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Abstract

Trade facilitation policy focuses on accelerated and transparent shipment processing to reduce trade costs. A common measure to evaluate processing frictions is the time it takes to import. In this paper we translate import processing times to costs. Our theory considers that shipment processing times at the port of entry are random and firms choose lead times to buffer processing shocks. Based on this theory, we employ detailed data on import processing dates, instrumental variables, and firm-product-origin level import data to estimate import processing costs. Evaluated at the median, import processing is equivalent to a 20 percent import tariff. For experienced importers, the import processing cost tariff drops to about 12 percent. Our time cost estimate generalizes existing approaches in the literature. We show that our extensions are economically relevant to determine import processing costs, predict who would benefits from trade facilitation, and interpret existing data on the time it takes to import.

JEL-Codes: F100, F130, F140.

Keywords: trade costs, border processing, trade policy.

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1. Introduction

The 2013 WTO Trade Facilitation Agreement is a worldwide policy initiative that focuses on provisions to simplify the processing of international shipments to reduce trade costs, but only limited research exists to inform such a major policy initiative. This lack of evidence is partially due to the difficulty of measuring non-tariff barriers (Goldberg and Pavcnik, 2016). A valuable measure to evaluate the restrictiveness of non-tariff regulations employed by academic research, firms, policy makers, and international institutions is the time it takes to import.[1] For such a measure to reach its full potential to inform policy, time must be translated into cost.

In this paper, we develop a theoretical framework based on firms' optimal management of the import process and use detailed import data that includes the date of completion of various import procedures to estimate import processing costs based on the number of days it takes to process imports.

To quantify processing costs, we must determine the appropriate cost function to estimate. We use theory to solve this problem. Our starting point is that *processing times*, the time it takes to physically handle, move, and clear shipments through the port of entry, are uncertain due to conditionally random inspections and port congestion. Then, firms must choose the *lead time*, the time between initiating and desired completion of a single or multiple steps in the supply chain before it knows the shipments' processing performance. Short lead times save money, but run a greater risk of missed delivery obligations. Delayed shipments are costly due to late fees, reputation effects and disruption of production processes (Boehm et al., 2019). Weighing the risk of late delivery against the cost of a slow supply chain, firms choose optimal lead

[1] e.g. Doing Business Trading Across Borders `http://www.doingbusiness.org/data/exploretopics/trading-across-borders/what-measured`

times to minimize the total expected processing costs. Based on this theory, we derive firms' expected import processing cost.

In our empirical work, we take advantage of a detailed transaction level customs data set from Peru. We observe import values, quantities, and freight charges across importing firms, trade partners, products, and years. Along with this import information, the data report dates of completion for various steps in the import process. We use this detailed date information to generate import processing times. We also observe the number of vessel arrivals and the shipments' assigned customs inspections. Both are useful to generate instrumental variables to account for possible endogeneity in processing times.

Before estimating cost functions, we first use these data and provide evidence for the main mechanism we formalize in our theory. At the transaction level, fixed-effect regressions show that long processing times in the early stages of the import process result in reduced storage times of shipments in later stages of the import process. Therefore, firms buffer shocks in processing time with shorter storage time.

Next, we estimate firms' import processing costs based on observed importer-product-origin-year median import processing times. To accomplish this, the theory shows that we have to estimate two parameters. First, the import processing cost elasticity with respect to median processing times. Second, a multiplier that captures costs associated with the risk of missing desired delivery dates due to uncertainty in processing times. This multiplier scales the cost associated with median processing time, but cancels out of the cost elasticity.

To estimate the first parameter, the processing cost elasticity, the theory relates import values to firms' beliefs about their median processing time. The main challenge is that we do not observe what firms know about the median processing time. Instead, we relate import values to observed median processing times using high-dimensional fixed-effect regressions. This potentially results in measurement error that leads to substantial bias in fixed-effect specifications (Grilliches and Hausman, 1986; McKinish, 2008). To address this bias, we apply our instruments based on shipments' customs inspection probabilities and port congestion. We examine the robustness of the instrumental variable approach in several ways including lagging the instruments.

The second parameter, the cost multiplier, is not recoverable from fixed-effect regressions that relate import values to processing times. Instead, we employ our theory and detailed import data to estimate this remaining parameter. We offer multiple robustness checks to examine the sensitivity of this parameter with respect to our identification assumptions.

Instrumental variable estimates show that a 1 percent increase in the median processing time lowers import values by $.24$ percent.[2] Conditional on a demand elasticity of 4, our theory translates the import processing time elasticity of $.24$ into a processing cost elasticity of $.06$; a one percent increase in the median time raises import processing costs by $.06$ percent. For the cost multiplier we obtain an estimate of 1.104 and we provide evidence that it significantly affects import processing costs based on bootstrapped standard errors. Evaluated at a median processing time of four days, these estimates combine to result in an import processing cost that equals a 20 percent import tariff.[3] Conditional on a demand elasticity of 6, the processing cost drops to about 13

[2] This elasticity is somewhat lower compared estimates in the existing literature based on export processing. For example, Djankov et al (2010) estimate that a 1 percent increase in the time it takes to deliver a shipment from the factory gate to the port lowers trade by 0.4 percent. Instrumenting raises the magnitude of our elasticity estimates by a factor of five compared to OLS. This increase is comparable to existing IV applications (Costinot et al., 2012; Paravisini et al., 2015).

[3] Consistent with our theory it is simply computed according to the log linear cost function $\lambda \times (MedianProcessingTime)^{\chi} - 1 = 1.104 \times 4^{.061} - 1 = 0.204$ where λ is the cost multiplier and χ is the processing-time cost elasticity.

percent.

Hopes for trade facilitation are high. Roberto Azevedo, former Director General of the WTO, noted that "*The impact will be bigger than the elimination of all existing tariffs around the world*".[4] Based on a level of import processing cost of 20 percent, this optimism for trade facilitation policy seems justified. For comparison, average import tariffs in Peru equal about 3 percent, and 6 percent worldwide.[5] WTO estimates suggest that the full implementation of the Trade Facilitation Agreement may result in a reduction of the time to import of 1.5 days.[6] Based on our estimate across all importers, this would reduce import processing costs from about 20 to 17 percent.[7]

Existing literature provides evidence that long delivery times reduce trade (Persson, 2008; Djankov et al., 2010; Freund and Rocha, 2011; Hummels and Schaur, 2013; Volpe Martincus et al., 2015; Heid et al. 2017; Oberhofer et al. 2018; Fernandes et al. 2021). This literature assumes empirically convenient functional forms and relates import and export values to various measures of the time it takes to trade.[8] We make at least two contributions to this literature.

First, we derive the time-cost function from theory. Our theory shows that the elasticity of trade with respect to processing time depends on the shape and form of the processing-time distribution. Therefore, existing elasticity estimates based on different countries, exports, modes of transport, and stages of the international supply chain likely do not generally apply to evaluate import processing costs.[9] Consequently, we develop a new identification

[4]https://www.wto.org/english/news_e/news17_e/fac_31jan17_e.htm

[5]https://data.worldbank.org/indicator/TM.TAX.MRCH.WM.AR.ZS?

[6]https://www.wto.org/english/news_e/news17_e/fac_31jan17_e.htm

[7]Formally, $\lambda \times (MedianProcessingTime)^{\chi} - 1 = 1.104 \times 2.5^{.061} - 1 = 0.167$.

[8]We follow this literature and develop time costs as a ad-valorem tariff equivalent. For a discussion of identification of per-unit costs versus ad-valorem costs see Irarrazabal et al. (2015).

[9]They only apply if the form and shape of the distribution that determines the time delays

approach based on novel import data reporting detailed information on shipments' import-processing procedures.

Second, when evaluating trade costs associated with long delivery times, the existing literature does not consider a cost multiplier consistent with our theory. We provide evidence that, evaluated at the median processing time, this multiplier is economically and statistically relevant and accounts for about half of the total import processing cost. Therefore, functional form is important to determine the level of costs associated with processing time and, accordingly, to predict who may gain the most from trade facilitation policy in reducing costs.

Who gains from trade facilitation is policy relevant. Often the hope is that small firms and new relationships will benefit and grow.[10] However, without cost estimates, it is a priori not clear how high processing costs are for new relationships and it is difficult to measure policies' performance to reduce these costs. We provide evidence that experienced importers incur a processing tariff of about 12 percent. New importers pay a processing cost tariff equivalent more than double compared to experienced firms. This is evidence that border related processing costs are especially relevant to the formation of new trade relationships (Bernard et al., 2017a, 2017b; Fitzgerald et al., 2017; Rodrigue and Tan, 2019).

The next section provides background information on import processing and import processing times. Section 3 develops a theory for expected costs of import processing. Section 4 introduces our detailed import data. Section 5 explains how we identify the effect of processing times on imports and reports

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is the same. This is unlikely, because the processing distribution captures local regulations, storage, and port procedures.

[10] `https://www.wto.org/english/news_e/news17_e/fac_31jan17_e.htm`

estimates. Section 6 develops estimates for border processing costs based on estimation results in Section 5. Section 7 delivers robustness checks. Section 8 examines the heterogeneity of border processing costs according to existing theory. Section 9 concludes.

2. Import Processing at the Border

In this section, we describe the import process at Peru's main seaport, Callao.[11] We use highly disaggregated data taken from customs import declarations and load manifests over the period 2007-2013 kindly provided by Peru's National Tax Agency (Superintendencia Nacional de Administración Tributaria - SUNAT). For each shipment clearing through the port of Callao, we observe the date when the ship arrived, the date the shipment was unloaded, the date the customs import declaration was created and registered, the customs channel, the date the physical inspection occurred, and the date the shipment was released by customs.

Port operators unload shipments from vessels and move them to shipyards or warehouses. To initiate customs clearance, firms submit an electronic customs document to the customs agency, SUNAT. SUNAT returns a message containing the date, as well as information on tariffs and customs payments. After payment of duties and fees, a customs risk management model randomly allocates shipments to one of the three customs verification channels according to administrative, fiscal, and security risk factors.[12] In the green channel shipments are waived through and not inspected. In the orange channel docu-

[11]The seaport of Callao represents over 70% of Peru's import value in a given year. See Table 3 for more detailed information.

[12]These include the exporting firm, origin country, transport mode, transport company, countries of intermediate stops, customs broker, customs branch, product, and importing firm in Peru.

ments are inspected. The red channel involves a physical inspection.[13] SUNAT charges small fees for moving, opening, unloading, and reloading of containers. These services cost an average 40 US dollars each. After verification of documents or physical inspections customs releases the shipments.[14]

We define three measures of border time. First, *total border time* measures the time between the arrival date of the shipment and the release of the shipment from customs. Second, *processing time* measures the time each shipment takes in necessary processing steps such as customs inspection (the time between the filing of the customs declaration and release by customs), unloading (the time between when the vessel arrives and the shipments are unloaded from the vessel), and movements of shipments between stages. These steps depend on actions of border agencies, so they are largely out of the hands of individual firms. Third, *storage time* measures the time that shipments are idle between necessary processing steps. Contrary to processing time, storage time does potentially depend on firms' actions to move shipments along the supply chain. Table 1 presents percentiles of our time measures by customs verification channel for all shipments clearing through the seaport of Callao in 2013.[15] The percentiles show that total border times are a combination of official and necessary processing times of shipments, as well as a substantial amount of storage time after and between necessary processing steps.

About 50 percent of all shipments are processed in 4 days or less (for comparison, the median total border time including storage is 12 days), but Figure 1 shows that there is a long right tail of the processing-time distribution.

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[13]No more than 15% of the DUAs numbered in a given month in Callao can be subject to material control (see SUNAT, 2010).

[14]Unfortunately, our customs data sets does not include information after the release of the shipments.

[15]Data in other years are very similar. Detailed tables are available upon request. We count 1 day for stages cleared within the same day.

The percentiles in Table 1 show that processing times are associated with the (conditionally) random assignment of each shipment to a customs channel, as processing time systematically increases with the scrutiny of the customs inspection. For more summary statistics related to the import processing of shipments see the working paper version, Carballo et al. (2016).[16]

With detailed data on the import process at hand, we examine if processing stages are related to storage stages. If firms absorb random shocks in the physical handling of shipments with shorter storage times to meet contractual delivery dates, then we expect that longer processing times result in shorter storage times. To provide evidence, we regress log storage times after unloading on log unloading times at the transaction level.[17] The top panel of Table 2 shows that longer unloading times are absorbed by shorter storage times, conditional on firm, product-origin, and day of the week fixed effects; and various combinations of these fixed effects. These results are consistent with firms using intermediate storage steps to buffer against long and random processing times. The theory we develop in the next section formalizes this idea to model firms' optimal timing of the import process.

3. Theory

3.1. Expected Total Border Entry Costs

International trade involves both physically moving shipments and administrative steps regulated by governments such as customs procedures. To allow

[16]Descriptive statistics show that shipments of small firms and new importers are associated with longer border times. Evidence also shows that a substantial amount of variation in border times is due to importing and exporting firm characteristics. These and more descriptive statistics are available in the working paper: `https://publications.iadb.org/publications/english/document/Endogenous-Border-Times.pdf`. Any other summary statistics regarding border clearance times are available upon request.

[17]We focus on data from 2013 for the ease of exposition. We also run these regressions on the other years of our data and results are the same.

for these procedures, firms choose a shipment's lead time by placing shipments in advance of their desired delivery dates. Short lead times save money, but they increase the expected costs associated with missing the delivery date. We model this trade-off focusing on border procedures consistent with the empirical results in Section 2, but our approach extends to the entire supply chain.

Let v denote the total import value including transportation costs, tariffs, and insurance. Let $t_l > 1$ be the lead time that firms allow for shipments to clear import procedures. Slow supply chains are costly. Therefore, let the cost of a greater lead time to clear import procedures, $t_l^{\vartheta} v$, be proportional to the shipment value, v, and increasing with constant elasticity, $\vartheta > 0$.[18] If actual processing times are deterministic, then firms choose a lead time equal to the processing time and $\vartheta > 0$ captures a log-linear time cost elasticity similar to what is currently estimated in the existing literature (e.g. Djankov et al., 2010; Volpe Martincus et al., 2015).

However, processing times are random due to equipment failure, congestion, and customs inspection, and, according to Figure 1, distributed with a long right tail.[19] Following this pattern, let the actual processing time t_p be Pareto distributed $t_p \sim \frac{\varphi t_{min}^{\varphi}}{t_p^{\varphi+1}}$ with support $[t_{min}, \infty)$ and shape parameter $\varphi > 1$ to ensure a finite mean.[20] For a given location of the processing distribution determined by t_{min}, a greater shape parameter φ increases the probability that the processing time t_p is less than some pre-determined lead time t_l.

If the processing time turns out shorter than planned, $t_p \leq t_l$, then the firm stores the shipment until the desired delivery date at zero additional cost.[21]

[18] Greater lead times in our model are similar to greater time costs of money.

[19] It is difficult to examine the distribution for each importer-exporter-product combination. In those cases with sufficient observations the distributions show a long tail similar to the overall distribution.

[20] We also solved our model with a general import processing-time distribution. However, in that case, we do not obtain a parametric cost function to estimate.

[21] From a theory point of view, whether shipments are stored or delivered early is irrelevant as

This is in line with the evidence in Section 2, shorter unloading times result in longer storage times. Late shipments, $t_p > t_l$, accrue container demurrage, late fee penalties, and supply chain management costs. These costs, $(t_p/t_l)^{\omega} rv$, increase in the proportion by which the processing time exceeds the lead time as a factor of the import value, $v > 0$. The parameters ω and r determine the level and elasticity of these costs. Taking these costs into account, firms consider the total expected cost of importing:

$$ETC(t_l) = \int_{t_l}^{\infty} \left(\frac{t_p}{t_l}\right)^{\omega} \left(\frac{t_{min}}{t_p}\right)^{\varphi} \frac{\varphi r v}{t_p} dt_p + t_l^{\vartheta} v. \tag{1}$$

Allowing for more lead time, t_l, lowers the probability of missing the delivery date and expected costs of late arrivals, but raises time costs $t_l^{\vartheta} v$ due to slower supply chains. Firms choose the optimal lead time, t_l^*, to minimize expected total costs of import processing:

$$t_l^* = \min_{t_l} ETC(t_l) = t_{min}^{\frac{\varphi}{\varphi+\vartheta}} \left(\frac{r}{(\varphi-\omega)} \frac{\varphi^2}{\vartheta}\right)^{\frac{1}{\varphi+\vartheta}} \tag{2}$$

Equation (2) shows that lead time is determined by distribution parameters (t_{min}, φ) and cost parameters (ω, r, ϑ) and we prove our proposition.[22]

Proposition 1. *For interior solutions and a given processing-time distribution, firms schedule longer lead times t_l^* if (i) late fees are more elastic in missing the delivery date (i.e. if ω increases), (ii) late fees are a greater proportion of the*

long as the costs associated with lead times are not refundable. However, we observe storage time in our data. Furthermore, from conversations with logistics companies serving the port of Lima we understand that storage is free up to 19 days. Therefore, this modeling assumption is reasonable for us. Extending the model to include additional storage costs is feasible in case this is relevant to consider different ports.

[22]For interior solutions, we require $r > \vartheta(\varphi - \omega) t_{min}^{\varphi} \varphi^{-2}$ or that firms care enough about late delivery costs such that they choose $t^* > t_{min}$. In the expected cost function, the cost elasticity and shape parameter combine to the restriction that $\omega - \varphi - 1 < -1$ for the integral on the expected time cost to exist, as standard in the Pareto distribution. This results in the parameter restriction $\varphi > \omega$.

import value (i.e. if r increases), (iii) if lead time costs are less elastic (i.e. if ϑ decreases).

For proof see Section A.1.

Proposition 1 has implications for the cross-country evaluation of trade facilitation measures based on processing times. Two countries' processing time distributions may be identical, but lead times and expected costs associated with import processing differ. Therefore, simple comparisons of processing time distributions, in our case t_{min} and φ, do not necessarily result in cost rankings of import processing. Thus, for data on the time it takes to import to be fully informative for policy, we must translate it into cost.

Proposition 1 also shows that comparing border processing performance based on total border times can be misleading. For two ports of entry with the same processing-time distribution, firms allow longer lead times if lead time costs are less elastic perhaps due to differences in available storage space. Therefore, longer lead times may not be a sign that processing costs are high, but that storage space is cheap.[23] In this case, longer lead times may be a sign of lower import costs and we would expect that longer lead times are associated with an increase in trade. This result emphasizes the importance of measuring effects of trade facilitation and import processing costs based on the fundamentals of the processing distribution.

We make two steps to translate import-processing times to costs. First, substitute t_l^* into (1) to obtain minimized expected costs as a function of the minimum processing time. Second, based on the Pareto distribution, substitute $t_{min} = T/\sqrt[\varphi]{2}$, to obtain total minimized expected costs as a function of the

[23] Applying the envelope theorem to equation (1) in optimum, $ETC(t_l^*)$, it is straightforward to see that $\frac{\partial ETC(t_l^*)}{\partial \vartheta} > 0$ as long as the processing times take at least one day, $t_p > 1$, and we are at an interior solution.

median processing time T:

$$ETC = \lambda T^{\chi} v, \tag{3}$$

where $\chi = \varphi\vartheta/(\varphi+\vartheta)$ and

$$\lambda\left(\frac{r}{\varphi-\omega}, \varphi, \vartheta\right) = \left(\frac{r}{\varphi-\omega}\right)^{\frac{\vartheta}{\vartheta+\varphi}} \left(\vartheta^{\frac{\varphi}{\vartheta+\varphi}} \varphi^{-\frac{\varphi-\vartheta}{\vartheta+\varphi}} + \vartheta^{-\frac{\vartheta}{\vartheta+\varphi}} \varphi^{\frac{2\vartheta}{\vartheta+\varphi}}\right) 2^{-\frac{\vartheta}{\varphi+\vartheta}} \tag{4}$$

The multiplier, λ, median processing time, T, and elasticity, χ, combine to define the border-processing cost factor, λT^{χ}, as an ad-valorem tariff equivalent on the total import value, v.

Trade facilitation policy emphasizes costs associated with slow shipment processing due to regulations of international commerce. Equation (3) then highlights potential benefits of trade facilitation policy. The elasticity χ and the multiplier λ translate policy driven reductions in median processing times, T, into lower border processing costs. To understand what determines the benefits of trade facilitation policy, we may further examine the fundamentals of χ and λ.

According to equation (3), the processing-time cost elasticity, $\chi = \varphi\vartheta/(\varphi+\vartheta)$, increases in ϑ and φ. Therefore, processing costs are more elastic with respect to a percentage change in median processing times, if lead time costs are more elastic (a greater ϑ) and the processing time distribution is subject to less probability of long delays (a greater φ) due to a steeper processing-time distribution. In addition to providing fundamentals for existing elasticity estimates, this has an important consequence for the evaluation of import-processing costs. The processing distribution, including φ, is determined by local regulations, port procedures, equipment failures, and risk management methods. Therefore, to evaluate import-processing costs, we cannot rely on existing elasticity estimates based on data from different countries, modes of transport, and legs of the international supply chain (Djankov et al., 2010; Hummels and Schaur 2013; Volpe Martincus et al., 2015; Fernandes et al., 2019). Instead, we must estimate our own processing cost elasticities. To do so, we follow the existing literature and relate processing times to trade flows.

In addition to the shape parameter, φ, and the lead time cost elasticity, ϑ, the multiplier λ also depends on costs of supply chain disruptions and late fees collected in r and ω. For a given shape of the processing distribution and lead time cost elasticity a greater cost of supply chain disruptions, an increase in r or ω, raises the multiplier λ and the expected border processing costs.[24] Consequently, the multiplier λ captures costs associated with missing desired delivery windows that are not included in the processing cost elasticity χ.

Estimating border processing costs requires an empirical strategy for λ. Taking advantage of the structure of our model and detailed data, we provide a estimation strategy for $r/(\varphi - \omega)$ to obtain estimates for λ. In particular, conditional on the processing-time distribution and elasticity parameters (φ, ϑ), equation (2) shows that firms choose a greater optimal lead time t_l^* the greater $r/(\varphi - \omega)$. Therefore, information on the processing-time distribution, elasticities, and a proxy for the optimal lead time determine a value for $r/(\varphi - \omega)$ from our data. To determine the remaining parameters in λ, (φ, ϑ), we examine the elasticity χ.

[24] If $\lambda > 1$, then import processing is costly even if the median processing time is one, $T = 1$. The intuition is that even in that case where firms at the median do not experience delays, they take into account the probability of experiencing a delay and the associated costs of missing the delivery window determined by the parameters r, ω and the probability distribution, as well as the costs of hedging against such delays by scheduling longer lead times determined by ϑ.

3.2. Import-Processing Cost and Imports

To link import-processing times to import values, let us focus on a given importer-exporter relationship.[25] Firm i imports m_{ihxy} units of product h from country x in year y. The firm combines the imported product with a domestic input, l_{ihxy}.[26] Output, q_{ihxy}, is produced and distributed according to the Cobb-Douglas production function $q_{ihxy} = \alpha_{ihx} \times \alpha_{iy} \times m_{ihxy}^{\beta} \times l_{ihxy}^{1-\beta}$. We maintain $0 < \beta < 1$. The productivity parameters α_{ihx} and α_{iy} allow for heterogeneity in productivity across importers, origin, products, and time.[27] Final products are differentiated and demand on the domestic market follows CES, $q_{ihxy} = A_y \left(p_{ihxy}^{f}\right)^{-\sigma}$. Final goods producers are monopolistically competitive on output markets and optimally source the local and international input taking prices as given.

Domestic factor markets are competitive such that the price of the domestic input, w_{hy}, varies across products and time, but not across firms. Let p_{hxy} be the f.o.b. price of the imported input and $\tau_{hxy} > 1$ be the ad-valorem import cost factor including freight and tariffs.[28] Taking into account import processing costs, an importer's profit maximizing[29] import demand then is $m_{ihxy} = \kappa_{iy} \times \kappa_{ihx} \times \kappa_{hy} \times \left(\lambda\, T_{ihxy}^{\chi}\right)^{-\gamma} \times p_{hxy}^{-\gamma}$, where the constants κ_{ihx}, κ_{iy}, κ_{hy} ab-

[25]Bernard et al. (2017a) model the endogenous sorting of importers and exporters. This is beyond our object in this paper and we take a importer-exporter relationship as given. Nevertheless, we derive a log-linear import value relationship similar to their theory.

[26]Note that the local factor l_{ihxy} has a x subscript. This is to distinguish that a firm may import the same product from multiple source countries and allocates some labor to finish and distribute each of these products on the market.

[27]Alternative sourcing modeling assumptions, such as CES production, result in similar log-linear import demand functions. For example, see Halpern et al. (2015), Gopinath and Neiman (2015) and Antràs et al. (2017). In that case we can think of firms importing varieties to combine to a single output according to a CES production function, but we would obtain a similarly log-linear import equation.

[28]In the empirical section we discuss how our identification strategy extends to the case where export prices vary across importers p_{ihxy}, and we provide robustness checks considering exporting firms.

[29]Firms maximize expected profits: $A_y^{\frac{1}{\sigma}} \left(\alpha_{ihx} m_{ihxy}^{\beta} l_{ihxy}^{1-\beta}\right)^{1-\frac{1}{\sigma}} - \lambda\, T_{ihxy}^{\chi} \tau_{ihxy} p_{ihxy} m_{ihxy} - w_{hy} l_{ihxy}$.

sorb productivity and demand parameters and $\gamma = \beta(\sigma - 1) + 1$. The exporter produces a differentiated variety with constant marginal cost z_{hxy}, takes the importers demand as given and charges the profit maximizing constant markup over marginal cost price $p_{hxy} = \frac{\gamma}{\gamma-1} z_{hxy}$. Combining import demand with the exporter's pricing rule the import value equals

$$v_{ihxy} = m_{ihxy} p_{hxy} = \kappa_{iy} \kappa_{ihx} \delta_{hxy} \times \left(\lambda \, T_{ihxy}^{\chi}\right)^{-\gamma}. \tag{5}$$

The constant δ_{hxy} now accounts for demand in the importing country as well as the exporter's marginal cost. The processing costs parameters λ and χ translate an increase in the median processing time into an increase in processing cost. The parameter γ translates this cost increase into a reduction in trade flows.

In the following sections we take advantage of equation (5) to estimate import elasticities, $\gamma\chi$, and to back out estimates for χ. The time cost multiplier, λ, is not separable from other constants in this log-linear demand equation. We use our elasticity estimates to develop an alternative estimation strategy to determine λ. Before we explain how we obtain elasticity estimates and determine import processing costs, the next section explains the import data we use throughout the rest of the paper.

4. Trade Data

To implement equation (5) empirically requires data on imports and border processing. In this section, we discuss data sources and summary statistics.

We observe highly detailed import data obtained from Peru's National Tax Agency, SUNAT, from 2007 to 2013. Our dataset reports import values, quantities in kilograms, freight, and tariff charges for each recorded transaction. In addition, for each record we see the ID of each importing firm, the origin country of the flow, the exporting firm, the product code (10-digit HS), the customs office clearing the shipment, and the vessel that carried the shipment. These data cover all transactions entering Peru. We merge these import data with our detailed information on processing times we observe for the port of Callao described in Section 2 at the transaction level and generate an estimation sample to identify the import demand equation.[30]

Before doing so, Table 3 compares the universe of import transactions for Peru with the sample of imports that arrive at the seaport of Callao. Imports clearing Callao account for approximately three quarters of the total import value, two thirds of the total number of importers, and 90% or more of all imported products and countries of origin. We therefore capture most of Peru's imports. An advantage of focusing on Callao is that the majority of business activity is concentrated around Lima which mitigates concerns that heterogeneity in inland transportation impacts our results. Furthermore, the Callao-average importer is similar to the national-average importer. More specifically, the Callao-average importer has 65 employees, is eight years old, and buys 12.4 products from 2.8 countries for approximately 650,000 US dollars (See Table A1 in the appendix for details).[31]

There are 22 customs offices in Peru, but the average firm uses only 1.03 customs offices and does not appear to use multiple ports of entry in response to port congestion, long queues at customs, or other delays. Consequently, im-

[30]We do not lose data due to this merge since we have transaction IDs that connect processing data with customs data.

[31]The national-average importer has 52 employees, is seven years old, and buys 14 products from 3.1 countries for roughly one million US dollars (See Table A1 in the appendix for details). Hence the Callao-average importer looks like the national-average importer, but imports less in terms of value spread over a smaller number of shipments. The difference are due to heavy goods being imported through other ports located closer to the production facilities and imports entering through airports which typically consists of smaller and more frequent transactions (see Table A1 in the appendix).

ports arriving at Callao represent the majority of the firm's imports. Therefore, merging the processing information at Callao with the firm's import information is akin to merging the firm's total imports with its processing data.

We aggregate firms' import data processed at the seaport of Callao to the importer-product-origin-year level. Similarly, using the shipment level processing data for the port of Callao described in Section 2, and applying our definition of processing times, we generate median processing times, $\hat{T}_{ihxy}$, across all shipments within each importer-product-origin-year unit of observation. In addition to median processing time, we will also use a measure of the total border time. Section 2 defines the total border time for each shipment as the difference in days between the date when the vessel arrives and the shipment clears from customs. For the following empirical sections, we employ the median of the total border time across all shipments within each importer-product-origin-year unit of observation as our measure of total border time.

Aggregation to the importer-product-origin-year level facilitates standard empirical approaches. For example, it is straight forward to account for time varying fixed effects and use lagged variables to achieve identification. This is much more challenging in transaction level data where shipments across different importers, exports, and products arrive on different days resulting in much noisier variation. While convenient, this aggregation results in a seeming disconnect between our theory and data. Our theory is based on an importer-exporter relationship, but for most of our empirical applications, we aggregate to the importer-product-origin-year level. Aggregating across exporting firms is relatively inconsequential. Within an importer-product-origin-year combination, Peruvian firms tend to source only from a few exporters. Nevertheless, we will examine this with a robustness check. Aggregating to annual observations sums over multiple shipments within the year. Our theory is mute on the frequency of shipments, but we also examine potential consequences of this aggregation with robustness checks.

Combined, we have an estimation sample that includes f.o.b. import values (v^{fob}_{ihxy}), freight charges, tariffs, insurance charges, the median processing time, $\hat{T}_{ihxy}$, and a measure of the median total border time within each importer-product-origin-year unit of observation. See Table A2 for descriptive statistics on these variables computed using our main estimation sample.

5. Identification of Import Elasticities w.r.t. Import-Processing Time

With detailed import data at hand, in this section we explain how we identify the effect of import-processing times on imports. We develop the empirical model, discuss the identification strategy, and report baseline results. We discuss robustness checks in a later section.

5.1. Empirical Specification and Identification

We take equation (5) to our data to estimate $\gamma\chi$. This presents a challenge. In our theory, firms know the median processing time, T_{ihxy}. Unfortunately, we do not see what firms know, but observe realized median processing times, $\hat{T}_{ihxy}$, for importer i across products h, origin of exports x, and within each year y. To bridge this gap, we apply a proxy variable approach. Let actual processing performance equal a firm's beliefs regarding shipment processing time plus a random shock such that, $ln\hat{T}_{ihxy} = lnT_{ihxy} + e_{ihxy}$ where $E(e_{ihxy}) = 0$. Then, taking logs of the import value equation, equation (5), and substituting the proxy $\hat{T}_{ihxy}$ for the unobserved information T_{ihxy} we obtain the empirical model:

$$ln(v_{ihxy}) = \delta_{hxy} + \kappa_{iy} + \kappa_{ihx} + \gamma\chi ln\hat{T}_{ihxy} + u_{ihxy}, \tag{6}$$

where the disturbance u_{ihxy} contains measurement error e_{ihxy}. The main parameter of interest is $\gamma\chi < 0$. The empirical model shows that log-linear specifications, the common approach in this literature, implicitly fix the shape of the processing-time distribution, φ, within the elasticity χ. We follow the literature and treat $\gamma\chi$ as a parameter to estimate.[32] Importer-year fixed effects account for firm-level changes in productivity. Importer-product-origin fixed effects, κ_{ihx}, absorb heterogeneity in importer-exporter relationships. Product-origin-year fixed effects, δ_{hxy}, account for exporter productivity and changes in supply as well as trade policy conditions.

The main identification challenge is that measurement error, e_{ihxy}, is contained in the disturbance and is correlated with the main regressor of interest, $ln\hat{T}_{ihxy}$, according to our proxy variable approach.[33] In fixed-effects regressions, classical measurement error is known to lead to substantial attenuation bias because variation of the independent variable around the fixed effects usually emphasizes variation in idiosyncratic measurement error (Griliches and Hausman, 1986; Mckinish, 2008). We develop two instruments based on port congestion and inspection probabilities to solve this problem. We will first introduce the instruments and then discuss their necessary identification assumptions.

Simultaneous arrival of several vessels translates into longer border handling and processing times due to congestion. In our data, we observe the arrival date of each vessel and use it to compute the number of vessels that

[32]The alternative is to treat the shape parameter as data. This would require a non-linear identification strategy that accommodates a large number of fixed effects, avoids the incidental parameter problem, and handles instrumental variables to break endogeneity. We are not aware of a convenient estimator to handle these challenges.

[33]The alternative is to make the much more convenient assumption that $T_{ihxy} = \hat{T}_{ihxy} + e_{ihxy}$ and e_{ihxy} is not systematically related to $\hat{T}_{ihxy}$. In that case OLS is consistent and we would expect that IV and OLS estimates are similar, unless there are additional sources of bias.

arrived the day before each shipment. Then, for each importer-product-origin-year combination, we take the median of this measure across all shipments as a measure of congestion and our first instrument.[34]

Our second instrument is based on the fact that handling time in customs depends on the assignment to different inspection channels. A customs' risk management model allocates shipments to different processing channels. Some shipments pass customs without further inspection. Other shipments experience additional processing burden due to document and physical inspections. Within each importer-product-origin-year observation, we compute the fraction of shipments that were assigned to more intensive inspection channels. This instrument captures the exogenous probability of assignment to more time-consuming inspection channels. We examine sensitivity of our results with respect to alternative definitions of the instruments, including lagging the instruments, in the robustness section.

The instruments must predict realized median processing times, $ln\hat{T}_{ihxy}$. This is easily verifiable from first stage statistics. The instruments must also not be related to the outcome in specification (9) after conditioning on the other explanatory variables. To achieve this, we absorb omitted variables that may be correlated with inspection probabilities and port congestion with fixed effects. If customs selects inspection probabilities based on relationship specific information, or, based on the origin country and product, then firm-product-origin fixed effects, κ_{ihx}, and product-origin-year fixed effects, δ_{hxy}, account for this information. These fixed effects also account for changes in product

[34]A concern might be that importers would bring large shipments right before the Christmas shopping season, which is exactly the time of high congestion in the port. This is challenging to examine at high frequency, because of lumpy shipments in international trade. However, we estimated our baseline model at quarterly frequency and report the results as a robustness check in the appendix. In general they confirm our findings.

specific demand, heterogeneity in the sophistication of existing supply chains such as the use of information technology, and distance related transportation costs. Finally, firm-year fixed effects, κ_{iy}, control for firms' size, experience, importer-year specific productivity, and firms' supply chain complexity. In the robustness section, we will also account for heterogeneity across carriers and exporting firms.[35] This mitigates concerns that high performing imports are associated with better logistics providers that result in reduced import processing.

Finally, according to the theory, specification (9) accounts for export prices and freight charges with fixed effects. In turn, the same specification adds price and freight charges to the disturbance if they are not fully captured by the fixed effects, for example, if the prices and freight charges are importer-product-origin-year specific. This is not a concern as long as our instruments based on port congestion and inspection are not systematically related to this information. To support this identification approach we provide test statistics and a series of robustness checks including lagging our instruments.

To facilitate estimation, given the substantial number of fixed effects, we estimate specification (9) in first differences. We cluster standard errors by the importing firm.

5.2. Import Regression Estimates

The left panel of Table 4 reports OLS (column 1) and 2SLS (column 2) estimates for the elasticity of imports with respect to processing time, $\gamma\chi$. Following equation (9), we relate log import values to the log of median processing times at the (importing)firm-product-origin-year unit of observation. We first

[35]Heterogeneity across carriers accounts for variation in the ability of shipment handling in the supply chain, or, the possibility that more productive importers sort with more productive logistics providers.

difference our data. Therefore, the reported fixed effects are in addition to firm-product-origin fixed effects. First-stage statistics support the instrumental variable approach. For convenience, the right panel of Table 4 reports our quantification of import processing costs. We will discuss these estimates in the next section, but report them here because they derive from the elasticity estimates.

OLS estimates in Table 4 column 1 show that a one percent increase in the processing time reduces import values by 0.049 percent. Column 2 reports 2SLS estimates applying inspection probabilities and port congestion as instruments for endogenous processing times. The instrumental variable approach estimates an elasticity of negative 0.243 percent. The estimate is statistically significant at the 1 percent level. Therefore, as predicted in our theory, we conclude that longer border-processing times reduce import values.

As anticipated in the identification section, OLS estimates based on our proxy variable approach are subject to attenuation bias. The magnitude of the OLS estimates is about five times lower than the magnitude of the 2SLS estimate. Based on measurement error, the intuition is that fixed effects raise the noise to signal component of the identifying variation (Griliches and Hausman, 1986; McKinish, 2008). The observed bias compares to existing literature. For example, Costinot et al. (2012) and Paravisini et al. (2015) report similar magnitudes of attenuation bias.

Despite the increase in the magnitude of the IV estimate compared to OLS, the elasticity of import values with respect to import-processing time is still lower than estimates in the existing literature. Djankov et al. (2010) report that a 10 percent increase in the time it takes to move cargo from the factory gate to the ship reduces exports in the range of 4 percent. A possible explanation for the difference in elasticity estimates is that the existing elasticity estimates in the literature combine intensive and extensive margin variation since they are based on more aggregate data. However, in firm-level export data, Volpe Martincus et al. (2015) report that a 10 percent increase in customs export delays reduces exports by 3.8 percent.

We take away two insights from our results with respect to this existing literature. First, from an identification point of view, the magnitudes of our estimates are reasonable and comparable to the existing literature. Second, our elasticities based on import processing are lower than estimates in the literature based on export processing. Our theory provides an explanation. The elasticity $\gamma\chi$ increases in the shape of the processing-time distribution φ. An increase in φ results in a steeper processing distribution with a lower likelihood of long delays. Therefore, if import rules and regulations lead to a flatter processing distribution, a lower φ, then we would expect that imports are less elastic with respect to processing times.

First stage results provide evidence that our instruments work. As expected, congestion and a higher likelihood of inspection predict greater median processing times. The effective F statistics suggest that the instruments are not weak. Hansen's test statistic provides evidence that, after conditioning on fixed effects, overidentifying restrictions cannot be rejected. Both instruments are in logs.[36]

As of now, we have estimates for the import elasticity, $\gamma\chi$, with respect to border processing times. We discuss the robustness of these elasticity estimates in section 7. Before doing that, the next section explains how we obtain the parameter estimates in the right hand panel of Table 4 to quantify border

[36]The tests for overidentifying restrictions is a test of joint-exogeneity and, as such, does not strictly provide information on the validity of the instruments, but on their coherence, i.e., whether they identify the same vector of parameters (see Parente and Santos Silva, 2012).

processing costs.

6. Estimates for Border Processing Costs

In the theory, the tariff equivalent processing cost equals $\lambda T^{\chi} - 1$ where $\chi = \varphi\vartheta/(\varphi + \vartheta)$ and λ is defined by equation (4). Estimating its magnitude requires information on $r/(\varphi - \omega)$ in addition to φ and ϑ. The right-hand panel of Table 4 reports structural parameters and processing costs that we explain in this section. We develop and discuss step-by-step structural estimates assuming an import demand elasticity of $\gamma = 4$ (column 3) consistent with the literature (Soderbery, 2015). For comparison, we also report structural estimates assuming an import demand elasticity of $\gamma = 6$ (column 4).

In order to evaluate the significance of these structural parameters and keeping things comparable, we bootstrap standard errors for all the structural parameters. We re-sample across firms and across strata when appropriate to account for clustering and estimate all parameters on these sub-samples of data. In all cases, the bootstrapped standard errors are based on 500 repetitions (see Efron and Tbshirani, 1994).

Dividing the import-processing-time elasticity from our IV estimation, 0.243, by the import demand elasticity, $\gamma = 4$, we obtain the processing-time-cost elasticity $\hat{\chi} = 0.061$. To put this parameter in perspective, Table 1 shows that at the median, document inspection more than doubles the time to import from 2 to 5 processing days. Based on our elasticity of 0.061, automating physical document review to cut associated inspection times would reduce import processing costs by 5.4 percent. This implies a cost reduction of about 2 percent per day.

Next, we compute the elasticity ϑ using the processing-time cost elasticity $\hat{\chi} = \varphi\vartheta/(\varphi + \vartheta) = 0.061$. This requires an estimate for φ. In the Pareto distribution, the flatter is the shape determined by φ, the greater is the median processing time, T_{ihxy}, relative to the minimum processing time. Expressing the median as a function of the minimum processing time according to the Pareto distribution this means $T_{ihxy} = 2^{\frac{1}{\varphi}} \times t_{min,ihxy}$. Taking logs, we estimate the auxiliary regression $\ln T_{ihxy} = b_0 + b_1 \ln t_{min,ihxy} + u_{ihxy}$ and obtain $\hat{\varphi} = \frac{ln(2)}{\hat{b}_0} = 2.072$. We estimate $b_1 = .87$ with standard error of 0.002. Applying $\hat{\varphi} = 2.072$ and $\hat{\chi} = 0.061$, we obtain $\hat{\vartheta} = \hat{\chi}\hat{\varphi}/(\hat{\chi} + \hat{\vartheta}) = 0.063$.

For intuition, when shipments do not get inspected, the average storage time is about 10 days on average. If we take this as our measure of lead time that firms allocate to clear the border, then an additional day of lead time increases lead-time costs by about $.61$ percent. This estimate is comparable to the low-end of time-cost elasticities estimated in Hummels and Schaur (2013).

As of now we focused on estimating the cost elasticity with respect to processing times and the associated percentage changes in processing costs. To determine the total tariff equivalent cost of import processing, we next quantify the level of cost by evaluating the cost multiplier λ.

Given our elasticity estimates, to compute λ we only need the ratio $r/\left(\varphi - \omega\right)$. Equation (2) says that all else equal, if $r/\left(\varphi - \omega\right)$ increases, then firms schedule greater lead times relative to processing times to avoid running late. Therefore, with observed information on processing times, elasticity parameters, and proxies for the lead time, we can estimate the constant $r/\left(\varphi - \omega\right)$ from equation (2).

To stay consistent with our identification strategy, we substitute median processing times for minimum processing times, $T = t_{min} \sqrt[\varphi]{2}$, in equation (2) and rearrange to obtain

$$2\varphi^{-2}\vartheta T^{-\varphi}(t^{*})^{\vartheta+\varphi} = \frac{r}{\varphi-\omega}. \tag{7}$$

Now, if we can generate an empirical counterpart to the left hand side of equation (7) in our data, then we can use it to estimate $r/(\varphi-\omega)$.

To generate the left hand side of equation (7) with our data, we substitute the parameters φ and ϑ with the estimates $\hat{\varphi} = 2.072$ and $\hat{\vartheta} = 0.063$. Next, as we did in (9), we substitute realized importer-product-origin-year specific observed median processing times, $\hat{T}_{ihxy}$, for the median processing time T. The only remaining variable to compute the left hand side of (7), is then the optimal lead time t^{*}.

Lead time measures the total time that firms optimally allocate to clear the border being mindful of delivery dates. It includes processing and storage steps. Firms' optimal lead times are not directly reported in our data. Instead, we approximate lead times with a measure based on the observable total border time. In our data, a shipment's total border time includes all storage and processing steps that the shipment follows in the port of entry. Then, as an approximation, we set the optimal unobserved lead time, t^{*}, equal to the median total border time of all shipments within each importer-product-origin-year observation. We define this importer-product-origin-year specific median of the total border time as $\widehat{t^{*}}_{ihxy}$.

Substituting estimated parameters and observed measures of time into the left hand side of (7), and, considering that by doing so we measure the left hand side of (7) with random measurement error, e_{ihxy}, we obtain

$$2\hat{\varphi}^{-2}\hat{\vartheta}\hat{T}_{ihxy}^{-\hat{\varphi}}(\widehat{t^{*}}_{ihxy})^{\hat{\vartheta}+\hat{\varphi}} = \frac{r}{\varphi-\omega} + e_{ihxy}. \tag{8}$$

Regressing the left hand side of (8) on a constant then returns the estimate $\widehat{r/(\varphi - \omega)} = 0.299$, as reported in column 3 of Table 4.

Applying all parameter estimates as reported in column 3 of Table 4 in equation (4), we then obtain $\hat{\lambda} = 1.104$. In our robustness section, we discuss several alternative choices for the lead time and examine λ's sensitivity with respect to these alternative measures.

With all parameters at hand, we can now estimate the import cost due to border processing. Table 1 reports that across all shipments, the 50th percentile of the processing distribution is 4 days. Based on equation (3), we then compute the median tariff equivalent cost of import processing as $\tau^{\widehat{Equiv}} = \hat{\lambda} T^{\hat{\chi}} = 1.104 \times 4^{0.061} = 1.201$. Therefore, evaluated at the 50th percentile, total border processing costs equal about 20 percent of the value of the import. The last line of Table 4 column 3 reports bootstrapped standard errors and shows that our estimate of the import processing tariff is statistically significant.

To evaluate the economic significance of the processing cost multiplier, set $\lambda = 1$. In this case the import processing cost simplifies to $T^{\hat{\chi}}$ and the import processing cost drops to about 9 percent, $4^{0.061} = 1.088$. Therefore, from an economic point of view, ignoring the multiplier would significantly under estimate border processing costs. Furthermore, even if a policy could reduce the median processing times to one day, then trade flows still experience a 11 percent import tariff due to costs of uncertainty captured by the multiplier.

Knowing the level of border processing costs, we can compare them to import tariffs and potential tariff liberalizations. World Bank data show that the average world wide applied tariffs have decreased to about 6 percent in

2010.[37] Consequently, evaluated at the median, import processing costs are much greater than applied import tariffs. Eliminating all import tariffs, a reduction in tariffs of 100 percent, reduces import tariffs by 6 percentage points. If trade facilitation policy reduces processing times by 1.5 days[38], then at the overall median processing time of 4 days, this reduces import processing costs by about 3.4 percentage points.[40]

What would it take to achieve a 6 percentage point reduction in processing costs with trade facilitation policy? Table 1 shows that, at the 50th percentile, processing times in the orange channel equal 5 days, while processing in the green channel takes 2. Eliminating all document inspections, by switching from the orange channel to the green channel, therefore reduces processing times from 5 to 2 days at the median. This results in a 6.6 percentage point reduction in import processing cost.[41] Thus, according to our estimates, eliminating all document inspection, perhaps with the use of information technology, lowers import processing costs by the same amount as completely eliminating a 6 percent applied import tariff.

Following the same steps as above, we also estimate the model parameters at $\gamma = 6$. We report results in Table 4 column 4. In this case, a 10 percent increase in the processing time raises costs by $\chi = .4$ percent and the total border processing cost tariff equivalent drops to 12.8 percent. Based on existing demand elasticity estimates, we consider this value at the low end of the potential import processing tariff equivalent.

[37] See http://data.worldbank.org/indicator/TM.TAX.MRCH.SM.AR.ZS
3839

[40] This is a straight application of the tariff equivalent: $1.104 \times 4^{0.061} - 1.104 \times 2.5^{0.061} = 0.066$.
[41] We compute $1.104 \times 5^{0.061} - 1.104 \times 2^{0.061} = 0.066$.

7. Robustness Checks

This section reports robustness checks for the import specification, the cost multiplier, and the processing cost. We start with the import specification and then explore the sensitivity of the cost multiplier.

7.1. Robustness Checks for Import Estimates

The following subsections examine the robustness of the instrumental variable estimates for the import regressions in the left hand panel of Table 4. We consider alternative definitions of the instrumental variables, import regulations and corruption, specification error, and aggregation bias.

7.1.1. Alternative Definitions of the Instruments

We start by examining the robustness of our main instrumental variable estimates, reported in Table 4, with respect to alternative definitions of the instruments. Results are reported in Table 5. Rows of results report various robustness checks. For all robustness checks, we re-estimate our import specification, equation (9), using 2SLS. Across the columns we report the IV estimate for the effect of processing time on import values, $\gamma\chi$.

Before explaining details, it is straight forward to summarize the results. Across all robustness checks in Table 5, the estimated effect of the processing time on import values is very similar to our estimate in Table 4, -0.243. Across all robustness checks, we confirmed that the F-Statistics and Hansen test support the first stage of the IV approach.

The top panel of Table 5 examines robustness of our customs inspection instrument, channel. Our main specification uses the fraction of inspected shipments within importer-product-origin-year observations as a measure of the probability of getting inspected. Volpe Martincus et al. (2015) propose an alternative instrument. Their instrumental variable is an indicator that equals one if more than 50 percent of the shipments in a given year within an existing trade relationship were inspected. The first row of Table 5 reports the results when we apply this median channel assignment as an instrument. The effect of processing times on imports remains similar as in the baseline IV estimate in Table 4.

The fraction of inspected shipments may be a noisy measure of the inspection probability in small samples. To examine this, we re-estimate our baseline focusing on annual observations that contain at least 5 shipments at the importer-product-origin-year level. The second row of results in Table 5 shows that over this sample the effect of the border processing time on the import value remains negative and significant, but turns out slightly smaller than our baseline estimate.

The middle panel of Table 5 examines the robustness of our port congestion instrument. Firms' ability to update beliefs about the processing time may depend on the time window we consider before arrival of the shipment to compute the measure of congestion. For our main estimates, we focused on vessel arrivals the day before each shipment arrives at the port. We now extend that time window from 1 to 5 days. The estimates of border processing costs on import values are very similar to our baseline specification.

In the bottom panel of Table 5 we report estimates when we lag both instruments by one period. Even though our instruments are due to a random customs process and aggregate port congestion, one may be concerned that contemporaneous instruments are correlated with the contemporaneous disturbance. Coefficient estimates are similar to our main specification. A one log point increase in import processing time reduces import values by about 0.214 log points.

7.1.2. Alternative Specifications of Fixed Effects

In Table 6 we examine robustness of the baseline IV estimate reported in Table 4 with respect to alternative specifications of fixed effects. We estimate the import regression, equation (9), with 2SLS applying our standard inspection and port congestion instrument as explained in the identification section, but vary the set of fixed effects. More rigorous fixed effects lend credibility that our instruments meet the exclusion restriction, but they also absorb useful identifying variation.

The first row of results in Table 6 reports the IV estimates for the effect of processing time in import values. Across the columns, the effect varies between -0.19 and -0.268. This is remarkably similar to the effect we report in Table 4, -0.243. First stage results show that both the congestion instrument and the inspection instrument significantly predict the processing time. F-statistics confirm the strength of the instruments. We conclude that the choice of fixed effects does not significantly affect our results.

7.1.3. Import Regulations, Trade Policy, and Transportation Channels

In Table 7 we examine how regulations in import processing, transportation, and standard trade policy affect our conclusions. Across the columns, we report 2SLS estimates for the effect of the log processing time on log import values according to equation (9). The instruments are port congestion and inspection frequencies as explained in the identification section. Across the columns, we estimate the effect from various sub-samples that exclude shipments subject to special regulations and policies.

To clear the border Peruvian firms may use an express channel for their shipments. This channel allows firms to file customs documents while still in transit. Column 1 provides estimates when we drop shipments that cleared through this channel. The coefficient estimate on the processing time equals -0.247, is statistically significant, and comparable to the baseline estimate in Table 4, -0.243.

In column 2 we report estimates focusing on low tariff products. We consider trade flows with less than a 5% tariff. Dutt and Traca (2010) and Sequeira (2016) consider the possibility of tariff evasion. The concern is that especially when tariffs are high firms interact with officials to lower their tariff burden. In that case, they may also attempt to reduce the processing burden. The estimates remain comparable to our baseline.[42] We conclude that tariff evasion does not significantly affect our conclusions.

Column 3 augments the baseline specification with ad-valorem freight, tariff, and insurance charges.[43] The theory maintains that tariffs, transportation, and insurance markets are independent of processing time. If transportation providers' quality depends on processing speed and higher quality providers charge higher rates, then excluding this information may result in omitted variable bias. Our results show that this is not the case. Estimates remain similar to the baseline estimates. We conclude that freight charges do not lead to omitted variable bias and that our fixed effects sufficiently account for this information.

Column 4 reports results where we exclude all products that require special import permits (Bowen and Crowley, 2016; Carballo et al. 2016b). These products require additional processing that may affect the estimates. Again, we conclude that this does not affect our baseline estimates and that our fixed effects sufficiently account for this potential product heterogeneity.

[42]We also estimated the model for high tariff products and the estimates are comparable.

[43]We first compute τ_{ihxy} as the sum of f.o.b import value, freight charges, insurance charges, tariff charges and divide this sum by the f.o.b. value. We then augment our baseline specification with τ_{ihxy}.

7.1.4. Aggregation

Next we examine a seeming disconnect between the theory and the empirics. In the theory, we model the processing costs for an individual shipment. In the data, as is standard in many empirical trade papers involving firm level data, we aggregate to annual levels.[44] Table 8 reports two robustness checks with respect to this aggregation.

First, we estimate the effect of import processing times on import values according to specification (9) with quarterly data. To do so, we construct the import processing time and associated inspection and congestion instruments at the quarterly level. We also account for quarter-year fixed effects to account for seasonality. Table 8 column 1 reports the 2SLS estimates. A one percent increase in processing time reduces imports by about 0.153 percent. This estimate is slightly smaller than the baseline estimate in Table 4. Perhaps this is to be expected, as the coefficient captures the effect of the processing time only for a quarter as opposed to the entire year.

Second, we examine the effect of import processing time on the import value per shipment. To do so, we divide the annual import value by the total number of shipments within each firm-product-origin-year observation and take logs. We then estimate the effect of log processing times on the log import value per shipment applying 2SLS and our congestion and inspection instruments. Table 8 column 2 reports the results. The effect of the processing time on the import value per shipment is -0.238 and almost identical to the effect of processing times on total import values reported in Table 4. We conclude that considering the number of shipments does not affect the results.[45]

[44]This avoids lumpiness of trade and seasonal issues within the year.

[45]For theory that determines shipping frequency see Hornok and Koren (2015a, 2015b) and Kropf and Sauré, (2014).

Finally, we estimate specification (9) at the (importing)firm-product-carrier-exporter(firm)-year unit of observation. We re-construct our instruments and estimate 2SLS. We extend the fixed effects to account for exporting firm heterogeneity. In addition, we account for heterogeneity across carriers. Ben-Daya and Abdul (1994) consider that firms may shorten lead times, but at an added cost. A way to accomplish this may be to choose faster carriers. We note that our identification approach relies on processing times, not lead times. Nevertheless, accounting for carrier fixed effects accounts for this mechanism. Appendix Table A3 reports the results. Across all specifications an increase in import processing times reduces imports. Coefficient estimates are comparable to the baseline IV estimate in Table 4.

7.1.5. Alternative Measures of Border Time

In the previous sections we estimate import-processing cost elasticities based on the actual processing time as defined in Section 2. In this subsection, we examine if the definition of the time it takes to import matters for elasticity estimates.

Measurements of the time it takes to import vary across publicly available data sources. For example, in 2017, the Enterprise Survey reports the number of days to clear shipments from customs in Peru as 14 days, on average.[46] Compared to our statistics in Section 2, this measure is closer to our definition of the total time to clear imports, including storage steps in the import process, rather than actual processing time. For comparison, the 2010 Doing Business Business Trading Across Border's data reports that the time to import into Peru is 24 days. However, a recent methodology change results in much lower measures, 72 hours for border compliance and 72 hours for documen-

[46] `https://www.enterprisesurveys.org/en/data/exploreeconomies/2017/peru#trade`

tary compliance to cross the border.[47] Thus, while the previous methodology seems more consistent with our definition of the total time shipments take to import, the current methodology is closer to our measure of processing time. Does the distinction between processing time and total border time matter for elasticity estimates? We use our data to answer this question.

We estimate our import specification, equation (9), but instead of our measure of processing time, we focus on a measure of median total border time. As defined in Section 6, let $\hat{t^*}_{ihxy}$ be the median total border time (including all storage steps in the import process) of all shipments within each importer-product-origin-year observation. Then, we estimate

$$ln(v_{ihxy}) = \delta_{hxy} + \kappa_{iy} + \kappa_{ihx} + \beta ln\hat{t^*}_{ihxy} + u_{ihxy}. \tag{9}$$

Table 9 reports OLS and 2SLS estimates. The instruments are inspection rates and port congestion, as explained in the identification section. The estimated import elasticities with respect to the total border time are -0.057 and -0.556. For comparison, Table 4 reports import elasticity estimates with respect to the median processing time as -0.049 and -0.243 for OLS and IV estimates. Therefore, our prefered import elasticities based on processing time lead to a more conservative estimate of the import processing cost elasticity.

7.2. Robustness Checks for Cost Multipliers

In addition to elasticity parameters, the key component we back out from the data to obtain λ is $r/(\varphi - \omega)$. In section 6 we used a measure of total border time, $\widehat{t^*}_{ihxy}$, as proxy for lead time. We examine the sensitivity of λ with respect to several alternative choices of lead time proxies.

[47] http://www.doingbusiness.org/data/exploretopics/trading-across-borders/what-measured

Equation (7) shows that our approach overestimates $r/(\varphi-\omega)$ and therefore λ, if our lead time proxy is greater than the optimally chosen lead time. All else equal, the greater the proxy for t^*, the greater $r/(\varphi-\omega)$.

Our lead time proxy overstates the unobserved lead time chosen by firms if, for example, a firm chooses a lead time of five days, but the actual processing takes six. In this case, we observe a total border time of six days and overstate the optimal lead time by one day. Then, the identification issue is that the longest total border times are actually measures of long processing time instead of lead time. To examine this, we use our transaction level data. First, we compute the median processing time at firm-product-origin-year observations. Second, we drop the highest 5th and 10th percentiles of total border time. We then compute the median total border time, $\widehat{t^*}_{ihxy}$, over this more limited sample as proxy for our lead time measure. Following the same approach as in section 6, but using the corrected lead time proxy, we obtain a new $\hat{\lambda}$.

Table 10 column (1) repeats the baseline estimates for comparison. Columns (2) and (3) show the results with the corrected measures with different cutoffs. We find that by correcting the lead time proxy $r/(\varphi-\omega)$, λ increase compared to the baseline specification. This means that when total border times are high in our sample, they are high due to long storage times instead of unusually high processing times.

Next, we recognize that we do not observe the ocean transit time. It is possible that the storage time we observe at the border is not just buffering for random shocks in border processing, but also captures the lead time for ocean transit. To examine the sensitivity of λ with respect to this data problem, we make two adjustments.

First, we focus on countries that are close by to eliminate lengthy ocean transit times.[48] In this case, we re-estimate all of the structural parameters over the restricted sample and compute $\hat{\lambda}$. Table 10 column (4) shows the results. The multiplier λ increases due to a greater cost of late delivery, $r/(\varphi - \omega)$. Therefore, imports sourced from countries close by are subject to especially high costs of running late. This evidence complements Evans and Harrigan (2003) who provide evidence that firms move closer to the destination market if they face short selling seasons and high demand uncertainty.

Second, we focus on the top 6 source countries in the sample.[49] We collect average ocean transit times from searates.com and add them to the processing time and total border time for that sample. Then we re-estiamte the elasticities and the cost parameters. Table 10 column five shows the results. With increased time measures due to ocean transit, λ decreases by about 4 percentage points. Therefore, accounting for ocean transit time results in slightly lower import processing costs.

Finally, it is possible that shipments are stored after clearing customs, which we do not observe in our data. If there is storage after the port then our lead time proxy, $\widehat{t^*}_{ihxy}$, underestimates optimal lead time, t^*, and we underestimate λ. In this case, our cost multipliers are conservative estimates for import processing costs.

8. Border Processing Costs and New Relationships

Recent literature examines the importance of new trade relationships (Bernard et al., 2017a, 2017b). The hope for trade facilitation policy often is that it especially reduces trade costs and affects export growth dynamics by reducing

[48] More specifically, we consider Ecuador, Chile, Colombia, Panama, Costa Rica, Nicaragua, Guatemala, Mexico, Brazil, Argentina and Uruguay as the closest countries.

[49] More specifically, we consider import flows from China, United States, Germany, Italy, Spain, and Brazil.

costs for new importers, exporters, and trade relationships.[50] Less experienced firms may find it more challenging to comply with regulations and experience greater import processing costs. On the other hand, more experienced firms may run more complicated supply chains. In that case, we expect that processing delays are especially costly. Therefore, how firms' import experience relates to border processing costs is an empirical question.

We provide evidence for this in Table 11. Column 1 reports estimates for new importers, firms that never imported before. Column 2 reports estimates for experienced importers. To obtain these estimates, we run one regression, but interact the processing time and the instruments with an indicator to distinguish new from old importers.

Estimates show that, as a tariff equivalent, import processing costs for new importers are more than double the cost of experienced importers, 28.3 percent of the import value versus 11.8 percent. This difference is driven by both cost parameters and longer processing times. At the median, shipments by new importers take eight days to clear while shipments of established importers take only four. Therefore, trade facilitation policy that lowers median processing times for new importers can be especially effective in lowering import costs to increase trade. However, the difference in costs between new and experienced importers is not only due to differences in processing times. Processing costs of new importers are subject to a greater cost elasticity (0.067 versus 0.041) and multiplier (1.117 versus 1.057). The difference in the multiplier derives from the fact that new importers have greater costs of running late as captured by $r/(\varphi - \omega)$. Therefore, the differences in costs between new and experienced importers are not only due to differences in processing times, but also due to

[50] https://www.wto.org/english/news_e/news17_e/fac_31jan17_e.htm

supply chain management strategies as captured by the cost parameters.

9. Conclusions

Trade facilitation is a major policy initiative that means to lower trade costs by reducing regulatory burden to accelerate international supply chains. However, policies related to non-tariff barriers are difficult to measure and evaluate (Goldberg and Pavcnik, 2016). As a result, the level of trade processing cost and the potential for trade facilitation policy is not clear. To make progress, this paper focuses on a common measure of non-tariff import costs, the time it takes to process shipments at the border. We use theory to translate processing times into costs. Then, we employ highly detailed import data to estimate these costs.

We draw several policy relevant conclusions. Costs associated with import processing are high and trade facilitation policies to reduce median processing times have the potential to substantially reduce these costs. For example, we provide evidence that a policy that eliminates delays due to document inspection could reduce border processing costs by about six percentage points. This is comparable to eliminating the average worldwide applied tariff of about six percent.[51]

Our evidence also provides insights for trade theory. Import processing costs are especially high for new importers. Therefore, trade theory that formalizes trade policy to reduce non-tariff barriers associated with border processing costs ought to consider the formation of new trade relationships.

Finally, we apply our theory and identification strategy to Peru due to data availability. However, delays in the import process and concerns of port effi-

[51] `https://data.worldbank.org/indicator/TM.TAX.MRCH.WM.AR.ZS?`

ciency are not unique to Peru (Blonigen and Wilson, 2008). Recently, long processing times in the port of Los Angeles have received much attention.[52] This raises the question of external validity of our parameter estimates to evaluate, for example, import processing times at the port of LA. Our theory provides fundamentals for our parameter estimates. As a consequence, our approach is clear under what pooling restrictions our results apply to other countries and links of the international supply chain.

[52] https://www.marketplace.org/2021/03/08/dozens-container-ships-waiting-unloaded-port-los-angeles/

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10. Tables

Table 1: Border Times (in Days): Total and Stages in 2013, by Customs Verification Channel

Stage	Channel	Average	Percentile						
			5th	10th	25th	50th	75th	90th	95th
Total Border Time	All	16.5	4.0	5.0	7.5	12.0	20.0	33.0	44.0
	Green	11.6	4.0	4.5	6.0	8.0	13.0	21.0	29.5
	Orange	16.9	5.0	6.0	8.0	13.0	21.0	31.0	42.5
	Red	23.2	7.0	9.0	13.0	19.0	29.0	42.0	55.0
Processing Time	All	6.4	1.0	2.0	2.0	4.0	8.0	15.0	19.0
	Green	3.8	1.0	2.0	2.0	2.0	3.0	5.0	6.0
	Orange	8.1	2.0	3.0	3.0	5.0	9.0	14.0	19.0
	Red	12.1	4.0	4.0	6.0	9.0	14.0	20.0	26.0
Storage Time	All	11.0	2.0	3.0	5.0	7.0	13.0	22.0	32.0
	Green	9.7	2.0	3.0	4.5	7.0	11.0	19.0	27.0
	Orange	10.7	1.0	3.0	4.5	7.0	13.0	22.0	31.0
	Red	12.5	2.0	3.0	5.0	8.0	15.0	27.0	37.0

Source: Authors' calculations based on data from SUNAT.
The table reports the average and percentiles of the distribution of the total time to import, the total processing time, and storage time by customs verification channel (i.e., green, orange, and red) for 2013. The sample corresponds to all maritime imports entering into Peru through the port of Callao.

Table 2: Effect of Unloading Time on Storage Time

	(1)	(2)	(3)	(4)
Unloading Time	-0.152***	-0.169***	-0.111***	-0.132***
	(0.011)	(0.013)	(0.011)	(0.012)
		Customs Time		
Firm Fixed Effect	Yes	No	Yes	No
Product-Origin Fixed Effect	Yes	No	Yes	No
Firm-Product-Origin Fixed Effect	No	Yes	No	Yes
Day Fixed Effects	No	No	Yes	Yes

Source: Authors' calculations based on data from SUNAT.
The table presents the effect of long unloading times on storage times conditional on fixed effects. The dependent variable is the natural log of storage time and the main explanatory variable is the natural log of the unloading time at the port. Standard errors clustered at importing firm-level are reported in parentheses below the estimated coefficients. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 3: Aggregate Import Indicators

Year	Import Value	Number of Importers	Number of Origins	Number of Products
All Imports				
2007	19,100	19,290	199	6,989
2008	27,900	22,542	205	6,230
2009	20,600	23,597	201	6,174
2010	28,200	25,592	203	6,233
2011	36,100	26,804	210	6,177
2012	40,200	28,799	211	6,302
2013	41,100	30,131	209	6,303
Percentage Share Callao				
2007	72.3	64.0	86.4	92.4
2008	72.4	65.4	87.3	92.6
2009	73.8	65.7	93.0	93.0
2010	75.5	64.8	84.7	92.9
2011	76.7	65.8	84.8	93.2
2012	75.9	65.5	90.5	93.3
2013	74.7	65.6	88.5	93.2

Source: Authors' calculations based on data from SUNAT.
The table reports aggregate import indicators for each year of our sample period. In the first panel, all imports are considered. Import values are expressed in millions of US dollars. In the second panel, only maritime imports entering through Callao are considered. This panel shows the percentage share of total Peruvian imports accounted for by these maritime imports along the dimensions that correspond to the selected indicators.

Table 4: Effect of Processing Time on Imports and Processing Costs

Estimation			Quantification		
	(1)	(2)		(3)	(4)
	OLS	IV		$\gamma = 4$	$\gamma = 6$
Processing Time $(\gamma\chi)$	-0.049***	-0.243***	χ	0.061***	0.040***
	(0.005)	(0.015)		(0.004)	(0.004)
		First Stage	φ	2.072***	2.072***
Congestion		0.028***		(0.037)	(0.037)
		(0.000)	ϑ	0.063***	0.041***
Channel		0.743***		(0.007)	(0.007)
		(0.009)			
F-Test		4,317.239	$r/(\varphi - \omega)$	0.299***	0.189***
		[0.000]		(0.039)	(0.039)
Hansen Test		0.025	$(\lambda - 1)$	0.104***	0.066***
		[0.874]		(0.008)	(0.008)
Fixed Effect					
Firm-Year	Yes	Yes	$(\lambda \cdot T^{\chi} - 1)$	0.204***	0.128***
Origin-Product-Year	Yes	Yes		(0.014)	(0.014)
Observations	589,842	589,842			

Source: Authors' calculations based on data from SUNAT.
The table reports OLS and IV estimates of equation (9) along with the first stage estimates and the effective F-test statistics and the Hansen test statistics for the latter. The dependent variable is the change in the natural log of import values at the firm-product-origin-year level. In the IV estimations, the instruments are port congestion as proxied by the median number vessels that arrived at the port the day before the vessel carrying the shipment in a given year, and the average allocation to inspection (either documentary or physical) in a given year. Firm-year and origin country-product-year fixed effects are included (not reported). Standard errors clustered by importing firm are reported in parentheses below the estimated coefficients. Unit of observation: importing firm by origin by product by year. In the case of the right panel (Quantification), bootstrapped standard errors with 500 replications are reported. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 5: Robustness Checks: Alternative Instrumental Variables

	IV Estimate Processing Time
Robustness Channel Instrument	
Median Channel	-0.239***
	(0.014)
5 or more transactions	-0.168***
	(0.020)
Robustness Congestion Instrument	
Window: 2 Days	-0.238***
	(0.015)
Window: 3 Days	-0.239***
	(0.015)
Window: 4 Days	-0.238***
	(0.015)
Window: 5 Days	-0.239***
	(0.015)
Robustness Lagged Instruments	
Lag 1	-0.214***
	(0.013)

Source: Authors' calculations based on data from SUNAT. The table reports IV estimates of equation (9). The dependent variable is the change in the natural log of the import value at firm-product-origin-year level. The independent variable is the change in the log of the import processing time. Firm-year and origin country-product-year fixed effects are included (not reported). Unit of observation: importing firm by origin by product by year. Standard errors clustered by firm are reported in parentheses below the estimated coefficients. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 6: Robustness Checks: Alternative Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Processing Time	-0.230***	-0.190***	-0.268***	-0.242***	-0.239***
	(0.013)	(0.013)	(0.017)	(0.034)	(0.020)
			First Stage		
Congestion	0.028***	0.027***	0.029***	0.028***	0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Channel	0.739***	0.738***	0.757***	0.718***	0.740***
	(0.008)	(0.008)	(0.009)	(0.015)	(0.010)
F-Test	4,624.1	4,587.6	3,910.9	1,278.9	3,027.1
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Hansen	0.029	2.753	0.562	0.076	1.039
	[0.865]	[0.097]	[0.454]	[0.783]	[0.308]
Fixed Effect:					
Firm-Year	Yes	No	No	No	Yes
Origin-Product-Year	No	Yes	Yes	Yes	Yes
Firm-Origin-Year	No	No	Yes	No	No
Firm-Product-Year	No	No	No	Yes	No
Firm-Product-Origin	No	No	No	No	Yes
Observations	589,842	589,842	589,842	589,842	589,842

Source: Authors' calculations based on data from SUNAT.
The table reports IV estimates of alternative specifications of equation (9) along with the first stage estimates and the effective F-test statistics and the Hansen test statistics. The dependent variable is the change in the natural log of the import value at the firm-product-origin-year level. The main explanatory variable is the change in the natural log of the median processing time. Standard errors clustered by importing firm are reported in parentheses below the estimated coefficients. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 7: Robustness Checks: Port and Customs Regulation

	(1)	(2)	(3)	(4)
	No Express	Low Tariffs	Transport Quality	No Permits
Processing Time	-0.247***	-0.235***	-0.240***	-0.241***
	(0.016)	(0.020)	(0.015)	(0.016)
Trade Costs			-1.535***	
			(0.068)	
		First Stage		
Congestion	0.028***	0.029***	0.028***	0.029***
	(0.001)	(0.001)	(0.001)	(0.001)
Channel	0.744***	0.719***	0.742***	0.733***
	(0.009)	(0.008)	(0.008)	(0.009)
F-Test	4,249.0	3,705.1	4,317.0	3,727.2
	[0.000]	[0.000]	[0.000]	[0.000]
Hansen	0.001	0.053	0.025	0.052
	[0.973]	[0.818]	[0.874]	[0.819]
Fixed Effect				
Firm-Year	Yes	Yes	Yes	Yes
Origin-Product-Year	Yes	Yes	Yes	Yes
Observations	566,082	343,002	589,842	493,384

Source: Authors' calculations based on data from SUNAT.
The table reports IV estimates of equation (9) along with the first stage estimates and the effective F-test statistics and the Hansen test statistics. The dependent variable is the change in the natural log of the import value at the firm-product-origin-year level for columns (1)-(5). In column (6), the dependent variable is the change in the natural log of the average import value per transaction at firm-product-origin-year level. The main explanatory variable is the change in the natural log of the median processing time. The instruments are inspection frequency and port congestion. In column (1) imports processed through the expressed channel are excluded. In column (2) imports with tariffs above 5% are excluded. In column (3), the baseline regression is augmented incorporating the change in the natural log of the freight, tariff and insurance costs at firm-product-origin-year. In column (4) imports from products with additional documents required are excluded. Standard errors clustered by firm are reported in parentheses below the estimated coefficients. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 8: Robustness Checks: Aggregation

	(1)	(2)
	Quarterly	Value Per Shipment
Processing Time	-0.153***	-0.238***
	(0.012)	(0.014)
	First Stage	
Congestion	0.023***	0.028***
	(0.001)	(0.001)
Channel	0.714***	0.743***
	(0.008)	(0.009)
F-Test	4737.20	4317.239
	[0.000]	[0.000]
Hansen	58.742	0.949
	[0.000]	[0.330]
Fixed Effects:		
Firm-Year	Yes	Yes
Country-Product-Year	Yes	Yes
Quarter-Year	Yes	No
Observations	2,020,086	589,842

Source: Authors' calculations based on data from SUNAT.
The table reports OLS and IV estimates of alternative specifications of equation (9) along with the first stage estimates and the F-test statistics and the Hansen test statistics for the latter. For quarterly estimates the dependent variable is the change in the natural log of the import value at the importing firm-product-origin-quarter-year level. For value per shipment estimates the dependent variable is the log changes in the log annual value per shipments. Standard errors clustered by firm are reported in parentheses below the estimated coefficients. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 9: Robustness Checks: Effect of total border time on Imports

	(1)	(2)
	OLS	IV
Total Time	-0.057***	-0.556***
	(0.005)	(0.026)
	First Stage	
Congestion		0.009***
		(0.000)
Channel		0.281***
		(0.003)
F-Test		834
		[0.000]
Hansen		0.949
		[0.330]
Fixed Effects:		
Firm-Year	Yes	Yes
Origin-Product-Year	Yes	Yes
Observations	589,842	589,842

Source: Authors' calculations based on data from SUNAT.
The table reports OLS and IV estimates of log import values on the log of the total border time along with the first stage estimates and the F-test statistics and the Hansen test statistics for the latter. Standard errors clustered by firm are reported in parentheses below the estimated coefficients. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 10: Robustness Checks: Different Lead Time Measures and Sourcing Patterns

	(1)	(2)	(3)	(4)	(5)
	Baseline	Lead Time		Sourcing	
		5%	10%	Close	Ocean Time
χ	0.061***			0.073***	0.066***
	(0.004)			(0.003)	(0.004)
φ	2.072***			1.888***	1.958***
	(0.037)			(0.039)	(0.036)
ϑ	0.063***			0.077***	0.069***
	(0.007)			(0.004)	(0.005)
$r/(\varphi-\omega)$	0.299***	0.600***	0.607***	0.615***	0.078***
	(0.039)	(0.075)	(0.076)	(0.0789)	(0.049)
$(\lambda-1)$	0.104***	0.127***	0.128***	0.155***	0.0631***
	(0.008)	(0.009)	(0.009)	(0.008)	(0.007)
$(\lambda \cdot T^{\chi}-1)$	0.204***	0.229***	0.230***	0.279***	0.164***
	(0.014)	(0.016)	(0.016)	(0.011)	(0.012)

Source: Authors' calculations based on data from SUNAT.
Column (1) reports our baseline estimates. Columns (2) and (3) re-estimate $r/(\varphi-\omega)$ and subsequent parameters dropping all the observations where the difference between total time and processing time is below the 5 and 10 percentiles. Columns (4) re-estimates all the parameters including only trade flows from the following countries: Ecuador, Chile, Colombia, Panama, Costa Rica, Nicaragua, Guatemala, Mexico, Brazil, Argentina and Uruguay. Column (5) re-estimates all the parameters with average ocean transit times added to total and processing times only for trade flows from the following countries: China, United States, Germany, Italy, Spain and Brazil. Bootstrapped standard errors clustered by firm based on 500 repetitions are reported in parentheses below the estimated coefficients. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

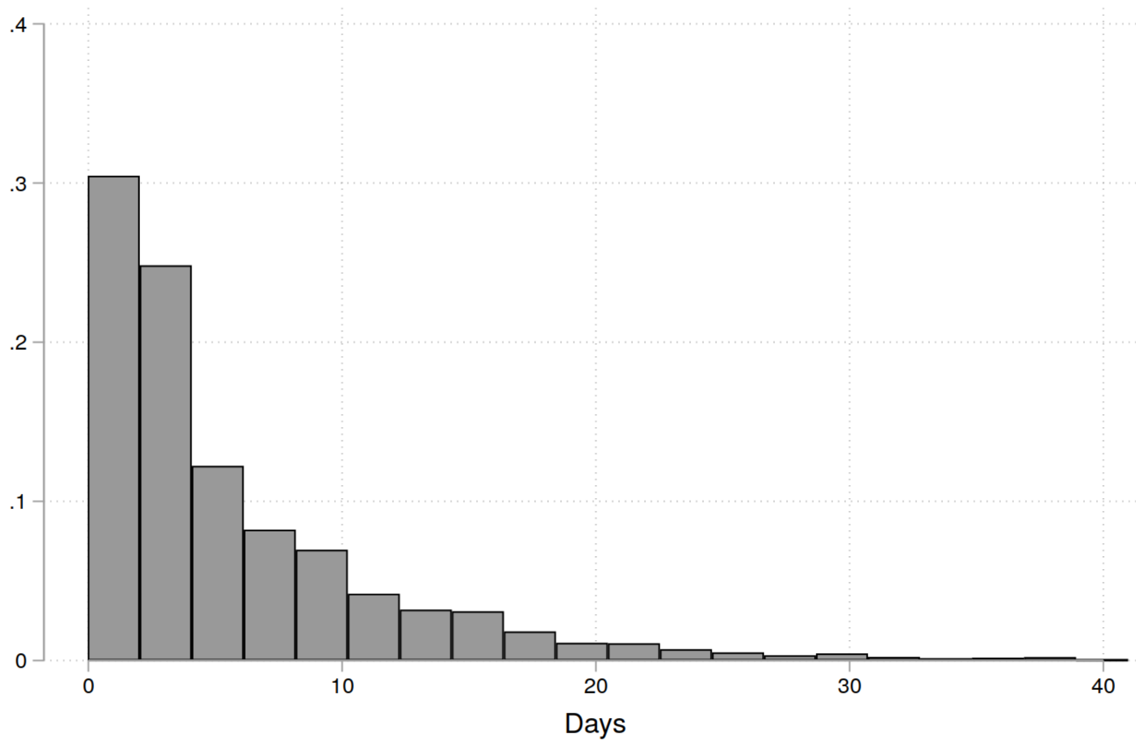
Table 11: Processing Costs by Importer Experience

	(1)	(2)
	Estimation	
	New Importer	Experienced Importer
Processing Time	-0.269***	-0.164***
	(0.018)	(0.018)
Fixed Effect:		
Firm-Year	Yes	
Origin-Product-Year	Yes	
Observations	589,842	
	Quantification	
χ	0.067***	0.041***
	(0.027)	(0.008)
φ	2.020***	2.058***
	(0.039)	(0.180)
ϑ	0.069***	0.042***
	(0.017)	(0.008)
$r/(\varphi - \omega)$	0.346***	0.120***
	(0.050)	(0.050)
$(\lambda - 1)$	0.117***	0.057***
	(0.033)	(0.013)
$(\lambda \cdot T^{\chi} - 1)$	0.283***	0.118***
	(0.011)	(0.010)

Source: Authors' calculations based on data from SUNAT.
The table reports IV estimates of variants of equation (9) that allows for different effects across types of firms: new importers (firms that never imported before) and incumbent importers (firms that have imported before). Firm-year and product-origin country-year fixed effects included (not reported). Standard errors clustered by firm are reported in parentheses below the estimated coefficients. In the case of the lower panel (Quantification), bootstrapped standard errors with 500 replications are reported. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

11. Figures

Figure 1: Border Processing Time Distribution, 2013



Source: Authors' calculations based on data from SUNAT.
The figure is a histogram of the processing time distribution. Data correspond to the year 2013.

A. Appendix - Tables

Table A1: Average Importer

Year	Import Value	Number of Origins	Number of Products	Number of Employees	Age
Callao					
2007	623.5	3.1	14.2	63.6	7.4
2008	785.1	3.0	13.2	60.4	7.4
2009	618.9	2.9	12.5	58.4	7.6
2010	660.8	2.9	12.7	58.1	7.7
2011	715.1	2.9	12.8	63.2	7.9
2012	700.5	2.9	12.8	64.8	8.0
2013	653.9	2.8	12.4	65.4	8.3
All Imports					
Year	Import Value	Number of Origins	Number of Products	Number of Employees	Age
2007	764.8	3.5	16.2	52.2	7.0
2008	1,009.3	3.3	14.8	48.4	7.0
2009	722.3	3.2	14.0	47.6	7.2
2010	904.8	3.2	14.2	47.8	7.3
2011	1,036.5	3.2	14.5	52.2	7.4
2012	1,057.4	3.2	14.4	52.2	7.5
2013	1,011.3	3.1	14.0	52.3	7.7
Excluding Minerals, Metals and Air-Shipped Imports					
Year	Import Value	Number of Origins	Number of Products	Number of Employees	Age
2007	718.5	2.8	12.2	65.6	8.3
2008	657.1	3.1	14.1	63.6	7.4
2009	814.5	3.0	13.1	60.5	7.4
2010	629.2	2.9	12.5	57.8	7.6
2011	723.6	2.9	12.6	58.1	7.7
2012	796.3	2.8	12.6	63.2	7.9
2013	792.4	2.8	12.6	64.8	8.0

Source: Authors' calculations based on data from SUNAT.
The table reports average import indicators for firms importing by sea through the Port of Callao, for all importers (including other ports), and for firms that do not import minerals, metals, or air-shipped goods. Import values are expressed in thousands of US dollars.

Table A2: Summary Statistics for the Estimation Sample

	Average	Standard Deviation
Total Imports	8.044	2.770
Trade Costs	0.107	0.136
Total Border Time	14.01	11.50
Processing Time	5.754	5.408
Channel	0.447	0.462
Congestion	5.424	1.985

Source: Authors' calculations based on data from SUNAT.
The table reports average and standard deviation for the variables used in our regressions.

Table A3: Robustness Checks: Exporting Firms and Carriers

	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Time	-0.184***	-0.180***	-0.167***	-0.187***	-0.156***	-0.174***	-0.153***
	(0.009)	(0.008)	(0.008)	(0.010)	(0.013)	(0.010)	(0.012)
First Stage							
Congestion	0.030***	0.030***	0.030***	0.030***	0.031***	0.030***	0.031***
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Channel	0.682***	0.680***	0.681***	0.685***	0.682***	0.677***	0.690***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Test Statistics							
F-Statistics	26726	31519	31207	23499	15917	19917	13088
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Hansen	1.873	2.324	0.453	1.161	0.00552	0.939	1.741
	[0.171]	[0.127]	[0.501]	[0.281]	[0.941]	[0.333]	[0.187]
Fixed Effects:							
Firm-Year	Yes	Yes	No	No	No	Yes	No
Origin-Product-Year	Yes	No	Yes	Yes	Yes	Yes	Yes
Carrier-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Origin-Year	No	No	No	Yes	No	No	No
Firm-Product-Year	No	No	No	No	Yes	No	No
Firm-Origin-Product	No	No	No	No	No	Yes	No
Firm-Origin-Product-Year	No	No	No	No	No	No	Yes
Exporting Firm-Year	No	No	No	No	No	No	Yes
Observations	685,971	685,971	685,971	685,971	685,971	685,971	685,971

Source: Authors' calculations based on data from SUNAT.
The table reports IV estimates of alternative specifications of equation (9) along with the first stage estimates and the effective F-test statistics and the Hansen test statistics. The dependent variable is the change in the natural log of the import value at the firm-product-carrier-exporter-year level. The main explanatory variable is the change in the natural log of the median processing time. The instruments are port congestion as proxied by the median number of other vessels that arrive at the port the day before the vessel carrying the firm-product-carrier-exporter imports in question does in a given year and the average allocation to inspection. Columns correspond to different sets of fixed effects as indicated in the table. Standard errors clustered by importing firm are reported in parentheses below the estimated coefficients. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

A. Appendix - Theory

A.1. Proof Proposition 1

By observation, as long as $\varphi > \omega$, then $\frac{\partial t^*}{\partial \omega} > 0$. By the envelope theorem, $\frac{\partial ETC(t_l^*)}{\partial \omega} = \frac{t^{*\varphi} t_{min}^{\varphi} {}^{\varphi} rv}{(\omega-\varphi)^2} > 0$. Also by the envelope theorem it is easy to observe that $\frac{ETC(t_l^*)}{\partial r} > 0$, because for any t_l^* the term $\frac{\varphi rv}{t_p} dt_p$ increases in r. By observation of equation (2), $\frac{\partial t_l^*}{\partial \omega} > 0$ and $\frac{\partial t_l^*}{\partial r} > 0$.

In order to prove that $\frac{\partial t^*}{\partial \vartheta} < 0$, we show that the semi-elasticity is negative. Taking logs on (2) and the partial derivative with respect to ϑ we obtain:

$$\frac{\partial \ln t}{\partial \vartheta} = -\frac{\ln t_{min}^{\varphi}}{[\vartheta+\varphi]^2} - \frac{1}{[\vartheta+\varphi]^2} \ln\left(\frac{r\varphi^2}{(\varphi-\omega)}\right) - \frac{[\vartheta+\varphi]\frac{1}{\vartheta} - \ln\vartheta}{[\vartheta+\varphi]^2}$$
$$\frac{\partial \ln t}{\partial \vartheta} = -\frac{1}{[\vartheta+\varphi]^2}\left[\ln\left(\frac{t_{min}^{\varphi} r\varphi^2}{(\varphi-\omega)\vartheta}\right)\right] - \frac{1}{\vartheta[\vartheta+\varphi]}$$

Then $\frac{\partial \ln t^*}{\partial \vartheta} < 0$ as long as $\left(\frac{t_{min}^{\varphi} r\varphi^2}{(\varphi-\omega)\vartheta}\right) > 1$. Imposing an interior solution then we can show that $\frac{r\varphi^2}{(\varphi-\omega)\vartheta} > 1$. Hence for $t_{min} \geq 1$ then $\frac{\partial \ln t}{\partial \vartheta} < 0$.

The condition derived from the interior solution goes as follows:

$$t_{min}^{\frac{\varphi}{\vartheta+\varphi}} \left(\frac{r\varphi^2}{(\varphi-\omega)\vartheta}\right)^{\frac{1}{\vartheta+\varphi}} > t_{min}$$
$$t_{min}^{\frac{\varphi}{\vartheta+\varphi}-1} \left(\frac{r\varphi^2}{(\varphi-\omega)\vartheta}\right)^{\frac{1}{\vartheta+\varphi}} > 1$$
$$t_{min}^{\frac{-\vartheta}{\vartheta+\varphi}} \left(\frac{r\varphi^2}{(\varphi-\omega)\vartheta}\right) > 1$$
$$t_{min}^{\frac{-\vartheta}{\vartheta+\varphi}} \left(\frac{r\varphi^2}{(\varphi-\omega)\vartheta}\right) > 1$$
$$\left(\frac{r\varphi^2}{(\varphi-\omega)\vartheta}\right) > t_{min}^{\frac{\vartheta}{\vartheta+\varphi}} > 1$$