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Do imports of intermediate inputs generate higher productivity? Evidence from Ecuadorian manufacturing firms

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Abstract

This paper examines the causal effect of importing on firm productivity. We use an augmented Cobb–Douglas production function in which the static and dynamic effects of importing and exporting are estimated for formal manufacturing firms in Ecuador. We use a rich administrative data set that covers the period 2007–2018 and estimate total factor productivity (TFP) at the firm level. Our results show that both static and dynamic effects are important sources of gains from importing. We find that static and dynamic gains in productivity from importing intermediates are higher in more innovative industries than in less innovative industries, which implies an industrial heterogeneity effect. We also find that the elasticity of substitution between imported and domestic intermediates in all the industries are substitute inputs. Finally, we provide robust evidence in favour of self-selection on the entry and exit side sides of the market. Our estimation results provide support to the learning-by-importing hypothesis.

KEYWORDS

Ecuador, imported intermediates, learning-by-importing, productivity, self-selection

1 | INTRODUCTION

The relationship between international trade and economic growth has been much discussed in the literature, mostly since the seminal paper by Bernard et al. (1995). Moreover, it is well known that international trade positively affects economic growth either in the long or in the short run because, through it, domestic firms may gain access to foreign technologies, develop markets and establish cooperation agreements with foreign firms (Eaton & Kortum, 1999; European Commission, 2012; Linarello, 2018).[1] Furthermore, it constitutes an important way through which firms in developing countries can absorb more efficient technologies—compared with those produced locally—especially those created in the developed world (Acharya & Keller, 2009; Amiti & Konings, 2007).

In addition, international trade agreements related to specific imported goods, intermediates or services can facilitate agreements of a political or financial nature, which can be highly beneficial for participating countries (for instance, in terms of productivity at the firm level) (Amiti & Konings, 2007; De Loecker, 2011; Topalova & Khandelwal, 2011). Thus, imports have an even more pronounced role as sources of technology transfer for developing countries, which makes them highly demanded. Specifically, firms in developing countries could benefit from research and development (R&D) performed in developed countries through imports (Coe et al., 1997). Moreover, it is particularly important for these countries that firms' productivity gains generated by imports can in the long run translate to improvements in growth and development levels.

In addition, it is well documented that there is a positive effect of imports on firm productivity, which suggests that importing firms are more productive than non-importing firms (Abreha, 2019; Kasahara & Rodrigue, 2008; Mo et al., 2021; Zhang, 2017). More important is that there are at least two widely discussed mechanisms (hypotheses) that explain how importers perform better than non-importers: self-selection and learning-by-importing. Self-selection into importing argues that more productive firms are able to enter the import market because they can cover sunk and fixed costs (Vogel & Wagner, 2010; Zhang, 2017). Learning-by-importing, meanwhile, argues that firms that import improve their performance (productivity) after entering import markets (Abreha, 2019; Caselli, 2018; Kasahara & Rodrigue, 2008; Máñez-Castillejo et al., 2020). These two different mechanisms have been used to explain the causal effect of imports and firm productivity.

Nevertheless, these two mechanisms have scarcely been analysed in the context of industrial heterogeneity. Specifically, very little is known about the differential effect of these two hypotheses across industries, which are classified according to technology intensity. Blalock and Veloso (2007) argue that large firms and firms in intermediate goods sectors are better able to learn from imports.[2] In this line, Smith (2014) found that importing sophisticated goods or inputs leads to greater domestic innovation when industry structure is more concentrated in leading industries, providing a competitive kick-start; however, this effect is not present in lagging industries. According to Battisti et al. (2020), this might happen because the productivity advantage of internationalised firms might be interpreted more accurately in terms of proximity to the technological frontier.

[1]See Keller (2004) for a review of the literature on the relationship of international technology diffusion to other factors that affect economic growth in open economies.

[2]Salomon and Jin (2008) argue that engaging in exporting provides firms, especially firms in technologically lagging industries, the opportunity to benefit disproportionately from knowledge spillovers.

Our paper directly relates to the literature on the causal effect of imports and firm productivity by analysing these two aforementioned mechanisms in the context of industrial heterogeneity. Thus, we aim to answer the following question: Do imports of intermediate inputs generate higher productivity? Additionally, we capture the elasticity of substitution to analyse the substitutability between imported intermediate inputs and domestic inputs. Furthermore, we study this causal link from a perspective of industrial heterogeneity to show the different impacts of imported intermediates on productivity depending on the level of innovation and the use of technology. We use Ecuadorian manufacturing firms as a case study because this effect has been studied in depth for developed countries. Scarce evidence has been obtained for developing countries at the firm level, and no evidence has been obtained for Ecuador.

We make at least three contributions to the empirical literature on imports and firm productivity. First, we fill the gap in the literature by using Ecuadorian manufacturing firms to estimate the static and dynamic (learning-by-importing) effect of imports on productivity with a modified version of the Levinsohn and Petrin (2003) semi-parametric estimator.[3] This allows us to use two additional state variables and endogenise the law of motion for productivity, which enables past decisions to import and export to affect future productivity as in Navas et al. (2020), Mo et al. (2021), and Camino-Mogro and López (2021) which allows us to test the static effect of imports and exports, and the learning-by-importing and learning-by-exporting hypotheses. This empirical approach is scarcely analysed because many studies do not use the export variable with the import variable. We include the export decision in the law of motion of productivity because exporting and importing activities are complements (Camino-Mogro & López, 2021).

Second, we analyse the static and dynamic (learning-by-importing) effect of imports on productivity for two different industry classifications (the Pavitt Taxonomy and industries according to the OECD technological intensity classification) since restricting the analysis to the manufacturing sector could mask varying roles of different technology transfer channels among firms. We study the heterogeneity that may exist in the self-selection and learning-by-importing hypotheses between less and more innovative industries. Intuition tells us that firms that operate in industries close to the technological frontier and are therefore more innovative can produce goods with greater added value because they can import better intermediate inputs than their counterparts. However, the gains from learning can be small compared with firms operating in less innovative industries. Additionally, firms that operate in more innovative industries and have better technology can be more productive and therefore self-select to enter international markets compared with firms that operate in less innovative industries.

Third, we analyse the elasticity of substitution between imported intermediate inputs and domestic intermediates in the whole sector and for the two different proposed industry classifications. Finally, we test the self-selection and learning-by-importing hypotheses using the trajectories of TFP in extended pre- and post-export entry periods for groups with different import histories and examine the pre- and post-entry behaviour of importers. To address the selection bias of more productive firms, we employ a difference-in-difference matching (DDM) estimator as a robustness check. We use new, detailed and underexplored unbalanced annual panel data for the period 2007–2018, which allows us to capture the existing heterogeneity across firms and time. The data were collected from the balance sheets

[3]We also use a modified version of the Wooldridge (2009) semi-parametric estimator. The results are available upon request.

and financial statements reported by firms to the Superintendencia de Compañías, Valores y Seguros (SCVS) in Ecuador.

The structure of this paper is as follows. Section 2 provides a review of the literature. Section 3 explains the methodology applied. Section 4 describes the data and variables used. Section 5 details the results obtained and their interpretation. Finally, Section 6 states the conclusions and policy implications of the research.

2 | LITERATURE REVIEW

Since the seminal paper by Bernard et al. (1995), who analyse the relationship between firm productivity and international trade, a proliferation of research that studies this effect has been done. Nevertheless, the relationship between exports and productivity has received more attention than the effect of imports on productivity. Despite this imbalance, in the last decade, several studies have explored the latter relationship for developed and developing countries (although for the latter, such studies have been relatively scarce).[4]

Overall, the evidence consistently agrees that productivity is higher in importing firms than non-importing firms (Cassiman & Golovko, 2018; Wagner, 2016). Furthermore, this conclusion is well documented for developed countries (Farinas & Martín-Marcos, 2010; Halpern et al., 2015; Lööf & Andersson, 2010; Máñez-Castillejo, Rochina-Barrachina, & Sanchis, 2020; Muûls & Pisu, 2009; Smeets & Warzynski, 2013). However, for the case of developing countries, empirical evidence is still scarce and results are mixed (Cassiman & Golovko, 2018; Máñez-Castillejo, Rochina-Barrachina, & Sanchis, 2020).[5] Nonetheless, Halpern et al. (2015) mention that the next step in this research agenda is to investigate the underlying mechanism through which imports increase productivity.

There are two classical mechanisms that explain the positive relationship between imports and productivity. These two mechanisms are grounded in causal evidence: self-selection on the entry or exit side of the market and learning-by-importing. The self-selection hypothesis is based on the premise that when firms are exposed to international markets, only the most productive choose to enter the international market because of the high-entry costs involved. Therefore, only efficient firms are qualified to become importers (exporters) (Melitz, 2003). On the other hand, the learning-by-importing hypothesis is based on the premise that imports (exports) increase productivity and refers to the mechanisms through which a firm's performance improves after entering import (export) markets (De Loecker, 2013).[6]

There are several reasons for the positive effect of imports and firm productivity: (i) firms have better information about products and processes, thereby reducing costs and increasing the technology transfer that comes from imported inputs (Acharya & Keller, 2009; Amiti &

[4]For an extensive literature review on this topic, see, Wagner (2012) and Cassiman and Golovko (2018).

[5]Some studies that analyse the effect of imports and firm productivity in developing countries are Kasahara and Rodrigue (2008), Zhang (2017), Caselli (2018), Zaclicever and Pellandra (2018), Abreha (2019), and Camino-Mogro et al. (2021).

[6]There are few studies that analyse these mechanisms in developed and developing countries (see, e.g., Kasahara & Rodrigue, 2008; Vogel & Wagner, 2010; Farinas & Martín-Marcos, 2010; Halpern et al., 2015; Elliott et al., 2016; Zhang, 2017; Máñez-Castillejo, Mínguez Bosque, et al., 2020; Máñez-Castillejo, Rochina-Barrachina, & Sanchis, 2020; Navas et al., 2020).

Konings, 2007; Bas & Strauss-Kahn, 2014; Fariñas et al., 2014; Hasan, 2002) and capital goods (Caselli, 2018; Mo et al., 2021); (ii) firms can exploit global specialisation and employ inputs at the forefront of knowledge and technology (Lööf & Andersson, 2010); (iii) firms access larger markets in which the superior technology that is embedded in advanced economy imports would boost firm productivity (Bas & Strauss-Kahn, 2014; Lööf & Andersson, 2010; Muûls & Pisu, 2009; Zaclicever & Pellandra, 2018).

Another important strand in the literature of imports and productivity is the complementarity–substitutability relationship between foreign intermediate inputs and domestic inputs. However, this point has scarcely been analysed in the empirical literature and the evidence is inconclusive. In particular, Kasahara and Rodrigue (2008), Halpern et al. (2015), Navas et al. (2020) and Camino-Mogro et al. (2021) found that foreign and domestic intermediate inputs are substitute inputs in Chilean manufacturing plants, Hungarian manufacturing firms, Italian manufacturing firms and Ecuadorian manufacturing firms, respectively. However, contrary results are found by Zhang (2017), who suggests that foreign and domestic intermediate inputs are complementary inputs in Colombian manufacturing plants. Furthermore, the analysis of the complementarity–substitutability between imported and domestic intermediate inputs is important since it could help make public policy decisions related to trade opening or restriction.

Also, the study of causality between imports and productivity has been the subject of important methodological contributions. De Loecker (2007, 2013) and Kasahara and Rodrigue (2008) made important contributions about the link between exports and imports and productivity. These authors argue that past export–import status affects future firm productivity, so the law of motion of productivity is endogenised. This methodological contribution definitely clarified the debate on this matter. Using this approach, several authors have found positive effects on productivity (Abreha, 2019; Camino-Mogro & López, 2021; Halpern et al., 2015; Máñez-Castillejo, Mínguez Bosque, et al., 2020; Máñez-Castillejo, Rochina-Barrachina, & Sanchis, 2020; Mo et al., 2021; Navas et al., 2020; Zhang, 2017). However, the self-selection and learning-by-importing hypotheses have scarcely been compared or analysed by technological sectors or industrial classifications with the approach proposed by De Loecker (2007, 2013) and Kasahara and Rodrigue (2008).

This could be of great interest since firms that operate in more technologically intensive industries (R&D, innovation, etc.) could import better-quality intermediate inputs and therefore produce better products than their counterparts and thus be more productive (learning-by-importing). Furthermore, firms operating in industries that are closer to the technological frontier self-select entry into the import market (self-selection). However, these same firms might benefit less from learning since they are very close to the technological frontier, so one may presume that firms in less technologically intensive industries could benefit more from learning-by-importing (Blalock & Veloso, 2007; Salomon & Jin, 2008; Smith, 2014; Battisti et al., 2020). Analysing the complementarity–substitutability between imported and domestic intermediate inputs by exploring industrial heterogeneity might also be of interest because the input variety effect of imported inputs might vary depending on the industry and the existence of different quality effects between imported intermediates and domestic intermediates, which also depends on the industry.

In this vein, this research seeks to contribute to the increasing empirical literature on this topic by analysing the heterogeneity that may exist in the self-selection and learning-by-importing hypotheses between less and more innovative industries. As we have mentioned before, little is known about which technological and innovative sectors benefit the most from learning-by-importing and which self-select to import. Finding evidence of this is of vital importance since it could reorient public policies to improve access to international markets. In addition, we analyse the elasticity of substitution between imported intermediate inputs and domestic intermediates in the whole sector and for the two different proposed industry classifications (the Pavitt Taxonomy and the OECD technological intensity classification). Finding heterogeneous evidence on the complement-substitute relationship between domestic and imported inputs would help in understanding that there are fewer technological or innovative sectors whose product is more substitutable than in more innovative sectors, since there may be better quality or differentiation of product. Finally, knowing that imports of inputs and exports are complementary, we take advantage of the methodological advances mentioned above and propose to modify the law of motion of productivity by including past decisions to import and export to capture the learning effect of both variables on productivity. We use a developing Latin American country such as Ecuador because this relationship has been studied in depth for developed countries; nevertheless, scarce evidence has been obtained for developing countries at the firm level, and no evidence has been researched for Ecuador.

3 | THEORETICAL FRAMEWORK AND EMPIRICAL STRATEGY

3.1 | Empirical model and estimation method

Following Kasahara and Rodrigue (2008), Camino-Mogro and López (2021) and Camino-Mogro et al. (2022), we take logarithms of our production function[7] and include discrete import and export variables, which suggests the use of imported intermediates and the decision to export in the production process. The relevant expression to be estimated is:

$$y_{it} = \omega_{it} + \beta k_{it} + \alpha l_{it} + \gamma m_{it} + \delta d_{it} + \sigma x_{it} + \epsilon_{it}, \tag{1}$$

where ω_{it} is a serially correlated productivity shock (not observed by the econometrician but observable or predictable by firms), k_{it} is capital input, l_{it} is labour input, m_{it} represents the intermediate inputs (domestic and foreign intermediate goods) in logarithms, and ϵ_{it} is a standard i.i.d. error term that is neither observable nor predictable by the firm. β, α and γ are elasticities of output with respect to each input. Moreover, a firm's discrete choice to import intermediate inputs is denoted by d_{it} to capture the static effect of use of foreign inputs $\frac{\gamma}{\theta-1} ln\left(N\left(d_{it}\right)\right)$. Import status is included as a dummy variable, which takes the value 1 if firm i imports intermediates at time t and zero otherwise. In addition, as a control variable we include a firm's discrete choice to export goods denoted by x_{it}, which captures the static effect of export activity on productivity.

We use this modification of the traditional production function because one may be concerned about the fact that firms which are importers are also exporters, so the result captured by the import dummy may contain the effect of being an exporter. In this case, Kasahara and Lapham (2013) and Zaclicever and Pellandra (2018) argue that failing to control for the linkages between importing and exporting might lead to an upward bias in the coefficient of imported inputs since 'good' firms often both export and import. Moreover, Camino-Mogro and López (2021) find that there is complementarity between exports and imports in determining productivity.

For these reasons, we include export status as a dummy variable, which takes the value 1 if firm i exports at time t and zero otherwise in our augmented production function. In this sense, we include the variables d_{it} and x_{it} as additional state variables in Equation (1). Máñez-Castillejo,

[7]A detailed explanation of our production function is in Appendix 3.

Mínguez Bosque et al. (2020), Máñez-Castillejo, Rochina-Barrachina and Sanchis (2020) argue that there are sunk costs associated with importing intermediates and that exporting implies that the firm's past import and export activities should be considered a state variable in the firm's import and export decisions, respectively. Therefore, if the firm's current productivity depends on past exporting and importing experience, the firm's payoffs from exporting (importing) raise current productivity, so the law of motion of productivity should be modified.[8] In this sense, we modify the law of motion of productivity, considering an endogenous Markov process in which past import and export decisions may affect the dynamics of productivity. In addition, this new specification allows us to capture the static and dynamic effect of the export (learning-by-exporting) and import (learning-by-importing) decisions on productivity. Thus, we consider the following stochastic process of ω_{it}:

$$\omega_{it} = \xi_t + \rho\omega_{it-1} + \eta d_{it-1} + \varphi x_{it-1} + u_{it}, \tag{2}$$

where ξ_t is an innovation term (or a year-specific productivity shock) uncorrelated by definition with k_{it}, and u_{it} is independent of ω_{it-1}, d_{it-1} and x_{it-1} with a known distribution. Zhang (2017) and De Loecker (2007) argue that if a firm was an importer and exporter, respectively, at date t–1, its productivity would be enhanced because of the importing and exporting experience, and this increased productivity further affects future importing and exporting decisions, which in turn has an impact on future productivity. The importing and exporting decisions are endogenous. This setup implies that productivity is endogenous and, similar to De Loecker (2013), we assume that productivity evolves according to an endogenous Markov process. In Equation (1), we can examine the static effect of importing on firm output and productivity by testing $\delta > 0$. It implies that using imported intermediate inputs immediately improves output for a fixed quantity of inputs in production (Abreha, 2019) and firm-level evidence of R&D spillovers through trade in intermediate goods (Kasahara & Rodrigue, 2008). Moreover, if $\eta > 0$ and statistically significant at standard levels in Equation (2), it is evidence in favour of the learning-by-importing hypothesis. Finally, the long-run effect of the learning-by-importing hypothesis could be measured by $\frac{\eta}{1-\rho}$. Furthermore, in Equations (1) and (2), we can examine the static and dynamic effect of exporting on firm output and productivity by testing $\sigma > 0$, which implies that the decision to export immediately improves output, and by testing $\varphi > 0$, which indicates a dynamic productivity gain that should be considered firm-level evidence of the learning-by-exporting hypothesis (Camino-Mogro et al., 2022).

Similar to Kasahara and Rodrigue (2008) and Abreha (2019), our specification for production technology differs from Levinsohn and Petrin (2003) and Olley and Pakes (1996) since we use two additional state variables: import status (d_{it}) and export status (x_{it}). Also, the import and export status have a dynamic effect on productivity as specified in Equation (2). The main indicator for considering the firm's past import activities an additional state variable in the firm's import decision is the existence of sunk costs linked to importing intermediates (Máñez-Castillejo, Mínguez Bosque, et al., 2020; Kasahara & Lapham, 2013). In addition, the underlying hypothesis that justifies including x_{it} as an additional state variable is that the contemporaneous export decision at time t is not reversible once the productivity shock occurs, and also that the past export decision affects the law of motion of productivity (Camino-Mogro et al., 2022; Camino-Mogro & López, 2021). Therefore, the demand function of the material is given as $m_{it} = m_t^*(\omega_{it}, k_{it}, d_{it}, x_{it})$.

[8]Also, Zhang (2017) in section 3.4 and Máñez-Castillejo, Rochina-Barrachina and Sanchis (2020) in section 3.2 mention other reasons why it is necessary to include the import and export decisions as state variables and the past export and import decisions in the endogenous Markov process.

Assuming that $m_t^*(\cdot)$ is strictly increasing in ω_{it}, the unobserved productivity can be expressed in terms of observable capital, intermediate inputs, imports and exports as $\omega_{it} = \omega_t^*\left(m_{it}, k_{it}, d_{it}, x_{it}\right)$, and the estimating equation is the following:

$$y_{it} = \alpha l_{it} + \phi_t\left(m_{it}, k_{it}, d_{it}, x_{it}\right) + \epsilon_{it}, \tag{3}$$

where $\phi_t\left(m_{it}, k_{it}, d_{it}, x_{it}\right) = \beta k_{it} + \gamma m_{it} + \delta d_{it} + \sigma x_{it} + \omega_t^*\left(m_{it}, k_{it}, d_{it}, x_{it}\right)$. In the first stage, the estimation of α from Equation (3) is consistent and similar to Levinsohn and Petrin (2003), using a third-order polynomial approximation. In the second stage, we estimate β, γ, δ and σ once we define the innovations in productivity conditional on ω_{it-1}, d_{it-1}, x_{it-1}[9]:

$$\xi_{it} = \omega_{it} - E\left[\omega_{it} \mid \omega_{it-1}, d_{it-1}, x_{it-1}\right]. \tag{4}$$

This new Equation (4) allows the productivity innovations ξ_{it} to be orthogonal to all information at time t–1. Moreover, with ϵ_{it} in Equation (3), we can construct the orthogonality conditions. Following Kasahara and Rodrigue (2008), for each candidate parameter vector $\Gamma^* = (\beta^*, \gamma^*, \delta^*, \sigma^*)$, we may construct and estimate the residual as:

$$\left(\widehat{\xi}_{it} + \widehat{\epsilon}_{it}\right)\left(\Gamma^*\right) = y_{it} - \widehat{\alpha} l_{it} - \beta^* k_{it} - \gamma^* m_{it} - \delta^* d_{it} - \sigma^* x_{it} - \widehat{E}\left[\omega_{it} \mid \omega_{it-1}, d_{it-1}, x_{it-1}\right]. \tag{5}$$

In this sense, we estimate Equation (1) with two differences from the traditional Levinsohn and Petrin (2003) estimator.[10] First, d_{it} and x_{it} are treated as an additional state variable given that the import and export decisions are not reversible once the productivity shock occurs (Camino-Mogro et al., 2021, 2022; Camino-Mogro & López, 2021). Second, d_{it-1} and x_{it-1} affect ω_{it}, modifying the law of motion of productivity and allowing past import and export decisions to affect TFP. We extend this model to consider the extent to which imported intermediates are used relative to domestic intermediates, as suggested in Equation (A2). Kasahara and Lapham (2013) show that when firms have heterogeneous transportation costs of imported intermediates, the benefit from importing may be different across firms. Also, the higher the ratio of total intermediates to domestic intermediates is, the larger the productivity effect from importing. For this reason, we introduce the term $n_{it} = ln\frac{M_{it}}{M_{it}^h}$, which captures the intensity of the foreign and domestic intermediate inputs, as in Kasahara and Rodrigue (2008). Also, we introduce the term $EI_{it} = ln\frac{Sales_{it}}{Sales_{it}^h}$, which captures the intensity of foreign and domestic sales, as in Navas et al. (2020). Replacing d_{it} with n_{it} and x_{it} with EI_{it} in Equation (1), we get:

$$y_{it} = \omega_{it} + \beta k_{it} + \alpha l_{it} + \gamma m_{it} + \psi n_{it} + \sigma EI_{it} + \epsilon_{it}. \tag{6}$$

[9]We do not control for selection bias by considering the expectation conditional on the survival probability since we use an unbalanced panel dataset. Levinsohn and Petrin (2003) argue that this issue is unimportant in this kind of data.

[10]It is well known that the direct ordinary least squares (OLS) estimator is subject to an endogeneity and simultaneity problem because the labor and intermediate input choices are dependent on ω_{it} (Kasahara & Rodrigue, 2008; Zhang, 2017). In this sense, if a firm's decision to use more inputs is based on productivity shocks, it is coherent to think that higher productivity firms will use more inputs, and this issue will upwardly bias the coefficients estimated by OLS because the firm does not make input decisions independent of its productivity. In addition, the importing status d_{it} and the exporting status x_{it} are also correlated with ω_{it} because productivity is a Markov process, and this correlation aggravates the endogeneity problem (De Loecker, 2013; Zhang, 2017).

As mentioned, this new specification proposed by Kasahara and Rodrigue (2008) allows us to capture the impact of imported intermediates on productivity and the elasticity of substitution between domestic and imported intermediates. In addition, we modify the law of motion of productivity to capture the dynamic effect of the intensity of foreign and domestic intermediate inputs and the dynamic effect of the intensity of foreign and domestic sales. Replacing the term n_{it-1} and EI_{it-1} in Equation (2), the law of motion of productivity that considers an endogenous Markov process is:

$$\omega_{it} = \xi + \rho\omega_{it-1} + \eta n_{it-1} + \varphi EI_{it-1} + u_{it}. \tag{7}$$

This augmented production function in Equation (6), with the variable (n_{it}) as the ratio of total intermediate materials to domestic inputs $\left(ln\frac{M_{it}}{M_{it}^{h}}\right)$ in logarithms, allows the determination of the elasticity of substitution between domestic and imported intermediate inputs in such a way that, by estimating Equation (6), the value of θ is captured: $\overline{\theta} = \frac{\overline{\gamma}}{\psi} + 1$. If it is >1, there is elasticity of substitution, and if it is less than 1 or negative, there is complementarity between these two inputs.

As an alternative specification, we use the approach proposed by Abreha (2019) to estimate the impact and intensity of foreign intermediates on TFP. The author proposes to use the ratio between foreign intermediate inputs and total intermediates $FI_{it} = \left(ln\frac{M_{it}^{f}}{M_{it}}\right)$, in logarithms, to examine whether or not intensive use of foreign varieties improves productivity. Also, in this approach, the import is treated as a continuous variable depending on the intensity of the use of foreign varieties among importing firms. By introducing this ratio into the augmented production function and productivity equation, we obtain:

$$y_{it} = \omega_{it} + \beta k_{it} + \alpha l_{it} + \gamma m_{it} + \mu FI_{it} + \sigma EI_{it} + \epsilon_{it}. \tag{8}$$

This new ratio is estimated similarly to the discrete import variable d_{it} and the continuous import variable n_{it}. Again, we modify the law of motion of productivity to capture the dynamic effect of FI_{it-1}. When we replace the term FI_{it-1} in Equation (2), the law of motion of productivity that considers an endogenous Markov process is:

$$\omega_{it} = \xi + \rho\omega_{it-1} + \eta FI_{it-1} + \varphi EI_{it-1} + u_{it}. \tag{9}$$

Finally, to present a robustness check of the learning-by-importing hypothesis, we use a difference-in-difference matching (DDM) estimator, controlling for self-selection, similar to Mallick and Yang (2013). The estimator allows us to capture the magnitude of different productivity growth between new import market entrants and non-importers in a period after entry. The magnitude of learning effect from importing on firm productivity could be obtained by estimating the following equation:

$$DDM_{ATT} = E\left[\omega_{it} - \omega_{it\prime} \mid \rho, D = 1\right] - E\left[\omega_{it} - \omega_{it\prime} \mid \rho, D = 0\right], \tag{10}$$

where $t^{'}$ refers to the entrant year and t is a given year after entry; $\omega_{it} - \omega_{it}^{'}$ therefore measures the magnitude of the different productivity growth of firm i in a given period after entry. D is a dummy equal to 1 if the firm is a new import market entrant, and it takes the value zero if the firm remains a non-importer during the period between $t^{'}$ and t. ρ is the propensity score of being a new importer based on the given firm characteristics X, which in our case is the initial level of TFP, year, industry and region fixed effects, and ρ is used to find matched treated (new entrants) and untreated (non-importers) firms, allowing like-for-like comparison. Finally, DDM_{ATT} is the magnitude of different productivity growth between new import market entrants and non-importers in a given period after entry (Mallick & Yang, 2013). We regress Equation (10) for the entire manufacturing sector and for each industry in our two classifications: the Pavitt Taxonomy and the OECD technological intensity classification. We use a subsample of entering importers and non-importers during the period 2007–2018.[11] In this sense, we only include a dummy variable for entering importers constructed in the following way: value 1 the year the firm enters the import market and value 0 in both the years prior to becoming an importer and all years of firms that never imported during the sample period. For entering importers, we do not use observations for years after entry, but for non-importers, we use all year observations.[12]

3.2 | Testing self-selection into importing

The aim of this subsection is to analyse self-selection into the import market on both the entry and the exit sides. In this sense, the methodology used so far does not allow us to test this hypothesis. There is much evidence that indicates that breaking into foreign markets involves significant sunk startup costs and fixed costs (Melitz, 2003; Mo et al., 2021; Zhang, 2017). In this sense, it is expected that firms self-select into the import market according to their productivity level. To test the self-selection hypothesis on the entry and the exit sides, we use our modified Levinsohn and Petrin (2003) estimator to recover the TFP by estimating Equations (1) and (2). In these equations, the learning-by-importing and the learning-by-exporting are included in the law of motion for productivity, allowing the dynamics of productivity to potentially depend on importing and exporting behaviour (as argued by De Loecker, 2013; Kasahara & Rodrigue, 2008). Then, we regress the estimated TFP which includes both the import and the export dummies in the production function directly and in the period t–1 in the endogenous law of motion of productivity.

Following Abreha (2019), Caselli (2018), Castellani et al. (2010) and Vogel and Wagner (2010), and in order to test self-selection on the entry side of the market, we consider a subsample of firms that are entering importers and non-importers during the period 2007–2018. Moreover, to test self-selection on the exit side of the market, we consider a subsample of firms that are continuing importers and exiting importers during the period of analysis. Controlling for firms' capital stock, employment, year, industry and region fixed effects, we estimate the following equation of lagged values of productivity ω_{it-s} on current import status d_{it}.

$$\omega_{it-s} = \beta_0 + \beta_1 d_{it} + \beta_2 k_{it-s} + \beta_3 l_{it-s} + \beta_4 ControlVariables + \varepsilon_{it-s}; s = 1, 2, 3. \qquad (11)$$

[11]To learn how the matching is done, see Mallick and Yang (2013) and Girma et al. (2004). We first identify the probability of importing (or 'propensity score') for all firms by using a probit model. Then, for each treated firm, the matched untreated (control) firm is in the same industry, same year and same state as the matched treated firm. We employ the kernel matching method.

[12]Camino-Mogro et al. (2022) use a similar approach for testing the learning-by-exporting hypothesis. Moreover, this approach is only used as a robustness of our main specification in Equations (1) and (2).

Our main coefficient of interest is β_1, which represents whether there is self-selection on the entry or exit side of the market. For the case to test self-selection on the entry side of the market, we estimate Equation (11) with a subsample of firms explained above where the dummy variable d_{it} takes the value 1 the year a firm enters import intermediates, and the value zero for all the years which have data on non-importers during the sample period. For entering importers, we do not include observations of sample years before and after the entry year in the estimation sample. By contrast, we use all the period observations for non-importers during the sample period. If $\beta_1 > 0$ and statistically significant at standard levels, then there is evidence of pre-entry productivity premia and support for the selection of more productive firms into import markets (selection into entry). The idea behind this approach is that s years before starting to import, firms that import might be more productive than their non-importing counterparts. Also, this shows the average percentage difference between today's importers and today's non-importers s years before starting to import (Caselli, 2018; Castellani et al., 2010).

For the case to test self-selection on the exit side of the market, we estimate Equation (11) with a subsample of firms explained above where the dummy variable d_{it} takes the value 1 if the firm exits from importing in period t and zero for all the years of the subsample of continuing importers. For exiting importers, we do not include sample observations of sample years before and after the exit year in the estimation. By contrast, we use all the period observations for continuing importers during the whole sample period. If $\beta_1 < 0$ and statistically significant at standard levels, then there is evidence of selection on the exit side of the market, which suggests that the average pre-productivity of continuing importers is greater than the pre-productivity of exiting exporters. Again, the idea behind this approach is that s years before exiting from importing, firms might be less productive than continuing importers. Also, this shows the average percentage difference between today's exiting importers and today's continuing importers s years before exiting from importing.

To perform this analysis, firms are classified into four different categories according to their importing decisions: (1) continuing importers (firms that import over the entire period), (2) entering importers (firms that become importers during the period), (3) exiting importers (firms that exit the international market and do not re-enter) and (4) non-importers (firms that do not import during the period).

4 | DATA, VARIABLES AND DESCRIPTION

We use novel, underexplored, unbalanced panel data compiled from the balance sheets and financial statements of Ecuadorian manufacturing firms from 2007 to 2018 and registered on the official website of the Superintendencia de Compañías, Valores y Seguros (SCVS).[13] This information is reported annually by firms to the SCVS. It contains detailed information about the geographical location, the industry (economic activity) based on the ISIC Rev. 4, the date of firm creation and death, and the economic and financial accounts of all formal Ecuadorian firms.

[13]We use administrative data from firms' financial statements in contrast to most studies, which use surveys. There are several advantages of using administrative data in our case. First, we do not use a representative sample but instead use the entire universe of manufacturing firms. Second, firms self-report the information; nevertheless, this information is doubly analysed since it serves the tax administration and the supervisory institution of companies, so accounting errors are usually minimal. Third, we can track firms over time and detect market exits and entries, something that is limited in surveys.

From here, we obtain our variables of interest such as gross revenue, net tangible assets (capital stock), investments, number of formal employees, domestic intermediates purchases, foreign intermediates purchases, electricity, fuels and many other firm characteristics (e.g., age, wages, exports, region, state, city location and firm size, which is measured as amount of gross revenue or as number of employees), all measured in real values (using the respective annual price deflater).

Like Camino-Mogro et al. (2018, 2021), who use a similar database of Ecuadorian manufacturing firms, we first proceeded to debug the financial statements by eliminating all firms that had reported values less than or equal to 0 in gross revenue, number of formal workers, total fixed assets or consumption of intermediate inputs. Firms that had reported the number of formal workers but zero values in wages were eliminated as well. Finally, firms that were inactive in all the years of analysis were also eliminated. In Table A1, in the Appendix 1-3, we show how the main variables used for the estimation of the production function and the TFP were constructed.

After cleaning the data, the unbalanced panel dataset contained 36,061 observations and 5745 formal firms. As we are interested in exploring industrial heterogeneity, we also divided the dataset into two different industry classifications: the Pavitt (1984) Taxonomy and the OECD technological intensity classification. The Pavitt Taxonomy can be classified by sources of technology, requirements of users and possibilities for appropriation. This definition has implications for our understanding of the sources and directions of technical change, the diversification behaviour of firms, the dynamic relationship between technology and industrial structure and the formation of technological skills and advantages at firm, region and country levels (Pavitt, 1984). In Table A2, in the Appendix 1, the disaggregation of each industry is shown. For the technological intensity classification, we use the traditional disaggregation of technology industry proposed by the OECD. In Table A3, in the Appendix 1, the grouping of each industry is shown.[14]

Similar to Zhang (2017), we are also interested in the consumption of intermediate inputs and the quantity of them that are imported from foreign countries. In the data, intermediate input refers to the summation of a list of inputs which the firm is allowed to write for 'raw materials, materials, and packaging'. This includes expenditure on raw materials such as water, electricity, maintenance, repair of goods and gasoline, but does not include 'general expenses' such as professional services and advertising, all of which are reported separately. Also, firms are allowed to import some of their intermediate inputs from abroad and use both domestic and imported intermediate inputs in their production.

Table 1 shows mean values for many firm characteristics. The difference between importers and non-importers with regard to gross revenue, number of formal employees, capital stock, intermediate inputs, domestic and foreign intermediates, TFP, exports, wages and age is very large, and this trend is maintained when firms are broken down by size. This suggests that size differentials between importers and non-importers are substantial. Importing firms generate more gross revenue, employment, wages and exports and consume more intermediate inputs than non-importers. On average, importers are 14.65 times larger than non-importers in terms of gross revenue, eight times larger in terms of employment and 14 times larger with regard to capital stock. The difference is slightly larger for total intermediates, where importers are 22 times larger

[14]For the purpose of this paper, we group the medium-high tech industry and high-tech industry into one, because there are few observations in this latter industry group. Also, the high-tech industry in the OECD is different from that in Ecuador.

TABLE 1 Mean characteristics for importers and non-importers

	All firms		Large firms		MSME firms	
Variable	**Importers**	**Non-importers**	**Importers**	**Non-importers**	**Importers**	**Non-importers**
Y	29.30	2.00	46.80	20.90	2.28	0.66
L	231	29	352	204	43	16
K	8.54	0.60	13.50	6.21	0.83	0.20
M	16.70	0.76	26.70	8.85	1.20	0.19
D	7.61	0.76	12.20	8.85	0.56	0.19
F	9.07	0.00	14.50	0.00	0.65	0.00
TFP	10.88	10.03	11.19	10.81	10.35	9.97
Exports	4.14	0.34	6.85	4.75	0.11	0.03
Wages	1.83	0.14	2.86	1.34	0.25	0.05
Age	29	12	33	20	24	12

Note: Importers are defined as continuing over the entire period. Values are in millions of US dollars, except for workers (L), which is in number of people. TFP is in logarithms. *Source*: Superintendencia de Compañías, Valores y Seguros.

TABLE 2 Transition probabilities of international trade activities

	Status *t*+1		
	Non-importers	**Importers**	**Total**
Status *t*			
Non-importers	96.02	3.98	100
Importers	11.80	88.20	100
Total average	72.94	27.06	100
	Non-exporters	**Exporters**	**Total**
Status *t*			
Non-exporters	97.08	2.92	100
Exporters	14.89	85.11	100
Total average	83.27	16.73	100

Source: Superintendencia de Compañías, Valores y Seguros.

than non-importers. Also, importers have better access to international markets because they are 12 times larger than non-importers in value of exports. Additionally, they pay better wages since they are 13 times larger than non-importers and have more experience in the market. Finally, importers have higher TFP than non-importers (1.1 times) in the whole sample. When we break down the sample into large and micro, small and medium enterprises (MSME), the differences between importers and non-importers are similar. These preliminary results are in concordance with the exhaustive literature: Importers have better economic and productive performance than non-importers.

Table 2 presents transition probabilities across import and export status separately. There is a high persistence in import status because more than 96% of firms that did not import in year *t* did not import in year *t*+1, while about 88% of firms that did import intermediates in year *t* did import in year *t*+1. Something similar happens when we analyse persistence in export status because there is a high dependence of firms that sell in domestic markets (97.08%) and firms that sell in foreign markets (85.11%). Additionally, it is shown that the probability of transition from being a non-importer at time *t* to an importer at *t*+1 (3.98%) is less than going from being an importer to a non-importer (11.80%), and something similar occurs with the status of exporter. This shows that entering the international market is more complex than leaving the international market, perhaps because of the sunk costs that exist when entering international trade.

Additionally, Tables 3 and 4 show transition probabilities across import and export status by the Pavitt Taxonomy and the OECD technological intensity classification, respectively. Here we show that there is a high persistence in import status because more than 95% of firms that did not import in year *t* did not import in year *t*+1, while 87% of firms that did import intermediates in year *t* imported in year *t*+1 in each industry of the Pavitt Taxonomy and the OECD technological intensity classification. Something similar happens when we analyse persistence in export status because there is a high dependence of firms that sell in domestic markets (more than 96%) and firms that sell in foreign markets (more than 80%). Again, it is shown that the probability of transition from being a non-importer at time *t* to an importer at *t*+1 (about 3%) is less than going from being an importer to a non-importer (11%). Something similar occurs with the status of exporter in each industry of the Pavitt Taxonomy and the OECD technological intensity classification (Table A5, in the Appendix 1).

TABLE 3 Transition probabilities of international trade activities: Pavitt Taxonomy

	Status *t*+1							
	Scale-intensive		**Science-based**		**Specialised suppliers**		**Supplier-dominated**	
	Non-importers	**Importers**	**Non-importers**	**Importers**	**Non-importers**	**Importers**	**Non-importers**	**Importers**
Status *t*								
Non-importers	96.55	3.45	95.07	4.93	98.78	1.22	93.99	6.01
Importers	12.71	87.29	10.79	89.21	12.35	87.65	11.40	88.60
Total average	77.07	22.93	66.33	33.67	90.74	9.26	63.25	36.75
	Non-exporters	**Exporters**	**Non-exporters**	**Exporters**	**Non-exporters**	**Exporters**	**Non-exporters**	**Exporters**
Status *t*								
Non-exporters	97.21	2.79	96.93	3.07	97.35	2.65	96.83	3.17
Exporters	12.60	87.40	18.10	81.90	24.79	75.21	14.94	85.06
Total average	82.52	17.48	85.49	14.51	90.85	9.15	80.21	19.79

Source: Superintendencia de Compañías, Valores y Seguros.

TABLE 4 Transition probabilities of international trade activities: OECD technological intensity classification

	Status *t*+1					
	Low-tech industry		**Medium-low tech industry**		**Medium-high & High-tech industry**	
	Non-importers	**Importers**	**Non-importers**	**Importers**	**Non-importers**	**Importers**
Status *t*						
Non-importers	95.90	4.10	96.67	3.33	95.32	4.68
Importers	12.70	87.30	11.46	88.54	10.54	89.46
Total average	74.43	25.57	74.74	25.26	66.96	33.04
	Non-exporters	**Exporters**	**Non-exporters**	**Exporters**	**Non-exporters**	**Exporters**
Status *t*						
Non-exporters	96.89	3.11	97.63	2.37	96.71	3.29
Exporters	13.40	86.60	15.26	84.74	19.19	80.81
Total average	80.43	19.57	86.75	13.25	85.21	14.79

Source: Superintendencia de Compañías, Valores y Seguros.

TABLE 5 Transition probabilities of international trade activities

	Non-exporters		Exporters	
	Status $t+1$			
	Non-importers	Importers	Non-importers	Importers
Status t				
Non-importers	96.55	3.45	91.70	8.30
Importers	16.02	83.98	5.41	94.59
Total average	80.97	19.03	34.67	65.33

Source: Superintendencia de Compañías, Valores y Seguros.

In Table 5, we present the transition probabilities of exporting and importing intermediate inputs. Regardless of whether firms export or not, there is a high persistence in import status because more than 96% of firms that did not import and did not export in year *t* did not import in year *t*+1, while about 84% of among the firms that did import intermediates and did not export in year *t* did import in year *t*+1. Furthermore, when firms exported and did not import in year *t*, more than 91% of them did not import in year *t*+1, while about 94% of firms that did import intermediates and did export in year *t* imported in year *t*+1. This shows that the probability of continuing to import intermediate inputs increases when the firm exports. Therefore, exporting helps keep importing, as we mentioned in Section 3.

Furthermore, in Table A4, in the Appendix 1, we present the main descriptive statistics for the output and inputs involved in the analysis, also considering differences by year, firm size, industries and cities. The table shows that the mean output (gross revenue) was approximately equal in 2007, 2012 and 2018. However, the input variables showed a different trend: capital stock and labour are larger in 2018 than in the other years, but there are fewer domestic and foreign intermediates in 2018. In terms of size, it is shown that the larger the firm is, the more output and inputs it has. This is in line with larger firms' needing more inputs for production and given that the size of the firm is measured according to sales, this behaviour is logical and expected. With regard to the different industry classifications, scale-intensive industries (in the Pavitt Taxonomy) had the most inputs and output on average during the period 2007–2018, except for foreign intermediates, where the science-based industry is the largest. This is also in line with the development of Ecuadorian industry, where the economy is dependent primarily on commodities and also has little added value. Regarding technological innovation industries, the low-tech industry has more output and inputs than the other industries, except for foreign intermediates. Finally, we show the descriptive statistics for the three most important cities in Ecuador, where there is no clear pattern to the use of inputs.[15] Finally, correlations between export, import intermediate inputs and TFP are positive and statistically significant at the 1% level, ranging from 0.31 to 0.45 for the whole manufacturing sector and for each industry of the Pavitt Taxonomy and the OECD technological intensity classification. Interestingly, more innovative industries present higher correlations between the three variables than less innovative industries.

[15]In Appendix 2, we present an overview of imports and productivity in Ecuador.

5 | RESULTS

In this section, we present the main results. First, we show the results from OLS and our modified LP estimator using the discrete choice import variable (d_{it}) and two continuous measures of import variables, (n_{it}) and (FI_{it}).[16] The variable (n_{it}) corresponds to the theoretical model of Kasahara and Rodrigue (2008), and the variable (FI_{it}) is similar to Abreha's (2019) assumption that this variable captures the intensity of the use of foreign intermediates among importing firms. Our modified Levinsohn and Petrin (2003) method is augmented by the decision to export (x_{it}) and a continuous measure of export activity (EI_{it}). Second, we present the results by two industry classifications: the Pavitt Taxonomy and the OECD technological intensity classification. We use only the Levinsohn and Petrin (2003) method with the modification that we explained in Section 3 for that part. Third, we analyse the complement-substitute relationship between domestic and imported inputs. Finally, we present a formal test to identify whether there is self-selection into the import market on the entry or exit side and also a robustness check for the learning-by-importing process. For the last exercise, we use matching techniques in order to give causal interpretations as a robustness check of our main specification.

5.1 | Static and dynamic effects of imports on productivity

Table 6 shows the results of OLS and our modified Levinsohn-Petrin (LP) estimator,[17] which uses three different variables for imports: a discrete variable (d_{it}) and two continuous variables, (n_{it}) and (FI_{it}). It also includes two different variables for exports: a discrete variable (x_{it}) and one continuous variable, (EI_{it}). Columns (1) and (2) present the parameter estimates where importing and exporting are treated as discrete variables. The OLS result in column (1) shows that all input coefficients (elasticities) are positive and significant. However, the discrete import variable (d_{it}) is not statistically significant at standard levels. In addition, we show that compared with our modified LP estimator in column (2), the OLS estimator biases all the estimated inputs upwards. This is because of the endogeneity problem of the labour and intermediates choices that are dependent on ω_{it}.[18] To relax the restrictive assumptions of OLS, our modified LP estimator is applied to correct the simultaneity and endogeneity problems. We impose a richer structure in the form of the endogenous productivity process to control for both selection and correlation between inputs and the unobserved productivity shock by using intermediate inputs as proxies for the shock (Kasahara & Rodrigue, 2008).

Column (2) of Table 6 reports the LP estimator by using a linear first-order Markov process of (ω_{it-1}, d_{it-1}, x_{it-1}) as in Equation (2). The estimated coefficients of inputs are positive and statistically significant at standard levels. However, we find that there is no immediate (static) effect on productivity from the use of imported intermediate inputs (d_{it}), but there is an immediate improvement (static effect) of 38.8% in productivity that comes from being an

[16]Results from FE and LP estimators with an exogenous import variable are available upon request.

[17]We perform our estimations using the *prodest* command of Stata, developed by Rovigatti and Mollisi (2018).

[18]When we use the FE estimator, the results are similar to the OLS estimator. Again, this estimator does not address the simultaneity between inputs and productivity shocks.

TABLE 6 Effect of import–export decision and import intensity on TFP

	OLS	LP	OLS	LP	OLS	LP
	(1)	(2)	(3)	(4)	(5)	(6)
Estimators	(Discrete import variable)		(Continuous import variable)			
k_{it}	0.125***	0.104***	0.130***	0.135***	0.132***	0.157***
	(0.012)	(0.029)	(0.012)	(0.032)	(0.012)	(0.033)
l_{it}	0.378***	0.308***	0.394***	0.312***	0.396***	0.311***
	(0.012)	(0.011)	(0.013)	(0.011)	(0.013)	(0.011)
m_{it}	0.333***	0.230***	0.332***	0.229***	0.338***	0.249***
	(0.008)	(0.019)	(0.008)	(0.023)	(0.008)	(0.022)
d_{it}	0.030	0.006				
	(0.027)	(0.020)				
n_{it}			0.071***	0.085***		
			(0.018)	(0.019)		
FI_{it}					0.027***	0.046**
					(0.008)	(0.020)
x_{it}	0.375***	0.388***				
	(0.033)	(0.019)				
EI_{it}			0.326***	0.326***	0.325***	0.343***
			(0.094)	(0.018)	(0.093)	(0.018)
P		0.820***		0.796***		0.758***
		(0.014)		(0.022)		(0.029)
H		0.041***		0.038***		0.004**
		(0.005)		(0.004)		(0.002)
Φ		0.055***		0.078***		0.072**
		(0.005)		(0.029)		(0.029)
Implied $\frac{\eta}{1-\rho}$		0.228		0.186		0.017
Implied θ			5.676	3.694		
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	28,602	28,602	28,602	28,602	28,602	28,602

Note: Standard errors in parentheses clustered at the firm level with 300 bootstrapped replications in LP estimations. The Levinsohn-Petrin estimator uses the stochastic process of ω_t of Equation (2) for discrete import, Equation (7) for continuous import and Equation (9) for import intensity variables.*$p<.10$, **$p<.05$, ***$p<.01$.

exporter.[19] This evidence is not unexpected because firms might need to adjust their production structure to benefit from the technology transfer that comes from importing intermediate inputs (Abreha, 2019; Camino-Mogro & López, 2021; Smeets & Warzynski, 2013). Furthermore,

[19]When we do not control for the decision to export (x_{it}), we find that $\delta>0$ and significant. This also indicates a productivity effect of 3%, which comes from the use of imported intermediate inputs. This result is shown in Table A6 in Appendix 1.

Kasahara and Lapham (2013) and Zaclicever and Pellandra (2018) argue that failing to control for the linkages between importing and exporting might lead to an upward bias in the coefficient of imported inputs, as we can see in Table A6 in the Appendix 1. Additionally, our results show that the immediate gains in productivity are greater for exporting. We conjecture that this might be because imported intermediates need to be introduced into the production process, and the absorptive capacity of the technology transfer of Ecuadorian firms seems to be slow.[20] Moreover, we find that the estimated value of η is positive and significant (4.1%). This suggests a positive dynamic effect of the past import decision on productivity, which supports the learning-by-importing hypothesis. It is also shown that there is strong persistence in the evolution of productivity, as $\rho = .820$. Finally, the estimates of $\frac{\eta}{1-\rho}$ show that long-run effects of importing predict a firm productivity improvement of 22.8% when the discrete import variable is analysed.[21]

In columns (3) and (4) in Table 6, we show the results by using the continuous measure of import intermediates proposed by Kasahara and Rodrigue (2008). This measure is the ratio of total intermediate inputs to domestic intermediate inputs, $n_{it} = \left(ln\frac{M_{it}}{M_{it}^h} \right)$, in logarithms. Also, we include the continuous measure of exports proposed by Navas et al. (2020). This measure is the ratio of total sales to domestic sales, $EI_{it} = \left(ln\frac{Sales_{it}}{Sales_{it}^h} \right)$, in logarithms. Thus, we estimate Equations (6) and (7) to capture the static and dynamic effects of importing and exporting, which depend on the number of imported intermediates used relative to domestic intermediates (import participation) and export participation. The variable n_{it} implies that a higher ratio of total intermediates to domestic intermediates leads to higher production levels, contrary to the traditional production function, where this variable is total intermediates consumption and does not differentiate between domestic and foreign intermediates. Also, the variable EI_{it} implies that a higher ratio of total sales to domestic sales leads to higher production levels.

The modified LP estimator reported in column (4) supports an important impact of an increase in the share of imported intermediates on productivity since after controlling for export participation, year, industry and region (location), we obtain robust evidence that a 100% decrease in the share of domestic intermediates to total intermediates increases productivity by 8.5% (static effect). Again, this evidence supports the significant effect of using foreign intermediate inputs on firm production in Ecuadorian manufacturing firms. This result is similar to, though less pronounced than, those of Kasahara and Rodrigue (2008), who found that a 100% decrease in the share of domestic intermediates increases productivity by 17.7% to 27% in Chilean manufacturing plants. Furthermore, our results suggest a positive dynamic effect (3.8%) of past use of a higher ratio of total intermediates to domestic intermediates on productivity, which supports the learning-by-importing hypothesis. Again, it is also shown that there is strong persistence in the evolution of productivity: $\rho = .796$. Moreover, the estimates of $\frac{\eta}{1-\rho}$ show that the long-run dynamic effect of a 100% decrease in the share of domestic intermediates is 18.6%. In addition,

[20]This issue is not formally tested in this paper because of data ability constraints.

[21]We also estimate our augmented production function with the modification in the law of motion of productivity by using the Wooldridge (2009) estimator. The results are very similar in magnitude and significance and are available upon request.

our results suggest that there is an immediate improvement (static effect) of 32.6% and a dynamic effect (learning-by-exporting) of 7.8% that comes from being an exporter.[22]

According to the second measure of the continuous imports variable (FI_{it}) that was proposed by Abreha (2019) and Zaclicever and Pellandra (2018) and which captures the effect of the relative weight of foreign intermediates (import intensity), we shown in columns (5) and (6) in Table A6 the results of this estimation. To deal with the fact that firms may anticipate the impact of imports on their productivity as described by Abreha (2019) and Zaclicever and Pellandra (2018), we estimate Equation (8), which implies that a higher ratio of total intermediates to domestic intermediates leads to higher production levels, for $FI_{it} = ln\frac{F_{it}}{M_{it}}$, which is the share of foreign intermediate inputs (or its 'intensity') in total intermediates. This adaptation in Equation (8) does not capture the elasticity of substitution. Nevertheless, the results obtained from this specification allow us to confirm the results obtained using the Kasahara and Rodrigue (2008) approach and provide robustness of our evidence of the effect of imported intermediate inputs on productivity.

Moreover, we estimate Equation (8) using our modified LP estimator, which modifies the law of motion of productivity as in Equation (9), and find that a 100% increase in the share of imported intermediates increases firm productivity by 4.6% immediately (static effect), when controlling for export intensity. Our results are similar to those of Abreha (2019), who found that the import intensity ratio increased productivity by 15.5% to 18.5% in Ethiopian manufacturing firms. Zaclicever and Pellandra (2018) also found evidence in favour of a positive association (with similar magnitudes) between imported intermediate inputs intensity and firms′ productivity for the case of Uruguayan manufacturing firms. In addition, column (6) shows that there is a positive dynamic effect (0.4%) of past import intensity on productivity, which supports the learning-by-importing hypothesis. Again, it is also shown that there is a strong persistence in the evolution of productivity: $\rho = .758$. Finally, the estimates of $\frac{\eta}{1-\rho}$ show that the long-run dynamic effect of a 1% increase in the intensity of using imported intermediates is 1.7%. Also, our results suggest that there is an immediate improvement (static effect) of 34.3% and learning-by-exporting (dynamic effect) of 7.2% in productivity that comes from the exporting intensity.[23]

Overall, we find that there are static and dynamic gains in productivity by importing intermediates and exporting. In addition, our results are very similar when we use discrete or continuous import and export variables with our modified LP estimator. Furthermore, in all the cases, we find evidence in favour of the learning-by-importing and learning-by-exporting hypotheses. Finally, our results suggest that the learning-by-exporting process is longer than the learning-by-importing process. In particular, we find that there is a positive dynamic effect of exporting on productivity since $\varphi > 0$ and ranges from 5.5% to 7.8% depending on the import variable analysed. Our evidence is in concordance with authors who suggest that firms involved in international trade activities (both exporting and importing) have larger gains in productivity (Castellani et al., 2010; Kasahara & Lapham, 2013; Muûls & Pisu, 2009; Wagner, 2013), but the gains are

[22]When we do not control for export participation (EI_{it}), we find $\psi > 0$ and significant which also indicates that a 100% decrease in the share of domestic intermediates to total intermediates increases productivity by 5.5% (static effect) and has a learning-by-importing effect of 3.3%. This result is shown in Table A6 in the Appendix 1.

[23]When we do not control for export intensity (EI_{it}), we find $\mu > 0$ and significant which also indicates that a 100% increase in the share of imported intermediates increases firm productivity by 5% (static effect) and a learning-by-importing effect by 0.2%. This result is shown in Table A6 in the Appendix 1.

larger also because there is complementarity between exports and import intermediates in determining productivity (Camino-Mogro & López, 2021).[24]

5.2 | Industrial heterogeneity: Static and dynamic effects of imports on productivity

In order to show that there might be some industrial heterogeneity in the static and dynamic effects of imports on productivity, we present our results for two industry classifications (the Pavitt Taxonomy and industries according to the OECD technological intensity classification) using only our modified LP estimator. We rely on these classifications because the taxonomy presented by Pavitt has a different purpose from the traditional classifications (e.g., firm size, the nature of the products, durable and non-durable products and consumption and investments goods) since it is devoted to classifying firms on the grounds of their technological competence. Pavitt's taxonomy competes with (and has often replaced) another technology-based classification which has long been very popular, namely, the grouping of industries according to their R&D intensity (i.e. high, medium and low R&D-intensive industries) (Archibugi, 2001). In this sense, the grouping of firms by these two classifications allows us to address the heterogeneity of the effect of the imported intermediates that may exist between firms that are farther from or closer to the technological frontier, as a proxy of innovation. Furthermore, the classification in these two groups is relevant for the Ecuadorian manufacturing sector because it allows us to make international comparisons with other countries.

In Table 7, the results of the static and dynamic effects of the three measures of import variables on productivity are presented for the Pavitt Taxonomy. Using the discrete import variable d_{it}, we show that for the science-based industry, there is a negative and significant effect of imported intermediates of 13.8% on productivity. Also, for the specialised-suppliers industry, the discrete import variable suggests a negative static effect of 43.6% on productivity, an unexpected result. Nevertheless, firms in this industry might need to adjust their production structure to benefit from the availability of cheaper and probably better imported intermediates (Abreha, 2019). On the other hand, using imported intermediates in the scale-intensive and supplier-dominated industries has a positive effect of 14.1% and 3.9%, respectively. Moreover, the elasticities of the traditional inputs are different across industries, but in all the cases, labour input is the dominant input. The different results of the effect of imports on output suggest heterogeneity in the use of foreign intermediates across Pavitt industries.

Moreover, our results suggest that there is a learning-by-importing process since the estimated values of η are positive and significant (with the exception in the specialised-suppliers industry), ranging from 3.6% to 4.3% depending on the industry analysed. We find strong persistence in the evolution of productivity in all the industries as we do in the whole manufacturing sector; ρ ranges from .608 to .849. Finally, we find that the long-run dynamic effect of importing intermediates predicts an improvement in firm productivity that ranges from 1.8% to 28.5% depending on the industry. Furthermore, there is an immediate improvement (static effect) of 27.3% to 59.3% in productivity (depending on the industry analysed) that

[24]Also, Zhang (2017) found that the learning-by-exporting process is longer than the learning-by-importing process in Colombian manufacturing firms. Moreover, and similar to Zhang (2017), to make sure that our estimates of the gains from importing are not due to exporting, we further conduct robustness checks by performing the same estimation on a subsample of firms which do not export. The subsample results are similar to what we find in the whole sample. This indicates that our results on the gains from importing are robust.

TABLE 7 Effect of import–export decision and import intensity on TFP: Pavitt Taxonomy

	Scale-intensive	Science-based	Specialised suppliers	Supplier-dominated
Discrete import variable				
k_{it}	0.124***	0.034	0.177***	0.049
	(0.029)	(0.040)	(0.012)	(0.032)
l_{it}	0.274***	0.373***	0.385***	0.296***
	(0.015)	(0.032)	(0.031)	(0.020)
m_{it}	0.244***	0.312***	0.228***	0.243***
	(0.023)	(0.030)	(0.017)	(0.030)
d_{it}	0.141***	−0.138***	−0.436***	0.039***
	(0.021)	(0.017)	(0.010)	(0.014)
x_{it}	0.273***	0.464***	0.593***	0.282***
	(0.018)	(0.018)	(0.011)	(0.014)
ρ	0.828***	0.827***	0.608***	0.849***
	(0.016)	(0.018)	(0.159)	(0.011)
η	0.036***	0.042***	0.007	0.043***
	(0.007)	(0.010)	(0.038)	(0.006)
ϕ	0.049***	0.040***	0.023	0.050***
	(0.007)	(0.015)	(0.020)	(0.007)
Implied $\frac{\eta}{1-\rho}$	0.209	0.243	0.018	0.285
Continuous import variable: n_{it}				
k_{it}	0.123***	0.027	0.145***	0.103**
	(0.030)	(0.040)	(0.015)	(0.041)
l_{it}	0.278***	0.387***	0.397***	0.297***
	(0.017)	(0.035)	(0.035)	(0.020)
m_{it}	0.245***	0.277***	0.213***	0.217***
	(0.023)	(0.034)	(0.017)	(0.037)
n_{it}	0.115***	0.077***	0.032***	0.104***
	(0.022)	(0.019)	(0.011)	(0.016)
EI_{it}	0.285***	0.269***	0.384***	0.382***
	(0.021)	(0.019)	(0.012)	(0.017)
ρ	0.856***	0.862***	0.625***	0.809***
	(0.016)	(0.020)	(0.097)	(0.019)
η	0.043***	0.054***	0.003	0.044***
	(0.006)	(0.016)	(0.002)	(0.006)
ϕ	0.027**	0.182**	0.310***	0.180***
	(0.015)	(0.085)	(0.116)	(0.057)
Implied $\frac{\eta}{1-\rho}$	0.299	0.391	0.0001	0.230
Implied θ	3.130	4.597	7.656	3.086

(Continues)

TABLE 7 (Continued)

	Scale-intensive	Science-based	Specialised suppliers	Supplier-dominated
Continuous import variable: FI_{it}				
k_{it}	0.126***	0.022	0.139***	0.104**
	(0.032)	(0.042)	(0.013)	(0.042)
l_{it}	0.276***	0.391***	0.393***	0.295***
	(0.017)	(0.035)	(0.034)	(0.020)
m_{it}	0.246***	0.299***	0.214***	0.228***
	(0.025)	(0.035)	(0.017)	(0.038)
FI_{it}	0.023	0.091***	0.238***	0.032*
	(0.017)	(0.017)	(0.011)	(0.017)
EI_{it}	0.201***	0.290***	0.387***	0.381***
	(0.021)	(0.021)	(0.012)	(0.017)
ρ	0.859***	0.868***	0.641***	0.829***
	(0.016)	(0.015)	(0.089)	(0.021)
η	0.005*	0.006**	0.027	0.005*
	(0.003)	(0.003)	(0.032)	(0.003)
ϕ	0.015*	0.147*	0.336***	0.166***
	(0.009)	(0.082)	(0.119)	(0.062)
Implied $\frac{\eta}{1-\rho}$	0.035	0.045	0.075	0.029
No. of obs.	12,502	4561	3343	8196

Note: Standard errors in parentheses clustered at the firm level with 300 bootstrapped replications. The Levinsohn-Petrin estimator uses the stochastic process of ω_t of Equation (2) for discrete import, Equation (7) for continuous import and Equation (9) for import intensity variables. We include year fixed effects, industry fixed effects (two-digit ISIC Rev. 4.0), and region fixed effects. $^*p<.10$, $^{**}p<.05$, $^{***}p<.01$.

comes from being an exporter. Additionally, we find evidence in favour of the learning-by-exporting hypothesis in all the industries except the specialised-suppliers industry. Overall, we find evidence in favour of static and dynamic effects of the import decision on productivity. In this line, importing firms engaged in innovative industries have the largest dynamic gains from importing.[25]

Additionally, Table 7 reports the results for the use of the continuous measure of imports n_{it} in the production function controlling for an export intensity variable EI_{it}. We show that the traditional inputs are very similar (in magnitude and significance) to the results reported when we use the discrete variable d_{it}. Also, we find evidence that supports an important impact of an increase in the share of imported intermediates on productivity (static effect). A 100% decrease in the share of domestic intermediates in total intermediates increases productivity from 3.2% to 11.5% depending on the industry. Furthermore, we find evidence in favour of the learning-by-importing hypothesis (dynamic effect), which ranges from 4.3% to 5.4% depending on the

[25]Table A7 in the Appendix 1 shows the results when we do not control for the discrete export variable (x_{it}) or export intensity (EI_{it}). The results of the static and dynamic effects of imported intermediates on productivity are similar in each Pavitt taxonomy.

industry analysed. The only industry in the Pavitt Taxonomy where there are no learning effects is the specialised-suppliers industry, where the estimated value of η is not statistically significant at standard levels. Again, we find strong persistence in the evolution of productivity in all the industries: ρ ranges from .625 to .862. In addition, we find that the long-run dynamic effect of a 100% decrease in the share of domestic intermediates ranges from 0.001% to 39.1% depending on the industry when the continuous import variable (n_{it}) is analysed. Also, we find evidence in favour of static and dynamic effects of export intensity on productivity in each Pavitt taxonomy.

Furthermore, we compare the evidence we obtained using n_{it} by using the FI_{it} variable in each industry. Again, the results of the coefficients of traditional inputs are quite similar to the other specifications. Our variable of interest, FI_{it}, which captures the intensity of imported intermediates (static effect) on firm production and productivity, is always positive and significant, except in the scale-intensive industry, where it is not statistically significant at standard levels. This result is in concordance with the theoretical framework of Kasahara and Rodrigue (2008), not only in the whole manufacturing sector but also when we desegregate with the Pavitt Taxonomy. Okafor et al. (2017) argue that international access to foreign inputs is one of the channels for enhancing productivity; they suggest that firms in industries such as machinery have high levels of absorptive capacity and are better positioned than other industries to enjoy productivity gains from the use of imported intermediates. Similar to the other specifications, our results suggest that there is strong persistence in the evolution of productivity in all the industries: ρ ranges from .641 to .868. Again, we find evidence in favour of the learning-by-importing hypothesis (dynamic effect) in three industries: scale-intensive (0.5%), science-based (0.6%) and supplier-dominated (0.5%).

Our results in the Pavitt Taxonomy suggest that there is a heterogeneity effect of the dynamics of importing on TFP that comes from specialisation in different industries, but also that in some industries (specialised suppliers), there are no learning effects regardless of the import variable analysed when we control for export intensity static and dynamic effects. In general, our results suggest that importing firms that operate in innovative industries (science-based) have higher dynamic effects of importing than firms that operate in labour-intensive industries.[26]

Finally, the results by the OECD technological intensity classification are shown in Table 8. We present the estimates with the three measures of imported intermediates, controlling for the export dummy and the export intensity variables. In general, our results are very similar to the Pavitt Taxonomy and the evidence obtained from the whole manufacturing sector.

The results of the coefficients of traditional inputs are quite similar to the three specifications of the production function (d_{it}, n_{it}, FI_{it}) in Table 8. Our results support the idea that firms that operate in high-tech sectors are likely to have a higher static effect in productivity due to importing than firms involved in low-tech sectors. The static effect of importing intermediates on productivity ranges from 5.3% (low-tech industry) to 14.6% (medium-high and high-tech industries) when we use the discrete import variable d_{it}. Moreover, our evidence supports the learning-by-importing hypothesis in the three OECD technological intensity classifications since $\eta > 0$, which suggests that there is a positive, dynamic effect of the past import decision on productivity, an effect that ranges from 3% to 4.1%. Again, importing firms engaged in innovative industries have the largest gains from importing. Also, we find strong persistence in

[26]This evidence is similar to the results found by Camino-Mogro et al. (2022), who suggest that firms that operate in innovative sectors are likely to have higher static and dynamic effects in productivity because of exporting than firms involved in less innovative sectors.

TABLE 8 Effect of import–export decision and import intensity on TFP: OECD technological intensity classification

	Low-tech industry	Medium-low tech industry	Medium-high and High-tech industry
Discrete import variable			
k_{it}	0.109***	0.044***	0.035
	(0.036)	(0.016)	(0.051)
l_{it}	0.277***	0.303***	0.383***
	(0.014)	(0.019)	(0.029)
m_{it}	0.240***	0.246***	0.281***
	(0.027)	(0.012)	(0.040)
d_{it}	0.053***	0.054***	0.146***
	(0.017)	(0.012)	(0.020)
x_{it}	0.245***	0.426***	0.447***
	(0.017)	(0.015)	(0.017)
ρ	0.858***	0.844***	0.849***
	(0.011)	(0.012)	(0.014)
η	0.030***	0.030***	0.041***
	(0.005)	(0.009)	(0.010)
ϕ	0.051***	0.061***	0.042***
	(0.006)	(0.010)	(0.012)
Implied $\frac{\eta}{1-\rho}$	0.211	0.192	0.272
Continuous import variable: n_{it}			
k_{it}	0.127***	0.107***	0.032
	(0.045)	(0.018)	(0.047)
l_{it}	0.279***	0.307***	0.396***
	(0.014)	(0.021)	(0.032)
m_{it}	0.242***	0.235***	0.279***
	(0.034)	(0.014)	(0.037)
n_{it}	0.051**	0.114***	0.075***
	(0.024)	(0.017)	(0.020)
EI_{it}	0.220***	0.349***	0.306***
	(0.019)	(0.017)	(0.015)
ρ	0.856***	0.749***	0.849***
	(0.016)	(0.032)	(0.019)
η	0.026***	0.044***	0.049***
	(0.005)	(0.008)	(0.011)
ϕ	0.054**	0.314**	0.129***
	(0.026)	(0.129)	(0.049)
Implied $\frac{\eta}{1-\rho}$	0.180	0.175	0.325
Implied θ	5.745	3.061	4.720

TABLE 8 (Continued)

	Low-tech industry	Medium-low tech industry	Medium-high and High-tech industry
Continuous import variable: FI_{it}			
k_{it}	0.122***	0.109***	0.029
	(0.045)	(0.017)	(0.052)
l_{it}	0.278***	0.307***	0.395***
	(0.014)	(0.020)	(0.032)
m_{it}	0.237***	0.233***	0.264***
	(0.035)	(0.013)	(0.039)
FI_{it}	0.014	0.072***	0.121***
	(0.020)	(0.013)	(0.018)
EI_{it}	0.182***	0.685***	0.280***
	(0.027)	(0.017)	(0.017)
ρ	0.864***	0.774***	0.886***
	(0.015)	(0.031)	(0.014)
η	0.004**	0.010**	0.011*
	(0.002)	(0.005)	(0.006)
ϕ	0.048*	0.369***	0.111**
	(0.025)	(0.130)	(0.054)
Implied $\frac{\eta}{1-\rho}$	0.029	0.044	0.096
No. of obs.	14,226	8377	5999

Note: Standard errors in parentheses clustered at the firm level with 300 bootstrapped replications. The Levinsohn-Petrin estimator uses the stochastic process of ω_t of Equation (2) for discrete import, Equation (7) for continuous import, and Equation (9) for import intensity variables. We include year fixed effects, industry fixed effects (two-digit ISIC Rev. 4.0), and region fixed effects. *$p<.10$, **$p<.05$, ***$p<.01$.

the evolution of productivity in all the industries: ρ ranges from .844 to .858. Finally, we find that the long-run dynamic effect of importing intermediates predicts a firm productivity improvement that ranges from 19.2% to 27.2% depending on the industry.[27] Also, we find evidence in favour of static and dynamic effects of exporting on productivity in each OECD technological intensity classification.

Additionally, when we use the continuous measure of imports n_{it} in the production function, we find evidence that supports an important impact of an immediate increase in the share of imported intermediates on productivity. A 100% decrease in the share of domestic intermediates in total intermediates increases productivity from 5.1% to 11.4% depending on the industry. Furthermore, our evidence supports the learning-by-importing hypothesis in the three OECD technological intensity classifications since $\eta > 0$, which suggests that there is a positive, dynamic effect of importing on productivity, an effect that ranges from 2.6% to 4.9%. Again, we find strong persistence in the evolution of productivity in all the industries: ρ ranges from .749 to .856. In

[27]Table A7 in the Appendix 1 shows the results when we do not control for the discrete export variable (x_{it}) or export intensity (EI_{it}). The results of the static and dynamic effects of imported intermediates on productivity are similar in each Pavitt taxonomy.

addition, we find that the long-run dynamic effect of a 100% decrease in the share of domestic intermediates ranges from 17.5% to 32.5% depending on the industry. Furthermore, there is a positive, static effect of the intensity of exports on productivity that ranges from 22% to 35% depending on the industry analysed. In addition, we find evidence in favour of the learning-by-exporting hypothesis (dynamic effect).

Regarding the effect of import intensity FI_{it} in each industry, the variable FI_{it} is always positive and significant for all high-tech industries. Again, this result is in concordance with the theoretical framework of Kasahara and Rodrigue (2008), and also implies that there is an immediate improvement of 7.2% to 12.1% in productivity depending on the industry. Also, our evidence supports the learning-by-importing hypothesis in the three OECD technological intensity classifications since $\eta > 0$, which suggests that there is a positive, dynamic effect of importing on productivity that ranges from 0.4% to 1.1%.

In general, the three different specifications are robust since the traditional inputs are quite similar for each innovative industry. Also, the effect of importing intermediates is always positive independent of using a discrete variable or a continuous measure of imports and controlling for export status and export intensity. However, the effect of imports varies depending on the industry and sectorial classification. This might be because, in some industries, the ability to acquire imported inputs is easier than in other industries, given different industrial policies or simply because the supply of raw materials is faster than in other industries.

Moreover, the productivity effect (static and dynamic) is even larger for more innovative industries than less innovative sectors. We conjecture that R&D investment is stronger in the most innovative industries and industries close to the technological frontier, which allows firms to import intermediates more intensively. This might motivate firms to generate high-quality, innovative products, which in addition might increase productivity. Furthermore, this might help firms operating in these industries to enter the import market and also to learn from importing faster than firms that operate in less innovative industries.[28] Another plausible explanation for this might come from absorptive capacity, which can make it difficult for firms to learn by importing (Abreha, 2019; Okafor et al., 2017).

Finally, we find that the learning-by-exporting process is longer than the learning-by-importing process. Again, this dynamic effect is larger for more innovative industries than less innovative sectors. Overall, our specification is robust whether or not we include the discrete (or the continuous) export variable. In addition, our specification is robust in the analysis of learning effects. Our results are not very comparable with the results in other papers since they do not include the learning-by-exporting process in the law of motion of productivity. Nevertheless, Navas et al. (2020) and Zhang (2017) are some exceptions, but their result that firms that operate in more innovative sectors have larger dynamic effects of the learning-by-importing process did not have a clear pattern. This might be because of the sectoral classification they use (very desegregated), which is one of the criticisms of Pavitt's taxonomy.

5.3 | Complement-substitute relationship between domestic and imported inputs

We estimate Equations (6) and (7) to quantify the elasticity of substitution between foreign and domestic intermediates. Once we obtain the estimated coefficients of intermediate inputs $\overline{\gamma}$ and

[28]However, we are not able to formally test this conjecture because of data availability constraints.

the continuous import variable $\overline{\psi}$, we can compute an estimate of the elasticity of substitution as $\overline{\theta} = \frac{\overline{\gamma}}{\overline{\psi}} + 1$. In columns (3) and (4) in Table A6, we show the elasticity of substitution ($\overline{\theta}$) in the whole Ecuadorian manufacturing sector. Similar to Navas et al. (2020), Kasahara and Rodrigue (2008) and Feenstra et al. (1992) but contrary to Zhang (2017), we obtain that the elasticity of substitution is 3.694 using the modified LP estimator. This result implies that foreign and domestic intermediate inputs are substitute inputs. In addition, our result in comparison to Chilean manufacturing plants is similar in terms of substitutable, but it also means that the input variety effect of the imported inputs is small since $\overline{\theta} > 1$.

This evidence is particularly interesting for formal manufacturing firms in Ecuador and for dollarised economies in general, because a policy of restricting imports (often of goods that serve as inputs to produce a final good) to prioritise local goods may be effective in the Ecuadorian manufacturing context since domestic and imported intermediates are substitutes. However, we do not investigate the input quality effect of imported inputs relative to domestic inputs like Zhang (2017) because we do not have the physical quantity of domestic and imported intermediates or their prices to capture a real quality effect parameter. As such, we cannot ensure that those inputs will have similar characteristics in quality or that the final good will be better with certain intermediate inputs.

Finally, in Tables 7 and 8, we explore the complement–substitute relationship between domestic and imported inputs for the Pavitt Taxonomy and industries according to the OECD technological intensity classification, respectively. According to the elasticity of substitution ($\overline{\theta}$), in all the industry classifications, domestic and imported intermediates are substitute inputs since in all the cases $\overline{\theta} > 1$. However, it is important to mention that the elasticity of substitution between imported and domestic inputs is, on average, higher in firms that operate in less innovative sectors compared with firms that operate in more innovative sectors or with higher technology. We conjecture that this result is associated with the quality of the imported input and the difficulty of accessing certain inputs with the same quality in the local market. More innovative industries need better inputs (high quality) to continue innovating, while less innovative industries can acquire their inputs quickly in the local market.

5.4 | Self-selection and a robustness of the Learning-by-importing hypothesis

Once we estimate the production function using Equation (1) with our augmented LP estimator and modify the law of motion of productivity as in Equation (2), we obtain the estimates of TFP at the firm level for the entire manufacturing sector and for each industry classification during the period 2007–2018. In Figure A1 in the Appendix 1, we compare the TFP of importing firms and non-importing firms. We show in panel (a) that importing firms are more productive than non-importing firms. The TFP for non-importing firms is similar to the mean of the manufacturing sector, while the TFP for importing firms is higher than the TFP for non-importing firms and the mean for the whole manufacturing sector. In addition, in panel (b), we present the mean TFP of continuing, entering, exiting and non-importing firms. We show that continuing importers have greater TFP than other firms. This preliminary evidence motivates us to test whether there is a self-selection process in the import market since it is well established that firms with previous higher TFP self-select into international markets.

In this sense, this first evidence in terms of productivity is similar to that of Zaclicever and Pellandra (2018), who found that the positive association between imported intermediate inputs and firms' productivity does not necessarily imply a productivity-enhancing effect of foreign intermediates (i.e. causality from imported inputs to productivity growth). In this vein, we test self-selection on the entry and exit sides of the market by estimating Equation (11). We also perform a robustness check to test the learning-by-exporting hypothesis by estimating Equation (10). To do this, we recover the TFP that includes the learning-by-importing and the learning-by-exporting effects as in Equation (2) for the whole manufacturing sector and for each industry in the Pavitt Taxonomy and the OECD technological intensity classification.[29]

To study the self-selection hypothesis on the entry side of the market, we compare the previous TFP of entering importers with that of non-importers. We should expect the previous TFP of entering importers to be higher than that of non-importers even before the former entered international markets. To test this issue, we use a subsample of firms explained in Section 3.2 where the (d_{it}) dummy variable takes the value 1 the year a firm starts to import and the value zero for all years with data on non-importers during the sample period. For entering importers, we do not include sample observations of sample years before and after the entry year in the estimation. By contrast, we use all period observations for non-importers during the sample period.

Moreover, to test the self-selection hypothesis on the exit side of the market, we compare the previous TFP of exiting importers with that of continuing importers. We should expect the previous TFP of exiting importers to be negative and smaller than that of continuing importers even before the former exits international markets. For this reason, we use a subsample of firms explained in Section 3.2 where the (d_{it}) dummy variable takes the value 1 if the firm exits from importing in period t and zero for all the years of the subsample of continuing importers. For exiting importers, we do not include sample observations of sample years before and after the exit year in the estimation. By contrast, we use all period observations for continuing importers during the entire sample period.

In Table 9, we present the main results of the self-selection hypothesis (entry and exit sides of the market). When the self-selection hypothesis on the entry side of the market is analysed, our results show that the import intermediate decision (d_{it}) in the current period is always positive and significant in the whole manufacturing sector, two Pavitt taxonomies, and in all the OECD technological intensity classification industries. In this sense, we find evidence in favour of the self-selection hypothesis on the entry side of the market, which suggests that firms with previous higher TFP self-select to enter the import market. Nevertheless, this evidence is not statistically significant in the science-based and specialised-suppliers industries. Again, we show the heterogeneous effect of the intermediate import decision (entering importers) not only on current productivity but also on past productivity. This evidence is in concordance with the extensive literature on international economics, which finds that more productive firms enter import markets because they are able to pay the higher sunk costs (Kasahara & Lapham, 2013). However, previously high TFP firms tend to become importers (but perhaps not for the most innovative industries) because firms that operate in innovative sectors are close to the technological frontier and are also continuing importers. This fact suggests that firms that operate in less innovative industries but have a high TFP might self-select to enter the import market.

[29]It is known that to analyse self-selection and the learning-by-importing hypotheses, the TFP of each of the industries should be used to relax the assumption that firms in different industries operate with different technology. However, we estimate the productivity for each industrial grouping as proposed by the Pavitt Taxonomy and the OECD, and we use the estimated TFP of each of them because each grouping assumes several similar characteristics between sectors, such as intensity of the use of labour, capital, access to international trade and R&D, among others. Additionally, two-digit fixed effects of the ISIC are included in each industry. In this way, we relax this assumption. We thank an anonymous reviewer for this observation.

TABLE 9 Self-selection and learning-by-importing

	Self-selection						Learning-by-importing
	Entry side			Exit side			Matched sample
	ω_{it-3}	ω_{it-2}	ω_{it-1}	ω_{it-3}	ω_{it-2}	ω_{it-1}	$\Delta\omega_{it}$
Manufacturing sector	0.063***	0.045***	0.099***	−0.124***	−0.130***	−0.207***	0.024***
	(0.019)	(0.016)	(0.013)	(0.022)	(0.020)	(0.019)	(0.010)
Pavitt taxonomy							
Scale-Intensive	0.080**	0.064**	0.081***	−0.157***	−0.174***	−0.241***	0.025**
	(0.035)	(0.029)	(0.022)	(0.038)	(0.034)	(0.034)	(0.012)
Science-Based	0.011	0.048	0.007	−0.050	−0.042	−0.158***	0.049**
	(0.044)	(0.038)	(0.037)	(0.040)	(0.043)	(0.035)	(0.028)
Specialised suppliers	0.041	0.086	0.019	−0.072	−0.419**	−0.335**	0.070
	(0.031)	(0.064)	(0.031)	(0.153)	(0.163)	(0.182)	(0.061)
Supplier-Dominated	0.051**	0.041*	0.102***	−0.131***	−0.100***	−0.160***	0.023**
	(0.024)	(0.023)	(0.019)	(0.030)	(0.027)	(0.025)	(0.011)
Technological intensity							
Low-tech industry	0.024	0.027	0.082***	−0.113***	−0.122***	−0.187***	0.027**
	(0.025)	(0.021)	(0.020)	(0.031)	(0.027)	(0.026)	(0.012)
Medium-low tech industry	0.100***	0.058*	0.088***	−0.159***	−0.157***	−0.217***	0.033***
	(0.038)	(0.034)	(0.022)	(0.043)	(0.041)	(0.039)	(0.011)
Medium-high & High-tech industry	0.016	0.005	0.059**	−0.103**	−0.138***	−0.235***	0.037***
	(0.038)	(0.034)	(0.026)	(0.047)	(0.045)	(0.044)	(0.016)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses. For the self-selection estimates, we use Equation (11), controlling for a set of industry, year and region dummies as explanatory variables. For the learning-by-importing estimates, we use Equation (10), controlling for initial level of TFP and a set of industry, year and region dummies as explanatory variables. In the learning-by-importing estimates, we use the *psmatch2* Stata command, and we employ the kernel matching method. *$p<.10$, **$p<.05$, ***$p<.01$.

In addition, Table 9 shows the results of the self-selection hypothesis on the exit side of the market. In this case, we do find evidence of this hypothesis in the whole manufacturing sector and in each industry of the Pavitt Taxonomy and the OECD technological intensity classification. In other words, our results suggest that exiting firms face declining productivity before they exit the import market and that the least productive importers will exit the import market because they are inefficient. Similar results are found by Mallick and Yang (2013) and Camino-Mogro et al. (2022) with self-selection on the exit side of the export market. Again, we conjecture that this result might be due to absorptive capacity but also the fact that very low-productivity firms cannot survive in the international market.

Finally, we test (again) the learning-by-importing hypothesis as a robustness check in Table 9 in the last column, where we obtain the results of the estimation of Equation (10).[30] This column reports the magnitude of different productivity growth between new import market entrants and non-importers. We expect that after entering the import market, the productivity of entering importers should increase in period $t+1$ compared with non-importers. Our results suggest that, after entry in the import market, (new importers) have higher productivity growth in the first year after entry than non-importers in the whole manufacturing sector, three Pavitt Taxonomy industries (with the exception of the specialised-suppliers industry) and each of the OECD technological intensity classifications. In this sense, we show the robustness of our main results. Nevertheless, we recommend analysing the learning-by-importing hypothesis by modifying the law of motion of productivity by including the past intermediate import decision and the past export decision instead of using matching techniques because matching techniques might be biased if the quality of matching is poor. Also, the results might vary with the use of other matching methods available to generate matched firms (Yang & Mallick, 2010).

Overall, we find evidence in favour of self-selection on the entry and exit sides of the market and the learning-by-importing hypothesis for formal Ecuadorian manufacturing firms. More importantly, we demonstrate (like other authors) that these two hypotheses are not mutually exclusive, and that in the case of developing countries, these hypotheses could coexist. In this sense, there could be a kind of self-reinforcing mechanism to access international markets, firms must have sufficiently high productivity; then, thanks to international activity, they become even more productive. Caselli (2018) finds similar results for Mexican manufacturing plants and mentions that this is suggestive of a potential virtuous circle for good performers, which, however, can pull these firms further away from the performance of all other plants, possibly creating a productivity gap, as suggested by Andrews et al. (2016).[31]

6 | CONCLUSIONS AND DISCUSSION

It is well known that there is a positive relationship between imports and firm productivity. However, there is scant evidence that this holds true for emerging markets and developing economies, and no evidence for Ecuadorian manufacturing (to the authors' knowledge). Particularly, for a small, open economy, international trade can be a major channel for productivity growth

[30] Probit estimates and balancing properties of the matching are available upon request.

[31] We thank an anonymous reviewer for this point.

(Zaclicever & Pellandra, 2018). This lack of availability of studies on Latin American manufacturing has been due mainly to a lack of available data.

To address this issue, in this paper, we give new evidence for Ecuadorian manufacturing firms during the period 2007–2018. We analyse the way in which imported intermediates affect firms' productivity, exploring the impact of the use of foreign intermediate inputs not only in the whole manufacturing sector but also by two industry classifications (the Pavitt Taxonomy and industries according to the OECD technological intensity classification). We estimate an augmented production function using the traditional inputs and three different measures of imported intermediate inputs such as a categorical variable of imports and two continuous measures of imported intermediates. Moreover, we include and estimate the static and dynamic (learning) effects of exported and imported intermediates on productivity. Finally, we test self-selection on the entry and exit sides of the import market and a robustness of the learning-by-importing hypothesis by using a difference-in-difference matching estimator.

Using each of our three measures of imported intermediates, we find evidence that suggests there is an immediate increase in productivity that comes from the use of imported intermediate inputs. Moreover, we find evidence in favour of the learning-by-importing hypothesis or a dynamic effect on productivity in the entire manufacturing sector and in most of the industry classifications (except in the specialised-suppliers industry). We also find that static and dynamic gains in productivity from importing intermediates are higher in more innovative industries than in less innovative industries, which implies an industrial heterogeneity effect. We also find evidence in favour of static and dynamic effects of the decision to export on productivity, but the learning-by-exporting effect is greater than the learning-by-importing effect. Again, this result is similar when we divide the industries by the Pavitt Taxonomy and the OECD technological intensity classification. This may occur because the absorptive capacity of the technology transfer received by firms through imported intermediates is lower than the productivity gains received from exporting. Thus, the dynamics of exports over productivity is faster than the dynamics of imports.

Furthermore, we determine the elasticity of substitution between foreign and domestic intermediate inputs and find that these intermediates are substitute inputs. This conclusion is similar to the findings of Kasahara and Rodrigue (2008) for Chilean manufacturing plants, but different from those of Zhang (2017) for Colombian manufacturing plants. We argue that in a dollarised, developing economy, intermediates are subject to the condition of the international exchange rate with respect to the main suppliers of raw materials, so an increase in the price of imported inputs would generate a decrease in the domestic demand for inputs, given that the great majority of products depend on imported inputs to produce output. Furthermore, the elasticity of substitution in the whole manufacturing sector and in each industry classification is small, meaning that the input variety effect of imported inputs is small. This result might occur because of the different import restriction policies pursued by the Ecuadorian government during the period analysed.

Finally, we find evidence in favour of selection on the entry side of the market (self-selection hypothesis) since entering importers have a higher productivity level than non-importing firms in most of the industries. Also, our results confirm selection on the exit side of the market in the whole manufacturing sector since exiting importers have lower productivity levels than continuing importers. These results are very similar in the whole industry classification, meaning that more productive firms self-select into importing. Likewise, and according to the learning-by-importing hypothesis, robust evidence is found since entering importers have a positive effect on TFP growth in the entire manufacturing sector and in the desegregation of the different industries.

Our results are important not only for firms (managerial or production strategy) that conclude access to imports boosts production and productivity, but also for policymakers (government policy) for the same reason. Our evidence that foreign and domestic intermediate inputs are substitutes implies that restrictions on imports such as increasing duties to the maximum limits or tariff safeguards could harm production because the majority of firms that import combine foreign inputs with domestic inputs even if the elasticity of substitution is very small. This implies that the input variety effect of imported inputs is small, and if there are different quality effects between imported intermediates and domestic intermediates, this will be interpreted with caution.[32] Moreover, policymakers should be careful not to implement policies that act as disincentives to the import decision because doing so could reduce productivity, affecting growth in the long run. In this sense, and with the results obtained in this study, public policymakers should consider tariff liberalisation, particularly that of productive input tariffs, since they play an important role in productivity. Also, they should promote intersectoral networks and external supply from countries that have higher quality inputs so that the product can have high-quality standards and then be exported.

Finally, the origin of imports could be very important in this analysis. Knowing the destination and type of imported inputs would help in determining the quality of the input and obtaining more refined results. However, because of database limitations, this information is not available. Therefore, this topic could be addressed as a line of future research, particularly in developing countries. Additionally, the analysis of imports of capital goods is another pending issue in this paper; likewise, limits on information have not allowed us to address this issue. One line of analysis would be to find out whether imports of inputs and capital goods are complementary.

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[32] Imports may make higher-quality inputs available to domestic firms, which would allow them to increase the efficiency of the production process (Eaton & Kortum, 1999). In this sense, Zaclicever and Pellandra (2018) argue that these effects of variety and quality are especially relevant for developing countries, where the range or quality of domestically produced inputs can be limited.

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DATA AVAILABILITY STATEMENT

We do not have permission to share the data but they are available to researchers upon request to the Superintendencia de Compañías, Valores y Seguros.

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APPENDIX 1

TABLE A1 Definition of variables

	Code	Definition
Gross revenue	Y	Total income from sales = revenues from sales of ordinary activities of the company (income from extraordinary activities is excluded from the business of each company, for example sale of land, machinery, etc.). This variable is deflated using the industry-specific price index obtained from the Ecuadorian National Institute of Statistics
Workers	L	Number of legally registered employees
Capital stock	K	Net tangible assets = the sum of the real dollar value of buildings, machinery, and vehicles, assuming a depreciation of 5, 10, and 20 percent, respectively, similar to Camino-Mogro and Bermudez-Barrezueta (2021). We measure the capital stock with gross investment in equipment in year t (I_{it}), net fixed assets in real value (physical capital in year t–1) (k_{it-1}), a depreciation rate (d_{it}) and the price index for equipment at the industry level (P_t) obtained from the Ecuadorian National Institute of Statistics
Total intermediates	M	Initial intermediates inventory + imports of intermediates inputs + local net purchases of intermediates + transport expenses + fuel expenses + spending on office supplies + expenditure on maintenance and repair + basic services expenditure – final intermediates inventory – final inventory of products in process – final inventory of finished products. This variable is deflated using the industry-specific price index obtained from the Ecuadorian National Institute of Statistics
Domestic intermediates	D	Initial intermediates inventory + local net purchases of intermediates + transport expenses + fuel expenses + spending on office supplies + expenditure on maintenance and repair + basic services expenditure – final intermediates inventory – final inventory of products in process – final inventory of finished products. This variable is deflated using the industry-specific price index obtained from the Ecuadorian National Institute of Statistics
Foreign intermediates	F	Imports of intermediates to produce a final good
Exports	X	Total Foreign sales

Source: The authors based on data provided by the Superintendencia de Compañías, Valores y Seguros.

TABLE A2 Correspondence between ISIC codes and the Pavitt Taxonomy

Industry	Subsectors	ISIC codes
Scale-intensive industry	Food, beverages and tobacco	10 + 11 + 12
	Editing and printing	18
	Coke manufacturing and oil refining	19
	Manufacture of other non-metallic mineral products	23
	Mineral-based products	24
	Metal products	25
	Motor vehicles	29
Science-based industry	Chemical industry and pharmaceutical products	20 + 21
	Agricultural and industrial machines	28
	Other transport material	30
Specialised-suppliers industry	Manufacture of computer, electronic, and optical products	26
	Machinery and electrical equipment	27
	Repair and installation of machinery and equipment	33
Supplier-dominated industry	Textile and clothing	13 + 14 + 15
	Wood products	16
	Paper manufacturing	17
	Manufacture of rubber and plastic products	22
	Furniture and other manufacturing industries	31 + 32

Source: Pavitt (1984); Superintendencia de Compañías, Valores y Seguros.

TABLE A3 Correspondence between ISIC codes and industries according to technological intensity

Industry	Subsectors	ISIC codes
Low-tech industry	Food, beverages and tobacco	10 + 11 + 12
	Textile and clothing	13 + 14 + 15
	Wood products	16
	Paper manufacturing	17
	Editing and printing	18
	Furniture and other manufacturing industries	31 + 32
Medium-low tech industry	Coke manufacturing and oil refining	19
	Manufacture of rubber and plastic products	22
	Manufacture of other non-metallic mineral products	23
	Mineral-based products	24
	Metal products	25
	Repair and installation of machinery and equipment	33
Medium-high and High tech industry	Chemical industry	20
	Machinery and electrical equipment	27
	Agricultural and industrial machines	28
	Motor vehicles	29
	Other transport material	30
	Pharmaceutical products	21
	Manufacture of computer, electronic, and optical products	26

Source: Eurostat indicators for high-tech industry and knowledge; Superintendencia de Compañías, Valores y Seguros.

TABLE A4 Descriptive statistics

	N	Means	*SD*	1%	Median	99%	*N*	Means	*SD*	1%	Median	99%	*N*	Means	*SD*	1%	Median	99%
	Output						**Capital stock**						**Labour**					
Total	36,061	13.45	2.11	8.04	13.38	18.61	36,061	11.47	2.81	5.28	11.50	17.44	36,061	2.70	1.54	0	2.56	6.75
Year																		
2007	2694	13.09	2.12	7.50	13.03	18.27	2694	10.95	2.60	4.78	10.99	16.48	2694	2.62	1.50	0	2.56	6.64
2012	3043	13.55	2.06	8.49	13.44	18.76	3043	11.58	2.88	5.22	11.65	17.45	3043	2.75	1.55	0	2.56	6.86
2018	2951	13.61	2.17	7.72	13.56	18.87	2951	11.81	2.86	5.32	11.82	17.86	2951	2.87	1.41	0.69	2.56	6.93
Firm size																		
Micro	5520	10.26	1.34	5.04	10.66	11.50	5520	8.98	2.68	3.60	9.14	13.792	5520	1.21	.71	0	1.10	3.04
Small	15,773	12.75	.63	11.55	12.78	13.79	15,773	10.52	2.18	5.36	10.72	14.27	15,773	2.13	.92	0	2.20	4.02
Medium	8896	14.53	.45	13.83	14.49	15.40	8896	12.41	1.72	7.43	12.61	15.51	8896	3.21	1.11	0	3.40	5.24
Large	5872	16.71	1.04	15.44	16.44	19.87	5872	14.94	1.72	9.85	15.01	18.84	5872	4.82	1.45	0	4.95	7.70
Pavitt taxonomy																		
Scale-intensive	15,619	13.67	2.27	7.67	13.58	19.13	15,619	11.88	2.83	5.62	11.91	17.85	15,619	2.84	1.62	0	2.71	7.17
Science-based	5741	13.38	2.02	8.04	13.34	18.26	5741	11.11	2.69	5.29	11.19	16.86	5741	2.49	1.42	0	2.40	6.16
Specialised suppliers	4343	12.68	1.81	8.21	12.61	17.41	4343	10.27	2.74	4.46	10.38	15.89	4343	2.09	1.29	0	1.94	5.77
Supplier-dominated	10,358	13.49	1.94	8.48	13.50	18.33	10,358	11.57	2.71	5.16	11.66	17.33	10,358	2.85	1.50	0	2.83	6.41
Technological intensity																		
Low-tech	17,908	13.53	2.21	7.67	13.47	18.71	17,908	11.68	2.78	5.32	11.71	17.45	17,908	2.84	1.60	0	2.71	7.07
Medium-low tech	10,570	13.33	1.98	8.48	13.23	18.39	10,570	11.32	2.97	4.99	11.36	17.66	10,570	2.54	1.48	0	2.40	6.43

TABLE A4 (Continued)

	N	Means	*SD*	1%	Median	99%	*N*	Means	*SD*	1%	Median	99%	*N*	Means	*SD*	1%	Median	99%
	Output						**Capital stock**						**Labour**					
Medium-high and High-tech	7583	13.45	2.03	8.35	13.37	18.65	7583	11.19	2.62	5.47	11.22	16.91	7583	2.56	1.45	0	2.40	6.26
Cities																		
Quito	14,189	13.43	2.01	8.45	13.32	18.71	14,189	11.31	2.78	5.31	11.30	17.26	14,189	2.72	1.46	0	2.56	6.75
Guayaquil	11,846	13.31	2.12	7.97	13.21	18.55	11,846	11.22	2.99	4.78	11.29	17.45	11,846	2.49	1.59	0	2.30	6.47
Cuenca	2277	13.41	2.12	7.71	13.41	18.72	2277	11.74	2.53	5.71	11.75	17.57	2277	2.88	1.55	0	2.77	6.91
Other cities	7749	13.74	2.24	7.58	13.77	18.59	7749	12.08	2.58	5.87	12.22	17.53	7749	2.91	1.57	0	2.83	7.14

	N	Means	*SD*	1%	Median	99%	*N*	Means	*SD*	1%	Median	99%
	Domestic intermediates						**Foreign intermediates**					
Total	36,061	11.41	2.82	4.13	11.62	17.46	36,061	3.12	5.74	0	0	17.22
Year												
2007	2694	11.55	2.53	4.94	11.73	16.97	2694	3.41	5.81	0	0	17.16
2012	3043	11.39	2.77	4.83	11.55	17.48	3043	3.10	5.75	0	0	17.35
2018	2951	11.10	3.12	3.44	11.36	17.57	2951	3.06	5.77	0	0	17.52
Firm size												
Micro	5520	8.06	1.96	2.44	8.33	11.14	5520	.10	.97	0	0	7.11
Small	15,773	10.55	1.92	4.88	10.97	13.33	15,773	1.05	3.23	0	0	12.40
Medium	8896	12.61	1.74	7.21	13.14	14.98	8896	4.35	6.02	0	0	14.56
Large	5872	15.01	1.73	9.90	15.13	18.76	5872	9.65	7.34	0	13.86	18.37

TABLE A4 (Continued)

	N	Means	*SD*	1%	Median	99%	*N*	Means	*SD*	1%	Median	99%
	Domestic intermediates						**Foreign intermediates**					
Pavitt taxonomy												
Scale-intensive	15,619	11.84	2.98	4.28	11.99	18.04	15,619	2.70	5.53	0	0	17.60
Science-based	5741	11.13	2.54	4.31	11.37	16.06	5741	3.76	5.94	0	0	16.78
Specialised suppliers	4343	9.83	2.40	3.91	9.73	15.74	4343	1.06	3.70	0	0	16.26
Supplier-dominated	10,358	11.57	2.63	4.03	12.02	16.75	10,358	4.27	6.31	0	0	17.21
Technological intensity												
Low-tech	17,908	11.71	2.94	4.01	11.97	17.75	17,908	2.91	5.61	0	0	17.23
Medium-low tech	10,570	11.08	2.68	4.30	11.22	16.68	10,570	3.01	5.71	0	0	17.26
Medium-high and High-tech	7583	11.14	2.62	4.27	11.32	16.52	7583	3.76	6.03	0	0	17.17
Cities												
Quito	14,189	11.38	2.62	4.39	11.59	17.29	14,189	3.29	5.79	0	0	17.01
Guayaquil	11,846	11.04	2.87	3.95	11.13	17.28	11,846	2.92	5.64	0	0	17.17
Cuenca	2277	11.52	2.80	4.04	11.82	17.02	2277	3.81	6.07	0	0	17.83
Other cities	7749	11.98	2.99	4.01	12.22	17.82	7749	2.91	5.69	0	0	17.51

Note: All values are in logs of dollars, except for labour, which is in logs of number of formal employees. *Source*: The authors, based on data from the Superintendencia de Compañías, Valores y Seguros.

TABLE A5 Effect of import decision and import intensity on TFP

Estimators	OLS (1)	LP (2)	OLS (3)	LP (4)	OLS (5)	LP (6)
	(Discrete import variable)		(Continuous import variable)			
k_{it}	0.117***	0.150***	0.116***	0.123***	0.117***	0.119***
	(0.010)	(0.032)	(0.009)	(0.025)	(0.010)	(0.030)
l_{it}	0.406***	0.312***	0.405***	0.313***	0.407***	0.313***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
m_{it}	0.367***	0.238***	0.364***	0.235***	0.368***	0.235***
	(0.007)	(0.022)	(0.007)	(0.018)	(0.007)	(0.020)
d_{it}	−0.001	0.030*				
	(0.026)	(0.018)				
n_{it}			0.040**	0.055***		
			(0.016)	(0.014)		
FI_{it}					0.028***	0.051***
					(0.008)	(0.015)
P		0.775***		0.826***		0.842***
		(0.026)		(0.019)		(0.017)
H		0.048***		0.033***		0.002**
		(0.006)		(0.004)		(0.001)
Implied $\frac{\eta}{1-\rho}$		0.213		0.190		0.012
Implied θ			10.10	5.273		
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	36,061	28,602	36,061	28,602	36,061	28,602

Note: Standard errors in parentheses clustered at the firm level with 300 bootstrapped replications in LP estimations. The Levinsohn-Petrin estimator uses the stochastic process of ω_t of Equation (2) for discrete import, Equation (7) for continuous import and Equation (9) for import intensity variables, we do not include export variables. *$p < .10$, **$p < .05$, ***$p < .01$.

TABLE A6 Effect of import decision and import intensity on TFP: Industry-level results using the Pavitt Taxonomy

	Scale-intensive	Science-based	Specialised suppliers	Supplier-dominated
Discrete import variable				
k_{it}	0.135***	0.030	0.138***	0.0421
	(0.027)	(0.035)	(0.014)	(0.041)
l_{it}	0.277***	0.382***	0.398***	0.297***
	(0.015)	(0.032)	(0.031)	(0.019)
m_{it}	0.246***	0.292***	0.228***	0.242***
	(0.016)	(0.026)	(0.017)	(0.037)
d_{it}	0.135***	−0.117***	−0.348***	0.070***
	(0.022)	(0.014)	(0.011)	(0.016)
ρ	0.840***	0.877***	0.708***	0.881***
	(0.018)	(0.015)	(0.104)	(0.010)
η	0.045***	0.054***	0.026	0.051***
	(0.007)	(0.010)	(0.033)	(0.006)
Implied $\frac{\eta}{1-\rho}$	0.281	0.439	0.089	0.428
Continuous import variable: n_{it}				
k_{it}	0.101***	0.029	0.147***	0.071**
	(0.024)	(0.039)	(0.011)	(0.035)
l_{it}	0.278***	0.384***	0.400***	0.298***
	(0.016)	(0.037)	(0.034)	(0.020)
m_{it}	0.254***	0.282***	0.221***	0.239***
	(0.016)	(0.029)	(0.016)	(0.033)
n_{it}	0.081***	0.090***	0.027**	0.112***
	(0.017)	(0.018)	(0.011)	(0.015)
ρ	0.886***	0.873***	0.663***	0.864***
	(0.011)	(0.020)	(0.116)	(0.012)
η	0.034***	0.056***	0.013	0.043***
	(0.006)	(0.015)	(0.019)	(0.006)
Implied $\frac{\eta}{1-\rho}$	0.298	0.441	0.038	0.316
Implied θ	4.135	4.133	8.185	3.134
Continuous import variable: FI_{it}				
k_{it}	0.131***	0.021	0.134***	0.080***
	(0.027)	(0.047)	(0.013)	(0.031)
l_{it}	0.276***	0.390***	0.401***	0.297***
	(0.016)	(0.033)	(0.034)	(0.019)
m_{it}	0.259***	0.294***	0.228***	0.239***
	(0.019)	(0.034)	(0.016)	(0.030)

TABLE A6 (Continued)

	Scale-intensive	Science-based	Specialised suppliers	Supplier-dominated
FI_{it}	0.021	0.054***	0.218***	0.020*
	(0.018)	(0.018)	(0.015)	(0.011)
ρ	0.859***	0.891***	0.670***	0.875***
	(0.017)	(0.013)	(0.102)	(0.012)
η	0.006**	0.016***	0.027	0.002
	(0.003)	(0.005)	(0.031)	(0.003)
Implied $\frac{\eta}{1-\rho}$	0.043	0.147	0.082	0.016
No. of obs.	12,502	4561	3343	8196

Note: Standard errors in parentheses clustered at the firm level with 300 bootstrapped replications. The Levinsohn-Petrin estimator uses the stochastic process of ω_t of Equation (2) for discrete import, Equation (7) for continuous import and Equation (9) for import intensity variables, we do not include export variables. We include year fixed effects, industry fixed effects (two-digit ISIC Rev. 4.0) and region fixed effects. *$p<.10$, **$p<.05$, ***$p<.01$.

TABLE A7 Effect of import decision and import intensity on TFP: Industry-level results by the OECD technological intensity classification

	Low-tech industry	Medium-low tech industry	Medium-high and High-tech industry
Discrete import variable			
k_{it}	0.103***	0.078***	0.037
	(0.029)	(0.013)	(0.039)
l_{it}	0.279***	0.310***	0.393***
	(0.014)	(0.021)	(0.029)
m_{it}	0.248***	0.246***	0.272***
	(0.022)	(0.014)	(0.028)
d_{it}	0.071***	0.006	0.150***
	(0.015)	(0.011)	(0.015)
ρ	0.877***	0.832***	0.880***
	(0.010)	(0.019)	(0.014)
η	0.036***	0.053***	0.045***
	(0.005)	(0.010)	(0.009)
Implied $\frac{\eta}{1-\rho}$	0.293	0.315	0.375
Continuous import variable: n_{it}			
k_{it}	0.114***	0.078***	0.034
	(0.035)	(0.012)	(0.050)
l_{it}	0.280***	0.310***	0.395***
	(0.015)	(0.021)	(0.029)
m_{it}	0.244***	0.239***	0.287***
	(0.027)	(0.014)	(0.041)

TABLE A7 (Continued)

	Low-tech industry	Medium-low tech industry	Medium-high and High-tech industry
n_{it}	0.054***	0.090***	0.102***
	(0.017)	(0.014)	(0.019)
ρ	0.882***	0.829***	0.852***
	(0.012)	(0.020)	(0.018)
η	0.024***	0.044***	0.056***
	(0.005)	(0.008)	(0.010)
Implied $\frac{\eta}{1-\rho}$	0.203	0.257	0.378
Implied θ	5.518	3.656	3.814
Continuous import variable: FI_{it}			
k_{it}	0.141***	0.087***	0.029
	(0.035)	(0.015)	(0.048)
l_{it}	0.279***	0.311***	0.396***
	(0.016)	(0.020)	(0.030)
m_{it}	0.250***	0.243***	0.267***
	(0.024)	(0.015)	(0.034)
FI_{it}	0.041**	0.054***	0.087***
	(0.017)	(0.013)	(0.015)
ρ	0.850***	0.837***	0.895***
	(0.016)	(0.022)	(0.013)
η	0.019***	0.002	0.001
	(0.002)	(0.004)	(0.006)
Implied $\frac{\eta}{1-\rho}$	0.127	0.012	0.009
No. of obs.	14,226	8377	5999

Note: Standard errors in parentheses clustered at the firm level with 300 bootstrapped replications. The Levinsohn-Petrin estimator uses the stochastic process of ω_t of Equation (2) for discrete import, Equation (7) for continuous import and Equation (9) for import intensity variables, we do not include export variables. We include year fixed effects, industry fixed effects (two-digit ISIC Rev. 4.0) and region fixed effects. *$p<.10$, **$p<.05$, ***$p<.01$.

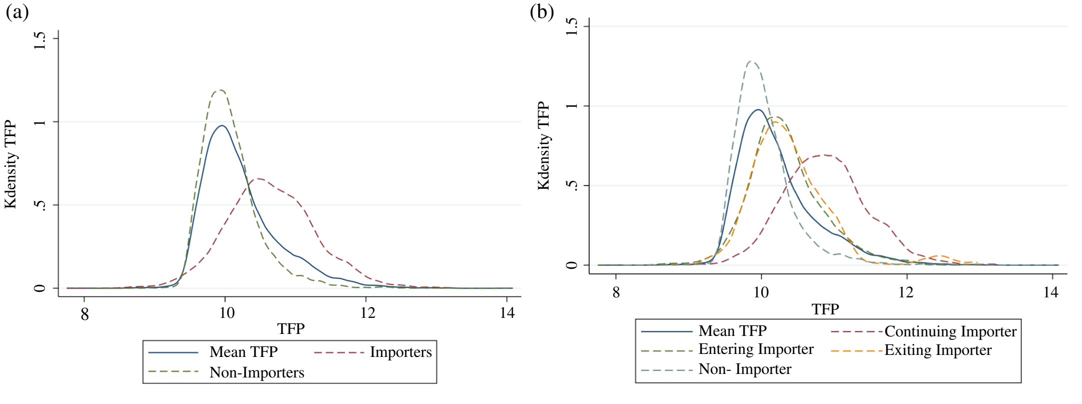

FIGURE A1 Mean TFP of firms. (a) Mean TFP of importers and non-importers (b) Mean TFP by importer strategies

APPENDIX 2

OVERVIEW OF IMPORTS AND PRODUCTIVITY IN ECUADOR

Ecuador is a middle-income, developing Latin American country.[33] According to information from the Banco Central del Ecuador (BCE), in 2018 its GDP reached $107,562 million (current terms) and showed an annual growth rate of 1.3% (measured in real terms). Tertiary sector industries accounted for 69.19% of the 2018 total gross added value (GAV).[34] Primary sector industries accounted for 17.02% and the secondary sector (manufacturing alone) for 13.79%. Such composition of added-value creation has remained relatively stable in the country since the early 2000s. In absolute terms, total GAV and total GDP continually increased until 2018.

The manufacturing sector in the country, therefore, represents by itself around 14% of the creation of the national added value. Given that the country is currently characterised essentially as a raw materials exporter (mainly crude oil and agricultural products) and an oil derivatives importer, this economic sector has a special importance since it constitutes the field where an industrialisation process can be enhanced and, consequently, a road on which development can be built. In fact, since 2007, the Ecuadorian government has pursued the so-called process of "Productive Matrix Change" as one of the main global economic objectives of the country. On this path, the manufacturing sector generated, during the period 2013–2017, around a quarter of the total net profits and gross revenues of the Ecuadorian economy and (on average) 18.7% of the formal employment at the national level.

However, Ecuador is a country that presents a dynamic led mostly by the global economic market. The principal reason for such behaviour is that the main export product of the country is oil, a commodity whose price is determined exogenously (to the country) in the international economic market.[35] Such sensibility of Ecuadorian exports to the international framework, along with the specific importer and exporter positions of the country in the international trade network, permanently causes Ecuador to show trade deficits (especially in the non-oil sectors). Given such a framework, the analysis of imports and their effects on important aggregate variables turn out to be of great relevance for Ecuador because, according to the BCE, the major share of imports are intermediate inputs[36] and capital goods, so these variables are an important part of the production of firms.

[33] According to the International Monetary Fund (IMF).

[34] Gross Added Value corresponds to the value of production minus intermediate consumption by industries.

[35] According to Borensztein and Ruiz-Arranz (2018), this might explain the Ecuadorian economy's strong dependence on the evolution of the global international market. The current "dollarization" of the country's currency may further contribute to this situation. In the early 2000s, Ecuador adopted the U.S. dollar as its currency with the objective of reducing the then-ongoing inflation and reversing the recession the country was facing. As Borensztein and Ruiz-Arranz (2018) mention, the monetary conditions in a dollarized economy depend on the liquidity of the dollar in monetary markets; therefore, the more aligned the local economic cycle is to that of the USA, the more appropriate the liquidity conditions related to those needed in the local economy will be.

[36] In imports of intermediate inputs, we include imports of fuels and lubricants because the government is the only party that can import these inputs and sell them in the country as inputs.

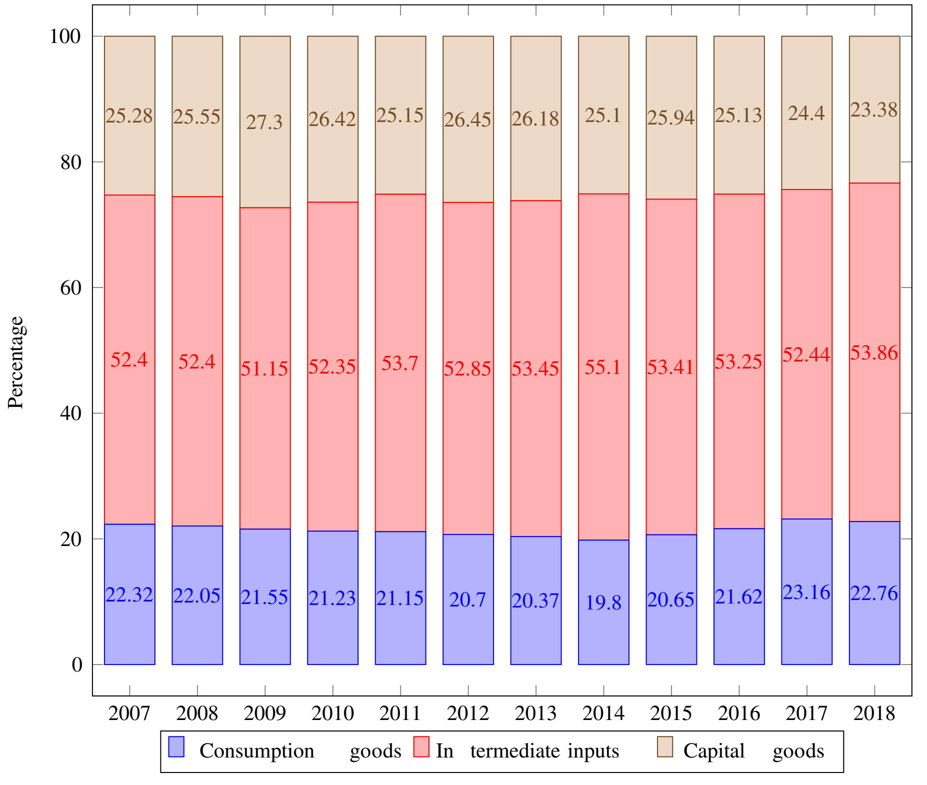

FIGURE A2 Share of total imports by type of good (2007–2018). *Source*: Banco Central del Ecuador. Elaboration: The authors

In Figure A2, we show the share of total imports in Ecuador during the period 2007–2018. We show that the imports of intermediate inputs have the largest share in the whole period compared with imports of capital goods and imports of consumption goods. Specifically, we show that imports of intermediate inputs during the period 2007–2018 represent more than 50% of total imports in Ecuador, followed by imports of capital goods and consumption goods. This evidence reveals the importance of imports of intermediate inputs in the country, but also the dependence of international inputs on the GDP.

Particularly in the manufacturing sector, imports of intermediates play an important role as part of the production processes. As can be seen in Panel 3(a) from Figure A3, from 2007 to 2018, the yearly participation of imports in total intermediates in this economic sector fluctuated around 39%, continuously decreasing from 43% in 2007 to 31% in 2016 and presenting an increase in the following years, until in 2018 it stood at 39%. This suggests that, currently, the share of imports in total intermediates in this sector is rising. However, participation of imports for the same period 2007–2018 differs depending on firm size (Panel 3[b]) and the region where the firm is located. While large firms import around 41% of their total intermediates, medium-size firms import just 22% of theirs, and micro and small firms import not even 1% of all their intermediates. Undoubtedly, therefore, there is either an important productivity effect of imports or a self-selection effect in this sector, so the larger the firm is, the more it imports.

When taking into account the classification of sectors according to Pavitt (1984) (Panel 3[c]), it can also be seen that the specialised suppliers and supplier-dominated sectors have the highest participation of imports in total intermediates (around 59% and 55%, respectively), followed by

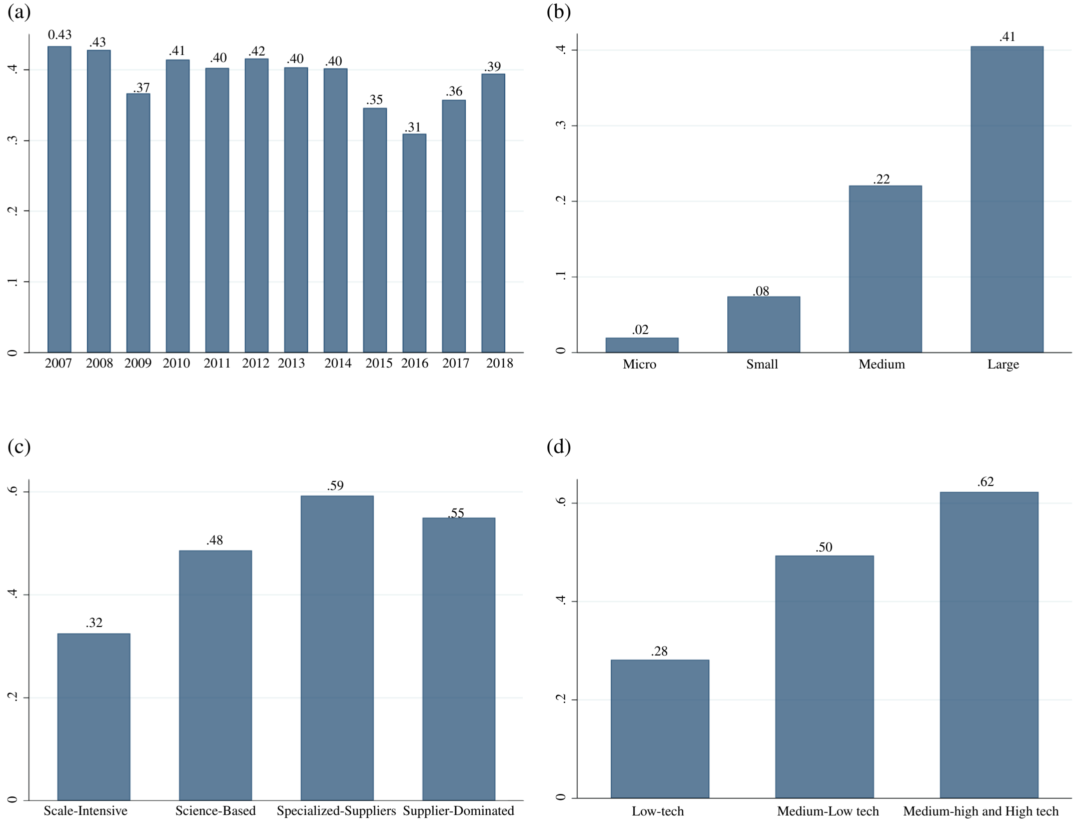

FIGURE A3 Share of Imported Intermediates in Total Intermediates (manufacturing sector, period 2007–2018). (a) By year (b) By firm size (c) By Pavitt's Taxonomy (d) By technological intensity

the science-based sector (with a participation of 48%) and the scale-intensive sector (with a participation of 32%). Finally, considering sectors categorised by the OECD technological intensity classification (Panel 3[d]), it can be seen that the medium-high technology sector has the highest participation share of imports over total intermediates (around 62%), while the medium-low technology sector and the low technology sector present a participation share of imports around 50% and 28%, respectively. This evidence is consistent given that more advanced technological sectors would tend to require a distinct quality or quantity of intermediates that are not likely to be available in the Ecuadorian domestic market.

Regarding productivity in Ecuador, the average contribution of TFP to the growth of per capita income in the period 1970–2016 was marginal (around 0.5%), and even experienced negative contributions in some years such as in the period 1980–1989 and in 2014–2016, after the oil price crash (Camino-Mogro et al., 2020). This is in concordance with Camino-Mogro et al. (2018), who found that Ecuadorian manufacturing TFP levels decreased during the periods around 2008 and 2015, which might be explained by the negative effects of the global financial crisis of 2008 and the oil price crisis of 2015, respectively. Moreover, manufacturing productivity levels also varied by firm size: large and medium-sized firms are, on average, more productive than small and micro firms. Likewise, when analysing productivity levels by region (in consideration of the significant differences between them in terms of weather, ethnic groups, employment types, and production, among others), it was concluded that the firms located in the Coast Region were, on average, more productive than those of other regions. Finally, Guayas and Cañar stood out as the most productive states, while Pichincha (where Quito, the capital of Ecuador, is located) presented productivity levels higher than the average in just 1 year of the period of study (Camino-Mogro et al., 2018; Camino-Mogro, 2021).

APPENDIX 3

SPECIFICATION OF THE PRODUCTION FUNCTION

We adopt the augmented production function of Kasahara and Rodrigue (2008) like other papers (Abreha, 2019; Caselli, 2018; Mo et al., 2021; Zhang, 2017). This specification allows us to analyse the impact of imported intermediate inputs on productivity and also the determination of the elasticity of substitution between domestic and imported intermediate inputs. The proposed technology considers that both domestic and foreign intermediate goods are produced and used symmetrically. Then, the production function of firm i to obtain output Y_{it} at time t is given by:

$$Y_{it} = e^{(\omega_{it}+\sigma x_{it}+\epsilon_{it})} K_{it}^{\beta} L_{it}^{\alpha} \left[\int_0^{N(d_{it})} m(j)^{\frac{\theta-1}{\theta}} dj \right]^{\gamma \frac{\theta}{\theta-1}}, \tag{A1}$$

where ω_{it} is a serially correlated productivity shock (not observed by the econometrician but observable or predictable by firms), K_{it} is capital input, L_{it} is labor input, $m(j)$ represents the intermediate inputs (domestic and foreign intermediate goods), x_{it} is the firm export decision to sell goods in international markets, and ϵ_{it} is a standard i.i.d. error term that is neither observable nor predictable by the firm. β, α, and γ are elasticities of output with respect to each input. σ is one of our parameters of interest and captures the direct and static effect of the export decision on firms' output. Moreover, the firm's decision to import and use foreign intermediate inputs is denoted by a dummy variable $d_{it} \in \{0,1\}$, and the variable $N(d_{it}) = (1-d_{it})N_{it}^{h} + d_{it}N_{it}^{f}$ denotes the range of intermediates used by firm i, with N_{it}^{h} being the range of intermediates produced domestically and N_{it}^{f} the range of intermediates available abroad (imported intermediates). The elasticity of substitution between domestic and foreign material inputs is denoted by θ. When θ is large, both inputs are more substitutable in the production process, meaning that the input variety effect of the imported inputs is small (Zhang, 2017); nevertheless, when $\theta < 1$, domestic and foreign material inputs are complementary. This specification of the production function closely follows Kasahara and Rodrigue (2008) and Abreha (2019).[37] However, we simplify our specification in the following manner: (i) we do not divide the labor force into skilled and unskilled as in these papers because our dataset does not allow this classification; (ii) we do not use energy separately because we assume that energy is a domestic intermediate input; and (iii) our specification is adapted to the firm level. However, we include the firm export decision to sell goods in international markets.

As both intermediate inputs are produced and used symmetrically, we assume that $\overline{m}$ units of each intermediate input variety j are used. Thus, total material inputs used by firm i in time

[37]The different varieties of intermediate inputs are treated as horizontally differentiated with no quality difference. Recently, Zhang (2017) included an input quality effect of the imported inputs relative to domestic inputs in his model. However, similar to Kasahara and Rodrigue (2008), our dataset does not contain information on firm-specific product prices or the range of the variety of intermediate inputs a firm uses. It is difficult to empirically differentiate between the quality or variety effect of foreign intermediates on productivity.

period t is $M_{it} = N\left(d_{it}\right)\overline{m}$ in equilibrium. Under such considerations, the production function is given by:

$$Y_{it} = e^{\left(\omega_{it}+\sigma x_{it}+\epsilon_{it}\right)} K_{it}^{\beta} L_{it}^{\alpha} M_{it}^{\gamma} N\left(d_{it}\right)^{\frac{\gamma}{\theta-1}}, \tag{A2}$$

where the total factor productivity (TFP) is defined as $e^{\left(\omega_{it}+\sigma x_{it}+\epsilon_{it}\right)} N\left(d_{it}\right)^{\frac{\gamma}{\theta-1}} = \frac{Y_{it}}{K_{it}^{\beta} L_{it}^{\alpha} M_{it}^{\gamma}}$. Then, from Equation (A2), we get:

$$ln\left(e^{\left(\omega_{it}+\sigma x_{it}+\epsilon_{it}\right)} N\left(d_{it}\right)^{\frac{\gamma}{\theta-1}}\right) = lnA\left(d_{it}, x_{it}, \omega\right) = \frac{\gamma}{\theta-1} ln\left(N\left(d_{it}\right)\right) + \sigma x_{it} + \omega_{it} + \epsilon_{it}. \tag{A3}$$

This equation indicates that productivity is positively related to the range of intermediate inputs employed in the production process. Firms that import intermediate inputs from abroad employ a large variety of intermediate inputs, so they exhibit higher productivity than those that use only domestic intermediates (Kasahara & Rodrigue, 2008).