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Import Processing and Trade Costs[†]

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Abstract

We estimate import processing costs based on the time it takes to import. Our theory extends existing time-cost measures to account for uncertainty in import processing. We use detailed, highly disaggregated data on import processing dates and import values to provide evidence for our theory and estimate processing costs consistent with the theory. The evidence shows that our extensions to time-cost estimates are economically relevant to determine processing costs. We estimate that the tariff equivalent import processing costs is as high as 18 percent. WTO estimates suggest that the full implementation of the 2013 Trade Facilitation Agreement would reduce the time to trade by 1.5 days. In that case, processing costs would decrease to 13 percent.

Keywords: Trade Costs, Border Processing, Trade Policy

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1. Introduction

The 2013 WTO Trade Facilitation Agreement is a major worldwide policy initiative that consists of provisions to simplify the processing of international shipments to reduce trade costs, but only limited research exists to inform such an 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, policymakers, and international organizations 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.

To quantify processing costs requires a cost function to estimate. We use theory to derive a cost function consistent with firms' optimal management of the import process. Our starting point is that *processing times*, the time it takes to physically handle, move, and clear shipments through the port of entry is uncertain due to port congestion and conditionally random inspections. 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 they know 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). By weighing the risk of late delivery against the cost of a slow supply chain, firms choose optimal lead times to minimize the total expected processing costs. Based on this theory, we derive firms' expected import processing cost.

To estimate this expected import processing cost, we take advantage of a unique dataset consisting of highly detailed, transaction-level import data for Peru's main seaport, Callao. In particular, we observe import values across importing firms, origin countries, and products. The data also report the completion dates for various steps

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

in the import process, including vessel arrivals, unloading, storage at wharehouse, customs processing, and if customs processing involved an inspection of documents and/or the shipment.

Based on our transaction level data, we provide evidence that long unloading times lead to subsequent shorter storage times. This is consistent with our theory where firms allocate longer lead times to avoid running late in the case of a random processing delay.

Next, we estimate firms' expected import processing cost. The theory shows that we need to estimate two parameters: an import processing cost elasticity with respect to the median processing time, and a multiplier that captures costs associated with the risk of missing desired delivery dates. Both parameters need to be combined with the median processing time to evaluate the total import processing cost.

Consistent with our theory, we estimate the first parameter, the processing cost elasticity, from the import demand elasticity with respect to processing times. To do so, our theory relates import values to firms' beliefs about their median processing time. The main challenge to estimate the processing cost elasticity is that we do not observe what the firms know about the median processing time. Instead, we relate import values to observed median processing times. 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 generate instrumental variables based on port congestion and customs inspections. The identifying assumption is that they affect firms' anticipated median processing time and observed processing time, but do not enter the import equation otherwise. Firms may anticipate median processing times based on learning including lagged observation, and information they obtain from shipping and logistics companies. We examine these specific mechanisms with robustness checks.

The second parameter, the cost multiplier, is not recoverable from fixed-effect regressions that relate import values to processing times. We use our detailed import processing information to determine this parameter and provide several robustness checks.

Instrumental variable estimates show that a 1 percent increase in the median processing time lowers import values by .24 percent.[2] Given an import demand elasticity of 4 (Soderbery, 2015), our theory translates the import processing time elasticity of .24 into a processing cost elasticity of .06. Hence, a 1 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 three days, our estimates combine to result in an import processing cost that equals a 18 percent import tariff.[3] Hopes for the 2013 Trade Facilitation Agreement are high.[4] Based on our estimates this is justified. 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.[5] Our estimates imply that this would reduce import processing costs from about 18 to 13 percent.[6] For comparison, average import tariffs worldwide equal about 5 percent in 2017.[7]

Existing literature shows that long delivery times reduce trade and increase costs (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 combine

[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 $\lambda \times (MedianProcessingTime)^{\chi} - 1 = 1.104 \times 3^{.061} - 1 = 0.18$ where λ is the cost multiplier and χ is the processing-time cost elasticity.

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

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

[6]Formally, $\lambda \times (MedianProcessingTime)^{\chi} - 1 = 1.104 \times 1.5^{.061} - 1 = 0.132$.

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

[8]We follow this literature and develop time costs as a ad-valorem tariff equivalent. For a discussion

theory and data to extend and improve our understanding of these elasticity and time-cost estimates. Our theory shows that available elasticities likely do not apply to evaluate import processing costs because they depend on the shape of the processing distribution. Our empirical results provide evidence that our extensions of existing cost estimates to account for uncertainty are economically meaningful and relevant to evaluate policy.

Our uniquely detailed import processing data has several advantages to accomplish this. These data allow us to compute a measure of processing time consistent with the theory, estimate the time cost multiplier that cannot be identified from import regressions, and, generally, provide evidence for the theory. In addition, we leverage these data for multiple robustness checks.

Who gains from trade facilitation is policy relevant. Often the hope is that small firms and new relationships will benefit and grow.[9] However, without cost estimates, it is a priori not clear how high processing costs are for these firms and relationships, and it is difficult to measure policies' ability 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 estimates. Section 6 develops estimates for border processing costs based on the estimation results in Section 5. Section 7 presents the results of several robustness checks. Section 8 examines the heterogeneity of border

of identification of per-unit costs versus ad-valorem costs, see Irarrazabal et al. (2015).

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

processing costs according to existing theory, and Section 9 concludes.

2. Import Processing at the Border

In this section, we describe the import process at Peru's main seaport, Callao.[10] 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, we observe the date when the ship arrived (arrival date), the date the shipment was unloaded and moved to the shipyard or warehouse (unload date), the date the customs import declaration was created and registered (declaration date), and the date the shipment was released by customs (release date). For the majority of shipments, over 90 percent, these dates follow a simple order:

$$\text{arrival date} \Rightarrow \text{unload date} \Rightarrow \text{declaration date} \Rightarrow \text{release date} \tag{1}$$

The remaining 10 percent of the shipments enter an express channel. In the express channel, firms may submit a customs declaration before the vessel arrives in port to expedite customs processing. Therefore, in the express channel the customs declaration date occurs first and the order of the dates changes to:

$$\text{declaration date} \Rightarrow \text{arrival date} \Rightarrow \text{unload date} \Rightarrow \text{release date} \tag{2}$$

Based on the dates we observe in our data, and taking into account the express channel, we measure the time it takes to clear three consecutive steps to import a shipment: unloading, storage, and customs processing.[11]

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

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

Unloading time is the number of days between the arrival date of the vessel and the date when the shipment was unloaded and moved to the shipyard or warehouse: unloading time = unloading date − arrival date. The time it takes to complete this step depends on port capacity, shipping companies, equipment failure, port strikes, etc.

Storage time is the number of days the shipment idles in port between unloading and customs processing. For shipments that do not use the express channel, see (1), the storage time is then the time between the unloading date and the declaration date: storage time = declaration date − unloading date. Therefore, the longer the firm waits to submit the customs declaration, the longer is the storage time. For shipments that use the express channel, see (2), the customs declaration is submitted before the vessel arrives at the port, and we assume that customs processing begins immediately after unloading. The reasoning is that customs inspections cannot begin until the shipment is unloaded, and firms that use the express channel do not let shipments idle in storage. Therefore, for the express channel, we set the storage time to zero: storage time = 0.[12] For all shipments, storage time depends on firms' own preference on when to submit the customs declaration.

Customs processing time is the number of days shipments spend with customs. For shipments that are not express, the customs processing time is the number of days between the date the customs declaration was submitted and the date the shipment was released: customs processing time = release date − declaration date. For express shipments, customs processing begins immediately after the date of unloading of the shipment: customs processing time = release date − unload date.

For express and regular shipments, a risk management model randomly allocates shipments to one of the three customs verification channels that determine the intensity of the customs inspection and the associated duration of the customs process.[13] The green

[12] We will perform multiple robustness checks dropping express shipments. The results do not change.

[13] Shipments are allocated according to administrative, fiscal, and security risk factors that include

channel clear shipments without inspection. The orange channel inspects documents. The red channel performs an often time consuming physical inspection.[14]

Based on unloading, storage, and customs processing times, we define two measures of border time. First, *total border time* is simply the sum of the unloading, storage, and customs processing times.

$$\text{total border time} = \text{unloading time} + \text{storage time} + \text{customs processing time}$$

Total border time potentially depends on firms' actions because firms decide when to initiate the customs process and the duration of the storage step.

Second, *processing time* is the sum of the unloading and customs processing time measures the time each shipment takes in the necessary processing steps.

$$\text{processing time} = \text{unloading time} + \text{customs processing time}$$

Contrary to total border time, the customs processing time depends only on actions of shipping companies, port, and border agencies and is out of the hands of individual firms.

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. About 50 percent of all shipments are processed in 3 days or less (for comparison, the median total border time including storage is 10 days), but Figure 1 shows that there is a long right tail of the

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

[14] No more than 15% of the DUAs numbered in a given month in Callao can be subject to material control (see SUNAT, 2010). SUNAT charges small fees for moving, opening, unloading, and reloading of containers. These services cost an average of 40 US dollars each.

[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.

processing-time distribution. The percentiles in Table 1 show that processing times are associated with the (conditionally) random assignment of each shipment to a customs channel, as the processing time systematically increases with the scrutiny of the customs inspection. Dropping shipments that use the express channel does not affect the averages or the percentiles (see Table A2).[16]

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 take advantage of the timing of the import steps and regress log storage times on log unloading times at the transaction level.[17] This relationship avoids potential issues of reverse causality, because the entire storage time we observe is after the unloading step.[18] In addition, various combinations of firm, product-origin, and day of the week fixed effects account for potentially omitted variables. Conditional on this identification strategy, results may be interpreted as causal. The top panel of Table 2 shows that longer unloading times are absorbed by shorter storage times. Table A3 reports the result where we drop express shipments from the sample. The conclusions remain the same. Conditional on fixed effects absorbing omitted variables and the avoidance of reverse causality, these results provide evidence that firms use storage time to buffer against random unloading shocks.

The theory we develop in the next section formalizes this idea. It takes into account that the processing time, i.e., unloading plus customs clearance, is random and that firms allocate longer lead times to buffer processing shocks.

[16]The working paper Carballo et al. (2016), provides additional statistics that show that shipments of small firms and new importers are associated with longer border times. `https://publications.iadb.org/publications/english/document/Endogenous-Border-Times.pdf`.

[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 the results are the same.

[18]Alternatively, we may relate storage time to total processing time or its other component, i.e., customs processing times. However, the latter are realized after the storage stage. We did examine if longer storage times predict shorter customs processing times because better preparation may lead to faster processing. We did not find evidence that supports this mechanism.

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 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, $\vartheta > 0$.[19] 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.[20] 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.[21] 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.

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

[20]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.

[21]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.

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.[22] 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:

$$ETC(t_l) = \int_{t_l}^{\infty} \left(\frac{t_p}{t_l}\right)^{\omega} \left(\frac{t_{min}}{t_p}\right)^{\varphi} \frac{\varphi r v}{t_p} dt_p + t_l^{\vartheta} v. \tag{3}$$

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.[23] Firms choose the optimal lead time, t_l^*, to minimize expected total costs of import processing:

$$t_l^* = \min_{t_l} ETC(t_l) = t_{min}^{\frac{\varphi}{\varphi+\vartheta}} \left(\frac{r}{(\varphi-\omega)} \frac{\varphi^2}{\vartheta}\right)^{\frac{1}{\varphi+\vartheta}} \tag{4}$$

Equation (4) shows that lead time is determined by distribution parameters (t_{min}, φ) and cost parameters (ω, r, ϑ) and we prove our proposition.[24]

Proposition 1. *For interior solutions and a given processing-time distribution, firms sched-*

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

[23] The processing shock t_p may be the sum over multiple steps in the supply chain. In that case, it is a caveat that we do not derive predictions on where in the supply chain firms allocate storage. A reasonable interpretation is that firms allocate storage at the end of the import process.

[24] 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 $\varphi > \omega$.

ule 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 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.[25] 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 (3) 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

[25]Applying the envelope theorem to equation (3) 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.

minimized expected costs as a function of the median processing time T:

$$ETC = \lambda T^{\chi} v, \tag{5}$$

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

$$\lambda\left(\frac{r}{\varphi-\omega}, \varphi, \vartheta\right) = \left(\frac{r}{\varphi-\omega}\right)^{\frac{\vartheta}{\vartheta+\varphi}} \left(\vartheta^{\frac{\varphi}{\vartheta+\varphi}} \varphi^{-\frac{\varphi-\vartheta}{\vartheta+\varphi}} + \vartheta^{-\frac{\vartheta}{\vartheta+\varphi}} \varphi^{\frac{2\vartheta}{\vartheta+\varphi}}\right) 2^{-\frac{\vartheta}{\varphi+\vartheta}} \tag{6}$$

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 (5) 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 (5), 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.[26] 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 (4) 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.

3.2. Import-Processing Cost and Imports

To link import-processing times to import values, let us focus on a given importer-exporter relationship.[27] Firm i imports m_{ihxy} units of product h from country x in year

[26] 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.

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

y. The firm combines the imported product with a domestic input, l_{ihxy}.[28] 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.[29] 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.[30] Taking into account import processing costs, an importer's profit maximizing[31] 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} absorb 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

$$v_{ihxy} = m_{ihxy} p_{hxy} = \kappa_{iy} \kappa_{ihx} \delta_{hxy} \times \left(\lambda\, T_{ihxy}^{\chi}\right)^{-\gamma}. \tag{7}$$

[28]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.

[29]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.

[30]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.

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

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 (7) 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. Data

To implement equation (7) 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.[32]

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

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

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).[33]

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, imports 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

[33]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).

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_{ihxy}^{fob}), 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 A4 for descriptive statistics on these variables computed using our main estimation sample.

5. Identification of Import Elasticities w.r.t. Border 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 (7) 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 (7), and substituting the proxy $\hat{T}_{ihxy}$ for the unobserved information T_{ihxy} we obtain the empirical model:

$$ln(v_{ihxy}) = \delta_{hxy} + \kappa_{iy} + \kappa_{ihx} + \gamma\chi ln\hat{T}_{ihxy} + u_{ihxy}, \tag{8}$$

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.[34] 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.[35]

Our identification strategy depends on the assumption that firms have knowledge about the median processing time T_{ihxy} and that this median processing time is related

[34] 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.

[35] These fixed effects also account for the seasonality of products. Furthermore, we assume that firms take the shipment schedule as given. If firms have means to reduce the cost of delays by adjusting their shipment schedule, then we expect that this reduces the elasticity of imports with respect to delays.

to the observed processing time $\hat{T}_{ihxy}$. There are several sources of information that firms may use to gain knowledge about the median processing time. They may obtain information from carriers and logistic companies, they may use past experience, and there may be learning from individual shipments within annual observations, i.e., firms that import frequently are able to observe year-to-year changes in processing times within the calendar year, and are thus able to update their priors about current processing times and adjust their import decisions accordingly. We will take advantage and examine all of these mechanisms. If firms do not have information about the median processing time which they can use to evaluate import processing costs, or, if their priors about the median processing costs are false and are not related to observed processing times, then we expect $\hat{\gamma\chi} = 0$.

The main challenge to obtain a consistent estimate for $\gamma\chi$ 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.[36] 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 arrived the day before each shipment. Then, for each importer-product-origin-year combination, we take the median of this measure

[36] 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.

across all shipments as a measure of congestion and our first instrument. Consequently, even if we aggregate to annual frequencies, this measure exploits within year variation of arrival dates of shipments. For example, for two shipments of the same product from the same origin the congestion measure may differ if they are imported on different dates within the year. As a consequence, for a given time period, the congestion instrument varies across importers, products and origins. [37]

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. We focus on this unit of observations, because the customs risk management model takes into account, firm, product, and origin information. As a result, the instrument captures the exogenous probability of assignment to more time-consuming inspection channels across time and importer-product-origin triplets within the same period. 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 (8) 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,

[37] 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.

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 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.[38] 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 (8) 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 (8) 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 (8), we relate log import values to the log of median processing times at the (importing)firm-product-origin-year unit of observation. We first difference our data. Therefore, the reported fixed effects are in addition to firm-product-origin fixed effects. First-stage statistics support

[38]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.

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.[39]

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 processing costs.

6. Border Processing Costs' Estimates

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 (6). 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).

[39] 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).

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 processing time from 2 (Green) to 5 (Orange) 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 1.8 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. 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 .6 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 $r/(\varphi - \omega)$. Equation (4) says that all else equal, if $r/(\varphi - \omega)$ 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 $r/(\varphi - \omega)$ from equation (4).

To stay consistent with our identification strategy, we substitute median processing times for minimum processing times, $T = t_{min} \sqrt[\varphi]{2}$, in equation (4) and rearrange to obtain

$$2\varphi^{-2}\vartheta T^{-\varphi} (t^*)^{\vartheta+\varphi} = \frac{r}{\varphi - \omega}. \tag{9}$$

Now, if we can generate an empirical counterpart to the left hand side of equation (9) in our data, then we can use it to estimate $r/(\varphi - \omega)$.

To generate the left hand side of equation (9) 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 (8), 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 (9), 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 (9), and, considering that by doing so we measure the left hand side of (9) with random measurement error, e_{ihxy}, we obtain

$$2\hat{\varphi}^{-2}\hat{\vartheta}\hat{T}_{ihxy}^{-\hat{\varphi}}(\widehat{t^*}_{ihxy})^{\hat{\vartheta}+\hat{\varphi}} = \frac{r}{\varphi-\omega} + e_{ihxy}. \tag{10}$$

Regressing the left hand side of (10) on a constant then returns the estimate $r/\widehat{(\varphi-\omega)} = 0.299$, as reported in column 3 of Table 4.

Applying all parameter estimates as reported in column 3 of Table 4 in equation (6), 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 3 days. Based on equation (5), we then compute the median tariff equivalent cost of import processing as $\tau^{\hat{Equiv}} = \hat{\lambda}T^{\hat{\chi}} = 1.104 \times 3^{0.061} = 1.181$. Therefore, evaluated at the 50th percentile, total border processing costs equal about 18 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 7 percent, $3^{0.061} = 1.069$. 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 10.4 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.[40] 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[41], then at the overall median processing time of 3 days, this reduces import processing costs by about 4.9 percentage points.[43]

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.[44] 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 11.3 percent. Based on existing demand elasticity estimates, we consider this value at the low end of the potential import processing tariff equivalent.

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

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[43]This is a straight application of the tariff equivalent: $1.104 \times 3^{0.061} - 1.104 \times 1.5^{0.061} = 0.049$.

[44]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 and Learning

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 (8), using 2SLS. In each case, 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.[45]

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

[45] Our first-stage F-Statistics corroborate that our instruments are strong.

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 for the instruments and all other variables that contain at least 10 and 20 transactions at the importer-product-origin-year level. Limiting the sample to annual firm-product-origin triplets that consist of at least 10 or 20 transactions also allows us to better assess whether the learning mechanism is at work, because such a sample includes observations with a sufficient number of shipments for firms to learn and update their prior about the median processing time to evaluate import processing costs as discussed in the identification section. Table 5 rows 2 and 3 show that over the samples that condition on at least 10 or 20 observations the effect of the border processing time on the import value remains negative and significant and similar to the baseline estimate, albeit slightly larger in magnitude.

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. For completeness, the last rows report results where we condition on observations that include at least 10 or 20 transactions in all variables. The elasticity remains negative and significant. The magnitudes of the elasticities decrease slightly compared to the baseline estimates. A potential reason is that these esimates emphasize lagged information as predictors of processing time and de-emphasize the within-year learning mechanism.

7.1.2. Alternative Specifications of Fixed Effects

In Table A5 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 (8), 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 A5 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.

Finally, even if we account for Origin-Product-Year, or, Firm-Origin-Year, or, Firm-Product-Year fixed effects, there is still sufficient variation in the instruments to predict the first stage. Consequently, we conclude that there is relevant importer-product-origin variation within years to identify the coefficients.

7.1.3. Import Processing Regulations, Tariffs, and Non-Tariff Measures

In Table 6 we examine how regulations in import processing, tariffs, and non-tariff measures 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 (8). 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.[46] 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.[47] 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 (Bown and Crowley, 2016; Carballo et al. 2016b). These products require additional processing that may affect the estimates. Again, we conclude that this does

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

[47] 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}.

not affect our baseline estimates and that our fixed effects sufficiently account for this potential product heterogeneity.

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. There are several reason why some level of aggregation is useful. It keeps the results comparable to the literature. Also, at the transaction level trade data includes tiny one-time shipments due to experimentation or emergency shipments unrelated to our theory. On the other hand, aggregating to annual levels potentially eliminates useful identifying variation within annual observations. Table 7 reports two robustness checks with respect to this aggregation problem.

First, we estimate the effect of import processing times on import values according to specification (8) with quarterly data and monthly data. To do so, we construct the import processing time and associated congestion and inspection instruments at the quarterly and monthly levels. Quarter-year and month-year fixed as well as country-product-quarter and country-product-month fixed effects account for product characteristics as well as seasonality and shopping seasons. Columns 1 and 2 of Table 7 report the 2SLS estimates for quarterly and monthly data respectively including quarter-year and month-year fixed effects. A one percent increase in processing time reduces imports by about 0.154 percent at quarterly observations and 0.130 percent at monthly observations. Columns 3 and 4 report similar results for specifications when we account for country-product-quarter and country-product-month fixed effects. Overeall, the estimates are 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. Furthermore, quarterly and monthly observation limit identifying variation due to learning mechanisms as explained in Section 5.1.

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 7 column 5 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.[48]

Finally, we estimate specification (8) 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.[49] 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 A6 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.

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

[49] Unfortunately we do not observe customs brokers in our data. If carriers sort systematically across customs workers, then we expect that carriers fixed effects account for this heterogeneity.

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.[50] 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 documentary compliance to cross the border.[51] 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 (8), 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

$$ln(v_{ihxy}) = \delta_{hxy} + \kappa_{iy} + \kappa_{ihx} + \beta ln\hat{t^*}_{ihxy} + u_{ihxy}. \tag{11}$$

Table 8 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 preferred import elasticities

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

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

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.

Equation (9) 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 **??**, but using the corrected lead time proxy, we obtain a new $\hat{\lambda}$.

Table 9 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.[52] In this case, we re-estimate all of the structural parameters over the restricted sample and compute $\hat{\lambda}$. Table 9 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.[53] 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 9 column (5) 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, New Trade Relationships, and Product Categories

In this section we examine if import processing-costs differ across trade relationships and different product categories.

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

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

8.1. Estimates by New versus Experienced Importers

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 costs for new importers, exporters, and trade relationships.[54] 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 10. 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

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

in processing times, but also due to supply chain management strategies as captured by the cost parameters.

8.2. Estimates by Product Categories

Using End-Use categories, Hummels and Schaur (2013) report estimates of time-cost elasticities for five broad product groups including Foods and Beverages, Industrial Supplies, Capital Goods, Automotive, and Consumer Goods. We employ Broad Economic Categories and report total import processing costs for the same product groups in Table 11. The theory shows that magnitudes of time cost elasticities are only comparable if the shape of the processing distribution is the same. However, if the shape of the processing distribution is relatively similar across products, then we may focus on relative comparisons.

We find that processing-time cost elasticities, χ, and lead-time cost elasticities, ϑ, are low for Food and Beverages and Transport Equipment, and relatively high for Industrial Supplies, Consumer Goods, and Capital Goods. This pattern is broadly consistent with the literature.[55]. Inputs, captured by Industrial Supplies, and consumer goods, particularly if including fashion items (Evans and Harrigan, 2005) are time- sensitive.[56]

While consistent with the literature, it is surprising that Foods and Beverages, including perishable items, have a relatively low processing-time cost elasticity, χ, compared to Capital Goods. However, Foods and Beverages have a greater cost multiplier λ. Therefore, adjusting for costs associated with uncertainty using the multiplier is relevant to determine the time-cost rankings of these two product categories. Taking into account the multiplier and the processing time cost elasticity, Industrial Supplies and Consumer

[55]See Hummels and Schaur (2013), Table 7 Columns 6 to 10

[56]A notable difference is that while we find a relatively low time-cost elasticity for transportation equipment, Hummels and Schaur (2013) report a relatively high elasticity for that sector. There are several potential reasons, including that the relatively high time-cost elasticity for that product group in Hummels and Schaur (2013) is due to an unusually low substitution elasticity, which amplifies the time-cost elasticity. They estimate $\sigma = 0.9$.

Goods experience the greatest import-processing costs. Consumer Goods in particular experience a large costs associated with uncertainty ($\lambda - 1 = 0.131$).

The question arises if import patterns in Peru, and specifically the Port of Callao, are comparable to import patterns in other countries like the U.S. Appendix Figure A.1 shows the product mix of imports in the U.S., based on WITS data, and import shares of the Port of Callao based on out trade data. Import shares across broad products for Peru and the US are surprisingly similar. The main exceptions are that Callao imports less mineral products and vehicles including vessels and aircraft, but more plastics. Across the other products, there are differences in magnitudes, but Callao shares tend to be high when the U.S. shares tend to be high as well.

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.[57]

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

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.

We apply our theory and identification strategy to Peru due to data availability. However, delays in the import process and concerns of port efficiency are not unique to Peru (Blonigen and Wilson, 2008). Recently, long processing times in the port of Los Angeles have received much attention.[58] 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.

As more detailed customs data sets with detailed information on processing times become available, the question of how firms price delays, i.e., what do they know about delays when they make their import or export decisions, will be important for identification strategies. We expect that this is a fruitful future area of research to determine how firms optimally respond to trade barriers and if the benefits of policies such as the Agreement on Trade Facilitation justify their costs.

[58]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	14.7	4	5	7	10	18	29	42
	Green	11.6	4	4	6	8	13	21	31
	Orange	15.7	5	6	8	13	20	28	38
	Red	23	7	8	13	19	28	42	56
Processing Time	All	4.3	1	2	2	3	6	12	16
	Green	1.8	1	1	2	2	3	5	6
	Orange	6	2	2	3	5	9	13	17
	Red	10.3	3	4	6	9	15	20	24
Storage Time	All	10.4	2	3	4	7	12	20	31
	Green	9.8	2	3	4	6	11	19	28
	Orange	9.8	2	3	5	7	12	20	28
	Red	12.7	2	3	5	8	15	27	40

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)
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 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		
	(1)	(2)
	OLS	IV
Processing Time ($\gamma\chi$)	-0.049***	-0.243***
	(0.005)	(0.015)
		First Stage
Congestion		0.028***
		(0.000)
Channel		0.743***
		(0.009)
F-Test		4,317.239
		[0.000]
Hansen Test		0.025
		[0.874]
Fixed Effect		
Firm-Year	Yes	Yes
Origin-Product-Year	Yes	Yes
Observations	589,842	589,842

Quantification		
	(3)	(4)
	$\boldsymbol{\gamma = 4}$	$\boldsymbol{\gamma = 6}$
χ	0.061***	0.040***
	(0.004)	(0.004)
φ	2.072***	2.072***
	(0.037)	(0.037)
ϑ	0.063***	0.041***
	(0.007)	(0.007)
$r/(\varphi - \omega)$	0.299***	0.189***
	(0.039)	(0.039)
$(\lambda - 1)$	0.104***	0.066***
	(0.008)	(0.008)
$(\lambda \cdot T^{\chi} - 1)$	0.180***	0.113***
	(0.012)	(0.011)

Source: Authors' calculations based on data from SUNAT.
The table reports OLS and IV estimates of equation (8) 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 estimation, 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: Instrumental Variables

	IV Estimate Processing Time
Robustness Channel Instrument	
Median Channel	-0.239***
	(0.014)
10 or more transactions	-0.285***
	(0.029)
20 or more transactions	–0.295***
	(0.039)
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)
Lag 1 and 10 or more transactions	-0.153**
	(0.076)
Lag 1 and 20 or more transactions	-0.176**
	(0.087)

Source: Authors' calculations based on data from SUNAT.
The table reports IV estimates of equation (8). 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: 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]
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 (8) along with the first stage estimates and the effective F-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. 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 7: Robustness Checks: Aggregation

	(1)	(2)	(3)	(4)	(5)
	Quarterly	Monthly	Quarterly	Monthly	Value Per Shipment
Processing Time	-0.154***	-0.130***	-0.160***	-0.137***	-0.238***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.014)
First Stage					
Congestion	0.024***	0.087***	0.024***	0.086***	0.028***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Channel	0.715***	0.693***	0.715***	0.694***	0.743***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
F-Test	4737	4368	4847	4201	4317.239
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Fixed Effects:					
Firm-Year	Yes	Yes	Yes	Yes	Yes
Country-Product-Year	Yes	Yes	Yes	Yes	Yes
Country-Product-Frequency	No	No	Yes	Yes	Yes
Frequency-Year	Yes	Yes	Yes	Yes	No
Observations	2,020,086	2,676,416	1,967,939	2,523,212	589,842

Source: Authors' calculations based on data from SUNAT.
The table reports IV estimates of alternative specifications of equation (8) along with the first stage estimates and the F-test statistics. 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 monthly estimates the dependent variable is the change in the natural log of the import value at the importing firm-product-origin-month-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 8: 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]
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 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 9: 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)
$(\lambda \cdot T^{\chi}-1)$	0.180***	0.205***	0.206***	0.235***	0.136***
	(0.012)	(0.015)	(0.014)	(0.010)	(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 10: Processing Costs by Importer Experience

	New Importer	**Experienced Importer**
	(1)	(2)
	Estimation	
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 (8) 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

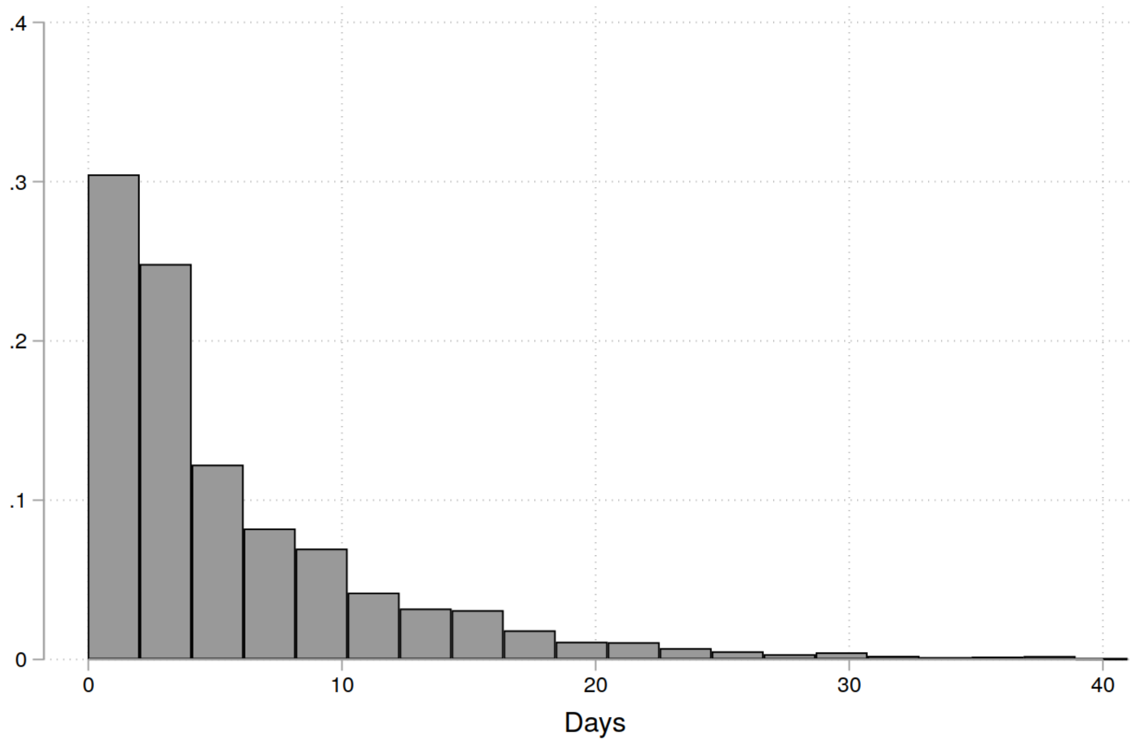
Table 11: Processing Costs by Product Categories

	Product Heterogeneity				
	Food and Beverage	**Industrial Supplies**	**Capital Goods**	**Transport Equipments**	**Consumer Goods**
OLS ($\gamma\chi$)	-0.0916***	-0.0523***	-0.0439***	-0.0215	-0.0565***
	(0.0297)	(0.00809)	(0.00816)	(0.0190)	(0.0105)
IV ($\gamma\chi$)	-0.185***	-0.256***	-0.231***	-0.187***	-0.265***
	(0.0564)	(0.0217)	(0.0210)	(0.0454)	(0.0246)
χ	0.0468***	0.0641***	0.0578***	0.0466***	0.0662***
	(0.000552)	(0.00438)	(0.00125)	(0.0165)	(0.000399)
φ	1.178***	2.072***	2.329***	1.785***	1.662***
	(0.00363)	(0.0195)	(0.0139)	(0.0341)	(0.0436)
ϑ	0.0479***	0.066***	0.0584***	0.0472***	0.0687***
	(0.0007)	(0.0056)	(0.0014)	(0.032)	(0.0004)
$r/(\varphi - \omega)$	0.274***	0.250***	0.237***	0.230***	0.392***
	(0.0028)	(0.0208)	(0.0155)	(0.0521)	(0.0369)
$(\lambda - 1)$	0.099***	0.101***	0.088***	0.083***	0.131***
	(0.0015)	(0.0104)	(0.0032)	(0.0366)	(0.0013)
$(\lambda \cdot T^{\chi} - 1)$	0.185***	0.233***	0.196***	0.163***	0.3***
	(0.022)	(0.021)	(0.032)	(0.026)	(0.027)

Source: Authors' calculations based on data from SUNAT.
The table reports OLS and IV estimates of the same model as in Table 4. We estimate one specification for each product group. Firm-year and origin-product-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

Callao					
Year	Import Value	Number of Origins	Number of Products	Number of Employees	Age
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: Border Times (in Days): Total and Stages in 2013, by Customs Verification Channel Excluding Express Shipments

Stage	Channel	Average	Percentile						
			5th	10th	25th	50th	75th	90th	95th
Total Border Time	All	14.9	4	5	7	11	18	29	42
	Green	11.7	4	4	6	8	13	21	32
	Orange	16.1	6	7	9	13	20	28	39
	Red	23.4	8	9	13	19	28	42	56
Processing Time	All	4.3	1	2	2	3	6	12	16
	Green	1.8	1	1	2	2	3	5	6
	Orange	6	2	3	3	5	9	13	17
	Red	10.4	3	4	6	10	15	20	24
Storage Time	All	10.6	3	3	5	7	12	21	32
	Green	9.9	3	3	4	6	11	19	28
	Orange	10.1	3	3	5	7	12	20	28
	Red	13.1	3	3	5	8	15	28	41

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 excluding shipments that enter under the express channel.

Table A3: Effect of Unloading Time on Storage Time - Excluding Express Channel Shipments

	(1)	(2)	(3)	(4)
Unloading Time	-0.174***	-0.185***	-0.150***	-0.164***
	(0.017)	(0.019)	(0.016)	(0.018)
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 A4: 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 A5: 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]
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 (8) along with the first stage estimates and the effective F-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 A6: 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-Test	26726	31519	31207	23499	15917	19917	13088
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
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 (8) along with the first stage estimates and the effective F-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, $\frac{\partial ETC(t_l^*)}{\partial \omega} = \frac{t^{*\varphi} t_{min}^{\varphi} \varphi r v}{(\omega-\varphi)^2} > 0$. 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 $\frac{\varphi r v}{t_p} dt_p$ increases in r. By observation of equation (4), $\frac{\partial t_l^*}{\partial \omega} > 0$ 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 (4) 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:

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

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

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

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

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

Appendix - Figures

Figure A.1: Import Product Shares, Callao versus U.S. (Source Data: UN Comtrade Database, Copyright ©United Nations 2012, and, SUNAT)