How the Breadth and Depth of Import Relationships Affect the Performance of Canadian Manufacturers*

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Abstract

This paper examines the relationship between a manufacturing firm's import behavior and its performance. The focus is on two aspects of imports, input variety and the dynamics of import relationships. Using identification conditions borrowed from the production function estimation literature, we show that firms importing more products from a larger set of suppliers tend to be larger, more productive, and more successful in export markets. Not only the number, but also the duration of supply relationships matter. Firms maintaining a higher share of continuous supply relationships also benefit from size and productivity effects. These results suggest that the breadth and depth of the import network are relevant factors for the performance of Canadian manufacturers, underscoring the importance of pursuing trade liberalizations with new partners and trade facilitation with established sources of suppliers.

Key words: Buyer-Supplier Relationships, Input Variety, Continuous Relationships.

JEL classification: F14.

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1 Introduction

The love of variety forms the basis for the gains from trade in all trade models based on the Armington (1969) assumption or on Dixit-Stiglitz monopolistic competition. It therefore underpins work based on Melitz (2003) and most computable general equilibrium evaluations of trade liberalizations. Most existing work focuses on the empirical relevance of the love of variety for final goods.[1] Since intermediate and capital goods constitute the bulk of trade,[2] more evidence is needed on the relevance of variety for firms. Ethier (1982) pioneered the extension of the love-of-variety idea to firms' production functions. He adopts a parallel version of the Dixit-Stiglitz utility function as an objective for the firm; in this framework, additional inputs increase output in proportion to the total number of products acquired for production. In this paper, our two proxies for *breadth* are the number of 10-digit products a manufacturing firm imports and the number of supplying firms per imported product. We estimate the elasticities of productivity with respect to both variables.

A complementary view on how import relationships shape firm performance comes from the management literature.[3] In particular, Uzzi (1996) applied Karl Polanyi's idea of *embeddedness* to production networks. He argues that "buyer-supplier networks operate in an embedded logic of exchange that promotes economic performance through inter-firm resource pooling, cooperation, and coordinated adaptation[...]" (Uzzi (1996), p. 675). Using data on New York-based apparel firms, he finds that a firm that systematically interacts with a network of suppliers enjoys better outcomes in terms of survival and productivity relative to firms that keep all their transactions at arm's length and do not engage in long-term relationships.[4] Inspired by Uzzi, we use the share of continuous suppliers over the total number of suppliers as our principal measure of relationship depth. It is expected to increase productivity and other performance measures.

Analogously to Kasahara & Rodrigue (2008), we adopt the control function approach of Levinsohn & Petrin (2003) to account for unobserved productivity shocks at the firm level, which may contemporaneously affect sourcing decisions. We further assume that importing decisions are dictated by the presence of fixed costs that are heterogeneous across firms and not perfectly correlated with productivity, so that the effect of importing decisions can be identified. This assumption is grounded in the finding of Armenter & Koren (2015) that

[1] The groundbreaking work by Broda & Weinstein, 2006 has been the first to structurally estimate the impact of increased variety for welfare. For a recent literature review, see Feenstra (2010).

[2] Miroudot et al. (2009) document that trade in intermediates and capital goods accounted for about 70% of the total Canadian imports in 2006.

[3] We interchangeably refer to interactions between buyers and suppliers as relationships; our use of the word "relationship", however, does not imply the existence of a relational contract.

[4] Uzzi (1997) and Uzzi (1999) extend these ideas.

more than one dimension of heterogeneity is needed to fit firm-level trade data, but also on the realistic view that a firm is subject to cost shocks that affect their ability to acquire new suppliers and maintain established ones. Such shocks to economic, political and geographical conditions determine which suppliers the firm meets or which go out of business, but also whether suppliers are capacity constrained because of commitments to other buyers. The recent U.S. tariffs on Chinese goods provide a good example of exogenous shocks that could affect the variability in relationship duration for Canadian firms. The increase in U.S. import tariffs on intermediate goods may force some U.S. suppliers to drop some products or exit. Canadian firms that are not forced to reorganize their supply chain will maintain longer relationships. Similarly, the Chinese retaliatory tariffs on U.S. exports may force some U.S. suppliers to look for new opportunities in other foreign markets like Canada. Within the control function framework, we discuss the alternative views that sourcing decisions are static, i.e. determined flexibly every period, or dynamic, i.e. stocks which can be modified every period subject to adjustment costs and provide the corresponding parameter estimates.

Our results show that the number of imported products and the number of suppliers per product increase firm size with elasticities of 0.15 and 0.12, respectively. The breadth effects drop to 0.03 and 0.02 after controlling for inputs and including a control function to account for unobserved productivity. We also quantitatively explore how important continuous relationships are to firm performance. We document that older relationships are more valuable and increase firm size and productivity. A firm that went from using all new suppliers to retaining all the prior year suppliers could increase its productivity by up to 2.4%. The importance of ongoing relationships is also reflected in our analysis of the size and value of transactions between an importing firm and its long-term partners: both the quantity imported and the associated unit value are larger. However, after controlling for inputs, the ongoing use of the same suppliers does not have any statistically significant effects on performance in foreign markets. The *number* of suppliers does have strong positive relationship with exports.

This paper contributes to the large empirical literature documenting productivity differences across firms differing in their import choices. Data from the United States, Belgium, Italy, Hungary, Colombia, and Chile reveal that importers are bigger in terms of employment, shipments, value added, and TFP if compared with non-importing firms.[5] In fact, firm heterogeneity in importing behavior has important implications for the measurement of the

[5]See Bernard et al. (2007) for the United States; Halpern et al. (2015) for Hungary; Muûls & Pisu (2009) for Belgium; Castellani et al. (2010) for Italy; Kugler & Verhoogen (2009) for Colombia; Kasahara & Rodrigue (2008) and Kasahara & Lapham (2013) for Chile. Episodes of trade liberalizations provide additional evidence on the productivity gains from importing; see, for example, Amiti & Konings (2007), Goldberg et al. (2009), and Topalova & Khandelwal (2011).

gains from trade, especially when large firms import proportionally more of their inputs.[6]

Our paper also relates to recent work that has emphasized the two-sided nature of trade relationships. Several contributions have analyzed the buyer-supplier margin using export and import transaction data. Bernard et al. (2018) and Carballo et al. (2018) describe the behaviour of Norwegian and South American (Costa Rica, Uruguay and Peru) exporters. More recently, other contributions have focused on the formation of buyer-supplier relationships. Eaton et al. (2015) calibrate a search-and-matching model to match the trade patterns between U.S. buyers and Colombian exporters. Monarch (2014) quantifies the magnitude of frictions between U.S. buyers and Chinese suppliers in finding new partners. Kamal & Sundaram (2016) identify the existence of importer-specific spillovers in the decision of Bangladeshi manufacturers to sell to U.S. importers. Dragusanu (2014) analyzes the matching between buyers and suppliers in a model of sequential production.

A closely related contribution is the paper by Lu et al. (2016), who build a model to analyze the switching behaviour of Colombian importers. Consistent with our findings, they document that Colombian firms importing more products from a larger set of suppliers tend to be larger. While their approach combines productivity and scale effects, our contribution, instead, tries to identify the productivity effects of different dimensions of importing using the control function approach.

The question of the importance of supplier networks for productivity is also the focus in a paper by Bernard et al. (2019), where the authors find a positive effect on productivity and on the number of domestic supplier connections after the opening of high-speed train lines in Japan. Our elasticity estimates, however, are not comparable to theirs because they focus on the reduced form effects in a difference-in-difference strategy; in fact, their identification relies on differences in performance between input intensive firms and labor-intensive firms located close to a new train station relative to firms in locations without a new station, before and after the high-speed train expansion. Our elasticities, instead, are informative of the productivity effects associated with an exogenous change in the breadth and depth variables.

The rest of the paper is organized as follows. We describe the data in section 2; we analyze the main features of the data in subsection 2.1. We present our empirical strategy in section 3. The results are shown in section 4. Section 5 concludes.

[6]See Blaum et al. (2018) and Ramanarayanan (2020).

2 Data

The data for our project come from three Canadian sources: the Import Registry, the Annual Survey of Manufactures (ASM)-T2LEAP, and the Export Registry.

The import registry collects transaction data using Form B3 from the Canadian Border Service Agency. Canadian importers are required to fill out information on the vendor's name and address, the country of export, the product (HS10 code), the imported value and quantity. Vendors' identifiers were created for each supplier from the vendor's name and address.[7] Transaction records with consistent suppliers' identifiers are available from August 2002 to June 2008.[8]

The raw data identifiers are the transaction number, the line number (a particular item in a transaction), and the date (month-year).[9] We aggregate the data across transactions to the firm-supplier-HS10-country of origin-year level. The initial dataset contains about 5.5 million observations (corresponding to the firm-supplier-HS10-origin-year combination).

In order to construct firm-level measures of performance, we merge the import customs with firm-level information drawn from the Annual Survey of Manufactures (ASM). The ASM is a survey covering the universe of manufacturing establishments. It includes data on shipments, industry classification (5-digit NAICS codes), employment, salaries and wages, cost of materials, and expenditure on electricity. We enrich the ASM dataset by adding information on assets and investment extracted from the T2-LEAP database. T2-LEAP links two administrative data sources, the Longitudinal Employment Analysis Program (LEAP) and the Corporate Tax Statistical Universal File (T2SUF). Those two sources include all firms that either register a payroll deduction account with the Canada Revenue Agency (CRA) or file a T2 tax return with the CRA. The capital/investment data reported in T2-LEAP encompass manufacturing and non-manufacturing activities of each firm; we therefore allocate capital/investment to the individual manufacturing establishments using the share of the establishment revenues in manufacturing over the total firm sales.

We merge the import registry with firm-level characteristics and we collapse the information on import choices at the firm-year level. This creates our final dataset with 93,386 observations (here an observation is a firm-year combination).

[7]To ensure that minor differences in the way a firm's name is expressed on a transaction form do not generate "fake" vendors, Statistics Canada followed a set of procedures to harmonize the orthography of each vendor name. Appendix B describes their methodology based on correspondence with the analyst in charge.

[8]Import records at the product, origin, and firm level are available since 1993.

[9]Within a transaction, "line numbers" correspond to different entries. Entries could vary by HS codes, but, in some cases, they capture geographic variation, i.e., they identify the same HS code coming from different countries because of different tariff treatment.

Export-related information on Canadian firms comes from the Canadian Export Customs. The custom data include export records at firm, product (HS8 code), and destination level for the universe of exporters located in Canada.

2.1 Import Network Characteristics: Breadth and Depth

This subsection explores the main features of the Canadian import registry. We focus our discussion on cross-sectional and dynamic characteristics of the importers' distribution. Table 1 summarizes the main cross-sectional aggregates by sector in 2007. While we focus on firms in the manufacturing sectors, the industry classification requires that the majority of firm revenues comes from manufacturing activities; thus, we cannot exclude that those firms may include plants whose industry code is in wholesale or in other non-manufacturing sectors.[10]

Columns (1)–(2) describe the intensive import margin: column (1) shows the total import value for each sector, while column (2) reports the share of imports out of total manufacturing sales. Transportation Equipment, the sector that has experienced one of the longest histories of trade liberalization, records the largest value of imports and is also among the industries most dependent on foreign products. Columns (3)–(7) focus on the extensive import margin: they show the number of countries, products (HS10 codes), Canadian buyers, foreign suppliers and buyer-supplier relationships. Each sector imports a large number of products (from 9% of all HS10 codes in Leather to 46% in Machinery) from a large number of countries (the median sector imports from 81 countries). Looking across columns (5)–(7), we note that the number of relationships is mainly driven by the number of suppliers. This fact suggests that Canadian firms tend to adopt a multi-sourcing strategy, as micro-level statistics will confirm.

Table 2 takes a closer look at the importing behavior of firms, with a focus on 2007. The first two columns report the firm-level average import value and import share across sectors, roughly confirming the patterns shown in columns (1)–(2) of Table 1. Transportation equipment manufacturers continue to be among the top importers by average value and as a share of total revenues. Columns (3)–(5) focus on the extensive margin. Column (3) reports the median number of countries a firm imports from, column (4) the median number of products and column (5) the median number of suppliers per firm. The quasi-median firm sources its inputs from two countries and imports multiple products from a large set of suppliers.[11] This evidence confirms a strong multi-sourcing nature of the Canadian import

[10]A similar caveat applies to the firm-level statistics reported in table 2. In the empirical analysis, we rely on firm fixed effects to capture time-invariant differences in activity classifications across firms.

[11]Quasi-median are calculated as the average of 10/11 observations around the true median. This proce-

Table 1: Aggregate Statistics by 3-digit industry, 2007

Industry	(1) Imp. Value	(2) Imp. Share	(3) Countries	(4) Products	(5) Firms	(6) Suppliers	(7) Relations
Food	7.90	0.09	115	6067	1396	18684	29624
Bev. & Tob.	2.01	0.34	71	2422	145	3641	4619
Text. Mills	0.61	0.58	55	2332	197	3251	4197
Text. Prod	0.55	0.55	55	2717	301	3947	4760
Apparel	1.18	0.67	80	3326	723	10217	14549
Leather	0.13	0.62	48	1518	146	1801	2190
Wood	1.99	0.11	72	3750	1052	11462	16401
Paper	3.75	0.22	74	3580	383	8989	12997
Printing	0.78	0.18	54	3077	941	6971	9875
Petrol	18.22	0.19	57	2392	86	3153	3840
Chemical	18.82	0.57	104	7345	948	22158	33878
Plastics	7.21	0.43	83	5964	1218	19204	28477
Mineral	2.23	0.25	72	4307	713	8361	11598
Metals	11.85	0.33	90	3756	325	8839	11436
Met. Prod	5.54	0.31	89	6987	2980	28155	40804
Machinery	11.23	0.48	118	7760	2436	40088	61318
Computing	9.84	0.80	115	5309	1008	30605	47549
Electrical	4.13	0.65	89	4385	588	13630	17644
Tran. Eq.	74.75	0.63	123	7143	1029	40726	65539
Furniture	3.27	0.29	87	5377	1104	12704	17651
Miscel.	3.68	0.63	102	6542	1648	17713	21608
n/a	0.16	1.32	62	4316	2065	5883	6594
Total Mfg	189.83	0.62	194	16721	21432	233718	467148

Imp. Value: Total value of imports, in millions.
Imp. Share: Ratio of imports to total revenues.
Countries: Number of import origin countries.
Products: Number of imported products.
Firms: Number of domestic firms.
Suppliers: Number of foreign suppliers.
Relations: Number of unique firm-supplier interactions.
Notes: Aggregate import statistics by sector, 2007. The last row reports the totals for all manufacturing.

Table 2: Firm-level statistics on importing, 2007

Industry	(1) Import value	(2) Import share	(3) Sources /firm	(4) Products /firm	(5) Supps /firm	(6) Avg age
Food	366.57	0.09	2	12	9	1.4
Bev. & Tob.	296.02	0.13	2	12	10	1.2
Text. Mills	484.16	0.39	3	13	11	1.5
Text. Prod	212.10	0.33	2	13	10	1.6
Apparel	299.75	0.38	4	17	12	1.3
Leather	165.65	0.36	3	11	9	1.7
Wood	170.38	0.07	1	7	5	1.5
Paper	638.63	0.21	1	11	10	1.7
Printing	82.53	0.06	1	7	6	1.3
Petrol	5140.36	0.14	2	41	25	1.6
Chemical	518.09	0.24	2	20	14	1.5
Plastics	344.65	0.17	2	14	11	1.6
Mineral	189.25	0.13	2	12	8	1.7
Metals	800.08	0.20	2	14	14	1.6
Met. Prod	162.28	0.11	1	10	7	1.6
Machinery	257.82	0.18	2	15	11	1.6
Computing	384.29	0.33	3	23	16	1.4
Electrical	363.42	0.31	3	16	14	1.5
Tran. Eq.	547.98	0.24	2	25	17	1.7
Furniture	137.99	0.10	2	11	8	1.5
Miscel.	125.33	0.21	2	9	8	1.5
n/a	19.32	-	1	3	3	1.9

Import Value: average firm-level value of imports, in thousands of dollars.
Import share: firm-level average ratio of imports to total revenues.
Sources/firm: Quasi-median number of import origin countries per firm.
Products/firm: Quasi-median number of imported products per firm.
Suppliers/firm: Quasi-median number of foreign suppliers per firm.
Avg age: Average age of firm-supplier interactions.
Note: Quasi-median are means of 10–11 observations around the median.

relationships.[12]

The firm-level statistics in table 2 hide a large degree of heterogeneity across suppliers and products. Figure 1 offers more details on the distributions of products (top panel) and suppliers per product (bottom panel). We measure the number of suppliers per product as follows:

$$SPP_f = \frac{\sum_p n_{pf}}{m_f},$$

where n_{pf} is the number of suppliers for product p imported by firm f and m_f is the total number of products imported by firm f. Figure 1 highlights that the modal firm imports one product from one supplier; however, more than 50 percent of firms rely on more than one foreign supplier for at least a few products, suggesting that firms may be diversifying to hedge against supply shocks.

While all the characteristics we have highlighted so far–sources, products, and suppliers–are instrumental in identifying the love-of-variety effects on output, we now introduce a second set of variables that characterize the dynamic dimension of import relationships and that we will show affect firm performance. Last column of table 2 captures an aspect of the dynamics of import relationships, that is, the average age across supplier relationships for a given firm. Martin et al. (2017) suggests that the longer duration of buyer-supplier transactions might be explained by the *specificity* of the relationship, due to the cost of switching to new suppliers. In our data, we set "Age" equal to 0 if a firm starts importing from a particular supplier in a given year and has never imported from the same supplier before; the "Age" variable is equal to 1 if the relationship with the supplier existed in the previous year and so on. In the data we used to build table 2, the longest relationships are of age 5; however, since we do not observe firm-suppliers interactions before 2002, our relationship age distribution is top-coded at 5. Column (6) reveals that, out of the exiting relationships in 2007, the average age of relationships across firms is 1.5 years, where newly formed relationships are coded as zero years old.

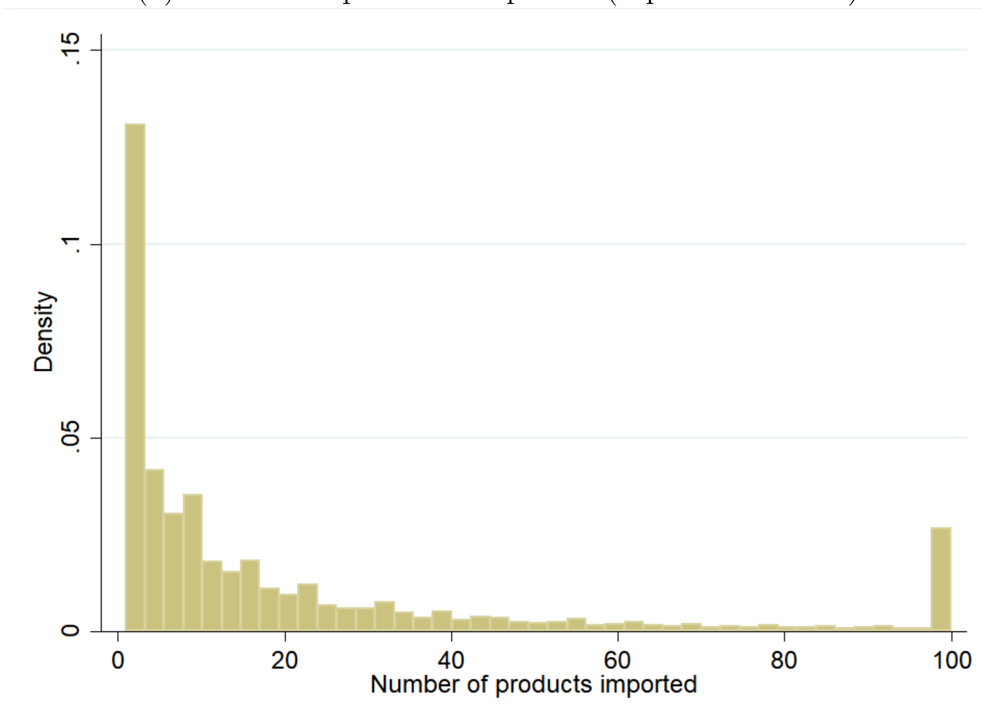
Figure 2 highlights that older relationships tend to be less common but are much more valuable. It plots the shares of the number of relationships and the import value they generate for 2007, where the oldest observed relationship is 5 years.[13] Relationships of five or more years account for only 10% of the total number of relationships but capture 40% of Canadian firms' total imports. Monarch & Schmidt-Eisenlohr (2016) document

dure is required to maintain data confidentiality.

[12]Blum et al. (2010) find that Chilean manufacturers import 11.9 HS8 products from 3.2 countries, roughly consistent with our findings.

[13]In the appendix, figure A1 extends our results to the partial year of 2008. The results are robust across 2007 and 2008; 2007 is our preferred year as the Custom Registry data for 2008 are available only through June.

(a) Number of products imported (top coded at 100)



(b) Log suppliers per product imported

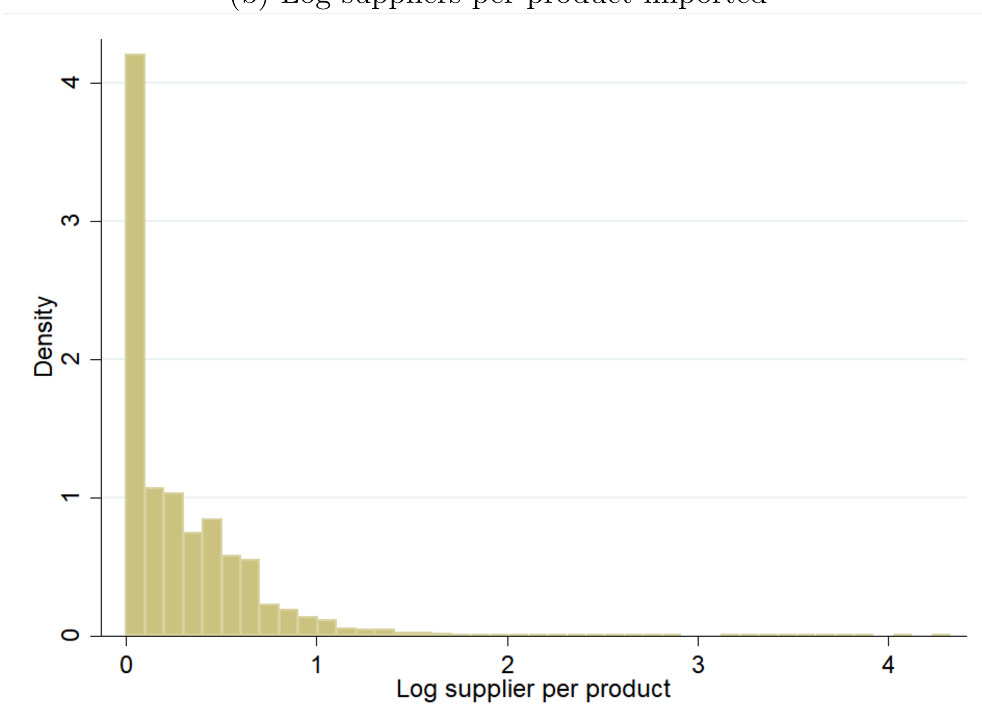


Figure 1: Modal firm imports one product from one supplier

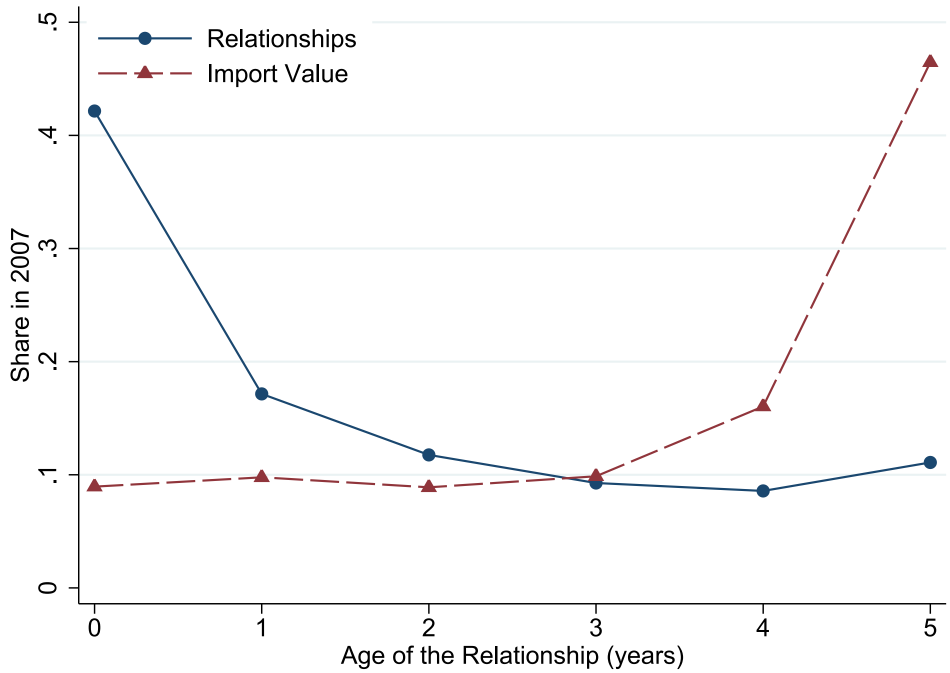


Figure 2: Older relations are less frequent, but more valuable

a similar finding for U.S. import relationships. The finding that older relationships are disproportionately valuable motivates the inclusion of measures of relationship persistence in the production function.

Table 3 looks further into the dynamic import margin. While we rely on the age distribution in our cross-sectional analysis in figures 2 and A1, extending such concept over time would be arduous due to changes in the composition of the different age groups over time. Thus, table 3 develops a time-series concept of import dynamics, classifying relationships by the last period of the interaction, a methodology we use later in the empirical analysis to construct a measure of the *depth* of import relationships. For example, gap_0 relationships denote "continuous" relationships, that is, those in which buyers and suppliers interacted also in the previous year; higher gaps indicate that the firm-supplier interaction last occurred at longer lags. We then identify the share of relationships and import value for each group. In each year, "continuous" relationships represent a large share of both all relationships and import value. Gap_1 relationships represent, instead, a much smaller share of all relationships and import value; relationships with longer lags account for an even smaller share.

Our analysis so far has highlighted the role of continuous interactions between buyers and suppliers and suggests possible implications for firm performance. However, the impact on firm performance may depend on the type of product exchanged, that is, whether firms

Table 3: Import Relationships over Time

A. Share of Total Relationships						
		Continuous	*Discontinuous*			
year	New	Gap_0	Gap_1	Gap_2	Gap_3	Gap_4
2002	1	0	0	0	0	0
2003	67.89	32.11	0	0	0	0
2004	59.79	36.83	3.39	0	0	0
2005	57.08	37.18	4.36	1.37	0	0
2006	49.86	43.10	4.68	1.76	0.59	0
2007	48.65	40.92	6.78	2.10	1.12	0.42
2008	35.66	55.70	4.92	2.07	0.93	0.72
B. Share of Import Value						
year	New	Gap_0	Gap_1	Gap_2	Gap_3	Gap_4
2002	1	0	0	0	0	0
2003	13.84	86.15	0	0	0	0
2004	17.14	79.90	2.95	0	0	0
2005	17.42	79.21	2.43	0.93	0	0
2006	12.63	84.87	1.60	0.61	0.26	0
2007	14.48	74.93	8.67	1.30	0.29	0.30
2008	11.49	84.33	2.93	0.83	0.20	0.20

New: newly formed relationships, never existed before.
Gap_0: existed at least in the previous year, i.e. the firm-supplier relationship last occurred at $t-1$.
Gap_1: firm-supplier link last occurred at least at $t-2$.
Gap_2: firm-supplier link last occurred at least at $t-3$.
Gap_3: firm-supplier link last occurred at least at $t-4$.
Gap_4: firm-supplier link last occurred at $t-5$.

continue to import the same product from the same suppliers. If, instead, a large amount of product churning happened even in continuous relationships, the effects on performance could be dampened. Table 4 decomposes the type of interactions with the suppliers by the type of product exchanged. In interactions with "continuous" suppliers, firms tend to buy the same product that they acquired in the previous year, while, in about a quarter of continuous transactions, firm purchase new products. Finally, exchanging discontinuous products is very unlikely in continuous relationships. Continuous products, an alternative proxy of the dynamic effects of importing, tend to have an important role also in new and discontinuous relations, even though interactions with new suppliers tend to be associated with the research for new inputs and discontinuous relationships represent a small share of our sample.

Table 4: Products and Relationships, 2007

		Relationships			
		New	Continuous	Discontinuous	Total
Products	New	17.2%	11.9%	2.4%	31.5%
	Continuous	12.8%	42.6%	3.5%	59.0%
	Discontinuous	3.0%	2.9%	3.5%	9.5%
	Total	33.0%	57.5%	9.5%	100%

Note: Cross-tabulation of type of product by type of buyer-supplier relationship, 2007. Total number of observations in 2007 is 1,201,279. Continuous relationships/products are defined as those in with interactions also in the previous year; discontinuous involve an interaction some time in the past but not the last year.

To summarize, in the rest of our empirical analysis, we will focus on two sets of variables:

- Breadth_{it}, to capture love-of-variety effects at the firm level. In this category we include two variables: the variety of imported inputs, $\ln \text{Products}_{it}$, and the ratio of suppliers to products, $\ln \text{Supp/Prod}$, which measures the number of different suppliers from whom firm i decides to import a given variety. The microfoundations for these variables come from the pioneering work of Ethier (1982). His assumption of constant elasticity of substitution between inputs implies that dividing a given expenditure on inputs over more varieties will increase productivity. An alternative microfoundation would build on the isomorphism between CES and discrete choice with a continuum. Suppose the manufacturing process involves a continuum of tasks, each of which combine labour and an intermediate input variety. The firm will choose the optimum input for each tasks. By inputting more types of inputs or importing from more suppliers, the firm achieves a closer match between each task and its ideal input variety. Under either mechanism, the manufacturing firm acts *as if* it were a consumer with love of variety. The difference is that rather than obtaining higher utility, the firm purchasing more varieties obtains higher output for a given amount of total labour and intermediate input purchases.

- Depth_{it}, to identify the dynamic aspects of the import network. We mainly use Previous Share_{it}, defined as the fraction of suppliers from which the buyer purchased in any of the previous years. As a robustness check, some specifications use the average age of the relationship in years.

How do our preferred firm measures relate to firm characteristics? Table 5 reports OLS regression results where the dependent variable is firm size, measured by ln Sales, and the independent variables are the number of products, the number of suppliers per product, the share of suppliers the firm interacted with some time in the past, and the average age of the firm's relationships, controlling for sector-year dummies in the spirit of Bernard et al. (2007) and Bernard et al. (2018).[14] Individual breadth and depth variables are positively correlated with firm size (columns (1)-(4)). If we include breadth and depth variables in a single equation (columns (5) and (6)), however, while the number of products and the number of suppliers per product are positively associated with ln Sales, our proxies of firm depth have negative and significant coefficients. The negative correlation likely captures the fact that larger firms tend to have more suppliers and the number of suppliers the firm interacted with in the past may vary less than the total number of suppliers. It may also reflect the fact that large firms can afford to "experiment" more in finding the right supplier, so they may have some short-lived relationships once the firm realizes a supplier is a bad match. The negative correlation of the depth variables with proxies of firm size also appears in tables A3 and A4 which report additional reduced-form results; however, after controlling for firm employment, depth variables tend to display positive and significant coefficients. It is, however, hard to give a deep interpretation to these correlations in the absence of a framework that allows to detect the causal effect of importing patterns and firm performance. This is our goal in the next section.

3 Estimation Framework

This section lays out an estimation framework that clearly identifies the conditions under which we can measure the effect of decisions related to the breadth and depth of import

[14] Additional reduced-form results are shown in tables A3 and A4

Table 5: Reduced-form regressions of firm size (log sales) on measures of breadth and depth of supply relationships

	(1)	(2)	(3)	(4)	(5)	(6)
ln Products	0.680^a				0.636^a	0.637^a
	(0.006)				(0.006)	(0.006)
ln Supp/Prod		1.561^a			0.418^a	0.418^a
		(0.040)			(0.021)	(0.021)
Previous Share			0.454^a		-0.081^a	
			(0.020)		(0.015)	
Avg Age				0.127^a		-0.056^a
				(0.010)		(0.007)
Observations	116,602	116,602	116,602	116,602	116,602	116,602
R^2	0.466	0.233	0.127	0.124	0.472	0.472

Note: OLS Regressions, 2002–2008. Regressions of log sales on log number of imported products (HS10 codes), log number of foreign suppliers per imported products, and share of suppliers from which the buyer purchased in a previous year. All specifications include sector-year fixed effects. Standard errors, clustered at the level of the firms, are in parentheses. Significance symbols: ^{c} $p < 0.05$, ^{b} $p < 0.01$, ^{a} $p < 0.001$

relationships. The primary challenge we face is to disentangle the effect of import decisions from that of underlying and unobserved firm productivity that are correlated with those decisions. The baseline results assume a timing similar to Kasahara & Rodrigue (2008), which in turn modifies the standard assumptions in Levinsohn & Petrin (2003) (hereafter referred to as LP). In the baseline estimation we consider import variables as a free input, and in section 4.2 we modify the estimation to consider them as a dynamic input, i.e. a stock variable that can be modified over time and may be subject to adjustment costs.[15]

Establishment i starts each period t with a stock of capital K_{it} and productivity draw ω_{it}. It subsequently chooses all variable inputs of production (labor, materials, electricity) and decides next period's capital $K_{i,t+1}$. At this point the firm also makes all decisions relating to importing, like the number of products to be imported and from how many suppliers, which we summarize here by d_{it} and discuss in detail later. The production function in logs is as follows:

$$y_{it} = \beta_0 + \beta_d d_{it} + \beta_l l_{it} + \beta_e e_{it} + \beta_m m_{it} + \beta_k k_{it} + \omega_{it} + \delta_{st} + \alpha_i + \varepsilon_{it} \tag{1}$$

where y_{it}, k_{it}, l_{it}, e_{it}, m_{it} are the logarithms of, respectively, the value of output, capital,

[15] We do not include the method proposed by Ackerberg et al. (2015) since it produced different results for different initial parameters in the "prodest, acf" optimization routine, an issue emphasized by Mollisi & Rovigatti (2018).

labor, electricity and material costs; δ_{st} is a sector-time dummy, α_i is the firm fixed effect and ε_{it} is an unexpected shock to firm output after all input and import decisions have been made.

The coefficient of interest throughout this paper is β_d, which measures the effect of importing decisions on output—holding the firm's fundamental productivity, $\omega_{it} + \alpha_i$, and all other inputs constant. We highlight that any time we talk about productivity, we in fact refer to *revenue productivity* (since firm-level prices are not available). More importantly, as in Melitz (2003), the CES demand assumption allows for interpreting $\omega_{it} + \alpha_i$ as either physical productivity or as a demand shifter (called appeal or quality in different contexts).

The main challenge that we face in identifying β_d is the endogeneity of importing decisions, which virtually any model would link to the unobserved productivity shock. To address this issue, we adopt the control function approach in LP. The specific assumption in LP is that material input choices are a function of capital, age of the firm, and productivity shock ω_{it}. We can therefore write:

$$m_{it} = f(k_{it}, \omega_{it}, \mathrm{Age}_{it}). \tag{2}$$

Notice that, in our framework, assumption (2) is more restrictive than in LP, because of the inclusion of firm fixed effects, α_i, in equation (1). We are imposing that materials depend on the innovation to firm productivity ω_{it} and we are effectively allowing the fixed effect to enter the material decision only through k_{it} so that we can preserve the standard monotonicity assumption that, conditional on k_{it} and Age_{it}, m_{it} is monotonic in ω_{it}. We can then invert the function to find ω_{it}:

$$\omega_{it} = f^{-1}(k_{it}, m_{it}, \mathrm{Age}_{it}). \tag{3}$$

We can then substitute equation (3) into (1) and collect all terms for k_{it}, Age_{it} and m_{it} into the function $\varphi(\cdot)$ to obtain

$$y_{it} = \beta_0 + \beta_d d_{it} + \beta_l l_{it} + \beta_e e_{it} + \varphi(k_{it}, m_{it}, \mathrm{Age}_{it}) + \delta_{st} + \alpha_i + \varepsilon_{it}, \tag{4}$$

where $\varphi()$ is a second-degree polynomial in capital, age and materials:

$$\begin{aligned} \varphi\left(k_{it}, m_{it}, \mathrm{Age}_{it}\right) = {} & \beta_1 k_{it} + \beta_2 m_{it} + \beta_3 \mathrm{Age}_{it} + \beta_4 k_{it}^2 + \beta_5 m_{it}^2 \\ & + \beta_6 \mathrm{Age}_{it}^2 + \beta_7 k_{it} m_{it} + \beta_8 m_{it} \mathrm{Age}_{it} + \beta_9 \mathrm{Age}_{it} k_{it}. \end{aligned} \tag{5}$$

All the β's are 3-digit industry specific parameters. The moment condition used in this LP first stage is

$$E\left[y_{it} - \beta_0 - \beta_d d_{it} - \beta_l l_{it} - \beta_e e_{it} - \varphi\left(k_{it}, m_{it}, \mathrm{Age}_{it}\right) - \delta_{st} - \alpha_i | I_{it}\right] = 0,$$

where I_{it} is the information set at the beginning of time t. We estimate the first stage by OLS. The OP/LP procedure entails a second stage to estimate the capital, material, and age coefficients, but we omit discussion of this portion of the estimation at this point, because we are not directly interested in those parameters. The second stage coefficients are industry-specific so we only report them in the industry-specific regressions shown in Appendix A. We modify this framework and the identification requirements when we consider d_{it} as dynamic in Section 4.2.

As our coefficient of interest is β_d, we now discuss under which conditions this coefficient can be identified. We rely on the discussion in Ackerberg et al. (2015) regarding the data generating process under which LP can identify the coefficient on labor. Because we are assuming that labor and imports are chosen similarly, their discussion applies and informs the timing we must impose on the choice of import variables. Ackerberg et al. (2015) emphasize a "functional dependence" problem in the OP/LP procedure whereby e.g. β_d could not be identified if d_{it} is chosen at the same time as m_{it}, even if d_{it} is determined by firm-varying costs of importing that are uncorrelated with the error term ε_{it}. The problem is that, if the costs are known when m_{it} is chosen, then there is no additional variation that can help identify β_d once we control for m_{it}.

To overcome this problem, we need to assume a specific type of data generating process. The intuition is that LP achieves identification if there is variation in d_{it} that is determined by shocks, for example in the availability or capacity of suppliers, which are not known when m_{it} is determined. The timing we require for the identification of β_d is that, after m_{it} is chosen conditional on ω_{it}, there are shocks to the network of available suppliers to i for any reason not known at time t. Examples of this sort include potential suppliers suddenly going out business or new firms becoming known to the firm, shocks to the cost of accessing certain suppliers due to health shocks to the marketing team. Because, differently from LP, we wish to estimate both β_d and β_l, we need to make assumptions about the timing of shocks to both costs of labor and imports.

To summarize, we assume that at the beginning of time t firm i observes ω_{it} and chooses m_{it}, then at $t+b$ an iid shock determines the cost of labor, which determines l_{it} and at $t+b'$, with $b' > b > 0$, an iid shock determines the cost of d_{it}. In principle we can allow the costs of d_{it} to be imperfectly correlated with productivity ω_{it} and orthogonal to ε_{it} (this would be similar for example to the assumption of hiring costs shocks imperfectly correlated with productivity in Helpman et al., 2016). What is important is a specific timing for those shocks: they must happen after m_{it} is chosen, but before productivity changes to ω_{it+1}. They thus cannot affect the choice of m_{it} and l_{it}. More formally, the identification condition is that, following Ackerberg et al. (2015):

$$E\left[[d_{it} - E[d_{it}|k_{it}, Age_{it}, \alpha_i, l_{it}, m_{it}]][d_{it} - E[d_{it}|k_{it}, Age_{it}, \alpha_i, l_{it}, m_{it}]]'\right] \text{ is positive definite.}$$

With the main components of d_{it}, a variable that so far has stood in for all importing decisions, corresponding to Breadth_{it} and Depth_{it} variables, which we described in section 2.1, our preferred specification (4) takes the following explicit form:

$$y_{it} = \beta_0 + \beta_{d1}\text{Breadth}_{it} + \beta_{d2}\text{Depth}_{it} + \text{Input Controls}_{ist} + \delta_{st} + \alpha_i + \varepsilon_{it} \tag{6}$$

where $\text{Input Controls}_{ist} \equiv \beta_{s,l}l_{it} + \beta_{s,e}e_{it} + \varphi_{s,t}(k_{it}, m_{it}, \text{Age}_{it})$. Notice that the coefficients in the $\text{Input Controls}_{ist}$ function are sector s specific to allow the production function to differ across sectors (3-digit NAICS codes in the regressions). Our coefficients of interest are (β_{d1}, β_{d2}). Ethier (1982) suggests that $\beta_1 > 0$ if the number of HS10 codes and the ratio of suppliers to products induce productivity gains from breaking up production into multiple stages. It should be noted at this point that, while we observe a detailed measure of import variety, we lack the equivalent level of detail for domestic varieties, a problem shared by other similar data sets. So, it could be the case that as a firm adds, for example, more foreign suppliers, it is contemporaneously cutting the same number of domestic suppliers. In that case the productivity boost could come from the fact that foreign varieties are of higher quality. Although we cannot completely rule out this interpretation, it should be noted that if these higher quality inputs bore a higher price, then this should appear in a higher total intermediate expenditure, which we control for. Put differently, it is not obvious why the number of suppliers, once we control for total intermediates expenditure, would affect revenue productivity through a quality channel. Finally, we expect $\beta_{d2} > 0$, that is the share of continuous suppliers to be positively correlated with firm productivity; a positive correlation emerges in Uzzi (1996), which argues that firms within a network benefit from continuing partnerships with their suppliers. We explore the source of productivity gains in continuous relationships in more details in section 4.5.

Finally, we would like to discuss in more detail some issues related to revenue productivity and multiproduct firms. A previously mentioned, in the absence of physical output data, we rely on the standard approach of identifying the production function coefficients in a revenue equation deflated by an industry price deflator. The (log of the) observed revenue, $r_{it} = p_{it} + y_{it}$, contains information on log firm-level prices, p_{it}. Controlling for the industry wide price index, p_{It} leads to the following estimating equation:

$$\begin{aligned}\tilde{r}_{it} &= r_{it} - p_{It} = y_{it} + p_{it} - p_{It} \\ &= \tilde{\beta}_0 + \tilde{\beta}_d d_{it} + \tilde{\beta}_l l_{it} + \tilde{\beta}_e e_{it} + \tilde{\beta}_m m_{it} + \tilde{\beta}_k k_{it} + \tilde{\beta}_a \text{Age}_{it} + \omega_{it} + \delta_{st} + \alpha_i + p_{it} - p_{It} + \varepsilon_{it}.\end{aligned}$$

This leaves among our regressors the firm-level price deviation from the average price index. De Loecker (2011) shows that when firms face a residual CES demand of the (logged) form $p_{it} = \frac{1}{\sigma}\left(y_{It} - y_{it}\right) + p_{It}$, the implied equation of the revenue production function is

$$\tilde{r}_{it} = p_{it} - p_{It} + y_{it} = \frac{\sigma - 1}{\sigma} y_{it} + \frac{1}{\sigma} y_{It}.$$

In our estimation, sector-time fixed effects absorb the variation in industry output, y_{It}. The reduced-form estimates, $\beta = \frac{\sigma-1}{\sigma}\tilde{\beta}$, however, combine the true production function coefficients, $\tilde{\beta}$, and the inverse of the constant mark-up. Finally, if the firm is multi-product, the revenue production function becomes $\tilde{r}_{it} = \frac{\sigma-1}{\sigma} y_{it} + \frac{1}{\sigma} y_{It} + \frac{\sigma-1}{\sigma}\tilde{\beta}_n n_{it}$, where n_{it} denotes the number of firm products. Because we do not observe the number of products sold by the firm, we cannot rule out that part of the revenue productivity effects of import variety is actually due to an increase in output variety. This is a mechanism that cannot be separately quantified with the available data.

4 Main Estimation Results

Table 6 shows the results for specification (6). Columns (1)–(4) report the coefficients of interest from a restricted version of this specification that excludes the input controls. The final column (5), the static LP, includes the input control function. The number of imported products and the number of suppliers per product increase firm size with elasticities of 0.11 and 0.14, respectively. The import breadth elasticities drop to 0.02 and 0.03 after controlling for inputs and including the control function. Importing from previous suppliers has also a positive effect on firm productivity; the coefficient on the share of continuous suppliers is positive across all specifications, but it is larger in columns (4) and (5), after controlling for the breadth measures.[16]

Theory suggests smaller coefficients in column (5) than column (4). The reason for this is that the last column estimates control for inputs and hence estimate productivity effects

[16]Table A5 reports our results with alternative proxy of import depth. Columns (1)–(2) rely on the share of continuous suppliers, while columns (3)–(4) show the coefficient estimates for the average age of buyer-supplier relationships. Our alternative definitions of import depth have roughly similar implications for firm productivity.

Table 6: Firm size and productivity regressions

	(1)	(2)	(3)	(4)	(5)
			ln Sales		
ln Products	0.110^a			0.108^a	0.021^a
	(0.004)			(0.004)	(0.002)
$\ln {}^{\text{Supp}}/_{\text{Prod}}$		0.137^a		0.118^a	0.027^a
		(0.009)		(0.009)	(0.005)
Previous Share			0.004	0.015^c	0.022^a
			(0.006)	(0.006)	(0.004)
Input Controls*	n	n	n	n	y
Firm Fixed Effects	y	y	y	y	y
Sector-Year FEs	y	y	y	y	y
Obs.	93,478	93,478	93,478	93,478	93,478
R^2	0.027	0.005	0.000	0.030	0.717

ln *Products*: log number of imported products (HS10).
$\ln \frac{\text{Supp}}{\text{Prod}}$: log number of foreign suppliers per imported products.
Previous Share: fraction of suppliers from which the buyer purchased in any previous year.
* Input Controls include employment, electricity, and quadratic in capital, materials and age. All controls are also interacted with 3-digit NAICS code dummies.
Notes: Firm FE regression, years 2002–2008. A sector represents a 3-digit NAICS code. Robust standard errors, clustered at the firm level, in parentheses. Significance thresholds are 0.1% (a), 1% (b), 5% (c). Column (5), the specification with input controls, is the static LP as shown in equation (6).

rather than sales effects. If an increase in a breadth variable raises a firm's productivity by β, then sales of that firm should rise by $(\eta-1)\beta$, where η is the local (absolute) price elasticity of demand. Thus, dividing a column (4) coefficient by its column (5) counterpart should give a rough estimate of $\eta-1$. In Table 6 those coefficients imply η estimates of $\{6.2, 5.2, 1.7\}$ for ln Products, ln Supp/Prod, and Previous Share. The corresponding average η of 4.4 lies in the range of recent estimates of the demand elasticity in the trade literature, such as the Antràs et al. (2017) estimate of 3.9 and the Feenstra & Romalis (2014) estimate of 6.1. We interpret this as evidence that our estimates pass a basic test for being reasonable.

Table 7: Summary Statistics for variables used in regressions

	Mean	Std Deviation
Explanatory variables		
ln Products (no. of HS10 imported)	2.22	1.45
ln Supp/Prod (suppliers per product)	0.30	0.36
Previous Share	0.36	0.33
Dependent variables		
ln Sales	15.03	1.54
Productivity (Levinsohn-Petrin residuals)	5.37	1.31
ln Exports	13.10	2.63
Export Status	0.64	0.48
ln Number of Destinations	0.62	0.93
ln Exported Products	1.38	1.04

How big are the breadth and depth effects we have estimated in Table 6? Perhaps the most natural thought experiment for the breadth effects is to double the number of products or suppliers per product. This would lead to a $2^{0.021}$ =1.5% increase in productivity for doubling products whereas doubling suppliers per product would yield a 1.9% productivity boost. These effects seem somewhat modest. Raising the share of previous suppliers from 0 to 100% would lead to a 2.2% productivity improvement. These hypothetical shocks may not be considered realistic. Another common way to quantify results is to express them in terms of standard deviations of the explanatory variables. A one-standard-deviation increase in ln Products correspond to an increase of 1.45, that is an increase of 4.2 products. Using the coefficient from Table 6, column (5), this implies that the dependent variable would increase by 0.03 units (dollars, in logs). To convert this result in a terms of standard deviation, we divide the effect by the standard deviation of the dependent variable, ln Sales; the summary statistics in table 2 implies that the overall effect of a one-standard-deviation increase in ln Products is an increase of 0.020 (or 2 percent) standard deviation of ln Sales. With a similar calculation, a one-standard-deviation increase in the number of suppliers, keeping the product margin constant, improves productivity by 0.6% of a sd. Continuous relationship are also associated with small productivity gains: a one-standard-deviation increase in *Previous Share* raises firm productivity by 0.5% of a sd.

The effects that we document are smaller than the firm-level productivity gains documented by Amiti & Konings (2007) and Topalova & Khandelwal (2011) (12% in the case of Indonesia, 4.8% for India for a 10% reduction in input tariffs); however, while the estimates in those papers reveal the aggregate effect on productivity, our estimates aim at identifying specific channels for the realization of those gains.

The productivity effects that we document are not exclusive to firms in related-party transactions. Related-party transactions, which represent about 13 percent of all transactions in our data, tend to be more stable: while the number of products is roughly similar between arm's length and related-party transactions, firms in related-party relationships tend to rely on a single supplier for each product and are more likely to have repeated interactions with their suppliers. However, we find that our baseline estimates for breadth and depth effects reported in table 6 are not significantly different from those in table A6, in which our main regressors are constructed only for arm's length transactions.

4.1 Heterogeneous Effects

We have so far assumed that the effect of having a wider network of suppliers has a homogeneous effect on all firms. We relax this restriction in this section and explore a number of dimensions along which these effects may differ. To begin with, we split the sample into two groups: industries with import share above the median and industries with import share below the median. The results are reported in table A7. As expected, we find that the effects tend to be stronger for more import intensive industries.

In addition, we investigate a dimension of heterogeneity that would follow from a "love of variety" interpretation of our results so far. In particular we interact our breadth and depth variables with a measure of substitutability, constructed as the firm-level share of imports classified as homogeneous products according to the Rauch (1999) classification. Table A8 reports our results. The interactions of our main variables with the share of homogeneous products tend to display a negative coefficient, confirming that importing very substitutable inputs tend to reduce the productivity gains; the effects, however, are mostly not significant.

4.2 Importing decisions as dynamic inputs

Our baseline estimation framework, which we refer to as static LP, relies on the assumption that the breadth and depth variables are chosen entirely after the productivity shocks occur.

As such, they are treated as *free* variables. It might, however, be equally reasonable to conjecture that a firm's network of international suppliers is determined at the beginning of period t and that only materials, labor and electricity are chosen after the productivity shock ω_{it}.

We therefore modify the estimation to allow for the alternative scenario in which d_{it} behaves similarly to capital k_{it} in that it follows a dynamic equation in terms of the lagged value and an investment term. Here we have current import relationships depth and breadth given by $d_{it} = h(d_{it-1}, n_{it-1})$, where n_{it-1} is "investment" in modifying features of the import network from the previous period, d_{it-1}. Adding or cutting suppliers would be one form of n_{it-1}. Under this scenario, which we call dynamic LP, d_{it} is predetermined at the start of period t, whereas materials, labor, and electricity, are chosen after d_{it}.

The dynamic LP approach estimates β_d in the second step of the LP methodology, similarly to how the coefficient β_k is estimated in the static LP method.[17] This methodology estimates the same production function in 1, under the assumption that:

$$m_{it} = f'(k_{it}, \omega_{it}, Age_{it}, d_{it}) \tag{7}$$

Inverting $f'(\cdot)$ allows us to control for the productivity shock ω_{it}. As a result, equation (4) is modified as follows:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_e e_{it} + \varphi'(d_{it}, k_{it}, m_{it}, Age_{it}) + \delta_{st} + \alpha_i + \varepsilon_{it} \tag{8}$$

where $\varphi'(d_{it}, k_{it}, m_{it}, Age_{it})$ is a second-order polynomial, similar to φ. In the first step of LP, we estimate β_l, β_e and $\varphi'(\cdot)$.

In the second stage of LP, β_k, β_m and β_d are estimated as follows. The productivity shock can be decomposed into its expected component, given the information set at time $t-1$, and a residual: $\omega_t = g(\omega_{t-1}) + \xi_{it}$ where g is, in our case, a second order polynomial and ξ_{it} is an iid innovation term, which by definition satisfies $E[\xi_{it}|I_{it-1}] = 0$. We can therefore rewrite (8) as a function of the estimated coefficients as follows:

$$\begin{aligned} y_{it} &= \beta_0 + \widehat{\beta}_l l_{it} + \widehat{\beta}_e e_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_d d_{it} \\ &+ g(\widehat{\varphi}'(d_{it-1}, k_{it-1}, m_{it-1}, Age_{it-1}) - \beta_0 - \beta_k k_{it-1} - \beta_d d_{it-1} - \beta_m m_{it-1}) \\ &+ \delta_{st} + \alpha_i + \varepsilon_{it} \end{aligned} \tag{9}$$

[17] We have explored, as an alternative, dynamic panel estimation methods. However, a known problem in this literature arises when inputs are highly persistent, a feature that affects some of our variables of interest and renders some of the estimates very imprecise.

The moment condition to estimate β_d, β_k, and β_m in this equation is:

$$\begin{aligned} E\left[\xi_{it} + \varepsilon_{it} | I_{it-1}\right] &= \\ E[y_{it} - \beta_0 - \beta_l l_{it} - \beta_e e_{it} - \beta_m m_{it} - \beta_d d_{it} - \delta_{st} - \alpha_i & \\ -g\left(\varphi'(d_{it-1}, k_{it-1}, m_{it-1}, Age_{it-1}) - \beta_0 - \beta_k k_{it-1} - \beta_d d_{it-1} - \beta_m m_{it-1}\right) | I_{it-1}] &= 0 \end{aligned}$$

We estimate (9) by non-linear least squares by solving the following minimization problem:

$$\min_{\beta_k, \beta_m, \beta_d, \gamma} \sum \left(y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_e e_{it} - \beta_k k_{it} - \beta_m m_{it} - \beta_d d_{it} - E\,\widehat{\left[\omega_t | \omega_{t-1}\right]} - \delta_{st} - \alpha_i \right)$$

where $\hat{\beta}$ denotes the coefficients estimated in the first stage and $E\,\widehat{\left[\omega_t | \omega_{t-1}\right]}$ is the empirical conditional expectation of ω_{it}, which is consistently estimated from the nonparametric regression, $\omega_{it} = \gamma_0 + \gamma_1 \omega_{it-1} + \gamma_2 \omega_{it-1}^2 + \xi_{it}$.

Table 8 reports the estimates of the β coefficients.[18] We find that the input coefficients are not significantly different from the static LP estimates (column (5) of table 6). Treating the breadth and depth variables as if they were a form of capital, rather than fully variable inputs, has only minor effects on their estimated coefficients.

4.3 Industry-specific estimation

The results we have presented so far pool over many potentially heterogeneous manufacturing activities. Tables A9–A10 in Appendix A show the results when we estimate the productivity specification 4 separately for 21 different manufacturing industries. These tables show Levinsohn-Petrin estimates of the breadth and depth effects along with the four factor input elasticities. The regressions are based on the same identifying assumption as presented in table 6, but also include the second-stage coefficients for capital and materials.

Importing more products tends to have a positive impact on productivity across industries: 20 of 21 coefficients on ln products have positive effects with magnitudes ranging from 0.004 to 0.082.[19] The coefficients on ln products average to 0.023 and 16 of 21 industries include the pooled estimate, 0.021, in their confidence intervals. Conditioning on the number of imported products, the supplier margin is also associated with a significant productivity increase that averages to 0.026. The pooled coefficient of 0.027 is included in 19 of 21 industry confidence intervals.

Tables A11–A12 present the industry-level estimates under the alternative assumption

[18] The γ coefficients are not reported since they are not of interest.

[19] The confidence interval for the sole negative estimate (oil, -0.018) extends to 0.026, and oil refining is not an industry where one would naturally expect input variety to yield higher productivity.

Table 8: Dynamic LP (d_{it} treated as a state variable)

	(1)	(2)
	ln Sales	
ln Empl	0.280^a	0.280^a
	(0.003)	(0.003)
ln Elec	0.106^a	0.105^a
	(0.002)	(0.002)
$\ln K$	0.041^a	0.042^a
	(0.009)	(0.008)
$\ln M$	0.455^a	0.457^a
	(0.008)	(0.008)
ln Products	0.021^a	0.006^a
	(0.002)	(0.002)
ln Supp per Prod	0.028^a	0.023^a
	(0.005)	(0.005)
Previous Share	0.026^a	
	(0.004)	
Avg Age		0.003
		(0.002)
Firm Fixed Effects	y	y
Sector-Year FEs	y	y
Obs.	93,478	93,478
First-stage R^2	0.696	0.696
Second-stage R^2	0.943	0.943

Significance: ^{a} at 0.1%, ^{b} at 1%, ^{c} at 5%.
Notes: LP Regressions, 2002–2008. Standard errors are clustered at the firm level. Breadth and depth variables are estimated in the second stage of an LP specification.

that breadth and depth variables are *dynamic* variables in the LP estimation. As with the static LP, industry-level results for dynamic LP are less precisely estimated than the pooled coefficients. While there are some industries that have statistically insignificant estimates, this stems from low power rather than precisely estimated zeros.

In the dynamic LP, input product variety has positive effects for 20 of 21 industries. The pooled coefficient, 0.021 is included in the confidence interval for 16 of 21. Increases in the numbers of suppliers has a positive effect in 18 industries, and again there are no industries with significant negative effects. Continuous relationships with suppliers tend to have a positive impact: 19 of 21 industries have positive experience effects on productivity. Additionally, 19 industry confidence intervals include the corresponding pooled estimate. The highest effects of continued relationships are for computers, chemicals, and electronics.

The input elasticities reported in tables A9-A12 are broadly similar across different specifications and are in line with the estimates by Halpern et al. (2015). In particular, they find that the capital share in production is around 0.04, which is equal to our average capital share estimate across sectors. Moreover, while their labour elasticity estimate (0.2) is in line with our results, their share of materials (0.75) appear significantly larger than ours. We believe that this difference may be due to the fact that we separately control for electricity.

4.4 Impact of import relationships on export performance

Table 9 investigates how the characteristics of the import network affect export performance. Past research has shown that the majority of firms do not export and, among the exporters, the modal firm exports a single product to a single destination.[20] In standard models of heterogeneous firms, more productive firms can cover fixed costs associated with exporting. Thus, to the extent that our breadth and depth variables trigger productivity gains, we expect them to raise export performance. We consider four measures of export performance: total exports (columns 1 and 2), the number of products (HS8 codes) exported (columns 3 and 4), whether a firm exports to any country (5 and 6), and the number of export destinations (7 and 8). The even-numbered columns adopt a specification similar to column (5) of Table 6, where we add controls for inputs and age and the LP quadratic function.

We find that firms importing more products from more suppliers are more likely to be exporters, export more, and sell more products to more destinations. The imported product and supplier elasticities imply similar magnitudes for the effects on performance. Considering the coefficient on ln Products, a one-standard-deviation increase in the number of imported products raises exports by 10.7% of a sd, raises the number of exported products by 10.3%

[20]See Bernard et al. (2007) for the United States and Mayer & Ottaviano (2007) for some European countries.

of a sd, raises the number of export destination by 4.7% of a sd and raises the probability of exporting by 2 percentage points. Our findings here corroborate the stylized facts of Amiti et al. (2014) that import intensive firms are also important exporters.

Table 9: How import relationships affect export performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln Exports		ln Exp. Products		Export Status		ln Destinations	
ln Products	0.186^a	0.194^a	0.079^a	0.074^a	0.018^a	0.015^a	0.057^a	0.030^a
	(0.011)	(0.014)	(0.005)	(0.006)	(0.002)	(0.002)	(0.004)	(0.005)
ln Supp/Prod	0.221^a	0.231^a	0.071^a	0.077^a	0.038^a	0.035^a	0.058^a	0.048^a
	(0.031)	(0.032)	(0.014)	(0.015)	(0.006)	(0.006)	(0.012)	(0.012)
Previous Share	-0.108^a	-0.015	0.050^a	-0.015	-0.005	-0.010^c	0.186^a	-0.006
	(0.021)	(0.029)	(0.009)	(0.013)	(0.004)	(0.005)	(0.008)	(0.009)
Input Controls⋆	n	y	n	y	n	y	n	y
Firm FE	y	y	y	y	y	y	y	y
Sector-Year	y	y	y	y	y	y	y	y
Obs.	59,851	59,851	59,851	59,851	93,478	93,478	59,851	59,851
R^2	0.012	0.067	0.009	0.041	0.002	0.022	0.025	0.077

ln *Products*: log number of imported products (HS10).
ln Supp/Prod: log number of foreign suppliers per imported products.
Share Previous: share of suppliers from which the buyer purchased in a previous year.
⋆ Input Controls include employment, electricity, and quadratic in capital, materials and age. All controls are also interacted with 3-digit NAICS code dummies.
Notes: Firm FE regression, years 2002–2008. A sector represents a 3-digit NAICS code. Robust standard errors, clustered at the firm level, in parentheses. Significance thresholds are 0.1% (*a*), 1% (*b*), 5% (*c*). The even-numbered columns implement our preferred specification with input controls as shown in equation (6).

The share of previous relationships, instead, does not have a robust effect on export outcomes. The coefficient on *Previous Share* tends to be mostly insignificant once we control for firms' other inputs.

4.5 The Dynamics of Import Relationships

In this section we have shown that the breadth and depth of import relationships are positively associated with firm (revenue) productivity. From a theoretical point of view, the results on breadth of import relationships can be interpreted, as previously discussed, through the lens of "love of variety," albeit at a much finer disaggregation. These results corroborate with Canadian data past work such as Amiti & Konings (2007) with Indonesian data and Kasahara & Lapham (2013) with Chilean data. The results associating continuity (depth) of relationships with higher productivity, are more novel and thus deserve further scrutiny. In this section we consider the possible sources of the productivity gains arising from continuous relationships by exploring the characteristics of long-lasting import relationships.

In particular, we explore whether continuous import relationships tend to feature higher value of total imports, and if they do, whether the higher value is the result of higher prices or higher quantities. We thus employ the follow specification relating the type of relationship to import outcomes:

$$\text{Import Outcome}_{ijpt} = \beta_0 + \beta_1 \cdot \text{Relationship Type}_{ijpt} + D_{pt} + \varepsilon_{ijpt}. \tag{10}$$

The dependent variable is either the import value, the quantity imported, or the unit value in the transaction of product p between firm i and supplier j at time t. Relationship Type_{ijpt} includes continuous, new, and discontinuous relationships. We also consider how *unique* relationships—supplier-product combinations that are linked to a single buyer—are related to import outcomes. It is possible that when a Canadian firm is the only buyer of a foreign product, it is because that product has been customized for that firm and that such customization might be reflected in the price paid for the imported product. The excluded category covers buyer-supplier-product relationships that are discontinuous and not unique. The specification also includes HS2 dummies, unit of measure dummies, as well as 3-digit NAICS-year dummies.

Presenting a formal model is beyond the scope of this paper, but there are theoretical mechanisms that would explain an association between continuous relationships and higher prices. For example, in a framework in which searching for a trade partner is costly and agents learn about their partner's productivity over time, better matches would tend to last longer and generate a larger surplus. This translates into larger pay-offs for all participants in the relationships. In particular, we expect that firms in continuous relationships tend to import larger values, not only because of bigger quantities, but also because they pay higher unit values. Alternatively, buyers and suppliers in continuous relationships may tend to exchange products that are better *tailored* to the production process of the buyer, and for which the seller is able to extract higher prices. Similarly, following Uzzi (1996), a firm embedded in a production network would have longer-lasting relationships and better-customized products.

Table 10 reports the OLS and Relationship FE regression results for specification (10).[21] All specifications control for the characteristics of the Canadian firm in its output market, i.e. the log of total sales and the log of total exports, so that we can compare firms with equal sales that adopt different strategies regarding the duration or exclusivity of their relationships. Firms in continuous relationships import larger values than in discontinuous connections.

[21] We include D_{pij} fixed effects in the even numbered columns of table 10.

Table 10: Import Relationships

	(1)	(2)	(3)	(4)	(5)	(6)
	ln Import Value		ln Imp. Quant.		ln Unit Value	
Continuous	1.121^a	0.116^a	1.107^a	0.079^a	-0.002	0.017^a
	(0.028)	(0.005)	(0.031)	(0.006)	(0.016)	(0.004)
New	-0.229^a	-0.159^a	-0.325^a	-0.180^a	0.102^a	0.010^c
	(0.030)	(0.005)	(0.031)	(0.007)	(0.017)	(0.005)
Unique	-0.409^a	0.093^a	-0.397^a	0.076^a	-0.034^c	0.007
	(0.023)	(0.005)	(0.029)	(0.006)	(0.014)	(0.004)
Rel. FE	n	y	n	y	n	y
Sector×Year	y	y	y	y	y	y
Observations	5.5mn	5.5mn	3mn	3mn	3mn	3mn
R^2	0.164	0.144	0.343	0.107	0.505	0.012

Continuous: dummy equal to one if a firm imported the same product from the same supplier at $t-1$.
New: dummy equal to one if a firm imports a product from a supplier for the first time.
Unique: dummy equal to one if a supplier sells a product only to one firm at t.
Notes: The odd-numbered columns report pooled OLS regressions, while the even-numbered columns report relationship (defined as firm-product-supplier dummies) fixed-effect regressions. In all columns, we also control for log sales, log export, HS2 product dummies, and dummies for the unit of measurement. A sector stands for a 3-digit NAICS code. Robust standard errors, clustered at the firm level, in parentheses. Significance thresholds are 0.1% (a), 1% (b), 5% (c).

Columns (3)–(6) decompose the impact on import values in terms of quantities and prices. We find that the effect on value comes both from larger quantities and higher unit values. The rise in unit values appears over time within relationships is consistent with the finding of Foster et al. (2016), and could be explained by the fact that firms learn about the buyer demand over time. New relationships, instead, involve lower import values; this outcome seems to be primarily a quantity rather than a price effect. Likely, buyers are reluctant to place large orders from firms they have no prior experience with.

Finally, let us consider the behavior of unique supplier-product combinations. Exploiting both the cross-sectional and time variation, unique relationships seem to be associated with lower import values, resulting both from lower quantities and lower unit values; however, suppliers becoming the unique provider of a certain good (columns (2), (4), and (6)) export larger values, larger quantities and sell their products at a higher unit value (the coefficient on Unique in column (6) is positive but not significant). We believe that our dummy for unique relationships captures attempts of buyers to find the best inputs compatible with their production process so in the cross section it tends to be associated with a lower import value because it involved smaller "experimental" transactions. When employing within-relationship variation though, a supplier that only ships to one client seems to raise the value and quantity of the inputs sold.

5 Conclusions

In this paper, we have explored the productivity effects of the breadth and depth of firms' import relationships. With the qualification that our identification strategy relies on the control function approach to partial out unobserved productivity shocks, we find significant and economically relevant breadth effects. Both the number of varieties imported and the number of suppliers per variety raise productivity. These results support the theoretical foundation in Ethier (1982) and are consistent with a wider literature in which we see that reductions in the costs of imported inputs (via tariff cuts or changes in transport access) lead to productivity improvements. These results on breadth have many other counterparts in the literature on gains from variety in final consumer goods.

We also find novel effects of import relationship depth, which open interesting future avenues of investigation. The share of continuous importing relationships the firm engages in also appears to raise firm performance. In addition, we find that firms with continuous import relationships with the same suppliers systematically feature transactions that are larger and more valuable. These results appear supportive of the causal mechanisms described in Uzzi (1996). The positive depth effects might also result from a search and matching process whereby only the importing firm's best supplier relationships survive. Because they are better matches, they take up a larger share of the firm's total imports. Further theoretical and empirical investigation of these novel results on relationship dynamics would improve understanding of where the productivity gains of importing come from. Our results suggest they come not only from wider variety of inputs, but also from a deeper pool of suppliers in which the firm can find an *ideal* partner.

To the extent that the empirical relationships estimated here are causal, they point to several important policy implications. First, import tariff reductions on intermediate inputs should help Canadian productivity and boost the performance of Canadian firms in international markets. This is consistent with evidence from less developed countries, but it was not previously known for a country like Canada with a well-developed manufacturing sector. Secondly, since the United States provides the majority of the suppliers used by Canadian firms, it would be helpful to shrink the fixed costs of adding and maintaining suppliers. It is not obvious how to achieve that, but travel and visa facilitation could help. There may also be gains from harmonization of technical standards. The most general policy implication of all is that even if trade policy makers are focused on export markets, they should not neglect that Canadian firms' success in selling abroad is very much predicated upon their ability to use a broad and deep roster of foreign suppliers.

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A Supplemental Empirical Results

Table A1: Average Market Share by sector, 2002–2008

NAICS	Industry	Domestic Mkt Share
311	Food	20.91%
312	Bev. & Tob.	1.80%
313	Text. Mills	0.44%
314	Text. Prod.	0.32%
315	Apparel	0.64%
316	Leather	0.07%
321	Wood	4.00%
322	Paper	4.91%
323	Printing	1.41%
324	Petrol	9.42%
325	Chemical	7.02%
326	Plastics	3.83%
327	Mineral	1.88%
331	Metals	6.82%
332	Met. Prod.	4.06%
333	Machinery	4.12%
334	Computing	2.90%
335	Electrical	1.54%
336	Trans. Eq.	21.30%
337	Furniture	1.54%
339	Miscel.	1.01%

Table A2: Summary Statistics from Import Registry

Variable	Mean	Std Deviation
ln Import Value	8.07	2.80
ln Unit Value	3.41	2.55
Continuous (Indicator)	0.30	0.46
Unique	0.78	0.42
New	0.65	0.48

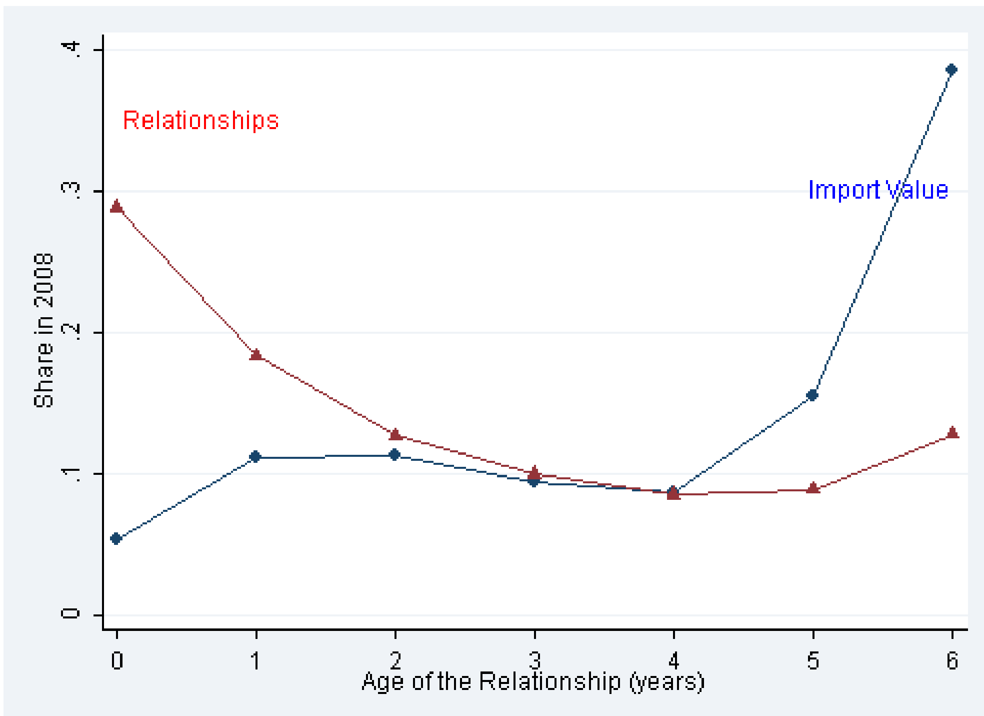

Figure A1: Relationship age in extended sample ending in June 2008

Table A3: Reduced-Form Regressions: Other Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ln Empl		ln Sales x Worker		ln VA		ln VA x Worker		ln K x Worker	
ln Products	0.554^a	0.554^a	0.082^a	0.083^a	0.619^a	0.620^a	0.065^a	0.065^a	0.038^a	0.038^a
	(0.005)	(0.005)	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)
ln $^{Supp}/_{Prod}$	0.301^a	0.301^a	0.117^a	0.118^a	0.334^a	0.334^a	0.038^a	0.038^a	-0.075^b	-0.076^b
	(0.019)	(0.019)	(0.008)	(0.008)	(0.021)	(0.021)	(0.007)	(0.007)	(0.024)	(0.024)
Previous Share	-0.126^a		0.046^a		-0.108^a		0.031^a		-0.095^a	
	(0.013)		(0.007)		(0.015)		(0.007)		(0.019)	
Avg Age		-0.066^a		0.010^a		-0.059^a		0.010^a		-0.041^a
		(0.006)		(0.003)		(0.007)		(0.003)		(0.008)
Sector-Year FEs	y	y	y	y	y	y	y	y	y	y
Obs.	116,926	116,926	116,550	116,550	115,003	115,003	114,954	114,954	97,120	97,120
R^2	0.424	0.425	0.269	0.269	0.436	0.437	0.192	0.192	0.147	0.147

ln *Products*: log number of imported products (HS10).
ln $^{Supp}/_{Prod}$: log number of foreign suppliers per imported products.
Previous Share: share of suppliers from which the buyer purchased in a previous year.
Legend: ^{c} $p < 0.05$, ^{b} $p < 0.01$, ^{a} $p < 0.001$
Note: Reduced-form OLS regressions between firm-level characteristics and measures of import breadth and depth. Standard errors, clustered at the level of the firms, are in parentheses.

Table A4: Reduced-Form Regressions: Export Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Export Dummy		ln Exports		ln Exp Products		ln Exp Destinations		Export Share	
ln Products	0.100^a	0.100^a	0.831^a	0.830^a	0.379^a	0.379^a	0.246^a	0.246^a	2.383	2.323
	(0.002)	(0.002)	(0.013)	(0.013)	(0.005)	(0.005)	(0.005)	(0.005)	(2.235)	(2.181)
ln Supp/Prod	0.070^a	0.070^a	0.645^a	0.644^a	0.106^a	0.105^a	0.177^a	0.176^a	-4.496	-4.640
	(0.007)	(0.007)	(0.048)	(0.048)	(0.018)	(0.018)	(0.019)	(0.019)	(3.991)	(4.127)
Previous Share	0.042^a		-0.167^a		-0.105^a		-0.033^c		-14.563	
	(0.006)		(0.041)		(0.016)		(0.014)		(14.302)	
Avg Age		0.016^a		-0.057^b		-0.037^a		-0.010		-5.354
		(0.003)		(0.018)		(0.007)		(0.007)		(5.317)
Sector-Year FEs	y	y	y	y	y	y	y	y	y	y
Obs.	117,723	117,723	72,705	72,705	72,705	72,705	72,705	72,705	116,602	116,602
R^2	0.145	0.145	0.292	0.291	0.304	0.304	0.244	0.244	0.002	0.002

ln *Products*: log number of imported products (HS10).
ln Supp/Prod: log number of foreign suppliers per imported products.
Previous Share: share of suppliers from which the buyer purchased some time in the past.
Legend: ^{c} $p < 0.05$, ^{b} $p < 0.01$, ^{a} $p < 0.001$
Note: Reduced-form OLS regressions between firm-level export market characteristics and measures of import breadth and depth. Standard errors, clustered at the level of the firms, are in parentheses.

Table A5: Alternative Measures of Import Depth

	(1)	(2)	(3)	(4)
	ln Sales			
ln Products	0.109^a	0.021^a	0.108^a	0.020^a
	(0.004)	(0.002)	(0.004)	(0.002)
ln $^{\text{Supp}}/_{\text{Prod}}$	0.121^a	0.028^a	0.118^a	0.027^a
	(0.009)	(0.005)	(0.009)	(0.005)
Continuous Share	0.024^a	0.024^a		
	(0.006)	(0.004)		
Avg. Age			-0.000	0.004^c
			(0.003)	(0.002)
Input Controls*	n	y	n	y
Firm Fixed Effects	y	y	y	y
Sector-Year FEs	y	y	y	y
Obs.	93,479	93,479	93,479	93,479
R^2	0.030	0.717	0.030	0.717

ln *Products*: log number of imported products (HS10).
ln $^{\text{Supp}}/_{\text{Prod}}$: log number of foreign suppliers per imported products.
Continuous Share: share of suppliers from which the buyer purchased in the previous year.
Avg. Age: average age of the relationships with suppliers.
Legend: ^{c} $p < 0.05$, ^{b} $p < 0.01$, ^{a} $p < 0.001$
Note: FE firm-level regressions, 2002–2008. Standard errors are clustered at the firm level.

Table A6: Import Relationships and Firm Performance, Arm's Length Interactions

	ln Sales				
	(1)	(2)	(3)	(4)	(5)
ln Products	0.108^{a}			0.105^{a}	0.019^{a}
	(0.004)			(0.003)	(0.002)
ln $^{\text{Supp}}/_{\text{Prod}}$		0.099^{a}		0.063^{a}	0.012^{b}
		(0.009)		(0.009)	(0.004)
Previous Share			0.006	0.013^{c}	0.020^{a}
			(0.006)	(0.006)	(0.004)
Input Controls*	n	n	n	n	y
Firm FE	y	y	y	y	y
Sector-Year	y	y	y	y	y
Obs.	93,231	93,231	93,231	93,231	93,231
R^2	0.026	0.003	0.000	0.028	0.716

Legend: ^{a} significant at 0.1%, ^{b} at 1%, ^{c} at 5%.
Notes: LP Regressions, 2002–2008, for arm's length relationships. Standard errors are clustered at the firm level.

Table A7: LP Regressions by Import Intensity

	Most Import Intensive Industries				
	ln Sales				
	(1)	(2)	(3)	(4)	(5)
ln Products	0.125^{a}			0.122^{a}	0.027^{a}
	(0.005)			(0.005)	(0.003)
ln $^{\text{Supp}}/_{\text{Prod}}$		0.148^{a}		0.124^{a}	0.034^{a}
		(0.014)		(0.014)	(0.008)
Previous Share			0.020^{c}	0.030^{a}	0.028^{a}
			(0.009)	(0.009)	(0.006)
Input Controls*	n	n	n	n	y
Firm Fixed Effects	y	y	y	y	y
Sector-Year FEs	y	y	y	y	y
Obs.	50,795	50,795	50,795	50,795	50,795
R^2	0.030	0.005	0.000	0.033	0.687

	Least Import Intensive Industries				
	ln Sales				
	(1)	(2)	(3)	(4)	(5)
ln Products	0.092^{a}			0.091^{a}	0.016^{a}
	(0.005)			(0.005)	(0.002)
ln $^{\text{Supp}}/_{\text{Prod}}$		0.120^{a}		0.111^{a}	0.023^{a}
		(0.012)		(0.012)	(0.006)
Previous Share			-0.011	0.002	0.018^{a}
			(0.008)	(0.008)	(0.005)
Input Controls*	n	n	n	n	y
Firm Fixed Effects	y	y	y	y	y
Sector-Year FEs	y	y	y	y	y
Obs.	42,684	42,684	42,684	42,684	42,684
R^2	0.022	0.004	0.000	0.026	0.756

ln *Products*: log number of imported products (HS10).
ln $\frac{\text{Supp}}{\text{Prod}}$: log number of foreign suppliers per imported products.
Previous Share: share of suppliers from which the buyer purchased in a previous year.
* Input Controls include employment, electricity, and quadratic in capital, materials and age. All controls are also interacted with 3-digit NAICS code dummies.
Notes: Firm FE regression, years 2002–2008. A sector represents a 3-digit NAICS code. Robust standard errors, clustered at the firm level, in parentheses. Significance thresholds are 0.1% (a), 1% (b), 5% (c). The last column implements our preferred specification with input controls as shown in equation (4).

Table A8: Heterogeneous Effects using the Rauch Classification

	(1)	(2)	(3) ln Sales	(4)	(5)
Hom. Share	0.000	-0.079	-0.040	0.060	-0.016
	(0.052)	(0.048)	(0.050)	(0.061)	(0.034)
ln Products	0.111^{a}			0.109^{a}	0.022^{a}
	(0.004)			(0.004)	(0.002)
Hom. Share * ln Products	-0.003			-0.004	-0.019
	(0.031)			(0.032)	(0.016)
ln Supp per Prod		0.141^{a}		0.120^{a}	0.028^{a}
		(0.010)		(0.010)	(0.005)
Hom. Share * ln Supp per Prod		-0.079^{c}		-0.062	-0.014
		(0.037)		(0.036)	(0.017)
Previous Share			0.007	0.018^{b}	0.023^{a}
			(0.006)	(0.006)	(0.004)
Hom. Share * Previous Share			-0.162^{a}	-0.152^{b}	-0.006
			(0.048)	(0.047)	(0.026)
Input Controls*	n	n	n	n	y
Firm Fixed Effects	y	y	y	y	y
Sector-Year FEs	y	y	y	y	y
N	92,091	92,091	92,091	92,091	92,091
R^2	0.027	0.005	0.000	0.030	0.718

Hom. Share: share of imported inputs classified as homogeneous products according to the Rauch classification.
ln *Products*: log number of imported products (HS10).
ln $\frac{\text{Supp}}{\text{Prod}}$: log number of foreign suppliers per imported products.
Previous Share: share of suppliers from which the buyer purchased in a previous year.
* Input Controls include employment, electricity, and quadratic in capital, materials and age. All controls are also interacted with 3-digit NAICS code dummies.
Legend: ^{a} significant at 0.1%, ^{b} at 1%, ^{c} at 5%.
Notes: FE firm-level regressions, 2002–2008. Standard errors are clustered at the firm level.

Table A9: LP Estimation: Nondurable Sectors

	ln Sales										
	Food	Bev.	Text. M.	Text. P.	App.	Leath.	Paper	Print.	Oil	Chem.	Plast.
ln Products	0.007	0.009	0.045^a	0.020	0.023^b	0.039^c	0.013	0.021^a	-0.018	0.046^a	0.012^c
	(0.006)	(0.026)	(0.013)	(0.012)	(0.009)	(0.019)	(0.008)	(0.005)	(0.022)	(0.009)	(0.005)
ln Supp per Prod	0.023	-0.053	-0.017	0.004	0.037	0.018	0.035	0.019	0.073	0.043	0.011
	(0.014)	(0.066)	(0.037)	(0.031)	(0.022)	(0.052)	(0.019)	(0.015)	(0.082)	(0.027)	(0.013)
Previous Share	0.021	-0.001	0.024	0.034	0.062^b	-0.007	0.049^b	0.012	-0.040	0.054^c	0.013
	(0.012)	(0.067)	(0.033)	(0.026)	(0.023)	(0.044)	(0.018)	(0.011)	(0.064)	(0.022)	(0.011)
ln Empl	0.161^a	0.151^a	0.302^a	0.255^a	0.299^a	0.178^a	0.228^a	0.358^a	0.112^a	0.213^a	0.290^a
	(0.008)	(0.040)	(0.020)	(0.017)	(0.014)	(0.024)	(0.012)	(0.012)	(0.026)	(0.011)	(0.009)
ln Elec	0.120^a	0.238^a	0.073^a	0.066^a	0.082^a	0.039^c	0.094^a	0.142^a	0.017	0.093^a	0.115^a
	(0.007)	(0.033)	(0.014)	(0.013)	(0.012)	(0.017)	(0.007)	(0.010)	(0.021)	(0.007)	(0.006)
ln M	0.562^a	0.262^a	0.428^a	0.373^a	0.506^a	0.493^a	0.589^a	0.411^a	0.594^a	0.331^a	0.517^a
	(0.043)	(0.050)	(0.033)	(0.035)	(0.024)	(0.041)	(0.017)	(0.028)	(0.036)	(0.043)	(0.013)
ln K	0.043^b	-0.013	0.052	0.084	-0.072^c	0.010	0.020^c	0.030	0.073^c	0.009	0.015
	(0.018)	(0.083)	(0.029)	(0.048)	(0.032)	(0.052)	(0.010)	(0.024)	(0.038)	(0.059)	(0.012)
Obs.	6,471	573	1,156	1,699	3,891	708	1,920	4,184	353	4,655	6,277
First-Stage R^2	0.737	0.642	0.766	0.666	0.713	0.728	0.891	0.768	0.706	0.613	0.801
Second-Stage R^2	0.971	0.951	0.945	0.944	0.907	0.967	0.986	0.943	0.991	0.943	0.970

ln *Products*: log number of imported products (HS10).

ln Supp/Prod: log number of foreign suppliers per imported products.

Previous Share: share of suppliers from which the buyer purchased in a previous year.

Legend: ^{a} significant at 0.1%, ^{b} at 1%, ^{c} at 5%.

Notes: LP Regressions, 2002–2008. Standard errors are clustered at the firm level. Breadth and depth variables are estimated in the second stage of an LP specification.

Table A10: LP Estimation: Durable Sectors

	ln Sales									
	Wood	Min.	Met.	Met. P.	Mach.	Comp.	Elect.	Tr. Eq.	Furn.	Misc.
ln Products	0.022^a	0.014	0.050^a	0.013^a	0.013^b	0.082^a	0.004	0.018^c	0.017^b	0.025^a
	(0.006)	(0.008)	(0.013)	(0.004)	(0.005)	(0.012)	(0.011)	(0.009)	(0.005)	(0.006)
ln Supp per Prod	0.019	0.047^c	0.106^b	0.016	0.020	0.042	-0.015	0.091^a	0.000	0.037^b
	(0.011)	(0.024)	(0.034)	(0.011)	(0.013)	(0.032)	(0.028)	(0.025)	(0.015)	(0.014)
Previous Share	0.013	0.018	0.016	0.016^c	0.007	0.080^c	0.052^c	0.032	0.002	0.017
	(0.012)	(0.018)	(0.028)	(0.008)	(0.011)	(0.031)	(0.023)	(0.022)	(0.012)	(0.013)
ln Empl	0.257^a	0.332^a	0.307^a	0.313^a	0.312^a	0.314^a	0.249^a	0.240^a	0.294^a	0.287^a
	(0.009)	(0.013)	(0.017)	(0.006)	(0.007)	(0.015)	(0.013)	(0.013)	(0.012)	(0.010)
ln Elec	0.120^a	0.097^a	0.067^a	0.101^a	0.095^a	0.121^a	0.096^a	0.141^a	0.104^a	0.105^a
	(0.007)	(0.007)	(0.014)	(0.005)	(0.006)	(0.011)	(0.010)	(0.012)	(0.009)	(0.007)
ln M	0.552^a	0.519^a	0.418^a	0.461^a	0.468^a	0.254^a	0.458^a	0.493^a	0.567^a	0.451^a
	(0.023)	(0.029)	(0.034)	(0.017)	(0.016)	(0.023)	(0.021)	(0.029)	(0.032)	(0.020)
ln K	0.030	0.007	0.024	0.049^b	0.053^b	0.088^b	0.110^a	0.124	0.016	0.019
	(0.034)	(0.021)	(0.024)	(0.017)	(0.018)	(0.040)	(0.021)	(0.074)	(0.020)	(0.021)
Obs.	4,784	3,381	1,430	14,362	12,031	5,112	2,895	4,847	5,233	7,516
First-Stage R^2	0.818	0.775	0.753	0.707	0.717	0.567	0.732	0.717	0.772	0.682
Second-Stage R^2	0.965	0.938	0.970	0.940	0.930	0.852	0.959	0.947	0.949	0.916

ln *Products*: log number of imported products (HS10).

ln Supp/Prod: log number of foreign suppliers per imported products.

Previous Share: share of suppliers from which the buyer purchased in a previous year.

Legend: ^{a} significant at 0.1%, ^{b} at 1%, ^{c} at 5%.

Notes: LP Regressions, 2002–2008. Standard errors are clustered at the firm level. Breadth and depth variables are estimated in the second stage of an LP specification.

Table A11: Dynamic LP (d_{it} treated as a state variable): Nondurable Sectors

	ln Sales										
	Food	Bev.	Text. M.	Text. P.	App.	Leath.	Paper	Print.	Oil	Chem.	Plast.
ln Products	0.009	-0.019	0.072^a	0.030	0.023	0.039	0.010	0.013^b	0.009	0.045^c	0.008
	(0.008)	(0.026)	(0.020)	(0.018)	(0.012)	(0.023)	(0.010)	(0.005)	(0.021)	(0.021)	(0.006)
ln Supp per Prod	0.021	0.018	0.116^c	-0.004	0.057^c	-0.053	0.015	0.021	0.005	0.048	0.033^c
	(0.015)	(0.082)	(0.053)	(0.042)	(0.026)	(0.058)	(0.022)	(0.014)	(0.074)	(0.036)	(0.016)
Previous Share	0.029^c	-0.140^b	0.034	0.050	0.010	0.020	0.025	0.017	-0.054	0.062^c	0.031^b
	(0.014)	(0.054)	(0.031)	(0.031)	(0.026)	(0.050)	(0.016)	(0.010)	(0.046)	(0.025)	(0.011)
ln Empl	0.162^a	0.141^a	0.291^a	0.256^a	0.299^a	0.177^a	0.223^a	0.357^a	0.113^a	0.211^a	0.289^a
	(0.008)	(0.041)	(0.020)	(0.017)	(0.014)	(0.025)	(0.012)	(0.012)	(0.025)	(0.011)	(0.009)
ln Elec	0.121^a	0.242^a	0.073^a	0.064^a	0.083^a	0.038^c	0.092^a	0.141^a	0.003	0.092^a	0.116^a
	(0.007)	(0.034)	(0.013)	(0.013)	(0.012)	(0.017)	(0.007)	(0.010)	(0.021)	(0.007)	(0.006)
$\ln M$	0.556^a	0.260^a	0.426^a	0.373^a	0.502^a	0.506^a	0.593^a	0.405^a	0.570^a	0.334^a	0.516^a
	(0.044)	(0.053)	(0.041)	(0.036)	(0.024)	(0.040)	(0.016)	(0.024)	(0.040)	(0.043)	(0.014)
$\ln K$	0.041^c	0.108	0.022	0.080	-0.075^c	0.001	0.026^b	0.027	0.061	0.010	0.014
	(0.017)	(0.096)	(0.032)	(0.049)	(0.032)	(0.055)	(0.009)	(0.018)	(0.052)	(0.058)	(0.013)
Obs.	6,471	573	1,156	1,699	3,891	708	1,920	4,184	353	4,655	6,277
First-Stage R^2	0.739	0.658	0.777	0.674	0.715	0.737	0.894	0.771	0.753	0.619	0.802
Second-Stage R^2	0.972	0.953	0.956	0.947	0.912	0.970	0.987	0.948	0.991	0.950	0.971

ln *Products*: log number of imported products (HS10).
ln Supp/Prod: log number of foreign suppliers per imported products.
Previous Share: share of suppliers from which the buyer purchased in a previous year.
Legend: ^{a} significant at 0.1%, ^{b} at 1%, ^{c} at 5%.
Notes: LP Regressions, 2002–2008. Standard errors are clustered at the firm level. Breadth and depth variables are estimated in the second stage of an LP specification.

Table A12: Dynamic LP (d_{it} treated as a state variable): Durable Sectors

	ln Sales									
	Wood	Min.	Met.	Met. P.	Mach.	Comp.	Elect.	Tr. Eq.	Furn.	Misc.
ln Products	0.020^{b}	0.013	0.042^{c}	0.009^{c}	0.009	0.073^{a}	0.017	0.028	0.010	0.033^{b}
	(0.006)	(0.011)	(0.018)	(0.004)	(0.006)	(0.017)	(0.015)	(0.015)	(0.006)	(0.010)
ln Supp per Prod	0.010	0.038	0.134^{b}	0.023	0.027	0.031	0.016	0.055^{b}	-0.013	0.029
	(0.011)	(0.026)	(0.044)	(0.012)	(0.015)	(0.041)	(0.033)	(0.025)	(0.018)	(0.016)
Previous Share	0.032^{b}	0.042	0.043	0.019^{b}	0.041^{a}	0.104^{b}	0.058^{c}	0.042	0.015	0.020
	(0.012)	(0.023)	(0.032)	(0.007)	(0.011)	(0.032)	(0.023)	(0.026)	(0.011)	(0.014)
ln Empl	0.257^{a}	0.331^{a}	0.293^{a}	0.312^{a}	0.309^{a}	0.311^{a}	0.246^{a}	0.238^{a}	0.297^{a}	0.286^{a}
	(0.009)	(0.013)	(0.017)	(0.006)	(0.007)	(0.015)	(0.013)	(0.014)	(0.012)	(0.010)
ln Elec	$0.120\ ^{a}$	0.097^{a}	0.075^{a}	0.102^{a}	0.096^{a}	0.118^{a}	0.097^{a}	0.141^{a}	0.103^{a}	0.104^{a}
	(0.007)	(0.007)	(0.014)	(0.005)	(0.006)	(0.011)	(0.010)	(0.012)	(0.009)	(0.007)
$\ln M$	0.553^{a}	0.517^{a}	0.413^{a}	0.461^{a}	0.467^{a}	0.264^{a}	0.455^{a}	0.498^{a}	0.567^{a}	0.445^{a}
	(0.024)	(0.032)	(0.037)	(0.017)	(0.016)	(0.023)	(0.019)	(0.027)	(0.033)	(0.019)
$\ln K$	0.029	0.004	0.051	0.052^{b}	0.050^{b}	0.104^{b}	0.111^{a}	0.042	0.019	0.016
	(0.032)	(0.021)	(0.033)	(0.017)	(0.017)	(0.037)	(0.016)	(0.032)	(0.021)	(0.019)
Obs.	4,784	3,381	1,430	14,362	12,031	5,112	2,895	4,847	5,233	7,516
First-Stage R^2	0.820	0.777	0.765	0.709	0.719	0.573	0.736	0.720	0.774	0.686
Second-Stage R^2	0.968	0.942	0.976	0.943	0.933	0.882	0.960	0.952	0.950	0.923

ln *Products*: log number of imported products (HS10).

ln Supp/Prod: log number of foreign suppliers per imported products.

Previous Share: share of suppliers from which the buyer purchased in a previous year.

Legend: ^{a} significant at 0.1%, ^{b} at 1%, ^{c} at 5%.

Notes: LP Regressions, 2002–2008. Standard errors are clustered at the firm level. Breadth and depth variables are estimated in the second stage of an LP specification.

B Coding Supplier Identifiers

Transaction records are collected from Form B3 of the Canadian Border Service Agency. Importers are required to report the vendors' name on the form among the other information. The vendor's name is transformed into a consistent identifier according to a procedure articulated into three stages. The first stage creates the basic vendor identifier according to the following steps:

1. Remove corporation words like *ltd*, *corp*, *inc*. The output of this stage is the *standard name*.
2. Remove punctuation but leave spaces into the vendor's name; this generates the *clean name*.
3. Put the name in all upper case letters.
4. Replace French characters with English characters.
5. Remove stop words not integrated in the vendor's name, e.g. *and*, *the*, *of*, a, etc.
6. Remove vowels from the name.
7. Assign the basic vendor identifier.

The second stage of the procedure tries to propagate identifiers across records likely to represent the same firm:

- Generate a second identifier using the first two words of the clean name, if the first two words are not blank and standard name contains at least 6 characters. Firms whose name has the same first and second words are assigned the same identifier.
- Construct a third identifier based on the clean name, if the first non-blank word does not contain more than 16 characters.
- Generate a fourth identifier based on the first 3 words from the vendor's name.
- Construct a fifth identifier based on the ZIP code and the first three words of the vendor's name.
- Generate a sixth identifier attributed to vendors exporting to the same Canadian firm the same product and with the same first word.

The second identifier is selected as the preferred identifier; if such identifier could not be created, the third identifier would be used and so on. Finally, the third stage constructs a measure to characterize the quality of the identifiers. The quality is measured over 9 levels:[22]

- Level 0 is assigned if the vendor's name and its address are consistent across observations carrying the same identifier.
- Level 1 is assigned if the clean name and the address are consistent across observations carrying the same identifier.
- Level 2 is assigned if the vendor's name is consistent across observations carrying the same identifier.
- Level 3 is assigned if the clean vendor's name is consistent across observations carrying the same identifier.
- Level 4 is assigned if the distance between the vendor's and the clean name normalized by their length is less than 10, the first word and the address match across observations carrying the same identifier.
- Level 5 is assigned if the normalized distance between the names is less than 6, the basic identifier and the first word match across observations carrying the same identifier.
- Level 6 is assigned if the normalized distance between the names is less than 6, the Canadian Business Number and the HS10 product-code imported from the vendor match across observations carrying the same identifier.
- Level 7 is assigned if the normalized distance between the names is less than 3.
- Level 8 is assigned if the normalized distance between the names is less than 10.

Let us work through an example. Consider three fictional vendor's names

- Great Oranges and Nuts, Corporation
- Great Orangines and Néwton
- Great Oranges

Following the steps of the first stage of the algorithm, we would be able to generate the basic identifiers

[22] The presence of a match quality indicator is very important as it allows to run robustness checks over groups of different match quality.

1. Remove Corp./ Corporations
   - Great Oranges and Nuts,
   - Great Orangines and Néwton
   - Great Oranges
2. Remove Punctuation
   - Great Oranges and Nuts
   - Great Orangines and Néwton
   - Great Oranges
3. Remove French Characters and accents
   - Great Oranges and Nuts
   - Great Orangines and Newton
   - Great Oranges
4. Remove stop words
   - Great Oranges Nuts
   - Great Orangines Newton
   - Great Oranges
5. Remove Vowels and go to all caps
   - GRT ORNGS NTS
   - GRT ORNGNS NWTN
   - GRT ORNGS
6. Assign the vendor basic identifier
   - 123
   - 456
   - 789

Following the second stage of the procedure, preferred identifiers are based on the matching the first two words of the clean vendor's name.

- 123
- 456
- 123

In the third stage, firms with equal identifiers from the second stage are assigned a measure of the quality of the match. In our example, the two firms with identifier 123 have a match quality of 4 if the address is the same. In case the two observations do not share the same address, the match quality would be 8.