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RESEARCH ARTICLE

The dynamic linkages between exporting and importing in Colombian manufacturing*

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Abstract

This paper analyses the dynamic linkages between firms' imports of intermediate inputs and exports, for Colombia, an emerging economy. We use data for manufacturing firms from the Colombian Annual Manufacturing Survey, for the period 2007-2016. We specially focus on the identification of direct and indirect effects of past importing/exporting experience on the likelihood of exporting and importing intermediates. We understand by indirect effects those that accrue from past experience (in exporting and importing intermediates) on the probability of exporting/importing intermediates, through enhanced productivity. Further, we analyse both own-direct effects of exporting (importing) and cross-direct effects of exporting (importing) on importing (exporting). In addition, we identify and quantify the role of sunk costs and learning in explaining exporting and importing persistence. The estimation results suggest the relevance of both direct and indirect effects (own and cross) to explain firms' exports and imports of intermediates decisions. Finally, we find evidence in favour of both importing and exporting spillovers.

Keywords: exports; imports of intermediates; bivariate probit; TFP.
JEL codes: C35, D24, F14.

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1. Introduction

Intermediate imports represented about 60% of the goods and services imported both by OECD countries and by EU-28, and most importantly, accounted for a significant share of exports. The OECD estimates that imported intermediate inputs content represented about one-quarter of OECD countries' exports and about 28% of EU-28 countries' exports (OECD., 2018). This evidence makes that in western economies exports and imports follow similar paths across time. Interestingly, this phenomenon is not exclusive of developed countries. The evolution over time of both exports and imports of intermediate inputs in Colombian manufacturing has been quite similar since the beginning of the new millennium. Both expansions and contractions of exports and imports of intermediates show similar growth rates and a high degree of synchronicity. In a recent study, (Elliott et al., 2019) find that Chinese exporting and importing firms also show analogous behaviours.

According to the Colombian Institute of Statistics, before the outbreak of the Great Recession, between 2000 and 2008, the average annual growth rate for exports and imports was about 16.8% and 14.4%, respectively. These figures have been attributed to the free trade agreements established with the U.S., the European Union and China. The Great Recession severely hit both exports and imports. Thus, the annual rates of growth for exports and imports fell to 10.7% and 7.1%, respectively. In 2010 and 2011, there was an important, although brief, recovery in international trade, as growth rates hiked to 32.1% for exports and 28.5% for imports. However, after this recovery, Colombian manufacturing has experienced decreases both for exports and imports (between 2012 and 2018 the average rates of growth were -9.8% and -3.1%, respectively). This reduction has been explained by the process of import substitution and the recession experienced by the Colombian economy.

Furthermore, it is key to acknowledge that the imported content of manufacturing exports has grown steadily along the last 10 years, increasing from 12.1% to 16.2% on average. Besides, there is evidence that the sectors with a higher export growth are those with a higher content of imports. Thus, Motor vehicles, Coking and refining products, Metallurgical products and Transport equipment are the sectors that show the highest average annual growth rates of exports in the period 2007-2016, and are the ones with higher rates of growth of imports of intermediate inputs (8% on average in the same period).

The related evolution of exports and imports of intermediates over time in Colombia suggests the existence of a link between these activities. This relationship could be attributable to some economic facts. Exporters acquire knowledge and experience operating in international markets and these might ease incorporating foreign inputs in their production process. Moreover, they may feel the competitive pressure of other traders that incorporate higher quality inputs. Further, imports boost exports as many firms in emerging economies purchase technologies incorporated in foreign capital goods, what might allow them to increase quality, reduce costs and so prices. This contributes to improve firms' performance in local and foreign markets. Both export and import may have an impact on firms' productivity what might reinforce firms' capacity to export and import, and, therefore, contribute to the competitiveness and economic growth of the economy. To analyse these international activities, it is important to acknowledge that both export and import may imply costs that are sunk in nature. However there might exist complementarity in these costs.[1] Therefore, this points to the convenience of a joint analysis of the determinants of firms' exports and imports of intermediates decisions. Further, the geographical proximity of other exporting/importing firms might have a positive and significant effect on the probability that firms engage in international trade (either exporting or importing). Agglomeration economies can help firms overcome start-up costs and ease firms' incorporation to international trade (Duranton and

[1] It should be considered that the sunk costs of importing are usually lower than those of exporting, at least for the developing economics (Seker, 2009)

Puga, 2004) Finally, foreign-owned firms, that usually are those being part of a global supply chain, are more likely to enter the export-import business (Manova and Zhang, 2009); (Boddin et al., 2017).

The aim of this paper is to contribute to the analysis of the dynamic linkages between firms' imports of intermediate inputs and export decisions.[2] We extend (Timoshenko, 2015b) model of export participation (which allows to separately quantify the role of sunk costs and demand learning on the firm's likelihood of exporting), and propose a dynamic bivariate model (in the same vein that (Mañez et al., 2020a) to analyse the dynamic interactions between both trading activities (export and import of intermediates) and the role of sunk costs and learning (demand learning in the case of exports and import supply learning in the case of imports). We will account for exporting and importing spillovers and for the fact that firms are foreign participated.

In our empirical research, we use a representative sample of Colombian manufacturing firms for the period 2007-2016, drawn from the Encuesta Anual Manufacturera (EAM, hereafter). This survey provides information on exports of final goods and imports of intermediate inputs and the necessary variables to estimate total factor productivity. We will complement this information using the Technological Development and Innovation Survey (EDIT), also for Colombia.

To anticipate our results, we find that firms past export and import experience have a positive effect on the probability of exporting and importing, respectively. These effects take place not only through a direct channel, but also through an indirect channel: both importing and exporting experience have a positive impact on current productivity, and current productivity affects the future likelihood of exporting and importing. Furthermore, direct effects of past export (import) experience on the probability of exporting (importing) result both from the existence of export (import) sunk costs and the process of learning triggered by continuity in these activities. Our results also suggest that the relative importance of learning to explain persistence is larger in the case of imports of intermediates than in the case of exports. We also detect the existence of both importing and exporting spillovers. Lastly, firms participated by foreign capital have a higher probability to engage in international trade (either exporting or importing intermediates).

The rest of the paper is organised as follows. In section 2, we introduce the theoretical framework on the direct and indirect effects of exports and imports. In section 3, we describe the data and present some descriptive analysis in which we pay special attention to the relationship between exporting and importing intermediates. In section 4, we present our empirical model and discuss methodological issues. Section 5 reports and comments our main results. Section 6 is devoted to some robustness exercises. Finally, section 7 concludes.

2. Theoretical framework on the direct and indirect effects of exports and imports.

In this research, we explore the possible direct and indirect links between firms' exporting and importing of intermediates strategies on the firm's likelihood of importing intermediates and exporting. We understand as indirect effects of importing (exporting) those that accrue to the likelihood of exporting and/or importing through their potential productivity enhancing effects. We recognise as direct effects of importing and exporting, those that may be attributed to importing and exporting strategies once we

[2] Henceforth, exports refer to exports of a final product of the firm (that could be an intermediate input for other firms) and imports refer to imports of intermediate inputs.

have controlled for indirect effects through enhanced productivity. Further, we will consider not only how past export experience may have a direct/indirect effect on the likelihood of exporting itself (we will refer to these effects as own-direct effects and own-indirect effects of exporting) but also possible direct/indirect effects of past export experience on the likelihood of importing (we refer to these as cross-direct and cross-indirect effects of exporting). Analogously, we will also consider own and cross effects of importing distinguishing also between direct and indirect effects. In Figure 1 we graphically summarise all these effects.

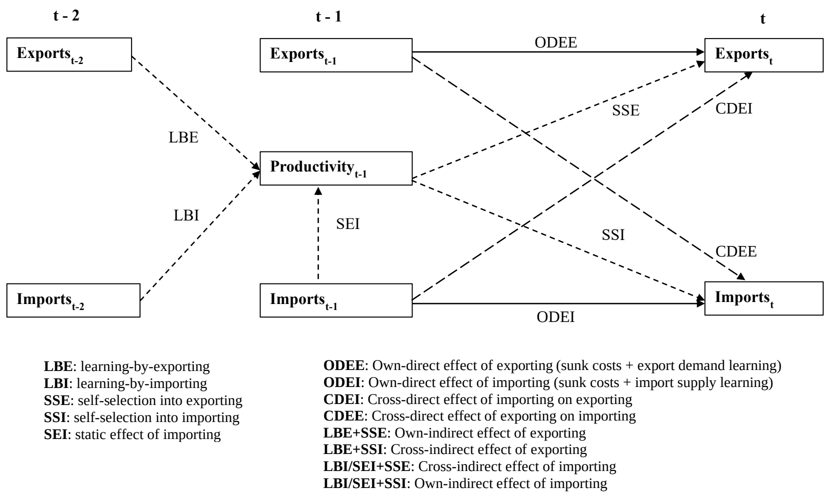

Figure 1: *Direct and indirect links between exporting and importing.*

A significant element to identify own-direct effects of exporting and importing intermediates is acknowledging that both activities may involve incurring some costs that are sunk in nature, and that these trading strategies might be subject to learning processes susceptible of generating dynamic increasing returns to scale. In what follows, we discuss sunk costs and learning processes issues in turn. Exporting sunk costs stems from factors such as the need of setting up marketing and distribution channels, exploring foreign demand and competition, customising own products characteristics to adapt them to foreign tastes and/or meet other countries' quality and security legislation. As for the sunk costs related to importing intermediates, one should consider that firms must invest resources to access higher quality inputs, a larger range of inputs or the foreign technology incorporated in intermediate inputs (Bustos, 2011). Recognising the existence of sunk costs implies that current imports of intermediates (exports) depend on past import (export) trajectories, and therefore, transitory changes in trade policy and/or economic conditions may have permanent effects on trade status. Thus, the existence of sunk costs generates hysteresis in trade flows.

(Roberts and Tybout, 1997) estimate the decision to export for Colombian manufacturing in a model in which firms' past export decisions affect future exports decisions. Further, they suggest that the estimated parameter for the past export decision, capturing state dependence, should proxy for the existence of export sunk costs.[3] In our analysis, we extend (Roberts and Tybout, 1997) sunk costs identification strategy to allow also past import decisions to affect future import decisions, using a similar strategy to (Kasahara and Lapham, 2013), as we aim at identifying sunk costs both for exports and imports. Notwithstanding, (Timoshenko, 2015b) suggests that state dependence of current exports might not be fully attributed to sunk costs as it could be the result of sunk costs, learning about export markets or both. As regards export market learning, (Arkolakis et al., 2018) and (Timoshenko, 2015a) consider that when firms start exporting they face some uncertainty about the external demand for their products and must learn about it. Likewise, we hypothesize that state dependence of current imports may be related to import sunk costs, learning about import supply opportunities or both of them. Likewise, we hypothesize that state dependence of current imports may be related to import sunk costs, learning about import supply opportunities or both of them. This is so as import starters need to learn customs procedures, search for potential foreign suppliers, testing whether the intermediate inputs match their production line, negotiation, contract formulation, etc. (Andersson et al., 2008); (Kasahara and Rodrigue, 2008); and (Zhang, 2017).[4] Nevertheless, as firms gradually acquire experience importing, uncertainty on these matters decreases, what fosters to continue importing.

Now we turn to explain the rationale behind cross-direct effects of importing and exporting. Cross-direct effects of importing intermediates on the probability of exporting may work through various channels.[5] First, it should be considered that if foreign sourcing results in lower prices for intermediates, and if this cost reduction is at least partially transmitted to prices, this may contribute to international competitiveness. Second if importing firms have access to a wider range of inputs, to higher quality inputs[6] or to the technology embodied in the intermediate inputs, this can favour product quality upgrading and/or the introduction of new products, what may foster competitiveness in export markets (Goldberg et al., 2010); (Fernandes and Paunov, 2013); (Bas and Strauss-Kahn, 2015); (Fieler et al., 2018); (Feng et al., 2016). Third, the international markets experience that firms gain through importing intermediates may be a valuable asset to improve sales abroad and may contribute to reduce the sunk costs associated to start exporting.

As for the cross-direct effects of exporting on the likelihood of importing, they may also arise from various channels. First, the foreign markets experience that firms gain through exports may ease foreign sourcing and reduce the sunk costs associated to start importing. Second, more intense price competition in foreign markets may force exporters to import inputs when imported inputs are cheaper than domestic ones. Finally, if international markets put a high weight on product quality and importing higher quality inputs allows exporters to upgrade the quality of their products, we expect exporters to be more prone to import intermediates.

However, to properly identify the set of own- and cross-direct effects described above we need to consider the own- and cross-indirect effects. Analysing the indirect effects of exporting and importing both on the likelihood of exporting and importing intermediates involves acknowledging: the links between exporting and importing, and productivity; and, the links between productivity and the likelihood of exporting and importing intermediates. The relationship between exporting and productivity has been

[3]Other works using the same strategy to identify the existence of export sunk costs are (Bernard and Jensen, 1999), (Bernard and Jensen, 2004) for the US and, (Campa, 2004) and (Mañez et al., 2008) for Spanish manufacturing.

[4]As pointed by one of the reviewers, it is important to acknowledge that many importers know in advance the price of the intermediate inputs they import, although there might be some other costs associated to importing that might be uncertain. Further, firms that are part of a global supply chain will have more information on the quality of imported inputs.

[5](Damijan and Kostevc, 2015) find a positive effect of importing on exporting for Spanish manufacturing, but they do not distinguish between importing of intermediates and other imports.

[6](Castellani et al., 2010) find that firms more exposed to international markets have a better performance. They suggest that the better performance of importers of intermediate inputs is related to the fact that they import mainly high-quality intermediates from major European countries.

extensively explored. Since (Bernard and Jensen, 1999) a plethora of papers have found empirical evidence suggesting that exporters are more productive that non-exporters. This exporting premium could be explained by a process of self-selection into exporting of the more productive firms and/or from potential productivity gains related to exporting. In the trade literature, the potential productivity gains related to exporting are associated to the process of learning-by-exporting (LBE, hereafter) that export participation may trigger. The gains in productivity associated to exporting are usually linked to growth in sales that allows firms to profit from economies of scale, knowledge flows from foreign customers and increased competition in international markets that forces firms to behave more efficiently. The gains in productivity associated to LBE are not *static* but *dynamic* since they accrue to the firm through exporting experience (De Loecker, 2007, 2013). Whereas there is widespread evidence of self-selection into exporting, evidence on LBE is mixed and far from conclusive, and among those that find evidence on LBE there are important differences about the magnitude and the duration of the LBE effect.[7]

The analysis of the impact of importing intermediates on productivity has deserved increasing attention in recent years. (Kasahara and Rodrigue, 2008) suggest that importing intermediates may have both *static (inmediate)* and *dynamic* effects on firms' productivity. The *static* effect of the use of intermediate inputs on firms' productivity is associated to the fact that firms importing intermediates have access to a wider variety of inputs and/or to higher quality inputs (Halpern et al., 2015), what could potentially result in an increase in output for a given total spending on intermediate inputs. (Kasahara and Rodrigue, 2008) attribute the *dynamic (long-run)* effect of import status on productivity to a process of learning-by-importing (LBI, hereafter) that could be related to the fact that importers of intermediate inputs profit from positive dynamic technological spillovers. As it happens with LBE, empirical evidence on the effects of importing intermediates on firms' productivity using firm level data is mixed. (Kasahara and Rodrigue, 2008), (Amiti and Konings, 2007) and (Halpern et al., 2015) find evidence suggesting a positive impact of importing intermediates on productivity for Chile, India and Hungary, respectively. Conversely, (Muendler, 2004) only finds a small contribution of imported intermediates and investment goods on Brazilian firms' productivity; and, results in (Van Biesebroeck, 2003) suggest that Colombian firms' productivity growth is more strongly correlated to export status than to importing intermediates.

The literature that jointly analyses the effects of exporting and importing intermediates on productivity is scarce. Among the few papers, it is worth mentioning (Kasahara and Lapham, 2013), who estimate a structural model in which heterogeneous final good producers simultaneously choose whether exporting and importing intermediates. Their results, using Chilean plant data, suggest the existence of aggregate productivity and welfare gains associated to exporting (final goods) and importing intermediates. (Mañez et al., 2020a,b) using firm level data for Spain also obtain evidence suggesting that both exporting and importing intermediates have a positive impact on firms' productivity. In Figure 1 we graphically summarise own and cross effects of importing and exporting distinguishing also between direct and indirect effects.

3. Data and descriptive statistics.

The data used in this paper are drawn from two databases. The Annual Manufacturing Survey (EAM) and the Technological Development and Innovation Survey (EDIT), published by the Colombian National Administrative Department of Statistics (DANE). The EAM is the annual census for industrial

[7] See for example (Silva et al., 2012) who offers a detailed survey on the LBE literature; (Martins and Yang, 2009) who provide a meta-analysis for 33 empirical studies; or, (Singh, 2010) who concludes that evidence on self-selection of the more productive firms into export markets overwhelms those works that find evidence in favour of the existence of learning-by-exporting.

establishments (identified according to the ISIC Revision 3 adapted for Colombia) with 10 or more employees or, failing that, firms that record an annual production value equal or greater than a value specified by the EAM for each reference year, which is indexed by the producer price index (PPI). It collects annual information at the firm level for variables such as value added, number of employees, energy consumption, among others. We use information of the EAM for the period 2007-2016. The EDIT is a biannual survey whose objective is to characterise the technological dynamics, innovation activities and technological development for manufacturing Colombian firms. It is a census of firms with establishments employing 10 or more workers or, failing that, have an annual production value equal or greater than a value specified by the EAM for each reference year. The statistical office uses, as in the case of the EAM, the ISIC Rev. 3, adapted for Colombia. We use five waves of the EDIT (from wave IV, for 2007-2008, to wave VIII, for 2015-2016).[8] After merging the EAM with the corresponding five EDIT waves and cleansing the data, we end up with an unbalanced panel data of ten years (2007-2016) with 68,215 observations corresponding to 9090 firms.[9] The final sample is composed by firms that provide information for output, capital, materials, number of workers, imports and exports, performing R&D, and other control variables used in the different econometric analyses carried out in this paper. Also, due to the small number of observations in specific sectors, these are merged into the following industries: 15 with 16 and 17 with 18.[10] Therefore, we end up with 18 industries.

Table 1: *Firms exporting and/or importing, 2007-2016.*

	Neither	**Export only**	**Import only**	**Both**
Observations	46,864	7,265	4,489	9,591
Percentage	68.70	10.65	6.58	14.06

Table 1 shows the distribution of firms' observations according to their trading strategies in our sample. The predominant strategy among Colombian manufacturing firms is not trading, as 68.70% of the firms neither export nor import (intermediate inputs). Further, 14.06% are both importers and exporters, 10.65% are only exporters and 6.58% are only importers. Furthermore, importing is more frequent among exporters than among non-exporters, whilst 53.46% of the exporters import intermediates, for nonexporters this percentage is much lower, 9.13%. Likewise, whereas 66.88% of the importers of intermediates also export, only 13.58% of the non-importers are involved in exporting activities.

In Figure 2, we plot the evolution across time of the proportions of firms classified according to their trade status (we leave out the firms that neither export nor import). These proportions remain quite constant along the period of analysis in general. The number of two-way traders and only exporters increases by 3% and 2%, respectively. However, the number of only importers decreases by 3%.

3.1. Persistence in exporting and importing.

To gain insight on persistence in exporting/importing, in Figure 3 we plot the Kaplan-Meier (KM, henceforth) exports and imports survivor functions. The KM (empirical) survivor function shows the percentage of exporting (importing) spells that continue in operation after a given number of years. We define an export (import) spell as a period of uninterrupted exporting (importing), i.e., the number of consecutive years exporting (importing). An export (import) spell is considered as starting in year t if the firm did

[8] We do not use previous versions of the EDIT due to important changes in the process gathering information on firms' innovations (Villarreal et al., 2014).

[9] We drop all observations with missing information in the relevant variables for our estimations as well as some outliers (firms with values in the variables we use to calculate TFP below and above the centiles 1 and 99, respectively).

[10] We merge these industries as they produce related outputs. The Industry 15 now is Beverage/Food and Tobacco and the industry 17 now is Textiles, Textile products, Leather and Footwear.

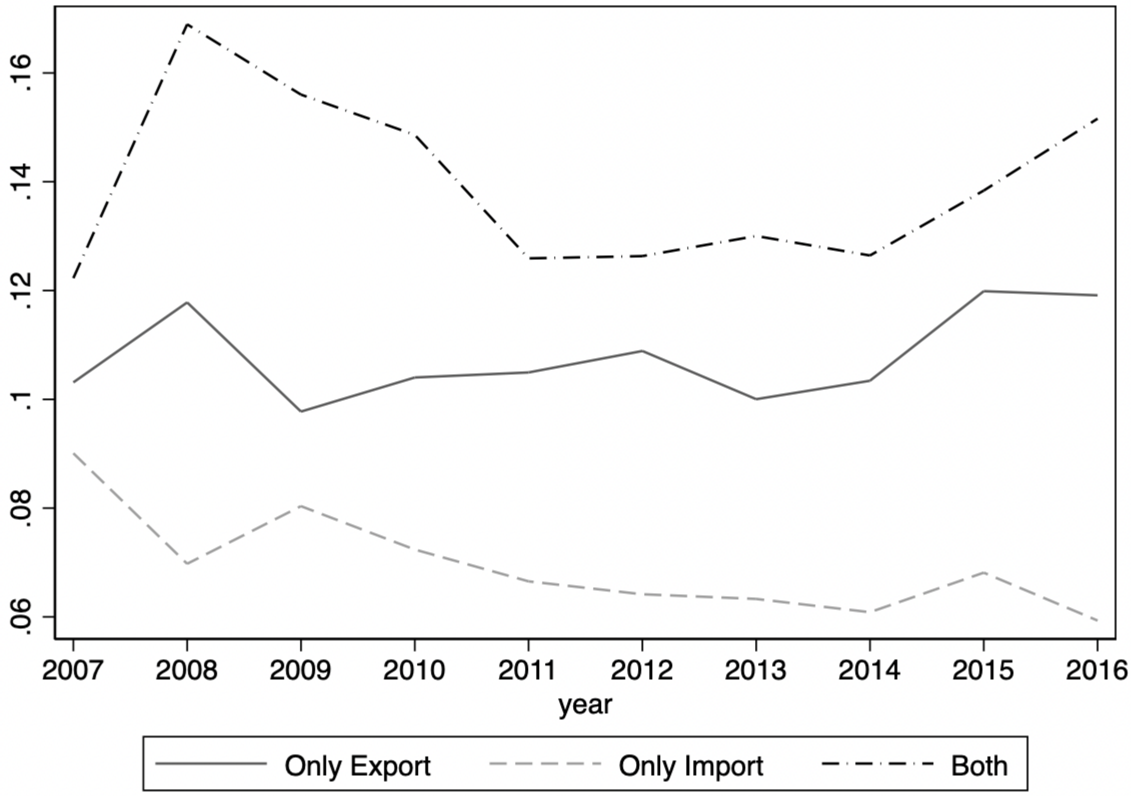

Figure 2: *Evolution of the rates of firms only exporting, only importing and both exporting and importing.*

not export (import) in year $t-1$ but exports (imports) in year t. Analogously, an export (import) spell is computed to end in year T if this is the first year in which the firm declares not exporting (importing), after one or more years continuously exporting (importing). Thus, we proxy persistence in exporting (importing) by the extent of continuous engagement in exporting (importing).

It is interesting to note that the export survival function is always above the import survival function, indicating that the export spells are longer than the import spells. Thus, whereas the median duration of import spells is 3 years, that for export spells is 4 years. Additionally, we can observe that both for export and import spells, the percentage of firms that abandon exporting and importing decreases as firms age in the corresponding trading activity (both KM survival functions get flatter as duration lengthens). This might indicate the existence of negative duration dependence attributable to learning in exporting and importing.[11]

3.2. On the relationship between exporting and importing.

In this sub-section we explore the relation between export and import of intermediate inputs strategies. We start the descriptive analysis of this relationship exploring the impact of import (export) experience over the probability of starting to export (import intermediate inputs). For this purpose, we estimate the following reduced form probit equations for export starters *(Xstarter)*,

[11] (?) relate the negative duration dependence of exports to a learning process arising from continuous exporting.

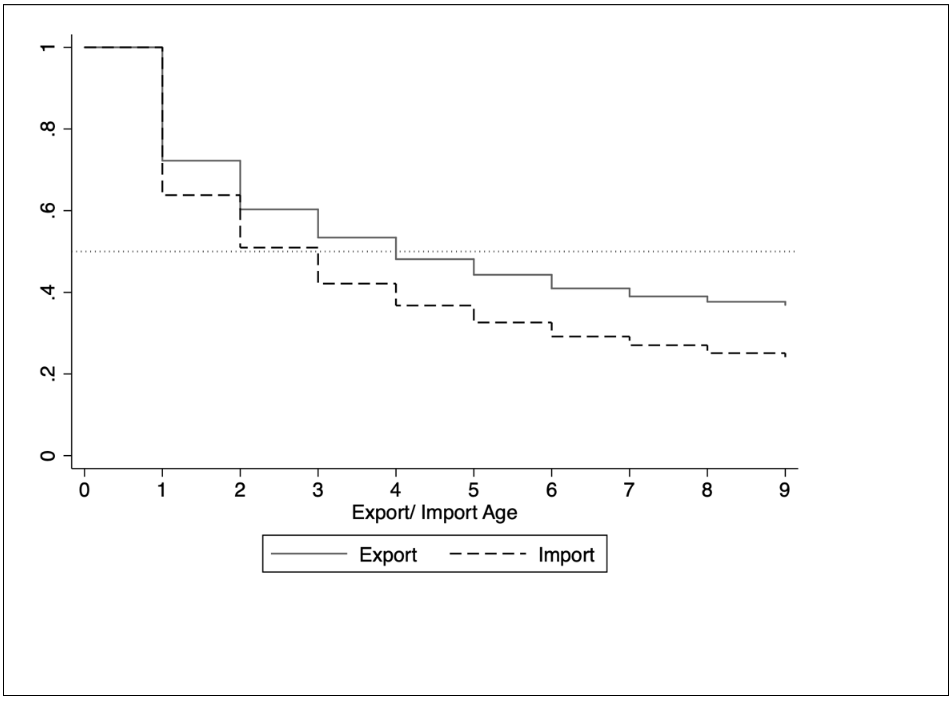

Figure 3: *Keplen maier.*

$$XStarter_{it} = \beta_0 + \beta_1 MExp_{it-1} + \gamma Z_{it-1} + \nu_t + \eta_s + u_{it} \quad (1)$$

and import (of intermediate inputs) starters *(MStarter)*,

$$MStarter_{it} = \beta_0 + \beta_1 XExp_{it-1} + \gamma Z_{it-1} + \nu_t + \eta_s + u_{it} \quad (2)$$

We consider as an export starter in t a firm not exporting either in $t-2$ or $t-1$, but exporting both in $t+1$ and $t-1$. Analogously, we consider as an import of intermediate inputs starter in t a firm not importing either in $t-2$ or $t-1$, but importing both in t and $t+1$.[12] We use two alternatives proxies for export experience *(XExp)* and import experience *(MExp)*: first, we proxy it using a dummy variable taking value 1 if the firm was an exporter (importer) in period $t-1$ (X_{it-1} and M_{it-1}); and, second, we use as a proxy the firm's export (import) age up to period $t-1$, defined as the number of continuous years exporting (importing) up to period $t-1$ (hereafter, we use *MA* to refer to import age and *EA* to refer to export age in equations). Z_{it} is a set of control variables (lagged one period to avoid problems of endogeneity) that includes the log total factor productivity (ω) and the log of firm size *(Size)*. ν_t is a vector of year dummies and η_s is a vector of industry dummies.[13]

In Table 2 we report the average marginal effects corresponding to the estimation of both the export and import starters equations. According to these results, we observe that regardless of whether we proxy import (export) experience using lagged import (export) participation or import (export) age, firms with past import (export) experience are more likely to start exporting (importing): both the marginal effects

[12]We require firms to export (import) at least two consecutive years to remove occasional exporters (importers).

[13]In estimation, we control for export age and import age using $log(XA_{it-1}+1)$ and $log(MA_{it-1}+1)$, respectively, to be consistent with the rest of the analyses in the paper.

of the lagged import (export) participation dummy and the import (export) age variables are positive and statistically significant in the export (import) starters equation. Furthermore, our results also suggest that larger and more productive firms in $t-1$ are more likely to start exporting and importing in t, what provides evidence in favour of the existence of selection into exporting and importing processes for Colombian manufacturing firms.

Table 2: *Impact of import (export) experience on the probability of becoming an export (import) entrant.*

	Export		**Import**	
	Spec. 1	**Spec. 2**	**Spec. 1**	**Spec. 2**
M_{it-1}	0.014***			
	(0.002)			
$log(MA_{it-1}+1)$		0.009***		
		(0.002)		
X_{it-1}			0.017***	
			(0.002)	
$log(EA_{it-1}+1)$				0.011***
ω_{it-1}	0.003***	0.003**	0.008***	0.008***
	(0.001)	(0.001)	(0.002)	(0.002)
$Size_{it-1}$	0.010***	0.001***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	23,913	23,613	24,405	24,405

Notes: We report average marginal effects.
Industry and time fixed effects are included in all the estimations.
Robust standard errors are in parenthesis.
***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Next, we analyse whether firms with more experience in importing (exporting) show a higher export (import) persistence, using survival models. In particular, we estimate a discrete time proportional hazard model in which the duration of exports (imports) spells is treated as a discrete time, not because it is intrinsically discrete but because data are available on a yearly basis (interval-censored data). Although the underlying transition process between exporting (importing) and not-exporting (notimporting) may occur in a continuous way, we only observe these transitions annually. This estimation method allows for a flexible specification of the baseline hazard and to control for unobserved heterogeneity, which helps to better identify the correlation between import (export) experience and export (import) persistence. More specifically, we estimate the discrete time representation of the following underlying continuous time proportional hazard function to analyse the duration of exports,

$$h^X(t, MExp_{it-1}, Z_{it-1}) = h_0(t)^X exp(\beta_0 + \gamma MExp_{it-1} + \beta Z_{it-1} + \eta_s + \mu_t)\nu_i \tag{3}$$

and the symmetric one to analyse the duration of imports,

$$h^M(t, XExp_{it-1}, Z_{it-1}) = h_0(t)^M exp(\beta_0 + \gamma xExp_{it-1} + \beta Z_{it-1} + \eta_s + \mu_t)\nu_i \tag{4}$$

where X and M denote exports and imports of intermediate, respectively. $h^K = (t, KExp_{it-1}, Z_{it-1})$ for $K = X, M$, is the hazard function of continuing exporting or importing; $h_0(t)^K$, the baseline hazard, is proxied by export survival time in the export survival equation and import survival time in the import equation. $MExp_{it-1}$ is firm's import experience, measured as the $log(MA_{it-1}+1)$ in the export survival equation, and $XExp_{it-1}$ is firm's exports experience, measured as the $log(EA_{it-1}+1)$ in the import survival equation; Z_{it-1} is a vector of control variables including one-period lagged logs of firm size and TFP. In estimation we also include a vector of year (μ_t) dummies and a vector of industry dummies (η_s). Unobserved heterogeneity (ν_i) is incorporated multiplicatively. The reason is that in this way, it measures a proportional increase or decrease in the hazard rate of a given firm, relative to an average firm. In estimation, we assume that unobserved heterogeneity (frailty) follows a gamma distribution (see (Allison, 1982) and (Jenkins, 2005))[14] It is important to remark that in proportional hazard survival models, the baseline hazard $(h_0(t)^k$ for $K = X, M)$ is the hazard that, after controlling for covariates and unobserved heterogeneity, can be attributed to the passage to time, i.e., the number of continuous years of exporting (importing) in the export (import) survival equation. We expect that sunk costs and learning will induce a pattern of negative duration dependence for the baseline hazard.[15]

In Table 3, we present the estimates of the export and import survival equations. In these two equations, the null that the variance of the unobserved heterogeneity component is equal to zero is rejected. Therefore, we confirm the need of controlling for the unobserved heterogeneity component.[16] The estimated coefficients indicate the effects of covariates on the hazard of termination of export and import spells. Positive coefficients should be interpreted as an increase in the hazard rate, and they are associated to a reduction in the expected duration of the export or import spell. On the contrary, negative coefficients indicate a reduction in the hazard rate, as they are associated to an increase in the expected duration of exporting or importing spells.

Table 3: *The effect of import (export) experience on export (import) survival.*

	Export Survival	**Import Survival**
$log(ExportSurv.time)_{it}$	-0.925***	
	(0.409)	
$log(importSurv.time)_{it}$		-0.943***
		(0.038)
$log(ImportAge_{it-1} + 1)$	-0.315***	
	(0.055)	
$log(ExportAge_{it-1} + 1)$		-0.238***
		(0.043)
$Size_{it-1}$	-0.230***	-0.182***
	0.021	0.019
ω_{it-1}	-0.054*	-0.081***
	(0.030)	(0.027)
Unobserved heterogeneity		
(test of significance of the variance of the frailty component)		
$\chi^2(01)$	12.128	16.504
$Prob \geq \overline{\chi}^2$	(0.000)	(0.000)
Number of observations	12,411	10,441
Number of spells	3,908	3,769

Notes: Industry and time effects are included in all estimations.
***, ** , * Indicate statistical significance at the 1%, 5% and 10% levels, respectively.

The negative estimate for export experience, *log(ExportSurv.Time)*, on the export survival equation

[14] We estimate the survival models using S. Jenkins Stata's routine pgmhaz8 that implements a cloglog model with a gamma distributed unobserved heterogeneity. It is available by typing ssc install pgmhaz8 inside Stata.

[15] The dependent variable of the export/import survival models, that we use to analyse exports/imports persistence, is not measured directly (in terms of the number of years of continuous exporting/importing) but consists of a binary variable taking value 1 for the survival period in which the firm quits exporting/importing and 0 as long as it remains exporting/importing.

[16] In Table 4, we present coefficients and not hazard ratios because when unobserved heterogeneity is relevant, the interpretation of the hazard ratios becomes burdensome and the exponentiated coefficients do not have any longer the interpretation of hazard ratios.

provides evidence in favour of a pattern of negative duration dependence (i.e. the probability of termination for an export spell decreases with the length of the spell), which could be related both to the existence of exporting sunk costs (Roberts and Tybout, 1997) and learning-by-exporting (Timoshenko, 2015a). Further, the estimated coefficient for import experience on the export survival equation is negative and statistically significant, suggesting that import experience is associated to longer duration of the exporting spells. Our estimates also suggest that larger and more productive firms enjoy longer exports spells.

The estimates corresponding to the import survival equation also indicate the existence of a pattern of negative duration dependence, as the coefficient of *log(ImportSurv.Time)* is negative and statistically significant. As before, we believe that this duration pattern is very likely related to the existence of sunk import costs and a process of learning associated to continuous importing. As for the relationship between import persistence and export experience, the negative and statistically significant estimate for the export experience variable signals that firms with more export experience enjoy longer imports spells. Finally, larger and more productive firms also endure longer importing spells.

4. Empirical modelling.

4.1. Modelling the joint decisions of exporting and importing.

We specify our model considering that the decisions of exporting and importing intermediates might be interrelated,[17] thus we will use a joint specification. Each of the two decisions would be specified in terms of sunk costs (Roberts and Tybout, 1997), learning (Timoshenko, 2015a) and a set of variables that proxy for the payoffs of each trading activity. We devote the rest of the section to justify the choice of this specification.

Both when entering export markets and when making the choice of importing intermediate inputs firms will face costs that are sunk in nature. Exporting sunk costs stem from factors such as setting up marketing and distribution channels, exploring foreign demand and competition, customising the characteristics of their products to adapt them to foreign tastes and/or to meet other countries quality and security legislations. Regarding to the sunk costs related to import intermediates, it should be considered that firms must invest resources to access higher quality inputs, a larger range of inputs, or to the foreign technology incorporated in intermediate inputs (Bustos, 2011). The existence of sunk costs related to both exporting and importing intermediates entails that firm's past export decisions (X_{it-1}) and past import of intermediates decisions M_{it-1} should be considered as state variables in the firm's current export and import of intermediates decisions, respectively.

After (Roberts and Tybout, 1997) research, the state dependence of exports and imports has been attributed to the existence of sunk starting-up and ceasing costs.[18] Nevertheless, (Timoshenko, 2015a) notes that the state dependence of current export status should not be fully attributed to sunk costs as it could be the result of sunk costs, demand learning in export markets or both. Analogously, we believe that state dependence of current imports may be related to sunk costs, import supply learning or both of them. As for the demand learning in exports markets, (Arkolakis et al., 2018) and (Timoshenko, 2015b)

[17] The specification does not impose that the two decisions are necessarily interrelated; instead, it considers that firms may implement distinct export and import strategies, i.e. some firms only export, some only import, and others decide to perform both activities

[18] (Roberts and Tybout, 1997) and (Timoshenko, 2015a) develop these arguments in the estimation of an export decision equation. However, we believe that they are also valid when analysing firms' import decisions.

assume that firms, when start exporting, are uncertain about the appeal of their products and must learn about it. As firms continue exporting they learn about their appeal. In the same line, we hypothesize that when firms start importing intermediates they face some uncertainty as they need to learn customs procedures, search for potential foreign suppliers, testing whether the intermediate inputs match their production line, negotiation, contract formulation, etc. However, as firms gradually acquire experience importing intermediate inputs this initial uncertainty about intermediate input supply gets reduced and so eases to continue importing intermediates. Thus, following (Timoshenko, 2015a), in order to disentangle the effect of export sunk costs and demand learning in the export decision, and the effect of import sunk costs and import supply learning in the imports of intermediates decision, we include as additional regressors the log of export age ($log(EA_{it-1} + 1)$) and the log of import age ($log(MA_{it-1} + 1)$) in the export and imports equations, respectively. EA_{it-1} and MA_{it-1} are measured as the number of years continuously exporting and importing intermediates up to period $t - 1$, respectively.[19]

Using the terminology proposed in section 2, we consider that both the export sunk cost and the demand learning effects proxy for own-direct effect of exporting. Analogously, the import sunk cost and the import supply learning effects proxy for the own-direct effect of importing.

In this dynamic framework, a firm will export and/or import intermediates in year t whenever the current increase in gross operating profits associated to the decision of exporting and/or importing intermediates plus the discounted expected future returns from being an exporter (importer) in year t exceed sunk costs.

Insofar as the value function of a firm that decides to import intermediates may be influenced by its optimal past export decisions and vice versa, our joint likelihood will include firms' past imports of intermediates experience ($MExp_{it-1}$) as a variable explaining the current probability of exporting, and firms' past exports experience ($XExp_{it-1}$) as a variable explaining the current probability of importing. These two variables capture cross-direct effects of importing on exporting and cross-direct effects of exporting on importing, respectively.

Furthermore, when past export and/or import experience may affect future productivity, the proper identification of own- and cross-direct effects of exporting and importing intermediates requires to explicitly considering the effect of past export and import experience on current productivity (see (De Loecker, 2013) for exports and (Kasahara and Rodrigue, 2008) for imports). Accounting for the role of past import and export experience in shaping firms' future productivity requires departing from (Timoshenko, 2015b) assumption of an exogenous Markov process for the law of motion of productivity. Thus, as explained in detail in the next section, we will consider a more general (endogenous) Markov process that allows for past experience importing intermediates and exporting to affect current productivity. In addition, this will allow us to analyse learning-by-exporting and learning-by-importing processes not explicitly considered in (Timoshenko, 2015b) analysis.

Note that if productivity evolves endogenously depending on past import and export decisions, firms' payoffs from importing intermediates (exporting) depend positively on how much past importing intermediates (exporting) experience increases future productivity. Thus, in our empirical model the net benefits from exporting and importing intermediates are increasing in productivity. This implies endogenizing the self-selection mechanism, since firms' past import/export experience may increase produc-

[19]The log transformation of the Export and Import Age variables is specified as $log(EA_{it-1} + 1)$ and $log(MA_{it-1} + 1)$. (Timoshenko, 2015a) shows that it allows separating the state dependence effects into its two components, sunk costs and learning. Further, this transformation avoids the problem of calculating the log value of 0 for firms without export or import experience.

tivity, and hence, would positively affect the probability of firms self-selecting or continuing in such trading activities. Therefore, we include the log total factor productivity (ω_{it-1}) in our our specification of the joint likelihood of exporting and importing intermediates.

As discussed in the section 2, we refer to the effects of exporting on the likelihood of exporting and the likelihood of importing intermediates that are channelled through enhanced productivity, own-indirect effect and cross-indirect effect of exporting, respectively. Likewise, we refer to the effects of importing that accrue to the likelihoods of importing and exporting, through increased productivity, as own-indirect effects and cross-indirect effects of importing, respectively.

Moreover, proper identification of own- and cross-effects of importing and exporting requires controlling for other variables that, in addition to productivity, may potentially affect the exporting and importing payoffs, and therefore firms' export and import decisions. Thus, we control for observable firm/market characteristics, a vector of time dummies μ_t and a vector of industry specific dummies, μ_s.

The vector of control variables, Z_{it}, includes firm's size, firms' markups,[20] demand evolution, whether the capital of the firm has foreign participation[21] and firm complementary assets such as the intensity of skilled labour or whether firms performs R&D. Further, we also aim to capture the existence of positive and significant effects (on the probability of exporting/importing) related to the geographical proximity of other exporting/importing firms. Agglomeration economies can help firms overcome start-up costs and engage in trade. Positive spillovers might arise from the sharing of indivisible goods and facilities and a greater variety of more specialized inputs, from a better mix of specialized employment or intermediate inputs and services, and from learning and spreading knowledge about, among others, production technologies and market opportunities (Duranton and Puga, 2004). Therefore, we also control for the existence of exporting (importing) spillovers stemming from geographical proximity of other exporters (importers).[22] We lag the set of control variables one period to avoid potential problems of simultaneity. Including the vector of time dummies, μ_t allows capturing macro-level changes in market conditions that are common across firms, such as the business cycle, credit market conditions, overall changes in demand and other time varying factors. The inclusion of the vector of industry dummies, μ_s, allows controlling for unobservable characteristics on the specific behaviour of firms in each industry.

The econometric model we estimate is a dynamic bivariate probit model for the joint decisions of exporting and importing intermediates. We condition these decisions on the set of variables above described:

$$X_{it}=\begin{cases}1 & \text{if} \quad \gamma_0^X+\gamma_1^X X_{it-1}+\gamma_2^X log(EA_{it-1}+1)+\gamma_3^X MExp_{it-1}+\gamma_4^X \omega_{it-1}+\beta^X Z_{it-1}+\Sigma_{j=2}^4 \tilde{\gamma}_{it-j}^X \tilde{X}_{it-j}+\mu_t^X+\mu_s^X+u_{it}^X \geq 0\\ 0 & \text{otherwise}\end{cases}$$
$$X_{it}=\begin{cases}1 \text{ if } \gamma_0^M+\gamma_1^M M_{it-1}+\gamma_2^M log(MA_{it-1}+1)+\gamma_3^M XExp_{t-1}+\gamma_4^M \omega_{it-1}+\beta^M Z_{it-1}+\Sigma_{j=2}^4 \tilde{\gamma}_{it-j}^M \tilde{M}_{it-j}+\mu_t^M+\mu_s^M+u_{it}^M \geq 0\\ 0 \text{ otherwise}\end{cases} \tag{5}$$

In the system of equations 5, positive and significant estimates for γ_1^X and/or γ_2^X should be considered as evidence in favour of the existence of own-direct effects of exporting: γ_1^X measures the export

[20]We calculate markups using (De Loecker and Warzynski, 2012) methodology.

[21]Unlike local firms, firms that are foreign owned are more likely to enter the export-import business. (Manova and Zhang, 2009), (Boddin et al., 2017) provide evidence in this regard.

[22]We calculate export (import) spillovers as the percentage of exporting (importing) firms that export (import) in the same Colombian department, year and technological sector, excluding the own firm. An alternative possibility would have been to calculate them at the industry level. Nevertheless, there is a significant number of year-industry-department combinations with no exporters or importers. Industries are classified into three technological intensity sectors, in accordance with the OECD technological intensity classification (ISIC Rev. 3) (Hatzichronoglou, 1997). Due to low number of observations in the high-tech sector, we merge it with the med/high-tech sector. See Table A2 in the Appendix for the industry classification into technological sectors.

sunk cost effect and γ_2^X measures the demand learning effect. Analogously, positive and significant estimates for γ_1^M and/or γ_2^M suggest the existence of own-direct effects of importing. Whilst γ_1^M measures the import sunk cost effect, γ_2^M measures the import supply learning effect.

At this point, it is relevant to deepen into the differences of a model without demand learning and import supply learning effects. Let us use as example the export equation. In a model without demand learning the total own-direct effect of one-year export experience is given by γ_1^X and it is fully attributed to export sunk costs. Nevertheless, in a model with demand learning effects, the total own-direct effect of one-year exporting experience is $\gamma_1^X + \gamma_2^X log(EA_{it-1} + 1) = \gamma_1^M + \gamma_2^M log(2)$, and it can be decomposed in the corresponding export sunk costs effect, γ_1^X, and the demand learning effect, $\gamma_2^X log(2)$. Therefore, to the extent that the estimate of γ_2^X results positive and significant, in a model without demand learning we would be overestimating the true sunk cost effect. An identical argument can be applied to the decomposition of the total own-direct effect of one-year importing experience into the import sunk cost effect (γ_1^M) and the import supply learning effect ($\gamma_2^M log(2)$).

As for the cross-direct effects of past export experience ($XExp_{it-1}$) on the probability of importing and cross-direct effect of past import experience ($MExp_{it-1}$) on the probability of exporting, we consider two different proxies for past export (import) experience: whether the firm exported (imported) in period $t-1$ and the number of years of continuous exporting (importing) up to $t-1$. Positive and significant estimates of γ_3^X and γ_3^M suggest that past import experience positively affects the probability of exporting and past export experience positively affects the probability of importing, respectively.

In addition, the estimates γ_4^X and γ_4^M should provide evidence on the existence of a self-selection /continuation mechanism of the most productive firms into exporting and importing. It should be considered that for firms that start exporting/importing they capture the well-known self-selection mechanism into exporting and importing. In contrast, for firms already exporting/importing, γ_4^X and γ_4^M capture an endogenous selfs-election mechanism (Mañez et al., 2020b), that is at work when firms' previous export and import experience shape future productivity, and, therefore the probability of continuing exporting and importing. More specifically, a positive and significant estimate of γ_4^X is a necessary condition for the existence of the own-indirect effect of exporting and the cross-indirect effect of importing. Likewise, a positive and significant estimate of γ_4^M is a necessary condition for the existence of the own-indirect effect of importing and the cross-indirect effect of exporting.

(Timoshenko, 2015a) theoretical model assumes full depreciation of sunk costs and export experience once a firm stops exporting. Nevertheless, as she does in her empirical application, it is sensible to assume that this depreciation happens gradually as firms remain without exporting/importing. To account for the possibility of lower sunk start-up costs for firms that re-start exporting (importing) after j years without doing so, we follow (Roberts and Tybout, 1997) and broaden the export decision equation to include $\tilde{X}_{it-j}$(for $j = 2, ..., J$) and the import decision equation to include $\tilde{M}_{it-j}$(for $j = 2, ..., J$). $\tilde{X}_{it-j}$ is a dummy variable taking value one if the last time the firm exported was in $t-j$; and, analogously, $\tilde{M}_{it-j}$ is a dummy variable taking value one if the last time the firm imported was in $t-j$. Furthermore, observation of the evolution of $\tilde{\gamma}_{it-j}^X$ and $\tilde{\gamma}_{it-j}^M$ as j increases will allow us to infer the pattern of depreciation of export and import experience.

Finally, there may be firm unobserved factors that may affect firms' imports and export decisions such as managerial skills or the ability of the personnel in the firm's exports or purchases departments. Thus, we assume that the error term, u_{it}, has two components, a permanent firm specific effect (α_i) and a transitory component ϵ_{it}, then $u_{it} = \alpha_i + \epsilon_{it}$. Hence, we allow for two sources of serial correlation in u_{it}. This is an important issue since, whether or not the error term ϵ_{it} is independent across t, u_{it} will be always serially correlated because of α_i.

In the estimation of the dynamic bivariate probit model 5, we control for correlated unobserved firm heterogeneity using the approach proposed by (Blundell et al., 1999, 2002). It implies making assumptions about the distribution of the unobserved effects (α_i) conditional on observed variables and adopting a conditional maximum likelihood approach (Chamberlain, 1982). Therefore, following (Blundell et al., 1999, 2002) we may model the distribution of α_i as:

$$\alpha_i = \gamma_0 + \gamma_1 \overline{q}_i + e_{it} \tag{6}$$

Where $\bar{q}_i$ includes the pre-sample means of the dependent variables of the export and import equations ($\bar{y}_{i0}^{Exp}$ and $\bar{y}_{i0}^{Imp}$, respectively.) (Blundell et al., 1999) suggest that firm permanent effects might be captured by the entry pre-sample means of the dependent variables, which should act as sufficient statistics for unobserved firm heterogeneity. Thus, $\bar{y}_{i0}^{Exp}$ and $\bar{y}_{i0}^{Imp}$ are added as additional regressors of the export and imports equations in 5. Finally, e_{it} represents the error term which is assumed to be independent of the pre-sample means of the dependent variable, the explanatory variables and the idiosyncratic error term of the main equation. As we use as pre-sample period 2007-2009 and the explanatory variables in equation 5 are lagged one period, we carry out estimation for the period 2010-2016.

4.2. Production function estimation.

We assume that firms produce using a Cobb-Douglas technology:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{dm} dm_{it} + \omega_{it} + \eta_{it} \tag{7}$$

Where y_{it} is the natural log of production (output in real terms) for firm i in period t, l_{it} is the natural log of labour (as measured by the number of employees), k_{it} is the natural log of capital and m_{it} is the natural log of intermediate inputs (materials in real terms). As for the unobservables, ω_{it} is the log of firm's productivity (not observable for the econometrician but observable or predictable by the firm) and η_{it} is a standard $i.i.d$ error term (neither observable nor predictable by the firm). Further, we assume that capital is a state variable, whereas labour and materials are adjustable inputs when a firm faces a productivity shock (i.e., they are variable non-dynamic factors).[23]

In line with (Kasahara and Rodrigue, 2008) and (Halpern et al., 2015) we augment the production function 7 to include as a shifter the term dm_{it} (a dummy variable for the firm's discrete choice of importing intermediates). Using (Kasahara and Rodrigue, 2008) terminology, the estimated coefficient of dm_{it} captures the *static* contribution of importing intermediate inputs to firms' production. Thus, a positive and significant β_{dm} would suggest an *inmediate* effect from the use of importing intermediates on firm's productivity. This *static* effect of the use of intermediate inputs on output is associated to the fact that firms importing intermediates have access to a wider variety of inputs and/or to higher quality inputs, what could potentially result in an increase in output for a given total spending on intermediate inputs.

[23]It is assumed that K_{it} is accumulated according to a dynamic investment process, $K_{it} = (1-\delta)K_{it-1} + i_{it-1}$, where i_{it-1} is the firm investment in period $t-1$ chosen after observing ω_{it-1}. The implicit assumption is that it takes a full time period for the new capital to be ordered, delivered, installed and become fully productive.

The procedure we use to obtain consistent estimates of input elasticities and estimates of TFP residuals relies on (Wooldridge, 2009) who argues that both the semiparametric (Olley and Pakes, 1996) and (Levinsohn and Petrin, 2003) *control function* approaches can be reconsidered as consisting of two equations which can be jointly estimated by GMM using the appropriate instruments. The first of these equations tackles the problem of endogeneity of non-dynamic inputs, and the second equation deals with the problem of the law of motion of productivity. In the first equation, to solve the problem of endogeneity of variable inputs (labour and materials), following (Levinsohn and Petrin, 2003) we proxy for *unobserved* firm productivity by inverting the intermediate material demand function.[24] Thus, productivity can be expressed as a function of observables. As for the second equation, to proxy for *unobserved* firm productivity, we assume the following endogenous Markov process for the law of motion of productivity (see (De Loecker, 2013) (Kasahara and Rodrigue, 2008), for exports and imports, respectively):

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}, dm_{it-1}, dx_{it-1}] + \xi_{it} = f(\omega_{it-1}, dm_{it-1}, dx_{it-1}) + \xi_{it} \tag{8}$$

where$f(\cdot)$ is an unknown function that relates productivity in t with productivity in $t-1$ and with past firm's import (dm_{it-1}) and export decisions (dx_{it-1}), and ξ_{it} is an innovation term uncorrelated with k_{it}.[25] The specification of the endogenous Markov process in 8 allows capturing both the potential increase in productivity stemming from a process of learning-by-exporting (De Loecker, 2013); and, the potential existence of *dynamic/long run* effects arising from the usage of imported intermediate inputs on firms' productivity (see (Kasahara and Rodrigue, 2008)). This dynamic effect of importing intermediates on productivity through learning-by-importing could be related to the fact that importers of intermediate inputs profit from positive dynamic technological spillovers through contact with foreign suppliers and suppliers' technology embodied in intermediate inputs (Mañez et al., 2020b).

After controlling in our estimation procedure for the endogeneity of variable inputs (using the approach suggested by (Levinsohn and Petrin, 2003)) and the *dynamic* effect of productivity related to the usage of imported intermediate inputs, the estimated coefficient β_{dm} in 7 captures the increase in productivity that a firm enjoys from switching from not importing intermediates to importing them, and that (Kasahara and Rodrigue, 2008) coined as *inmediate/static* effect of importing intermediates.

We estimate the production function 7 separately for eighteen industries and obtain estimates of firms' TFP as the residuals from the Cobb-Douglas production function:

$$\hat{\omega}^s_{it} = y^s_{it} - \hat{\beta}^s_l l_{it} - \hat{\beta}^s_m m_{it} - \hat{\beta}^k_k k_{it} - \hat{\beta}_d m^s dm_{it} \tag{9}$$

Where $\hat{\omega}^s_{it}$ is the estimated log total factor productivity of firm i operating in industry s in period t.[26]

4.3. Identification of the indirect effects of exporting and importing.

We consider as indirect effects of exporting and importing, on the likelihood of exporting and importing, those that happen through enhanced productivity, e.g. past export experience contributes to increase current productivity and this may have a positive impact on the probability of exporting and/or importing. Therefore, detection of indirect effects of exporting/importing requires checking whether importing intermediates and/or exporting has an effect on productivity in previous periods and then to check whether

[24] We assume that the demand of materials function is strictly monotonic in unobserved productivity to invert it.

[25] The non-parametric components implied in the estimation of the production function 7 using (Wooldridge, 2009) method are proxied by third-degree polynomial in their arguments.

[26] The estimated industry-specific input elasticities and the shifter coefficients in production function 7 are shown in Table 5.

this has an effect on the likelihood of exporting/importing intermediates in t.

As discussed previously, we hypothesize that importing intermediates may have both a *static* effect and a *dynamic* effect on productivity. The static effect, captured by the shifter dm_{it} in the production function 7, implies that importing intermediates has an immediate/contemporaneous effect on productivity (i.e. importing intermediates in $t-1$ impacts firm's productivity in $t-1$). The *dynamic* effect operates through the endogenous Markov process that determines the evolution of productivity (see equation 8), in which we allow past import experience to affect current productivity. Hence, we expect that firm's experience importing intermediates up to $t-2$ will have a positive impact on productivity in $t-1$.

Differently to what we hypothesize for imports of intermediate inputs, following (De Loecker, 2007, 2013) we do not expect exports to have a *static* effect on productivity. We assume that export experience will affect productivity through the endogenous Markov process that determines the law of motion of productivity (see equation 8). Thus, we expect firms' export experience up to $t-2$ to enhance firm's productivity in $t-1$.

The estimate of β_{dm} in the production function 7 provides information about the *static* effect of importing intermediates on productivity. Our starting point to exploring the *dynamic* effects of importing intermediates and exporting is the endogenous Markov process described in equation 8. Further, if following (Aw et al., 2011) we specify linearly the conditional expectation in equation 8, we get the following specification for the Markov process:

$$\hat{\omega}_{it-1} = \lambda_0 + \lambda_1 \hat{\omega}_{it-2} + \lambda_2 dm_{it-2} + \lambda_3 dx_{it-2} + \nu_s + e_{it-1} \tag{10}$$

where dm_{it-2} and dx_{it-2} are firm's decisions (or experience) to export and import up to $t-2$, respectively; and, e_{it-1} is an error term that allows for the potential existence of unobserved heterogeneity. To account for the fact that in estimation we pool the TFPs estimated for all industries, we include in equation 10 a set of industry dummies (ν_s). Additionally, we control for other factors that may affect the evolution of productivity by including a vector of observed firm characteristics (Z_{it-2}), and year effects (ν_t) aimed to capture time effects that are common across industries. The vector Z_{it-2} includes firm's size, markups, the proportion of skilled labour, whether the firm performs R&D activities and the firm's demand evolution. Thus, our final estimation equation is:

$$\hat{\omega}_{it-1} = \beta_0 + \lambda_1 \hat{\omega}_{it-2} + \lambda_2 dm_{it-2} + \lambda_3 dx_{it-2} + \gamma Z_{it-2} + \nu_s + \nu_t + e_{it-1} \tag{11}$$

We assume that e_{it-1} has two components, a firm specific effect a_i and a transitory component ζ_{it}, then $e_{it} = a_i + \zeta_{it}$. In the estimation of equation 11, we control for correlated unobserved firm heterogeneity using the approach suggested by (Blundell et al., 1999, 2002) and explained in section 4.1. In this particular case, this approach amounts to include as an additional regressor the pre-sample mean of $\omega_{it}(\overline{\omega}_{i0})$. We consider as pre-sample period the years 2007 to 2009.

We estimate two different specifications of 11. In the first specification, we proxy past export/import decisions (or experience) using lagged export/import participation dummies (X_{it-2} and M_{it-2}). In the second specification, we use import/export age, measured by $log(MA_{it-2}+1)$ and $log(EA_{it-2}+1)$. A positive sign of λ_1 signals the existence of productivity persistence. Positive and significant estimates of λ_2 and λ_3 should be interpreted as evidence of learning-by-importing and learning-by-exporting, respectively. According to the terminology of (Kasahara and Rodrigue, 2008), λ_2 captures the *dynamic* effect arising from the usage of imported intermediate inputs.

5. Estimation results.

Table 4 presents the estimation results of our dynamic bivariate probit model for the decisions to export and import intermediates (equation 5). Specification 1 shows the estimation results corresponding to a model in which we do not allow either demand learning effects or import supply learning effects. Specification 2 includes learning effects both in the export and import decisions equations. Both in specification 1 and 2, we use as proxies for the cross-direct effects of importing on exporting and exporting on importing, the one-period lag of import status and export status, respectively. The only difference between Specifications 2 and 3 is that in Specification 3 we proxy for these cross-direct effects using import age and export age (instead of the dummy variables) in the export and import equations, respectively.

Table 4: *Bivariate model estimations for export and import activities.*

	Specification 1		**Specification 2**		**Specification 3**	
	Export	**Import**	**Export**	**Import**	**Export**	**Import**
X_{it-1}	2.149***	0.228***	1.440***	0.218***	1.427***	
	(0.035)	(0.033)	(0.055)	(0.032)	(0.055)	
M_{it-1}	0.118***	1.769***	0.106***	1.099***		1.134***
	(0.034)	(0.034)	(0.033)	(0.053)		(0.052)
$log(EA_{it-1}+1)$			0.674***		0.674***	0.109***
			(0.043)		(0.043)	(0.023)
$log(MA_{it-1}+1)$				0.656***	0.075***	0.635***
				(0.042)	(0.025)	(0.043)
$Export\ Spillover_{it-1}$	0.013***		0.009***		0.009***	
	(0.003)		(0.001)		(0.001)	
$Import\ Spillover_{it-1}$		0.008***		0.007***		0.007***
		(0.002)		(0.001)		(0.001)
ω_{it1}	0.155***	0.187***	0.147***	0.177***	0.145***	0.183***
	(0.038)	(0.039)	(0.036)	(0.038)	(0.036)	(0.038)
$Markup_{it-1}$	-0.084**	-0.164***	-0.079**	-0.158***	-0.077**	-0.158***
	(0.037)	(0.038)	(0.036)	(0.037)	(0.036)	(0.037)
$Size_{it-1}$	0.108***	0.082***	0.095***	0.072***	0.096***	0.077***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$Skill\ Lab_{it-1}$	0.018	0.025***	0.016	0.025***	0.016	0.025***
	(0.012)	(0.009)	(0.011)	(0.009)	(0.011)	(0.009)
$R\&D_{it-1}$	0.109***	0.124***	0.111***	0.128***	0.111***	0.127***
	(0.026)	(0.024)	(0.025)	(0.024)	(0.025)	(0.024)
$Positive\ growth\ sales_{it-1}$	-0.011	0.0149	0.002	0.029	0.0033	0.032
	(0.021)	(0.020)	(0.021)	(0.020)	(0.021)	(0.020)
$Foreign\ capital_{it-1}$	0.416***	0.467***	0.408***	0.456***	0.409***	0.453***
	(0.037)	(0.034)	(0.037)	(0.034)	(0.037)	(0.034)
$\tilde{y}^{Exp}_{it-2}$	0.803***		0.916***		0.916***	
	(0.042)		(0.042)		(0.042)	
$\tilde{y}^{Exp}_{it-3}$	0.531***		0.648***		0.647***	
	(0.056)		(0.056)		(0.056)	
$\tilde{y}^{Exp}_{it-4}$	0.312***		0.442***		0.440***	
	(0.074)		(0.074)		(0.074)	
$\tilde{y}^{Imp}_{it-2}$		0.709***		0.827***		0.827***
		(0.039)		(0.039)		(0.039)
$\tilde{y}^{Imp}_{it-3}$		0.303***		0.424***		0.424***
		(0.052)		(0.052)		(0.052)
$\tilde{y}^{Imp}_{it-4}$		0.092		0.219***		0.215***
		(0.069)		(0.069)		(0.070)
$\tilde{y}^{Exp}_{i0}$	0.751***	0.102***	0.525***	0.088**	0.534***	0.124***
	(0.039)	(0.038)	(0.039)	(0.036)	(0.039)	(0.038)

$\tilde{y}_{i0}^{Imp}$	0.143***	0.759***	0.126***	0.547***	0.121***	0.541***
	(0.038)	(0.038)	(0.037)	(0.038)	(0.038)	(0.038)
constant	-3.401***	-2.852***	-3.106***	-2.730***	-3.099***	-2.748***
	(0.133)	(0.125)	(0.114)	(0.111)	(0.113)	(0.112)
Observations	44,464	44,464	44,464	44,464	44,464	44,464
ρ	0.500 (p-value = 0.000)		0.501 (p-value = 0.000)		0.499 (p-value = 0.000)	
Log-pseudo likelihood	-18650.451		-18406.356		18420.464	

Notes: Industry, department and year dummies are included in all specifications. Robust standard errors are in parentheses. ***, ** , * Indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Before analysing our estimation results, it is worth to note that the positive and statistically significant estimated correlation of the error terms of the two equations (ρ coefficients), in the three specifications considered (see bottom of Table 4), confirms the simultaneity of firms' exports and imports of intermediates decisions, and that, therefore, the joint estimation of both equations is the right estimation strategy.

5.1. Own-direct effects of exporting and importing.

We devote this section to the discussion of the results on own-direct effects of exporting and importing, in turn. Recall that the own-direct effect of exporting is composed of the export sunk costs effect and the demand learning effect. Likewise, the own-direct effect of importing is the sum of the import sunk cost effect and the import supply learning effect.

It is possible to observe, in the estimates corresponding to the export equation in Table 4, that regardless of whether we proxy own-direct effects of exporting just using one-year lagged export participation (Specification 1) or one-year lagged export participation plus export age (Specifications 2 and 3), own-direct effects of exporting are positive and statistically significant, i.e. past export experience has a direct positive effect on the probability of exporting. However, it is important to note that not including export age in the estimation leads to an overestimation of the real sunk cost effect. Comparison of the estimate corresponding to Specification 1 (2.149) with those corresponding to Specifications 2 and 3 (1.440 and 1.427, respectively) reveals that including export age (to capture demand learning effects) results in approximately a 33% reduction in the estimated sunk costs parameters. Further, the positive and significant estimate of the export age variable suggest that demand learning effects have a positive impact on the likelihood of exporting (these estimates are 0.674 in Specifications 2 and 3).

We can use the estimates corresponding to Specification 2 to show the decomposition of the total effect of one-year export experience (own-direct effect of exporting). Thus, the increase in the firm's latent utility of exporting in period t from one year export experience can be calculated as $\gamma_1^X + \gamma_2^X ln(EA_{it-1} + 1) = 1.440 + 0.674$ x $ln(2) = 1.907$. Therefore, 75.5% of the one-year own-direct effect of exporting corresponds to export sunk costs and the remaining can be attributed to learning. (Timoshenko, 2015a), also for Colombia, attributes a larger weight to the learning effect (52.68% of the total own-direct effect of one-year export experience).[27] Nevertheless, it should be considered that (Timoshenko, 2015a) considers an exogenous Markov process for the law of motion of productivity that precludes the existence of own-indirect effects of exporting and that very likely results in an overestimation of the learning component of the own-direct effect of exporting.

As for the own-direct effects of importing, we can observe in the estimates for the imports equation in Table 4 that in all specifications the variables used to capture owndirect effects of importing are positive and statistically significant (M_{it} in Specification 1; and M_{it} and $log(MA_{it-1})$ in Specifications 2 and 3) suggesting that import experience is a relevant determinant of the probability of importing. As it happens in the export decision equation, comparison of the sunk costs coefficient of Specification 1 with those of Specifications 2 and 3 suggests that not considering the possibility of import supply learning effects (i.e. not including $log(MA_{it-1})$ in estimation) leads to an overestimation of the real import sunk costs. When considering the learning effect, the estimate of the sunk costs effect experiments a reduction of almost 40% (from 1.769 in Specification 1 to 1.099 and 1.134

[27] See column 4 of Table 5 in (Timoshenko, 2015a).

in Specifications 2 and 3, respectively). Using specification 2, the increase in the firm's latent utility of one-year experience can be calculated as $\gamma_1^M + \gamma_2^M ln(MA_{it-1} + 1) = 1.099 + 0.656$ x $ln(2) = 1.553$. Thus, 71% of the total own-direct effect of importing corresponds to import sunk costs and the remaining 29% to import supply learning. Therefore, our estimations suggest that the weight of the learning component of the own-direct effect of importing is larger than that of the own-direct effect of exporting, i.e. the scope for import supply learning seems to be higher than that of export demand learning.

The high export and import of intermediates persistence implied by the own-direct effects of exporting and importing is reinforced by the positive and highly statistically significant effects of the pre-sample means of the export ($\overline{y}_{i0}^{Exp}$) and import decisions ($\overline{y}_{i0}^{Imp}$) (capturing their permanent effect through the firms' individual effects) in the export and import equations, respectively.

At this point it is interesting analysing the pattern of depreciation of export and import experience. The estimates for the variables $\tilde{y}_{it-2}^{Exp}, \tilde{y}_{it-3}^{Exp}$ and $\tilde{y}_{it-4}^{Exp}$ in the exports equation capture the reduction in the starting-up export sunk costs for a firm that last exported 2, 3 or 4 years ago, respectively (in comparison to the starting-up sunk costs that must face a firm that has never exported before). Analogously, the estimates for the variables $\tilde{y}_{it-2}^{Imp}, \tilde{y}_{it-3}^{Imp}$ and $\tilde{y}_{it-4}^{Imp}$ in the imports equation measure the reduction in starting-up import sunk costs for firms that last imported 2, 3 or 4 years ago, as compared to the starting-up import sunk costs that must incur a firm that has never imported before. The estimates corresponding to the variables capturing the depreciation of export experience show in all specifications a decreasing pattern, suggesting that the reduction in the starting-up export sunk costs is inversely related to the number of years since last the firm exported (thus, for example, in Specification 3, the estimates for $\tilde{y}_{it-2}^{Exp}, \tilde{y}_{it-3}^{Exp}$ and $\tilde{y}_{it-4}^{Exp}$ are 0.916, 0.647 and 0.440, respectively).

As for the pattern of depreciation of import experience, firms that last imported two, three or four years ago enjoy an import sunk cost reduction if they restart importing, that is decreasing with the number of years without importing (in Specification 3, for example, the estimates for $\tilde{y}_{it-2}^{Imp}, \tilde{y}_{it-3}^{Imp}$ and $\tilde{y}_{it-4}^{Imp}$ are 0.827, 0.424 and 0.215, respectively).

5.2. Cross-direct effects of exporting and importing.

Next, we explore the cross-direct effects of firms' importing experience on export participation and firms' exporting experience on import participation.

Estimation results of the different specifications of the export equation in Table 4 suggest the existence of a cross-direct effect of import experience on the likelihood of exporting. Whereas in Specifications 1 and 2, we proxy past import experience using one-period lagged import participation (M_{it-1}), in specification 3 we use the log of import age ($log(MA_{it-1}+1)$), with the aim of capturing possible learning effects associated to continuous importing. Our estimates for the export equation in Specifications 1 and 2 suggest that firms that imported in $t-l$ are more likely to export in period t (the estimate for the variable M_{it-1} is in both specifications positive and statistically significant, 0.118 and 0.106, respectively). Estimates for Specification 3 of the export equation suggest that firms with more import experience (higher import age) are also more likely to export in period t (the estimate of $log(MA_{it-1}+1)$ is 0.075). Therefore, as in (Mañez et al., 2020b) for Spanish manufacturing, our estimates suggest the existence of a process of learning-by- importing in terms of the probability of exporting. As sketched in section 2, there are two possible channels that explain this process: the price channel and the quality channel. As for the price channel, if importing allows firms accessing to lower price intermediates and this is at least partially translated to prices, the result would be that firms improve their competitiveness in international markets. With respect to the quality channel, if importing firms access higher quality inputs, it may contribute to upgrade firm's product quality fostering international competitiveness.

We find that past export experience has a positive cross-direct effect on the likelihood of importing, regardless the proxy variable we use for export experience in the imports equation. In Specifications 1 and 2, where we use as proxy for export experience one-period lagged export participation (X_{it-1}), the estimated coefficients of this variable in the import decision equation are positive and statistically significant (0.228 and 0.218 in Specification 1 and 2, respectively). Also, in Specification 3, where we proxy past export experience using export age ($ln(EA_{it-1}+1)$, the estimate of the past export experience variable is positive and significant (0.109). Thus, our estimation results suggest the existence of a process of learning-by-exporting in terms of the probability of importing. As already put forward in section 2, the positive direct effect of past export experience on the likelihood of importing may arise from various channels: i) benefiting from knowledge about international market characteristics gained through exporting; ii) if international markets are more competitive, exporting firms may be forced to seek lower price intermediates in international markets; and, iii) if international markets demand higher quality products, a possibility to upgrade product quality may be importing higher quality inputs.

Furthermore, the cross-direct effect of exporting on the likelihood of importing and vice versa are reinforced by the positive and highly significant effects of the presample means of the export decisions ($\overline{y}_{i0}^{Exp}$) and import decisions ($\overline{y}_{i0}^{Imp}$) in the imports and exports equations, respectively.

As regards the spillover effects, we find that both the estimate of the export spillover variable in the export participation equation and the import spillover variable in the import participation equation are positive and significant. Therefore, our results suggest that the geographical proximity to other exporting (importing) firms exerts a positive and significant effect on the probability of exporting (importing), as agglomeration economies can help firms to overcome start-up costs and engage in trade. This evidence for exports is in line with (Aitken et al., 1997) and (Cardoso-Vargas, 2017, 2019) for Mexico, (Koenig et al., 2010) for France, and (Fernandez and Tang, 2014) and (Mayneris and Poncet, 2015) for China. Further, the evidence for imports confirms previous results by (Bekes and Harasztosi, 2020) for Hungary. The estimates for the rest of the variables in the vector of control variables are robust to the different specifications of equation 5 considered, and quite similar in the exports and imports equations. Thus, larger firms, firms performing R&D and firms whose capital is foreign participated are more likely to both import and export.[28] Further, firms with a higher percentage of skilled workers are more likely to import intermediates. However, firms with higher markups are less likely to export and import.

5.3. *Indirect effects of exporting and importing.*

As explained above, we consider as indirect effects of exporting on importing and vice versa those that happen through enhanced productivity, e.g. past export experience contributes to increase current productivity and this has a positive impact on the future probability of importing. Therefore, detection of an indirect effect of exporting (importing) requires, first, to test whether exporting and/or importing have a positive effect on productivity, ω_{it-1}; and, second, whether ω_{it-1} has a positive impact on the probability of exporting (importing) in t.

We start analysing whether importing intermediates has an impact on productivity. As explained in section 4.3, we consider that importing may have both a *static* effect on productivity (captured by the impact of using imported inputs in $t-1$ on ω_{it-1}) and a *dynamic* effect (captured by the impact of import experience accumulated up to $t-2$ on ω_{it-1}). The *static* effect is given by the estimate of the industry shifter (β_{dm}) in the production function 7. As reported in Table 5, $\hat{\beta}_{dm}$ is positive and significant for all industries except for the industry "Wood and products of wood and cork (20)". Furthermore, the *static* effect of the usage of imported intermediates on productivity is sizeable as it ranges from 7.5% to 25.9%, with a mean (median) effect of 16.2% (14.8%).[29]

Table 5: *Total factor productivity estimation: input elasticities and shifter coefficients.*

Industry	β_l	β_m	β_k	β_{dm}	Mean TFP
15	0.213***	0.769***	0.050***	0.105***	2.607
	(0.004)	(0.006)	(0.005)	(0.011)	

[28]Evidence for the positive impact of foreign participated firms can be found in (Manova and Zhang, 2009) and (Boddin et al., 2017)

[29]Our estimates of the *static* effect of importing intermediates do not differ much from (Kasahara and Rodrigue, 2008) results using a sample of Chilean plants. They estimate a *static* effect of the usage of imported intermediates of about 22% when assuming an endogenous Markov process for the law of motion of productivity, in which past import experience is allowed to affect current productivity.

17	0.306***	0.607***	0.049***	0.075***	4.314
	(0.004)	(0.008)	(0.008)	(0.014)	
19	0.251***	0.743***	0.030***	0.075**	2.777
	(0.008)	(0.013)	(0.011)	(0.030)	
20	0.204***	0.728***	0.082***	0.058	3.120
	(0.017)	(0.016)	(0.014)	(0.047)	
21	0.115***	0.779***	0.082***	0.158***	2.773
	(0.010)	(0.018)	(0.015)	(0.030)	
22	0.307***	0.541***	0.128***	0.116***	4.857
	(0.010)	(0.012)	(0.013)	(0.027)	
23	0.050***	0.901***	0.059***	0.152***	1.411
	(0.017)	(0.024)	(0.019)	(0.041)	
24	0.263***	0.718***	0.057***	0.259***	3.246
	(0.006)	(0.012)	(0.012)	(0.017)	
25	0.241***	0.729***	0.050***	0.189***	3.023
	(0.005)	(0.01)	(0.009)	(0.012)	
26	0.204***	0.769***	0.099***	0.143***	2.520
	(0.009)	(0.01)	(0.009)	(0.021)	
27	0.295***	0.759***	0.038**	0.145***	2.502
	(0.017)	(0.014)	(0.015)	(0.038)	
28	0.276***	0.642***	0.072***	0.250***	3.999
	(0.008)	(0.01)	(0.01)	(0.019)	
29	0.372***	0.615***	0.046***	0.227***	4.085
	(0.01)	(0.013)	(0.011)	(0.023)	
31	0.187***	0.761***	0.061***	0.121***	2.852
	(0.020)	(0.019)	(0.013)	(0.031)	
33	0.453***	0.508***	0.071***	0.250***	5.138
	(0.028)	(0.037)	(0.036)	(0.055)	
34	0.234***	0.718***	0.069***	0.245***	3.081
	(0.012)	(0.015)	(0.015)	(0.029)	
35	0.128***	0.769***	0.045**	0.240***	3.153
	(0.026)	(0.034)	(0.026)	(0.070)	
36	0.216***	0.700***	0.059***	0.111***	3.453
	(0.007)	(0.01)	(0.009)	(0.018)	

Notes: Robust standard errors are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. See industry classification in Table A1 in the Appendix.

Exploring the *dynamic* effect of importing experience (associated to LBI) on productivity requires to check the sign and statistical significance of the coefficient associated to import experience (λ_2) in equation 11. The results of the estimation of equation 11, displayed in Table 6, show that regardless of whether we proxy past import experience using whether firms imported or not in $t-2$ (Specification 1) or firms' import age up to $t-2$ (Specification 2), the estimate for λ_2 is positive and significant, i.e. import experience up to $t-2$ has a positive impact on ω_{it-1}. This should be interpreted as evidence in favour of a process of LBI or, using (Kasahara and Rodrigue, 2008) terminology, of a *dynamic* effect of importing intermediates on productivity.

As for the possible effect of exporting on productivity, we expect it to be associated to a dynamic learning-by-exporting process, that would be captured by the estimated coefficient for the exporting experience variable (λ_3) in equation 11. Estimates of equation 11 (see Table 6) show that regardless of whether we proxy export experience using an export status dummy in $t-2$ (Specification 1) or export age up to $t-2$ (Specification 2), λ_3 is positive and significant suggesting the existence of a process of LBE in terms of productivity.[30]

[30]With respect to the estimates of the rest of the variables in equation 11: first, the estimated coefficient for ω_{it-2} is positive and statistically significant suggesting a high degree of persistence in the evolution of productivity over time; second, we find that larger firms, those with higher markups, higher proportion of skilled labour, involved in R&D activities and facing an expansive demand enjoy a higher productivity; and, third, the productivity persistence suggested by the positive estimate for lagged productivity is reinforced by the positive and highly significant effect of the productivity pre-sample mean ($\overline{\omega}_{i0}$),

Table 6: *Total factor productivity on Export and Import experience.*

	Specification 1	**Specification 2**
ω_{it-2}	0.310***	0.311***
	(0.005)	(0.005)
X_{it-2}	0.022***	
	(0.004)	
M_{it-2}	0.011***	
	(0.004)	
$logEA_{it-2}+1)$		0.019***
		(0.003)
$log(MA_{it-2}+1)$		0.004*
		(0.002)
$log(Markup_{it-2}$	0.189***	0.188***
	(0.005)	(0.005)
$log(Size)_{it-2}$	0.004***	0.004***
	(0.001)	(0.001)
$Skill\ Lab_{it-2}$	0.004***	0.004***
	(0.001)	(0.002)
$R\&D_{it-2}$	0.007**	0.007**
	(0.003)	(0.003)
$Positive\ growth\ sales_{it-2}$	0.018***	0.017***
	(0.002)	(0.002)
$\overline{\omega}_{i0}$	0.073***	0.073***
	(0.004)	(0.004)
Constant	1.499***	1.495***
	(0.014)	(0.014)
Observations	44,578	43,578
R^2	0.909	0.909

Notes: Industry and year dummies are included in all specifications. Robust standard errors are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

As put forward above, once we have found evidence of a positive effect of both past exporting and importing intermediates on productivity, the empirical confirmation of export and import indirect effects requires to check whether ω_{it-1} has a positive effect on the probability of exporting and importing in t. This implies to check the sign and the statistical significance of ω_{it-1} in equation 5. Both in the exports and imports equations the estimated coefficient for ω_{it-1} is positive and statistically significant and quite similar in size across the different specifications, about 0.15 in the exports equation and 0.18 in the imports equations (these estimates are reported in Table 4). However, the fact that both export and import experience have a positive effect on productivity precludes the separated identification of the own-indirect effect of exporting and the cross-indirect effect of importing on exporting, on the one hand; and, of the own-indirect effect of importing and the cross-indirect effect of exporting on importing, on the other hand.

Positive and significant estimates for λ_3 in equation 11 and γ_4^X in equation 5, suggest the existence of a positive own-indirect effect of exporting. Analogously, positive and significant estimates for λ_2 and γ_4^X are evidence in favour of a positive cross-indirect effect of importing on exporting. Nevertheless, the fact that both past export and import experience enhance current productivity prevents the separate identification of each effect.

Likewise, positive and significant estimates for λ_2 in equation 11 and γ_4^M in equation 5 should be interpreted as evidence of a positive own-indirect effect of importing; and, positive and significant estimates of λ_3 and γ_4^M suggest that cross-indirect effects of exporting on importing are in operation. Again, the problem is that given that both past import and export experience positively impact on productivity, we cannot identify each effect separately.

capturing its permanent effect through the firm's individual effect.

All in all, although we cannot identify some of the indirect effects separately, our results suggest the existence of both own- and cross-indirect effects of both exporting and importing experience. These effects are linked, on the one hand, to the productivity enhancing effects associated to using imported intermediates (static effects and learning-by-importing) and exporting (learning-by-exporting); and, on the other hand, to a process of self-selection/continuation of the more productive firms into exporting and importing intermediates.

6. Robustness exercises

In this section we carry out two robustness exercises. The first exercise is addressed to identify whether some firm characteristics may impact how importing intermediates affects the probability of exporting. In other words, we aim to identify for which type of firms the cross-direct effect of importing on the probability of exporting is higher. The second robustness exercise is targeted to explore whether the cross-direct effect of importing on the probability of exporting differs for firms operating in different technological intensity industries.

More specifically, in our first robustness exercise we investigate if the size of the firm, the qualification of its labour force and whether the firm performs R&D or not have any differential impact on the size of the cross-direct effect of importing intermediates on the probability exporting. Recall that the cross-direct effect of importing measures the effect of past import experience on the probability of exporting. Thus, we widen Specifications 1 and 2 of the export equation of our dynamic bivariate probit model (equation 5) with interactions of M_{it-1} with $Size_{it-1}, SkillLab_{it-1}$ and $R\&D_{it-1}$. Analogously, we enlarge Specification 3 with interactions of $log(MA_{it-1}+1)$ with $Size_{it-1}, SkillLab_{it-1}$ and $R\&D_{it-1}$.[31] These results are reported in Table 7.

As it is possible to observe in Table 7, when introducing the interactions terms, the estimates of M_{it-1} in Specifications 1 and 2 are still positive and significant (0.395 and 0.408, respectively). Likewise, the estimate of $log(MA_{it-1}+1)$ in Specification 3 is also positive and significant (0.278). These results confirm the existence of a positive cross-direct effect of importing on the probability of exporting. Next, we analyse how size, labour qualification and undertaking R&D impact these effects.

Table 7: *Bivariate model estimations for export and import activities. Robustness 1.*

	Specification 1		**Specification 2**		**Specification 3**	
	Export	**Import**	**Export**	**Import**	**Export**	**Import**
X_{it-1}	2.151***	0.227***	1.437***	0.217***	1.415***	
	(0.034)	(0.033)	(0.0550)	(0.032)	(0.055)	
M_{it-1}	0.395***	1.77***	0.408***	1.104***		1.140***
	(0.097)	(0.034)	(0.0938)	(0.052)		(0.052)
$log(EA_{it-1}+1)$			0.679***		0.684***	0.109***
			(0.0425)		(0.044)	(0.023)
$log(MA_{it-1}+1)$				0.653***	0.278***	0.632***
				(0.042)	(0.070)	(0.043)
$Export\ Spillover_{it-1}$	0.013***		0.00878***		0.009***	
	(0.003)		(0.00141)		(0.001)	
$Import\ Spillover_{it-1}$		0.008***		0.007***		0.007***
		(0.002)		(0.001)		(0.002)
ω_{it1}	0.156***	0.187***	0.148***	0.177***	0.147***	0.183***
	(0.038)	(0.039)	(0.0363)	(0.038)	(0.036)	(0.038)
$Markup_{it-1}$	-0.086**	-0.164***	-0.0805**	-0.158***	-0.079**	-0.158***
	(0.037)	(0.038)	(0.0359)	(0.037)	(0.036)	(0.037)
$Size_{it-1}$	0.130***	0.081***	0.118***	0.071***	0.113***	0.076***
	(0.014)	(0.012)	(0.014)	(0.012)	(0.013)	(0.012)
M_{it-1} x $Size_{it-1}$	-0.072***		-0.078***			

[31] Recall that in Specifications 1 and 2 we proxy past export experience using one period lagged import participation, and in Specification 3 we use the log of import age.

	(0.022)		(0.021)			
$log(MA_{it-1} + 1)$ x $Size_{it-1}$					-0.051***	
					(0.015)	
$Skill\ Lab_{it-1}$	0.017	0.025***	0.016	0.024***	0.018	0.025***
	(0.012)	(0.009)	(0.012)	(0.009)	(0.012)	(0.009)
M_{it-1} x $Skill\ Lab_{it-1}$	0.010		-0.002			
	(0.067)		(0.043)			
$log(MA_{it-1} + 1)$ x $Skill\ Lab_{it-1}$					-0.010	
					(0.013)	
$R\&D_{it-1}$	0.088***	0.125***	0.089***	0.129***	0.096***	0.127***
	(0.031)	(0.024)	(0.030)	(0.024)	(0.026)	(0.024)
M_{it-1} x $R\&D_{it-1}$	0.064		0.069			
	(0.051)		(0.051)			
$log(MA_{it-1} + 1)$ x $R\&D_{it-1}$					0.070**	
					(0.033)	
$Positive\ growth\ sales_{it-1}$	-0.011	0.015	0.001	0.0291	0.002	0.032
	(0.021)	(0.019)	(0.021)	(0.020)	(0.021)	(0.020)
$Foreign\ capital_{it-1}$	0.425***	0.468***	0.419***	0.458***	0.415***	0.455****
	(0.037)	(0.034)	(0.037)	(0.034)	(0.037)	(0.034)
$\tilde{y}^{Exp}_{it-2}$	0.799***		0.912***		0.913***	
	(0.043)		(0.042)		(0.042)	
$\tilde{y}^{Exp}_{it-3}$	0.527***		0.645***		0.645***	
	(0.056)		(0.056)		(0.056)	
$\tilde{y}^{Exp}_{it-4}$	0.307***		0.438***		0.438***	
	(0.074)		(0.074)		(0.074)	
$\tilde{y}^{Imp}_{it-2}$		0.712***		0.830***		0.828***
		(0.039)		(0.039)		(0.039)
$\tilde{y}^{Imp}_{it-3}$		0.306***		0.426***		0.426***
		(0.052)		(0.052)		(0.052)
$\tilde{y}^{Imp}_{it-4}$		0.095		0.222***		0.217***
		(0.069)		(0.069)		(0.069)
$\tilde{y}^{Exp}_{i0}$	0.751***	0.103***	0.524***	0.089**	0.534***	0.124***
	(0.039)	(0.038)	(0.039)	(0.036)	(0.039)	(0.038)
$\tilde{y}^{Imp}_{i0}$	0.142***	0.758***	0.126***	0.547***	0.114***	0.540***
	(0.038)	(0.038)	(0.037)	(0.038)	(0.038)	(0.038)
Constant	-3.478***	-2.847***	-3.190***	-2.727***	-3.164***	-2.746***
	(0.135)	(0.125)	(0.116)	(0.111)	(0.115)	(0.111)
Observations	44,464	44,464	44,464	44,464	44,464	44,464
ρ	0.500 (p-value = 0.000)		0.501 (p-value = 0.000)		0.499 (p-value = 0.000)	
Log-pseudo likelihood	-18650.451		-18406.356		18420.464	

Notes: Industry and year dummies are included in all specifications. Robust standard errors are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

We start analysing the effect of firm size. Both the estimates of the interaction term M_{it-1} x $Size_{it-1}$ in Specifications 1 and 2 and the interaction term $log(MA_{it-1} + 1)$ x $Size_{it-1}$ in Specification 3 are negative and significant. This negative sign indicates that, regardless of whether we proxy past import experience using one-period lagged import participation (Specifications 1 and 2) or the log of import age (Specification 3), the effect of past experience importing intermediate inputs on the probability of exporting is inversely related to firm size. Therefore, our results suggest that the possibility of using lower price and/or higher quality imported inputs and profiting from the experience about international markets acquired importing intermediates, has a higher impact on the probability of exporting for SMEs than for large firms. Using the terminology of the paper, our estimates indicate that the cross direct effect of importing on the probability of exporting is inversely related to firm size.

As for the impact of labour qualification on the cross-direct effect of importing, neither the estimates of the interaction term M_{it-1} x $SkillLab_{it-1}$ in Specifications 1 and 2, nor the estimate of the interaction term $log(MA_{it-1}+1)$ x $SkillLab_{it-1}$ in Specification 3, are statistically significant. These results should be interpreted as evidence neglecting a potential complementarity between the imports of intermediate inputs and firms' labour qualification.

Finally, we analyse the impact of whether the firm undertakes or not R&D activities, on the cross-direct effect of importing on the probability of exporting. Whereas the estimates of the interaction term M_{it-1} x $R\&D_{it-1}$ in Specifications 1 and 2 are not significant, the estimate of the interaction term $log(MA_{it-1}+1)$ x $R\&D_{it-1}$ in Specification 3 is positive and significant. These results suggest that firms R&D activities and importing intermediates only become complements (in terms of the probability of exporting) when firms import intermediates continuously (as measured by the log of import age). Sporadic imports of intermediate inputs (that are captured by whether or not the firm imports intermediates in the previous period) do not seem to have an effect in the cross-direct effect of importing. A possible interpretation is that to learn how to profit from the technology embedded in the import of intermediate inputs, firms must import continuously, and in these situations performing R&D ease/accelerates this learning process. This would result in more efficient production processes and/or improved products that would make easier for firms to export.

In the second robustness exercise, we study whether the cross-direct effect of importing intermediates changes across the technology intensity regime in which the firm operates (i.e., in industries that use low, med-low or med-high technology to manufacture their products).[32] Our initial hypothesis is that firms operating in high technological intensity industries are more likely to produce and export differentiated products. Further, producing differentiated products is intrinsically linked to product quality enhancing processes; and, importing high quality intermediate inputs may become crucial in these processes of product quality upgrading. Therefore, we expect the cross-direct effect of importing on the probability exporting to be higher for firms operating in the med-high technological sector.

To test this hypothesis, we widen Specifications 1 and 2 of the export equation 5 with interactions of M_{it-1} and the technological intensity sector in which the firm operates ($Low, Med-Low$ and $Med-High$). Analogously, we enlarge Specification 3 with interactions of $log(MA_{it-1}+1)$ and the technological intensity sector dummies ($Low, Med-Low$ and $Med-High$).

The results for this exercise are reported in Table 8, where for the sake of brevity we just report the estimates for the variables of interest (the export and import variables and the interactions with the technological intensity sector dummies).[33] The estimates for the interaction terms M_{it-1} x Low, M_{it-1} x $Med-Low$ and M_{it-1} x $Med-High$, in Specifications 1 and 2, and the interaction terms $log(MA_{it-1}+1)$ x $Low)$, $log(MA_{it-1}+1)$ x $Med-Low)$ and $log(MA_{it-1}+1)$ x $Med-High)$, in Specification 3, are all positive and highly significant (except for the $Med-Low$ sector, for which the statistical significance is at the 15% level).

In specifications 1 and 2, where we proxy the cross-direct effect of importing using one-year lagged import participation, the cross direct effect of importing is larger for firms operating in the med-high technological intensity sector than for firms operating in the Low and $Med-low$ technological intensity sectors. This could be considered as evidence in favour of our initial hypothesis. Nevertheless, these results do not hold in Specification 3 where we use import age to proxy the cross-direct effect of importing. In this case, the cross-direct effect of importing is similar for Low and $Med-high$ technological sectors and, for both, higher than in the $Med-low$ sector. Therefore, the estimation results in Specification 3 do not support our starting hypothesis.

All in all, our results confirm the heterogeneity of the cross-direct impact of importing across technological sectors. However, our results are not robust across the variable used to proxy for past export experience: we only confirm that the cross-direct effect of importing on the probability of exporting is larger for the $Med-high$ technological sector when using the one-year lagged import decision to proxy for import experience.

[32]See Table A2 in the Appendix for the industry classification into technological sectors.

[33]In these specifications the results for the rest of variables are quite similar to those reported in 7. These results are available from the authors upon request.

Table 8: *Sunk costs and learning effects by technological intensity sector. Robustness 2.*

	Specification 1		Specification 2		Specification 3	
	Export	**Import**	**Export**	**Import**	**Export**	**Import**
X_{it-1}	2.125***	0.219***	1.418***	0.208***	1.411***	
	(0.034)	(0.033)	(0.055)	(0.032)	(0.054)	
M_{it-1}		1.764***		1.109***		1.122***
		(0.034)		(0.052)		(0.052)
M_{it-1} x Low	0.142***		0.129***			
	(0.042)		(0.042)			
M_{it-1} x $Med-Low$	0.088*		0.073*			
	(0.052)		(0.051)			
M_{it-1} x $Med-High$	0.176***		0.168***			
	(0.052)		(0.051)			
$log(EA_{it-1}+1)$			0.672***		0.669***	0.106***
			(0.0422)		(0.043)	(0.023)
$log(MA_{it-1}+1)$				0.658***		0.641***
				(0.041)		(0.042)
$log(MA_{it-1}+1)$ X Low					0.113***	
					(0.031)	
$log(MA_{it-1}+1)$ X $Med-Low$					0.054	
					(0.0250)	
$log(MA_{it-1}+1)$ X $Med-High$					0.092***	
					(0.038)	
Observations	44,449		44,449		44,449	
ρ	0.573 (p. value = 0.000)		0.574 (p. value = 0.000)		0.570 (p. value = 0.000)	
Log-pseudo likelihood	-18819.174		-18566.306		-18579.507	

Notes: Industry and year dummies are included in all specifications. Robust standard errors are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

7. Concluding remarks.

In this paper we have analysed in depth the dynamic links between exports and imports of intermediate inputs decisions. We have analysed not only the direct links between exports and imports of intermediates, but also the possible indirect links channelled through enhanced productivity resulting from firms exports and imports of intermediates experience. Furthermore, we have been able to identify and quantify the importance of sunk costs and learning as determinants of firms' (exporting and importing of intermediates) persistence.

Our estimation results confirm both the direct and indirect links between exporting and importing. Past exporting (importing intermediates) has a positive direct impact on the current likelihood of importing (exporting). Further, experience in both trading activities contributes to enhance productivity (this is evidence supporting LBI and LBE), and current productivity has a positive impact on the future likelihood of both exporting and importing. Therefore, as stated above, we find evidence not only of direct effects of exporting (importing) experience on importing intermediates (exporting) decisions but also evidence on indirect effects through increased productivity.

Our estimates also shed light on the quantification of the relative importance of sunk costs and learning on exporting and importing intermediates persistence. Both sunk costs and learning are relevant determinants of exports and imports persistence, but our estimates suggest a higher weight for learning in the case of imports of intermediates than in the case of exports. Furthermore, considering an endogenous Markov process in the estimation of total factor productivity (differently to (Timoshenko, 2015b)) allows us to distinguish between the well-known LBI and LBE processes in terms of productivity, and the demand learning linked to export experience and the import supply learning related to imports of intermediates experience.

Further, our results also uncover that the geographical proximity to other exporting (importing) firms exerts a positive and significant effect on the probability of exporting (importing), suggesting that agglomeration economies might help firms to overcome start-up costs and engage in trade strategies.

These results turn out to be highly relevant in the design of economic policies for an emerging country such as Colombia. First, our results uncover that both exporting and importing intermediates contribute to increase productivity, thus, economic policies should be addressed to ease firms' export participation and avoid protectionist measures that difficult the imports of intermediate materials. Very likely, a country like Colombia will profit from the imports of high-quality intermediate materials that incorporate foreign technology. Further, our results show that importing intermediates fosters export participation and therefore these inputs might be a crucial element in firms' competitiveness.

Moreover, our results show that both exporting and importing intermediates are selffuelled activities (as the probability to continue undertaking them increases with the years of experience accumulated in these activities). And, geographical proximity to other exporting (importing) firms has a positive impact on the decisions to export (import). These results are especially relevant in the case of exporting, as to maintain a base of firms continuing exporting, an emerging country like Colombia should launch economic programmes aimed not only to ease the access of firms to sell in international markets but also help firms to continue exporting during some initial years. After these initial years, the probability of continuing exporting increases considerably.

References

Aitken, B., G.H. Hanson, and A.E. Harrison (1997), "Indirect effects, foreign investment and behavior of exports." *Journal of International Economics*, 43(1–2), 103–132.

Allison, P. D. (1982), "Discrete-time methods for the analysis of event histories." *Sociological Methodology*, 13, 61–98.

Amiti, M. and J. Konings (2007), "Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia." *American Economic Review*, 97 (5), 1611–38.

Andersson, M., H. Lööf, and S. Johansson (2008), "Productivity and international trade: firm level evidence from a small open economy." *Review of World Economics*, 144, 774–801.

Arkolakis, C., T. Papageorgiou, and O. A. Timoshenko (2018), "Firm learning and growth." *Review of Economic Dynamics*, 27, 146–68.

Aw, B. Y., M. J. Roberts, and D. Y. Xu (2011), "R&D investment, exporting, and productivity dynamics." *American Economic Review*, 101 (4), 1312–44.

Bas, M. and V. Strauss-Kahn (2015), "Input-trade liberalization, export prices and quality upgrading." *Journal of International Economics*, 95 (2), 250–62.

Bekes, G. and P. Harasztosi (2020), "Machine imports, technology adoption and local spillovers." *Review of World Economics*, 156, 343–375.

Bernard, A. B and J. B. Jensen (1999), "Exceptional exporter performance: Cause, effect, or both?" *Journal of International Economics*, 14 (1), 1–25.

Bernard, A. B and J.B. Jensen (2004), "Why some firms export." *Review of Economics and Statistics*, 86 (2), 561–69.

Blundell, R., R. Griffith, and J. Van Reenen (1999), "Market share, market value and innovation in a panel of british manufacturing firms." *The Review of Economic Studies*, 66 (3), 529–54.

Blundell, R., R. Griffith, and F. Windmeijer (2002), "Individual effects and dynamics in count data models." *Journal of Econometrics*, 108 (1), 113–31.

Boddin, D., H. Raff, and N. Trofimenko (2017), "Foreign ownership and propensities to export and import of firms from developing countries." *The Worldwide Economy*, 40 (12), 2543–2563.

Bustos, P. (2011), "Trade liberalization, exports, and technology upgrading: Evidence on the impact of mercosur on argentinian firms." *American Economic Review*, 101 (1), 304–40.

Campa, J. M. (2004), "Exchange rates and trade: How important is hysteresis in trade?" *European Economic Review*, 48 (3), 527–48.

Cardoso-Vargas, C.E. (2017), "Does the type of neighbor matter? heterogeneous export spillovers on domestic companies in mexico." *Economic Studies*, 32(2), 255–292.

Cardoso-Vargas, C.E. (2019), "Distance to core and selection of export productsdestinations." *Revue d'Economie Regionale Urbaine*, 2, 389–419.

Castellani, D., F. Serti, and C. Tomasi (2010), "Firms in international trade: Importers' and exporters' heterogeneity in italian manufacturing industry." *World Economy*, 33 (3), 424–57.

Chamberlain, G. (1982), "Multivariate regression models for panel data." *Journal of Econometrics*, 18 (1), 5–46.

Damijan, J. P. and C. Kostevc (2015), "Learning from trade through innovation." *Oxford Bulletin of Economics and Statistics*, 77 (3), 408–36.

De Loecker, J. (2007), "Do exports generate higher productivity? evidence from slovenia." *Journal of International Economics*, 73 (1), 69–98.

De Loecker, J. (2013), "Detecting learning by exporting." *American Economic Journal: Microeconomics*, 5 (3), 1–21.

De Loecker, J. and F. Warzynski (2012), "Markups and firm-level export status." *American Economic Review*, 102 (6), 2437–71.

Duranton, G. and D. Puga (2004), "Micro fundamentals of the economies of agglomeration of cities." In *Handbook of regional and urban economics, chapter 48.* (J.V. Henderson and J.F. Thisse, eds.), Vol 4, pp. 2063–2117, Elsevier, Amsterdam.

Elliott, R.J., N. J. Horsewood, and L.Y. Zhang (2019), "Importing exporters and exporting importers: A study of the decision of chinese firms to engage in international trade." *Review of International Economics*, 27 (1), 240–66.

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

Fernandes, A.M and C. Paunov (2013), "Does trade stimulate product quality upgrading?" *Canadian Journal of Economics/Revue Canadienne d'économique*, 46 (4), 1232–64.

Fernandez, A.P. and H. Tang (2014), "Learning to export from neighbors." *Journal of International Economics*, 94 (1), 67–84.

Fieler, A. C., M. Eslava, and D. Y. Xu (2018), "Trade, quality upgrading, and input linkages: Theory and evidence from colombia." *American Economic Review*, 108 (1), 109–46.

Goldberg, P. K., A. M. Khandelwal, N. Pavcnik, and P. Topalova (2010), "Imported intermediate inputs and domestic product growth: Evidence from india." *Quarterly Journal of Economics*, 125 (4), 727–67.

Halpern, L., M. Koren, and A. Szeidl (2015), "Imported inputs and productivity." *American Economic Review*, 105 (12), 3660–3703.

Hatzichronoglou, T. (1997), *Revision of the high-technology sector and product classification*. OECD Science, Technology and Industry Working Papers, No. 1997/2.

Jenkins, S. P. (2005), "Survival analysis." *Unpublished Manuscript, Institute for Social and Economic Research, University of Essex, Colchester, UK*, 42, 54–56.

Kasahara, H. and B. Lapham (2013), "Productivity and the decision to import and export: Theory and evidence." *Journal of International Economics*, 89 (2), 297–316.

Kasahara, H. and J. Rodrigue (2008), "Does the use of imported intermediates increase productivity? plant-level evidence." *Journal of Development Economics*, 87 (1), 106–18.

Koenig, P., F. Mayneris, and S. Poncet (2010), "Indirect effects of local exports in france." *Journal of European Economics*, 54 (4), 622–641.

Levinsohn, J. and A. Petrin (2003), "Estimating production functions using inputs to control for unobservables." *The Review of Economic Studies*, 70 (2), 317–41.

Manova, K. and Z. Zhang (2009), "China exporters and importers - firms, products and trading partners (no. w15249)." *National Bureau of Economic Research.*

Martins, P. S and Y. Yang (2009), "The impact of exporting on firm productivity: A meta-analysis of the learning-by-exporting hypothesis." *Review of World Economics*, 145 (3), 431–45.

Mayneris, F. and S. Poncet (2015), "Chinese firms' entry to export markets: The role of foreign export spillovers." *The World Bank Economic Review*, 29 (1), 150–179.

Mañez, J. A, C. Mínguez-Bosque, M.E. Rochina-Barrachina, and J.A. Sanchis-Llopis (2020a), "Trading activities, productivity and markups: Evidence for spanish manufacturing." *The World Economy*, 43 (3), 644–80.

Mañez, J. A, M. E Rochina-Barrachina, and J. A. Sanchis-Llopis (2020b), "Foreign sourcing and exporting." *The World Economy*, 43 (5), 1151–87.

Mañez, J. A, M.E. Rochina-Barrachina, and J. A. Sanchis (2008), "Sunk costs hysteresis in spanish manufacturing exports." *Review of World Economics*, 144 (2), 272–94.

Muendler, M.A. (2004), "Trade, technology and productivity: A study of brazilian manufacturers 1986-1998." Technical report, Department of Economics, UC San Diego.

OECD. (2018), *TiVA Indicators 2018*. https://www.oecd.org/industry/ind/tiva-2018-flyer.pdf.

Olley, G. S. and A. Pakes (1996), "The dynamics of productivity in the telecommunications equipment industry." *Econometrics*, 64 (6), 1263–2197.

Roberts, M. J. and J. R Tybout (1997), "The decision to export in colombia: An empirical model of entry with sunk costs." *The American Economic Review*, 545–64.

Seker, M. (2009), *Importing, Exporting and Innovation in Developing Countries*. The World Bank.

Silva, A., O. Afonso, and A. P. Africano (2012), "Learning-by-exporting: What we know and what we would like to know." *The International Trade Journal*, 26 (3), 255–88.

Singh, T. (2010), "Does international trade cause economic growth? a survey." *The World Economy*, 33 (11), 1517–64.

Timoshenko, O. A. (2015a), "Learning versus sunk costs explanations of export persistence." *European Economic Review*, 79, 113–28.

Timoshenko, O. A. (2015b), "Product switching in a model of learning." *Journal of International Economics*, 95 (2), 233–49.

Van Biesebroeck, J. (2003), "Revisiting some productivity debates." Technical report, National Bureau of Economic Research.

Villarreal, N. F., D. L. Arias, N. Albis-Salas, and H. Mora Holguin (2014), "Determinantes de la innovación y la productividad en la industria manufacturera colombiana por tamaño de firma." Technical report, Observatorio Colombiano de Ciencia y Tecnología.

Wooldridge, J. M. (2009), "On estimating firm-level production functions using proxy variables to control for unobservables." *Economics Letters*, 104 (3), 112–14.

Zhang, H. (2017), "Static and dynamic gains from costly importing of intermediate inputs: Evidence from colombia." *European Economic Review*, 91, 118–145.

A. Appendix

Table A1: *Variables definition.*

Variables	Definition
X_{it}	Dummy variable that takes value 1 if the firm exports in period t, and 0 otherwise
M_{it}	Dummy variable that takes value 1 if the firm import intermediate inputs in period t, and 0 otherwise
$log(EA_{it-1}+1)$	Log of export age (number of continuous years exporting) up to $t-1$.
$log(MA_{it-1}+1)$	Log of import age (number of continuous years importing) up to $t-1$.
$XExp_{it-1}$	Firm's export experience up to $t-1$.
$MExp_{it-1}$	Firm's import experience up to $t-1$.
ω_{it}	Logarithm of firm's total factor productivity in period t.
$log(Markup)_{it}$	Markups have been calculated using (De Loecker, 2013) procedure as the ratio of the estimated output elasticity of labour over the revenue share of labour input costs
$Size_{it}$	Logarithm of the number of employees in period t.
$Skill\ Lab_{it-1}$	Proportion of high skilled workers in total firm's labour force in period t.)
$R\&D_{it-1}$	Dummy variable that takes value 1 if the firm performs R&D in period $t-1$, and 0 otherwise.
$Positive\ growth\ sales_{it}$	Dummy variable that takes value 1 if the firms shows positive growth sales in period t, and 0 otherwise.
$Foreign\ capital_{it}$	Dummy variable that takes value 1 if the capital of the firm has foreign participation in period t, and 0 otherwise.
$Export\ Spillover_{it}$	Percentage of firms that export in period t, in Colombian department d and technological intensity sector s, excluding the own firm.
$Import\ Spillover_{it}$	Percentage of firms that import in period t, in Colombian department d and technological intensity sector s, excluding the own firm.
$\tilde{y}_{it-j}^{Exp}$	Dummy variable that takes value 1 if the last year. the firm exported was in year $t-j$ (for $j=2,3$ and 4), and 0 otherwise.
$\tilde{y}_{it-j}^{Imp}$	Dummy variable that takes value 1 if the last year. the firm imported was in year $t-j$ (for $j=2,3$ and 4), and 0 otherwise.
$\tilde{y}_{i0}^{Exp}$	Pre-sample mean of the export decision variable.
$\tilde{y}_{i0}^{Imp}$	Pre-sample mean of the import decision variable.
$\overline{w}_{i0}$	Pre-sample mean of the log of total factor productivity.

Table A2: *Industry classification per technological sector*

	Low-tech industries
15	Food, beverages and tobacco
17	Textiles and wearing apparel
19	Tanning and leather
20	Wood and products of wood and cork
21	Paper and paper products
22	Publishing, printing and reproduction recorded media
36	Manufacture of furniture; manufacturing n.e.c.
	Med/low tech industries
23	Coke and refined petroleum products
25	Rubber and plastic products
26	Non-metallic mineral products
27	Basic metals
28	Fabricated metal products except machinery and equipment
35	Other transport equipment
	Med/high tech industries
24	Chemical and chemical products
29	Machinery and equipment n.e.c.
31	Machinery and electrical machinery and apparatus
33	Medical, precision and optical instruments, watches and clocks
34	Motor vehicles, trailers and semi-trailers