once imports reach the median range, their positive impact becomes significant. Therefore, import decisions are more than operational—they are strategic: firms should view import strategies as a lever for export growth, especially when sourcing from high-income countries. That is, by aligning sourcing strategies with target export markets, especially in high-income economies, firms can leverage imports as a powerful lever for sustainable export growth. Crucially, imports from wealthier countries not only enhance overall export performance but also increase exports specifically to those same markets, a pattern not observed with imports from lower-income nations. Therefore, firms aiming to grow internationally should prioritize high-income suppliers, align their sourcing with target export destinations, and consider scaling imports strategically to unlock greater export potential.

The rest of the paper is organised as follows. Section 2 presents the econometric model, section 3 contains the results and section 4 concludes.

2. Econometric specification

We will rely on the generalized propensity score (GPS) methodology developed by Hirano and Imbens (2004) and Imai and van Dyk (2004) rather than standard regression analysis [3] to make possible the estimation of the DR function. The GPS approach can accommodate continuous treatment variables, allowing for more

[3] One of the advantages of the GPS methodology is that it is not necessary worrying about instruments to deal with possible endogeneity problems, since all the identification properties relay on the GPS:

nuanced analysis of dose-response relationships. Besides its reduced dependence on the parametric assumptions and flexibility in outcome modelling, this approach allows to conduct a quasi-experimental analysis based on three key assumptions. The first one, the unconfoundedness assumption, states that conditioned on the GPS, the assignment of individuals (firms) to a level of treatment (imports) is random and independent of the outcome. The second one, the common support condition, allows the selection of identical individuals in terms of their observables and their likelihood to be assigned a level of treatment -their GPS conditioned on the observables. The third one, the balancing property of the GPS, guarantees that, once conditioning on the GPS, individuals in the same group of GPS are identical in terms of their observables. Based on the GPS identification properties, the experimental approach involves randomly assigning different amounts of imports -or even differentiating import types- to similar firms and then analyze their response in terms of their export performance. More specifically, the goal of our analysis is to estimate an average dose-response (DR) function, $\mu(t) = E[Y_i(t)]$, across our sample of *N* firms indexed by $i = 1, \dots, N$, and where the random variable $Y_i(t)$ is a set of potential outcomes (exports) for each firm *i,* that maps a given level of treatment (imports) $t \in T$ to a potential outcome, where *T* is an interval of continuous treatments. [4]

We will use a flexible parametric specification of the GPS with special attention to assess the validity of the assumptions (Hirano and Imbens, 2004). We do not only intend to analyse the impact of total intermediate imports on the level of exports, but we are also interested in analyzing the possibility of heterogeneous effects on exports, linked to different types of imports through the technology channel or the prices channel. Therefore, we must consider both a univariant approach for the former study and a bivariant approach for the latter.

[4] For simplicity, the subscript i will be dropped in subsequent explanations.

In an univariant approach, we model the conditional level of the treatment, that is, the firm's imports, *T=imp,* given the covariates *X* using a log-normal distribution:[5]

[1] $imp|X \approx N\left(\beta_0 + X'\beta_1\ , \sigma^2\right)$

The OLS estimates of $(\beta_0, \beta_1, \sigma^2)$ are used to estimate the GPS:[6]

[2] $\hat{R} = \frac{1}{\sqrt{2\pi\widehat{\sigma^2}}} exp\left(\frac{1}{2\widehat{\sigma^2}}\left(imp - \widehat{\beta_0} - X'\widehat{\beta_1}\right)^2\right)$

For the bivariant approach, we consider two treatments, as firms may import technological intermediate goods from high-income countries (imp_H) and/or cheaper intermediate goods from low-income countries (imp_L). Therefore, we regress each treatment on the covariates X using a bivariant log-normal distribution. The estimated GPS is calculated as:

[3] $\hat{R} = \frac{1}{2\pi\hat{\sigma}_H\hat{\sigma}_L\sqrt{(1-\hat{\rho}^2)}} exp\left\{-\frac{1}{2(1-\hat{\rho}^2)}\left(\left(\frac{\hat{u}_H}{\hat{\sigma}_H}\right)^2 + \left(\frac{\hat{u}_L}{\hat{\sigma}_L}\right)^2 - \frac{2\,\hat{\rho}\,\hat{u}_H\hat{u}_L}{\hat{\sigma}_H\hat{\sigma}_L}\right)\right\}$

where $\hat{u}_H$ and $\hat{u}_L$ are the residuals of the OLS estimation of the reduced form of each treatment regressed on the vector of covariates X. Besides, $\hat{\sigma}_H$ and $\hat{\sigma}_L$ are the respective estimated standard deviations of the residuals and $\hat{\rho}$ is the estimated covariance between them (see, Green (2011) for a general treatment of bivariate normal).

Next, we estimate the dose-response (DR) function using the estimated GPS by following two steps. The first step involves estimating the conditional expectation of the response -see equation [B1] in Appendix B, assuming some functional form of the relationship between the three variables: the outcome Y (the export value), the estimated GPS ($\hat{R}$), and the level of treatment T (the import value). Following

[5] Variables in lower-case letters are in natural logarithms.

[6] Though Hirano and Imbens (2004) point out other model specifications to estimate the GPS, OLS is the best estimator in our case since the dependent variable is continuous, and we aim to satisfy the normality assumption when the treatments are measured in logs.

Hinaro and Imbens (2004), we implement a partial mean approach by assuming a (flexible) parametric form for the regression function of Y on T and on $\hat{R}$ for each firm:

[4] $$\mathrm{E}\left[exp|imp,\hat{R}\right] = h(imp,\hat{R};\alpha)$$

In a second step, we define a set of values for T= τ ranging from 0 to percentile 95. The estimated coefficients $\hat{\alpha}$ from [4] are used to estimate the response at treatment level τ:

[5] $$\mathrm{E}\left[\widehat{exp(\tau)}\right] = \frac{1}{N}\left(\sum h\left(\tau,\widehat{R^{\tau}};\hat{\alpha}\right)\right)$$

where $\widehat{R^{\tau}} = \hat{r}(\tau, X)$ is the score function evaluated at τ, that is, the probability of receiving such treatment level τ.

In addition, we also compute the first derivative of the DR function $\mu(\tau)$, with respect to the argument, i.e., we estimate the treatment effect function, $\theta(\mu) = \mu(\tau + \delta) - \mu(\tau)$, which can be defined as the marginal causal effect of a variation, $\Delta\tau = \delta$, in the value of imports on exports. This will allow us to capture the heterogeneity in the magnitude of the impacts on the level of outcome (exports) arising from different dosages of treatment (imports). Finally, we bootstrap 250 times the entire estimation process to obtain the standard errors of the estimated response and derivative functions.

3. DATA AND GPS ESTIMATION

3.1. Data

Our main dataset is the result of merging two databases. Spanish Custom database (www.aeat.com) provides the annual export and import values for each triplet firm-product-country over the period 2001-2004.[7] Firm characteristics such

[7] Products are defined at 6-digit level of the Harmonized System (HS 1992 classification).

as sales, employment, age, financial indicators, location and primary sector of manufacturing activity (NACE two digits) are obtained from Bureau van Dyck-SABI database (www.SABI.com). First, we select all the manufacturing firms that import and export regularly over the period 2001-2004 and select as the dependent variable the level of aggregate exports in the year 2004.[8] Second, we use the import activity of the firm in the year 2003 as a treatment variable to mitigate endogeneity or reverse causality problems. Third, we consider only imported intermediate goods, that is, foreign inputs transformed during the production process. For that purpose, we use the BEC classification and select the HS1992 6-digit level products classified as intermediate goods. In our analysis, we identify the origin of the imports into two groups of countries: high-income ("rich") and low-income ("poor") countries. A country is in the first group if its income per capita in 2002 is equal or higher than the 50th percentile for the sample of 191 countries of the World Bank Indicators database. Four, we use SABI database to identify firms whose main activity is manufacturing. We restrict the sample to firms with at least 10 workers in order to obtain high quality measures of firm performance (productivity, liquidity, solvency and profitability). All the control variables refer to the year 2003.

We use other three databases to obtain additional explanatory variables, calculated at the firm level in the year 2003: tariffs, real exchange rates, the world's potential demand of firm's exports, the world's potential supply of intermediates and export/import spillovers. First, we use data from UNCTAD's TRAINS database to obtain the most-favored-nation (MFN) tariff rates applied by the EU at the HS1992 6-digit product classification, *tariff*. Second, we use data from IMF database to calculate the bilateral real exchange rate of Euro per unit of foreign currency, *rer*, expressed as an index (2010=100), and CPI is the consumer price index of Spain and the trading partners (2010=100). Therefore, an increase

[8] The selected period guarantees we use the largest dataset of firms when merging SABI dataset and the universe of manufacturing exporters in the Spanish Custom database.

in the value of rer indicates a real depreciation of the Euro currency, so Spanish exports become cheaper and Spanish imports become more expensive. Third, we use COMTRADE database to obtain the annual value of world's imports (excluding Spain), approximating the potential *demand of* firm's exports, and the annual value of world's exports (excluding Spain) for each product at the HS1992 6-digit classification, approximating potential *supply* of intermediates for the firm. Finally, we use the Custom database to calculate an indicator of export and import *spillovers*: the number of exporting/importing firms from the same province (NUTS III) selling/buying the (main) product of each firm in the sample. Appendix A provides a description of the construction of these explanatory variables.

3.2 A preliminary exploration of the import-export nexus using IV approach. Discarding reverse causality.

Our final dataset contains 7,684 manufacturers exporting and importing regularly over the period 2001-2004, see Table A1. Before presenting the results of the GPS methodology, it is important to address the possibility of reverse causality between imports and exports.[9] We estimate the following equation:

[6] $$ln(exp_{it}) = \beta \ln(imp_{it-1}) + Z_{it-1}'\gamma + \alpha_{sector} + \alpha_{province} + \varepsilon_{it}$$

where the dependent variable, $ln(exp_{it})$, is the log of firm i's exports value in year t=2004; the main explanatory variable -our treatment variable- is the log of firm i´s import value of intermediate inputs in 2003, $\ln(imp_{it-1})$. As additional control variables (Z_{it-1}), we include four firm characteristics. (1) $employment$ is the number of employees as a measure of firm size; and (2) $productivity$ is the firm's labor productivity, calculated as total sales divided by the number of workers. Productivity and size account for indirect effects of imports on the firm's exports both through the diffusion of new technologies embodied in imported

[9] Endogeneity is a potential case of violation of weak unconfoundedness (also called the assumption of selection on observables), the key assumption of the GPS methodology.

intermediates and through scale economies from combining more varieties of imported intermediate inputs. (3) *foreign* ownership is a dummy variable that takes value of 1 if the firm declares foreign ownership, 0 otherwise. (4) the *world potential demand* is included to capture shocks in the international markets where the firm sells its products. All variables refer to year 2003 to alleviate potential reverse causality. Equation [6] includes a full set of firm's province and sector dummies (α_i) to control for unobserved place of production and product characteristics.

In addition to lagging our explanatory variables, we adopt an instrumental variables (IV) approach to investigate possible endogeneity problems. We instrumented the log of imports in 2003 by the log of imports in 2002 and 2001. Table 1 reports both the OLS and the IV estimates. The lagged import coefficients in the OLS estimates and IV estimates are positive and statistically different from zero. The OLS coefficient estimates are quite similar to the IV ones since both OLS and IV interval estimates of each coefficient overlapped, pointing to the consistency of both estimates. The results of the Hansen's J test do not allow us to reject the null hypothesis of orthogonality of the instruments; thus, firm's imports in the previous year does not suffer from endogeneity in our cross-section analysis.

<INSERT TABLE 1 HERE>

3.3. Estimation of the GPS

In our estimation of the dose-response function, the first step is to estimate GPS from equations [2] and [3] for the case of one treatment and the case of two treatments, respectively.

We include all available explanatory variables that may affect the level of imports in order to remove any potential selection bias in the analysis of the impact of imports on exports. Thus, the set of covariates includes firm characteristics obtained from the balance sheet and revenue and the financial accounts in the year 2003: *employment*, *productivity*, *age*, *tangible* asset intensity, *liquidity* ratio, *solvency* ratio, *profit* ratio. As additional explanatory variables we include those described in the previous section: *import spillovers*, international *supply* of inputs, the potential *demand* of exports, the import *tariff* and the import *rer*. Table A1 in Appendix A presents the statistical descriptives of the variables used in the paper while Appendix B provides a description of the construction of these explanatory variables.

Table 2 reports the estimated coefficients and standard errors of the GPS model in equations [2] and [3], for the case of one treatment and the case of two treatments respectively, considering a cubic polynomial for each continuous covariate and a set of sector and province fixed effects. [10] Column (1) reports the estimates for the aggregate imports, while columns (2) and (3) report those of imports from high-income countries and from low-income countries, respectively. The R-squared is 0.46 for one treatment, providing an estimate of the GPS that works well in balancing the covariates. For two treatments, the R-squared is 0.47 and 0.30, respectively.

<INSERT TABLE 2 HERE>

After we obtain the estimated GPS for one treatment and for two treatments, we check whether the common support and the balancing property of the GPS are validated in our data. For the interested reader, we present these analyses in Appendix B.

4. Main results.

[10] We included both quadratic and cubic terms of covariates with and without fixed effects. We report the preferred specification based in the value of R-square and in the assessment of the balancing property. For the analysis of one continuous treatment, we have used the STATA do file in Serrano-Domingo and Requena-Silvente (2013). We have written a new code for the analysis of two continuous treatments. Both codes are available on request.

In this section we present our main results, first for the case of one treatment (total imports) and next for the case of two treatments (imports from low-income countries and imports from high-income countries).

4.1 The import-exports relationship (one treatment)

Table 3 shows the estimates of eq [5] used to calculate the dose-response (DR) function for one treatment. We begin with the basic specification including the GPS estimates, the treatment and their interaction in column (1). The significance of the GPS estimates points to its relevance in reducing the bias of the predicted response of the log of firm's exports to changes in the log of firm's total imports. Next, we include combinations of quadratic terms and cubic terms of both variables and their interactions in columns (2) to (6). Our preferred specification based on the Akaike Information Criterion (AIC) is in column (6), which includes the full set of terms and their interactions. Notice that the coefficients' estimates do not have a direct interpretation. We use them to calculate the DR function and then we run 250 bootstraps to obtain the corresponding standard errors.[11]

<INSERT TABLE 3 HERE>

Figure 1 presents the DR function for the case of one treatment. The upper panel A shows the DR function: the expected post-treatment level of firm's (log) exports associated to a level of treatment (here, the (log) value of total imports). The medium panel B shows the marginal effect function: the change in the post-treatment level of firm´s (log) exports after a one percent change in (log)

[11] Each bootstrap replication is based on N random draws with replacement from the original sample with which we apply the common-support restriction, we estimate the GPS, the DR function and derivative function.

imports.[12] The bottom panel C shows the distribution of exporting firms by deciles according to their level of imports.[13]

The key findings are the following. First, exports response is always positive over the entire range of positive treatment doses considered. Second, there is a soft J-shaped relationship between the firm's imports and the firm's average potential exports. Firm's exports response is decreasing for imports between 2.5 (percentile 5 in our sample) and 5 (percentile 26): for example, for a value of imports around 4 (percentile 14), the expected exports value is positive but lower than expected for lower doses of imports. Firm's exports response is increasing for import doses between 4.5 (percentile 19) and 7 (percentile 65). Third, firm's exports response is still increasing but at slower path for import doses between 7 (percentile 65) and 8.5 (percentile 95). We interpret the non-linear response of exports to imports as follows: firms begin importing some intermediate products to enhance their exports, but when the level of their imports reaches a certain level, the firm needs some production adjustments and retooling to benefit fully from additional foreign inputs. Four, when the firm's imports of intermediate inputs are very low or irrelevant, it is observed an unexpected negative but small marginal effect of imports, see Figure 1 panel B. When imports reach a certain level: 5.3 (percentile 30), the positive marginal effect becomes significant and increasing until it reaches a maximum as the firm's imports value is 6.5 (percentile 55). Fifth, since the relationship is not linear, continuously higher values of imports would not translate into continuously increasing marginal effects on exports.

<INSERT FIGURE 1 HERE>

[12] That is a 1% increase in log(imports), but approximately a 5% increase in imports.
[13] Notice that we have excluded the 5% extreme values of the distribution.

4.2 The effects of the composition of imports of intermediates on exports (two treatments)

Next, we examine whether the shape of the non-linear relationship between the level of firm's exports and imports is affected by the composition of imports. As we stated earlier, the origin of imports of intermediates proxies the type of intermediate inputs imported: i.e., imported inputs from high-income countries are those assumed to be technologically embodied inputs that allow firms to improve the quality of exports to supply more demanding and difficult markets (technology channel); while imports from low-income countries are assumed to be cheaper inputs that help to export more by reducing costs (price channel).

Now the DR function is estimated using two treatments: imports from high-income ("rich") countries, imp_H, and imports from low-income ("poor") countries, imp_L. We first use the bivariate GPS , $\hat{R}$, estimated earlier from equation [3] and both levels of imports to estimate of our preferred specification of equation [4] considering two treatments obtaining the estimated coefficients $\hat{\alpha}$:

[4'] $$\mathrm{E}\left[exp|imp_L, imp_H, \hat{R}\right] = h(imp_L, imp_H, \hat{R}; \alpha)$$

Table 4 column (1) shows the basic specification for equation [4'] including the bivariate GPS estimates, both treatments -that is imports form high-income countries and imports from low-income countries (in logs) in the previous period- and their interactions. Again, we get significant GPS terms supporting its relevance in reducing the bias of the predicted response to changes in the firm's imports from both high-income and low-income countries. The inclusion of quadratic and cubic terms improves the adjustment in columns (2) and (3), having the last one the lowest AIC criteria and becoming our preferred specification with all the terms including the bivariate GPS still significant at 1%.

Second, we obtain the corresponding DR function as the average potential outcome, that is the expected value of firm's exports, for any two combinations of firm's imports from high-income, τ_H, and low-income, τ_L, countries according to eq. [5']:

[5'] $$\mathrm{E}\left[\widehat{exp(\tau_H}, \tau_L)\right] = \frac{1}{N}\left(\sum \quad h\left(\tau_H, \tau_L, \widehat{R^{\tau_H, \tau_L}};\ \hat{\alpha}\right)\right)$$

The resulting 3-dimensional graph is shown in Figure2, Panel A. We find a positive and significant relationship between the expected value of exports and both imports coming from high-income and low-income countries. We find the highest values of the average potential exports along the main diagonal, that is, when the composition of firm's imports is mixed. So, we conclude that the polarization of imports is not the best strategy for firms to maximize exports. Additionally, it is observed that the level of expected exports is always higher for the highest high-income origin imports than for the highest level of low-income origin imports.

<INSERT FIGURE 2 HERE>

In Figure 2 Panel B we represent the shape of the DR function for the continuum of levels of one treatment, given the values of the other treatment. Specifically, we keep one of the treatments at percentiles 5, 50 or 95 in order to analyze the response of exports to different doses of the other treatment. In the bottom-right panel B, in Figure 2b, we keep imports from low-income countries at percentiles 5, 50 and 95 levels. For a given level of imports from low-income countries, higher values of imports from rich countries are linked always to higher expected export values. This finding is consistent with literature pointing to technological imports as export-enhancers. In the bottom-left panel B, in Figure 2a, we keep the level of imports from high-income countries fixed in order to analyze how exports respond to different levels of imports from low-income countries. Now, higher values of imports from poor countries are linked only to higher level of exports when these (log) imports from low-income countries are very high (above 6, percentile 90). In this case, values of (log) imports from low-income countries lower than 6 show high export responses if they are combined with very high levels of imports from rich countries. For example, given the percentile 95 of imports from rich countries, the response of (log) exports to imports from poor countries is the highest and stable around 8. We conclude that low values of imports of any of the two treatments, when they are treated separately, are not linked to the highest expected values of exports. Therefore, rather than polarization, we observe a complementarity between imports from low-income and high-income countries, being the later the stronger engine leading to faster growth in firm's exports.

Figure 3 presents the treatment effect function, considering the change in one of the treatments while the other remains constant. Again, the treatment effect function provides a 3D figure for the marginal effect of each treatment, which is not easy to read. Rather than presenting such 3D figures of the marginal effects of imports from high-income (or low-income) countries on expected firm's exports, we decompose it into two bidimensional figures. Figure 3, Panel A, shows the marginal effect of an increase in imports from rich countries. In Figure 3a we analyse this marginal effect at percentiles 5, 50 and 95 as initial levels of imports from rich countries over the range of imports from poor countries. The marginal effect of imports from rich countries is not significant at very low levels (percentile 5) of imports from poor countries. The positive marginal effect of rich-origin imports is higher, the higher the initial levels of imports from rich countries of the firm (percentile 50 shows a marginal effect around 0.01, and percentile 95 shows a marginal effect around 0.05) over the range of values of imports from poor countries. Figure 3b shows the marginal effect of imports from high-income countries over the range of initial levels of this type of imports. In this case, it is shown that the positive marginal effect of imports form high-income countries is increasing with the initial level of these imports from rich countries. Notice that the different levels of imports from poor countries determine the initial level of imports from which the marginal effect is significant: the lower the initial level of imports from rich countries, the higher the level of imports from poor countries. Anyway, the (significant) marginal effects of rich-origin imports on firms do not significantly differ depending on the level of poor-origin imports.

Figure 3 Panel B shows the marginal effect of an increase in imports from poor countries. In Figure 3c, the marginal effect of imports from low-income countries on exports is positive and increasing with the level of imports from low-income countries. The highest marginal effect is reached when imports from low-income countries are combined with imports from high-income countries fixed at percentile 50. Nevertheless, the marginal effects are not significant until de initial level of imports from poor-origin countries is high: between 4 (45 percentile) and 6 (65 percentile). Figure 3d provides a clearer illustration of this idea. Positive and significant marginal effects of low-income-origin imports across the range of rich-country import values are only observed when the initial level of low-income-origin imports is very high (at the 95th percentile). Lower levels of imports from low-income countries yield insignificant marginal effects across the entire range of imports from high-income countries. Therefore, the technology channel dominates the effect of imports on exports.

<INSERT TABLE 3 HERE>

In summary, Figures 3a and 3d indicate that the positive effects of imports on firms' exports are clearly driven by increases in technological imports from high-income countries. However, achieving the highest export gains requires these imports to be combined with a certain level of imports from low-income countries. Similarly, Figures 3b and 3c show that a strong specialization in only one type of import does not maximize the marginal effects of the other type on exports. Overall, these results reinforce the idea that a certain degree of complementarity between imports from high- and low-income countries is necessary to fully enhance export performance.

<INSERT FIGURE 3 HERE>

4.3 Does the country of origin of imported inputs affect the destination composition of firm's exports?

Assuming that fixed costs of exporting depend on destination countries' regulations and administrative procedures, language, culture and network accessibility, importing inputs from a country may help to reduce the fixed costs the firm faces when exporting to that country by improving the firm's knowledge of it.[14] Thus, if market information spillovers arise through imports of intermediates, we would expect a positive link between imports from and exports to the same country. To test this hypothesis, we consider the ratio of firm's exports to high-income (rich) and low-income (poor) destination markets, ($XSrich_i/XSpoor_i$), as an alternative response to imports from high-income and low-income countries.

Figure 4 presents the dose response function. The 3D response function surface in Figure 4a points clearly to the existence of relevant composition effects. Imports from high-income countries increase the difference between firm's (log) exports to high-income countries and its exports to low-income countries. Figures 4b and 4c analyse the composition effect in more detail. When we fix the level of imports from high-income or rich countries, Figure 4b on the left, we observe a negative slope of the response function. Thus, higher levels of imports from low-income countries would lead to lower differences between exports to high versus low-income countries. However, this difference is never negative, no matter how high the values of imports are. This idea is reinforced when imports from high-

[14] Bas & Strauss-Kahn (2014), Choquette and Meinen (2015), Meinen (2015) and Choquette(2019) provide evidence that market-specific import experience reduces the sunk costs associated with subsequent export market entry by increasing a firm's knowledge of a particular foreign market.

income countries are at their lowest level (5th percentile); even in this case, the firm would not primarily export to low-income countries.

Figure 4c on the right shows the expected distribution of a firm's exports by destination, for different levels of imports from high-income countries, given the level of imports from low-income countries. We observe that higher levels of imports from high-income countries are associated with a greater difference in favour of exports to high-income countries, with this difference being highest when imports from low-income countries are at very low levels (5th percentile). Thus, comparing Figures 4b and 4c, the higher the imports from high-income countries and the lower the imports from low-income countries, the higher the rate of exports to high-income markets, that is, the higher the specialisation of the firm in exporting to high-income countries. However, the reverse does not lead to a specialisation of the firm’s exports in low-income markets. This asymmetric behaviour is more clearly observed when analysing the marginal effects of both treatments on the destination composition of exports.

<INSERT FIGURE 4 HERE>

Figure 5 shows the marginal effects of a one percent increase in (log) imports from high-income countries (panel A) and from low-income countries (panel B). Figure 5a shows that the marginal effects of imports from high-income countries on the composition of exports destination markets are not significant but when the initial value of imports from high-income countries is very high (95th percentile) compared to median or low values. The marginal effect of this type of imports will positively affect exports to high-income relative to low-income countries, regardless of the level of imports from low-income countries. Additionally, this marginal effect reaches a maximum value of 0.036 when the level of (log) imports from low-income countries is 5.5; that is, an increase in imports from high-income countries has the greatest positive impact on relative exports when the firm's imports include both types of imports but specialise in the technologically and quality-intensive ones.

Figure 5b shows the marginal effect of imports from high-income countries across the range of initial import levels from which the change occurs. The marginal effect is significant and increases exports to high-income markets relative to low-income markets when initial imports from high-income countries are large and imports from low-income countries are not at their highest levels. Notice that the marginal effect of imports from high-income countries increases exponentially when imports from low-income countries are on the 50th percentile.

Figure 5c shows the marginal effects of an increase in imports from low-income countries on the export composition of destination markets. As expected, the marginal effects are negative, since an increase in imports from low-income countries raises the share of exports to low-income markets. Nevertheless, this effect is not statistically different from 0. Thus, an increase in imports from low-income countries does not change export composition of destination markets. Finally, Figure 5d in Panel B shows the marginal effect of imports from low-income countries across the range of values of imports from rich countries. Again, the marginal effects are not significant, so they do not alter the composition of destination markets for firm exports.

So, in our analysis of the effect of imports on the destination structure of exports, we find an asymmetric behaviour of the effect of imports depending on their country of origin. When firms import mainly from low-income countries, the increase in imports from high-income countries does not significatively alter the relative composition of exports to more demanding markets. By contrast, when firms predominantly import from high-income countries, the change in exports towards more demanding markets clearly dominates. Additionally, increasing imports from low-income countries does not significantly change the ratio of exports to high and low-income markets. Therefore, intermediate inputs sourced from higher-income countries appear to significantly enhance firm’s ability to meet quality standards required to access more quality-demanding and challenging high-income markets.[15]

<INSERT FIGURE 5 HERE>

5 Conclusions.

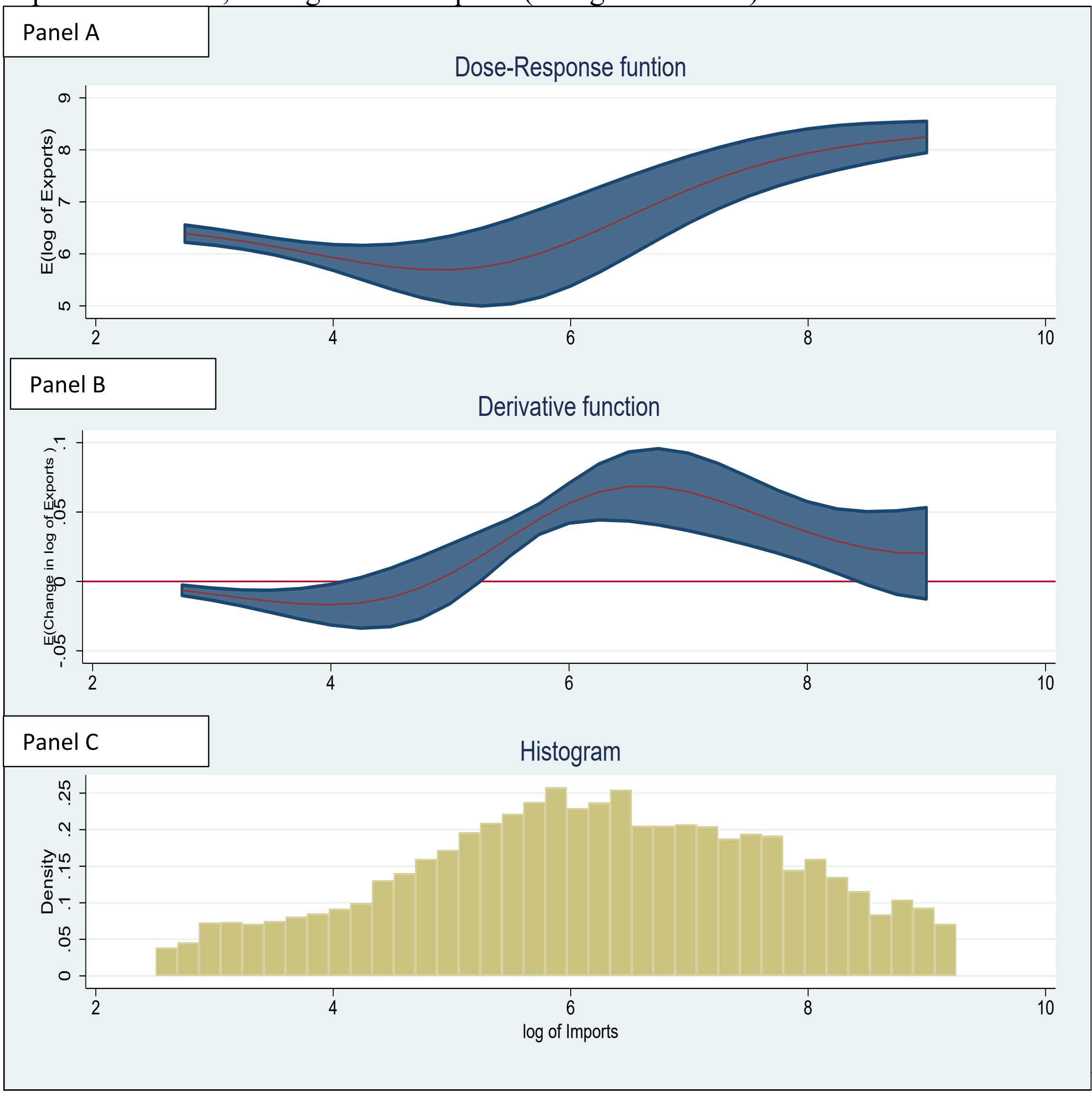
This study highlights the nuanced role that imports composition plays in enhancing firm exports. We base on a dose-response function to examine the import-export nexus among the universe of Spanish two-way trading manufacturing firms in 2004. We find a positive, though not always increasing relationship between the firm’s expected value of exports and the firm’s level of imports of intermediate inputs. The export-enhancing effect of imports is more strongly associated with increases in imports from high-income countries than with those from low-income countries. However, this effect is neither linear nor symmetrical. The highest gains in export performance are achieved when these imports are complemented by a minimum level of imports from low-income countries. A strong specialization in only one source type—whether high- or low-income—does not maximize the marginal effects of the other, suggesting that a balanced sourcing strategy creates synergies that better support export competitiveness.

Further analysis on the effect of imports on the destination composition of exports reveals an asymmetry: firms importing primarily from high-income countries tend to increase their share of exports to more demanding markets, whereas firms that focus on imports from low-income countries do not experience the same shift. This suggests that inputs from high-income countries are more

[15] Lo Turco and Maggioni (2013), Bas and Strauss-Khan (2014) and Feng et al. (2016) find a higher effect of imports from high-income countries on firm's exports to high-income countries.

closely associated with meeting the quality standards required to compete in high-income markets. Consequently, technological imports from high-income countries are a key driver of export growth and are especially effective in enabling firms to access more demanding and challenging markets.

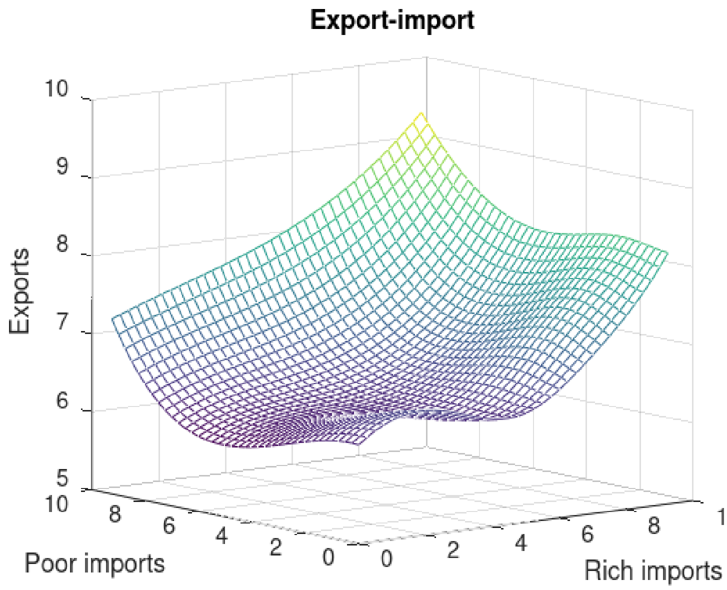
Figure 1 Dose-Response function and marginal effects of (log) firm's imports on (log) firm's exports. In X-axis, the log of total imports (a single treatment).



Note: Significance bands obtained are calculated from bootstrapped standard errors. Marginal effects shown by the derivative function are defined as changes in the response due to a 0.01 change in the level of log (imports).

Figure 2. Dose-Response Function of firm’s (log) imports from rich (high-income) countries and poor (low-income) countries on firm’s (log) exports.

Panel A. 3D Dose-Response function



Panel B. Decomposition of the Dose-Response function into 2-dimensions graphs.

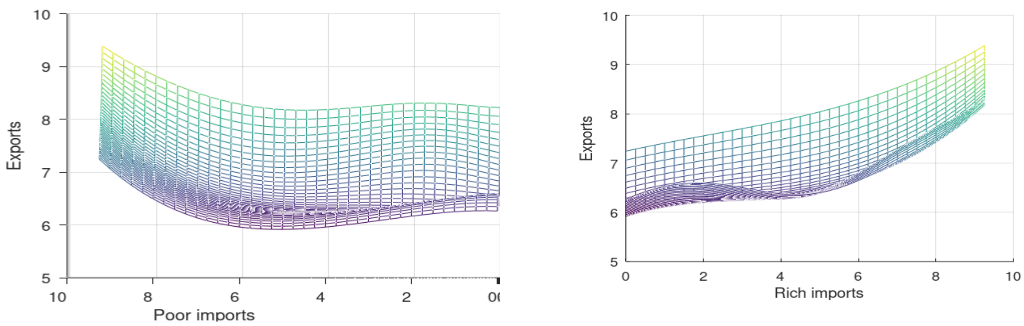


Fig. 2a E(exports | imports from poor for givenn percentile imports from rich)

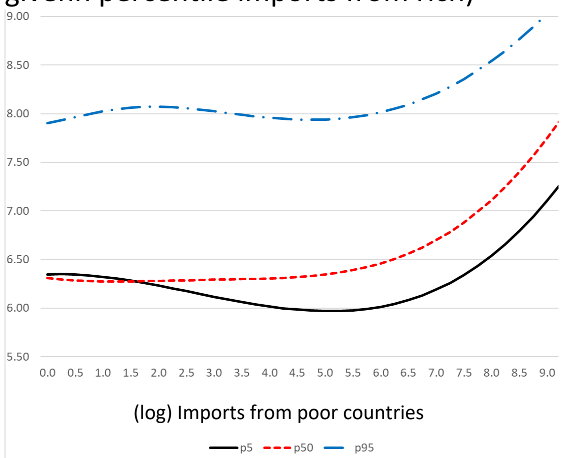
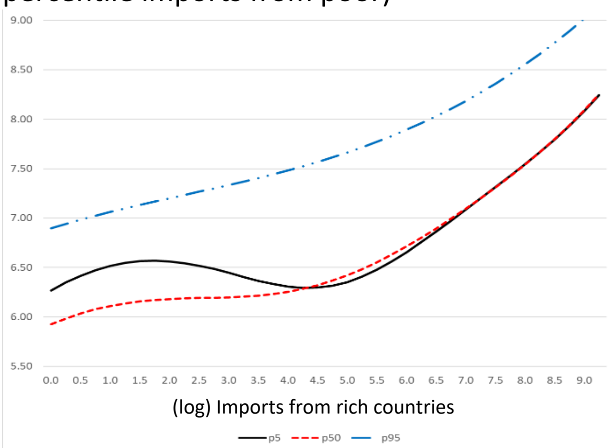


Fig. 2b E(exports | imports from rich for given percentile imports from poor)



Note: significance bands are not represented since all the response values are statistically different from 0.

Figure 3. Marginal effect of firm's (log) imports from rich (high- income) and poor (low-income) countries on firm's (log) exports.

Panel A. Marginal effects of imports from rich countries (imports from poor cou. do not change)

Fig. 3a. Marginal effect given a percentile of imports from rich countries

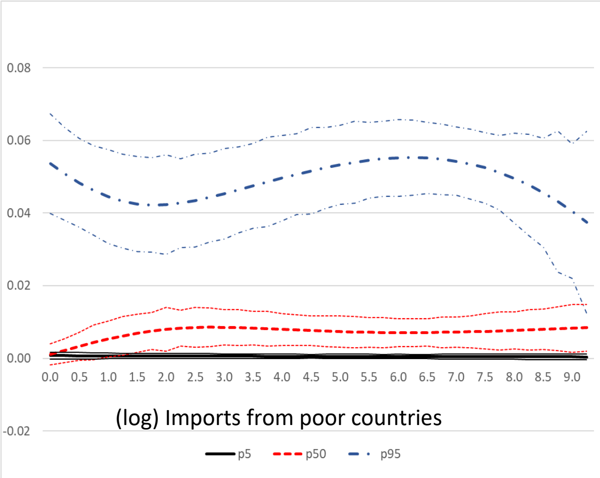
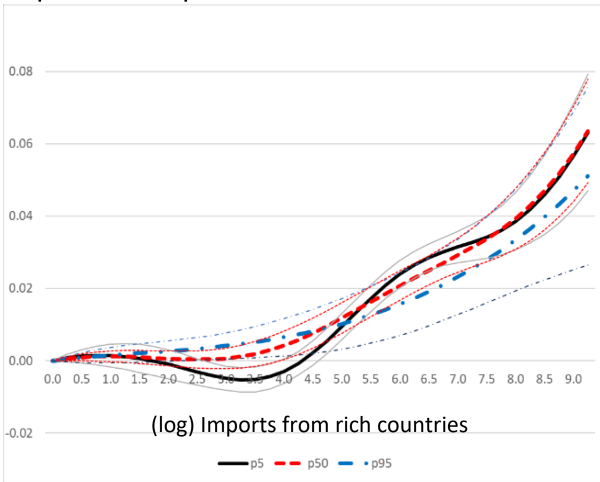


Fig. 3b. Marginal effect given a percentile of imports from poor countries



Panel B Marginal effects of imports from low-income countries (imports from high-income countries do not change)

Fig. 3c: Marginal effect given a percentile of imports from rich countries

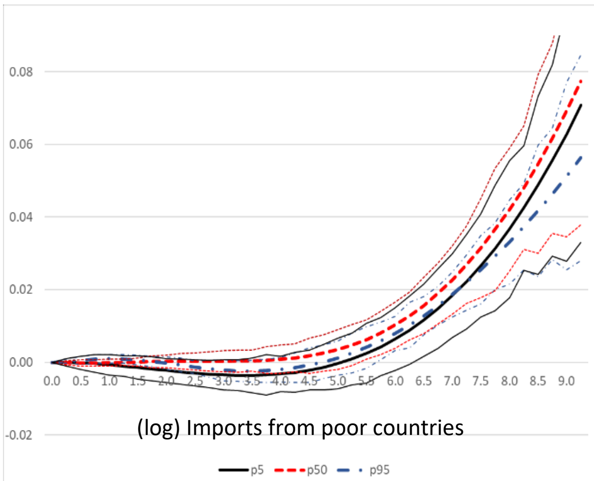
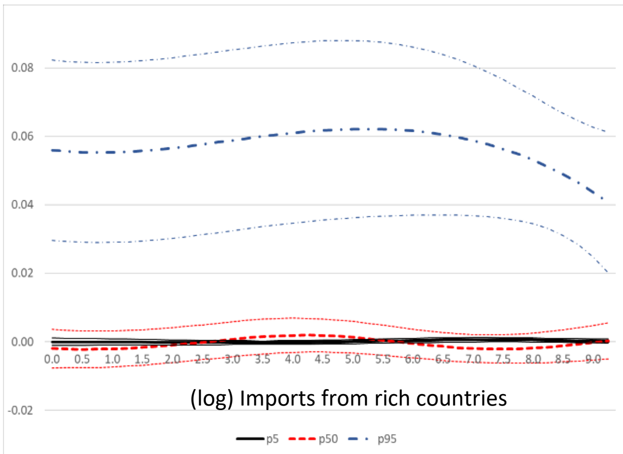


Fig. 3d Marginal effect given a percentile of imports from poor countries



Notes: Marginal effect is defined as the change in the log of exports when the log of imports increases in 0.01. Thick lines are the estimated marginal effects, thin lines the corresponding confidence intervals.

Figure 4. Dose-Response function effect of firm's (log) imports from rich and from poor countries on the firm's (log) ratio between the exports to rich countries and the exports to poor countries.

Fig. 4a. 3D Dose-Response function

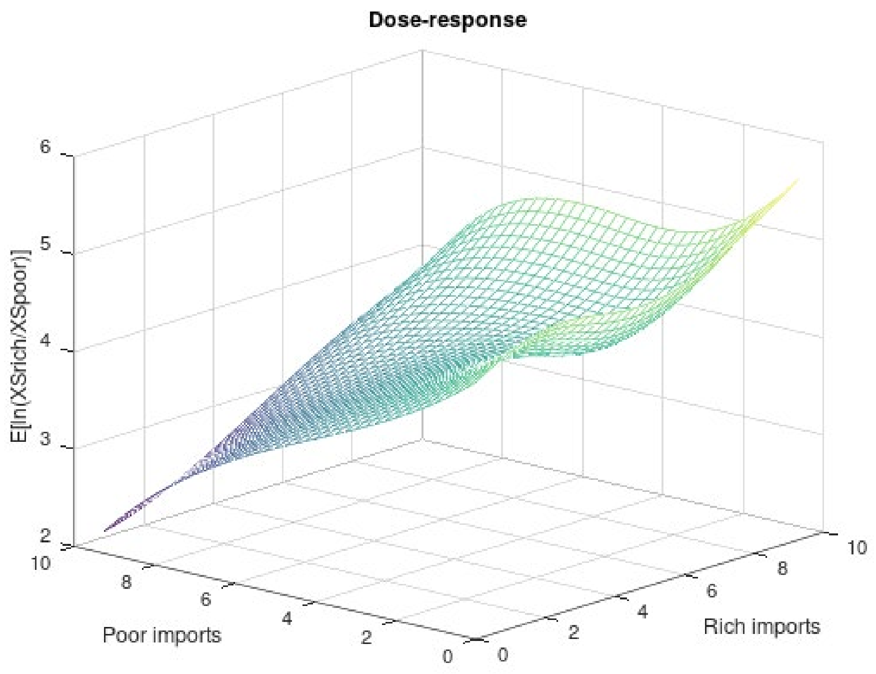


Fig 4b. E[ln(Exp_rich/Exp_poor | imports poor for a given percentile imports from rich)

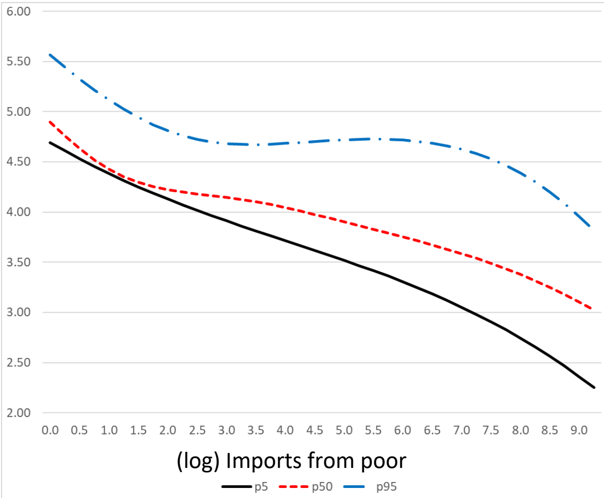
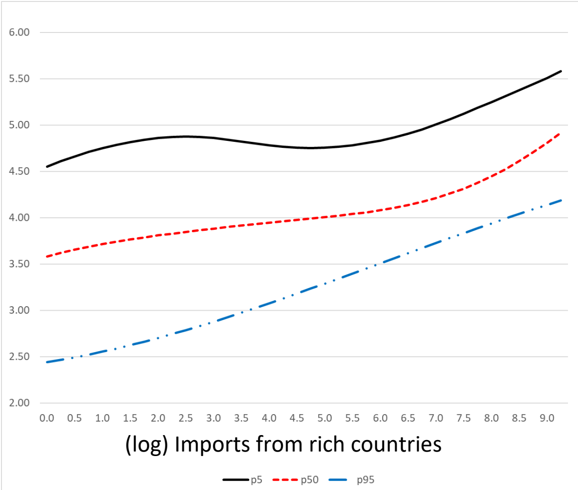


Fig 4c: E[ln(Exp_rich/Exp_poor | imports rich for a given percentile imports from poor)

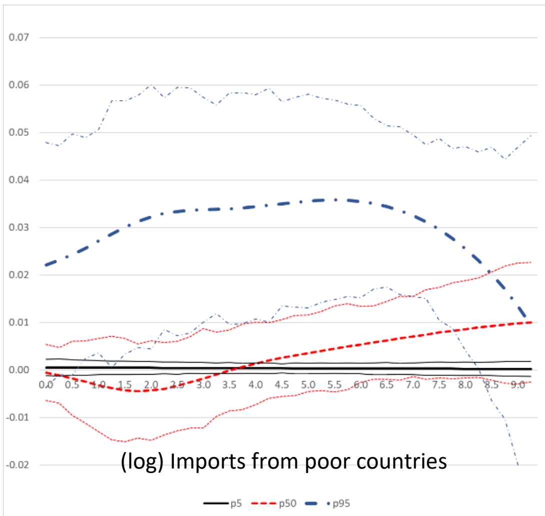


Note: significance bands are not represented since all the response values are statistically different from 0.

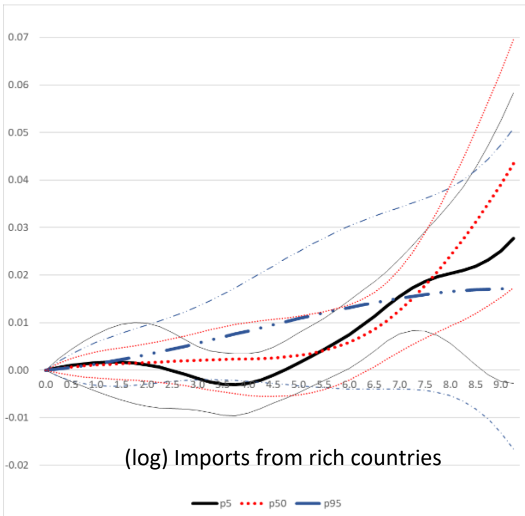
Figure 5. Marginal effects of firm's (log) imports from rich and poor countries on firm's (log) ratio between exports to rich countries and exports to poor countries.

Panel A Marginal effects of imports from rich (imports from poor do not change)

5a Marginal effect for a given percentile of imports from rich countries

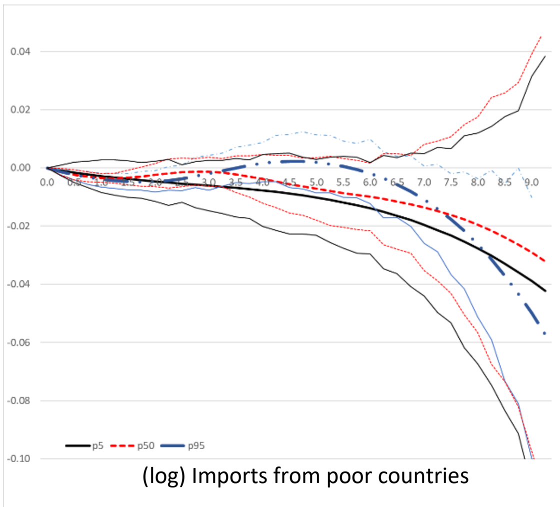


5b Marginal effect for a given percentile of imports from poor countries

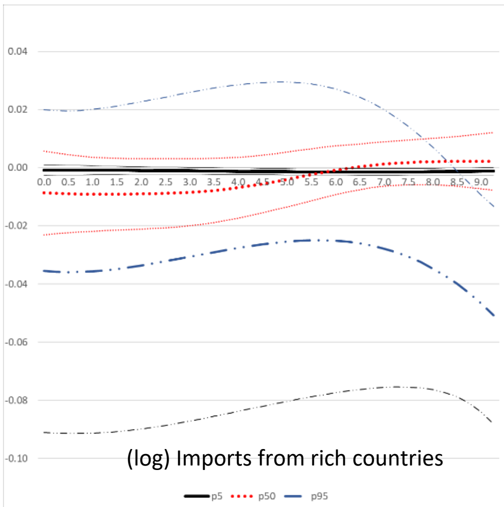


Panel B Marginal effects of imports from poor (imports from rich do not change)

5c Marginal effect for a given percentile of imports from rich countries



5d Marginal effect for a given percentile of imports from poor countries



Note: Marginal effects are defined as changes in the response due to a 0.01 change in the level of log of imports. Thin lines indicate confidence interval limits for the corresponding marginal effects estimations in thick lines.

Table 1. Preliminary analysis: OLS and IV estimations.

Dep. Variable exports $_{2004}$	OLS (1)	IV_GMM (2)
imports$_{2003}$	0.171***	0.215***
	(0.0124)	(0.0280)
employment $_{2003}$	0.964***	0.913***
	(0.0230)	(0.0285)
productivity $_{2003}$	0.562***	0.566***
	(0.0366)	(0.0542)
demand $_{2003}$	0.0113	0.0128
	(0.0174)	(0.0198)
Constant	-2.432***	-3.637
	(0.523)	(2.580)
Observations	7,355	5,811
R-squared	0.448	0.448
Instruments		(imports)$_{2002}$, (imports)$_{2001}$
Hansen's J P-Value		0.9999
Endogeneity Test P-value		0.9999

Note: All the variables are in logs. Both the OLS and IV estimations include sector, province and foreign ownership fixed effects.

TABLE 2. GPS estimation for One Treatment (total imports) and Two treatments (Imports from high-income (rich) countries and Imports from low-income (poor) countries)

	One treatment		Two treatments			
	(1)		(2)		(3)	
	imports		imp_H		imp_L	
	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error
tariff	-0.521	[0.807]	-1,361	[0.864]	1,517	[0.986]
$tariff_{2002}$	0.573*	[0.295]	0.633*	[0.328]	0.207	[0.388]
rer	1.189**	[0.489]	7.197***	[0.646]	-16.74***	[0.859]
rer_{2002}	-2.052***	[0.377]	-6.008***	[0.467]	10.42***	[0.603]
supply	-0.352	[0.219]	-0.397*	[0.215]	-0.246	[0.191]
$supply_{2002}$	-0.0461	[0.121]	0.0481	[0.124]	0.0397	[0.146]
demand	3,365	[2.049]	4.458*	[2.292]	2,392	[2.868]
demand^2	-0.222	[0.140]	-0.300*	[0.156]	-0.15	[0.197]
tariff^2	4,113	[2.856]	5.908**	[2.992]	-3,691	[3.285]
rer^2	-0.642	[0.658]	3.204***	[0.804]	-9.503***	[1.796]
supply^2	0.0760***	[0.0216]	0.0681***	[0.0211]	0.0556**	[0.0251]
demand^3	0.0048	[0.0032]	0.00664*	[0.0035]	0.00299	[0.0045]
tariff^3	-2,421	[1.524]	-3.225**	[1.592]	1,446	[1.739]
rer^3	-0.0902	[0.237]	1.074***	[0.293]	-2.719***	[0.687]
supply^3	-0.003***	[0.0007]	-0.003***	[0.0007]	-0.003***	[0.0009]
age	-0.2	[2.830]	0.186	[3.005]	-15.25***	[4.056]
employment	-1.105***	[0.425]	-1.105**	[0.459]	1,039	[0.729]
productivity	-8.699*	[4.852]	-2,114	[4.551]	-23.37***	[6.011]
tangibles	0.231*	[0.129]	0.273**	[0.139]	-0.115	[0.162]
liquidity	-0.0106	[0.0876]	-0.0377	[0.093]	0.037	[0.120]
solvency	-0.319**	[0.130]	-0.384***	[0.138]	-0.183	[0.198]
profitability	-0.0997	[0.225]	-0.182	[0.238]	-0.25	[0.295]
spillover	-0.232**	[0.101]	-0.197*	[0.110]	-0.289**	[0.147]
employment^2	0.304***	[0.0893]	0.312***	[0.096]	-0.233	[0.165]
productivity^2	1.010*	[0.525]	0.903*	[0.488]	2.537***	[0.651]
tangibles^2	0.0547	[0.0409]	0.068	[0.044]	-0.0278	[0.0492]
liquidity^2	0.0742	[0.0594]	0.0458	[0.063]	0.118	[0.0833]
solvency^2	-0.208**	[0.0947]	-0.135	[0.0999]	-0.167	[0.163]
profitability^2	0.108**	[0.0501]	0.0737	[0.0521]	0.0904	[0.0833]
spillover^2	0.0579*	[0.0340]	0.0387	[0.0374]	0.0821*	[0.0478]
employment^3	-0.0126**	[0.0059]	-0.0132**	[0.0064]	0.0226*	[0.0120]
productivity^3	-0.0351*	[0.0189]	-0.0099	[0.0174]	-0.0889***	[0.0235]
tangibles^3	0.00374	[0.0036]	0.00478	[0.0038]	-0.000283	[0.0039]
liquidity^3	-0.00992	[0.0071]	-0.00488	[0.0075]	-0.0187*	[0.0100]
solvency^3	-0.0313	[0.0228]	0.0161	[0.0228]	-0.0302	[0.0401]
profitability^3	0.00103**	[0.0005]	0.000718	[0.0005]	0.000884	[0.0008]
spillover^3	-0.0060*	[0.0033]	-0.0043	[0.0037]	-0.00579	[0.005]
Constant	10.84	[27.28]	-17.35	[28.38]	169.5***	[38.64]
Observations	6,475		6,475		6,475	
R-squared	0.464		0.466		0.291	

Note: All the variables are in logs except profitability. All the explanatory variables without subscript are lagged one period (t-1=2003). Symbol "^2" stands for "to the power of 2" and "^3" stands for "to the power of 3". All the GPS estimates include sector, province and foreign ownership dummies.

Table 3. Parametric dose-response model specification. One treatment: T=ln(imp)

	(1)	(2)	(3)	(4)	(5)	(6)
T1	0.137***	-0.433***	1.022***	0.143***	-0.217**	0.975***
	[0.0240]	[0.0695]	[0.204]	[0.0250]	[0.0846]	[0.214]
R	-13.90***	-9.376***	-15.05***	-15.15***	2,048	-17.96***
	[0.899]	[1.033]	[1.272]	[1.605]	[2.767]	[6.318]
R_T	1.959***	1.522***	2.404***	1.928***	-0.673	2.475**
	[0.146]	[0.153]	[0.192]	[0.149]	[0.468]	[1.067]
T^2		0.0515***	-0.229***		0.0405***	-0.205***
		[0.00590]	[0.0376]		[0.00641]	[0.0388]
T^3			0.0151***			0.0134***
			[0.00200]			[0.00208]
R^2				4,528	-20.88***	42.72
				[4.836]	[6.095]	[36.00]
(R*T) ^2					0.653***	-0.792
					[0.131]	[0.688]
R^3						-97.19
						[75.32]
(R*T) ^3						0.302*
						[0.163]
Constant	6.334***	7.355***	5.563***	6.378***	6.663***	5.531***
	[0.144]	[0.185]	[0.300]	[0.152]	[0.231]	[0.331]
Observations	6,318	6,318	6,318	6,318	6,318	6,318
R-squared	.162.00	.172.00	.180.00	0.162	0.176	0.182
AIC	26016.93	25943.04	25887.93	26018.05	25921.75	25881.19

Note: R denotes the GPS obtained according to equation (4) and T corresponds to the treatment: $\ln(\text{imports})_{t-1}$. The preferred specification includes also their interactions, squared and cubic terms.

Table 4. Parametric dose-response model specification.
Two treatments:

	(1)	(2)	(3)
imp_H	0.157***	-0.330***	0.386**
	[0.0257]	[0.0776]	[0.171]
imp_L	-0.166***	-0.462***	0.0429
	[0.0439]	[0.106]	[0.207]
imp_H^2		0.0497***	-0.0898***
		[0.00556]	[0.0291]
imp_L^2		0.0451***	0.001
		[0.0110]	[0.0452]
$imp_H * imp_L$	0.0313***	0.0307**	-0.0231
	[0.00620]	[0.0146]	[0.0264]
$(imp_H * imp_L)^2$		-0.000162	0.000895*
		[0.000136]	[0.000523]
R	-70.90***	-23.92	-40.18
	[6.223]	[17.74]	[37.02]
R^2		-229.9	38.76
		[219.7]	[1,167]
$R * imp_H$	9.285***	1.886	1.157
	[1.011]	[2.929]	[5.938]
$R * imp_L$	-2.09	1.508	-13.84
	[2.839]	[6.482]	[11.30]
$(R * imp_H)^2$		8.065*	25.96
		[4.900]	[22.64]
$(R * imp_L)^2$		-7.045	54.28
		[22.26]	[74.92]
$R * imp_H * imp_L$	0.472	1.387	4.051**
	[0.417]	[0.962]	[1.662]
$(R * imp_H * imp_L)^2$		-0.634	-2.755*
		[0.400]	[1.412]
imp_H^3			0.00766***
			[0.00156]
imp_L^3			0.00692**
			[0.00324]
R^3			-4,666
			[13,674]
$(imp_H * imp_L)^3$			-7.02e-06**
			[3.36e-06]
$(R * imp_H)^3$			-30.83
			[31.99]
$(R * imp_L)^3$			-47.7
			[167.1]
$(R * imp_H * imp_L)^3$			0.485
			[0.400]
Constant	6.298***	7.100***	6.279***
	[0.159]	[0.255]	[0.354]
Observations	6,380	6,380	6,380
R-squared	0.184	0.203	0.207
AIC	26331.903	26194.463	26180.122
F_stat R terms	49.97(0.00)	9.25(0.00)	7.49(0.00)

Note: R denotes the bivariate GPS estimated from equation (5). Both treatments imp_H and imp_L are lagged one period. The preferred specification includes also their interactions, squared and cubic terms.

Appendix A. Construction of some explanatory variables and Descriptive statistics.

In Appendix A, we describe the construction of four explanatory variables capturing demand and cost shocks: the potential world demand of the products that one firm exports; (2) the potential world supply of inputs that a firm imports; (3) the average exchange rate faced by the products of firms in the international markets; and (4) the average tariff faced by the products of a firm in the international markets.

The measure of the potential demand of products exported by each firm is constructed as follows:

$$demand_{it-1} = \sum_{p} \frac{exp_{p,it-1}}{exp_{it-1}} IMP^{*}_{p,t-1}$$

In words, $demand_{it-1}$ is the weighted average of world's imports (without Spain) of all products p exported by firm i in t-1, where the weight is the share of each product p in firm i's exports in t-1. Firm´s exports (exp) are obtained from Spanish Customs database and world imports (IMP*) are obtained from COMTRADE database.

The potential international supply of inputs available to the firm i in year t is a weighted average of the world's exports of intermediate inputs in year t, excluding sales to Spain (EXP_{pct}). It is obtained from COMTRADE database. The weights are the firm i's shares of the value of imports of intermediate products p from country c (imp^{ini}_{pc}) over firm i's total intermediate imported inputs in the set of sourcing countries of firm i's imports, C^{M}_{i} and the set of products imported by firm i, P^{M}_{i}. The year of reference of the weights is the beginning of firm's import activity to alleviate endogeneity problems:

$$supply_{it} = \sum_{p=1}^{P^{M}_{i}} \sum_{c=1}^{C^{M}_{i}} \frac{imp^{ini}_{pc}}{\sum_{p=1}^{P^{M}_{i}} \sum_{c=1}^{C^{M}_{i}} imp^{ini}_{pc}} EXP_{pct}$$

The real exchange rate for firm i is computed as the weighted average of real exchange rates applied to imports of intermediate products from country c, RER_{ct}. The weights are the shares of firm's imports of intermediate inputs sourced from each country c, IMP^{ini}_{ci}, in the set of sourcing countries of firm i's imports, C^{M}_{i} , in its initial year of activity:

$$rer_{it} = \sum_{c=1}^{C^{M}_{i}} \frac{IMP^{ini}_{ci}}{\sum_{c=1}^{C^{M}_{i}} IMP^{ini}_{ci}} RER_{ct}$$

Finally, the level of tariffs faced by the imports of firm i is computed as a weighted average of EU effective tariffs, TAR_{pt}, applied to the p products imported by Spanish firm i. The weights are the shares of imports of each product p imported by firm i, IMP_{pi}, belonging to the set of products imported by firm i, P_i^M, in its initial year of activity.

$$tariff_{it} = \sum_{p=1}^{P_i^M} \frac{IMP_{pi}^{ini}}{\sum_{p=1}^{P_i^M} IMP_{pi}^{ini}} TAR_{pt}$$

Table A1. Descriptive statistics

OUTCOME	Obs	Mean	Std. Dev.	Min	Max
exports $_{t=2004}$	7,684	6.893	2.304	0.409	15.310
TREATMENT					
imports $_{t-1}$	7,684	6.259	2.107	0.418	15.373
imp_H	7,679	6.060	2.269	0.000	14.919
imp_L	7,679	1.395	2.419	0.000	14.138
COVARIATES					
demand	7,355	14.717	1.378	8.844	19.010
tariff	7,672	0.089	0.065	0.000	1.737
rer	7,666	0.046	0.116	-2.723	0.336
supply	7,684	11.752	1.710	0.002	17.330
tar $_{t-2}$	7,672	0.100	0.071	0.000	2.084
rer $_{t-2}$	7,403	0.096	0.125	-2.611	0.474
supply $_{t-2}$	7,684	11.614	1.679	0.010	17.056
demand ^2	7,355	218.482	40.955	78.222	361.398
tar^2	7,672	0.012	0.054	0.000	3.019
rer^2	7,666	0.016	0.158	0.000	7.415
supply^2	7,684	141.027	37.099	0.000	300.339
demand^3	7,355	3271.637	925.720	691.820	6870.336
tar^3	7,672	0.004	0.083	0.000	5.244
rer^3	7,666	-0.012	0.380	-20.193	0.038
supply ^3	7,684	1719.479	651.750	0.000	5204.963
age	7,684	7.592	0.008	7.533	7.603
dforeign	7,684	0.144	0.351	0.000	1.000
employment	7,684	3.980	1.090	2.303	9.472
productivity	7,684	8.659	0.629	5.770	13.444
tangibles	7,668	-1.722	0.944	-10.399	-0.089
liquidity	7,683	0.387	0.543	-2.593	8.099
solvency	7,050	-0.586	0.465	-4.519	2.191
profitability	7,683	0.011	1.250	-105.032	23.038
spillovers	7,684	3.545	1.706	0.000	7.427
employment^2	7,684	17.030	9.849	5.302	89.719
productivity^2	7,684	75.382	11.238	33.293	180.742
tangibles^2	7,668	3.858	4.963	0.008	108.139
liquidity^2	7,683	0.444	1.286	0.000	65.591
solvency^2	7,050	0.560	0.930	0.000	20.423
profitability^2	7,683	1.563	126.037	0.000	11031.810
spillover^2	7,684	15.480	12.184	0.000	55.154
employment^3	7,684	78.352	73.503	12.208	849.813
productivity^3	7,684	659.818	152.592	192.098	2429.904
tangibles^3	7,668	-10.993	29.717	-1124.537	-0.001
liquidity^3	7,683	0.620	7.348	-17.433	531.204
solvency^3	7,050	-0.704	2.314	-92.298	10.518
profitability^3	7,683	-149.817	13220.0	-1158698.0	12226.92
spillovers^3	7,684	74.921	79.074	0.000	409.601

Note: All variables are in logs except *dforeign*, and *profitability*. All the explanatory variables without subscript are lagged one period.

Appendix B. The Generalised Propensity Score and the Dose-Response Function

The GPS method for continuous treatment allows us to determine the causal relationship between exports and imports (the treatment) at each value of the size of imports, without the positive or negative impact of other factors that can affect exports simultaneously with imports, overestimating or underestimating its effect. This empirical approach relies on two basic conditions. First, the *weak unconfoundedness* assumption states that, conditional on a set of observable characteristics (covariates) *X*, the level of treatment received can be considered as random concerning the outcome (Hirano and Imbens, 2004; Imai and van Dyk, 2004), being a non-testable hypothesis. Second, the testable *balancing property* implies the assumption of individuals in the same group of GPS being identical in terms of their observable characteristics *X*, independently of the level of treatment they receive.

Let us define the GPS as the conditional density of the treatment $T = t$, given the pre-treatment covariates *X:* $R = r(t, x) = \int_{T|X}(t|X = x)$. The combination of the *weak unconfoundedness* assumption and the *balancing property* implies that the assignment to treatment is weakly unconfounded *given the GPS* (see Hirano and Imbens, 2004). Hence, each value of imports will translate into a unique propensity score.

This result allows the estimation of the average DR function by using the GPS to remove any bias related to differences in the covariates among groups being assigned to (receiving) different levels of treatment. This estimation requires a two-stage procedure. First, we obtain the conditional expectation of the outcome $\beta(t, r)$, estimated as a function of two scalar variables, the treatment level *T* and the GPS at the treatment actually received, that is $R = r(T, X)$:

[B1] $\beta(t, r) = E[Y(t)|r(t, X) = r] = E[\, Y|T = \mathrm{t},\ R = r]$

In other words, in [B1] we define the potential outcome as the conditional mean of *Y*, given the observed value of the treatment and the probability of receiving that treatment.

Second, we estimate the value of the DR function at a particular level of treatment τ, by averaging $\beta(\tau, r)$ over the values of the GPS evaluated at that particular level of treatment τ:

[B2] $\mu(\tau) = E\left[\beta\left(\tau, r(\tau, X)\right)\right]$

Hirano and Imbens (2004) emphasized that the regression function in [B1] does not have a causal interpretation. Nevertheless, by averaging over the score, $\mu(t)$ corresponds to the value of the dose-response function for treatment value t, which compared with that obtained for another treatment level t', $\mu(t')$, does have a causal interpretation.

Common support and balancing property

The generalized propensity score methodology (GPS) lies on the testable hypothesis about its balancing property, that ensures the GPS performs well as a measure of comparability among individuals. Under this property, and conditioning on the GPS, individuals in the same group of GPS are identical in terms of their observable characteristics, independently of the level of treatment they receive. Under these conditions, can estimate the Dose-Response and the varying marginal effects of imports along the continuous of the firm's imports, the treatment effect function, which is the derivative of the corresponding dose-response function.

We first impose a common support condition based on the GPS to our sample to ensure comparability across firms, that is, firms with the same a-priori probability of being assigned a level of treatment. [16] We create treatment intervals independent of the covariates by distributing the entire sample of firms in quartile intervals according to firm's import values. Each interval contains 1921 observations.

For each one of the 4 intervals considered, we compute the value of the GPS for each *i*-observation evaluated at the interval's median level of the treatment, and the value of the GPS at that same median level for all firms that are not included in that interval -the control interval. Second, we check the comparability of both the interval of interest and its respective control interval, inspecting the overlapping of their respective propensity score distributions at different levels of treatment by superimposing their histograms (Kluve et al., 2012). Third, we keep only observations in the control interval if they share common GPS support with treated firms in the interval of reference. This is done for each of the four intervals so, each firm within a certain interval lies within the range of observable characteristics of each other interval. Figure B1 in the Appendix B shows that the overlap in the support of the estimated GPS across quartiles exists in all the range of

[16] Under unconfoundedness, the GPS methodology allows incorporating all information necessary for avoiding potential biases in one scalar, allowing the matching on one dimension only, instead of controlling for numerous covariates that may enter in different functional forms, and without imposing strong assumptions about the functional form of the relationship. Furthermore, compared with propensity score methods for multivalued treatments, the GPS has the advantage that we do not have to discretize the continuously distributed number of import varieties in the firm and thus can make use of more comprehensive information.

import values. At the end, we keep 6,298 comparable observations lying in the overlapped areas.

We assess the balancing of covariates by testing the significance of the differences in means for all the covariates at various levels of the treatment (import values) before and after conditioning on the GPS.[17] Th idea is that after conditioning on the propensity to import, the various treatment groups should not differ based on covariates, independent of their level of treatment.[18] The t-statistic values reported in Table B1. Before balancing on the GPS, there are significant differences in means of covariates in columns (1) to (4): 71 out of 152 (38×4) possible mean differences have t-statistics whose absolute value exceeds 1.96 (critical value at 5% significance level and the number of observations at the bottom of Table B1). Columns (5) to (8) display the mean t-statistics for the four intervals after conditioning on the GPS. Using comparable observations, the differences in means are not significant at 5% significant level since the values of the t-statistics are within the [-1.96, 196] interval. Additionally, the last row in Table B1 columns (5) to (8) shows that the mean t-statistic values drop drastically for all the intervals after balancing on the GPS. Thus, the GPS as estimated has the desired property of balancing the sample.[19]

We repeat the exercise considering two treatments: imports from high-income countries (approximating the technology channel through which imports would enhance firm's exports) and imports from low-income countries (approximating the prices mechanism enhancing firm's exports). We estimate the corresponding bivariate GPS in equation (6) by regressing each treatment on all the covariates and their quadratic and cubic terms plus both sector and province fixed effects. We keep the intervals and groups structure of the sample to establish the common support condition and to check the balancing property of the bivariate GPS. We distribute the entire sample of firms in a grid of 2x2

[17] By focusing on balancing covariates rather than modelling outcomes directly, GPS methods can reduce model dependence. This means the results are less sensitive to the specific functional form of the outcome model

[18] We follow Hirano and Imbens´s (2004) approach of "blocking on the score". After we divided our sample according to the levels of the treatment into several intervals (quartile in our case), in each of those treatment intervals, we stratify firms into several groups according to the ascending-ordered values of the GPS evaluated at the median value of the treatment (in our case we choose 6 groups). For each of these GPS groups, we then compare the average covariate values for the observations in that GPS group with those average values for observations that are in the same group but belonging to the control interval. These differences in the average of covariate values within each of the six GPS groups across treatment levels are combined into a single figure, weighted by the number of respondents at each level of the GPS.

[19] We tried different specifications, increased the number of intervals (up to 8) and increased the number of groups (up to 10) showing our preferred specification.

intervals based on the median of each treatment.[20] Figure B2 shows the overlap of estimated GPS histograms for each interval and its corresponding control in all the range of import values for high-income (rich) countries (Treatment 1), and for low-income (poor) countries (Treatment 2), separately. We drop observations in the control interval that lie outside the histogram area of the interval of reference.

Table B2 columns (1) to (4) display the results of the test for the equality of means in each interval prior to balancing on the GPS. We highlighted the significant t-statistics that point to the rejection of the null hypothesis of equality of means of covariates across the four intervals. However, after balancing on the GPS, the mean comparisons in Table B2 columns (5) to (8), show t-statistic values that are statistically equal to zero pointing to the balancing property of the bivariate GPS.

[20] In the case of two treatments, the number of observations in each interval is similar but not the same, since we have the 66% of firms in our sample with 0 imports coming from low-income countries.

Figure B1. GPS Support Condition. One treatment.

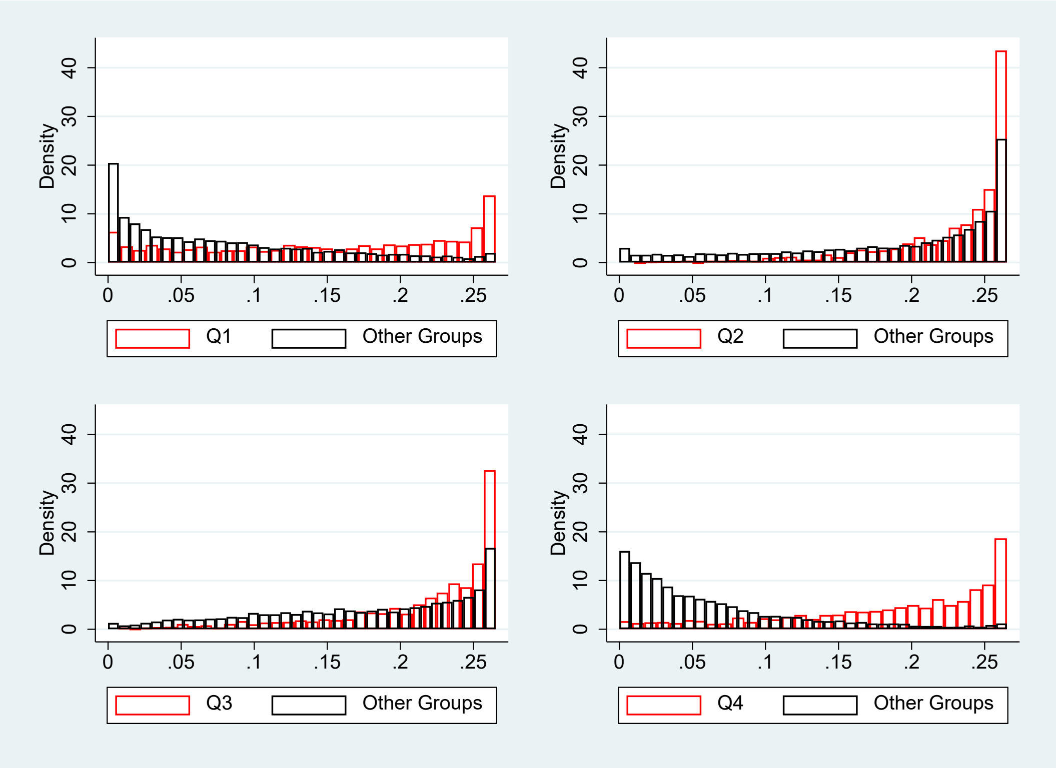


Figure B2. GPS Support Condition. Two treatments.

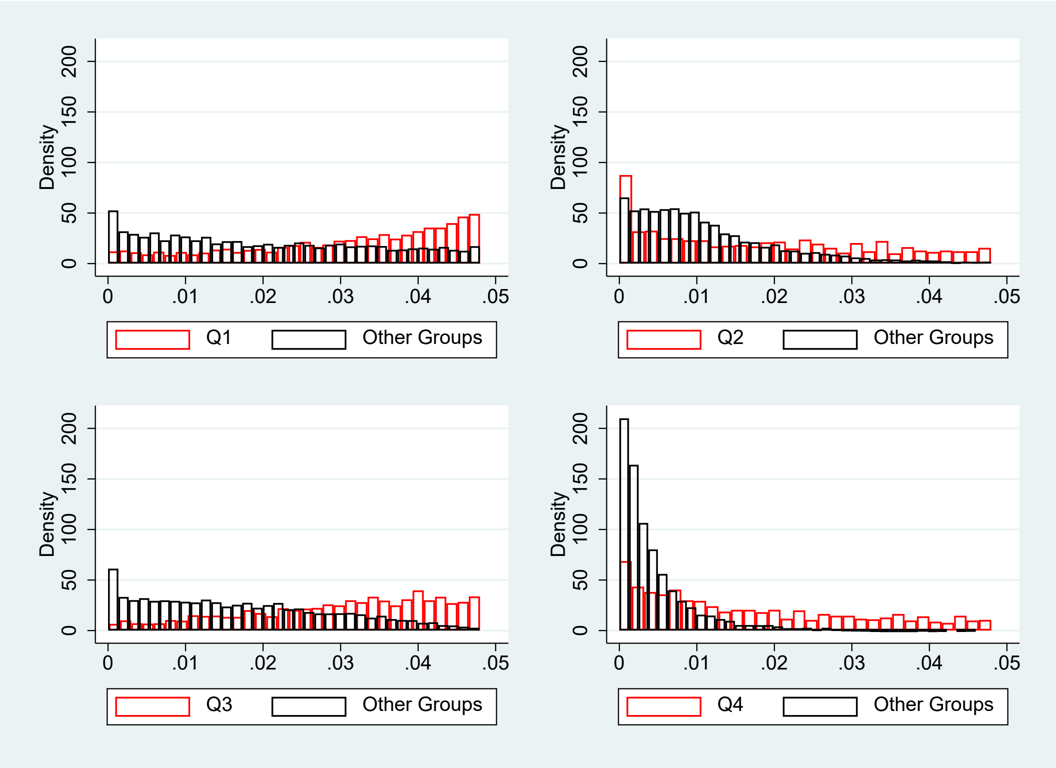


Table B1. Differences in the treatment levels before and after balancing on the GPS: t-stats for equality of means (One treatment)

	Prior to balancing on the GPS				After balancing on the GPS			
Interval:	*Q1*	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*
demand	**4.0314**	**3.8106**	1.7912	**-9.5589**	0.2961	-0.5653	-0.6111	0.0534
tariff	-1.7631	-1.9157	0.1783	**3.4997**	-0.5439	0.6540	0.1712	-0.3809
rer	**3.6495**	**-2.4896**	-0.9613	-0.1935	-0.7905	0.8958	-0.0762	-0.0967
$tariff_{t-2}$	0.9618	-0.5960	-1.6460	1.2816	0.0102	0.1423	0.2173	0.1178
rer_{t-2}	**-2.1815**	-0.7455	1.5029	1.3633	-0.2842	0.2587	-0.4112	0.6922
supply	**12.9952**	**4.8440**	**-2.2255**	**-15.7131**	-0.4727	-0.7292	-0.1460	0.3494
$supply_{t-2}$	**12.8100**	**4.8548**	**-2.2580**	**-15.5025**	-0.4502	-0.7797	-0.1154	0.3482
$demand^2$	**4.0422**	**3.8013**	1.7990	**-9.5683**	0.3073	-0.5606	-0.6030	0.0380
$tariff^2$	0.1655	-0.6149	0.0295	0.4200	-0.6836	0.2123	0.2609	-0.3264
rer^2	**-3.6227**	0.7084	1.5705	1.3371	0.5870	-0.3662	-0.7407	0.0022
$supply^2$	**12.0988**	**5.4262**	-1.7534	**-15.9034**	-0.3556	-0.8107	-0.1627	0.2724
$demand^3$	**4.0584**	**3.7712**	1.7977	**-9.5528**	0.3123	-0.5485	-0.5920	0.0200
$tariff^3$	0.8663	-0.4117	0.2041	-0.6576	-0.7390	-0.0147	0.4018	-0.3328
rer^3	**2.9724**	-0.5969	-1.2230	-1.1476	-0.5460	0.2869	0.4806	0.2458
$supply^3$	**11.0085**	**5.6201**	-1.2888	**-15.4785**	-0.2493	-0.8345	-0.1566	0.1903
age	**-9.0117**	**-3.4938**	-0.5857	**13.1880**	0.2067	-0.1363	0.8124	-0.5072
employment	**22.9716**	**15.9483**	1.7726	**-44.5073**	-0.2749	-1.8363	-1.1145	0.4759
productivity	**11.9414**	**8.0331**	-0.7676	**-19.5317**	0.4830	-1.3123	-1.0185	0.9792
tangibles	**2.7960**	**2.5802**	-1.4077	**-3.9674**	-0.2573	-0.4542	0.5222	-0.1529
liquidity	0.6084	**-2.5114**	-1.8215	3.7260	-0.3812	0.4050	0.5362	-0.2015
solvency	**-3.7089**	0.5908	**2.5762**	0.5894	0.7185	-0.1299	-0.6079	0.0967
profitability	1.5624	0.0498	-0.7820	-0.8300	-0.3799	-0.1151	0.5895	-0.2304
spillover	**-2.3482**	1.4555	-1.0794	**1.9719**	0.5036	-0.8303	0.4575	0.1844
$employment^2$	**21.8639**	**15.9244**	**3.3312**	**-45.2541**	-0.2246	-1.7686	-1.2182	0.4686
$productivity^2$	**11.6483**	**7.9409**	-0.4575	**-19.4604**	0.5014	-1.2901	-1.0750	0.9540
$tangibles^2$	**-2.5434**	**-2.3429**	1.8771	**3.0074**	0.3109	0.5598	-0.8176	0.1179
$liquidity^2$	-0.8166	-0.3845	-0.6684	1.8698	-0.0495	-0.2123	0.3668	-0.0862
$solvency^2$	**1.9685**	-0.3028	-1.8357	0.1616	-0.4066	-0.0309	0.4988	-0.0188
$profitability^2$	-1.7950	0.5606	0.6226	0.6116	-0.6371	0.1642	-0.2888	0.3976
$spillover^2$	**-2.1590**	1.6598	-1.2726	1.7716	0.4637	-0.8174	0.5372	0.0879
$employment^3$	**19.9577**	**15.1916**	**4.6491**	**-43.6471**	-0.1710	-1.6539	-1.2930	0.4497
$productivity^3$	**11.2849**	**7.7956**	-0.1357	**-19.2715**	0.5207	-1.2651	-1.1301	0.9266
$tangibles^3$	1.4737	**2.0267**	**-1.9872**	-1.5123	-0.2855	-0.6236	0.9922	-0.0970
$liquidity^3$	-1.1807	-0.0614	-0.1297	1.3717	0.2148	-0.2448	0.3765	-0.2526
$solvency^3$	-0.9690	0.0472	1.8875	-0.9955	0.1703	0.2907	-0.5595	0.0350
$profitability^3$	1.7115	-0.5648	-0.5735	-0.5730	0.2022	-0.0198	0.3376	-0.7779
$spillover^3$	**-2.0696**	1.6840	-1.4136	1.7992	0.4060	-0.7861	0.6114	0.0000
Observations	1921	1921	1921	1921	1533	1660	1684	1421
Averg. abs(t-value)	**5.9704**	**3.7266**	1.4255	**9.4095**	0.3872	0.6118	0.5805	0.2986

Table B2 Differences in the treatment levels before and after balancing on *the GPS: t-stats for equality of means (Two treatments)*

	Prior to balancing on the GPS				After balancing on the GPS			
Interval:	*Q1*	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*
demand	**2.3004**	**8.5782**	**-8.6041**	0.1729	-0.2243	-0.6435	0.1068	0.5314
tariff	-0.9733	**-3.6211**	1.6582	**2.4259**	-0.6177	0.9926	0.1605	-0.2075
rer	**-3.5287**	**10.7317**	**-8.8831**	**6.0912**	-0.3010	0.0728	0.6445	-0.2188
tariff $_{t-2}$	1.6578	-2.2570	-0.2875	0.2560	-0.3131	0.5127	0.1472	-0.3445
rer $_{t-2}$	-1.1910	-0.9855	-0.1066	2.5220	-0.0471	0.5321	0.4326	0.2215
supply	**10.4833**	**8.7455**	**-12.0123**	**-6.3071**	-1.5917	-0.8960	1.4033	0.6476
supply $_{t-2}$	**10.3802**	**8.7270**	**-11.8146**	**-6.4032**	-1.5750	-0.9641	1.3835	0.7173
demand^2	**2.3252**	**8.4562**	**-8.6069**	0.2519	-0.1854	-0.6494	0.1075	0.4970
tariff^2	-0.2560	-0.2820	0.7550	-0.3662	-0.6719	0.5843	0.5891	-0.2626
rer^2	-1.9491	-1.6133	**2.9738**	0.2240	0.7745	-0.2268	-0.3288	-0.2924
supply^2	**9.8554**	**9.2113**	**-12.0441**	**-5.8841**	-1.3771	-0.9028	1.4577	0.6405
demand^3	**2.3564**	**8.3076**	**-8.5794**	0.3089	-0.1468	-0.6506	1.0798	0.4601
tariff^3	-0.0162	0.5979	0.5750	-1.2408	-0.6613	0.3179	0.7366	-0.0409
rer^3	1.4802	1.2326	-1.8821	-0.6494	-0.5324	-0.1764	-0.0162	0.3452
supply^3	**9.0247**	**9.1484**	**-11.5369**	**-5.3934**	-1.1435	-0.8613	1.4378	0.6045
age	**-8.9317**	**-3.0428**	**2.9411**	**10.5806**	-0.1772	0.2836	0.2834	-0.7867
employment	**24.7971**	**15.6354**	**-18.2867**	**-22.8606**	-1.1494	-2.2384	3.5549	2.4617
productivity	**12.7839**	**5.7457**	**-7.5971**	**-12.0730**	-0.0899	-1.6793	1.7248	-0.0302
tangibles	**2.4687**	**4.2263**	**-5.7505**	0.2357	-0.3059	-0.6576	1.4195	-0.0780
liquidity	0.8181	**-4.4282**	**3.7984**	-1.8497	-0.1439	0.1738	-0.5814	0.4930
solvency	**-3.5841**	1.4171	-0.0476	**3.5177**	0.4660	0.2566	-0.1598	-0.6235
profitability	1.4614	-0.1164	-0.9702	-0.5596	-0.4365	-0.3880	0.0821	0.6226
spillover	1.2988	**-3.8510**	0.7366	0.8631	-0.8286	0.5979	-0.0549	0.3313
employment^2	**24.1758**	**15.0610**	**-16.7959**	**-23.4785**	-1.0082	-2.2342	0.3724	2.5876
productivity^2	**12.5022**	**5.6039**	**-7.2940**	**-11.9682**	-0.0045	-1.6408	1.7185	-0.0644
tangibles^2	**-2.9342**	**-2.4274**	**4.1852**	0.7070	0.6256	0.4376	-1.2418	-0.0434
liquidity^2	-0.0212	**-2.2979**	**2.0907**	-0.5348	0.0044	-0.1815	0.0963	0.2882
solvency^2	**2.7929**	**-2.8243**	0.6639	-1.9213	-0.4283	-0.1382	0.2641	0.4159
profitability^2	-1.3926	0.4163	0.7527	0.4744	-0.1390	-0.0928	0.3606	-0.3384
spillover^2	1.4517	**-3.6060**	0.5038	0.7387	-0.7690	0.5015	0.0540	0.2545
employment^3	**22.5708**	**13.8614**	**-14.5243**	**-23.2803**	-0.8431	-2.1825	3.7927	2.7225
productivity^3	**12.1350**	**5.4437**	**-6.9586**	**-11.7776**	0.0851	-1.5985	1.7078	-0.0955
tangibles^3	**2.7651**	0.5290	**-2.2906**	-1.1593	-0.9441	-0.2047	0.9562	0.1014
liquidity^3	-1.1305	-0.2667	1.1168	0.2932	0.2588	-0.3495	0.1491	0.0877
solvency^3	-1.5836	**3.0730**	-1.2074	0.7695	0.2542	0.3315	-0.2367	-0.3664
profitability^3	1.2968	-0.3848	-0.6994	-0.4462	0.0466	0.0190	-0.3634	0.2436
spillover^3	1.4157	**-3.3173**	0.2865	0.7993	-0.7458	0.4462	0.1737	0.1902
Observations	2837	1003	2547	1292	2315	863	2175	1027
Average abs(t-value)	**4.2425**	**3.1545**	**-4.1369**	**-3.0940**	-0.3994	-0.3859	0.6217	0.3488

REFERENCES

Amiti, M., & Konings, J. (2007). Trade liberalisation, intermediate inputs, and productivity: Evidence from Indonesia. *American Economic Review*, *97*, 1611–1638.

Aristei, D., Castellani, D., & Franco, C. (2013). Firms' exporting and importing activities: There is a two-way relationship? *Review of World Economy*, *149*(1), 55–84.

Bas, M. (2012). Input-trade liberalization and firm export decision: Evidence from Argentina. *Journal of Development Economics*, *97*(2), 481–493.

Bas, M., & Strauss-Khan, V. (2014). Does importing more inputs raise exports? Firm-level evidence from France. *Review of World Economy*, *150*, 241–275.

Bas, M., & Strauss-Khan, V. (2015). Input trade liberalisation, export prices and quality upgrading. *Journal of International Economics*, *95*(2), 250–262.

Castellani, D., Serti, F., & Tomasi, C. (2010). Firms in international trade: Importers' and exporters' heterogeneity in Italian manufacturing industry. *The World Economy*, *33*, 424–457.

Choquette E. (2019). Import-based market experience and firms'exit from export markets Journal of International Business Studies (2019) 50, 423–449.

Choquette, E., & Meinen, P. (2015). Export spillovers: Opening the black box. The World Economy, 38(12), 1912–1946.

Di Gregorio, D., Musteen, M., & Thomas, D. E. (2009). Offshore outsourcing as a source of international competitiveness for SMEs. Journal of International Business Studies, 40(6), 969–988.

Edwards, L., Sanfilippo, M., & Sundaram, A. (2018). Importing and export performance: New evidence from South Africa. *South African Journal of Economics*, *86*(1), 79–95.

Feenstra, R., & Hanson, G. (1996). Globalization, outsourcing, and wage inequality. *The American Economic Review*, *86*(2), 240–245.

Feng, L., Li, Z., & Swenson, D. L. (2016). The connection between imported intermediate inputs and exports: Evidence from Chinese firms. *Journal of International Economics*, *101*, 86–101.

Forlani, E. (2017). Irish firms' productivity and imported inputs. *The Manchester School*, *85*(6), 710–743.

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., & Topalova, P. (2010). Imported intermediate inputs and domestic product growth: Evidence from India. *Quarterly Journal of Economics*, *125*, 1727–1767.

Halpern, L., Koren, M., & Szeidl, A. (2015). Imported inputs and productivity. *American Economic Review*, *105*, 3660–3703.

Helpman, E., & Grossman, G. (1991). *Innovation and growth in a global economy*. MIT Press.

Imbens, G., 2000. The role of the propensity score in estimating dose–response functions. Biometrika 87, 706–710.

Johanson, J., & Vahlne, J.-E. (2009). The Uppsala internationalization process model revisited: From liability of foreignness to liability of outsidership. Journal of International Business Studies, 40(9), 1411–1431.

Karlsen, T., Silseth, P. R., Benito, G. R. G., & Welch, L. S. (2003). Knowledge, internationalization of the firm, and inward–outward connections. Industrial Marketing Management, 32(5), 385–396.

Kasahara, H., & Lapham, B. (2013). Productivity and the decision to import and export: Theory and evidence. *Journal of International Economics*, *89*, 297–316.

Kasahara, H., & Rodrigue, J. (2008). Does the use of imported intermediates increase productivity? Plant-level evidence. *Journal of Development Economics*, *87*, 106–118.

Kluve, J., Schneider, H., Uhlendorff, A., Zhao, Z. (2012). Evaluating continuous training programmes by using the generalized propensity score. Journal of the Royal Statistical Society 175 (2), 587–617.

Kugler, M., & Verhoogen, E. (2009). Plants and imported inputs: New facts and an interpretation. *American Economic Review*, *99*(2), 501–507.

Lo Turco, A., & Maggioni, D. (2013). On the role of imports in enhancing manufacturing exports. *The World Economy*, *40*, 93–120.

Máñez, J. A., Rochina-Barrachina, M. E., & Sanchis, J. A. (2020). Foreign sourcing and exporting. *The World Economy*, *43*(5), 1151–1187.

Muûls, M., & Pisu, M. (2009). Imports and exports at the level of the firm: Evidence from Belgium. *The World Economy*, *32*(5), 692–734.

Requena, F., Serrano, G., Mínguez, R, (2023). The enhancing effect of imports of intermediate inputs on firms' exports. *The World Economy*, 46. 2654–2683.

Rosenbaum, P., Rubin, D., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70 (1), 41–55.

Rubin, D.B., 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. Journal of Educational Psychology 66, 688–701.

Serrano-Domingo G., Requena-Silvente F. (2013) Re-examining the migration–trade link using province data: An application of the generalized propensity score. Economic Modelling 32. 247–261

Stirbat, L., Record, R., & Nghardsaysone, K. (2015). The experience of survival: Determinants of export survival in Lao PDR. World Development, 76(December), 82–94.

Topalova, P., & Khandelwal, A. (2011). Trade liberalization and firm productivity: The case of India. *The Review of Economics and Statistics*, *93*(3), 995–1009.

Vogel, A., & Wagner, J. (2010). Higher productivity in importing German manufacturing firms: Self-selection, learning from importing or both? *Review of World Economy*, *145*(4), 641–665.

Welch, L. S., & Luostarinen, R. K. (1993). Inward–outward connections in internationalization. Journal of International Marketing, 1(1), 44–56.