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Carlos Arturo Salamanca Malagon

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The dissertation of Carlos Arturo Salamanca Malagon was reviewed and approved by the following:

Kala Krishna
Liberal Arts Professor of Economics
Dissertation Advisor
Chair of Committee

Mark Roberts
Liberal Arts Professor of Economics

Michael Gechter
Assistant Professor of Economics

Edward Jaenicke
Professor of Agricultural Economics

Barry Ickes
Professor of Economics
Department Head

Abstract

Chapter 1 is based on collaborative work with Kala Krishna, Yuta Suzuki, and Christian Volpe (Krishna et al., 2021). Meeting Rules of Origin (ROOs) to obtain lower tariffs in a Preferential Trading Area (PTA) is costly both in terms of production costs and fixed documentation costs. Using a model-based approach that corrects for endogeneity and a unique exporter-importer matched transaction-level customs dataset from Latin American countries, we show that preference usage patterns suggest that these fixed costs fall with exporters' experience in preference utilization, particularly in the same product and with the same partner, indicating both the existence and channel of learning. Exploiting a natural experiment, we also show that newly covered products have much more learning as might be expected.

Chapter 2 is based on collaborative work with Yuta Suzuki. We develop and estimate a dynamic structural model of export behavior with a focus on the utilization of preferential trade agreements (PTAs) and the associated rules of origin (ROOs). We model the decision of firms to use PTAs as a function of the fixed costs associated with complying with ROOs, which decrease as firms gain experience. We estimate the model using data on Colombian importers and their transactions with exporters from Argentina and Peru. Our findings indicate that the fixed costs of using PTAs are substantial, particularly for firms with limited experience. However, these costs decrease significantly as firms gain experience, highlighting the importance of learning in utilizing PTAs. We also conduct counterfactual policy experiments to assess the impact of government subsidies on PTA utilization. Our results suggest that subsidizing the first transaction under a PTA can substantially increase utilization and reduce exit rates among exporters and that subsidizing subsequent transactions has limited additional effects.

Chapter 3 is based on collaborative work with Kala Krishna, Yuta Suzuki, and Christian Volpe. Using a unique dataset on imports of Colombia from Argentina and Peru, we find clear evidence of quantity discounting, and more so for Argentinian exporters. We find that a 100 % increase in quantity results in a 7.5% fall in price for Peruvian exporters and a 16.8% fall in price for Argentinian ones. We find that quantity discounts are larger for differentiated goods and for importers with a larger network of exporters (where there could be more room for bargaining). In Peru, doubling quantity results in a price fall of 6.6% assuming the importer has a history of dealing with only one exporter, and it increases to 14.4% when the importer has dealt with five or more exporters in the past. Similarly, in Argentina, this number for differentiated products ranges from 17.1% with one exporter to 18.5% with five or more exporters. Our results challenge the traditional assumption of linear pricing, especially in International Trade. This has widespread implications: for example, the positive correlation between firm size and TFPR would be biased upwards if linear pricing is assumed while quantity discounts prevail.

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Chapter 1
Learning to Use Trade Agreements

Based on collaborative work with Kala Krishna, Yuta Suzuki, and Christian Volpe (Krishna et al., 2021).

1.1 Introduction

Recent decades have seen a proliferation of free trade agreements (FTAs).[1] Rules of origin (ROOs) are used to distinguish between products that are eligible for preferential treatment (those originating in the member countries) and those from third countries. Meeting these rules of origin is costly as evidenced by preference utilization rates that are often far below unity.[2] Certainly, marginal costs could rise as firms change their production processes or use higher cost suppliers in order to meet ROOs. The more these marginal costs rise, the less profitable, and hence less likely, it would be for ROOs to be met. This would make meeting ROOs less likely overall for this product and be partially captured as a product specific fixed effect. In addition, fixed costs would rise as supply chains are altered and/or documentation costs are incurred to show that the shipment complies with ROOs.[3]

Do these fixed costs change with the experience of the exporting firm in obtaining preferential tariffs?[4] What type of experience, if any, matters? In this paper, we use the universe of

[1]From 1990 to 2019 they rose from 76 to 443 in number. See Figure 1A in Dinh et al. (2019).

[2]See for example UNCTAD (2018), which shows that utilization rates of EU exporters to countries with FTAs with the EU are only 67% between 2009 to 2013. For an overview of ROOs, see Cornejo & Harris (2007).

[3]For instance, firms may need to keep records that would not otherwise have been kept and learn to fill out the documentation required to show ROOs have been met. Cadot et al. (2006a) estimate that the administrative costs of the Pan-European preference scheme are around 6.8% of the value of trade compared to 1.9% for NAFTA. For details on the forms taken by these ROOs and the procedures involved see Dinh et al. (2019).

[4]We do not differentiate between fixed costs and sunk costs of using preferences as ours is a static model. If fixed costs are incurred only when preferences are used for the first time, we should observe an increase in the probability of using preferences only after the first experience. If the probability of using preferences keeps increasing as more experience is gained, as our estimates reveal, we argue that fixed costs exist and decrease with

export transactions from Argentina and Peru to Colombia over a long period to answer this question.[5] As ROOs vary across products and by country pair, we conduct our analysis for exports from Argentina and Peru to Colombia, separately. We make the case that the probability of using preferences decreases in the fixed costs of using preferences. Fixed costs of using preferences, in turn, should fall with experience if there is learning. Consequently, greater experience of the exporter should increase the probability of using preferences. We accordingly infer the shape of the fixed cost of meeting ROOs based on how an exporting firm's history of using preferences affects the likelihood of the firm using preferences in the current transaction.

Furthermore, we ask whether these costs are impacted differently by the type of the experience. Is experience in the same product and with the same importer (i.e., importing firm) more valuable than other kinds of experience? Does experience with specific importers and products spill over to other importers and products? For example, the costs of meeting or documenting ROOs for a particular product could fall once a particular exporter has successfully overcome the hurdles imposed by ROOs. In this case, the experience of the exporter with one importer and product would increase the probability of using preferences in transactions with other importers of the same product. If some of this experience can be useful with other products, it may even spill over to other products with the same importer or even to other products and other importers. In other words, the nature of these costs will cast its shadow on the patterns in preference usage across importers and products. Consequently, the patterns in preference usage are informative about the nature of these costs.

The choice of using preferences is a tradeoff between the benefits and the costs of using ROOs. One element of these benefits is the lower tariffs from using preferences, i.e., the difference in the MFN tariff and the preferential tariff times the value of the transaction, what we call “savings". We estimate the probability of using preferences on a particular transaction with a particular importer as a function of the history of preference use while controlling for these savings.

However, savings can be endogenous. Savings depend on transaction size and the difference in MFN and preferential tariffs. There could be reverse causation present: not only might a larger transaction size drive the use of preferences, but the use of preferences may also drive transaction size. To account for this we construct a new instrument for the size of the transaction which is model-based: namely the (lagged) daily exchange rate of the importing country.[6] Using this instrument, we show that spillovers across products are not evident, though

experience.

[5]We use experience by the exporter, not the importer as the burden of providing the documentation is on the exporter.

[6]We use the 60-day lagged exchange rate to account for the delay between orders and delivery.

spillovers within the same product, even with different importers, are sometimes present. In other words, experience in obtaining preferences in a particular product (defined as an HS 10-digit category) does not always seem to significantly improve the probability of obtaining preferences in another product, though experience in obtaining preferences in a product with a given importer tends to increase the likelihood of obtaining preferences for a transaction in the same product with the same or other importer.

The results we find make sense: complying with ROOs is costly and doing so for one buyer extends to other buyers, but this is less so across products. Our estimates suggest that learning with the same product and importer is larger for Argentina than for Peru. We argue that the FTA between Argentina and Colombia is newer, so Argentinian firms have a larger learning potential. We use a natural experiment to verify this intuition. In 2005 new products became covered for Argentina under the expanded FTA. One would expect that there would be more learning for these products which is exactly what we find. Moreover, once we distinguish between newly covered products and the previously covered ones, we see that the learning estimates for Argentina in the latter look much like the learning estimates for Peru.

Understanding the nature of these fixed costs of ROOs is important from theoretical, empirical, and policy perspectives. There is a large literature on ROOs on all these fronts. The first set of papers highlights what ROOs are and how they operate, whereas the second set of papers estimates their effects on trade. Krishna & Krueger (1995) is an early paper that shows theoretically how ROOs can provide hidden protection to input suppliers within the FTA.[7] Cadot et al. (2006b) focuses on ROOs and has several case studies as well as innovations in terms of measuring the restrictiveness of ROOs. Anson et al. (2005) argue that ROOs limit the use of preferential market access considerably. They estimate that in NAFTA, compliance costs are on average 6% in ad-valorem terms while administrative costs amount to 47% of the preference margin. Pelkmans-Balaoing & Manchin (2007) report that for the ASEAN FTA, preferential tariffs increase intra-regional imports only when preference margins are high (over 25 percentage points).[8] Demidova et al. (2012) show that the patterns in the use of preferences among Bangladeshi exporters are consistent with firms facing both fixed and marginal costs of meeting ROOs. Cherkashin et al. (2015) set up and estimate a heterogeneous firm model to evaluate the role of ROOs in Bangladeshi exports in Apparel. They find large predicted effects on Bangladeshi exports when fixed and/or marginal costs of meeting ROOs in apparel are reduced.

These papers present evidence consistent with high fixed and/or marginal costs of using

[7]Also, see Krishna (2006) for a slightly dated survey of the literature.

[8]They define preference margin as the MFN tariff minus the preferential tariff divided by the MFN tariff. We use the term just for the difference as this is what affects the savings from using preferences.

preferences. To our knowledge, ours is the first paper to use a model-based approach and address concerns about the endogeneity of transaction size to show that these fixed costs seem to be differentially affected by different kinds of experience.[9]

Thus, our paper makes contributions to several strands of literature. First, we complement several studies that examine the costs and determinants of using preferences in trade agreements and the Generalized Systems of Preferences (GSP), in general, and implications of Rules of Origin (RoO), in particular (e.g., Manchin (2006); Francois et al. (2006); Keck & Lendle (2012); Nilsson (2016); Ulloa & Wagner (2012); Hakobyan (2015); Ornelas & Turner (2024)).[10] We extend this line of research by explicitly showing that preferences are used more often with experience which is consistent with the fixed cost of using them falling.[11]

Second, we add to an emerging literature that specifically resorts to microdata to explore the utilization of trade agreements, such as Kasteng et al. (2022a), Lui et al. (2023), Benguria (2022), and Legge & Lukaszuk (2024). Relative to this literature, our innovation consists of combining, merging, and using, for the first time to our knowledge, transaction-level customs data from both the exporting and the importing countries. This allows us to accurately identify both the exporter and the importer involved in every single transaction and accordingly go beyond establishing whether and how (single-sided) firms' or transactions' characteristics such as firm size, transaction values, and tariff margins determine preference utilization. More precisely, we take advantage of the fact that we can track exporters' time-varying history in terms of use of preferences across products and importers and assess whether, and to what extent, experience of different kinds (e.g., with the same or other importers, in the same or other products, and combination thereof) matters as a determinant of this use.

Third, we offer a new explanation for the lagged effects of trade agreements identified in previous research (e.g., Baier & Bergstrand (2007), Baier et al. (2014), Baier et al. (2019), and Egger et al. (2022). In general, these lagged effects have been typically rationalized based

[9]Concurrent, interesting work by Benguria (2022) and Kasteng et al. (2022b) are not model-based, do not differentiate between types of experience, and do not fully account for endogeneity issues.

[10]An early influential paper by Krishna & Krueger (1995) theoretically demonstrates how ROOs can offer hidden protection to input suppliers within Free Trade Agreements (FTAs). Another noteworthy contribution to the literature is provided by Cadot et al. (2006b), who explore ROOs through case studies and introduce a method to measure the restrictiveness of these rules. See also Krishna (2006), who provides an early, comprehensive survey of the literature on ROOs. Other papers include: Pelkmans-Balaoing & Manchin (2007); Kohpaiboon (2010); Takahashi & Urata (2008); Nilsson (2011); and Cariola & Lanz (2022).

[11]There is a vast literature that evaluates the trade effects of utilization of preferences granted in the framework of trade agreements or the GSP: Sapir (1981), Sapir & Lundberg (1984), Herz & Wagner (2011), Gnutzmann & Gnutzmann-Mkrtchyan (2022), Cipollina et al. (2013), Gil-Pareja et al. (2014), Cirera et al. (2016), Persson & Wilhelmsson (2016), Sharma et al. (2019), Sharma et al. (2021), Akinmade et al. (2022), Borchert & Di Ubaldo (2020), Ornelas & Ritel (2020), Mueller & Riker (2021), Gnangnon (2022), Nilsson (2022), and Ridley & Shirin (2023).

on the gradual phased-in of the agreements or the progressive entry of new firms into export markets. Our findings indicate that, in addition to these developments, firms' learning over time can lead to increased use of trade agreements and hence larger trade effects thereof as time passes. Importantly in this regard, our empirical strategy to identify the learning effects effectively controls for these other potential mechanisms (e.g., by including the savings from using preferences and firms' fixed effects[12]).

Last, but not least, our paper makes a valuable contribution to the literature studying the distributional effects of trade policy (e.g., Volpe Martincus & Carballo (2010); Lileeva & Trefler (2010); Neri-Lainé et al. (2023)). Our estimates suggest that after controlling for experience, and possible endogeneity in the size of the order, larger transactions (greater savings) do not seem to make firms more likely to use preferences. Thus, the advantage large firms have in using preferences seems to be driven by their greater experience rather than larger transaction size. Hence, policies that help small firms accumulate experience should help level the playing field.

We proceed as follows. Section 2 contextualizes rules of origin and explains their associated costs. In Section 3 we first describe the institutional background for the Latin American countries in the data set. We then describe the data used, present some summary statistics, and show the data patterns that motivate our estimation strategy. Section 4 lays out a simple model of the choice of using preferences that guides our estimating equation. In Section 5, after accounting for possible endogeneity as well as possible measurement error of the saving variable, we show that learning is indeed increasing with experience and that the kind of experience matters. Learning estimates are larger for Argentina than for Peru, which we expect as trade agreements are longer standing for the latter. Moreover, we use a natural experiment that occurred in Argentina in 2005 (when new products became covered by the trade agreement with Colombia) to show that the learning in Argentina comes mostly from these newly covered products and that estimates for learning for old products are similar for both countries. Section 6 concludes.

1.2 Costs of Rules of Origin

In this paper, we model the effects of ROOs as an increase in both marginal and fixed costs of meeting them. It makes sense that ROOs will raise marginal costs of production: forcing a firm to produce or source in a way it would ordinarily not do to get preferences must raise marginal

[12]We define savings as the product of transaction value and tariff margin. This means that we only include tariff margin through savings.

costs.[13] Documenting that ROOs have been met to obtain the certificate of origin, as well as the costs of changing input suppliers, are examples of fixed costs of meeting ROOs.

How hard is obtaining the certificate of origin in Latin America? For example, in Argentina, the certificate of origin must be issued by the designated responsible authorities (or delegated entities) according to a pre-established template. Specifically, it must include the name and the signature of the authorized official and the stamp of the certifying entity, a description of the good that perfectly matches those of the relevant tariff line code and the commercial bill, be complete, and be neither damaged nor amended.[14] The procedure for verifying such documentation is clearly laid out.[15] As is evident from this document, suspicious documentation may be investigated and investigation can be very expensive for exporters.

Similar examples can be found in other parts of the world. In Vietnam, for example, obtaining origin for the ASEAN Free Trade Area requires a form (form D) to be filled out and the products to be inspected. Kirk (2007) (page 12, box 1) reproduced here, outlines the steps needed.

> "In Vietnam, the Export-Import Managing Department of the Ministry of Trade is the issuing institution for Form D. An application is submitted to an inspection company authorized by the Ministry of Science to conduct a cost screening to ensure local content of 40 percent or more. VINACONTROL remains the largest inspection firm, but the number of authorized companies has increased over the past few years. This provides for competition. Screening generally takes between one-half to a full day. The applications required for each shipment are submitted to a branch office of the Export-Import Managing Department (9 Branches nationwide). They are accompanied by a certifying letter from the inspection company, a commercial invoice, a customs declaration form, a bill of lading, and a copy of the exporter's commercial license. Form D is issued within 2

[13] For example, to obtain origin, Bangladeshi apparel exports to the EU under the EBA (Everything But Arms) are required to use cloth from Bangladesh which is more expensive than similar imported cloth, see Cherkashin et al. (2015). More recently, Conconi et al. (2018) look at NAFTA and show that the change in sourcing decisions to use NAFTA preferences led to increases in the marginal cost of production. Also see Anson et al. (2005) and Head et al. (2021).

[14] The commercial bill must be issued by the exporting firm in the origin country of the goods and a sworn declaration signed by the producer when this is also the exporter and by both, producer and exporter, when they are not the same. Firms must report a large amount of information including (1) the name of the producer (and exporter when they are not the same) and the firm's legal representative; (2) the address as registered with the tax agency; (3) description and tariff line code of the good to be exported; (4) FOB value; (5) information on the value and the tariff line code of each input according to whether it originates in (i) the exporting member country; (ii) other member countries; and (iii) the non-member countries; and (6) a description of the production process.

[15] See for example, article 20 of the document available at SICE website: `http://www.sice.oas.org/trade/mrcsrac/Anexos/AnexoIV_s.asp`

hours."

A quote from an automobile producer in Thailand gives more details about the costs involved:[16]

> "The preparation of documents for the initial cost screening takes two months and the screening procedures themselves about one month. There are 1,000 to 2,000 parts in a completed vehicle, and we must collect documentation (invoices, Form Ds, etc.) certifying local procurement from each supplier"

1.3 Institutional Background and Data Patterns

Since we focus on exports to Colombia from Argentina and Peru, we provide a short history of the relevant trade agreements between these countries. This is important because firms' behavior in terms of preference use comes from both changes in these trade policies and learning by exporters. The details of these treaties can be found in Online Appendix A.6.

1.3.1 Institutional Background

A long history of preferential trade agreements in Latin America, and in particular between Argentina, Colombia, and Peru, started in the late 1950s. These agreements were deepened over time. By 2000, when our data begins, the state of affairs was as follows.

Before 2000, the PTA between Colombia and Argentina (Economic Complementary Agreement of Partial Scope 11 — AAP.CE 11 for its name in Spanish) was quite shallow and preferences were given only for a limited number of products. In 2000, (under the AAP.CE 48) Colombia granted fixed preferences on around 1,250 products from Argentina (i.e., less than one-quarter of the total number of tariff lines), with the preference margin rates (defined as the MFN tariff less the preferential one divided by the MFN tariff) averaging 40 percent. In 2005, (under AAP.CE 59) additional cuts to tariffs were made and tariffs were reduced further on a group of products so that tariffs reached an average of 10 percent in 2005. Argentina is part of MERCOSUR, and Peru and Colombia are part of the Andean Community. Although the agreements were between two groups of countries, the negotiations on the details of RoOs were conducted on a bilateral basis (Mesquita Moreira, 2018). As might be expected, there are differences in the restrictiveness of ROOs between these agreements (see Cadot et al., 2006a). However, these differences are not substantial. More specifically, according to the

[16] Kirk (2007), page 13.

measures proposed by Estevadeordal (2000) and Harris (2007), approximately two thirds of the products are subject to ROOs with the exact same degree of restrictiveness in both agreements. Moreover, 80% of the products have an absolute difference in the respective measures of at most one.

Thus, the trade agreements between Argentina and Colombia were shallow, to begin with but were deepened in 2005. The average preference margin (defined as the value share weighted average of the difference in the MFN and preferential tariff) was 4.17% for Argentina with a bump up after 2005. As a result, the share of products with preferences as well as the value share of transactions using preferences, conditional on the product having preferences, rose after 2005 as depicted in Figure 1.1.[17] There was a sharp increase in the share of products with preferences in 2005Q2 and a continuing increase until 2006Q3 as products were phased in. Notice that the conditional value share initially falls, which is consistent with exporters being slow to begin using preferences. However, it soon starts to rise, which would be expected if firms were learning to use preferences.

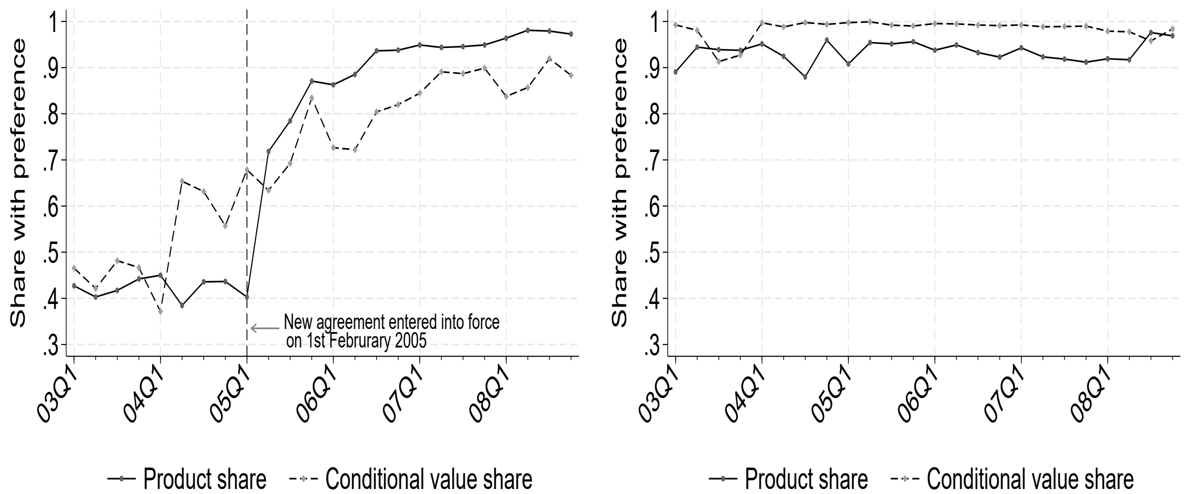
In contrast, the PTAs with Peru are long-standing and deep. Peru and Colombia had a long history of preferential trade as both were members of the Andean Pact from the late 1960s and its successor in 1996, the Andean Community. Though the aim was to create a customs union, i.e., bring tariffs down to zero and set a common external tariff for members, this goal was not achieved. Nevertheless, the median tariff imposed by Colombia on exports from Peru decreased from 46 percent in 1985 to 10 percent in 1995 and was close to zero by 2000. The average preference margin is 14.4% for Peru and does not change much over time. The share of products covered by preferences is above 90% and the value share conditional on having preferences is even higher. These shares are also very stable over time.

These differences in the nature, depth, and duration of the PTAs for Argentina and Peru with Colombia are why we analyze them separately. Note that both the higher average utilization of preferences pointed out above, as well as evidence of less learning for Peru relative to Argentina documented below make sense in terms of these differences.

[17] The figures cover the period 2003-2008 as 1999 to 2002 was a period of considerable turmoil in Argentina due to macroeconomic instability which adds noise to this figure.

Figure 1.1: Preference Utilization Over Time

(a) Argentina (b) Peru



Note: Product share is the simple average of the share of products covered by preferences. Conditional value share is the simple average of the value share of transactions using preferences, conditional on the product having preferences.

1.3.2 Data

The data used here is part of a set of administrative data gathered by the Inter-American Development Bank (IDB). It consists of three main databases. First, we have highly disaggregated import data for Colombia from the National Tax and Customs Agency (Dirección de Impuestos y Aduanas Nacionales -DIAN). These data are reported at the transaction level and cover all transactions entering Colombia over the period 2000-2011. Specifically, each record includes the importing firm's tax ID and name, the origin country, the product code (10-digit HS), the name of the foreign seller, the import value in US dollars, and the tariff paid.[18] These data allow us to construct time-specific, product-level MFN tariffs (inferred from tariffs on countries without preferential trade agreements with Colombia) and preferential margins applied when preferences are used (inferred from the difference in MFN tariffs and tariff paid).[19]

The second and third datasets consist of highly disaggregated export data for Argentina and Peru over 2000-2008 and 2000-2011, respectively, from their respective tax and customs agencies (Administración Federal de Ingresos Públicos–AFIP and Superintendencia Nacional de Administración Tributaria-SUNAT). In the export data, each record includes the exporting

[18]All transactions are denominated in dollars.

[19]We identify that preferences are used whenever the tariff paid is below the MFN one.

firm's tax ID and name, the destination country, the product code (10-digit HS), and the export value in US dollars.[20]

Using the names of the selling firms reported both in the import database of Colombia and the export databases of Argentina and Peru, we can match buyers and sellers for each Colombian import transaction over our sample period and accurately track each exporter's history of preference use and the various kinds of experience by product and importer.[21]

Our raw data (after cleaning and matching) consists of 157,939 observations for 12,974 firms. We limit our sample as follows. First, we dropped all firms with transactions in 2000 (57,684 observations). We do so to get a better measure of experience. Since we cannot tell whether a firm that exports in 2000 is doing so for the first time or not, it is rational to assume that firms that export in 2000 are experienced firms so we don't accurately observe their experience. We argue that firms with the first export transaction after 2000 are likely to be new exporters. We support this by noting that when we consider the median number of days between transactions for a firm, 95% (91%) of the firms in Peru (Argentina) have a median of less than a year. Since there is a tradeoff between dropping exporters with presence in the early years and keeping the number of observations high, we chose this cutoff of one year as being reasonable.[22]

Second, we drop all minerals (1,612 observations) [23]. We do this because minerals is a highly concentrated sector.[24] In addition, long-term contracts are prevalent making this sector a poor choice for our study. Third, we exclude all transactions smaller than $200 due to the de minimis clause that excludes such small transactions from tariffs (18,229 observations). We also drop observations for products where preferences are not available (2,180 observations). Lastly, we trim the data at the top by dropping the largest 1% of the data at the country and product level to deal with outliers (1,511 observations).[25]

Tables 1.1 and 1.2 give the summary statistics for the data for Argentina and Peru separately over the entire sample period, based on almost 16,000 transactions for Argentina and

[20]The quantity (weight) in kilograms is available though we do not use this data.

[21]The merging of these different datasets is challenging. Details of the data cleaning exercise as well as an explanation of the standardization and matching procedures can be found in Appendix A.1.

[22]If we used two years to exclude experienced exporters, 82.44% (48.78%) of firms (transactions) would remain in our analysis versus 91.34% (60.80%) when we use a single year.

[23]chapters 25,26,27 in the HS classification

[24]There are only a few firms in the sector on both the exporting and importing sides. As a result, data identifying the importer are suppressed for confidentiality reasons. This limits our analysis of interest; for example, we cannot identify the exporter's experience with a particular importer.

[25]Including the top one percent of the transactions or winsorizing the size of the transactions instead of dropping them makes little difference to our estimates of learning. Our findings remain qualitatively the same across these different specifications, supporting the robustness of our main results, see the Online Appendix for these results.

approximately 54,000 transactions for Peru. The first panel of each table gives the utilization rate by product. The median is 1.00 for exporters from Peru while exporters from Argentina have a lower utilization at the median of .89. The median value of a transaction was also higher for Peruvian exporters at US dollars 8,645 versus 4,400 for Argentinian ones.

The second panel presents information on several variables at the exporter level. At this level as well, the utilization rate is lower in Argentina than in Peru. In Argentina, 10 percent of exporters do not ever use preferences, while this is not the case in Peru. More than 40 percent of Argentinian exporters sell a single product in Colombia, whereas more than 20 percent of their Peruvian counterparts do so. More than 50 percent of exporters from Argentina have a single importer and over 30 percent have a single importer per product. The numbers are similar for Peru. This is important because with exporter-importer fixed effects only data on firms with more than one transaction per partner will be useful in identifying the shape of the cost of preferences. The median number of transactions per exporter is 6 and transactions per product are 3 for both countries. At the 90^{th} percentile of the relevant distributions, they reach 20 and 10 in the case of Argentina and 43 and 17 in the case of Peru, respectively. The value of transactions per exporter is higher for Peru at each decile, and this is so especially at the top deciles.

The third panel of both tables provides summary statistics for the same variables but for the importer side. Importers are larger than exporters in most dimensions, but similar patterns hold for importers. Importers tend to be older than exporters in both countries, with a median age of 3 in each case.

Table 1.1: Summary Statistics for Argentina

		Percentiles								
	Variable	10	20	30	40	50	60	70	80	90
	Utilization rate by product	23.1	50	66.7	76	88.9	100	100	100	100
	Value of transaction (1000 USD	0.4	0.8	1.5	2.6	4.4	7.5	11.7	19.6	36.2
per Exporter	Utilization rate	0	50	69.7	83.3	92.9	100	100	100	100
	#Products	1	1	1	1	2	2	3	4	6
	#Importers	1	1	1	1	1	2	2	2	4
	#Importers per product	1	1	1	1	1	1	1.3	1.7	2
	#Transactions	1	2	3	4	6	9	14	21	36
	#Transactions per product	1	1	1.7	2	3	4	5.3	8	15.6
	Average value of transactions	1.1	2.1	3.5	5.2	7.4	9.8	13.6	19.2	29.6
	Age in 2008	0	0	0	1	2	2	3	4	6
per Importer	Utilization rate	0	50	69.7	83.3	95	100	100	100	100
	#Products	1	1	1	1	2	2	3	4	7
	#Exporters	1	1	1	1	1	1	2	2	3
	#Exporters per product	1	1	1	1	1	1	1	1	1.4
	#Transactions	1	1	2	4	5	7	11	19	39
	#Transactions per product	1	1	1.2	1.8	2.2	3	4	6	11.2
	Average value of transactions	10.3	18.2	33.7	51.5	74.7	10.2	13.9	19.3	33.8
	Age in 2008	0	0	0	1	2	3	4	6	7
per Exporter - Importer	#Transactions	1	1	1	1	2	3	4	7	14
	#Transactions per product	1	1	1	1	1	2	2	3.4	6.2

Note: Data for Argentina is from 2001Q1 to 2008Q4. Per Exporter #Importers per product is defined at the exporter level as the average of the number of importers per product. Similarly, per Importer #Exporters per product is defined at the importer level as the average of the number of exporters per product. Age in 2008 measures the number of years that exporting (or importing) firms were active in the Colombian market during our sample period, as of 2008. The numbers are integers as would be expected, except where we look at per product or the value of transactions (expressed in thousand USD).

Table 1.2: Summary Statistics for Peru

		Percentiles								
	Variable	10	20	30	40	50	60	70	80	90
	Utilization rate by product	31.3	63	87.5	98	100	100	100	100	100
	Value of transaction (1000 USD	0.7	1.7	3.2	5.1	8.6	13.5	22.0	36.6	61.1
per Exporter	Utilization rate	42.9	91.9	98.4	100	100	100	100	100	100
	#Products	1	1	2	2	3	4	6	8	14
	#Importers	1	1	1	2	2	3	4	5	8
	#Importers per product	1	1	1	1	1.2	1.5	1.8	2.1	3.3
	#Transactions	2	3	6	11	19	30	46	77	171
	#Transactions per product	1	1.7	2.2	3.1	5	7	10.3	15.3	31
	Average value of transactions	1.6	3.6	6.0	9.1	11.9	16.6	24.6	34.1	51.2
	Age in 2008	0	0	0	0	1	2	3	5	6
per Importer	Utilization rate	48.3	91.5	99.4	100	100	100	100	100	100
	#Products	1	1	2	2	3	4	5	7	13
	#Exporters	1	1	1	1	2	2	3	3	5
	#Exporters per product	1	1	1	1	1	1	1.2	1.5	2
	#Transactions	1	3	6	8	15	23	37	62	138
	#Transactions per product	1	1.4	2	3	4.3	6.1	9	14.5	23.5
	Average value of transactions	1.5	3.3	5.8	9.7	13.4	19.9	25.8	37.8	60.1
	Age in 2008	0	0	0	1	2	3	4	6	7
per Exporter - Importer	#Transactions	1	1	1	2	3	4	7	12	28
	#Transactions per product	1	1	1	1	2	2	3	5	11

Note: Data for Peru is from 2001Q1 to 2011Q4. Per Exporter #Importers per product is defined at the exporter level as the average of the number of importers per product. Similarly, per Importer #Exporters per product is defined at the importer level as the average of the number of exporters per product. Age in 2008 measures the number of years that exporting (or importing) firms were active in the Colombian market during our sample period, as of 2008. The numbers are integers as would be expected, except where we look at per product or the value of transactions (expressed in thousand USD).

1.3.3 Data Patterns

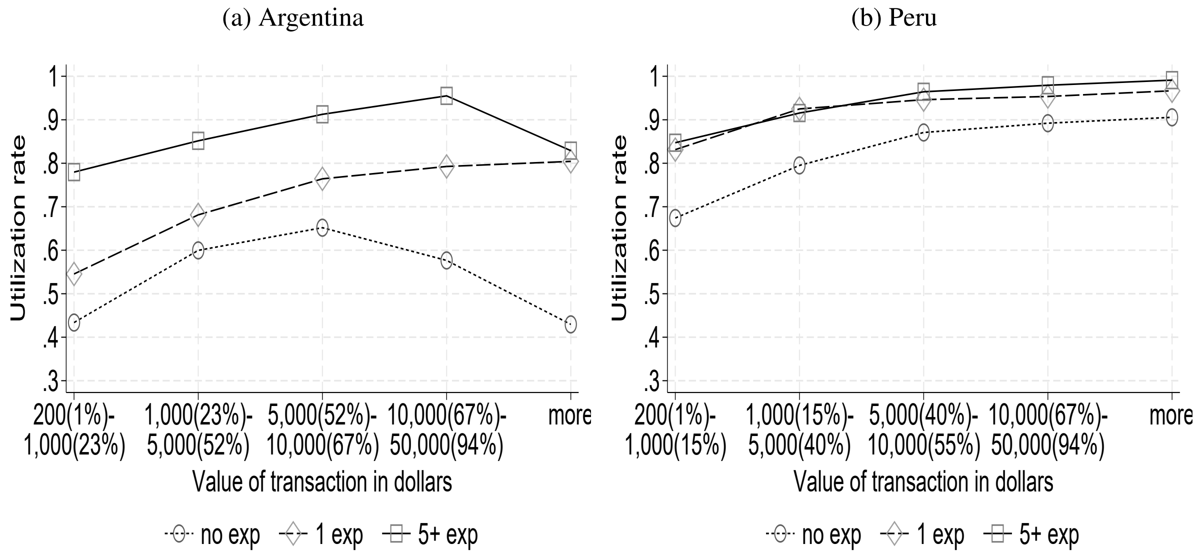
A pattern evident in the data is that preference use becomes more likely with experience and when the transaction value rises. This is depicted in Figure 1.2 for Argentina and Peru separately. Greater experience seems to be associated with the likelihood of using preferences for all transaction value levels, conditional on there being preferences that could be used.[26]

The curves show preference utilization as a function of transaction size for exporters with different levels of experience. There is a distinct upward slope. However, transaction size may be endogenous as larger orders may arise due to a desire to use preferences. If we want to interpret this pattern casually, we need an instrument. This is why we need a model-based regression approach which can also help identify a potential instrument.

Figure 1.3 looks at the preference use as a function of experience but distinguishes between the kinds of experience. Note that preference use (as measured by the utilization rate) when the total experience (across all products and importers) of the exporter to Colombia is considered lies below that when experience is restricted to that in the same product (conditional on the exporter having no experience in using preferences in other products). Note that here

[26]The transaction levels and the percentiles that those levels correspond to are depicted on the x-axis

Figure 1.2: Preference Utilization by Value of the Transaction and Experience



Note: Preference utilization rate is the ratio of the number of transactions using preferences over the total number of transactions at every value bin of the transactions. *no exp* shows the utilization rates for firms with no experience in using preferences before the time of the transaction, *1 exp* shows the utilization rates for firms with one experience, and *5+ exp* shows the utilization rates for firms with 5 or more experience.

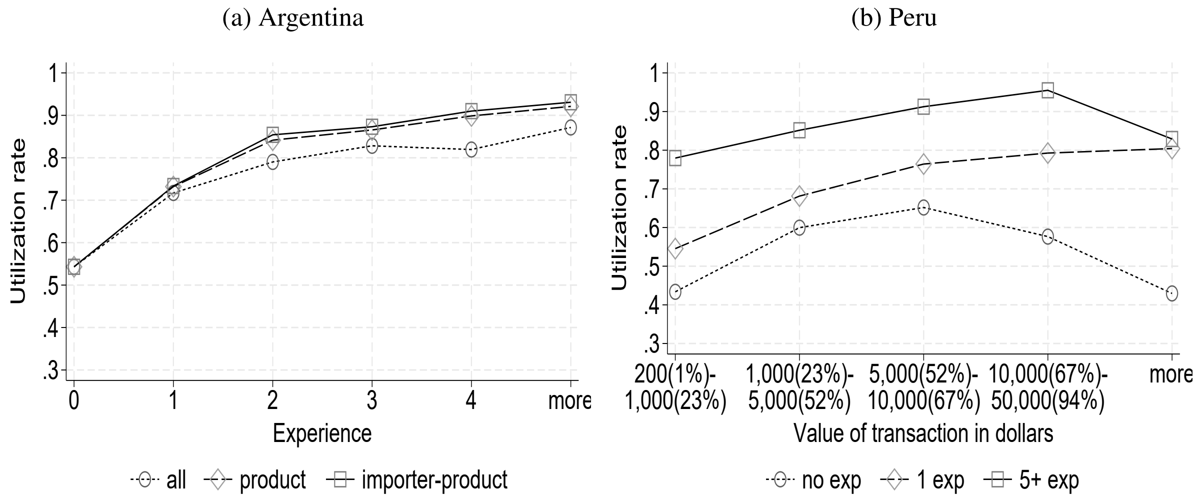
experience of the exporter could come from many importers of the given product. The third curve depicts preference use as a function of the experience of the exporter with a given importer and product, conditional on having no experience of preference use in other importer product combinations. This curve tends to be slightly higher than the one for a given product. This suggests that experience by importer-product is a bit more relevant than product-specific experience. However, to the extent that firms included in the importer-product definition of experience differ from those in the product definition, this may give a biased view of the importance of these two kinds of experience. These kinds of issues are exactly why we use a regression approach below.

1.4 Motivating the Empirical Specification

It seems reasonable, as we assume, to have the exporter choose whether to invoke preferences or not as it is the exporter who will need to prove that the products meet origin requirements.[27] Hence, for each transaction in a product, we can think of a supplier who decides whether to use preferences or not depending on whether the costs of doing so, both fixed and marginal,

[27] In the online appendix we also show that our results are robust to including importer experience.

Figure 1.3: Preference Utilization by Type of Experience



Note: This figure shows the preference utilization rates over transactions at every experience bin. *all* refers to all kinds of experience in using preferences before the current transaction, *product* refers to all experience in the product, while *importer-product* refers to all experience with the importer in the product.

exceed the benefits or not. On the one hand, the exporter gains from lower tariffs and this gain is larger the larger the preference margin. On the other hand, its costs may rise to meet Rules of Origin (ROOs). The increase in marginal costs comes about because the firm has to modify some aspects of its production to meet ROOs when it chooses to invoke preferences. It may also incur higher fixed costs such as the costs of changing its supply chain (i.e., finding new suppliers) and the administrative costs associated with proving compliance of the ROOs. In practice, an exporter needs to have a certificate of origin to obtain preferences. This requires the exporter to provide documentation that shows their product qualifies for preferences as it meets the relevant rules of origin.[28]

These fixed costs can depend on experience in using preferences. Knowledge about input suppliers and providing documentation in past transactions may reduce fixed costs and make it easier for an exporter to use preferences. There may also be spillovers to other importers or other products. That is, experience in one product and importer may help the exporter to use preferences with other products and/or importers. Our central insight is that if there is

[28]Implementation varies across settings. In some settings, like NAFTA, self-certification is enough. Formal approval and authorization may be required for the exporter to be allowed to issue origin declarations and incorrectness of the issued origin declaration can lead to withdrawal of the authorization and further consequences applicable under the domestic law. Exporters are also required to keep the needed paperwork to document origin for a certain period. Hence, even with self-certification, there are considerable documentation costs involved. In other instances, a governmental authority may be charged with this certification and additional bureaucratic costs may be involved.

no learning, then the probability of using preferences should be unaffected by any history the exporter has in using preferences. Marginal costs, in contrast, are likely not to depend on experience in using preferences but are likely to vary considerably by-product as the rules of origin are defined at a very detailed product level.

Formally, suppose that exporter e exports a particular product p and faces a constant elasticity of demand in quantity q from importer i for transaction t at time y.[29][30] The demand curve is:

$$q_{eipty}(a_{eipty}) = \Big((1+\tau_{py}^{\text{mfn}})^{1-a_{eipty}}(1+\tau_{py}^{\text{pref}})^{a_{eipty}} P_{eipty}(a_{eipty})\Big)^{-\eta}\psi_{eipty}, \tag{1.1}$$

where τ_{py}^{k} for $k = \text{mfn}, \text{pref}$ is the tariff imposed, a_{eipty} is the dummy variable for preference use in the transaction, P_{eipty} is the price in dollars, and ψ_{eipty} is the idiosyncratic demand shifter. In our context, ψ_{eipty} is the COP-USD exchange rate which acts like a demand shock. Note that we assume that the firms maximize their profits in dollars. We do control for the exporting country vs. USD exchange rate in our analysis to account for the possibility of the change in the input sourcing costs from abroad and thus the cost of complying with rules of origin. For the same reason, the bilateral exchange rates between the exporting and importing countries' is not a good IV. Since we control for the exporting country's exchange rates vs. USD, the variation of our instrument is conditional on the remaining variation after controlling for the exporting country's exchange rate vis a vis the dollar.[31]

Note that the demand in Colombia is a function of the price in Colombian Pesos. The exporting firm cares about what it earns in US dollars. As a result, if the Peso appreciates vis-a-vis the dollar, it acts exactly like a positive demand shock for the exporter, i.e., an increase in ψ_{eipty}. Thus, the importing country exchange rate vis-a-vis the dollar serves as a time-variant demand shifter which we use later as an instrument in our regression.[32] We control for the bilateral exchange rate between the importing and exporting countries as well in our regression

[29]The details of the derivations below are to be found in Appendix A.2.

[30]We index both for transaction (t) and time (y) as we observe multiple transactions within even the finest time period in the data we use in our regressions which is a day.

[31]The reader may want to know what the exchange rate trends of the importing country and the dollar and the exporting countries and the dollar look like. In particular, one might be interested in the extent of the residual variation in the importing country's exchange rate with the dollar after controlling for the exporting country's exchange rate with the dollar, which is what we use as an instrument. This is depicted in Figure A.5 in the Appendix A.11 It is clear that they are far from perfectly correlated, which is consistent with the first stage is significant.

[32]Transactions between the three countries are denominated in dollars. Gopinath & Stein (2021); Gopinath et al. (2020) explain why firms maximize profits in dollars. They argue that a currency's role as a unit of account for invoicing decisions is complementary to its role as a safe store of value. The exporter cares about his earnings being safe. This is why we assume they maximize in dollars.

to account for the fact that costs may be affected by this.

The profit from the transaction for the exporter is:

$$\pi_{eipty}(a_{eipty}) = \left(P_{eipty}(a_{eipty}) - R_p^{a_{eipty}} c_{ety}\right) q_{eipty}(a_{eipty}) - a_{eipty}\varepsilon_{eipty}F_{eipty}, \tag{1.2}$$

where c_{ety} is the marginal cost of production (in dollars), R_p is the increase of the marginal cost to meet the rules of origin, F_{eipty} is the fixed cost of using preferences, and ε_{ety} is the idiosyncratic shock in using preferences in the transaction.[33] The exporter maximizes his profit in two steps. First, the exporter determines the price of the transaction with and without using preferences. The profit-maximizing price of the transaction using preferences or not ($a_{ety} = 0$ or 1) is

$$P_{eipty}(a_{eipty}; c_{epty}) = \frac{\eta}{\eta - 1} R_p^{a_{eipty}} c_{epty}. \tag{1.3}$$

Note that the price does not depend on the importer country's exchange rate vis a vis the dollar.

Then the exporter chooses to use preferences only if doing so raises his profits. In Appendix A.2, we show that the decision rule is (see equation (A.8)):

$$a_{eipty} = \mathbb{1}\left\{\pi_{eipty}(1) - \pi_{eipty}(0) > 0\right\} = \mathbb{1}\left\{\ln s_{eipty} - \ln F_{eipty} + \chi_{py} > \epsilon_{eipty}\right\}, \tag{1.4}$$

where $s_{eipty} \equiv (\tau_{py}^{\text{mfn}} - \tau_{py}^{\text{pref}}) r_{ity}(0)$ is the tariff savings by invoking preferences, i.e., the preference margin times the value of the transaction if the preferences had not been met; and χ_{py} is a term that is product time-specific and captures the MFN tariff and the preferential tariff, and the increase in the marginal cost of production from meeting ROOs.[34]

Motivated by equation (1.4) we estimate a linear probability model.[35] For exporter e, importer i, product p, time y, and transaction t, we estimate the following equation:

$$a_{eipty} = \alpha \ln s^*_{eipty} + \boldsymbol{Exp}'_{eipty}\boldsymbol{\beta} + \boldsymbol{X}'_{et}\boldsymbol{\gamma} + \delta_{ei} + \delta_p + u_{eipty}, \tag{1.5}$$

[33]Note that, as pointed out in Section 1.1, we do not differentiate between fixed costs and sunk costs.

[34]This term, denoted as χ_{py}, is explicitly defined as follows:

$$\chi_{py} \equiv \ln\left(\left(\tau_{py}^{\text{mfn}}/\tau_{py}^{\text{pref}}\right)^{\eta} R_p^{-(\eta-1)} - 1\right)\left(\tau_{py}^{\text{mfn}} - \tau_{py}^{\text{pref}}\right)^{-1} - \ln\eta.$$

[35]We use the linear probability model as IV estimation with high dimensional fixed effects in a non-linear setting is still a work in progress to the best of our knowledge. In such settings, it can create an incidental parameters problem. Estimates of alternative non-linear specifications without IVs are presented in Online Appendix A.7. These estimates are in line with the baseline reported here.

where the dependent variable is one if preferences are used in the transaction and zero otherwise. Bold variables denote vectors. We allow F_{eipty} to be a function of experience ($\boldsymbol{Exp}'_{eipty}$) so that an increase in the probability of using preferences with experience can be seen as evidence that fixed costs fall with experience. u_{eipty} captures the idiosyncratic cost of using preference. s^*_{eipty} proxies for s_{eipty}. In the data, we cannot observe $r_{ity}(0)$ when preferences are used in the transaction. We use $r_{ity}(a_{eipty})$ as a proxy for the value of the transaction when preferences are used and define $s^*_{eipty} \equiv (\tau^{mfn}_{py} - \tau^{pref}_{py})r_{ity}(a_{eipty})$. This creates measurement error. In Appendix A.3, we show that this measurement error does not necessarily invalidate our results.[36] The time-invariant variation in χ_{py} coming from the differences in the tariff margin and the higher marginal costs from meeting the ROOs across products can be addressed by product fixed effects.[37] As control variables denoted by $\boldsymbol{X}_{et}$, we include the two-month lagged daily exchange rate of the origin country with respect to the dollar, and the exporter's age measured in the number of years the exporter has been conducting business with Colombia. The inclusion of the exchange rate of the exporting country with respect to the dollar aims to control for variations in costs of meeting the ROOs over time, influenced by changes in the cost of imported inputs. Meanwhile, the exporter's age serves to capture any potential impact on fixed costs associated with meeting ROOs that may vary depending on the firm's age as an exporter in this market at the time of the transaction.

Since our data start from 2000, the age variable is potentially truncated from above. One might be concerned that this would create measurement error and bias our results. However, our exporter-importer fixed effect will control for this. The experience variable could have a similar problem, even though we drop firms with transactions in 2000 to get a cleaner measure of experience. Any misclassification would be greatest in the earlier years of our data. Our rough estimate suggests that around 5% of all firms in 2001 would be misclassified as new when we drop one year so that this would be the maximum amount of misclassification. Our logic is laid out in Appendix A.10. Note that, in Section 1.5.3 where we look at products newly covered by the deepening of the trade agreement between Argentina and Colombia, this problem does not exist and our results on the pattern of learning are unaffected.

Our focus is on the coefficients of the exporter's experience, $\boldsymbol{Exp}_{eipty}$.[38] We consider four

[36]We also conducted an analysis using bin dummies of transaction sizes instead of continuous measures of savings for the OLS specification though we cannot do this for the IV due to a lack of instruments. The bins specification is less subject to measurement error and allows for a more flexible functional form for savings. With this specification even when including time-fixed effects, our results remain robust. These results can be found in the Online Appendix.

[37]We cannot use product-time fixed effects as it reduces the variation needed in instruments and weakens the first stage.

[38]The exporter's experience is relevant because the exporter needs to provide documentation that shows that goods comply with the relevant ROOs. To validate this hypothesis, we assessed whether the importer's experience

types of experience, as summarized in Table 1.3: (1) across the *s*ame *i*mporter and the *s*ame *p*roduct (si, sp), (2) the *s*ame *i*mporter and *o*ther *p*roducts (si, op), (3) *o*ther *i*mporters and the *s*ame *p*roduct (oi, sp), and (4) *o*ther *i*mporters and *o*ther *p*roducts (oi, op).

Table 1.3: Summary of Four Types of Experience

	Same Importer	Other Importers
Same Product	$Exp^{n}_{eipty}(si, sp)$	$Exp^{n}_{eipty}(oi, sp)$
Other Products	$Exp^{n}_{eipty}(si, op)$	$Exp^{n}_{eipty}(oi, op)$

Note: $Exp^{n}_{eipty}(m, \ell)$ for $m = si, oi$ and $\ell = sp, op$ is the dummy variable that takes the value 1 if the exporter has exactly n transactions of preference use up to time y with the relevant importer and relevant product types. We count the number of experiences from one to up to four, and the value is set to one if the number exceeds four (i.e., $Exp^{more}_{eipty}(m, \ell) = 1$ for $n > 4$).

To estimate the nonlinear effects of experience on preference use, we use dummy variables representing the four types of experience, with preferences ranging from one to five or more uses. For example, the dummy variable $Exp^{n}_{eipty}(si, sp)$ takes the value 1 if the exporter has exactly n transactions of preference use up to transaction t with the same importer for the same product in the transaction. If the number of relevant transactions with preference use is five or more, $Exp^{more}_{eipty}(si, sp) = 1$.[39]

By allowing for different coefficients on this four-way classification of experience, we can gain a better understanding of the shape of the fixed costs of obtaining preferences, something that has not been done to date. More precisely, we can explore how fixed costs of meeting ROOs vary by the various kinds of experience a firm might have in obtaining preferences and specifically the extent to which experience with using preferences creates positive spillovers across products and/or importers – the possibility that an exporter that learns how to use preferences for a product or with a specific importer might be more likely to use preferences with other products or importers. If, for example, using preferences in another product and the same importer in the past does not affect the likelihood of using preferences in the current transaction, then it must be that costs are not impacted by such an experience.

matters once the exporter's experience was accounted for and found that it did not. These results are available in Online Appendix A.4.

[39]To illustrate, consider an exporter at time y who has invoked preferences three times to date. In this case, the dummy variable equals 1 for the third experience but 0 for the rest. It is worth noting that we choose to group experiences with more than four transactions in one bin, as suggested by Figure 1.3, where the effects of experience appear to flatten out.

Our fixed effects account for a wide range of potential confounding factors. We include exporter-importer (ei) fixed effects and product (p) fixed effects. The former set of fixed effects controls for any unobservable heterogeneity across exporter-importer pairs as well as for any systematic variation in the fixed costs of meeting ROOs across exporters and importers –associated, for instance, with their different initial sourcing structures and locations and hence access to the physical location of the government agencies in charge of reviewing the documents needed to obtain preferences. The latter set of fixed effects absorbs any product-specific forces at work that might affect the choice of using preferences, including differences in the ROOs across products that raise the costs of meeting them. For example, if a firm changed its production process/supply chain to meet ROOs and this was easy for it to do, it would just make firms more likely to use preferences overall. This would be captured on average by product-specific fixed effects. If this supply chain change occurred slowly, and was driven by overall use of preferences in that product by the firm, it would be reflected in positive coefficients for other importer-same product experience as well as for same importer same-product experience. For Argentina, both for all products and for newly covered product, the former coefficients are by and large insignificant, though the latter are always significant. Both are however significant for Peru. The reason could be that the FTA between Peru and Colombia is long standing so there is more social learning going on which permits these spillovers. Given our fixed effects, our estimates exploit variation in preference use over transactions within a given importer-exporter, after controlling for variation across products.

A remaining concern might be that savings could be correlated with the residual for a variety of reasons including reverse causality and simultaneity. We do not take a stand on what the source of the bias is exactly since, whatever that source is, if we can find an instrument for savings, we would be able to correct it. We use the daily US dollar-Colombian peso exchange rate as an instrument because it affects the demand for imports (see equation (1.1)) and hence the value of the transaction and the savings variable without having direct effects on preference utilization.[40] In particular, we use this high-frequency data on exchange rates to maximize the variation and use 60-day lags to capture the relevant exchange rate at the time of the order.[41] We do not include time-fixed effects for the variation in exchange rates to be fully exploited. When we add year-fixed effects, our first stage weakens, leading to greater standard errors in the second stage estimates, making estimates for all variables insignificant. These results can be found in Tables A.15 and A.16 in the Appendix. We also give OLS results with product-year

[40]Appreciation of the Colombian peso relative to the dollar would raise the willingness to pay for imports, which would raise savings.

[41]We experimented with different lags, and the lag of 60 days worked best as an instrument. This makes sense in terms of the expected delay between the order and its arrival in the importers' port.

fixed effects. Point estimates for learning however remain very close to our original estimates.

1.5 Results

In this section, we present both IV and OLS estimates of equation (1.5) using the four-way classification of experience as in Table 1.3.[42] We do so separately for Argentina and Peru. Recall that Peru has a long-standing FTA with Colombia and, as a consequence, deeper integration with this country than Argentina. Because of these differences, we would expect that there is less room for learning in Peru than in Argentina. Consistently, the evidence indicated that there is indeed evidence of stronger learning effects for Argentina. In addition, preferences were extended to additional products in Argentina in the period studied. This natural experiment lets us further explore whether our hypothesis is correct. The results of this exercise reveal that the greater learning for Argentina comes from these newly covered products.

1.5.1 Baseline Results

Baseline results for each country, both for the IV and OLS regressions are presented in Tables 1.4 and 1.5. [43] The first stage estimates indicate that the exchange rate instruments are strongly correlated with the endogenous saving variables after conditioning on the relevant covariates and fixed effects in both countries. As suggested by the model, an increase in the price of the dollar in terms of the Colombian peso (depreciation of the peso) reduces the savings for both exporting countries. The first-stage Kleibergen-Paap F statistic for both countries is well over 10. The point estimate of the savings coefficient for Argentina, is positive (0.022) but not significantly different from zero in the OLS estimation. It turns negative but is still not significant in the IV estimation (-0.087). However, note that the IV estimate is about three times larger in absolute terms than the OLS one so that is is economically significant, if not statistically so. The point estimate of the savings coefficient for Peru is positive for both the OLS and IV (.01 and .036), and of a similar size to that for Argentina, though the IV estimate is not statistically significant.

Note that our estimates come from the variation within the exporter-importer pairs, and thus are not inconsistent with the general importance of transaction size for preference utilization. The fixed effects might capture most of the raw variations of the transaction sizes

[42]A problem which remains is measurement error. As argued in Appendix A.3, it would not affect the signs of our estimates, though it would affect the scale so that the ratios of the estimates would be unbiased.

[43]The estimates for the effects of experience do not change much if we incorporate separate exporter and importer fixed effects. These results for the IV version can be seen in Columns 3,6,9 and 12 of Table - in the Online Appendix.

across transactions, which might explain why the estimated coefficient is not too different from zero. One possibility for the negative coefficient in Argentina is that larger transactions, while potentially offering greater benefits, may also incur greater costs as much larger than usual transaction volumes may require firms to source from additional input suppliers, necessitating more documentation than otherwise. Once we control for the reverse causality—where transaction volume is greater with preference use — these potential cost effects may dominate, so the net effects are negative in the IV estimate.

Table 1.4: Linear Probability Model with Fixed Effects Argentina

IV				OLS			
$Savings$		-0.069				0.023***	
		(0.078)				(0.005)	
Age		0.034**				0.017***	
		(0.016)				(0.006)	
$ln(er_o)$		-0.027				-0.007	
		(0.045)				(0.040)	
$Exp^1(si, sp)$	0.063***	$Exp^1(oi, sp)$	0.023	$Exp^1(si, sp)$	0.052***	$Exp^1(oi, sp)$	0.010
	(0.019)		(0.023)		(0.015)		(0.020)
$Exp^2(si, sp)$	0.111***	$Exp^2(oi, sp)$	0.041	$Exp^2(si, sp)$	0.095***	$Exp^2(oi, sp)$	0.025
	(0.024)		(0.028)		(0.019)		(0.024)
$Exp^3(si, sp)$	0.127***	$Exp^3(oi, sp)$	0.066**	$Exp^3(si, sp)$	0.117***	$Exp^3(oi, sp)$	0.047*
	(0.025)		(0.028)		(0.023)		(0.024)
$Exp^4(si, sp)$	0.132***	$Exp^4(oi, sp)$	0.054	$Exp^4(si, sp)$	0.118***	$Exp^4(oi, sp)$	0.027
	(0.029)		(0.036)		(0.027)		(0.030)
$Exp^{more}(si, sp)$	0.154***	$Exp^{more}(oi, sp)$	0.006	$Exp^{more}(si, sp)$	0.135***	$Exp^{more}(oi, sp)$	-0.017
	(0.038)		(0.032)		(0.035)		(0.024)
$Exp^1(si, op)$	-0.005	$Exp^1(oi, op)$	-0.021	$Exp^1(si, op)$	0.024	$Exp^1(oi, op)$	-0.006
	(0.037)		(0.037)		(0.028)		(0.031)
$Exp^2(si, op)$	0.010	$Exp^2(oi, op)$	0.005	$Exp^2(si, op)$	0.019	$Exp^2(oi, op)$	0.033
	(0.032)		(0.042)		(0.030)		(0.029)
$Exp^3(si, op)$	0.035	$Exp^3(oi, op)$	-0.041	$Exp^3(si, op)$	0.059**	$Exp^3(oi, op)$	-0.024
	(0.031)		(0.081)		(0.027)		(0.081)
$Exp^4(si, op)$	0.052	$Exp^4(oi, op)$	-0.025	$Exp^4(si, op)$	0.068**	$Exp^4(oi, op)$	0.014
	(0.035)		(0.048)		(0.033)		(0.031)
$Exp^{more}(si, op)$	0.052	$Exp^{more}(oi, op)$	0.024	$Exp^{more}(si, op)$	0.051	$Exp^{more}(oi, op)$	0.046
	(0.035)		(0.047)		(0.034)		(0.036)
Observations		15,689				15,689	
Fixed Effects:							
Exporter-Importer		✓				✓	
Product		✓				✓	
First stage							
2 *month lagged* $ln(er_{CO})$			-0.603***				
			(0.151)				
Kleibergen-Paap F			16.05				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. Sample definition excludes transactions smaller than 200 USD, mineral sector, top percentile of value at the product-country level, and firms that enter the sample before 2001. *** p<0.01, ** p<0.05, * p<0.1.

Tables 1.4 and 1.5 also show how experience of different kinds affects preference utilization. Experience in the same product and with the same importer seems to matter the most. The coefficients for this kind of experience, $Exp^n(si, sp)$, are positive, significant, and increasing in both the OLS and IV versions. Our findings indicate that the difference between OLS and IV estimates for each specific type of experience seems to be quite small. The direction of

Table 1.5: Linear Probability Model with Fixed Effects Peru

	IV				OLS		
$Savings$	0.036				0.010***		
	(0.032)				(0.002)		
Age	-0.001				-0.001		
	(0.001)				(0.001)		
$ln(er_o)$	0.041				0.017		
	(0.043)				(0.029)		
$Exp^1(si,sp)$	0.020***	$Exp^1(oi,sp)$	0.014**	$Exp^1(si,sp)$	0.024***	$Exp^1(oi,sp)$	0.017**
	(0.006)		(0.007)		(0.004)		(0.007)
$Exp^2(si,sp)$	0.025***	$Exp^2(oi,sp)$	0.017**	$Exp^2(si,sp)$	0.030***	$Exp^2(oi,sp)$	0.020***
	(0.008)		(0.007)		(0.005)		(0.007)
$Exp^3(si,sp)$	0.028***	$Exp^3(oi,sp)$	0.023***	$Exp^3(si,sp)$	0.033***	$Exp^3(oi,sp)$	0.026***
	(0.009)		(0.009)		(0.006)		(0.009)
$Exp^4(si,sp)$	0.029***	$Exp^4(oi,sp)$	0.024***	$Exp^4(si,sp)$	0.036***	$Exp^4(oi,sp)$	0.028***
	(0.010)		(0.008)		(0.006)		(0.008)
$Exp^{more}(si,sp)$	0.022*	$Exp^{more}(oi,sp)$	0.025***	$Exp^{more}(si,sp)$	0.031***	$Exp^{more}(oi,sp)$	0.029***
	(0.013)		(0.009)		(0.007)		(0.010)
$Exp^1(si,op)$	-0.004	$Exp^1(oi,op)$	-0.019**	$Exp^1(si,op)$	-0.007	$Exp^1(oi,op)$	-0.019**
	(0.008)		(0.009)		(0.006)		(0.009)
$Exp^2(si,op)$	-0.010	$Exp^2(oi,op)$	-0.026**	$Exp^2(si,op)$	-0.013*	$Exp^2(oi,op)$	-0.030***
	(0.008)		(0.011)		(0.007)		(0.011)
$Exp^3(si,op)$	-0.002	$Exp^3(oi,op)$	-0.011	$Exp^3(si,op)$	-0.007	$Exp^3(oi,op)$	-0.013
	(0.010)		(0.012)		(0.007)		(0.012)
$Exp^4(si,op)$	-0.009	$Exp^4(oi,op)$	-0.026*	$Exp^4(si,op)$	-0.013	$Exp^4(oi,op)$	-0.027*
	(0.011)		(0.015)		(0.009)		(0.016)
$Exp^{more}(si,op)$	-0.007	$Exp^{more}(oi,op)$	-0.046**	$Exp^{more}(si,op)$	-0.014**	$Exp^{more}(oi,op)$	-0.047**
	(0.012)		(0.021)		(0.006)		(0.022)
Observations	54,188				54,188		
Fixed Effects:							
Exporter-Importer		✓				✓	
Product		✓				✓	
First stage							
2 *month lagged* $ln(er_{CO})$			-0.689***				
			(0.166)				
Kleibergen-Paap F			17.16				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. Sample definition excludes transactions smaller than 200 USD, mineral sector, top percentile of value at the product-country level, and firms that enter the sample before 2001. *** p<0.01, ** p<0.05, * p<0.1.

the bias in other variables due to endogeniety in savings is hard to predict econometrically as the expression for bias with many variables is complicated. It could also be that endogeneity concerns in other variables are less pronounced given the set of control variables and fixed effects we have. Note that there is an effect on the estimate for savings with and without the IV. It is not unusual for estimates of other variables to not change much from the OLS results to the IV results..[44]

To get some idea of how large these effects are, note that the increase in the probability of an exporter with a single transaction experience using preferential tariffs with the same importer-product is 6.3% compared to the inexperienced exporters in Argentina. The increase in probability for the second through fifth or more experience levels is 11.1%, 12.7%, 13.2%,

[44]Note that changing the supply chain to meet ROOs would also change fixed costs. This is likely to be a one-off cost and could be part of why it looks like there is large learning in early transactions.

and 15.4%. Analogously, for Peru, the probability increases are 2%, 2.5%, 2.8%, 2.9%, and 2.2%.

The coefficients are roughly two to three times larger for Argentina than for Peru. This was expected given the shorter history of the FTA between Argentina and Colombia and thus the larger learning potential for its firms. There is some evidence of cross-importer spillovers in the same product for both Peru and Argentina, with more significant coefficients for Peru. However, cross-product experience does not seem to be significant for Argentina, at least once we use the IV. There are a few significant negative coefficients for Peru (other importers and other products), which might be coming from constraints on the firm's capacity to handle the paperwork involved.[45]

1.5.2 Does Preference Use Increase with Experience?

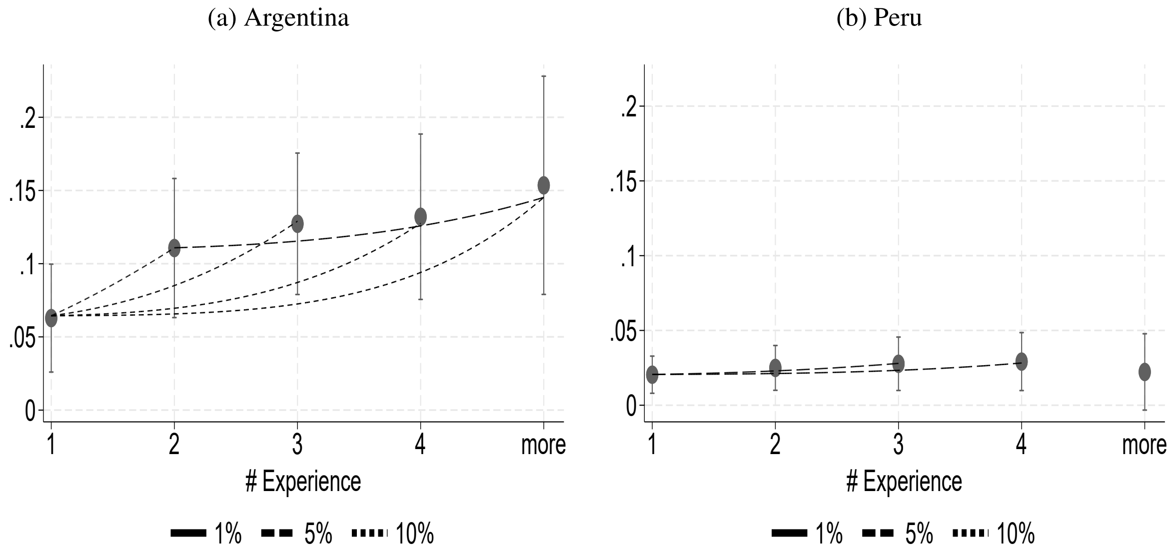
The significance tests in Tables 1.4 and 1.5 determine whether the estimated coefficients are significantly different from zero.[46] However, we are also interested in whether these coefficients increase with exporters' experience to determine whether preference usage rises with greater experience in using preferences. In this subsection, we focus on experience with the same importer and the same product since this is where most of the action is coming from for both countries. We highlight whether the coefficients for each kind of experience are significantly different from zero and whether the coefficients increase significantly with experience.

Panel (a) in Figure 1.4. is for Argentina and Panel (b) is for Peru. The vertical lines at each experience level depict the 95% confidence intervals for the respective estimate. Overall, all of these estimates are significantly positive though the confidence intervals are wider for Argentina. If the estimates of the coefficients on the level of experience are increasing significantly, we connect the two estimates with a line. If not, there is no line connecting the estimates. A significance level of 5 percent corresponds to a solid line, while a significance level of 10 percent corresponds to a dashed line. For both countries, the coefficient on the third and the fourth experience are significantly larger than that on the first. Furthermore, for Argentina, the coefficients on all the levels of experience are significantly larger than the first, and the coefficient on the third experience is also significantly higher than that on the second. This evidence suggests that preference use tends to increase with experience.

[45]However, these negative coefficients do not seem to be coming from smaller firms as might be expected if this was the explanation. Detailed results from the estimation are available upon request.

[46]The estimates for these coefficients of learning from the same product and same exporter are very similar when we cluster by exporter, by importer, by product, by exporter importer, or by exporter importer product. These results can be found in the Online Appendix as Table A.17

Figure 1.4: Preference Use and Experience (si,sp)



Note: This figure shows whether the coefficients for experience are significantly increasing and different from zero. The vertical lines at each experience level give the 95% confidence intervals. The lines connecting the different experience levels are only drawn when the coefficients are significantly larger for greater experience and the significance level is depicted by the coarseness of the lines.

1.5.3 Are Exporters Really Learning?

We saw that the coefficients on experience in the same product were larger for Argentina than for Peru. We expected this because the trade agreement between Argentina and Colombia was relatively new compared to Peru. More specifically, we argue that there might be social learning about how to use preferences. Due to the relative age of the two countries' trade agreements with Colombia, preference utilization was more generalized, and social learning could have been accordingly greater in Peru than in Argentina. As a consequence, the potential for learning from own specific experience would have been relatively more limited in the former country.

There is another dimension of variation we could use to see if our argument holds. New products became covered in 2005 in Argentina as the FTA coverage expanded.[47] We now allow learning to differ for newly covered products and old products. As experience with the same importer and same product was where the action was in our regression to date, we restrict attention to this kind of experience for new products. Let d^p_{new} be a dummy variable equal to one if product p is newly covered by the agreement in 2005. We interact this dummy for new products with the relevant experience to estimate the additional learning effects for newly

[47]See Section 1.3.1 for more.

covered products.

$$a_{eipty} = \alpha \ln s^*_{eipty} + \boldsymbol{Exp}'_{eipty}\boldsymbol{\beta} + d_p^{new}\boldsymbol{Exp}'_{eipty}(si, sp)\boldsymbol{\beta}^{new} + \boldsymbol{X}'_{et}\boldsymbol{\gamma} + \boldsymbol{\delta} + u_{eipty}, \quad (1.6)$$

The results from our new estimating equation (1.6) are presented in Table 1.6. Our results show that the learning is coming predominantly from newly covered products. For old products, the learning estimates for Argentina and Peru are much closer. This helps explain why the learning estimates seem to be so much larger for Argentina.[48]

To sum up, learning effects with the same product and the same importer in Tables 1.4 and 1.5 are higher for Argentina than for Peru. Arguably, this is most likely because the FTA between Argentina and Colombia was relatively new compared to that between Peru and Colombia. Evidence presented in Table 1.6 indicates that this is indeed the case. While estimated effects point to stronger learning for newly covered products, those for old products are much closer to those for Peru in Table 1.5.

[48]Could there also be learning by customs officials on newly introduced products? While this is possible, the experience of customs officers is likely to rise very fast compared to that of firms as they focus on handling such issues. The ease of getting through customs may vary by product and this will be picked up by product fixed effects. Additionally, we do not observe any effects on same-product other-importer experience for Argentina which would be expected with customs officers learning. Nor do our learning results change in the OLS regressions where we add product-year fixed effects to control for product-time-specific shocks. This specification could account for potential average learning effects by customs officials if they take years to learn. Customs may recognize firms over time and so wave their requests through. If so, this would spillover to other products and partners. We see little of this. If there is partner product recognition on the part of customs and firms know this, such behavior would be partly picked up by importer-exporter fixed effects.

Table 1.6: Interaction with Newly Covered Products Argentina

	IV				OLS		
$Savings$	-0.080				0.023***		
	(0.080)				(0.005)		
Age	0.037**				0.018***		
	(0.017)				(0.006)		
$ln(er_o)$	-0.002				0.018		
	(0.042)				(0.038)		
$Exp^1(si, sp)$	0.010	$Exp^1(oi, sp)$	0.022	$Exp^1(si, sp)$	0.009	$Exp^1(oi, sp)$	0.008
	(0.025)		(0.023)		(0.024)		(0.020)
$Exp^2(si, sp)$	0.038	$Exp^2(oi, sp)$	0.038	$Exp^2(si, sp)$	0.023	$Exp^2(oi, sp)$	0.021
	(0.030)		(0.028)		(0.029)		(0.025)
$Exp^3(si, sp)$	0.070**	$Exp^3(oi, sp)$	0.063**	$Exp^3(si, sp)$	0.064*	$Exp^3(oi, sp)$	0.042*
	(0.034)		(0.028)		(0.034)		(0.025)
$Exp^4(si, sp)$	0.068*	$Exp^4(oi, sp)$	0.052	$Exp^4(si, sp)$	0.052	$Exp^4(oi, sp)$	0.022
	(0.041)		(0.037)		(0.043)		(0.031)
$Exp^{more}(si, sp)$	0.054	$Exp^{more}(oi, sp)$	0.007	$Exp^{more}(si, sp)$	0.044	$Exp^{more}(oi, sp)$	-0.018
	(0.042)		(0.032)		(0.044)		(0.024)
$Exp^1(si, op)$	-0.004	$Exp^1(oi, op)$	-0.019	$Exp^1(si, op)$	0.027	$Exp^1(oi, op)$	-0.003
	(0.036)		(0.036)		(0.027)		(0.031)
$Exp^2(si, op)$	0.013	$Exp^2(oi, op)$	0.004	$Exp^2(si, op)$	0.023	$Exp^2(oi, op)$	0.035
	(0.033)		(0.043)		(0.030)		(0.029)
$Exp^3(si, op)$	0.036	$Exp^3(oi, op)$	-0.039	$Exp^3(si, op)$	0.062**	$Exp^3(oi, op)$	-0.020
	(0.031)		(0.080)		(0.028)		(0.080)
$Exp^4(si, op)$	0.059*	$Exp^4(oi, op)$	-0.023	$Exp^4(si, op)$	0.076**	$Exp^4(oi, op)$	0.020
	(0.035)		(0.047)		(0.033)		(0.031)
$Exp^{more}(si, op)$	0.054	$Exp^{more}(oi, op)$	0.028	$Exp^{more}(si, op)$	0.053	$Exp^{more}(oi, op)$	0.052
	(0.035)		(0.045)		(0.034)		(0.034)
$d_{new} \times Exp^1(si, sp)$	0.081**			$d_{new} \times Exp^1(si, sp)$	0.064**		
	(0.034)				(0.028)		
$d_{new} \times Exp^2(si, sp)$	0.112***			$d_{new} \times Exp^2(si, sp)$	0.108***		
	(0.037)				(0.036)		
$d_{new} \times Exp^3(si, sp)$	0.084**			$d_{new} \times Exp^3(si, sp)$	0.077*		
	(0.042)				(0.041)		
$d_{new} \times Exp^4(si, sp)$	0.092*			$d_{new} \times Exp^4(si, sp)$	0.096*		
	(0.051)				(0.052)		
$d_{new} \times Exp^{more}(si, sp)$	0.154**			$d_{new} \times Exp^{more}(si, sp)$	0.138**		
	(0.061)				(0.056)		
Observations	15,689				15,689		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		
First stage							
2 *month lagged* $ln(er_{CO})$			-0.599***				
			(0.151)				
Kleibergen-Paap F			15.80				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. Sample definition excludes transactions smaller than 200 USD, mineral sector, top percentile of value at the product-country level, and firms that enter the sample before 2001. *** p<0.01, ** p<0.05, * p<0.1.

1.5.4 Is There Heterogeneity by Preference Margin?

We also consider whether high-preference margin products have different learning effects from low-margin products. The presence of learning might result in high preference margin products having less estimated learning at the firm level. These results are presented in Table 1.7. Such heterogeneity is present as there is significantly less learning for high preference margin products, though this is more so for Argentina than Peru. This is so both for all products and newly covered products in Argentina.

Table 1.7: Interaction with Margin

	Peru	Argentina	Argentina Newly Covered Products
$Exp^1(si, sp)$	0.032***	0.086***	0.091**
	(0.012)	(0.032)	(0.045)
$Exp^2(si, sp)$	0.046***	0.179***	0.155***
	(0.013)	(0.038)	(0.046)
$Exp^3(si, sp)$	0.043**	0.212***	0.209***
	(0.018)	(0.039)	(0.050)
$Exp^4(si, sp)$	0.052***	0.234***	0.223***
	(0.017)	(0.045)	(0.060)
$Exp^{more}(si, sp)$	0.042*	0.279***	0.320***
	(0.025)	(0.061)	(0.072)
Margin	-0.003	0.019	0.029
	(0.002)	(0.015)	(0.031)
Margin $\times$			
$Exp^1(si, sp)$	-0.001	-0.006*	-0.007
	(0.000)	(0.003)	(0.005)
$Exp^2(si, sp)$	-0.001**	-0.013***	-0.010*
	(0.001)	(0.003)	(0.006)
$Exp^3(si, sp)$	-0.001	-0.015***	-0.020***
	(0.001)	(0.004)	(0.007)
$Exp^4(si, sp)$	-0.001**	-0.018***	-0.021***
	(0.001)	(0.004)	(0.008)
$Exp^{more}(si, sp)$	-0.001	-0.021***	-0.032***
	(0.001)	(0.005)	(0.007)
Observations	54,188	15,689	8,715
Fixed Effects:			
Exporter-Importer	✓	✓	✓
Product	✓	✓	✓
First stage			
2 *month lagged* $ln(er_{CO})$	-0.779***	-0.453***	-0.366*
	(0.157)	(0.158)	(0.192)
Kleibergen-Paap F	24.70	8.260	3.622

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. Controls: Savings, Age, and $ln(er_o)$. *** p<0.01, ** p<0.05, * p<0.1.

1.5.5 Additional Checks

In this section, we provide some additional support for our main findings: namely that there is learning and this learning comes mostly from experience in using preferences with the same product and partner.

A question of interest might be whose experience matters? The exporter's or the importer's. To cast light on this, we look at whether the importer's experience in using preferences matters, once the exporter's experience is controlled for. Note that the same importer- same exporter product experience would be the same on the exporter and importer sides. For this reason, we cannot directly add both sides experience. We address this issue in two ways. First, we run a regression where we include experience with any partner but in the same product and experience with any partner but in other products, separately for exporters and importers (i.e., exporter's and importer's product-specific experience). Tables A.1 and A.2 show the results. We find that the exporter's experience has a larger and more significant effect than the importer's experience for Argentina, while they appear to be equally large and significant for Peru. Furthermore, we run our baseline specification but control for the experience of importers with any other exporter and in any product. Tables A.3 and A.4 show the results. In this case, Argentina and Peru have coefficients for importer experience that are not significant, and more importantly, the coefficients for exporter experience remain close to the baseline estimation both in magnitude and significance. Both sets of estimation results consistently show the importance of the exporter's experience in preference use, even when accounting for the importer's experience.

Comparing our results to those in the literature on this issue, it is worth noting that Kasteng et al. (2022a,b), who look at preference use in Sweden, find that the importer's experience affects trade preference utilization. We allow for both importer and exporter experience in Tables A.1 to A.4 and find that most of the action seems to come from the latter. It is important to note that the difference between their findings and ours may well arise from the differences in the implementation of the ROOs. In the Swedish case, all that is needed is an attestation by the exporter that the ROOs are met. As a result, experienced importers would likely find it easy to get exporters to meet preferences by merely asking. This is exactly what the above authors suggest. In our context, in contrast, exporters have to complete burdensome paperwork to document that ROOs are met in production.

Another issue that arises is whether the decision to use preferences is influenced by the history of transactions rather than by the experience in using preferences. For example, given the fixed costs, the exporter may not be willing to pay for the documentation until the relationship with the importer is well established. We additionally control for the history of transactions involving the same importer, product, or both. We find that while the history of transactions has a positive effect for Argentina (but not for Peru) on the probability of using preferences, it does not change our main results regarding the effect of experience. Details can be found in Appendix A.5.

We also consider whether high preference margin products have different learning effects from low margin products. The presence of social learning might result in high preference products having less estimated learning at the firm level. These results are presented in Table

1.7. Such heterogeneity is present as there is significantly less learning for high preference margin products, though this is more so for Argentina than Peru.

A final issue concerns our specification. Our simple choice model suggests that the relationship between the probability of using preferences and the explanatory variables is nonlinear. However, we use the linear framework since the implementation of instrumental variables and high-dimensional fixed effects is streamlined whereas in the case of non-linear approaches adding both instrumental variables and high-dimensional fixed effects is challenging and still under construction in the literature to the best of our knowledge. To understand how our results change because of this choice we estimate our baseline specification using probit and logit models with the same fixed effects (importer-exporter and product) but no instrument. We find that the results are qualitatively similar to the linear specification. These results are reported in Appendix A.7.

1.6 Conclusion

This paper is the first to cast light on the shape of costs of meeting ROOs using a model-based empirical approach and addressing first-order endogeneity concerns. Our results suggest that the costs of using preferences fall with experience. Consequently, policies targeted to new exporters should have large payoffs in terms of preference utilization and exports. Not only would their current use rise but so would their future use. Furthermore, as larger firms tend to have more transactions and more experience, they are more likely to use preferences, so FTAs could –at least initially– negatively impact competition. Policies encouraging the exports of small young firms would help mitigate this.

Chapter 2 | Dynamic Structural Model for Learning to Use Trade Agreements

Based on joint work with Yuta Suzuki

2.1 Introduction

A striking feature of Preferential Trade Agreements (PTAs) is that firms don't always use them despite offering lower tariffs. For instance, between 2000 and 2008, Argentinian firms employed the preferential tariff granted by their trade agreement with Colombia on only 69.5% of their eligible transactions or 65.6% and 73.6% for small and large firms respectively. This underutilization happens because using PTAs is costly. Rules of origin associated (ROOs) with PTAs establish restrictions on when a product qualifies for preferential tariffs.

These restrictions are put in place to prevent trans-shipping. To illustrate, consider a scenario where Colombia has trade agreements with both Peru and Argentina, while Argentina and Peru do not have one with each other. In this situation, a Colombian firm could purchase wine from Argentina at a low or zero tariff and resell it to Peru, effectively using the tariff preference to its advantage without adding value to the product. Such practices distort trade patterns (as greater transport costs are incurred) and subvert the intended purpose of trade agreements. ROOs indicate a minimum proportion of the production that has to be done locally to obtain certification and access to preferential tariffs. This can only raise production costs. This process is costly, particularly for products with intricate production processes or numerous inputs since gathering invoices and presenting production plans to the certification authorities is time and labor-consuming.

In this follow-up paper to Krishna et al. (2021), we develop and estimate a dynamic structural model of export behavior focusing on PTAs utilization and the associated ROOs. We model the decision of firms to use PTAs as a function of the fixed costs associated with ROOs, which decrease as firms gain experience. We estimate the model parameters using the method of simulated moments on records of Colombian importers and their transactions with exporters from Argentina and Peru. We must use a matched dataset of importer-exporter since exporters are the ones who must gather the documentation required and submit it to the authorities, still, datasets about exports seldom report tariffs paid.

Our findings indicate that the fixed costs of using PTAs are substantial, particularly for firms with limited experience (1420 USD for the first transaction). However, these costs decrease significantly as firms gain experience (1 USD for the fifth transaction), highlighting the importance of learning in PTAs utilization. We also conduct counterfactual policy experiments to assess the impact of government subsidies on PTA utilization. Our results suggest that subsidizing the first transaction under a PTA for each firm can substantially increase utilization and overall trade and decrease exit rates of exporting firms.

For a comprehensive literature review, contextualization about ROOs and PTAs, and a description of the data please review Sections 2 and 3 of Krishna et al. (2021).

The remainder of this paper is organized as follows. Section 2 presents the theoretical model, detailing the demand structure, the firm's decision-making process regarding PTA utilization, and the Markov jump process governing market dynamics. Section 3 outlines the simulation methodology used to generate data for estimation. Section 4 describes the estimation procedure and the moments we employ for the simulated method of moments. Section 5 presents the estimation results, including parameter estimates and model fit assessment. Section 6 discusses the counterfactual policy experiments and their implications. Finally, Section 7 concludes the paper, summarizing the key findings and their policy relevance.

2.2 Model

2.2.1 Demand

We propose a modification to the model used in Eaton et al. (2021) to accommodate our question of interest focusing on estimating the fixed costs associated with using PTAs and complying with the associated ROOs. Our model has standard features in the literature, we use a CES demand function, and a convex intensity search cost function to model the occurrence of a transaction, and Markov jump processes for the states of macro and micro shocks that each exporter faces for a given transaction. We remove the home market to focus on the behavior of the exporters[1]. Additionally, to make our model simpler and facilitate estimation we abstract from product and importing partner dimensions, our exporters are making choices of whether to use or not PTAs on transactions exporting a single product to a single destination. We add to the model a fixed cost of using PTAs as a function of the experience of the exporter using PTAs, this allows us to have moments simulated from the model, match them to our dataset, and identify the parameters associated with the cost function of using PTAs. Based on these characteristics the model is set up as follows.

Assume that an exporter with base productivity φ faces a constant elasticity demand function for transaction t, as standard in described by:

$$\pi_\varphi(a;x,y) = \frac{1}{\eta} r_\varphi(a;x,y)$$

Where η is the elasticity of demand, $r_\phi(a_t : x, y)$ represents the revenue as a function of a_t that takes value 1 if the exporter uses trade agreements in transaction t. The maximization problem for the price derives the following operational profit function:

$$\begin{aligned}\pi_\varphi(a_t;x_t,y_t) &= \tau^{-\eta(1-a_t)} R^{-a_t(\eta-1)} \bar{\pi}\varphi x_t y_t && (2.1)\\ &= \left(\frac{\tau^\eta}{R^{\eta-1}}\right)^{a_t} \tau^{-\eta}\bar{\pi}\varphi x_t y_t && (2.2)\\ &= \mu^{a_t}\pi_\varphi(0;x_t,y_t) && (2.3)\end{aligned}$$

where τ is the (additional relative) tariff to pay, R is the increase in the marginal costs for using the trade agreement, $\bar{\pi}$ is the average profits of transactions, x_t is the macro demand trend, y_t is the exporter specific demand trend, and μ is the net (relative) gain from using the trade agreement. All the shocks are assumed to be independent from each other and over time.

Exporter φ decides to use a trade agreement or not by solving the following maximization problem:

$$\tilde{\pi}_\varphi(x,y,n;\varepsilon) = \max_{a\in\{0,1\}} \left\{\pi_\varphi(a;x,y) - a\varepsilon f(n) + \tilde{V}_\varphi(x,y,n+a)\right\}, \tag{2.4}$$

where $f(n)$ is the fixed costs to pay to use the trade agreement, $\varepsilon > 0$ is the idiosyncratic cost shock to use the trade agreement, and $V_\varphi(x,y,a)$ is the value function. We can derive that

$$a_\varphi(x,y,n;\varepsilon) = \mathbb{1}\left\{(\mu-1)\,\pi_\varphi(0;x_t,y_t) + \Delta\tilde{V}_\varphi(x,y,n+1) > \varepsilon f(n)\right\}, \tag{2.5}$$

[1] In Krishna et al. (2021) we present results that suggest that the experience of the importers is not important for the choice of using PTAs

where

$$\Delta\tilde{V}_{\varphi}(x, y, n+1) = \tilde{V}_{\varphi}(x, y, n+1) - \tilde{V}_{\varphi}(x, y, n). \tag{2.6}$$

Note that this model exactly the same as what we propose in Krishna et al. (2021) if the exporter is myopic (i.e., $V_{\varphi}(x, y, n) = 0$). Suppose ε is drawn from a distribution $G(\cdot)$. Then the probability of using the trade agreement is

$$\mathcal{P}_{\varphi}(x, y, n) = G\left(\frac{(\mu - 1)\,\pi_{\varphi}(0; x, y) + \Delta\tilde{V}_{\varphi}(x, y, n+1)}{f(n)}\right), \tag{2.7}$$

$$= G(\bar{\varepsilon}_{x,y,n}), \tag{2.8}$$

where

$$\bar{\varepsilon}_{x,y,n} = \frac{(\mu - 1)\,\pi_{\varphi}(0; x, y) + \Delta\tilde{V}_{\varphi}(x, y, n+1)}{f(n)}. \tag{2.9}$$

Then, the expected value function of the transaction is

$$E_{\varepsilon}\tilde{\pi}_{\varphi}(x, y, n; \varepsilon) \tag{2.10}$$

$$= \int_{\bar{\varepsilon}_{x,y,n}}^{\infty} \left(\pi_{\varphi}(0; x, y) + V_{\varphi}(x, y, n)\right) dG(\varepsilon) + \int_{0}^{\bar{\varepsilon}_{x,y,n}} \left(\pi_{\varphi}(1; x, y) - \varepsilon f(n) + \tilde{V}_{\varphi}(x, y, n+1)\right) dG(\varepsilon), \tag{2.11}$$

$$= \pi_{\varphi}(0; x, y) + \tilde{V}_{\varphi}(x, y, n) + \mathcal{P}_{\varphi}(x, y, n)\left((\mu - 1)\pi_{\varphi}(0; x, y) + \Delta\tilde{V}_{\varphi}(x, y, n+1)\right) - f(n)\int_{0}^{\bar{\varepsilon}_{x,y,n}} \varepsilon dG(\varepsilon). \tag{2.12}$$

We assume $G(\cdot)$ is log-normal standardized so that the mean of $\varepsilon = 1$. Then, the last term of the previous equation, the partial expectation, can be derived as follows.

$$\int_{0}^{\bar{\varepsilon}_{x,y,n}} \varepsilon dG(\varepsilon) = e^{\mu + \frac{\sigma^2}{2}}\,\Phi\left[\frac{\ln\bar{\varepsilon}_{x,y,n} - \mu - \sigma^2}{\sigma}\right], \tag{2.13}$$

$$= \Phi\left[\frac{\ln\bar{\varepsilon}_{x,y,n} - \frac{\sigma^2}{2}}{\sigma}\right]. \tag{2.14}$$

In sum,

$$E_{\varepsilon}\tilde{\pi}_{\varphi}(x, y, n; \varepsilon) = \pi_{\varphi}(0; x, y) + \tilde{V}_{\varphi}(x, y, n) \tag{2.15}$$

$$+\mathcal{P}_\varphi(x,y,n)\left((\mu-1)\pi_\varphi(0;x,y)+\Delta\tilde{V}_\varphi(x,y,n+1)\right)-f(n)\Phi\left[\frac{\ln\bar{\varepsilon}_{x,y,n}-\frac{\sigma^2}{2}}{\sigma}\right]. \tag{2.16}$$

After every transaction, the exporter decides whether to stay in the market. We assume that the exporter needs to pay fixed costs F to stay in the market.

$$\tilde{V}_\varphi(x,y,n)=\max\left\{V_\varphi(x,y,n)-F,0\right\}. \tag{2.17}$$

With this section of the model, we have stipulated how the exporters choose whether they use PTAs. Now we model the Markov jump processes for the macro and micro shocks that firms face at each transaction and the search costs that determine the hazard at which an exporter encounters a partner and has transactions.

2.2.2 Markov Jump Process

With hazard $q^X_{xx'}$, x will jump to some new market-wide state $x'\neq x$. Similarly, with hazard $q^Y_{yy'}$, y will jump to some new exporter-specific trend $y'\neq y$. Define

$$\lambda^X_x=\sum_{x'\neq x}q^X_{xx'}, \tag{2.18}$$
$$\lambda^Y_y=\sum_{y'\neq y}q^Y_{yy'}. \tag{2.19}$$

An exporter continuously chooses a hazard s to encounter a transaction, incurring the instantaneous flow search cost $c(s)$, which is increasing and convex in s.

Let τ_r be the random time that elapses until one of these events occurs. Then, we can express the value function of the exporter as follows.

$$\begin{aligned}V_\varphi(x,y,n)=\max_s\frac{1}{\rho+s+\lambda^X_x+\lambda^Y_y}\Bigg(&-c(s)+\sum_{x'\neq x}q^X_{xx'}V_\varphi(x',y,n)+\\&\sum_{y'\neq y}q^Y_{yy'}V_\varphi(x,y',n)+sE_\varepsilon\tilde{\pi}_\varphi(x,y,n;\varepsilon)\Bigg).\end{aligned} \tag{2.20}$$

The optimal search intensity satisfies

$$c'(s^*)\geq E_\varepsilon\tilde{\pi}_\varphi(x,y,n;\varepsilon)-V_\varphi(x,y,n) \tag{2.21}$$

Assume search cost function $c(s)$ as follows.

$$c(s) = \frac{\kappa_0}{\kappa_1} \left(s^{\kappa_1} - 1 \right). \tag{2.22}$$

Then we have

$$s^* = \max \left\{ \left(\frac{E_\varepsilon \tilde{\pi}_\varphi(x, y, n; \varepsilon) - V_\varphi(x, y, n)}{\kappa_0} \right)^{\frac{1}{\kappa_1 - 1}}, 0 \right\}. \tag{2.23}$$

We assume $\kappa_1 = 2$ (c.f. Eaton et al. (2021)). Hence,

$$s^*_\varphi(x, y, n) = \frac{1}{\kappa_0} \max \left\{ E_\varepsilon \tilde{\pi}_\varphi(x, y, n; \varepsilon) - V_\varphi(x, y, n), 0 \right\}. \tag{2.24}$$

2.3 Simulation

Following Eaton et al. (2021), We discretize the space for x and y. They follow the next process

$$\ln h' = \begin{cases} \ln h + \Delta_h & \frac{1}{2}\left(1 - \frac{\ln h}{g_h \Delta_h}\right) \\ \ln h - \Delta_h \text{ with probability} & \frac{1}{2}\left(1 + \frac{\ln h}{g_h \Delta_h}\right) \\ \text{others} & 0 \end{cases} \tag{2.25}$$

for $h = x, y$. There are $2 \times g_h + 1$ number of equally spaced grids, and the grid size is Δ_h. Define the probability p_h^+ that h moves to $h + \Delta_h$ when an even for h happens.

For the fixed costs of using the trade agreement, We assume that

$$f(n) = \begin{cases} f - \Delta_n & \text{if } n \leq 5 \\ f(5) & \text{otherwise} \end{cases} \tag{2.26}$$

2.3.1 Value function iteration

1. Guess the value function $V_\varphi(x, y, n)$
2. Update $\tilde{V}_\varphi(x, y, n)$ using equation (2.17) and the change (2.6)
3. Derive the cutoff $\bar{\varepsilon}_{x,y,n}$ from equation (2.9)

	Description	Value	Source
ρ	discount factor	0.05	Eaton et al. (2021)
δ	exogenous exit	0.40	Average exit rate in the data
η	demand elasticity	5	Eaton et al. (2021)
τ_{MFN}	MFN tariff	13.18%	Average tariff paid without preferences
μ	gains from using trade agreements	1.1478	Average margin using preferences
λ_x	hazard rate for x	4	Eaton et al. (2021)
Δ_x	size of grid for x	0.05	Eaton et al. (2021)
λ_y	hazard rate for y	4	Eaton et al. (2021)
Δ_y	size of grid for y	0.05	Eaton et al. (2021)
g	the number of grids (2*g + 1)	50	Eaton et al. (2021)
$\bar{\pi}$	average transaction size	12.413	From data
σ	s.d. of normal dist	1	Assumed
ϕ	productivity	1	Assumed

4. Derive the probability of using trade agreement (2.8)

5. Derive the expected value function of the transaction (2.16)

6. Derive the optimal search intensity and the search costs using equations (2.24) and (2.22)

7. Update the value function using equation (2.20)

8. Keep iterating steps from 2 to 7 until achieving convergence

2.4 Estimation

From our model and simulation specification, we still have the parameters of search intensity cost (κ_0), fixed cost of staying in the market (F), and the parameters associated with the fixed cost of using preferences as a function of experience $(f_{exp=0} - f_{exp=5 \text{ or more}})$. To estimate them, we use the simulated method of moments as first introduced by McFadden (1989). We chose eight moments to pin our parameters. The moments are $M = \{$average number of transactions, the initial exit rate of firms, average preference utilization, coefficient of the dummies for having from a single transaction to five or more of experience using PTAs from a linear probability model of preference utilization $\}$[2]. We choose the exporters' average number of transactions and initial exit rate to pin down the intensity search cost and fixed cost of staying in the market to find parameters congruent with how many transactions we observe per exporter in the data and how often firms exit the exporting market. Average preference utilization pins down the

[2]Since in our simulation we are not including product or importer dimensions we calculate the average number of transaction at the exporter-importer-product-year level, and for the same reason we use the predicted probability of using preferences after controlling for importer-exporter-product and product-year fixed effects to calculate the average preference utilization. To avoid potential time dependence we use the exit rate of the first year in our data.

cost of using PTAs for the first time. Finally, we chose the last five moments so that our parameters generate similar patterns to those we find in Krishna et al. (2021), positive and significant effects of experience using PTAs in the probability of using PTAs, these moments pin down the costs of using PTAs with experience of one through five or more transactions.

We simulate 8500 firms, for 5 years and calculate the moments associated with the simulation. Our estimation procedure minimizes the weighted differences between the moments in the data and the moments in the simulation as described next:

$$\hat{\mathbf{\Theta}} = \underset{\mathbf{\Theta}}{argmin} \left(M^{data} - M^{sim}(\mathbf{\Theta})\right)' W \left(M^{data} - M^{sim}(\mathbf{\Theta})\right)$$

where $\hat{\mathbf{\Theta}}$ is the vector of parameters to estimate, M^{data} is the vector of 8x1 moments in the dataset and M^{sim} are the corresponding moments calculated from the simulated data. We use the inverse of the moments covariance matrix in the data as W [3]. The estimation procedure starts from an initial guess of the parameters, simulates the dataset according to the procedure described in the previous section, calculates the moments, and measures the weighted difference[4]. Following a Nelder-Mead algorithm, we search for the parameter values that bring the moments of the simulation as close to those of the dataset as possible. We use two samples for our estimation: full sample, and keeping newly covered products in Argentina. The rationale behind this choice is very simple, we expect that Peru having a much longer standing deep treaty with Colombia has less room for learning (decrease in fixed cost of using PTAs with experience) than Argentina. This is true, particularly for the products that were newly added to the agreement with Argentina in 2005.

While it would be ideal to use bootstrap to calculate the standard errors, we use the Delta method. Each bootstrap estimation takes several hours to run so, to estimate the standard errors using bootstrap we would require around 90 days for at least 1000 routines based on different bootstrapped samples. In future versions of this work, we plan on using bootstrap for this portion of the estimation but due to time constraints, we opt for the Delta method.

2.5 Results

This section presents the results from the estimation procedure described previously. in Table 2.1 we present the estimates of $\hat{\mathbf{\Theta}}$, the corresponding standard errors, and the confidence intervals. All of our estimates are presented in thousands of USD. The intensity search cost and

[3]We use bootstrap to calculate the matrix of covariance with 1000 samples

[4]To avoid local minima we started our estimation procedure from different starting points and present the results for the estimation that reached the lowest value among the starting point candidates.

fixed cost of staying in the market we find are substantial ($\kappa_0 = 13.887$ and $F = 6.030$) the intensity search cost implies that when an exporter chooses a hazard rate of 1 of finding a buyer, they face a cost of 13,887 USD which is close to the average transaction size without using PTAs. The fixed cost of staying in the market is 6,030 USD. Both have narrow confidence intervals. Comparing these estimates to those in Eaton et al. (2021) we find much larger values. A potential source for the difference is our choice of not including the foreign and the home versions of these parameters and instead focusing on the exporters' costs in the context of matching with foreign buyers.

The parameters of interest in our case are those associated with the fixed cost of using preferential tariffs. They exhibit the characteristics that we expected. A first transaction using preferences carries a cost of 1420 USD. This is a prohibitive cost for smaller firms and can explain why PTA utilization is lower in smaller firms. Moreover, as firms gain experience this cost is reduced substantially. The second transaction has a cost of 408 USD and while still large shows that firms learn a lot from the first transaction. The costs keep going down with experience, taking values of 279, 176, 31, and 1 USD for the second to fifth or more experience respectively. It is worth noting that the cost by the 5th experience is statistically not different from zero so by the time firms have used preferences 5 times the fixed cost becomes negligible.

In Table 2.2 we present the estimates for Argentinian newly covered products. It is worth mentioning that in this case, the fixed cost of staying in the market is larger ($F = 12.490$) and the fixed cost of using preferences is larger in levels and also has a more steep decrease. This goes in line with our hypothesis that since Argentina has a more recently deepening of their trade agreement with Colombia there is more room for leaning.

Table 2.1: Parameters Estimates

	Estimate	SE	95% CI LB	95% CI UB
κ	13.887	0.082	13.722	14.044
F	6.030	0.052	5.942	6.133
$f_{exp=0}$	1.420	0.009	1.404	1.436
$f_{exp=1}$	0.408	0.009	0.394	0.421
$f_{exp=2}$	0.279	0.007	0.268	0.289
$f_{exp=3}$	0.176	0.006	0.168	0.183
$f_{exp=4}$	0.031	0.004	0.024	0.038
$f_{exp=5}$	0.001	0.016	-0.029	0.031

Standard errors are calculated using the Delta method and the covariance matrix of the moments in the data.

Table 2.2: Parameters Estimates: Argentina

	Parameter Value	Standard Error	95% CI LB	95% CI UB
κ	14.749	0.0261	14.698	14.800
F	12.490	0.0013	12.487	12.493
$f_{exp=0}$	12.861	0.0002	12.861	12.862
$f_{exp=1}$	4.136	0.0004	4.135	4.136
$f_{exp=2}$	3.123	0.0004	3.122	3.123
$f_{exp=3}$	1.807	0.0005	1.806	1.808
$f_{exp=4}$	0.261	0.0005	0.260	0.262
$f_{exp=5}$	0.011	0.0054	0.001	0.022

Standard errors are calculated using the Delta method and the covariance matrix of the moments in the data.

2.5.1 Model Fit

In Table 2.3 we compare the moments used for the estimation, in the data versus the simulation based on the estimated parameters. The model generates average transactions, exit rates, and preference utilization that closely match those in the data. The simulated version of the coefficients of the linear probability model of preference utilization in experience do not match as well being at least an order of magnitude larger in the simulation compared to the data. Still, the simulation generates positive and significant coefficients associated with exporters' experience.

We conjecture that the difference can be attributed to the different sets of fixed effects we use for the coefficients in the data versus the simulation. For the regressions in the data, we have importer-exporter-product and product-year fixed effects to homogenize the data and clean the patterns of any variation we don't explicitly model since our model does not include different products or trading partners. It would be ideal to have the estimation procedure done for each product at least but even defining products at the 2-digit HS code would require computational resources we don't have. Additionally, there would be products for which the number of transactions would not be enough to perform the estimations, so we opt for an aggregate average estimation and a single simulation for the overall data. Taking into account the limitations of our strategy the parameters are still in line with the empirical learning patterns we have identified in Krishna et al. (2021). In terms of identification, we present the heat plot of the elasticities of the moments to the parameters in Figures 2.1 and 2.2. While most of the moments help pin down every parameter at the estimated values there is no interaction between the parameters for fixed cost of using preferences with experience of two through five and the moments for number of transactions, exit rate, or preference utilization. In particular, the parameter of the fixed cost of using preferences with five transactions of experience is only

Table 2.3: Moments in the Data vs. in the Simulation

	Pooled		Newly Covered	
	Data	Sim.	Data	Sim
Avg. # of Transactions	2.930	2.6886	1.880	2.977
Avg. Exit Rate	0.451	0.4381	0.375	0.530
Avg. Pred. Preference Utilization	0.924	0.9218	0.865	0.521
$\beta_{Exp=1}$	0.004	0.0415	0.050	0.242
$\beta_{Exp=2}$	0.006	0.0363	0.088	0.205
$\beta_{Exp=3}$	0.008	0.0229	0.096	0.237
$\beta_{Exp=4}$	0.010	0.0103	0.106	0.294
$\beta_{Exp=1}$	0.011	0.0001	0.142	0.329

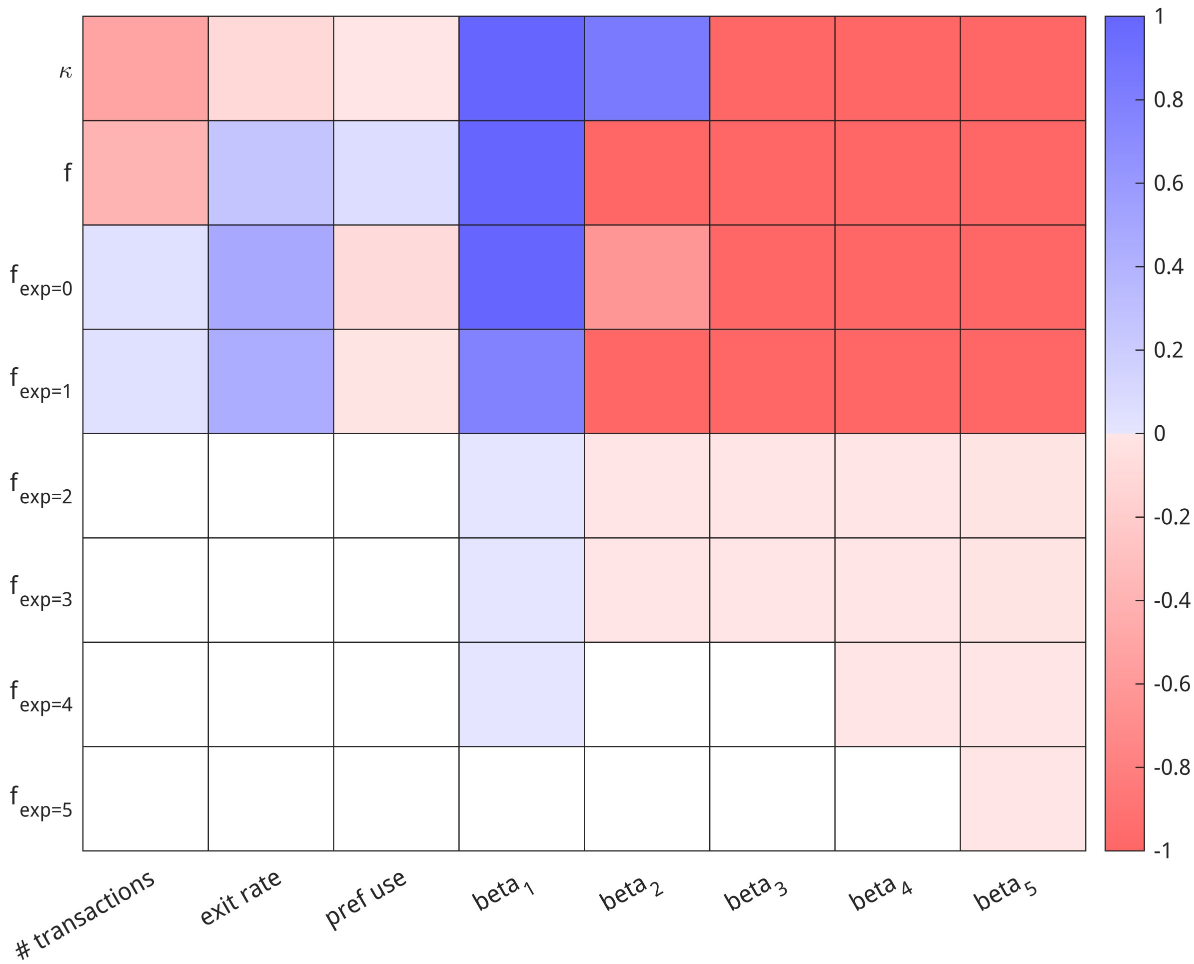


Figure 2.1: Heatplot of moment elasticities to changes in structural parameters at estimated values

pinned down by the analogous coefficient in the regression.

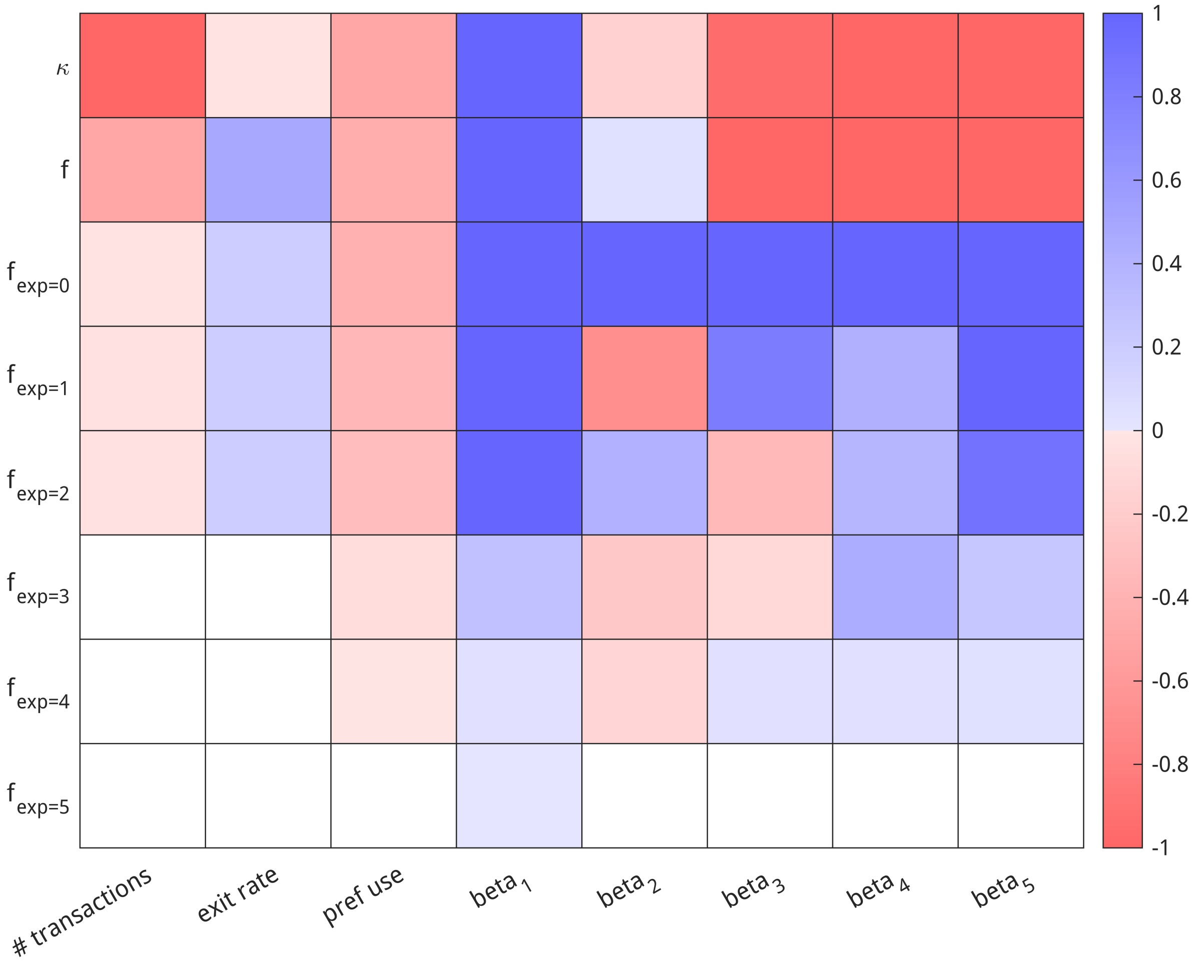


Figure 2.2: Heatplot of moment elasticities to changes in structural parameters at estimated values (Argentina)

2.6 Counterfactual Exercises

In this section, we use the model and the estimated parameters for the simulation of policy scenarios. Given the accumulating nature of experience in reducing fixed costs of using preferences, we propose a policy where the government of the exporting side subsidizes a percentage of the first transactions where a firm uses preferences. In Tables 2.4 and 2.5 we present the results of this exercise for the full sample and the sample including only Argentinian newly covered products. We record the average transaction size, average yearly trade, exit rate, preference utilization, and cost of the subsidy calculated using the dataset, the baseline simulation with our estimated parameters, and a simulation for a subsidy of 10%, 25%, 50%, 75%, 90%, and the full fixed cost of using preferences for the first time.

In the full sample exercise, we learn that the subsidy is mostly flat in terms of preference utilization while on the Argentinian newly covered product sample we observe a much steeper increase in the preference utilization. This again shows how important is to include this kind of subsidy schedule early on in the adoption of FTAs to help smaller firms compete and remain in the market. The subsidy of the full first-time use for both samples seem to maximize the preference utilization.

An additional note to this exercise is that since we don't have explicitly any data source that allows us to estimate the distribution of productivity of the firms we cannot say much in the avenue of policy targeting smaller firms which would be ideal since the smaller firms are the ones that have more trouble complying with rules or origin to gain access to preferential tariffs. Targeting only smaller firms for potential subsidy of preferential tariff use would reduce cost. Still, in the case of our estimations, it would be impossible to accurately simulate since we don't have information about the productivity or production costs of the exporters.

Table 2.4: Counterfactual Exercises

	Data	Baseline	Subsidy 10%	Subsidy 25%	Subsidy 50%	Subsidy 75%	Subsidy 90%	Subsidy 1st Use
Avg. Transaction	19.536	66.953	66.900	66.758	66.690	66.632	66.746	66.697
Avg. Yearly Trade	30051.449	668128.722	668147.972	668848.201	668096.508	667572.381	668836.641	668367.920
Exit Rate	0.542	0.442	0.443	0.442	0.442	0.442	0.442	0.442
Pref. Use	0.660	0.922	0.928	0.939	0.960	0.983	0.996	0.999
Cost		0.000	12317.333	32127.698	69271.329	113379.397	142884.658	160291.232

Table 2.5: Counterfactual Exercises: Argentina

	Data	Baseline	Subsidy 10%	Subsidy 25%	Subsidy 50%	Subsidy 75%	Subsidy 90%	Subsidy 1st Use
Avg. Transaction	19.536	73.722	73.758	73.700	73.498	73.496	73.476	73.653
Avg. Yearly Trade	30051.449	140469.581	140538.640	140428.858	138999.847	138657.803	138620.299	139041.829
Exit Rate	0.542	0.527	0.528	0.527	0.530	0.531	0.530	0.529
Pref. Use	0.660	0.524	0.535	0.550	0.594	0.653	0.742	0.915
Cost		0.000	891.293	2347.200	5253.869	9810.009	18115.237	38635.550

2.7 Conclusion

Our study contributes to the understanding of the dynamics of PTA utilization and the role of learning and experience in overcoming the fixed costs associated with ROOs. The substantial fixed costs we find, especially for inexperienced firms, underscore the challenges faced by smaller firms in utilizing PTAs. Our counterfactual policy experiments demonstrate the potential of government subsidies in promoting PTA utilization and boosting trade, particularly among smaller, less experienced firms. This is particularly true if the policy is put in place early in the adoption of the PTAs given the cumulative nature of the effects. These findings have important implications for policymakers seeking to improve the uptake of PTAs and promote local firms' activity in International Trade.

Chapter 3 | Nonlinear Pricing in International Trade

Based on joint work with Kala Krishna, Yuta Suzuki, and Christian Volpe.

3.1 Introduction

The recent availability of transaction-level data in International Trade makes it natural to look for evidence of non-linear pricing. Recent research findings of quantity discounts' presence challenge the assumption of linear pricing in International Trade. Non-linear Pricing has been much studied in Economic Theory as a part of Mechanism Design from the work of Mirrlees (1971, 1976), Mussa & Rosen (1978) and Myerson (1981) onwards. See Wilson (1996) for a survey.

It has been widely studied in Industrial Organization, both theoretically as a tool to exert monopoly power and in practice in particular industries, and Econometric tools developed for Auctions are extended to estimate models of non-linear pricing as in Luo et al. (2018a,b) and Attanasio & Pastorino (2020) [1]. See Wilson (1996) for some background on how non-linear pricing works in particular industries and why it matters.

However, there is far less work on this topic in International trade. As discussed below, the existing work tends to focus on structural models and the implications of nonlinear pricing through the lens of the model. However, no work looks for patterns in the data without forcing a model on the data. This is surprising as the transaction level data that has recently become available in Trade should make it a natural place to document both its form and variation across industries and agents, as well as its implications through the lens of a model. In this

[1]For some recent work see Villas-Boas (2009); Grennan (2013)

paper, we show the prevalence of quantity discounts using a unique dataset combining highly disaggregated import data from Colombia with export data from Argentina and Peru.

How do we know that what we estimate are quantity discounts? We identify quantity discounts by the use of fixed effects. We argue that at a point in time, for a particular product, between a given buyer and seller there is only one price schedule. At this level, we see nonlinear pricing if the price paid by the buyer depends on the quantity he buys. Thus, to estimate quantity discounts, we perform OLS regressions on transaction-level data of log price on log quantity controlling for tariff margin, age of the exporter, preference utilization, and high-dimensional fixed effects that absorb demand, supply, and product-time specific shocks. We find significant quantity discounts of 7.5% and 16.8% for Peru and Argentina respectively.

We explore how the importance of quantity discounts varies for differentiated products versus homogeneous and across the size of the importers' network. We interact the quantity with a dummy for differentiated products and with a set of dummies that characterize the importer's network size[2]. These interaction coefficients pin down the heterogeneity in quantity discounting across these two dimensions. Broadly speaking, we find that quantity discounts are more important in differentiated products. This makes sense as the inability to re-sell is a prerequisite for quantity discounts to exist and resale is likely to be easier in homogeneous products. We also find that quantity discounts are larger when the importer's network is large.

We contribute to a growing field of research about the shape and consequences of quantity discounts in International Trade. In Alviarez et al. (2023) the authors develop a model of firm-to-firm trade where both importers and exporters have market power and use it to show that US importers have significant market power and that ignoring two-sided market power can overstate tariff pass-through. Ignatenko (2020) uses freight price data from Paraguay to show that freight prices vary within narrowly defined routes, inconsistent with the "iceberg" trade cost assumption, and develops a model of price discrimination by freight carriers to explain this. Jung et al. (2019) build and estimate a quantitative trade model with firm heterogeneity and non-homothetic preferences to reconcile empirical regularities like price dispersion. They show that their model offers a plausible framework for analyzing gains from trade. Meleshchuk (2017) uses Colombian import data to show the existence of quantity discounts and develops a model where firms charge buyer-specific markups, finding that welfare losses from second-degree price discrimination can be substantial. Alviarez et al. (2022) study industry concentration in global supply chains with two-sided market power, proposing a model where markups depend on both exporter and importer concentration, and use Colombian data to show that unit values increase with exporter concentration and decrease with importer concentration.

[2]We use the conservative definition of a differentiated good from Rauch (1999)

Ignatenko (2019) investigates price discrimination in international trade, finding significant price variations for the same product sold by the same seller to different buyers, and develops a model suggesting that larger buyers obtain lower prices. Morlacco (2019) investigates buyer power in input markets, showing that larger French firms under spend on foreign inputs, suggesting buyer power, and develops a model showing that buyer power leads to lower aggregate output and productivity. Ignatenko (2021) studies market power's role in price variation across buyers, showing substantial price variation for the same product from the same seller, even after controlling for quality, and develops a model explaining this as oligopoly price discrimination where sellers charge lower markups to more productive buyers. A lot of the evidence thus far focuses on exporter-side price discrimination. We contribute to this literature by providing estimates of the extent of discounting and showing that it varies by product type, importer network and country. In contrast to the work above, we do not seek to put a particular model structure on the data, rather report on the patterns we find that are new and potentially important.

The rest of the paper is organized as follows. Section 2 discusses the data sources and presents descriptive evidence of quantity discounts. Then, in Section 3, we propose our empirical strategy and present the results of our estimation of quantity discounts and the interaction with product differentiation and importer network size. Finally, in Section 4, we conclude and discuss the implications of our findings.

3.2 Data

The data used here is administrative and accessed through the Inter-American Development Bank (IDB). It consists of three main databases. First, we have highly disaggregated import data for Colombia from the National Tax and Customs Agency (Dirección de Impuestos y Aduanas Nacionales-DIAN). These data are reported at the transaction level and cover all transactions of products entering Colombia from 2000 to 2011. Specifically, each record includes the importing firm's tax ID and name, the origin country, the product code (10-digit Harmonized System), the name of the foreign seller, the import value in US dollars, and the tariff paid.[3] These data allow us to construct time-specific, product-level MFN tariffs (inferred from tariffs on countries without preferential trade agreements with Colombia), preferential margins applied when preferences are used, inferred from the difference in Most Favored

[3]All transactions are denominated in dollars.

Nation (MFN) tariffs, and tariff paid [4], and the network of the importer[5].

The second and third datasets consist of highly disaggregated export data for Argentina and Peru over 2000-2008 and 2000-2011, respectively, from their respective tax and customs agencies (Administración Federal de Ingresos Públicos–AFIP and Superintendencia Nacional de Administración Tributaria-SUNAT). In the export data, each record includes the exporting firm's tax ID and name, the destination country, the product code (10-digit HS), the export value in US dollars, and the quantity (weight) in kilograms.

Using the names of the selling firms reported both in the import database of Colombia and the export databases of Argentina and Peru; we can match buyers and sellers for each Colombian import transaction over our sample period and accurately track each exporter's history of preference usage and the various kinds of experience by product and importer.[6]

First we provide some close to raw data that suggests that quantity discounts are present. We construct the empirical density function of the transaction price after controlling for potential demand and supply shocks. To do so we regress the log of transaction prices on fixed effects for importer-exporter-product combinations, exporter-product-year, importer-product-year, and product-month. We also control for variables that affect prices, such as preference utilization, tariff margin, and exporter age. We extract the residuals from this regression and estimate the kernel density function. To account for potential heterogeneity in pricing across transaction sizes, we divide the sample by the median transaction size calculated at the exporter-product-year level before plotting the density.

The results of this exercise are presented in Figure 3.1. The distribution of prices is more dispersed in Argentina than in Peru. Still, in both cases, the density of prices for transactions above the median (in terms of quantity) is first-order stochastically dominated by that of the transactions at or below the median, as shown by Kolmogorov-Smirnov and Somers' D tests. This suggests nonlinear prices as transactions with a higher size are more likely to have lower prices even after removing shocks associated with demand, supply, or production costs.

3.3 Results

Our empirical strategy uses a fixed effect regression that estimates the relation between price and quantities for each transaction and how the quantity discount interacts with product

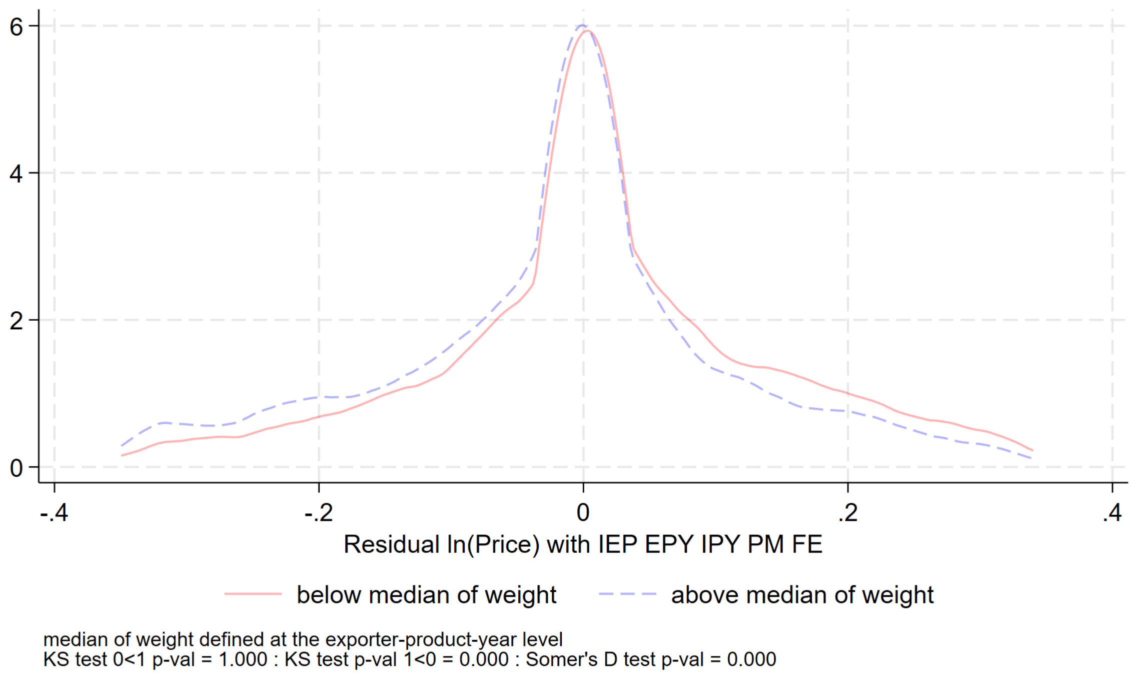
[4]We identify that preferences are used whenever the tariff paid is below the MFN one.

[5]We define the network of the importer for a specific transaction as the number of other exporters the importer has had transactions with for the same product in the last year

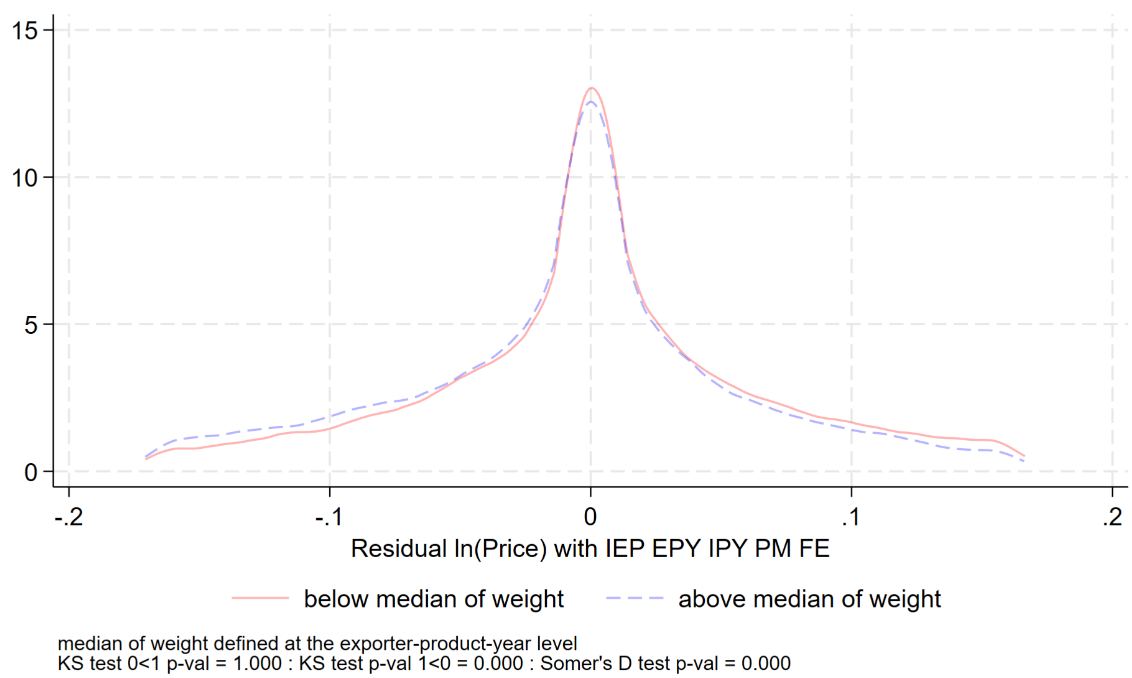
[6]The merging of these different datasets is challenging. Details of the data cleaning exercise and an explanation of the standardization and matching procedures can be found in the Appendix of Krishna et al. (2021)

Figure 3.1: Residuals of Log(Price) by transaction size

(a) Argentina



(b) Peru



differentiation and importers' network size. To measure importers' network size we count the number of exporters that an importer has had transactions within the past year for the same product. With this data, following Krishna et al. (2021), we construct a set of dummies that characterize if an importer has, before the current transaction, a network of one through five (or more) additional exporters. The omitted group is importers with only the current exporter.

Table 3.1: Quantity discounts

	Peru					Argentina				
Log(quantity)	-0.075***	-0.039***	-0.070***	-0.064***	-0.040***	-0.168***	-0.161***	-0.167***	-0.167***	-0.158***
	(0.011)	(0.011)	(0.010)	(0.008)	(0.011)	(0.026)	(0.060)	(0.025)	(0.029)	(0.057)
Log(quantity)×										
Differentiated product		-0.049***			-0.017		-0.011			-0.003
		(0.017)			(0.013)		(0.065)			(0.064)
Log(quantity)×										
$\#Exp^1(sp, ly)$			-0.001		0.001*			0.000		0.005
			(0.001)		(0.001)			(0.003)		(0.004)
$\#Exp^2(sp, ly)$			-0.003*		0.002			0.004		0.009**
			(0.001)		(0.001)			(0.005)		(0.004)
$\#Exp^3(sp, ly)$			-0.005**		0.002			-0.004		-0.002
			(0.002)		(0.001)			(0.007)		(0.006)
$\#Exp^4(sp, ly)$			-0.008**		0.002			-0.007		-0.012
			(0.003)		(0.001)			(0.012)		(0.015)
$\#Exp^{more}(sp, ly)$			-0.015***		0.001			-0.010		-0.016
			(0.005)		(0.002)			(0.011)		(0.010)
Log(quantity)×										
Differentiated product ×										
$\#Exp^1(sp, ly)$				-0.006***	-0.010**				-0.005	-0.016
				(0.002)	(0.005)				(0.009)	(0.022)
$\#Exp^2(sp, ly)$				-0.010***	-0.021***				-0.004	-0.030
				(0.003)	(0.008)				(0.014)	(0.031)
$\#Exp^3(sp, ly)$				-0.016***	-0.033***				-0.010	-0.009
				(0.004)	(0.011)				(0.017)	(0.036)
$\#Exp^4(sp, ly)$				-0.023***	-0.042***				0.001	-0.019
				(0.007)	(0.014)				(0.017)	(0.058)
$\#Exp^{more}(sp, ly)$				-0.037***	-0.088***				0.006	-0.009
				(0.010)	(0.023)				(0.023)	(0.062)
Differentiated product ×										
$\#Exp^1(sp, ly)$					0.043					0.052
					(0.034)					(0.131)
$\#Exp^2(sp, ly)$					0.115**					0.143
					(0.055)					(0.175)
$\#Exp^3(sp, ly)$					0.185**					0.053
					(0.084)					(0.225)
$\#Exp^4(sp, ly)$					0.226**					0.279
					(0.107)					(0.379)
$\#Exp^{more}(sp, ly)$					0.550***					0.315
					(0.157)					(0.431)
Observations	45,793	45,793	45,793	45,793	45,793	11,185	11,185	11,185	11,185	11,185

Importer-exporter clustered standard errors in parentheses. Every estimation included exporter-importer-product, exporter-product-year, importer-product-year, and product-month fixed effects sp=same products, ly=last year. Sample definition excludes transactions smaller than 200 USD, mineral sector, top percentile of value at the product-country level, and firms that enter the sample before 2001. *** p<0.01, ** p<0.05, * p<0.1.

The regression results in Table 3.1 show the relationship between the log of price and the log of quantity for imports from each country separately, with the results for Peru on the left and Argentina on the right. The first column presents the results without allowing for any heterogeneity by product type or importer's network size. The coefficient on quantity is significantly negative in both countries and more so for Argentina (-.075 versus -.168). This means that the quantity discount is greater for Argentina overall. Where might this difference be coming from? The next column's results cast some light on this.

Column 2 allows for differences in quantity discounts by product type, homogeneous and differentiated. The coefficient on quantity is significantly negative and more so for Argentina (-.039 for Peru versus -.161 for Argentina). This means that the quantity discount for homogeneous goods is greater for Argentina. However, the coefficient on quantity interacted with the dummy for differentiated products is higher for Peru (-.049 versus -.011). Moreover, the interaction is not significant for Argentina. The sum of the coefficient on the quantity discount and the coefficient on the interaction between the log quantity and the dummy for differentiated products remains higher for Peru than for Argentina (-.039-.049=-.088, -.161-.011=-.172). This means that quantity discounts are also larger for differentiated products in Argentina than in Peru. However, quantity discounts are much higher for differentiated products relative to homogeneous products in Peru, while in Argentina, they are very similar.

In Column 3, we focus attention only on the network size of the importer. [7] The coefficients on the interaction between log quantity and network size are uniformly negative, highly significant, and increasing in absolute value for Peru (they go from -.006 to -.015) but are not significant and at most -.010 for Argentina. This suggests that network size is not that important for Argentina, but has a role to play for Peru in driving quantity discounts.

In the last column, we saturate the model. This is the column to focus on as our results in the first three columns do not incorporate the full set of interactions and so would be subject to omitted variable bias.

To make the estimates easier to interpret we present them in Table 3.2 as the total quantity discount for each combination. We calculate the total quantity discount for each combination by adding the coefficients corresponding to the quantity and the interaction coefficients for each group. The left-hand side of the table gives the results for Peru and the right-hand side gives those for Argentina. Thus, the entry in the row marked log (quantity) for the column marked "Homogeneous" shows the quantity discount for importers of homogeneous products with only the current exporter in their network. There is, of course, no entry in the column marked "Differentiated" for this row. The entries in the rows marked log(quantity) x Differentiated product has no entry in the row marked "Homogeneous" and gives the quantity discount for

[7] We cannot control for the exporter's network size as we do not have data on all countries.

importers of differentiated products in the two countries with only the current exporter in their network in the columns marked “Differentiated".

In the Peruvian case, the interaction term between log(quantity) and differentiated products is negative and significant (-0.057), implying that the price-quantity elasticity strengthens for differentiated products. The interaction with importers' network size is also negative and significant, suggesting that, an importer with a larger network and more outside options has a higher quantity discount. The saturated regression reveals that the relationship between quantity discounts and product differentiation is only significant for importers with larger exporter networks.

The log(quantity) coefficient exhibits a similar negative and significant relationship with price for Argentina. It is consistently larger in absolute value in Argentina, suggesting larger quantity discounts in Argentina than in Peru. However, the interaction term with differentiated products and importer's network size in the saturated regression is not statistically significant for Argentina suggesting that the quantity discount does not vary with network size for differentiated products in Argentina.

Table 3.2: Total quantity discounts

	Peru		Argentina	
	Homogeneous	Differentiated	Homogeneous	Differentiated
Log(quantity)+	-0.040***		-0.158***	
	(0.011)		(0.057)	
Log(quantity)× Differentiated product+		-0.057***		-0.160***
		(0.008)		(0.030)
Log(quantity)× Differentiated product×	-0.038***	-0.066***	-0.152***	-0.171***
$\#Exp^1(sp, ly)$	(0.011)	(0.010)	(0.055)	(0.032)
Log(quantity)× Differentiated product×	-.038***	-0.076***	-0.149***	-0.181***
$\#Exp^2(sp, ly)$	(0.011)	(0.011)	(0.057)	(0.034)
Log(quantity)× Differentiated product×	-.038***	-0.089***	-0.159***	-0.172***
$\#Exp^3(sp, ly)$	(0.011)	(0.013)	(0.059)	(0.026)
Log(quantity)× Differentiated product×	-.038***	-0.097***	-0.170**	-0.191***
$\#Exp^4(sp, ly)$	(0.011)	(0.015)	(0.069)	(0.050)
Log(quantity)× Differentiated product×	-.039***	-0.144***	-0.174***	-0.185***
$\#Exp^{more}(sp, ly)$	(0.011)	(0.023)	(0.062)	(0.053)
Observations	45,793	45,793	11,185	11,185

Importer-exporter clustered standard errors in parentheses. Every estimation included exporter-importer-product, exporter-product-year, importer-product-year, and product-month fixed effects sp=same products, ly=last year. Sample definition excludes transactions smaller than 200 USD, mineral sector, top percentile of value at the product-country level, and firms that enter the sample before 2001. *** p<0.01, ** p<0.05, * p<0.1.

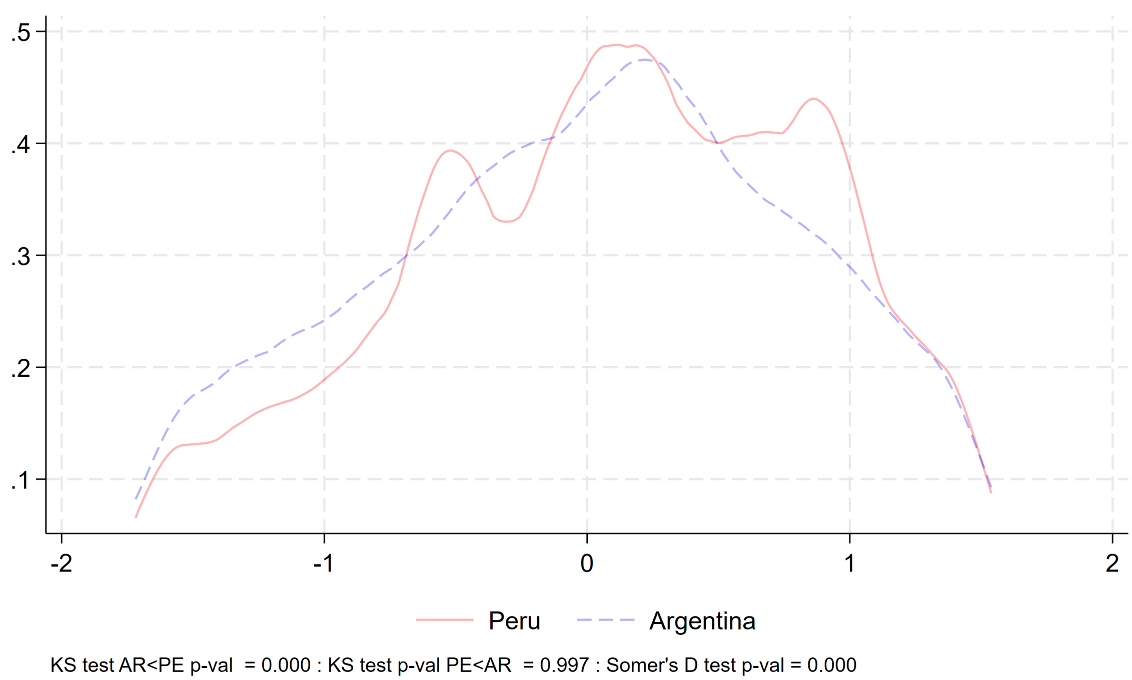
Table 3.2 presents the total quantity discounts, combining the direct effect of quantity on prices and the interaction with product differentiation and the number of exporters.

The results reveal that quantity discounts are larger for differentiated products than homogeneous products in both Peru and Argentina. In Peru, the quantity discount for differentiated products is estimated to be 6.6% when dealing with one exporter, and it increases to 14.4% when dealing with five or more exporters. For homogeneous products it varies from 3.8% when dealing with one exporter, and increases to 3.9% when dealing with five or more exporters. Similarly, in Argentina, the quantity discount for differentiated products ranges from 17.1% with one exporter to 19.1% with four exporters and 18.5% with five or more exporters. These findings suggest that the price-quantity relationship is more pronounced for differentiated products.

For homogeneous products, the network size has no significant effect on quantity discounts in both countries. However, for differentiated products, quantity discounts increase with network size but this is significant only for Peru. Thus, the network size seems to matter only for differentiated products, and only for Peru. Why?

Why might quantity discounts be larger in Argentina than in Peru? If the transaction size is different for Peru and Argentina, we might be estimating different parts of the demand curve. In Figure 3.2 we graph the distribution of log quantities for Peru and Argentina after removing product fixed effects to account for different weights of products equally for each country. While it is not visually evident both the Kolmogorov-Smirnov and Somers' D tests support that the distribution of transaction size in Argentina is smaller than in Peru. On average, they are 17.64 and 13.83 kg larger for Peru and Argentina respectively. If quantity discounts are convex, i.e., logp falls fast to begin with and then slows down, this could explain the larger quantity discounts in Argentina. Homogeneous goods and differentiated goods are not very different in

Figure 3.2: Quantity



Argentina in terms of their quantity discounts, but they are different in Peru. Moreover, network size seems to matter only for differentiated products and only for Peru. What might lie behind this pattern? This could be due to a composition effect. If Homogeneous and differentiated goods are further apart in Peru than in Argentina we could see both these patterns if network size and quantity discounts mattered more, the more differentiated the product. We leave this to future work.

3.4 Conclusion

Our analysis reveals the existence of non-linear pricing in international trade between Colombia, Peru, and Argentina. We find significant quantity discounts, particularly for differentiated products and importers with larger networks. These findings challenge the traditional assumption of linear pricing in trade and highlight the importance of considering quantity, product differentiation, and network effects when analyzing pricing dynamics in international markets. The evidence of non-linear pricing in Peru and Argentina suggests that firms may be engaging in price discrimination to maximize profits. Our results challenge the traditional assumption of linear pricing almost universally made in International Trade. This has widespread implications: for example, the positive correlation between firm size and TFPR would be biased upwards if linear pricing is assumed, while quantity discounts prevail. Further research could explore the specific mechanisms behind these pricing patterns and their implications for trade flows, market competition, and welfare.

Appendix A
Appendix of Chapter 1

A.1 Construction of the Dataset

A.1.1 Data Matching

As explained in Subsection 1.3.2, the Colombian import database reports both the importing firm's tax ID and name and the exporting firm's name, whereas the Argentinean and Peruvian export databases include the exporting firm's tax ID and name, also for each transaction. Hence, the exporting and importing sides must be merged. We do so primarily using the exporting firms' names, supplemented with information on the dates, the origin/destination country, the product (code), the value, and the weight.

Firms' names generally differ in both databases. This could be due to the type of business structure or due to spelling. In the first case, a firm could appear, for instance, as an S.R.L. (Sociedad de Responsabilidad Limitada –the equivalent of a Limited Liability Company in the U.S.-) in one database and as an S.A. (Sociedad Anonima –the equivalent of publicly traded company in the U.S.-) in the other database. In the second case, data can be subject to typos, abbreviations, or missing words in one or both datasets. To address this issue, we first harmonized firms' names in each dataset separately. Specifically, we removed special and punctuation characters and conjunctions, then replaced business structures with their acronyms, and finally, we abbreviated common words in firms (e.g., Exportadora –Exporter- o Exportaciones –Exports- are replaced by EXP) before eliminating them.

Second, we resorted to a fuzzy matching algorithm (i.e., probabilistic linking) to compare and match the harmonized firms' names in both pairs of databases (i.e., considering the specific origin/destination countries). This algorithm found the best match (or group of matches) in the standardized data, up to a similarity score of 85%. In the final step we performed a manual review to validate the matches that are 100% similar and to decide on the matches that are in a range of 85% to 99% similarity, using, in addition, the data on the dates, the product (code), the value, and the weight.

The match is very good. For Argentina, we can match 95.1% of exporting firms, 98.9% of transactions, and 99.3% of the value of the transactions. For Peru, we can match 94.9% of exporting firms, 99.7% of transactions, and 99.9% of the value of the transactions.

A.1.2 Data Cleaning

The challenge in the data comes from the absence of clear information on the MFN tariff relevant to the transaction. To construct two key variables used in the regressions, namely savings and the preference utilization dummy, we need information on both the MFN tariff and the preferential tariff as well as whether preferences were invoked. No field gives us the MFN tariff. However, for each transaction, we do know the tariff applied. Hence, we imputed the MFN tariff to be the tariff applied in the given month of the transaction on the same product at HS 10-digit level on Colombia's imports from countries that did not have trade agreements with it at that time. If no such transaction exists, we use the tariff paid on the previous transaction. In the data, some products have more than one MFN tariff in a given month. Since MFN tariffs are very slow to change, we treat these observations as suspect and drop all observations on these products. This loses us 0.19% of the data.

In addition, transactions of a size below "the de minimis level" are exempt from paying tariffs. We dropped all transactions below 200 dollars, which was the de minimis level for Colombia in 2016.[1] This loses us 11.6% of the data.

After these two cleaning processes, we construct a preference utilization dummy by comparing the tariff paid to the MFN rate. If the tariff paid is below the MFN rate, we infer that preferences were used in the transaction. By definition, all members of the WTO are given MFN status so any tariff below the MFN tariff must come from preferential trade agreements. There is a field for the trade agreement used in the transaction, but this field is missing for 84.9% of the data. For this reason, we could not use this variable. The preferential tariff for a given product exported by a given country is constructed as the most recent tariff paid below the MFN tariff to date on the 10-digit product by exporters from the particular country.

Once we know when preferences were used, we can construct for each exporter a history of experience in using preferences in past transactions. These experiences can also be broken down into four categories used in the paper. The preference margin is defined as the difference between the MFN tariff and the preferential tariff, i.e., the lowest tariff observed in all

[1] See `https://global-express.org/assets/files/Customs\%20Committee/de-minimis/GEA-overview-on-de-minimis_April-2016.pdf`.

transactions up to a given month for a given product. This allows us to construct the savings variable as the preference margin times the FOB value of the transaction. Perceptive readers might be concerned about the products where preferences exist but are not utilized. In our construction, this would show up as the constructed preference margin being zero, while the true margin could be positive. We are not that concerned about this as the fraction of products with a positive margin (Product share in Figure 1.1) is quite stable in Peru. In Argentina, it is stable before 2005 and then reaches a stable level within one to two years after the new products are introduced. In addition, if there was a trade war or shock that raised tariffs, we would not have our constructed margin fall. To partially deal with this, we drop observations for which the tariff paid exceeds the MFN tariff. This loses us 2.6% of the data.

Preferential tariffs are usually phased in over time, in other words, they are negotiated to fall over the period until they reach the negotiated level. As a result, when we see preferential tariffs that rise over a period, we are concerned. To be cautious, we drop such products in their entirety from the data. This loses us 31.1% of the data. Note however that as the histories were constructed before dropping these observations, we are not concerned about this affecting our experience variables.

A.2 A Simple Model

The exporter has to choose whether to meet ROOS in order to obtain preferences when he meets an importer at time y. Importer i has the following constant elasticity demand for transaction t

$$q_{eipty} = \Big((\tau_{py}^{\text{pref}})^{a_{eipty}} (\tau_{py}^{\text{mfn}})^{1-a_{eipty}} P_{eipty} \Big)^{-\eta} x_{eipty}, \tag{A.1}$$

where p is the product, a_{eipty} is the dummy variable which is equal to one if preference is applied in the transaction, τ_{py}^{h} for $h = \text{pref}, \text{mfn}$ summarizes one plus the tariff to pay with and without preferences, P_{eipty} is the price of the transaction, x_{eipty} is the demand shock of the importer, and η is the constant elasticity of demand.

Exporter e maximizes the profit of the transaction by choosing the price and determines if preferences are used or not in the transaction t. The profit of the transaction is

$$\pi_{eipty} = \Big(P_{eipty} - R_p^{a_{eipty}} c_{eipty} \Big) q_{eipty} - a_{eipty} \varepsilon_{eipty} F_{eipty}. \tag{A.2}$$

Using preferences is costly in two ways. First, the exporter needs to meet the rules of origin that may increase the marginal costs of production which is why $R_p \geq 1$. Second, the exporter needs to pay the fixed costs of documentation for the certificate of origin, $F_{eipty} > 0$. This fixed cost may depend on their experience in using preferences in past transactions. We also assume that this cost includes some shocks $\varepsilon_{eipty} > 0$, which rationalizes why some transactions with large values do not use preference.

Exporters solve the problem in two stages. In the first stage, exporters decide whether they use preferences or not. In the second stage, they set the price. We can solve the problem backwards. Given the preference application, the exporter sets the price that maximizes equation (A.2). The first order condition implies

$$P_{eipty}(a_{eipty}) = \frac{\eta}{\eta - 1} R_p^{a_{eipty}} c_{eipty}. \tag{A.3}$$

Substituting this into equation (A.2), we can derive the profit as a function of preference application

$$\pi_{eipty}(a_{eipty}) = \frac{1}{\eta} r_{eipty}(a_{eipty}) - a_{eipty}\varepsilon_{eipty}F_{eipty}, \tag{A.4}$$

where $r_{eipty}(a_{eipty})$ is the value of the transaction t

$$\begin{aligned} r_{eipty}(a_{eipty}) &= \left(\left(\frac{\tau_{py}^{\text{mfn}}}{\tau_{py}^{\text{pref}}}\right)^{\eta} R_p^{-(\eta-1)}\right)^{a_{eipty}} \left(\tau_{py}^{\text{mfn}}\right)^{-\eta} \left(\frac{\eta}{\eta-1} c_{eipty}\right)^{1-\eta} x_{eipty} \\ &= \left(\left(\frac{\tau_{py}^{\text{mfn}}}{\tau_{py}^{\text{pref}}}\right)^{\eta} R_p^{-(\eta-1)}\right)^{a_{eipty}} r_{eipty}(0) \qquad \text{(A.5)} \\ &\equiv B_{pt}^{a_{eipty}} r_{eipty}(0), \qquad \text{(A.6)} \end{aligned}$$

where $B_{pt}^{a_{eipty}}$ is the benefits of using preferences, which we assume to be more than one. Given the profits with and without the preference, the exporter chooses to use the preference if the profit with preference is larger than the other

$$\begin{aligned} a_{eipty} &= \mathbb{1}\left\{\pi_{eipty}(1) - \pi_{eipty}(0) > 0\right\} \\ &= \mathbb{1}\left\{\frac{1}{\eta}\left(r_{eipty}(1) - r_{eipty}(0)\right) > \varepsilon_{eipty}F_{eipty}\right\}. \qquad \text{(A.7)} \end{aligned}$$

We can then rewrite the problem as follows[2]

$$a_{eipty} = \mathbb{1}\left\{\ln\left(\left(\frac{\tau_{py}^{\text{mfn}}}{\tau_{py}^{\text{pref}}}\right)^{\eta} R_p^{-(\eta-1)} - 1\right) + \ln r_{eipty}(0) - \ln\eta > \ln\varepsilon_{eipty} + \ln F_{eipty}\right\}$$

[2]Both sides of equation (A.7) are positive so that we can take logs. We have already assumed that ε_{eipty}, F_{eipty}, and $r_{eipty}(1) - r_{eipty}(0) = (B_{pt} - 1)r_{eipty}(0)$ are positive.

$$
\begin{aligned}
&= \mathbb{1}\Bigg\{\ln(\tau_{py}^{\text{mfn}} - \tau_{py}^{\text{pref}}) r_{eipty}(0) - \ln F_{eipty} \\
&\qquad + \ln\left(\frac{\left(\frac{\tau_{py}^{\text{mfn}}}{\tau_{py}^{\text{pref}}}\right)^{\eta} R_p^{-(\eta-1)} - 1}{\tau_{py}^{\text{mfn}} - \tau_{py}^{\text{pref}}}\right) - \ln\eta > \ln\varepsilon_{eipty}\Bigg\} \\
&= \mathbb{1}\left\{\ln s_{eipty} - \ln F_{eipty} + \chi_{py} > \ln\varepsilon_{eipty}\right\},
\end{aligned} \tag{A.8}
$$

where

$$
s_{eipty} \equiv (\tau_{py}^{\text{mfn}} - \tau_{py}^{\text{pref}}) r_{eipty}(0), \tag{A.9}
$$

$$
\chi_{py} \equiv \ln\left(\frac{\left(\frac{\tau_{py}^{\text{mfn}}}{\tau_{py}^{\text{pref}}}\right)^{\eta} R_p^{-(\eta-1)} - 1}{\tau_{py}^{\text{mfn}} - \tau_{py}^{\text{pref}}}\right) - \ln\eta. \tag{A.10}
$$

A.3 Measurement Error

One potential problem is that, in the data, we cannot observe $r_{eipty}(0)$ if $a_{eipty} = 1$. We therefore use $r_{eipty}(1)$ as a proxy to construct the saving variable. However, if the simple model is actually the data-generating process, this proxy generates the measurement error bias. Specifically, our saving variable can be expressed as follows

$$
\ln s_{eipty}^{*} = \ln s_{eipty} + a_{eipty}\Delta\ln r_{eipty}, \tag{A.11}
$$

where

$$
\Delta\ln r_{eipty} \equiv \ln r_{eipty}(1) - \ln r_{eipty}(0) = \ln\left(\left(\frac{\tau_{py}^{\text{mfn}}}{\tau_{py}^{\text{pref}}}\right)^{\eta} R_p^{-(\eta-1)}\right) \equiv \frac{\kappa_{pt}}{\gamma} > 0, \tag{A.12}
$$

where the second equality comes from equation (A.5) in Appendix A.2. Notice that the gain in the log of revenue from using preferences depends only on product-time-specific parameters.

Let $\ln\varepsilon_{it}$ be independently drawn from a distribution $G(\cdot)$. Then we have

$$
\Pr(a_{eipty} = 1 | X_{eipty}) = G(\ln s_{eipty} - \ln F_{eipty} + \chi_{py}), \tag{A.13}
$$

where X_{eipty} summarizes $\left(c_{eipty}, x_{eipty}, F_{eipty}, \tau_{py}^{\text{mfn}}, \tau_{py}^{\text{pref}}, R_p\right)$. Suppose $G(\cdot)$ is a uniform distribution with mean μ and density γ

$$G(x) \equiv \gamma \left(x + \frac{1}{2\gamma} - \mu \right). \tag{A.14}$$

Then we can derive the probability of using preference conditional on the saving from the transaction, fixed cost, and product-time specific parameter as

$$\Pr(a_{eipty} = 1 | X_{eipty}) = \gamma \ln s_{eipty} - \gamma \ln F_{eipty} + \gamma \chi_{py} + \frac{1}{2} - \gamma\mu, \tag{A.15}$$

which can be summarized as

$$\Pr(a_{eipty} = 1 | X_{eipty}) = \gamma \ln s_{eipty} - \mathcal{F}_{eipty} + \xi_{pt}. \tag{A.16}$$

Substituting the definition of our saving variable into equation (A.16), we have

$$\Pr(a_{eipty} = 1 | X_{eipty}) = \gamma \ln s^*_{eipty} - \mathcal{F}_{eipty} + \xi_{pt} - a_{eipty}\kappa_{pt}, \tag{A.17}$$

where X_{eipty} summarizes $\left(c_{eipty}, x_{eipty}, F_{eipty}, \tau^{\text{mfn}}_{py}, \tau^{\text{pref}}_{py}, R_p\right)$. Define the difference between the realized and expected values of a_{eipty} conditional on X_{eipty} as follows

$$u_{eipty} \equiv a_{eipty} - E\left[a_{eipty} | X_{eipty}\right]. \tag{A.18}$$

Note that the conditional expectation of u_{eipty} is zero ($E\left[u_{eipty}|X_{eipty}\right] = 0$) and $E\left[a_{eipty}|X_{eipty}\right] = \Pr(a_{eipty} = 1|X_{eipty})$. By substituting equation (A.18) into (A.17) and rearranging it, we obtain the empirical specification we used in the previous sections.

$$a_{eipty} = \frac{\gamma}{1+\kappa_{pt}} \ln s^*_{eipty} - \frac{\mathcal{F}_{eipty}}{1+\kappa_{pt}} + \frac{\xi_{pt}}{1+\kappa_{pt}} + \frac{u_{eipty}}{1+\kappa_{pt}}. \tag{A.19}$$

There are a few implications of equation (A.19) to highlight here. Note that the bias introduced by the mis-measurement of the savings variable creates another source of endogeneity bias in addition to any endogeneity biases arising from omitted variable biases or reverse causation discussed in the body of the paper. Since we have an instrument for savings, this will take care of endogeneity biases irrespective of their source. Hence, we know that our estimate of the coefficient of savings using the IV will be downward biased due to mis-measurement ($\kappa_{pt} > 0$).[3]

[3] When we look at equation (A.19), we see κ_{pt} is likely to be small as long as the preference margin is small, the marginal cost of meeting ROOs is small, the demand elasticity is not too large, and the variance of the shock,

Our interest in the paper is primarily in the coefficients of experience. Although the levels of these coefficients are biased downward, it is worth noting that their ratios are unbiased. Thus, an increasing pattern in the coefficient of the experience variables still indicates falling fixed costs with experience.

A.4 Importer's versus Exporter's Experience

Does the exporter's experience matter or does the importer's experience matter or both? We have been using exporter experience because, we argued, it is the exporter who ensures that the ROOs are met and provides any documentation needed to verify this. In this subsection, we add the experience of the importer to see if there is any effect on our estimates of learning. Note that in Tables A.1 and A.2 we use two-way experience on the part of the importer, that is experience in the same product and in other products only. We cannot use four-way experience as when we add importer experience, the pair-specific experience on the importer and exporter sides are the same variable by definition. For clarity, we now differentiate between exporter experience and importer experience. For example, the variable $Exp\ exp^i(ai, sp)$ denotes the ith experience of the exporter with the same importer in the same product. The variable $Imp\ exp^i(ae, sp)$ gives the ith experience of the importer with all exporters in the same product while the variable $Imp\ exp^i(ae, op)$ is the ith experience of the importer with all exporters in other products. Note that once we control for experience on the exporter side, adding importer experience does little. Most of the coefficients on importer experience are insignificant and the patterns we saw in Table 1.4 are unchanged.

For completeness, we also run this check when we use four-way experience for the exporter with the importer's experience with any exporter for any product. These results are to be found in Tables A.3 and A.4 for the two countries. Once again, our central results that there is learning and it's mostly from the same product and partner are unchanged.

A.5 Controlling for Transaction History

We conduct estimations related to possible concerns about our interpretation of the coefficients on the experience of various kinds of learning. It might be argued that experience in using preferences is correlated with experience with the partner or product and this is what is being

ε_{eipty} is large. For example, suppose the tariff ratio is 1.1 (the average preference margin (in level) is 4.7% for Argentina and 14.4% for Peru), R is 1.1 (R needs to be small enough relative to the preference margin for preference use to be profitable), the demand elasticity is 4 (average in the literature), and $\gamma = 0.2$ (recall that γ is the coefficient of saving). In this example, we have $\kappa \approx 0.02$. In this case, the bias is small.

Table A.1: Exporter's and Importer's Experience: Argentina

	IV				OLS		
$Savings$	-0.079				0.032***		
	(0.105)				(0.006)		
Age	0.046**				0.027***		
	(0.020)				(0.008)		
$ln(er_o)$	0.021				0.048		
	(0.106)				(0.101)		
$Exp\ exp^1(ai,sp)$	0.044	$Imp\ exp^1(ai,sp)$	0.006	$Exp\ exp^1(ai,sp)$	0.045*	$Imp\ exp^1(ai,sp)$	-0.011
	(0.028)		(0.031)		(0.027)		(0.024)
$Exp\ exp^2(ai,sp)$	0.075**	$Imp\ exp^2(ai,sp)$	0.041	$Exp\ exp^2(ai,sp)$	0.070**	$Imp\ exp^2(ai,sp)$	0.020
	(0.031)		(0.039)		(0.028)		(0.029)
$Exp\ exp^3(ai,sp)$	0.060*	$Imp\ exp^3(ai,sp)$	0.064	$Exp\ exp^3(ai,sp)$	0.065**	$Imp\ exp^3(ai,sp)$	0.031
	(0.034)		(0.046)		(0.032)		(0.030)
$Exp\ exp^4(ai,sp)$	0.062	$Imp\ exp^4(ai,sp)$	0.060	$Exp\ exp^4(ai,sp)$	0.061*	$Imp\ exp^4(ai,sp)$	0.034
	(0.039)		(0.047)		(0.036)		(0.035)
$Exp\ exp^{more}(ai,sp)$	0.099**	$Imp\ exp^{more}(ai,sp)$	0.041	$Exp\ exp^{more}(ai,sp)$	0.098**	$Imp\ exp^{more}(ai,sp)$	0.006
	(0.049)		(0.054)		(0.043)		(0.038)
$Exp\ exp^1(ai,op)$	-0.031	$Imp\ exp^1(ai,op)$	-0.011	$Exp\ exp^1(ai,op)$	-0.023	$Imp\ exp^1(ai,op)$	0.033
	(0.047)		(0.055)		(0.044)		(0.036)
$Exp\ exp^2(ai,op)$	-0.054	$Imp\ exp^2(ai,op)$	0.023	$Exp\ exp^2(ai,op)$	-0.055	$Imp\ exp^2(ai,op)$	0.043
	(0.056)		(0.051)		(0.051)		(0.044)
$Exp\ exp^3(ai,op)$	0.026	$Imp\ exp^3(ai,op)$	-0.003	$Exp\ exp^3(ai,op)$	0.054	$Imp\ exp^3(ai,op)$	0.016
	(0.060)		(0.056)		(0.050)		(0.045)
$Exp\ exp^4(ai,op)$	0.032	$Imp\ exp^4(ai,op)$	-0.007	$Exp\ exp^4(ai,op)$	0.040	$Imp\ exp^4(ai,op)$	-0.001
	(0.071)		(0.060)		(0.065)		(0.053)
$Exp\ exp^{more}(ai,op)$	0.097	$Imp^{more}(oi,op)$	-0.043	$Exp\ exp^{more}(ai,op)$	0.092	$Imp^{more}(oi,op)$	-0.034
	(0.072)		(0.062)		(0.068)		(0.055)
Observations	8,438				8,438		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		
First stage							
2 *month lagged* $ln(er_{CO})$			-0.522**				
			(0.205)				
Kleibergen-Paap F			6.489				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

picked up. For this reason, we add controls for various kinds of experience in conducting transactions, irrespective of whether the transaction used preferences or not, related to the partner, the product, or both. Tables A.5 and A.6 present the results when we add controls for experience with the partner whether or not preferences are used for Argentina and for Peru in Tables 1.4 and 1.5 respectively. Table A.7 and A.8 do the same thing but when we add controls for experience with the product whether or not preferences are used. Tables A.9 and A.10 repeat the exercise when we add controls for both product and partner experience whether or not preferences are used. Note that our estimates for learning and savings are roughly the same.

Table A.2: Exporter's and Importer's Experience: Peru

IV				OLS			
$Savings$	-0.025				0.012***		
	(0.035)				(0.003)		
Age	-0.004**				-0.003*		
	(0.002)				(0.001)		
$ln(er_o)$	-0.148*				-0.086**		
	(0.087)				(0.040)		
$Exp\ exp^1(ai,sp)$	0.017*	$Imp\ exp^1(ai,sp)$	0.001	$Exp\ exp^1(ai,sp)$	0.014	$Imp\ exp^1(ai,sp)$	-0.001
	(0.009)		(0.008)		(0.009)		(0.007)
$Exp\ exp^2(ai,sp)$	0.012	$Imp\ exp^2(ai,sp)$	0.009	$Exp\ exp^2(ai,sp)$	0.009	$Imp\ exp^2(ai,sp)$	0.003
	(0.010)		(0.010)		(0.010)		(0.008)
$Exp\ exp^3(ai,sp)$	0.026***	$Imp\ exp^3(ai,sp)$	0.013	$Exp\ exp^3(ai,sp)$	0.020**	$Imp\ exp^3(ai,sp)$	0.010
	(0.009)		(0.008)		(0.008)		(0.008)
$Exp\ exp^4(ai,sp)$	0.024***	$Imp\ exp^4(ai,sp)$	0.008	$Exp\ exp^4(ai,sp)$	0.018**	$Imp\ exp^4(ai,sp)$	0.004
	(0.009)		(0.009)		(0.008)		(0.008)
$Exp\ exp^{more}(ai,sp)$	0.024**	$Imp\ exp^{more}(ai,sp)$	0.006	$Exp\ exp^{more}(ai,sp)$	0.014*	$Imp\ exp^{more}(ai,sp)$	0.000
	(0.011)		(0.009)		(0.008)		(0.008)
$Exp\ exp^1(ai,op)$	-0.021	$Imp\ exp^1(ai,op)$	-0.007	$Exp\ exp^1(ai,op)$	-0.017	$Imp\ exp^1(ai,op)$	-0.006
	(0.014)		(0.008)		(0.014)		(0.008)
$Exp\ exp^2(ai,op)$	-0.025	$Imp\ exp^2(ai,op)$	-0.014	$Exp\ exp^2(ai,op)$	-0.018	$Imp\ exp^2(ai,op)$	-0.011
	(0.022)		(0.012)		(0.020)		(0.012)
$Exp\ exp^3(ai,op)$	0.002	$Imp\ exp^3(ai,op)$	-0.008	$Exp\ exp^3(ai,op)$	0.010	$Imp\ exp^3(ai,op)$	-0.006
	(0.023)		(0.019)		(0.023)		(0.018)
$Exp\ exp^4(ai,op)$	0.003	$Imp\ exp^4(ai,op)$	-0.024	$Exp\ exp^4(ai,op)$	0.009	$Imp\ exp^4(ai,op)$	-0.019
	(0.024)		(0.016)		(0.024)		(0.016)
$Exp\ exp^{more}(ai,op)$	-0.001	$Imp^{more}(oi,op)$	-0.020	$Exp\ exp^{more}(ai,op)$	0.009	$Imp^{more}(oi,op)$	-0.012
	(0.024)		(0.062)		(0.020)		(0.012)
Observations	15,230				15,230		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		
First stage							
2 *month lagged* $ln(er_{CO})$			-1.340***				
			(0.407)				
Kleibergen-Paap F			10.86				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

A.6 Details of the Trade Agreements

Integration initiatives among Latin American countries go back to the late 1950s and early 1960s. The first formal agreement, the Latin American Free Trade Association (LAFTA — ALALC for its name in Spanish), was signed in Montevideo in 1960 and involved the South American countries and Mexico.[4] Consistent with the import substitution strategy prevailing at the time, and different from their more recent counterparts, LAFTA was an agreement on a framework to conduct bilateral negotiations to liberalize trade in products based on positive lists of tariff concessions. Given that these lists had to be discussed and agreed line-by-line, the process resulted in a high degree of selectivity and complexity and the progress towards

[4]The Montevideo Treaty was initially signed by Argentina, Brazil, Chile, Mexico, Paraguay, Peru, and Uruguay. In subsequent years, Colombia (1961), Ecuador (1961), Venezuela (1966), and Bolivia (1967) joined the agreement.

Table A.3: Exporter's Four Way Experience with Importer's Experience with Other Exporters: Argentina

IV				OLS			
$Savings$	-0.074				0.031***		
	(0.126)				(0.006)		
Age	0.042*				0.026***		
	(0.022)				(0.009)		
$ln(er_o)$	0.032				0.058		
	(0.107)				(0.100)		
$Imp\ exp^1(oe, ap)$	-0.032			$Imp\ exp^1(oe, ap)$	-0.022		
	(0.049)				(0.043)		
$Imp\ exp^2(oe, ap)$	0.008			$Imp\ exp^2(oe, ap)$	0.015		
	(0.043)				(0.039)		
$Imp\ exp^3(oe, ap)$	-0.005			$Imp\ exp^3(oe, ap)$	0.004		
	(0.050)				(0.045)		
$Imp\ exp^4(oe, ap)$	0.030			$Imp\ exp^4(oe, ap)$	0.024		
	(0.047)				(0.045)		
$Imp\ exp^{more}(oe, ap)$	-0.030			$Imp\ exp^{more}(oe, ap)$	-0.021		
	(0.061)				(0.054)		
$Exp^1(si, sp)$	0.049	$Exp^1(oi, sp)$	0.017	$Exp^1(si, sp)$	0.033	$Exp^1(oi, sp)$	0.015
	(0.032)		(0.031)		(0.022)		(0.030)
$Exp^2(si, sp)$	0.084**	$Exp^2(oi, sp)$	0.070	$Exp^2(si, sp)$	0.064**	$Exp^2(oi, sp)$	0.054
	(0.041)		(0.047)		(0.028)		(0.039)
$Exp^3(si, sp)$	0.109**	$Exp^3(oi, sp)$	0.001	$Exp^3(si, sp)$	0.089***	$Exp^3(oi, sp)$	-0.026
	(0.046)		(0.051)		(0.033)		(0.030)
$Exp^4(si, sp)$	0.086*	$Exp^4(oi, sp)$	0.023	$Exp^4(si, sp)$	0.069*	$Exp^4(oi, sp)$	0.015
	(0.048)		(0.055)		(0.039)		(0.049)
$Exp^{more}(si, sp)$	0.121*	$Exp^{more}(oi, sp)$	0.011	$Exp^{more}(si, sp)$	0.093**	$Exp^{more}(oi, sp)$	-0.002
	(0.064)		(0.059)		(0.043)		(0.047)
$Exp^1(si, op)$	-0.046	$Exp^1(oi, op)$	0.012	$Exp^1(si, op)$	-0.011	$Exp^1(oi, op)$	0.025
	(0.053)		(0.051)		(0.042)		(0.044)
$Exp^2(si, op)$	-0.038	$Exp^2(oi, op)$	0.068	$Exp^2(si, op)$	-0.037	$Exp^2(oi, op)$	0.079*
	(0.046)		(0.056)		(0.043)		(0.047)
$Exp^3(si, op)$	0.026	$Exp^3(oi, op)$	0.082	$Exp^3(si, op)$	0.054	$Exp^3(oi, op)$	0.088
	(0.046)		(0.081)		(0.038)		(0.072)
$Exp^4(si, op)$	0.055	$Exp^4(oi, op)$	0.004	$Exp^4(si, op)$	0.060	$Exp^4(oi, op)$	0.009
	(0.053)		(0.064)		(0.052)		(0.051)
$Exp^{more}(si, op)$	0.062	$Exp^{more}(oi, op)$	0.125**	$Exp^{more}(si, op)$	0.050	$Exp^{more}(oi, op)$	0.127***
	(0.059)		(0.049)		(0.054)		(0.041)
Observations	8,438				8,438		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		
First stage							
2 *month lagged* $ln(er_{CO})$			-0.467**				
			(0.199)				
Kleibergen-Paap F			5.486				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

intra-regional free trade was consequently limited (see Devlin & Estevadeordal (2001)).

At the end of the 1960s and unsatisfied with this initiative, Bolivia, Chile, Colombia, Ecuador, and Peru signed the Cartagena Treaty to establish the Andean Pact in 1969 to accelerate and deepen the integration and ultimately create a common market among them.[5] Unlike LAFTA, the trade liberalization program defined in this agreement included a list

[5]Venezuela joined in 1973 whereas Chile left the agreement in 1976.

Table A.4: Exporter's Four Way Experience with Importer's Experience with Other Exporters: Peru

	IV				OLS		
$Savings$	-0.028				0.012***		
	(0.036)				(0.003)		
Age	-0.004**				-0.003**		
	(0.002)				(0.001)		
$ln(er_o)$	-0.151*				-0.084**		
	(0.090)				(0.040)		
$Imp\ exp^1(oe, ap)$	-0.019*			$Imp\ exp^1(oe, ap)$	-0.015		
	(0.011)				(0.010)		
$Imp\ exp^2(oe, ap)$	-0.027**			$Imp\ exp^2(oe, ap)$	-0.024**		
	(0.013)				(0.012)		
$Imp\ exp^3(oe, ap)$	-0.008			$Imp\ exp^3(oe, ap)$	-0.004		
	(0.017)				(0.016)		
$Imp\ exp^4(oe, ap)$	-0.027			$Imp\ exp^4(oe, ap)$	-0.025		
	(0.017)				(0.017)		
$Imp\ exp^{more}(oe, ap)$	-0.024			$Imp\ exp^{more}(oe, ap)$	-0.020		
	(0.016)				(0.016)		
$Exp^1(si, sp)$	0.020**	$Exp^1(oi, sp)$	0.021	$Exp^1(si, sp)$	0.013*	$Exp^1(oi, sp)$	0.017
	(0.010)		(0.013)		(0.008)		(0.012)
$Exp^2(si, sp)$	0.025**	$Exp^2(oi, sp)$	0.013	$Exp^2(si, sp)$	0.016*	$Exp^2(oi, sp)$	0.007
	(0.012)		(0.017)		(0.009)		(0.016)
$Exp^3(si, sp)$	0.025**	$Exp^3(oi, sp)$	0.024*	$Exp^3(si, sp)$	0.017**	$Exp^3(oi, sp)$	0.016
	(0.010)		(0.014)		(0.008)		(0.011)
$Exp^4(si, sp)$	0.025**	$Exp^4(oi, sp)$	0.045**	$Exp^4(si, sp)$	0.015*	$Exp^4(oi, sp)$	0.031**
	(0.012)		(0.022)		(0.008)		(0.013)
$Exp^{more}(si, sp)$	0.024**	$Exp^{more}(oi, sp)$	0.034*	$Exp^{more}(si, sp)$	0.006	$Exp^{more}(oi, sp)$	0.023*
	(0.012)		(0.018)		(0.018)		(0.013)
$Exp^1(si, op)$	-0.012	$Exp^1(oi, op)$	-0.006	$Exp^1(si, op)$	-0.006	$Exp^1(oi, op)$	-0.013
	(0.013)		(0.025)		(0.010)		(0.022)
$Exp^2(si, op)$	-0.014	$Exp^2(oi, op)$	0.007	$Exp^2(si, op)$	-0.006	$Exp^2(oi, op)$	0.004
	(0.019)		(0.032)		(0.016)		(0.031)
$Exp^3(si, op)$	0.009	$Exp^3(oi, op)$	0.021	$Exp^3(si, op)$	0.019	$Exp^3(oi, op)$	0.022
	(0.021)		(0.019)		(0.019)		(0.020)
$Exp^4(si, op)$	-0.008	$Exp^4(oi, op)$	0.042	$Exp^4(si, op)$	0.002	$Exp^4(oi, op)$	0.048
	(0.021)		(0.035)		(0.019)		(0.035)
$Exp^{more}(si, op)$	-0.009	$Exp^{more}(oi, op)$	-0.022*	$Exp^{more}(si, op)$	0.006	$Exp^{more}(oi, op)$	-0.020*
	(0.025)		(0.013)		(0.018)		(0.012)
Observations	15,230				15,230		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		
First stage							
2 *month lagged* $ln(er_{CO})$			-1.271***				
			(0.386)				
Kleibergen-Paap F			10.86				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

of products subject to automatic tariff reductions that covered half of the universe of tariff lines and was scheduled to be implemented gradually to reach zero tariffs within a ten-year period and established that tariffs corresponding to the common lists agreed under LAFTA had to be eliminated within six months after the scheme entered into force.[6] Moreover, a

[6]The remaining products primarily corresponded to general exceptions or those related to industrial development plans. The agreement granted preferential treatment to Bolivia and Ecuador in accounting for their lower development level and, in general, more flexibility to implement the liberalization schedule, in particular.

Table A.5: With Pair History: Argentina

	IV			OLS			
$Savings$		-0.064				0.023***	
		(0.078)				(0.005)	
Age		0.035**				0.019***	
		(0.016)				(0.006)	
$ln(er_o)$		-0.012				0.007	
		(0.046)				(0.042)	
Pair history^1		0.101***				0.094***	
		(0.036)				(0.032)	
Pair history^2		0.067**				0.065**	
		(0.030)				(0.029)	
Pair history^3		0.044*				0.038	
		(0.027)				(0.024)	
Pair history^4		0.045*				0.038*	
		(0.025)				(0.022)	
Pair history^{more}		0.025				0.019	
		(0.024)				(0.022)	
$Exp^1(si, sp)$	0.075***	$Exp^1(oi, sp)$	0.023	$Exp^1(si, sp)$	0.063***	$Exp^1(oi, sp)$	0.011
	(0.021)		(0.023)		(0.018)		(0.020)
$Exp^2(si, sp)$	0.130***	$Exp^2(oi, sp)$	0.039	$Exp^2(si, sp)$	0.115***	$Exp^2(oi, sp)$	0.025
	(0.028)		(0.028)		(0.024)		(0.025)
$Exp^3(si, sp)$	0.151***	$Exp^3(oi, sp)$	0.061**	$Exp^3(si, sp)$	0.141***	$Exp^3(oi, sp)$	0.043*
	(0.030)		(0.028)		(0.028)		(0.025)
$Exp^4(si, sp)$	0.162***	$Exp^4(oi, sp)$	0.053	$Exp^4(si, sp)$	0.147***	$Exp^4(oi, sp)$	0.028
	(0.036)		(0.036)		(0.034)		(0.030)
$Exp^{more}(si, sp)$	0.184***	$Exp^{more}(oi, sp)$	0.004	$Exp^{more}(si, sp)$	0.165***	$Exp^{more}(oi, sp)$	-0.017
	(0.046)		(0.031)		(0.042)		(0.024)
$Exp^1(si, op)$	0.008	$Exp^1(oi, op)$	-0.018	$Exp^1(si, op)$	0.035	$Exp^1(oi, op)$	-0.004
	(0.036)		(0.036)		(0.028)		(0.031)
$Exp^2(si, op)$	0.022	$Exp^2(oi, op)$	0.009	$Exp^2(si, op)$	0.031	$Exp^2(oi, op)$	0.036
	(0.034)		(0.042)		(0.032)		(0.029)
$Exp^3(si, op)$	0.050	$Exp^3(oi, op)$	-0.035	$Exp^3(si, op)$	0.071**	$Exp^3(oi, op)$	-0.019
	(0.031)		(0.080)		(0.028)		(0.080)
$Exp^4(si, op)$	0.067*	$Exp^4(oi, op)$	-0.016	$Exp^4(si, op)$	0.081**	$Exp^4(oi, op)$	0.021
	(0.036)		(0.046)		(0.035)		(0.030)
$Exp^{more}(si, op)$	0.060*	$Exp^{more}(oi, op)$	0.032	$Exp^{more}(si, op)$	0.058	$Exp^{more}(oi, op)$	0.052
	(0.037)		(0.044)		(0.036)		(0.034)
Observations		15,689				15,689	
Fixed Effects:							
Exporter-Importer		✓				✓	
Product		✓				✓	
	First stage						
2 *month lagged* $ln(er_{CO})$			-0.603***				
			(0.151)				
Kleibergen-Paap F			15.96				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

common external tariff was to be in place by the end of 1980. While neither the full removal of internal tariffs nor the complete adoption of the common external tariff was achieved due to mounting disagreements among countries along the process, implementation problems, and non-compliance, trade barriers decreased significantly after 1969. More precisely, average tariffs between Colombia and Peru decreased from 92% in 1969 to 10% in 1978 for the products included in the liberalization program and 25% of the lines were free from tariffs (see Devlin & Estevadeordal (2001)). More recently, the Andean Pact was relaunched in 1992 to complete the free trade area and became the Andean Community in 1996 (see Mesquita Moreira et al. (2018)).

Table A.6: With Pair History: Peru

	IV			OLS			
$Savings$	0.035				0.010***		
	(0.034)				(0.002)		
Age	-0.001				-0.001		
	(0.001)				(0.001)		
$ln(er_o)$	0.041				0.017		
	(0.045)				(0.029)		
Pair history^1	0.005				0.014		
	(0.016)				(0.009)		
Pair history^2	-0.011				-0.004		
	(0.012)				(0.007)		
Pair history^3	-0.009				-0.005		
	(0.009)				(0.007)		
Pair history^4	-0.008				-0.004		
	(0.008)				(0.006)		
Pair history^{more}	-0.008				-0.005		
	(0.007)				(0.006)		
$Exp^1(si,sp)$	0.024***	$Exp^1(oi,sp)$	0.014**	$Exp^1(si,sp)$	0.028***	$Exp^1(oi,sp)$	0.017**
	(0.008)		(0.007)		(0.005)		(0.007)
$Exp^2(si,sp)$	0.027**	$Exp^2(oi,sp)$	0.017**	$Exp^2(si,sp)$	0.034***	$Exp^2(oi,sp)$	0.020***
	(0.011)		(0.007)		(0.006)		(0.007)
$Exp^3(si,sp)$	0.030**	$Exp^3(oi,sp)$	0.023***	$Exp^3(si,sp)$	0.037***	$Exp^3(oi,sp)$	0.025***
	(0.012)		(0.009)		(0.007)		(0.009)
$Exp^4(si,sp)$	0.031**	$Exp^4(oi,sp)$	0.025***	$Exp^4(si,sp)$	0.039***	$Exp^4(oi,sp)$	0.028***
	(0.014)		(0.008)		(0.007)		(0.008)
$Exp^{more}(si,sp)$	0.022	$Exp^{more}(oi,sp)$	0.025***	$Exp^{more}(si,sp)$	0.033***	$Exp^{more}(oi,sp)$	0.029***
	(0.018)		(0.009)		(0.009)		(0.010)
$Exp^1(si,op)$	-0.005	$Exp^1(oi,op)$	-0.019**	$Exp^1(si,op)$	-0.006	$Exp^1(oi,op)$	-0.019**
	(0.007)		(0.009)		(0.006)		(0.009)
$Exp^2(si,op)$	-0.013	$Exp^2(oi,op)$	-0.026**	$Exp^2(si,op)$	-0.013*	$Exp^2(oi,op)$	-0.030***
	(0.008)		(0.011)		(0.008)		(0.011)
$Exp^3(si,op)$	-0.006	$Exp^3(oi,op)$	-0.011	$Exp^3(si,op)$	-0.009	$Exp^3(oi,op)$	-0.012
	(0.009)		(0.012)		(0.007)		(0.012)
$Exp^4(si,op)$	-0.014	$Exp^4(oi,op)$	-0.025*	$Exp^4(si,op)$	-0.015	$Exp^4(oi,op)$	-0.027*
	(0.010)		(0.015)		(0.009)		(0.016)
$Exp^{more}(si,op)$	-0.011	$Exp^{more}(oi,op)$	-0.045**	$Exp^{more}(si,op)$	-0.016**	$Exp^{more}(oi,op)$	-0.047**
	(0.011)		(0.021)		(0.007)		(0.022)
Observations	54,188				54,188		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		
First stage							
2 *month lagged* $ln(er_{CO})$			-0.669***				
			(0.174)				
Kleibergen-Paap F			14.78				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

As a consequence, the movement towards deeper regional integration gained renewed impetus, and non-zero preferential tariffs were further reduced on an automatic basis across the board. Thus, the median tariff imposed by Colombia on exports from Peru decreased from 46% in 1985, to 10% in 1995, and 0% in 2005 (see Ludema et al. (2021)). The LAFTA was replaced by the Latin American Integration Association (LAIA — ALADI for its name in Spanish), which was established in 1980 through the Treaty of Montevideo. Argentina, Colombia, and Peru were among the founding members. In the framework of the LAIA, Argentina and Colombia signed a first agreement in 1988 to reduce bilateral tariffs on a limited number of products

Table A.7: With Product History: Argentina

	IV				OLS		
$Savings$	-0.070				0.023***		
	(0.079)				(0.005)		
Age	0.035**				0.018***		
	(0.016)				(0.006)		
$ln(er_o)$	-0.023				-0.001		
	(0.046)				(0.041)		
Product history^1	0.048				0.060*		
	(0.032)				(0.031)		
Product history^2	0.041				0.046*		
	(0.025)				(0.025)		
Product history^3	0.032				0.035		
	(0.023)				(0.023)		
Product history^4	0.006				0.013		
	(0.018)				(0.016)		
Product history^{more}	0.014				0.016		
	(0.017)				(0.016)		
$Exp^1(si,sp)$	0.070***	$Exp^1(oi,sp)$	0.031	$Exp^1(si,sp)$	0.063***	$Exp^1(oi,sp)$	0.020
	(0.021)		(0.023)		(0.019)		(0.020)
$Exp^2(si,sp)$	0.126***	$Exp^2(oi,sp)$	0.057**	$Exp^2(si,sp)$	0.115***	$Exp^2(oi,sp)$	0.043*
	(0.030)		(0.029)		(0.027)		(0.026)
$Exp^3(si,sp)$	0.152***	$Exp^3(oi,sp)$	0.080***	$Exp^3(si,sp)$	0.145***	$Exp^3(oi,sp)$	0.063**
	(0.033)		(0.028)		(0.032)		(0.027)
$Exp^4(si,sp)$	0.156***	$Exp^4(oi,sp)$	0.069**	$Exp^4(si,sp)$	0.147***	$Exp^4(oi,sp)$	0.045
	(0.037)		(0.035)		(0.037)		(0.030)
$Exp^{more}(si,sp)$	0.179***	$Exp^{more}(oi,sp)$	0.019	$Exp^{more}(si,sp)$	0.166***	$Exp^{more}(oi,sp)$	-0.002
	(0.046)		(0.030)		(0.045)		(0.023)
$Exp^1(si,op)$	-0.006	$Exp^1(oi,op)$	-0.023	$Exp^1(si,op)$	0.024	$Exp^1(oi,op)$	-0.008
	(0.037)		(0.037)		(0.028)		(0.031)
$Exp^2(si,op)$	0.010	$Exp^2(oi,op)$	0.001	$Exp^2(si,op)$	0.020	$Exp^2(oi,op)$	0.029
	(0.033)		(0.042)		(0.030)		(0.029)
$Exp^3(si,op)$	0.035	$Exp^3(oi,op)$	-0.042	$Exp^3(si,op)$	0.059**	$Exp^3(oi,op)$	-0.025
	(0.031)		(0.081)		(0.027)		(0.080)
$Exp^4(si,op)$	0.052	$Exp^4(oi,op)$	-0.028	$Exp^4(si,op)$	0.069**	$Exp^4(oi,op)$	0.011
	(0.035)		(0.048)		(0.033)		(0.031)
$Exp^{more}(si,op)$	0.052	$Exp^{more}(oi,op)$	0.019	$Exp^{more}(si,op)$	0.051	$Exp^{more}(oi,op)$	0.041
	(0.035)		(0.045)		(0.034)		(0.034)
Observations	15,689				15,689		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		
First stage							
2 *month lagged* $ln(er_{CO})$			-0.602***				
			(0.151)				
Kleibergen-Paap F			15.90				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

(Economic Complementary Agreement of Partial Scope 11 — AAP.CE 11 for its name in Spanish). This agreement was replaced by the AAP.CE 48 in 2000, which aimed at becoming a building block to create a free trade zone between the members of the Andean Community at that time—i.e., Bolivia, Colombia, Ecuador, Peru, and Venezuela— and the members of the MERCOSUR —i.e., Argentina, Brazil, Paraguay, and Uruguay— as formally agreed by these countries in 1998. Under the AAP.CE 48, Colombia granted fixed preferences on around 1,250 products from Argentina (i.e., less than one-quarter of the total number of tariff lines), with the preference margins (defined as the MFN tariff less the preferential one divided by the MFN

Table A.8: With Product History: Peru

	IV				OLS		
$Savings$	0.038				0.010***		
	(0.032)				(0.002)		
Age	-0.001				-0.001		
	(0.001)				(0.001)		
$ln(er_o)$	0.042				0.017		
	(0.043)				(0.029)		
Product history^1	-0.008				-0.011		
	(0.010)				(0.010)		
Product history^2	-0.009				-0.012		
	(0.008)				(0.007)		
Product history^3	-0.000				-0.002		
	(0.007)				(0.006)		
Product history^4	-0.002				-0.002		
	(0.006)				(0.006)		
Product history^{more}	-0.004				-0.005		
	(0.005)				(0.005)		
$Exp^1(si, sp)$	0.019**	$Exp^1(oi, sp)$	0.013*	$Exp^1(si, sp)$	0.023***	$Exp^1(oi, sp)$	0.015**
	(0.008)		(0.007)		(0.006)		(0.007)
$Exp^2(si, sp)$	0.020**	$Exp^2(oi, sp)$	0.015*	$Exp^2(si, sp)$	0.024***	$Exp^2(oi, sp)$	0.017**
	(0.009)		(0.008)		(0.007)		(0.008)
$Exp^3(si, sp)$	0.023**	$Exp^3(oi, sp)$	0.020**	$Exp^3(si, sp)$	0.027***	$Exp^3(oi, sp)$	0.023**
	(0.010)		(0.010)		(0.008)		(0.010)
$Exp^4(si, sp)$	0.025**	$Exp^4(oi, sp)$	0.022**	$Exp^4(si, sp)$	0.031***	$Exp^4(oi, sp)$	0.025***
	(0.011)		(0.009)		(0.008)		(0.009)
$Exp^{more}(si, sp)$	0.017	$Exp^{more}(oi, sp)$	0.023**	$Exp^{more}(si, sp)$	0.024***	$Exp^{more}(oi, sp)$	0.026**
	(0.013)		(0.010)		(0.009)		(0.011)
$Exp^1(si, op)$	-0.004	$Exp^1(oi, op)$	-0.019**	$Exp^1(si, op)$	-0.006	$Exp^1(oi, op)$	-0.020**
	(0.008)		(0.009)		(0.006)		(0.009)
$Exp^2(si, op)$	-0.010	$Exp^2(oi, op)$	-0.026**	$Exp^2(si, op)$	-0.013*	$Exp^2(oi, op)$	-0.030***
	(0.008)		(0.011)		(0.007)		(0.011)
$Exp^3(si, op)$	-0.001	$Exp^3(oi, op)$	-0.011	$Exp^3(si, op)$	-0.007	$Exp^3(oi, op)$	-0.013
	(0.010)		(0.012)		(0.007)		(0.012)
$Exp^4(si, op)$	-0.009	$Exp^4(oi, op)$	-0.026*	$Exp^4(si, op)$	-0.013	$Exp^4(oi, op)$	-0.028*
	(0.011)		(0.015)		(0.009)		(0.016)
$Exp^{more}(si, op)$	-0.006	$Exp^{more}(oi, op)$	-0.045**	$Exp^{more}(si, op)$	-0.014**	$Exp^{more}(oi, op)$	-0.047**
	(0.012)		(0.021)		(0.006)		(0.022)
Observations	54,188				54,188		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		
First stage							
2 *month lagged* $ln(er_{CO})$			-0.707***				
			(0.168)				
Kleibergen-Paap F			17.69				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

tariff) averaging 40% and ranging from 10% to 100%. Median tariffs applied by Colombia on products coming from Argentina consequently reached 10% in 2005.

This agreement was superseded by the AAP.CE 59, which established a free trade zone between Colombia, Ecuador, and Venezuela, on one side, and Argentina, Brazil, Paraguay, and Uruguay, on the other side. This new agreement, which was signed in 2004 and entered into force in 2005, included a trade liberalization program consisting of automatic tariff phasing-out to reach 100% preference margin within different time horizons depending on the products: immediately, in 4-12 years for some products not covered in the previous agreement, and in

Table A.9: With Pair-product History: Argentina

	IV				OLS		
$Savings$	-0.064				0.023***		
	(0.077)				(0.005)		
Age	0.036**				0.020***		
	(0.016)				(0.006)		
$ln(er_o)$	-0.017				0.003		
	(0.052)				(0.048)		
Pair-product history^1	0.139***				0.150***		
	(0.039)				(0.038)		
Pair-product history^2	0.093***				0.102***		
	(0.033)				(0.034)		
Pair-product history^3	0.058**				0.065**		
	(0.028)				(0.028)		
Pair-product history^4	0.019				0.024		
	(0.022)				(0.021)		
Pair-product history^{more}	0.012				0.012		
	(0.023)				(0.022)		
$Exp^1(si, sp)$	0.100***	$Exp^1(oi, sp)$	0.026	$Exp^1(si, sp)$	0.091***	$Exp^1(oi, sp)$	0.014
	(0.025)		(0.023)		(0.023)		(0.020)
$Exp^2(si, sp)$	0.176***	$Exp^2(oi, sp)$	0.047*	$Exp^2(si, sp)$	0.165***	$Exp^2(oi, sp)$	0.032
	(0.035)		(0.027)		(0.033)		(0.024)
$Exp^3(si, sp)$	0.216***	$Exp^3(oi, sp)$	0.066**	$Exp^3(si, sp)$	0.213***	$Exp^3(oi, sp)$	0.048*
	(0.039)		(0.028)		(0.039)		(0.026)
$Exp^4(si, sp)$	0.226***	$Exp^4(oi, sp)$	0.057	$Exp^4(si, sp)$	0.220***	$Exp^4(oi, sp)$	0.032
	(0.044)		(0.035)		(0.044)		(0.029)
$Exp^{more}(si, sp)$	0.244***	$Exp^{more}(oi, sp)$	0.015	$Exp^{more}(si, sp)$	0.234***	$Exp^{more}(oi, sp)$	-0.007
	(0.055)		(0.030)		(0.054)		(0.023)
$Exp^1(si, op)$	-0.001	$Exp^1(oi, op)$	-0.022	$Exp^1(si, op)$	0.027	$Exp^1(oi, op)$	-0.008
	(0.036)		(0.037)		(0.027)		(0.031)
$Exp^2(si, op)$	0.013	$Exp^2(oi, op)$	0.001	$Exp^2(si, op)$	0.022	$Exp^2(oi, op)$	0.028
	(0.033)		(0.041)		(0.030)		(0.028)
$Exp^3(si, op)$	0.039	$Exp^3(oi, op)$	-0.040	$Exp^3(si, op)$	0.062**	$Exp^3(oi, op)$	-0.023
	(0.031)		(0.080)		(0.027)		(0.080)
$Exp^4(si, op)$	0.058*	$Exp^4(oi, op)$	-0.026	$Exp^4(si, op)$	0.074**	$Exp^4(oi, op)$	0.011
	(0.035)		(0.045)		(0.033)		(0.029)
$Exp^{more}(si, op)$	0.054	$Exp^{more}(oi, op)$	0.023	$Exp^{more}(si, op)$	0.053	$Exp^{more}(oi, op)$	0.044
	(0.034)		(0.043)		(0.033)		(0.032)
Observations	15,689				15,689		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		
First stage							
2 *month lagged* $ln(er_{CO})$			-0.607***				
			(0.151)				
Kleibergen-Paap F			16.16				

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

12-15 years for other products. According to data from ALADI, as of 2020, approximately 97% of the tariff lines are subject to preferences, and such preferences average 99% for the trade between Argentina and Colombia.[7]

One might be concerned that the products newly covered in 2005 for Argentina differ from those previously covered and for this reason, have intrinsically different learning. Comparing these new products with old products in terms of the commonly used measures of restrictiveness of the rules of origin as in Estevadeordal (2000) and in Harris (2007), we find that these indices

[7]A new agreement, the AAP.CE 72 was firmed between Colombia and MERCOSUR countries in 2017.

Table A.10: With Pair-product History: Peru

	IV				OLS		
$Savings$	0.033				0.010***		
	(0.033)				(0.002)		
Age	-0.001				-0.001		
	(0.001)				(0.001)		
$ln(er_o)$	0.040				0.018		
	(0.043)				(0.028)		
Pair-product history^1	0.031				0.034		
	(0.027)				(0.026)		
Pair-product history^2	-0.003				-0.001		
	(0.020)				(0.020)		
Pair-product history^3	0.006				0.008		
	(0.016)				(0.016)		
Pair-product history^4	-0.004				-0.001		
	(0.013)				(0.013)		
Pair-product history^{more}	-0.011				-0.009		
	(0.009)				(0.009)		
$Exp^1(si,sp)$	0.049***	$Exp^1(oi,sp)$	0.015**	$Exp^1(si,sp)$	0.053***	$Exp^1(oi,sp)$	0.017**
	(0.016)		(0.007)		(0.014)		(0.007)
$Exp^2(si,sp)$	0.046**	$Exp^2(oi,sp)$	0.018**	$Exp^2(si,sp)$	0.052***	$Exp^2(oi,sp)$	0.020***
	(0.023)		(0.007)		(0.020)		(0.007)
$Exp^3(si,sp)$	0.058**	$Exp^3(oi,sp)$	0.023***	$Exp^3(si,sp)$	0.063**	$Exp^3(oi,sp)$	0.026***
	(0.028)		(0.008)		(0.025)		(0.009)
$Exp^4(si,sp)$	0.064**	$Exp^4(oi,sp)$	0.025***	$Exp^4(si,sp)$	0.071***	$Exp^4(oi,sp)$	0.029***
	(0.030)		(0.008)		(0.026)		(0.008)
$Exp^{more}(si,sp)$	0.048	$Exp^{more}(oi,sp)$	0.026***	$Exp^{more}(si,sp)$	0.059**	$Exp^{more}(oi,sp)$	0.030***
	(0.033)		(0.009)		(0.028)		(0.010)
$Exp^1(si,op)$	-0.004	$Exp^1(oi,op)$	-0.019**	$Exp^1(si,op)$	-0.007	$Exp^1(oi,op)$	-0.020**
	(0.008)		(0.009)		(0.006)		(0.009)
$Exp^2(si,op)$	-0.010	$Exp^2(oi,op)$	-0.027**	$Exp^2(si,op)$	-0.013*	$Exp^2(oi,op)$	-0.031***
	(0.008)		(0.011)		(0.007)		(0.011)
$Exp^3(si,op)$	-0.002	$Exp^3(oi,op)$	-0.011	$Exp^3(si,op)$	-0.007	$Exp^3(oi,op)$	-0.012
	(0.010)		(0.012)		(0.007)		(0.012)
$Exp^4(si,op)$	-0.010	$Exp^4(oi,op)$	-0.025*	$Exp^4(si,op)$	-0.013	$Exp^4(oi,op)$	-0.027*
	(0.011)		(0.015)		(0.009)		(0.016)
$Exp^{more}(si,op)$	-0.008	$Exp^{more}(oi,op)$	-0.046**	$Exp^{more}(si,op)$	-0.014**	$Exp^{more}(oi,op)$	-0.047**
	(0.013)		(0.021)		(0.006)		(0.022)
Observations	54,188				54,188		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		
First stage							
2 *month lagged* $ln(er_{CO})$			-0.684***				
			(0.166)				
Kleibergen-Paap F			17.01				

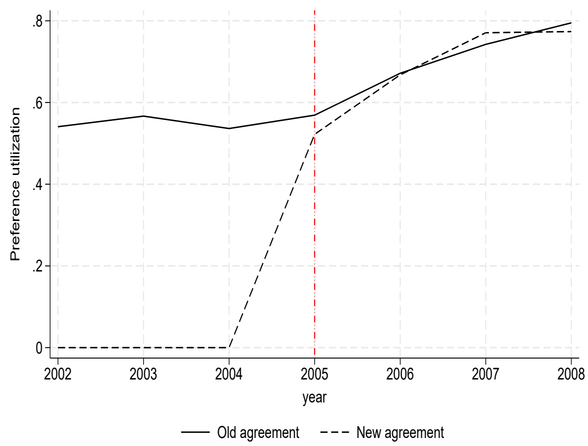
Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

are very close and their rankings reverse depending on which index we use. Using the index by Estevadeordal (2000) gives us an average restrictiveness of 4.5 for new products and 4.7 for old products. Using the index by Harris (2007) gives us an average restrictiveness of 4.1 for new products and 3.5 for old products.

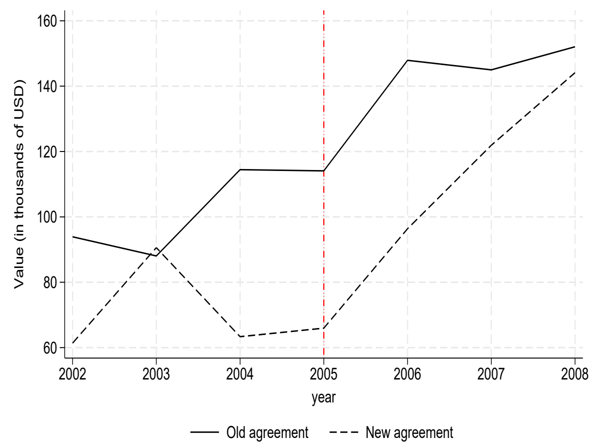
Figure A.1 depicts four other dimensions in which new and old products could differ: (average over products) preference use, value of transactions, number of transactions, and value per transaction. Preference use for new products rapidly catches up with that for old products. Value for new products is slightly below that for old products. The same goes for the number of transactions and value per transaction. Although value, transactions, and value per transaction are different across old and new products, this should not affect our learning estimates because of the fixed effects. In addition, conversations with policy experts in the area also failed to come up with selection mechanisms that could bias our estimates of learning.

Figure A.1: Products Covered by New versus Old Trade Agreements

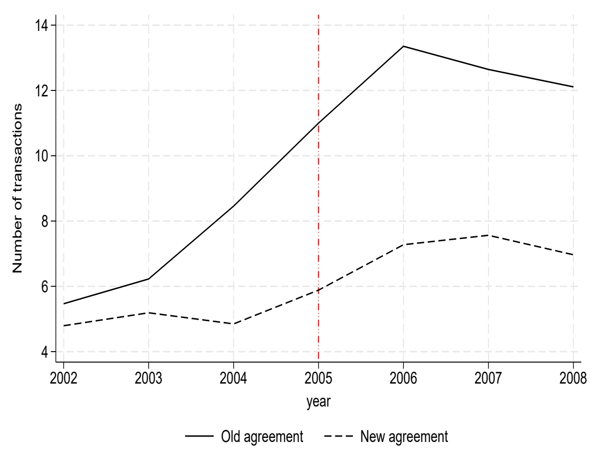
(a) Preference use



(b) Value



(c) Transactions



Note: We show the simple average over products for preference use, value, number of transactions, and value per transaction. We restrict attention on products that were present before 2005. We do so to remove any bias coming from new products entering because of the expansion of the free trade area. We also remove mining (HS27) from this data because these exports are extremely volatile.

A.7 Non Linear Specification

We chose to use the linear probability set up in the body of the paper as we can do IV regressions in that setting even with high dimensional fixed effects. Work estimating an IV with high dimensional fixed effects in a non-linear setting is still a work in progress to the best of our knowledge. In such settings using IVs can create an incidental parameters problem. For this reason, we focus on the results without IVs. To understand how much our results change between an LPM and a nonlinear specification like Logit or Probit, we estimate Equation (1.5) with the same fixed effects using both non-linear methods and report the results in Table 3. Since there are no IV results, we present the estimates for both Argentina and Peru in one table. Overall, the results are quite similar; coefficients for experience are positive and significant and roughly of the same magnitude, as is the coefficient for savings. Preferences are also more likely to be used in Peru than in Argentina, as before, and the size of the learning effects are larger for Argentina than for Peru, as might be expected given the longer history of the trade agreements with Peru.

Table A.11: Logit with Fixed Effects: Argentina

Logit				Average marginal effect			
$Savings$	0.372***				0.021***		
	(0.033)				(0.002)		
Age	-0.471**				-0.027***		
	(0.186)				(0.01)		
$ln(er_o)$	0.209***				0.012***		
	(0.041)				(0.002)		
$Exp^1(si,sp)$	0.39***	$Exp^1(oi,sp)$	0.265	$Exp^1(si,sp)$	0.022***	$Exp^1(oi,sp)$	0.015
	(0.105)		(0.183)		(0.006)		(0.01)
$Exp^2(si,sp)$	0.795***	$Exp^2(oi,sp)$	0.762***	$Exp^2(si,sp)$	0.043***	$Exp^2(oi,sp)$	0.041***
	(0.137)		(0.249)		(0.007)		(0.013)
$Exp^3(si,sp)$	1.243***	$Exp^3(oi,sp)$	1.134***	$Exp^3(si,sp)$	0.064***	$Exp^3(oi,sp)$	0.058***
	(0.175)		(0.301)		(0.008)		(0.014)
$Exp^4(si,sp)$	1.012***	$Exp^4(oi,sp)$	0.731**	$Exp^4(si,sp)$	0.053***	$Exp^4(oi,sp)$	0.039**
	(0.187)		(0.333)		(0.009)		(0.017)
$Exp^{more}(si,sp)$	1.34***	$Exp^{more}(oi,sp)$	0.617***	$Exp^{more}(si,sp)$	0.082***	$Exp^{more}(oi,sp)$	0.034***
	(0.13)		(0.219)		(0.009)		(0.013)
$Exp^1(si,op)$	0.413**	$Exp^1(oi,op)$	-0.448*	$Exp^1(si,op)$	0.023**	$Exp^1(oi,op)$	-0.027
	(0.193)		(0.267)		(0.011)		(0.017)
$Exp^2(si,op)$	0.406**	$Exp^2(oi,op)$	0.23	$Exp^2(si,op)$	0.023*	$Exp^2(oi,op)$	0.013
	(0.2)		(0.318)		(0.012)		(0.018)
$Exp^3(si,op)$	0.509**	$Exp^3(oi,op)$	-0.316	$Exp^3(si,op)$	0.028**	$Exp^3(oi,op)$	-0.019
	(0.223)		(0.355)		(0.012)		(0.025)
$Exp^4(si,op)$	1.06***	$Exp^4(oi,op)$	-0.194	$Exp^4(si,op)$	0.055***	$Exp^4(oi,op)$	-0.011
	(0.253)		(0.355)		(0.012)		(0.02)
$Exp^{more}(si,op)$	0.807***	$Exp^{more}(oi,op)$	0.438*	$Exp^{more}(si,op)$	0.048***	$Exp^{more}(oi,op)$	0.025*
	(0.142)		(0.245)		(0.009)		(0.015)
Observations	15,689				15,689		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

Table A.12: Probit with Fixed Effects: Argentina

Probit				Average marginal effect			
$Savings$		0.209***				0.021***	
		(0.018)				(0.002)	
Age		-0.221**				-0.022**	
		(0.106)				(0.011)	
$ln(er_o)$		0.103***				0.011***	
		(0.022)				(0.002)	
$Exp^1(si,sp)$	0.237***	$Exp^1(oi,sp)$	0.161	$Exp^1(si,sp)$	0.023***	$Exp^1(oi,sp)$	0.016
	(0.06)		(0.1)		(0.006)		(0.01)
$Exp^2(si,sp)$	0.482***	$Exp^2(oi,sp)$	0.415***	$Exp^2(si,sp)$	0.046***	$Exp^2(oi,sp)$	0.04***
	(0.077)		(0.137)		(0.007)		(0.013)
$Exp^3(si,sp)$	0.715***	$Exp^3(oi,sp)$	0.618***	$Exp^3(si,sp)$	0.065***	$Exp^3(oi,sp)$	0.057***
	(0.097)		(0.164)		(0.008)		(0.014)
$Exp^4(si,sp)$	0.577***	$Exp^4(oi,sp)$	0.416**	$Exp^4(si,sp)$	0.054***	$Exp^4(oi,sp)$	0.04**
	(0.103)		(0.181)		(0.009)		(0.017)
$Exp^{more}(si,sp)$	0.785***	$Exp^{more}(oi,sp)$	0.348***	$Exp^{more}(si,sp)$	0.085***	$Exp^{more}(oi,sp)$	0.034***
	(0.073)		(0.119)		(0.009)		(0.013)
$Exp^1(si,op)$	0.216**	$Exp^1(oi,op)$	-0.29*	$Exp^1(si,op)$	0.021**	$Exp^1(oi,op)$	-0.031*
	(0.107)		(0.149)		(0.011)		(0.016)
$Exp^2(si,op)$	0.175	$Exp^2(oi,op)$	0.145	$Exp^2(si,op)$	0.017	$Exp^2(oi,op)$	0.015
	(0.111)		(0.175)		(0.012)		(0.017)
$Exp^3(si,op)$	0.297**	$Exp^3(oi,op)$	-0.11	$Exp^3(si,op)$	0.029**	$Exp^3(oi,op)$	-0.011
	(0.122)		(0.198)		(0.011)		(0.026)
$Exp^4(si,op)$	0.585***	$Exp^4(oi,op)$	-0.159	$Exp^4(si,op)$	0.054***	$Exp^4(oi,op)$	-0.017
	(0.141)		(0.197)		(0.012)		(0.02)
$Exp^{more}(si,op)$	0.451***	$Exp^{more}(oi,op)$	0.182	$Exp^{more}(si,op)$	0.048***	$Exp^{more}(oi,op)$	0.018
	(0.079)		(0.134)		(0.009)		(0.015)
Observations		15,689				15,689	
Fixed Effects:							
Exporter-Importer		✓				✓	
Product		✓				✓	

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

A.8 Alternative Specifications

In this section, we present a set of different specifications to test the robustness of our results to different choices of Fixed Effects and Clusters for the standard errors associated with our estimations.

In Tables A.15 and A.16 we present the OLS and IV results using different Fixed Effects focusing on the coefficients of experience with the same importer-product combination. Columns (1) and (5) present our baseline for Peru and Argentina for reference. In columns (2) and (6) we present the results using the importer and exporter fixed effects separately. We do this because a large portion of our firms are single-partnered, so in using combined importer-exporter fixed effects we exclude a large portion of firms. The results don't change significantly compared to our baseline. In columns (3),(4),(7), and (8) we add a fixed effect of year or product-year to the baseline specification. Notice that in this case for the OLS estimates the results are not affected in the significance but the estimates using product-year fixed effects are smaller in magnitude.

Table A.13: Logit with Fixed Effects: Peru

	Logit				Average marginal effect		
$Savings$	0.266***				0.005***		
	(0.021)				(0.00)		
Age	0.725				0.015		
	(0.738)				(0.014)		
$ln(er_o)$	-0.081***				-0.002***		
	(0.025)				(0.00)		
$Exp^1(si,sp)$	0.921***	$Exp^1(oi,sp)$	0.882***	$Exp^1(si,sp)$	0.016***	$Exp^1(oi,sp)$	0.016***
	(0.114)		(0.182)		(0.002)		(0.003)
$Exp^2(si,sp)$	1.308***	$Exp^2(oi,sp)$	1.03***	$Exp^2(si,sp)$	0.022***	$Exp^2(oi,sp)$	0.018***
	(0.139)		(0.217)		(0.002)		(0.003)
$Exp^3(si,sp)$	1.356***	$Exp^3(oi,sp)$	1.59***	$Exp^3(si,sp)$	0.022***	$Exp^3(oi,sp)$	0.025***
	(0.152)		(0.301)		(0.002)		(0.004)
$Exp^4(si,sp)$	1.361***	$Exp^4(oi,sp)$	1.517***	$Exp^4(si,sp)$	0.022***	$Exp^4(oi,sp)$	0.024***
	(0.158)		(0.371)		(0.002)		(0.004)
$Exp^{more}(si,sp)$	1.998***	$Exp^{more}(oi,sp)$	1.039***	$Exp^{more}(si,sp)$	0.056***	$Exp^{more}(oi,sp)$	0.02***
	(0.099)		(0.164)		(0.004)		(0.003)
$Exp^1(si,op)$	-0.399	$Exp^1(oi,op)$	-0.991***	$Exp^1(si,op)$	-0.009	$Exp^1(oi,op)$	-0.023***
	(0.261)		(0.149)		(0.006)		(0.005)
$Exp^2(si,op)$	-0.936***	$Exp^2(oi,op)$	-0.81***	$Exp^2(si,op)$	-0.022***	$Exp^2(oi,op)$	-0.019**
	(0.275)		(0.301)		(0.008)		(0.008)
$Exp^3(si,op)$	-0.484	$Exp^3(oi,op)$	-0.311	$Exp^3(si,op)$	-0.011	$Exp^3(oi,op)$	-0.007
	(0.306)		(0.481)		(0.008)		(0.01)
$Exp^4(si,op)$	-1.134***	$Exp^4(oi,op)$	-1.559***	$Exp^4(si,op)$	-0.028***	$Exp^4(oi,op)$	-0.041***
	(0.298)		(0.391)		(0.009)		(0.014)
$Exp^{more}(si,op)$	-0.923***	$Exp^{more}(oi,op)$	-1.922***	$Exp^{more}(si,op)$	-0.017***	$Exp^{more}(oi,op)$	-0.037***
	(0.185)		(0.188)		(0.003)		(0.004)
Observations	54,188				54,188		
Fixed Effects:							
Exporter-Importer	✓				✓		
Product	✓				✓		

Importer-exporter clustered standard errors in parentheses. *sp*=same products, *op*=other goods, *si*=same importer, *oi*=other importers. *** p<0.01, ** p<0.05, * p<0.1.

Still, the IV results stop being significant although remain close in magnitude to the baseline. We attribute this result to a poor-performing first stage. When we include year fixed effects in our estimation these leave very little variation from the exchange rate we use as an instrument.

In Table A.17 we present our baseline using different sets of clusters for the standard errors. Even in the most constraining cases, our estimates remain significant and don't deviate largely from the baseline estimation.

A.9 Results without Trimming for Transaction Size

In Table A.18 we present the results without removing outliers for size of the transactions focusing on the experience of exporters with the same importer-product combination. The results change very little compared to our baseline.

Table A.14: Probit with Fixed Effects: Peru

Probit				Average marginal effect			
$Savings$		0.148***				0.006***	
		(0.011)				(0.00)	
Age		0.099				0.004	
		(0.383)				(0.014)	
$ln(er_o)$		-0.038***				-0.001***	
		(0.013)				(0.00)	
$Exp^1(si,sp)$	0.532***	$Exp^1(oi,sp)$	0.39***	$Exp^1(si,sp)$	0.017***	$Exp^1(oi,sp)$	0.013***
	(0.062)		(0.094)		(0.002)		(0.003)
$Exp^2(si,sp)$	0.727***	$Exp^2(oi,sp)$	0.447***	$Exp^2(si,sp)$	0.023***	$Exp^2(oi,sp)$	0.015***
	(0.075)		(0.108)		(0.002)		(0.003)
$Exp^3(si,sp)$	0.755***	$Exp^3(oi,sp)$	0.669***	$Exp^3(si,sp)$	0.023***	$Exp^3(oi,sp)$	0.021***
	(0.081)		(0.153)		(0.002)		(0.004)
$Exp^4(si,sp)$	0.775***	$Exp^4(oi,sp)$	0.749***	$Exp^4(si,sp)$	0.024***	$Exp^4(oi,sp)$	0.023***
	(0.085)		(0.187)		(0.002)		(0.004)
$Exp^{more}(si,sp)$	1.109***	$Exp^{more}(oi,sp)$	0.443***	$Exp^{more}(si,sp)$	0.062***	$Exp^{more}(oi,sp)$	0.016***
	(0.052)		(0.082)		(0.004)		(0.003)
$Exp^1(si,op)$	-0.208	$Exp^1(oi,op)$	-0.544***	$Exp^1(si,op)$	-0.009	$Exp^1(oi,op)$	-0.025***
	(0.137)		(0.077)		(0.006)		(0.005)
$Exp^2(si,op)$	-0.528***	$Exp^2(oi,op)$	-0.429***	$Exp^2(si,op)$	-0.024***	$Exp^2(oi,op)$	-0.019**
	(0.147)		(0.157)		(0.009)		(0.009)
$Exp^3(si,op)$	-0.278*	$Exp^3(oi,op)$	-0.144	$Exp^3(si,op)$	-0.012	$Exp^3(oi,op)$	-0.006
	(0.163)		(0.261)		(0.008)		(0.011)
$Exp^4(si,op)$	-0.659***	$Exp^4(oi,op)$	-0.883***	$Exp^4(si,op)$	-0.032***	$Exp^4(oi,op)$	-0.046***
	(0.157)		(0.186)		(0.01)		(0.015)
$Exp^{more}(si,op)$	-0.547***	$Exp^{more}(oi,op)$	-0.984***	$Exp^{more}(si,op)$	-0.019***	$Exp^{more}(oi,op)$	-0.036***
	(0.099)		(0.099)		(0.003)		(0.004)
Observations		54,188				54,188	
Fixed Effects:							
Exporter-Importer		✓				✓	
Product		✓				✓	

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. *** p<0.01, ** p<0.05, * p<0.1.

Table A.15: Additional FE OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Peru				Argentina		
$Exp^1(si,sp)$	0.024***	0.025***	0.024***	0.014***	0.052***	0.054***	0.049***	0.019
	(0.004)	(0.004)	(0.004)	(0.004)	(0.015)	(0.016)	(0.015)	(0.015)
$Exp^2(si,sp)$	0.030***	0.030***	0.030***	0.018***	0.095***	0.095***	0.092***	0.059***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.019)	(0.020)	(0.019)	(0.020)
$Exp^3(si,sp)$	0.033***	0.033***	0.033***	0.017***	0.117***	0.118***	0.113***	0.080***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.023)	(0.024)	(0.023)	(0.025)
$Exp^4(si,sp)$	0.036***	0.036***	0.036***	0.020***	0.118***	0.118***	0.112***	0.086***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.027)	(0.028)	(0.025)	(0.029)
$Exp^{more}(si,sp)$	0.031***	0.031***	0.031***	0.017***	0.135***	0.134***	0.127***	0.129***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.035)	(0.036)	(0.035)	(0.040)
Observations	54,188	54,543	54,188	52,876	15,689	15,842	15,689	14,937
Fixed Effects:								
Exporter-Importer	✓		✓	✓	✓		✓	✓
Product	✓	✓	✓		✓	✓	✓	
Exporter		✓				✓		
Importer		✓				✓		
Year			✓				✓	
Product-Year				✓				✓

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. Controls: Savings, Age, and $ln(er_o)$. *** p<0.01, ** p<0.05, * p<0.1.

Table A.16: Additional FE IV

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Peru				Argentina		
$Exp^1(si, sp)$	0.020***	0.021***	0.022	0.022	0.063***	0.064***	0.091	0.092
	(0.006)	(0.007)	(0.017)	(0.018)	(0.019)	(0.019)	(0.081)	(0.186)
$Exp^2(si, sp)$	0.025***	0.025***	0.028	0.030	0.111***	0.110***	0.149	0.125
	(0.008)	(0.008)	(0.021)	(0.024)	(0.024)	(0.025)	(0.110)	(0.166)
$Exp^3(si, sp)$	0.028***	0.027***	0.031	0.030	0.127***	0.127***	0.150*	0.111
	(0.009)	(0.009)	(0.024)	(0.027)	(0.025)	(0.025)	(0.077)	(0.088)
$Exp^4(si, sp)$	0.029***	0.029***	0.033	0.035	0.132***	0.132***	0.165	0.144
	(0.010)	(0.010)	(0.029)	(0.034)	(0.029)	(0.030)	(0.108)	(0.155)
$Exp^{more}(si, sp)$	0.022*	0.021	0.027	0.037	0.154***	0.152***	0.189	0.213
	(0.013)	(0.014)	(0.037)	(0.045)	(0.038)	(0.039)	(0.129)	(0.217)
Observations	54,188	54,543	54,188	52,876	15,689	15,842	15,689	14,937
Fixed Effects:								
Exporter-Importer	✓		✓	✓	✓		✓	✓
Product	✓	✓	✓		✓	✓	✓	
Exporter		✓				✓		
Importer		✓				✓		
Year			✓				✓	
Product-Year				✓				✓
First stage								
2 *month lagged* $ln(er_{CO})$	-0.689***	-0.668***	-0.190	-0.161	-0.603***	-0.596***	0.112	0.077
	(0.166)	(0.167)	(0.212)	(0.232)	(0.151)	(0.157)	(0.175)	(0.188)
Kleibergen-Paap F	17.16	15.93	0.805	0.478	16.05	14.45	0.405	0.169

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. Controls: Savings, Age, and $ln(er_o)$. *** p<0.01, ** p<0.05, * p<0.1.

A.10 Time Between Transactions

We don't think that treating firms not present in the first year of data as new is too generous. We could be more strict about defining new firms but this would be at the cost of having less data. How much would we gain by being more strict? This is what we aim to show below. We look at all the firms present in the last year of the data, including those present in 2000 (the first year of our sample period). For the firms in the last year of the data, we can observe their entire history of transactions from 2000 so that we are able to accurately label firms that are new in the last year of the data. Assuming we are in steady state, we can do more. In fact, we can get an estimate of misclassification for alternative cut-off definitions for new firms.

Figure A.2 depicts the percentage of firms that were present in the last year of the data and that had a transaction within the number of months depicted on the x-axis. About 72% of the firms in Argentina (and 70% in Peru) that were present in the last year of the data had a transaction in the last 10 years (120 months). Thus, if we think not having had a transaction in the last 10 years makes you a new firm, then the remaining 28% (30%) of the firms in Argentina (Peru) were new.

This also gives us some idea of the extent of misclassification of firms as new. Some firms are truly new like the 28% we identify above for Argentina. Others may be misclassified as

Table A.17: Additional Clusters IV

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Peru					Argentina		
$Exp^1(si, sp)$	0.020***	0.020***	0.020***	0.020***	0.020***	0.063***	0.063***	0.063***	0.063***	0.063***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.019)	(0.018)	(0.019)	(0.020)	(0.018)
$Exp^2(si, sp)$	0.025***	0.025***	0.025***	0.025***	0.025***	0.111***	0.111***	0.111***	0.111***	0.111***
	(0.008)	(0.007)	(0.008)	(0.006)	(0.006)	(0.024)	(0.024)	(0.025)	(0.027)	(0.022)
$Exp^3(si, sp)$	0.028***	0.028***	0.028***	0.028***	0.028***	0.127***	0.127***	0.127***	0.127***	0.127***
	(0.009)	(0.008)	(0.009)	(0.007)	(0.007)	(0.025)	(0.025)	(0.025)	(0.027)	(0.023)
$Exp^4(si, sp)$	0.029***	0.029***	0.029***	0.029***	0.029***	0.132***	0.132***	0.132***	0.132***	0.132***
	(0.010)	(0.009)	(0.010)	(0.008)	(0.007)	(0.029)	(0.030)	(0.029)	(0.033)	(0.027)
$Exp^{more}(si, sp)$	0.022*	0.022**	0.022	0.022***	0.022**	0.154***	0.154***	0.154***	0.154***	0.154***
	(0.013)	(0.011)	(0.014)	(0.009)	(0.009)	(0.038)	(0.038)	(0.038)	(0.042)	(0.034)
Observations	54,188	54,188	54,188	54,188	54,188	15,689	15,689	15,689	15,689	15,689
Fixed Effects:										
Exporter-Importer	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clusters:										
Exporter		✓					✓			
Importer			✓					✓		
Product				✓					✓	
Exporter-Importer	✓					✓				
Exporter-Importer-Product					✓					✓
First stage										
2 *month lagged* $ln(er_{CO})$	-0.689***	-0.689***	-0.689***	-0.689***	-0.689***	-0.603***	-0.603***	-0.603***	-0.603***	-0.603***
	(0.166)	(0.167)	(0.190)	(0.137)	(0.127)	(0.151)	(0.145)	(0.153)	(0.136)	(0.148)
Kleibergen-Paap F	17.16	17.14	13.19	25.44	29.25	16.05	17.41	15.65	19.59	16.52

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. Controls: Savings, Age, and $ln(er_o)$. *** p<0.01, ** p<0.05, * p<0.1.

Table A.18: Not Trimming top 1% in Terms of Transaction Size

	Peru	Argentina
Savings	0.033	-0.084
	(0.031)	(0.088)
$Exp^1(si, sp)$	0.021***	0.062***
	(0.006)	(0.020)
$Exp^2(si, sp)$	0.025***	0.110***
	(0.007)	(0.026)
$Exp^3(si, sp)$	0.028***	0.127***
	(0.009)	(0.025)
$Exp^4(si, sp)$	0.029***	0.132***
	(0.009)	(0.029)
$Exp^{more}(si, sp)$	0.023*	0.153***
	(0.012)	(0.038)
Observations	54,857	15,964
Fixed Effects:		
Exporter-Importer	✓	✓
Product	✓	✓
First stage		
2 *month lagged* $ln(er_{CO})$	-0.717***	-0.551***
	(0.174)	(0.151)
Kleibergen-Paap F	17.02	13.28

Importer-exporter clustered standard errors in parentheses. sp=same products, op=other goods, si=same importer, oi=other importers. Controls: Savings, Age, and $ln(er_o)$.*** p<0.01, ** p<0.05, * p<0.1.

new, and this is especially so when we have little previous data. After 5 years in Figure A.2 above, the cumulative density is almost flat for both countries. This means it is very unlikely that a firm would be misclassified as new had we dropped firms in the first five years of data in order to avoid mis-classifying firms as new. But we would be losing a lot of data. We choose to only drop firms in the first year of data to not lose too much data. How much misclassification would occur in this case if we were in a steady state(so that the data for firms present in the first year of data looks like that in the last year of data)? Roughly 56% of the firms in the last year of data for Argentina have shown up in 12 months. Thus, 72%-56%=16% of the firms

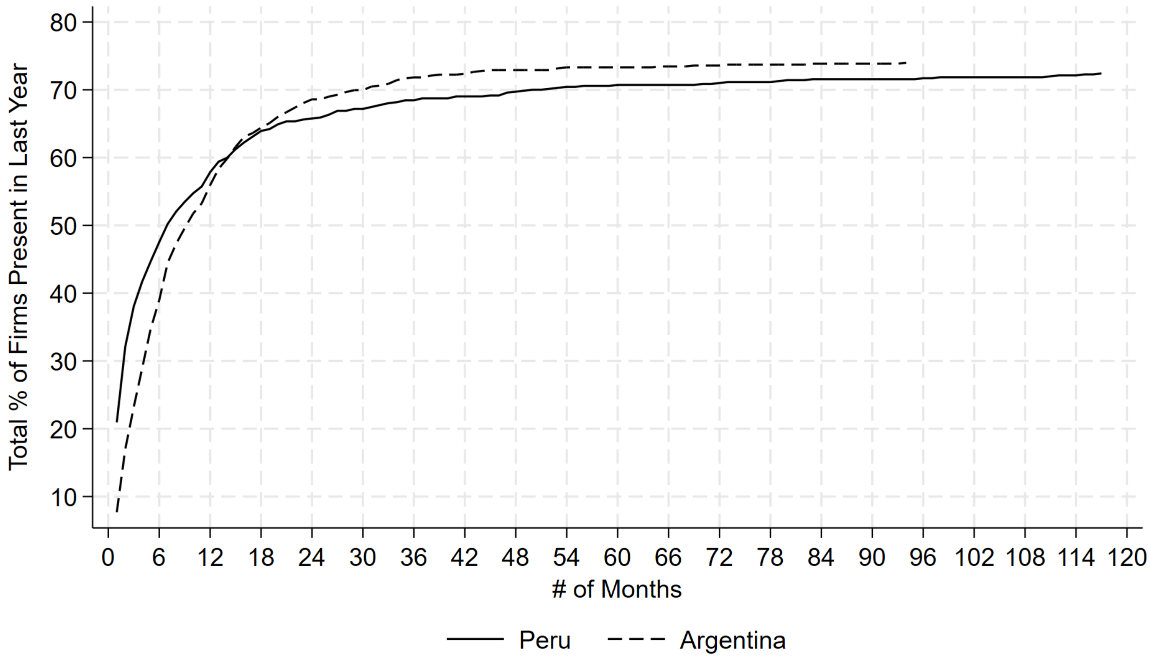


Figure A.2: Time Since Last Transaction for Firms Present in the Last Year of Data

present in the last year of data for Argentina would be misclassified as new in the first month of January 2001. That is, the difference in the maximum of the CDF, and the CDF at t months gives the percentage of firms misclassified in t months. This is depicted in Figure A.3. The average over the data we use would be the average misclassification over months 13 onwards. Since the misclassification falls fast as t rises, this average is low. It is 2.32% for Argentina and 2.66% for Peru. Had we chosen to be more strict and defined firms as new if they had not shown up in the previous two years, the average misclassification percentage would have been 1.14% in Argentina and 1.88% in Peru. The remainder of the firms would be new firms. Of these many would be present for only a single year.

A.11 Correlation of Exchange Rates (Normalized to Have Mean 0 and Variance 1)

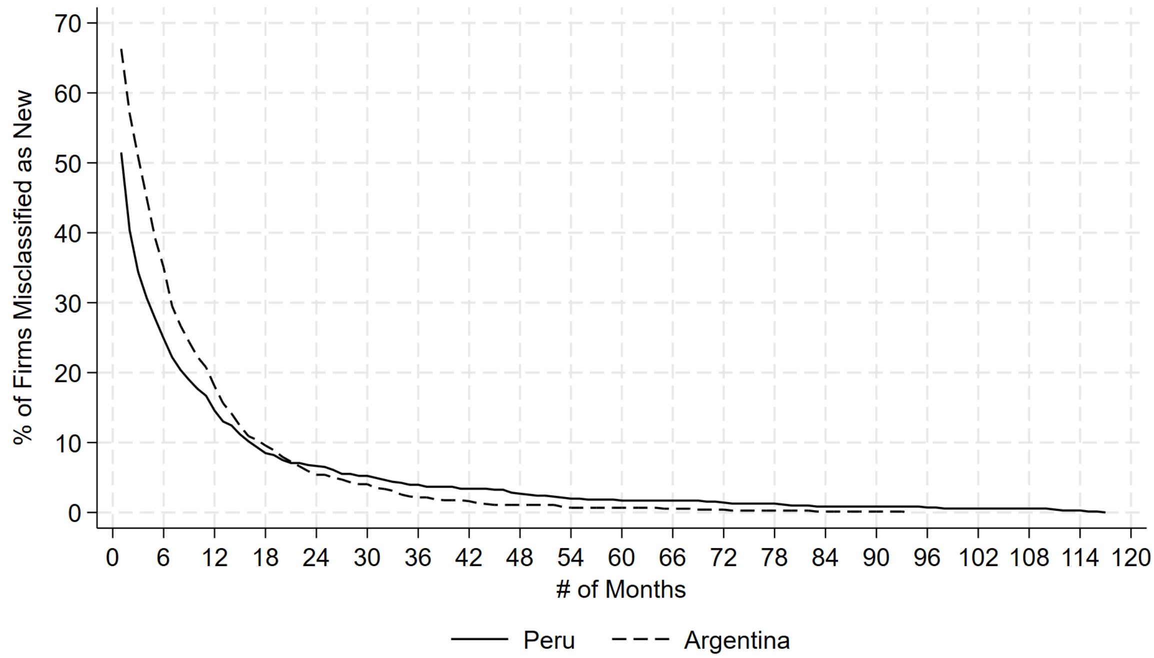


Figure A.3: Misclassification

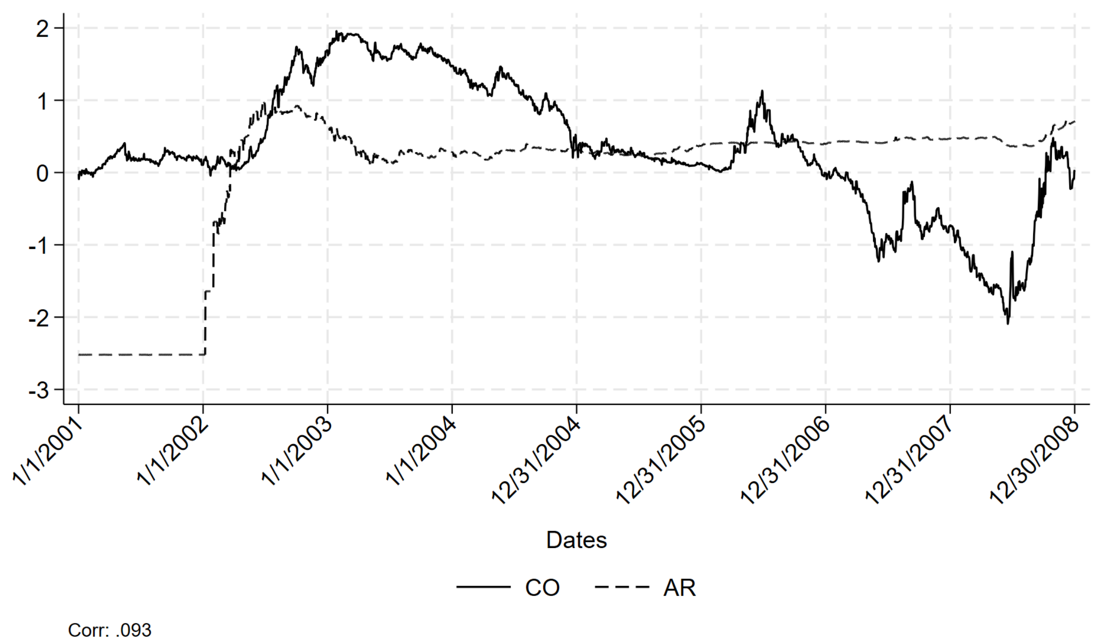


Figure A.4: Normalized dollar exchange rates for Colombia and Argentina

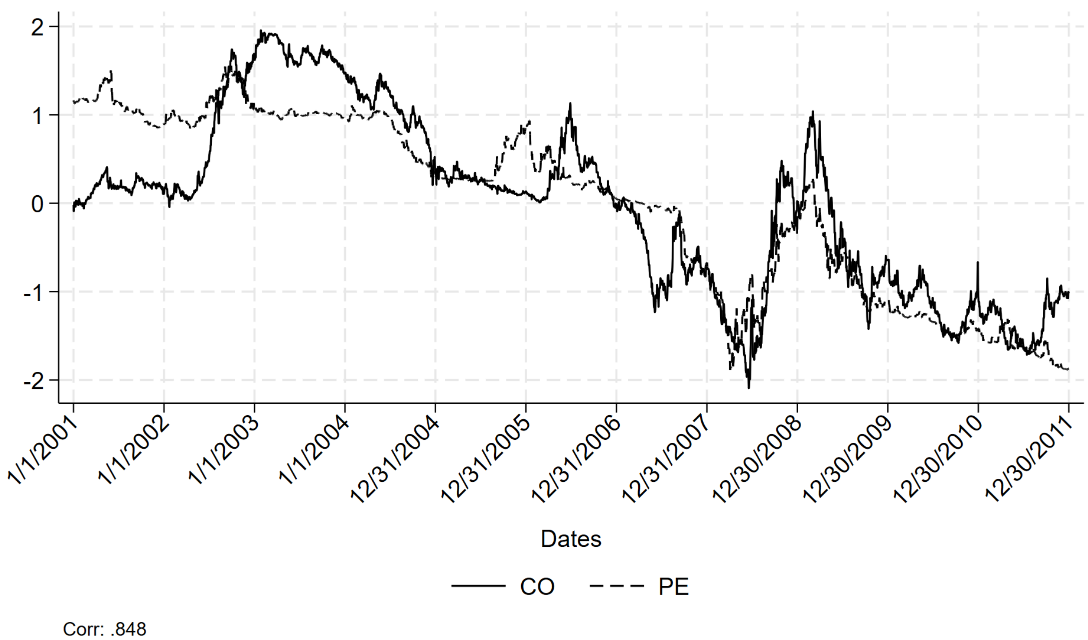


Figure A.5: Normalized dollar exchange rates for Colombia and Peru

Appendix B
Appendix of Chapter 2

B.1 Calculation

Suppose X follows a normal distribution with mean μ and variance σ^2. We are interested in

$$\int_{-\infty}^{a} e^x \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx. \tag{B.1}$$

Note that

$$\begin{aligned} e^x e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} &= e^{-\frac{1}{2}\left(\frac{x^2-2\left(\mu+\sigma^2\right)x+\mu^2}{\sigma^2}\right)} && \text{(B.2)} \\ &= e^{-\frac{1}{2}\left(\left(\frac{x-(\mu+\sigma^2)}{\sigma}\right)^2-2\mu-\sigma^2\right)} && \text{(B.3)} \\ &= e^{-\frac{1}{2}\left(\frac{x-(\mu+\sigma^2)}{\sigma}\right)^2} e^{\mu+\frac{\sigma^2}{2}} && \text{(B.4)} \end{aligned}$$

Thus,

$$\begin{aligned} \int_{-\infty}^{a} e^x \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx &= e^{\mu+\frac{\sigma^2}{2}} \int_{-\infty}^{a} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-(\mu+\sigma^2)}{\sigma}\right)^2} dx && \text{(B.5)} \\ &= e^{\mu+\frac{\sigma^2}{2}} \Phi\left(\frac{a-(\mu+\sigma^2)}{\sigma}\right) && \text{(B.6)} \end{aligned}$$

B.2 Simulation of Firms and Transactions

B.2.1 Steps to Simulate Poisson Arrival Time

Each event is independent and Poisson with some constant hazard rate. Suppose that the hazard rate is λ. Suppose an event happens at period T (random variable). The probability that the event happens before period t is

$$\begin{aligned} F(t) &= 1 - \Pr(T > t) && \text{(B.7)} \\ &= 1 - \Pr\left(N(t) = 0\right) && \text{(B.8)} \\ &= 1 - e^{-\lambda t}. && \text{(B.9)} \end{aligned}$$

We can then simulate inter-arrival times by using the inversion method.

1. Simulate a draw from a uniform distribution, $1 - p \sim p \sim U[0, 1]$.

2. We can derive a corresponding T from the inverse function

$$1 - p = 1 - e^{-\lambda T} \Leftrightarrow T = -\frac{\ln p}{\lambda}. \tag{B.10}$$

B.2.2 Steps to Simulate an Exporter and its Transactions

B.2.2.1 Productivity Trends

First, we simulate the macro trend, changes in x. Then, I simulate the trend for each exporter, changes in y. Define T_ℓ^h as the time interval between $\ell - 1$-th and ℓ-th events for $h = x, y$, where $\ell \in \mathcal{N}$. The actual time that ℓ-th event happens for h is

$$\bar{T}_\ell^h = \sum_{m=1}^{\ell} T_m^h. \tag{B.11}$$

Then, we can align the time of the events that happen in chronological order. For instance, for exporter e, we can have

$$\mathbf{T}_e = \left\{ \bar{T}_1^x, \bar{T}_1^y, \bar{T}_2^y, \bar{T}_3^y, \bar{T}_2^x, \ldots \right\}. \tag{B.12}$$

Note that our sample for Argentina is for 8 years (2001-2008). Most firms enter in later periods. Thus, We simulate events for 5 years (i.e., $\bar{T}_\ell^h < 5$).

B.2.2.2 Transactions (Search Intensity)

Since we endogenize the search intensity, we need to draw transaction events sequentially and check if each event happens before the others occur.

Let $h = b$ denote an event of transaction. Let $T_{e\ell}$ denote the period when firm e's ℓ-th event for $h = x, y$ occurs. Let $\tilde{T}_{e\ell}$ denote the period when the firm e's ℓ-th event for $h = x, y, b$ occurs. We simulate transaction events for each firm in the following steps.

1. Draw the time-interval for a transaction, T^b, given the initial (φ, x, y) and $n = 0$.
   (a) If $T^b < T_{e\ell}$, a firm makes a transaction.
      i. Simulate a draw $p \sim U[0, 1]$. If $p \leq \mathcal{P}_\varphi(x, y, 0)$, update $n = 1$ for the firm.
      ii. Check if the firm survives or not by equation (2.17). If the firm exits, stop the simulation for the firm.
      iii. If the firms survives, update $\tilde{T}_{e1} = T^b$.
   (b) Otherwise, update the firm's state following the change in x or y and $\tilde{T}_{e1} = T_{e1}$.
2. Draw $\bar{T}^b$, given the updated state (x, y, n).
   (a) Suppose the last event is ℓ-th one. If $T^b < \min_k \left\{T_{ek} | T_{ek} > \tilde{T}_{e\ell}\right\} - \tilde{T}_{e\ell}$, the firm makes a transaction.
      i. Simulate a draw $p \sim U[0, 1]$. If $p \leq \mathcal{P}_\varphi(x, y, n)$, update $n' = n + 1$ for the firm.
      ii. Check if the firm survives or not by equation (2.17). If the firm exits, stop the simulation for the firm.
      iii. If the firms survives, update $\tilde{T}_{e\ell+1} = \tilde{T}_{e\ell} + T^b$. Terminate the simulation and drop the simulated ℓ-th event if $\tilde{T}_{e\ell+1} > 5$.
   (b) Otherwise, update the firm's state following the change in x or y and $\tilde{T}_{e\ell+1} = \min_k \left\{T_{ek} | T_{ek} > \tilde{T}_{e\ell}\right\}$.
3. Repeat Step 2 until $T_{e\ell} > 5$.

B.2.3 Firm's Productivity Distribution

We assume that φ follows log-normal distribution with mean μ_φ and variance σ_φ. We assume that the mean of φ is one.[1] Thus, $\mu_\varphi + \frac{\sigma_\varphi^2}{2} = 0$. We assume $\sigma_\varphi = 1$. For out simulation we generate 500 firms for each bin of productivity.

[1] Note that we cannot identify μ_ϕ and $\bar{\pi}$ separately.

percentile	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90
phi	0.17	0.22	0.26	0.31	0.36	0.41	0.47	0.53	0.61	0.69	0.78	0.89	1.02	1.19	1.41	1.71	2.18

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Vita

Carlos Arturo Salamanca Malagon

Education

The Pennsylvania State University *2018 - 2024*
Ph.D. in Economics
Universidad del Rosario *2013-2015*
M.A. in Economics
Universidad del Rosario *2008-2012*
B.A. in Economics
Universidad del Rosario *2010-2012*
B.A. in Finance and International Trade

Fields of Specialization

Primary: International Trade, Development
Secondary: Applied Microeconomics, Regulation Economics, Econometrics