Micro-Anatomy of Import Substitution

Massimiliano Calì*[2] and Giorgio Presidente†[1]

[2] *World Bank*
[1] *Institute for European Policymaking, Bocconi University*

February 8, 2026

Abstract

We document three novel mechanisms underlying the substitution of inputs by firms in response to an increase in intermediates' import costs. First, within inputs, plants substitute higher-quality foreign varieties with lower-quality domestic ones, increasing physical quantities while unit values fall—a quality-quantity tradeoff. Second, across inputs, the total number of varieties expands as plants adopt additional domestic inputs to compensate for quality losses due to the reduction in imports. Third, lower import competition induces entry of inefficient domestic suppliers, further degrading the average quality in domestic input markets. A framework with quality-differentiated inputs and endogenous variety choice rationalizes these patterns. These findings illustrate the complexity of firms' adjustment in input markets, which can help explain the large productivity effects of trade liberalization via the input channel found in the literature.

Keywords: intermediate inputs, raw materials, fixed trade costs, imports, import costs, productivity, technical efficiency, TFP, quality-quantity tradeoff

JEL classification: F1, L1, D2

*The views expressed in this paper are of the authors and do not necessarily reflect those of the affiliating institutions.

†Corresponding author: giorgio.presidente@unibocconi.it

1 Introduction

The positive link between imported inputs and firm productivity—a well-established empirical finding in the trade literature— is one of the key channels behind the gains from trade liberalization (Kasahara and Rodrigue, 2008; Amiti and Konings, 2007; Topalova and Khandelwal, 2011; Fernandes, 2007; Goldberg et al., 2009, 2010).[1] Yet, despite the rich empirical evidence, surprisingly little is known about the specific mechanisms underlying this positive link. While the literature recognizes that input quality matters for productivity (Halpern et al., 2015; Kugler and Verhoogen, 2009), it has not shed light on the specific micro-mechanisms through which trade costs affect input quality and their relative importance. At a time of rising trade protectionism, this gap appears salient especially as intermediates may have a higher pass-through elasticity of import tariffs than other goods (Olarreaga and Santander, 2025).

There are three related reasons for the paucity of evidence. The first is the scarcity of granular data on input usage, including information on unit values that is key to infer input quality (Kugler and Verhoogen, 2009). The second reason is that due to the lack of input-level data, it is hard to establish causality when measures of trade costs vary at the plant-level or higher level of aggregations. Finally, while the literature has focused on import tariffs as the source of trade policy changes, the latest big swings in tariffs occurred largely in the 1980s and 1990s, at least in developing countries, a time when firm-level data was not as rich as in the following decades. In more recent years, countries have increasingly used non-tariff measures, whose data is much less available than tariffs (Kee and Xie, 2024; Goldberg and Pavcnik, 2016).

To address these issues, we leverage a large representative survey of manufacturing plants from Indonesia, which provides information on the value and quantity of intermediate inputs used, distinguishing between domestically-sourced and imported variety. We match these data with a comprehensive record of trade policy measures, applied to the universe of 10-digit intermediate inputs used in Indonesia between 2008 and 2015,

[1] Earlier results include Tybout et al. (1991); Harrison (1994); Hay (2001); Tybout et al. (1991); Schor (2004); Muendler (1986).

and focus on a widely applied and costly non-tariff measure (NTM) in the Indonesian context, i.e. Pre-Shipment Inspection (PSI). This measure subjects shipments to costly inspections at the port of departure before leaving for Indonesia (Calì et al., 2026, 2024). By the end of the period of analysis PSI was applied to 24% of input used in our sample, compared to 17% at baseline.

There are two main advantages in our context of using an NTM like PSI relative to tariffs as the trade policy barrier. First, it ensures greater variation over time and across plants in our sample. Second, as it is a binary variable, it allows to implement an event study framework more naturally than a continuous variable like import tariff.

Our setup and data allow us to estimate the causal impact of trade costs via input markets at an unusually high level of granularity. We contrast within plant-input intermediate consumption subject to PSI against the consumption of PSI-free inputs, controlling for all other tariff and non-tariff measures applied to those inputs, along with plant-year and input market-year fixed effects. Our strategy mitigates the concerns of omitted variable bias and endogeneity of trade policy and input usage, for instance due to plant's market power or management quality.

Based on this framework, we provide three main contributions. First, we provide causal evidence on the impact of trade costs on input-level substitution patterns. We find that higher import costs lower the share of imported variety of a given input used by the plant, that the number of units consumed per variety increases, but the average unit value falls. The evidence is thus consistent with a pattern of substitution of high-quality foreign variety with lower-quality domestic varieties of a given input. We label this set of findings the quantity-quality tradeoff.

Second, higher trade costs lower the number of different imported varieties, but it increases the number of domestically-sourced ones. This entails a net increase in the number of units used, suggesting that one unit of high-quality foreign variety is substituted with more units of the lower-quality domestic one. One way to interpret this finding is that producers can increase the effective quality of domestic inputs by adding auxiliary ones—such as stabilizers, softeners, or catalysts which enhance the effectiveness

of domestic materials but require the use of a larger number of input units.

Third, we document that the reduction in the quality of inputs induced by import costs is not only due to a composition effect (domestic inputs have lower quality than imported inputs at baseline), but also to a drop in the average quality of domestically produced inputs in response to import protection (Melitz, 2003). This is proxied by the inputs' average unit value, whose reduction cannot be due to shrinking markups, which if anything appear to rise with NTMs. We thus contribute to a literature at the intersection between trade and industrial organization (Brandt et al., 2017; Bloom et al., 2016; Amiti and Heise, 2025), by documenting that the drop in quality is due to the entry of new plants producing low-price products, a result in line with recent evidence from the Indonesian steel sector (Kee and Xie, 2025).

We conclude the paper by presenting a model of import substitution with quality-differentiated inputs and endogenous variety choice that can rationalize the empirical results. We show that the model of import substitution in Halpern et al. (2015) can account only for the quantity-quality tradeoff, but not the other two findings. Additional assumptions about input quality need to be made. However, a simple extension based on Melitz (2003)—augmented with a productivity-quality mapping similar to Kugler and Verhoogen (2012)—is sufficient to produce declining quality of domestic inputs due to protection.

2 Data and Institutional Context

2.1 Trade Policy Measures

Data on trade policy measures are drawn from a novel, comprehensive database developed by the World Bank in collaboration with the United Nations Conference on Trade and Development (UNCTAD) (Montfaucon et al., 2023). The dataset uses the most disaggregated available classification of non-tariff measures (NTMs), namely the 3-digit MAST level.[2] We complement the NTM data with information on import tariffs from the

[2]The United Nations Conference on Trade and Development (UNCTAD) defines NTMs as "*policy measures other than ordinary customs tariffs that can potentially have an economic effect on international*

UNCTAD TRAINS database, which reports annual Most-Favored-Nation (MFN) applied import tariffs at the HS 10-digit product level.

Our main objective is to document how firms change their input sourcing in response to variations in policy barriers to imported inputs. To that end we need to focus on costly trade measures that provide substantial variation during our period of analysis (2008-15). The traditional measure used in the literature—import tariffs—displays virtually no variation in our sample. Figure 1 shows that consistent with the limited use of import tariffs across countries after the waves of trade liberalization of the 1980s and 1990s, the average tariff rate on inputs used by Indonesian manufacturing plants remained steady (varying by less than 10% from the 2008 baseline.

Conversely Indonesia, like many other countries, increased the use of NTMs during that period (Calì et al., 2024). While NTMs generally respond to a variety of objectives related to potential externalities of trade, such as concerns for product quality, consumers' health or safety, some measures can be more protectionist in nature. One such measure which Indonesia increasingly used during the period of analysis, is *Pre-Shipment Inspection* (PSI). That is particularly suitable as a measure of trade costs, as it creates significant importing costs without arguably addressing substantive externalities (Calì et al., 2026).

PSI requires shipments to be inspected at the port of departure from the exporting country before leaving for Indonesia. The objective of PSI is to ensure that the import declaration lists the correct classification of the goods to be imported as a way of detecting improper importing activities. A surveyor report outlining the surveyor firm's inspection results is a documentary requirement for certain goods. In Indonesia, at the time of our analysis, only two State-Owned Enterprises (SOEs) have the authority (granted by the Ministry of Trade) to perform PSI for the Indonesian government. The monetary cost of this service is typically charged as a fixed fee per container, or in certain cases as a share of the import value (usually 1 percent).

The cumbersome process to comply with this measure can increase the cost of im-

trade in goods, by affecting quantities traded, prices, or both."

porting by raising the uncertainty about the time required to import and the compliance costs for imports. Given their limited geographic presence, the SOEs at times further outsource the inspection to other companies in situ, adding to the length and uncertainty of the procedure. Complying with the PSI thus involves a per shipment cost related to the uncertainty of the procedure and a monetary cost of the inspection, which may or may not be related to the value of the goods.[3]

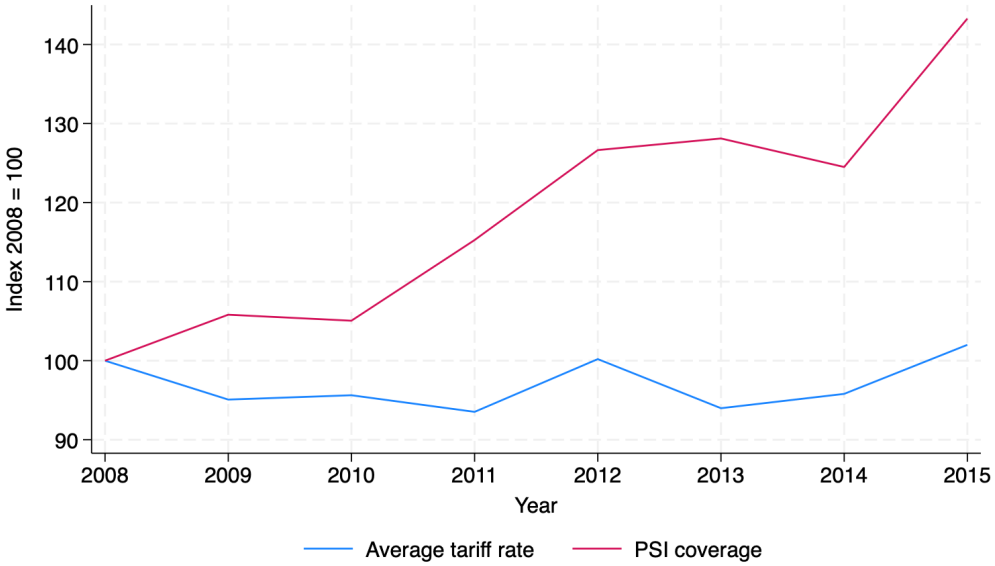
As shown in Figure 1 the use of PSI presents substantial variation during the period of analysis, particularly relatively to tariffs. PSI coverage expanded substantially by 41%, from affecting 17% of manufacturing inputs in 2008 to over 24% in 2015. This differential variation makes PSI the more suitable measure for identifying the effects of changing trade costs in our context. We are also cognizant of the potential endogeneity of PSI application, which we address below.

For robustness purposes, we also leverage a different NTM, *Import Approval Requirements*, which similarly to PSI appears to be protectionist in nature and widely applied in Indonesia (Calì et al., 2026). This has to be issued by the Ministry of Trade, with supporting recommendations from related ministries, and the approval must be obtained before the import procedure for each shipment can start. These recommendations aim to fulfill non-trade objectives, which are often related to the protection of domestic producers in the sector. Ministries have relatively high discretion in deciding on the recommendation, including whether or not to grant it, how long it takes for them to respond and the quantity allowed for the specific approval. The direct labor cost of complying with the requirement for each shipment is compounded by the time and uncertainty of the approval process, which acts as a fixed cost per shipment.[4]

[3]Interviews gathered with importers suggest that this uncertainty entails higher costs for the producers than the monetary cost of the actual inspection per shipment.

[4]When the import approval aims to protect producers, this NTM does not seem to comply with the WTO principle that "any person fulfilling the legal requirements should be equally eligible to apply for and obtain import licenses" (WTO GATT, Article 2.1).

Figure 1: Time-Series Variation in Trade Policy Measures



Notes: This figure shows the evolution of the average import tariff rate and the percentage of inputs subject to Pre-Shipment Inspections (PSI), both indexed to 2008=100. The tariff series represents the simple average across all inputs used by manufacturing plants in our sample. The PSI series shows the share of inputs subject to PSI requirements. While tariff rates remain largely stable throughout the period (varying by less than 6% from baseline), PSI coverage expands substantially by 41%, from affecting 17% of inputs in 2008 to 24% in 2015. In absolute terms, the average tariff rate varied between 5.3% and 5.7%, while PSI coverage expanded from 17% to 24% of inputs. This differential variation makes PSI the more suitable measure for identifying the effects of changing trade costs in our context.

2.2 Manufacturing Data

Intermediate inputs data are taken from the Indonesian survey of manufacturing plants with at least 20 employees (*Statistik Industri*, SI) administered by the *Indonesian Statistical Office* (BPS). The coverage of the survey is extensive; in fact, it becomes an actual census in 2006 and it is very close to a census in the remaining years, hence ensuring high representatives. The survey includes information on output, employment, investment and materials expenditure, as well as the 5-digit industry in which the plant operates.[5]

One challenge of the *Statistik Industri* data is the lack of complete series of capital stock. To address the issue, we develop an algorithm described in Online Appendix B.1. Once we obtain clean capital series, we deflate them using price indexes from BPS, distinguishing between machinery and equipment, vehicles, buildings, and land.

Crucially for our purposes, SI data provide information on quantities and values of the

[5] The industry classification is Klasifikasi Baku Lapangan Usaha Indonesia (KBLI), which is mostly compatible with ISIC coding. For multi-product plants, the survey provides the industry code corresponding to the product with the highest revenue share.

intermediate inputs—domestic and imported—used by each plant. These are defined at a highly granular level, namely 9 digits *Klasifikasi Komoditi Indonesia* (KKI), a classification used by Indonesian statistical office BPS and based on the International Standard Industrial Classification of All Economic Activities (ISIC). On average in our sample, each plant uses two different varieties of inputs, and up to twenty-seven. The drawback of the high level of detail in inputs data is that sometimes there are coding mistakes by the reporters. Online Appendix B.2 describes in detail the methodology we use to clean the input and output data. To link tariffs and non-tariff measures data, varying at the HS-10 digit good and year level, to SI plant-inputs-year data, we use a correspondence table between HS-10 digit and KKI-9 digit provided by BPS.

Table 1 presents key summary statistics based on our final sample, which includes 18,867 plants and 2,112 9-digit level inputs.

Of all plants, 16% directly import intermediate inputs in at least one year. The average annual expenditure for an input is 5.7 billion IDR (∼350,000 USD), although there is large variation across inputs.

The average unit value of an input is 310,000 IDR for domestic ones (∼20 USD), and 770,000 IDR for foreign imported inputs (∼60 USD). The higher unit value of imported inputs is consistent with evidence from Colombian plants Kugler and Verhoogen (2009).

Conditional on being importers, the average share of foreign variety of an input is around 60%, irrespective of whether we measure it in value or quantity terms.

Table 1: Summary statistics of input-level data.

	(1) N	(2) mean	(3) sd	(4) min	(5) max
Pre-Shipment Inspection (dummy)	99,958	0.185	0.388	0	1
Value of inputs used in production (million IDR)	99,958	5,587	27,539	0.00100	258,202
Average unit price of inputs (IDR)	99,958	311,263	1.439e+06	50	1.190e+07
Average unit price of imported inputs (IDR)	9,283	765,966	3.707e+06	46.05	2.999e+07
Share of imported inputs (quantity)	9,283	0.604	0.401	1.70e-07	1
Share of imported inputs (value)	9,283	0.617	0.386	0	1

Notes: this table shows the summary statistics of the variables used in the input-level analysis.

3 Intensive Margin of Import Substitution

3.1 Empirical model

We start by analyzing how the input use of firms change in response to the increase in trade cost. The empirical model used for the input-level analysis is:

$$y_{jmt} = \delta_0 + \sum_{k=-3}^{-2} \delta_k \cdot \tau_{m,t+k} + \sum_{k=0}^{3} \delta_k \cdot \tau_{m,t+k}$$
$$+ \Delta \cdot TRADEPOL_{mt} + u_{jm} + u_{jt} + u_{m't} + \epsilon_{jmt} \quad (1)$$

In Equation 1, y_{jmt} is the outcome variable for input m used by plant j in year t. The variable τ_{mt} is a dummy taking value 1 if a Pre-Shipment Inspection is applied to a 9-digit intermediate input m at time t. We choose to include 3 leads and lags in order to ensure at least five-hundred observations in each lead/lag.

We use plant-input (u_{jm}) fixed effects, which allow us to identify the parameters of interest by exploiting within-plant-input variation in intermediate input use over time. This allows to avoid issues with plants reporting the quantity of inputs in different units, as well as differences in the importance of a given inputs for different plants.

The vector $TRADEPOL_{mt}$ controls for import tariffs and other NTMs applied to inputs as controls. For the latter, we leverage higher order groupings rather than 3-digits to parsimoniously control for the other measures applied to each product. These groupings include: i) Sanitary and Phytosanitary Standards (chapter A in the MAST classification); ii) Technical Barriers to Trade (Chapter B), and a residual category including more rarely applied regulations involving licensing, quotas, quantity and price control (chapters D-P).[6]

We cannot rule out the possibility that PSI are used to protect domestic industries. That being the case, they might be endogenous to plants intermediate consumption decisions. For instance, lobby groups might exert pressure on the regulator to avoid the

[6] The aggregate NTM controls are dummy variables equals 1 if a specific measure is applied to a HS-10 digit in a given year, and zero otherwise. In addition to PSI (MAST C1 sub-chapter), Chapter C includes another measure C3 "Requirement to pass through specified port of customs". We control for this measure separately.

introduction of (or to remove) a measure on an input, thus generating a spurious negative correlation between the measure and imports. It is also possible that the government would regulate a specific input to protect domestic producers of the input or as a reaction to input price movements. To mitigate these concerns, we include plant-year fixed effects (u_{jt}) and 5-digit input category-year fixed effects ($u_{m't}$).[7]

In each time period, the treated group consists in inputs subject to a Pre-Shipment Inspection, while the control group is composed by cost-free inputs (never-treated units). The control group of never-treated inputs accounts for 74% of the sample.

Given that PSI are applied to inputs at different times, we estimate (1) with the estimator proposed by Sun and Abraham (2021), which allows for staggered treatment across inputs.

In all specifications, we cluster the errors at the plant level.

3.2 Results

Figure 2 presents the estimated within-input impact of trade costs i.e. the intensive margin pattern of import substitution. We focus on the log-change in input quantity (number of units), expenditure, and average unit value.

The estimates in Panel (a) suggest that upon being subject to import costs, plants increase the number of units, but the average unit value of the input falls, leaving total input expenditures unchanged. This suggests a shift towards lower-quality varieties of the same input.

Panel (a) also documents a quality-quantity trade-off induced by PSI. More units of a low-quality input are required to substitute one unit of high-quality input of the same variety of input. For instance, 1 kg of ice cream requires 0.15 kg of average milk powder, but only 0.12 kg if the powder has high fat content.[8] To the best of our knowledge, this is

[7] Notice that we need to aggregate inputs at a level higher than the 9-digit level used in the analysis, as the latter is the variation that identifies the coefficients of (1).

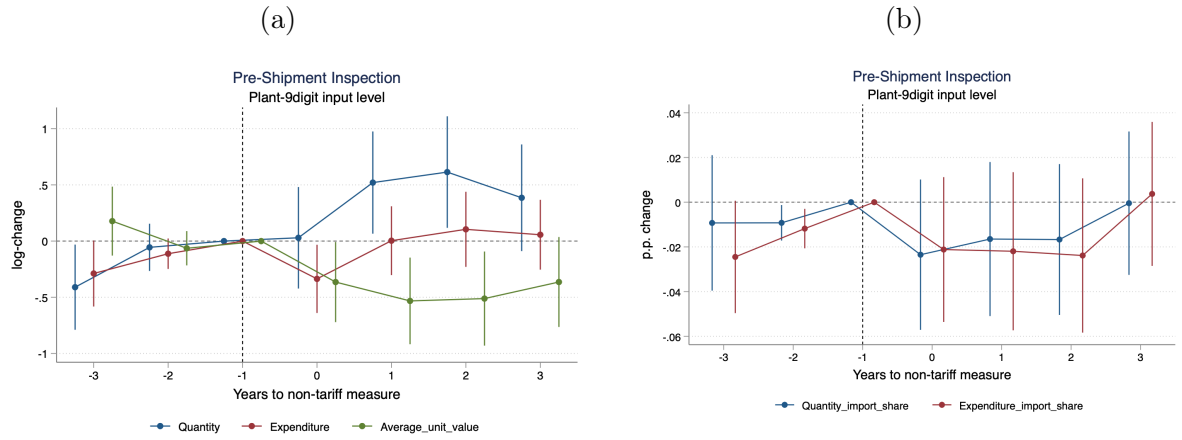
[8] Examples of this behavior abound in manufacturing. One example from the food industry—covering almost 30% of inputs usage in our data—is high-quality milk powder, which has a higher fat and protein content, requiring smaller amounts to produce creamy dairy products like yogurt, condensed milk, or ice cream. Another example from the wearing apparel industry, covering roughly 10% of inputs in our data, is low-quality cotton fabric with shorter fibers. More fabric may be required to account for shrinkage, tears, or irregularities during cutting. For instance, if the fabric has uneven edges or fraying,

the first analysis to document a negative relationship between input quality and quantity used in production.

Panel (b) presents the estimates for the share of imported inputs of a given variety, both in quantity and value terms. When a PSI is imposed, the share of imported variety falls, suggesting that plants substitute high-quality foreign inputs with lower-quality domestic ones.

Our results suggest that rising import costs – through PSI - trigger a substitution of higher-quality imported with lower-quality domestically-sourced inputs, a result in line with Halpern et al. (2015) . Importantly this substitution entails a quantity-quality tradeoff, whereby the manufacturing producer ends up consuming more quantity of the input subject to PSI at a lower average price.

Figure 2: Import substitution pattern: input-level impact of NTM.



Notes: this figure shows point estimates and 95% confidence intervals of the impact of Pre-Shipment Inspection (PSI) on (log-) quantity, expenditure and average unit value (a), and the quantity- and value-share of imported inputs over all inputs used (b).
The regressions control for plant-9-digit level input fixed effects, plant-year fixed effects, 5-digit input-year fixed effects, as well as import tariffs and dummy variables for NTMs other than PSI. Standard errors are clustered at the plant level. The estimates are based on the estimator by Sun and Abraham (2021).

4 Extensive Margin of Import Substitution

How does the within-input substitution pattern documented in the previous section affect the overall input use of the manufacturing plants? To address this question, we turn to

the usable area of the fabric is reduced, necessitating additional material; if the fabric lacks strength or thickness, multiple layers might be used to achieve the desired durability. Online Appendix D presents more examples.

examining the extensive margin of substitution across inputs. Specifically, we examine how the total number of distinct input varieties used changes when trade costs rise for the plant, distinguishing between domestically-sourced and imported inputs.

4.1 Empirical model

To study the extensive margin of import substitution we need to move the level of analysis at the plant level.

The empirical model used for the plant-level analysis is:

$$y_{jt} = \delta_0 + \sum_{k=-3}^{-2} \delta_k \cdot_{j,t+k} + \sum_{k=0}^{3} \delta_k \cdot_{j,t+k}$$

$$+ \Delta \cdot \tilde{TRADEPOL}_{jt} + u_j + u_{st} + u_{rt} + u_{m''t} + \epsilon_{jmt} \tag{2}$$

In Equation 2, y_{jt} is the outcome variable for plant j in year t.

To keep using an event study setup in the plant-level analysis, we proceed as follow. First, we construct Bartik-style variables for all trade policy measures by aggregating them using the 9-digit input shares fixed in the first year they are observed for each plant.[9] Then, we construct a dummy variable $_{ft}$ taking value 1 if the value of the Bartik is above the 75th percentile of its distribution and 0 if the value of the Bartik is 0. We drop observations with Bartik values between 0 and the 75th percentile.[10]

We use plant (u_j) fixed effects, which allow us to identify the parameters of interest by exploiting within-plant variation over time.

The vector $\tilde{TRADEPOL}_{jt}$ includes the Bartik-style variables for all other trade policy measures used as controls.

In the plant-level analysis, the potential endogeneity of PSI and plant outcomes cannot be controlled for by plant-year effects, which is the variation that identifies the coefficients of interest. Nonetheless, we can leverage the richness of our data and control for 5-digit

[9] We drop the observation before running regressions based on the Bartik variables.

[10] Results - available upon request - are very similar if we set $_{ft} = 1$ whenever at least one input is subject to PSI, or use the median or mean value of the Bartik as thresholds.

industry-year (u_{st}) and regency-year fixed effects (u_{rt}).[11] Given that plants use multiple inputs, we identify for each plant the 5-digit level input with the largest expenditure share and interact that with year fixed effects ($u_{m''t}$) to account for the potential endogeneity of trade policy at the plant level.

Given that the staggered nature of treatment carries over to the plant-level analysis, we keep using the estimator proposed by Sun and Abraham (2021). We again cluster errors at the plant level.

4.2 Results

Figure 3 presents the PSI results on the number of input varieties used by plants.[12] Consistent with Halpern et al. (2015), we find that the number of imported inputs falls when plants become exposed to a new source of trade cost. Yet the total number of inputs increases significantly due to the large increase in domestically-sourced inputs. This suggests that in analogy to the within-input quantity-quality trade-off discussed in the previous section, there is also substitution on the extensive margin: one variety of higher-quality input is substituted with several varieties of lower-quality inputs.

The switch to lower-quality inputs may require other materials to compensate for performance loss, such as adhesives, coatings, catalysts, and stabilizers. For instance, domestic fibers might have different tensile strengths and dye absorption properties. To make them usable, producers may need to introduce new types of finishing agents, softeners, and dyes suited to those fibers. This creates a complementarity: the introduction of one new material can pull in several additional new ones.

To the best of our knowledge, this is the first analysis to shed light on this pattern of import substitution on the extensive margin.

We also shed light on the relation between PSI and plant marginal costs. To estimate marginal costs, we first estimate plants' production functions using the Dynamic

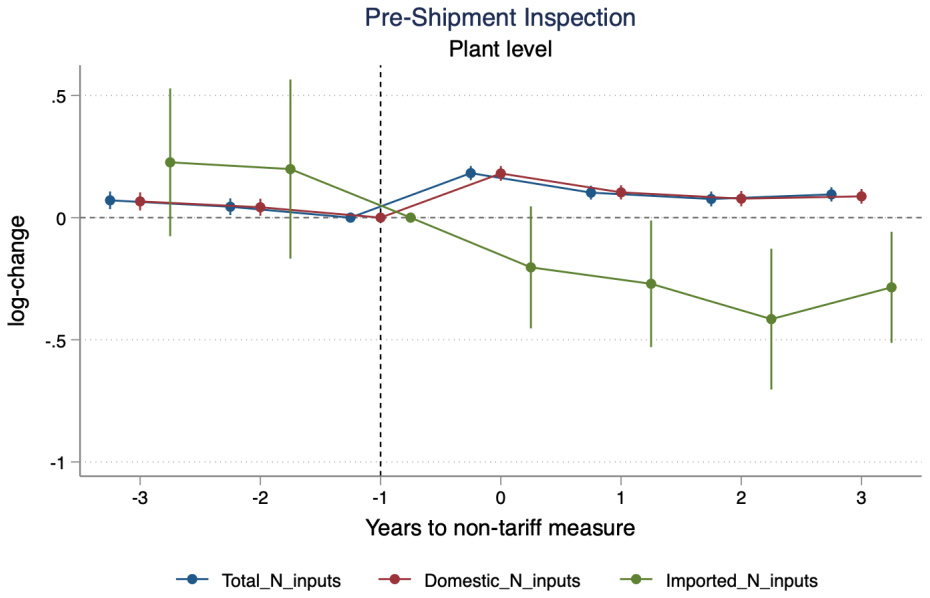
[11] Regencies are the second level of sub-national administrative divisions in Indonesia (the first being the province).

[12] Online Appendix Table A2 shows that plants use from 1 to 27 different 9-digit input varieties. Domestically-sourced inputs range from 1 to 19, while imported inputs range from 0 to 25 different varieties.

Panel estimator of Blundell and Bond (2000), then we obtain the price markup using the approach of De Loecker and Warzynski (2012). We recover marginal costs using the identity relating price to markup and marginal cost as in De Loecker et al. (2016). The details are presented in Online Appendix C.

The results are presented in Online Appendix Figure A4. Although imprecisely estimated, there are clear signs of a positive and persistent relation. This suggests that PSI might have a productivity-hampering effects, in line with the evidence for import tariffs (e.g. Amiti and Konings, 2007; De Loecker et al., 2016),

Figure 3: The extensive margin of import substitution: number of varieties.



Notes: this figure shows point estimates and 95% confidence intervals of the impact of a Bartik variable capturing exposure to Pre-Shipment Inspection (PSI) on the log-number of domestic, imported and total varieties of 9-digit level inputs used by plants. The regressions control for plant fixed effects, 5-digit product-year fixed effects, regency-year fixed effects, the top 5-digit input used by the plant interacted with year effects, as well as Bartik variables for import tariffs and NTMs other than PSI. Standard errors are clustered at the plant level. The estimates are based on the estimator by Sun and Abraham (2021).

5 Domestic Producers

The literature has interpreted the switch to lower-quality domestic inputs induced by trade costs as the result of a static composition effect (Goldberg et al., 2010; Halpern et al., 2015). However, trade protection could also affect the productivity of domestic input producers, further reducing the quality of the inputs used downstream. For instance,

lower foreign competition may reduce the minimum productivity threshold needed to compete in the domestic sector, thus changing its composition and average quality (Melitz, 2003).

To explore this hypothesis, we rely on 9-digit product level information and focus on Indonesian producers of inputs that are used by the plants in the sample. Specifically, we measure how PSI affects the unit value of the inputs produced, decomposing the total effect into two different margins. The first is the quality of existing domestic varieties by incumbent producers, which might fall as a result of the protection afforded by trade measures. The second margin is the entry of new plants. Evidence from Indonesia itself shows that less productive plants enter the steel sector in response to lower prices of the main raw material, nickel Kee and Xie (2025).

We estimate different versions of (1), in which we use the log of 9-digit level products' unit value as the dependent variable.[13] In the first specification, we substitute plant-product fixed effect with product fixed effect, which allows us to measure the impact of the introduction of PSI on the price of incumbents and new entrants producing existing products. Panel (a) of Figure 4 presents the results. We find a negative and significant impact, which is consistent with entry of inefficient firms as in Melitz (2003) and Kee and Xie (2025).

Next, we include plant-product fixed effect, which allows us to isolate the contribution of incumbent producers. We still find a negative impact, although imprecisely estimated. Thus, the evidence is consistent with a detrimental impact of trade protection (De Loecker et al., 2016; Amiti and Konings, 2007, e.g.), although the magnitude of this channel is modest compared to the other.

One concern may be the extent to which declining unit values may capture decreasing markups. While it is unlikely that import protection may reduce domestic markups, we still study the impact on markups as that may qualify the result on unit values. To estimate markups we apply the methodology of De Loecker and Warzynski (2012).[14] This

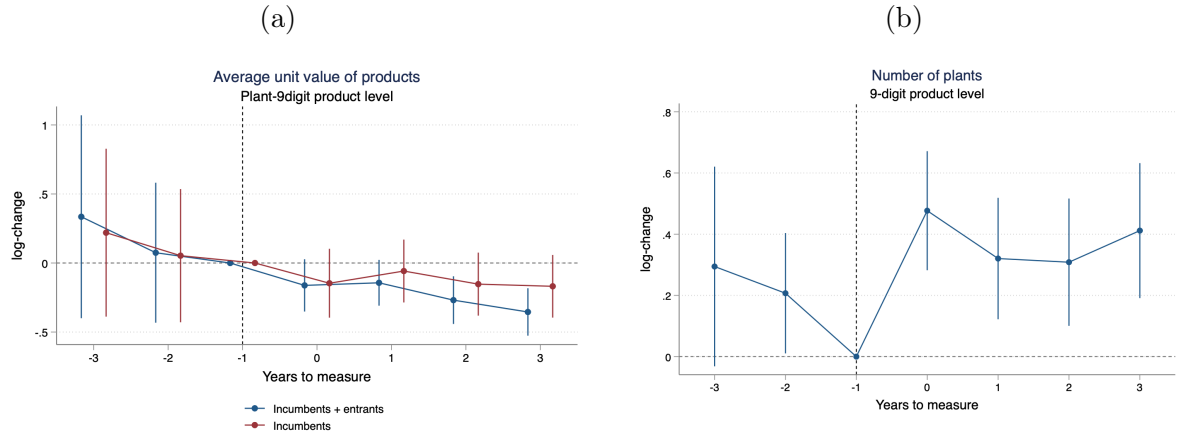
[13] Given that 70% of the plants in our sample are single-product, we replace plant-year effects with 2-digit industry-year effects.

[14] The details of the procedure is presented in Online Appendix C.

is shown in Online Appendix Figure A3. The markup tends to increase with PSI, albeit the effect is modest and imprecisely estimated. This is consistent with the protectionist nature of the trade policy instrument and it confirms that the decline in price may reflect a genuine quality effect, which in fact may be under-estimated given the positive markup effect.

Panel (b) of Figure 4 sheds light on the entry margin by presenting the impact of PSI on the number of plants producing the 9-digit product. We find that entry increases, in line with Kee and Xie (2025).

Figure 4: Domestic Producers.



Notes: this figure shows point estimates and 95% confidence intervals of the impact of Pre-Shipment Inspection (PSI) on log-average unit value of products (a), and the number of plants operating in a 9-digit level product market (b).
In Panel (a), the red estimates are obtained using plant-9-digit product fixed effects, 2-digit product-year fixed effects, as well as import tariffs and dummy variables for NTMs other than PSI. The blue estimates substitute plant-9-digit product fixed effects with 9-digit product fixed effect. Standard errors are clustered at the plant level.
In Panel (b), the data are aggregated at the 9-digit product level. The regression includes 9-digit product fixed effect. Standard errors are clustered at the product level.
All estimates are based on the estimator by Sun and Abraham (2021).

6 Alternative Trade Policy Instruments

We benchmark the results obtained so far against alternative trade policy instruments.

Online Appendix Figure A1 is based on other non-tariff measure that does not clearly address a negative externality (Calì et al., 2026). Panels (a)-(b) present the impact of Import Approval Requirements, which in our sample cover 18% of inputs.

We also look at import tariffs, which despite their low variation in our sample remain the most widely used trade policy tool. To examine the impact of import tariffs, which

are a continuous variable, we use two types of estimator. The first is a Two-Way Fixed Effect. The results are presented in Online Appendix Table A1. The estimates are fully consistent with the main results based on PSI.

Online Appendix Figure A2 presents the results on the extensive margin. Also in this case, the estimates are consistent with the results of Figure 3. In Panel (b) we do not detect a clear impact on the number of imported inputs. However, the increase in the number of different domestic inputs used is precisely estimated in all cases.

Finally, Online Appendix Figure A5 probes the robustness of the findings in Figure 4.

We conclude that the import substitution patterns documented in the previous section are general and do not depend on the specific trade policy input considered.

7 A Model of Import Substitution

This section presents an extension of Halpern et al. (2015) to rationalize the key empirical findings above: (i) PSI reduces the imported-input share of a given input variety, its unit value, but it increases the physical quantity used; (ii) PSI can increase the number of input varieties used by plants, and (iii) PSI lowers the average quality of domestically produced inputs.

A representative final-good producer uses capital K, labor L, and a continuum of potential intermediate input types indexed by $m \in [0, \bar{M}]$. The producer chooses which input types to adopt. Let $S \subseteq [0, \bar{M}]$ denote the endogenous set of adopted types, with measure $N \equiv |S|$. Conditional on adoption, production follows a nested CES technology:

$$Q = AK^{\alpha}L^{\beta}\left[\int_{m\in S} M_m^{\frac{\sigma-1}{\sigma}}\, dm\right]^{\frac{\sigma}{\sigma-1}\cdot\gamma}, \qquad \alpha+\beta+\gamma=1, \qquad \sigma>1. \tag{3}$$

7.1 Input-Using Firms

Consider a representative input bundle of a given variety indexed by m. The firm combines a foreign input x_{fm} and a domestic input x_{dm} to produce a composite M_m using a

CES aggregator:

$$M_m = \left[(a\, x_{dm})^{\frac{\theta-1}{\theta}} + (b x_{fm})^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \qquad \theta > 1, \tag{4}$$

where $a, b \geq 1$ are quality shifters to be further defined below.

Domestic inputs are purchased at price p_d. Imports face an iceberg cost $\tau \geq 1$ and a per-unit PSI cost $\tau_m \geq 0$, so the delivered foreign price is

$$\tilde{p}_f(\tau_m) = \tau p_f^* + \tau_m \tag{5}$$

A microfundation for the reduced form $\tilde{p}_f(\tau_m) = \tau p_f^* + \tau_m$ is presented in Online Appendix E.1

We hold the iceberg cost τ fixed - reflecting the limited tariff variation over time in our data - and focus on variation in PSI costs τ_m. We also assume throughout that $\tilde{p}_f(\tau_m) > p_d$, as apparent in Table 1.

Proposition 1 (Quality–Quantity Tradeoff)**.** *Fix an input variety m and hold the composite $M_m = \bar{M}_m$ fixed.*

Define the import share in physical units $\theta_{fm} \equiv x_{fm}/(x_{dm} + x_{fm})$, total physical quantity $T_m \equiv x_{dm} + x_{fm}$, and average unit value

$$\bar{p}_m \equiv \frac{p_d x_{dm} + \tilde{p}_f(\tau_m) x_{fm}}{x_{dm} + x_{fm}} = p_d(1 - \theta_{fm}) + \tilde{p}_f(\tau_m)\theta_{fm}.$$

Assume that

$$(\tilde{p}_f(\tau_m) - p_d) \left| \frac{d\theta_{fm}}{d\tau_m} \right| > \theta_{fm}.$$

Then, an increase in PSI (an increase in τ_m) implies: (i) lower import share $\frac{d\theta_{fm}}{d\tau_m} < 0$; higher total physical quantity $\frac{dT_m}{d\tau_m} > 0$, and (iii) lower average unit value $\frac{d\bar{p}_m}{d\tau_m} < 0$.

Proof. First notice that the condition

$$(\tilde{p}_f(\tau_m) - p_d) \left| \frac{d\theta_{fm}}{d\tau_m} \right| > \theta_{fm}$$

holds in our sample. Based on Table 1, $(\tilde{p}_f(\tau_m) - p_d) = 766 - 311 = 455$ and $\theta_{fm} = 0.6$. The estimates in Panel (b) Figure 1 imply $fracd\theta_{fm}d\tau_m = -0.014$ or larger if one considers only the short-run impact. Hence, $0.014 > 0.6/455 = 0.013$. Online Appendix E.2 proves the proposition. □

7.1.1 Extensive Margin: Number of Imported and Domestic Varieties

Following Halpern et al. (2015), the firm can choose the number of imported varieties $n_F \in \mathbb{N}$ to access; importing the k-th variety requires paying a fixed cost f_k, with f_k weakly increasing in k. This extensive margin affects the firm's variable profits through access to foreign sourcing opportunities.

To be able to interpret our empirics, we must add a second extensive margin so that the firm chooses the number of domestic varieties. A parsimonious way of doing so is assuming that $a \equiv a(n_H)$ is an endogenous domestic inputs quality shifter that depends on the firm's chosen domestic number of varieties n_H, with $a'(n_H) > 0$ and $a''(n_H) \leq 0$. The interpretation is that to compensate for quality losses one can adopt auxiliary inputs such as coatings, catalysts, and stabilizers in order to increase the effective quality of the domestic input in (4). We also assume that choosing n_H entails a convex cost $C(n_H)$, with $C'(n_H) > 0$, $C''(n_H) > 0$ and $C(0) = 0$.

Let $\pi(n_F, a(n_H); \tau_m)$ denote variable profits net of variable input costs, after choosing optimal (x_{fm}, x_{dm}) within each adopted bundle and optimal input quantities, given the domestic and imported number of varieties. The firm's problem is

$$\max_{n_F \in \mathbb{N}, n_H \geq 0} \Pi(n_F, n_H; \tau_m) \equiv \pi(n_F, a(n_H); \tau_m) - \sum_{k=1}^{n_F} f_k - C(n_H). \tag{6}$$

Define the total number of imported varieties and domestic inputs as

$$\mathcal{N} \equiv n_F + n_H. \tag{7}$$

Proposition 2 (Increase in Different Varieties Used)**.** *Let* $(n_F^*(\tau_m), n_H^*(\tau_m))$ *solve* (6).

Assume that: (i) PSI reduces the optimal imported scope as in Halpern et al. (2015),

$$\frac{dn_F^*}{d\tau_m} < 0; \tag{8}$$

(ii) the marginal value of improving domestic effectiveness rises when PSI increases,

$$\frac{\partial}{\partial \tau_m}\left(\frac{\partial \pi(n_F, a(n_H); \tau_m)}{\partial a(n_H)}\right) > 0 \tag{9}$$

Then, $dn_H^*/d\tau_m > 0$.

Proof. See Online Appendix E.3 □

Corollary: *Total scope* $\mathcal{N}^*(\tau_m) = n_F^*(\tau_m) + n_H^*(\tau_m)$ *increases with PSI if and only if*

$$\frac{dn_H^*}{d\tau_m} > \left|\frac{dn_F^*}{d\tau_m}\right|. \tag{10}$$

Empirically, we find that condition (10) is satisfied, so that PSI leads to a net increase in the number of varieties used.

7.2 Domestic Input Producers

We model domestic input producers using a standard Melitz (2003) framework, augmented with a productivity–quality mapping as in Kugler and Verhoogen (2012). This structure governs the composition and average quality of domestically sourced inputs within each input type m.

Consider the domestic market for input type m.[15] A continuum of potential domestic producers draw productivity $\varphi \sim G(\varphi)$ and face marginal cost $mc(\varphi) = \frac{w}{\varphi}$.

A producer with productivity φ supplies a variety with quality

$$q(\varphi) = q_{\min}\left(\frac{\varphi}{\varphi_{\min}}\right)^{\eta}, \qquad \eta > 0, \tag{11}$$

[15] Thus, in the input-using firm's problem in Section 7.1, x_{dm} should be interpreted as the quantity index of the domestic composite for type m, aggregating across active domestic producers within m.

so that higher-productivity producers supply higher-quality domestic inputs.

Domestic producers within type m compete monopolistically under CES demand with elasticity $\tilde{\sigma} > 1$.[16]. Each domestic producer charges a constant-markup price

$$p(\varphi) = \frac{\tilde{\sigma}}{\tilde{\sigma} - 1} \frac{w}{\varphi},$$

and earns operating profits

$$\pi(\varphi; \tau_m) = \frac{1}{\tilde{\sigma}} r(\varphi; \tau_m) - f,$$

where $f > 0$ is a fixed operating cost and $r(\varphi; \tau_m)$ denotes revenue.

Revenue depends on total domestic expenditure on input type m, denoted $D_m^d(\tau_m)$, and on the firm's relative price:

$$r(\varphi; \tau_m) \propto D_m^d(\tau_m) \left(\frac{p(\varphi)}{P_m^d} \right)^{1-\tilde{\sigma}},$$

where P_m^d is the domestic CES price index for type m.

Proposition 3 (Domestic entry and quality degradation)**.** *Let φ_m^* denote the cutoff productivity satisfying $\pi(\varphi_m^*; \tau_m) = 0$.*

Define the average domestic quality

$$\bar{q}_m^d(\tau_m) \equiv E[q(\varphi) \mid \varphi \geq \varphi_m^*(\tau_m)]$$

Then, an increase in PSI for type m (an increase in τ_m) implies: (i) lower entry cutoff $\frac{d\varphi_m^*}{d\tau_m} < 0$, which increases the mass of active domestic producers, and (ii) lower average domestic quality $\frac{d\bar{q}_m^d}{d\tau_m} < 0$.

Proof. See Online Appendix E.4 □

Taken together, propositions 1-3 rationalize the empirical patterns documented in sections 3, 4 and 5.

[16] Notice that $\tilde{\sigma}$ is distinct from the elasticity σ governing substitution between different varieties of inputs in (3)

8 Conclusions

Using comprehensive Indonesian manufacturing data and exploiting the staggered introduction of Pre-Shipment Inspections, this paper documents three mechanisms through which import costs affect firm productivity via input markets.

At the intensive margin, plants substitute high-quality foreign inputs with low-quality domestic ones, creating a quality-quantity tradeoff: 15% more physical units at 12% lower unit values. At the extensive margin, total varieties increase 4% despite declining imports, as plants adopt additional domestic inputs to compensate for quality losses. Third, reduced import competition triggers 18% additional entry of inefficient domestic supplier, further degrading average quality in domestic input markets.

A simple framework with quality-differentiated inputs and endogenous variety choice rationalizes these patterns. The three mechanisms compound: plants not only substitute toward lower-quality inputs, but the inputs they substitute toward are themselves of declining quality due to entry of inefficient producers producing low-quality inputs. However, we also show that additional assumptions about input quality need to be made in order for existing models of import substitution (e.g. Halpern et al., 2015) to account for the increase in domestic varieties, highlighting the overlooked complexity of firms' adjustment in input markets.

Our analysis highlights the quality channel—substitution from inputs with higher unit values combined with domestic quality decline—as an important source of productivity loss not captured by standard trade models. This illustrates the complexity of firms' adjustment in input markets, helping to explain the large productivity effects of trade liberalization via inputs found in the literature (Amiti and Konings, 2007; Goldberg et al., 2010; Topalova and Khandelwal, 2011). Hence policymakers should account for quality effects, not just trade volumes, when designing trade policies for intermediate inputs.

The granular input-level variation we exploit allows us to identify mechanisms obscured in aggregated data, demonstrating the value of detailed firm-product data for evaluating the economic impacts of NTMs as countries increasingly use trade protection.

References

Amiti, M. and S. Heise (2025). Us market concentration and import competition. *Review of Economic Studies 92*(2), 737–771.

Amiti, M. and J. Konings (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. *The American Economic Review 97*(5), 1611–1638.

Bloom, N., M. Draca, and J. Van Reenen (2016). Trade induced technical change? the impact of chinese imports on innovation, it and productivity. *The review of economic studies 83*(1), 87–117.

Blundell, R. and S. Bond (2000). Gmm estimation with persistent panel data: an application to production functions. *Econometric reviews 19*(3), 321–340.

Brandt, L., J. Van Biesebroeck, L. Wang, and Y. Zhang (2017). Wto accession and performance of chinese manufacturing firms. *American Economic Review 107*(9), 2784–2820.

Calì, M., S. C. Graciano, D. Ghose, A. F. Montfaucon, and M. Ruta (2026). Trade policy and exporters' resilience: Evidence from indonesia. *Journal of Development Economics 179*, 103561.

Calì, M., M. Le Moglie, and G. Presidente (2024). Gain without pain? non-tariff measures, plant markup, and productivity. *Review of International Economics 32*(3), 1364–1397.

De Loecker, J., P. K. Goldberg, A. K. Khandelwal, and N. Pavcnik (2016). Prices, markups, and trade reform. *Econometrica 84*(2), 445–510.

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

Eslava, M., J. Haltiwanger, A. Kugler, and M. Kugler (2004). The effects of structural reforms on productivity and profitability enhancing reallocation: evidence from colombia. *Journal of development Economics 75*(2), 333–371.

Fernandes, A. M. (2007). Trade policy, trade volumes and plant-level productivity in colombian manufacturing industries. *Journal of international economics 71*(1), 52–71.

Goldberg, P., A. Khandelwal, N. Pavcnik, and P. Topalova (2009). Trade liberalization and new imported inputs. *American economic review 99*(2), 494–500.

Goldberg, P. and N. Pavcnik (2016). The effects of trade policy. In *Handbook of commercial policy*, pp. 161–206. North-Holland.

Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova (2010). Imported intermediate inputs and domestic product growth: Evidence from india. *The Quarterly journal of economics 125*(4), 1727–1767.

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

Harrison, A. E. (1994). Productivity, imperfect competition and trade reform: Theory and evidence. *Journal of international Economics 36*(1-2), 53–73.

Hay, D. A. (2001). The post-1990 brazilian trade liberalisation and the performance of large manufacturing firms: Productivity, market share and profits. *The Economic Journal 111*(473), 620–641.

Javorcik, B. and S. Poelhekke (2017). Former foreign affiliates: Cast out and outperformed? *Journal of the European Economic Association 15*(3), 501–539.

Kasahara, H. and J. Rodrigue (2008). Does the use of imported intermediates increase productivity? plant-level evidence. *Journal of development economics 87*(1), 106–118.

Kee, H. L. and E. Xie (2024). Trade policies mix and match: Theory, evidence and the eu-sino electric vehicle disputes. World Bank Policy Research Working Paper 10855.

Kee, H. L. and E. Xie (2025). Nickel, steel and cars. *Development Research*.

Kugler, M. and E. Verhoogen (2009). Plants and imported inputs: New facts and an interpretation. *American Economic Review 99*(2), 501–507.

Kugler, M. and E. Verhoogen (2012). Prices, plant size, and product quality. *Review of Economic Studies 79*(1), 307–339.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica 71*(6), 1695–1725.

Montfaucon, A. F., M. Calì, B. Agnimaruto, J. M. Silberring, A. A. Hasmand, C. Lakatos, and M. Pasha (2023). Building a Dataset for Non-Tariff Measures and its Usage: The Case of Indonesia and Applicability for Other Countries. Technical report, The World Bank.

Muendler, M.-A. (1986). Trade, technology and productivity: a study of brazilian manufacturers 1986-1998. *Technology and productivity: A study of Brazilian manufacturers 1998*.

Olarreaga, M. and S. Santander (2025). Who pays for us tariffs?. the economic consequences of the second trump administration: A preliminary assessment. In *The Economic Consequences of the Second Trump Administration: A Preliminary Assessment*, pp. 269–78. CEPR Press.

Schor, A. (2004). Heterogeneous productivity response to tariff reduction. evidence from brazilian manufacturing firms. *Journal of development Economics 75*(2), 373–396.

Sun, L. and S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of econometrics 225*(2), 175–199.

Topalova, P. and A. Khandelwal (2011). Trade liberalization and firm productivity: The case of india. *Review of economics and statistics 93*(3), 995–1009.

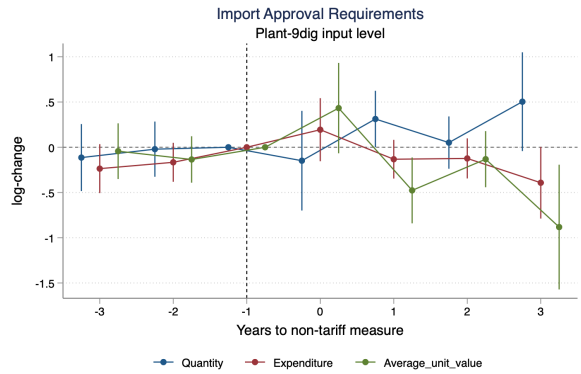
Tybout, J., J. De Melo, and V. Corbo (1991). The effects of trade reforms on scale and technical efficiency: New evidence from chile. *Journal of International economics 31*(3-4), 231–250.

Yeh, C., C. Macaluso, and B. Hershbein (2022). Monopsony in the us labor market. *American Economic Review 112*(7), 2099–2138.

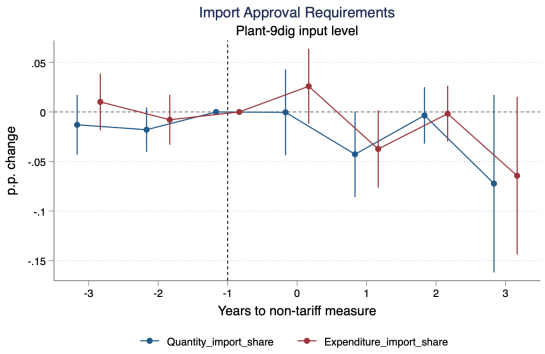
A Figures and Tables Appendix

Figure A1: Import substitution pattern: within-input impact of other non-tariff measures.

(a)



(b)



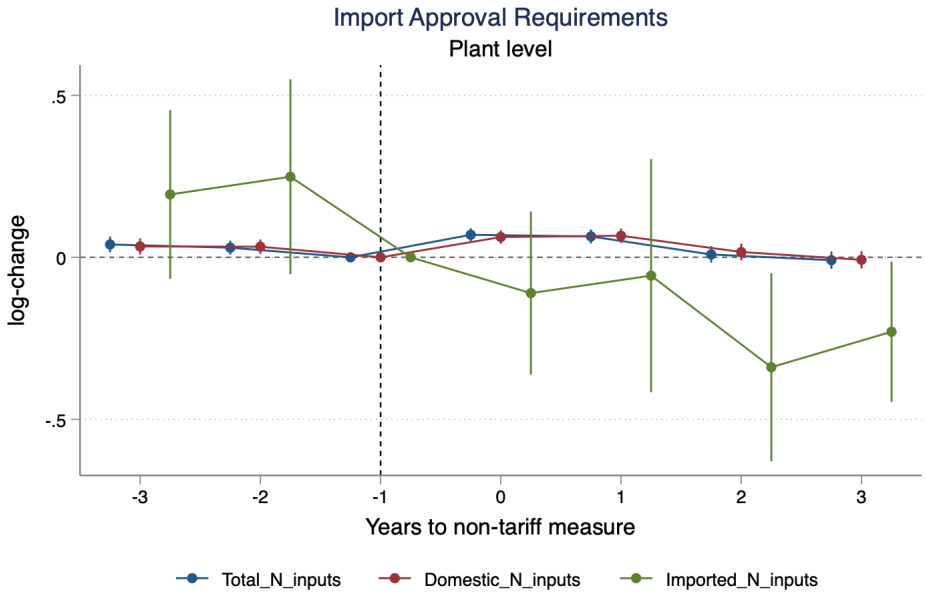
Notes: this figure shows point estimates and 95% confidence intervals of the impact of Import Approval Requirements (IAR) on (log-) quantity, expenditure and average unit value (a), and the quantity- and value-share of imported inputs over all inputs used (b). The regressions control for plant-9-digit level input fixed effects, plant-year fixed effects, 5-digit input-year fixed effects, as well as import tariffs and dummy variables for NTMs other than IAR. Standard errors are clustered at the plant level. The estimates are based on the estimator by Sun and Abraham (2021).

Table A1: Import substitution pattern: Two-Way Fixed Effect estimator.

	(1)	(2)	(3)	(4)	(5)
	Expenditure	Quantity	Unit value	Share imported (quantity)	Share imported (value)
Tariff rate (%)	0.627	6.225***	-5.546***	-0.236*	-0.162
	(1.526)	(1.967)	(1.592)	(0.121)	(0.119)
Observations	52,462	52,462	52,462	52,880	52,880
R-squared	0.950	0.940	0.908	0.915	0.914
Plant-input FE	yes	yes	yes	yes	yes
Plant-year FE	yes	yes	yes	yes	yes
Non-tariff measures	yes	yes	yes	yes	yes

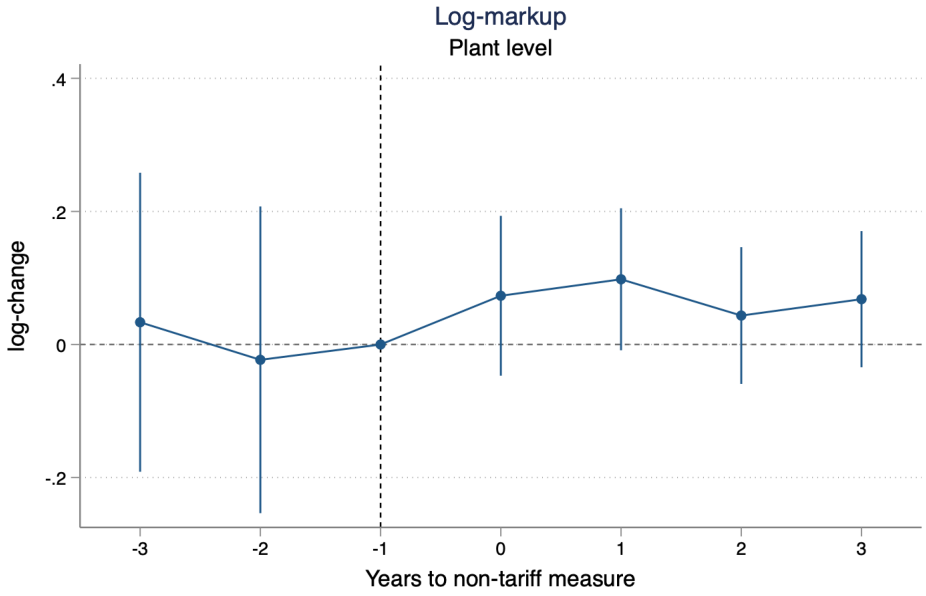
Notes: this table presents estimates from a Two-Way Fixed Effect estimator regressing log-expenditure, log-quantity, log-unit value, and the shares of imported inputs (quantity and value) on the percentage tariff rate applied to the input. Errors are clustered at the plant-level.

Figure A2: The extensive margin of import substitution: number of varieties using alternative trade policy instruments



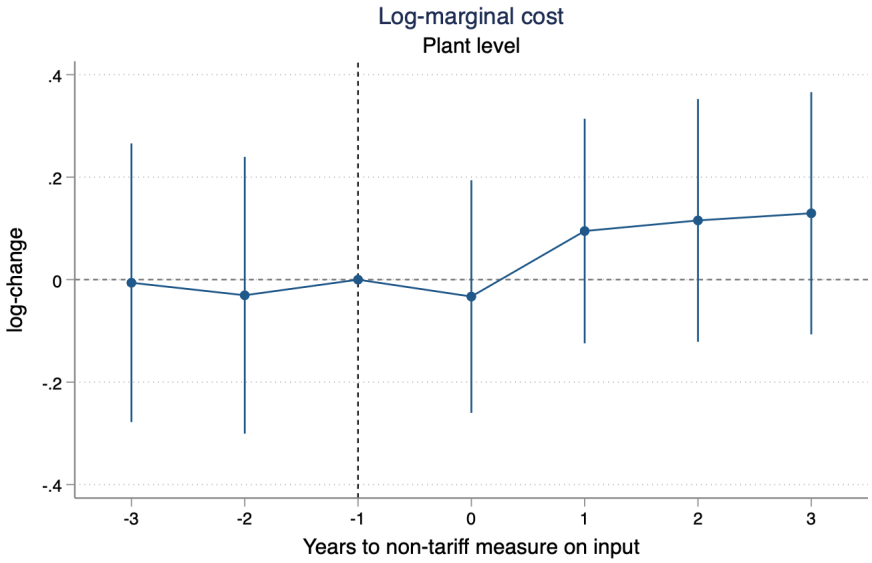
Notes: this figure shows point estimates and 95% confidence intervals of the impact of a Bartik variable capturing exposure to Import Approval Requirements (IAR) on the log-number of domestic, imported and total varieties of 9-digit level inputs used by plants.
The regressions control for plant fixed effects, 5-digit product-year fixed effects, regency-year fixed effects, the top 5-digit input used by the plant interacted with year effects, as well as Bartik variables for import tariffs and NTMs other than IAR. Standard errors are clustered at the plant level. The estimates are based on the estimator by Sun and Abraham (2021).

Figure A3: Domestic Producers: markup



Notes: this figure shows point estimates and 95% confidence intervals of the impact of a Bartik variable capturing exposure to Pre-Shipment Inspection (PSI) on the log-markup.
The regressions control for plant fixed effects, 5-digit product-year fixed effects, regency-year fixed effects, the top 5-digit input used by the plant interacted with year effects, as well as Bartik variables for import tariffs and NTMs other than PSI. Standard errors are clustered at the plant level. The estimates are based on the estimator by Sun and Abraham (2021).

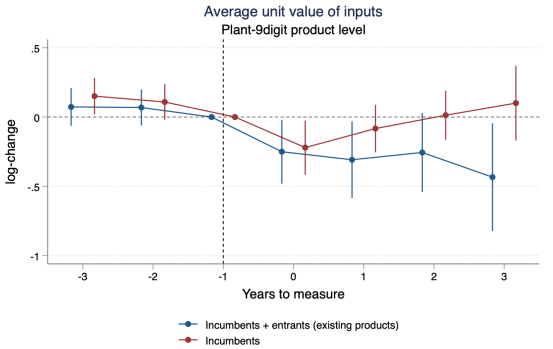
Figure A4: Input PSI and plants' efficiency



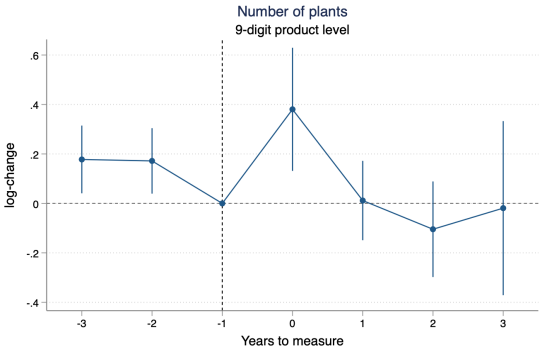
Notes: this figure shows point estimates and 95% confidence intervals of the impact of a Bartik variable capturing exposure to Pre-Shipment Inspection (PSI) on the log-marginal cost.
The regressions control for plant fixed effects, 5-digit product-year fixed effects, regency-year fixed effects, the top 5-digit input used by the plant interacted with year effects, as well as Bartik variables for import tariffs and NTMs other than PSI. Standard errors are clustered at the plant level. The estimates are based on the estimator by Sun and Abraham (2021).

Figure A5: Domestic Producers: alternative trade policy instruments

(a)



(b)



Notes: this figure shows point estimates and 95% confidence intervals of the impact of Import Approval Requirements (IAR) on log-average unit value of products (a), and the number of plants operating in a 9-digit level product market (b).
In Panel (a), the red estimates are obtained using plant-9-digit product fixed effects, 2-digit product-year fixed effects, as well as import tariffs and dummy variables for NTMs other than IAR. The blue estimates substitute plant-9-digit product fixed effects with 9-digit product fixed effect. Standard errors are clustered at the plant level.
In Panel (b), the data are aggregated at the 9-digit product level. The regression includes 9-digit product fixed effect. Standard errors are clustered at the product level.
All estimates are based on the estimator by Sun and Abraham (2021).

Table A2: Summary statistics of plant-level data.

	(1) N	(2) mean	(3) sd	(4) min	(5) max
Total number of inputs	31,087	1.899	1.179	1	27
Number of domestic inputs	31,087	1.855	1.138	1	19
Number of imported inputs	31,087	0.116	0.512	0	25
Plant price deflator (index)	31,087	5.662	2.077	-7.927	24.24
Marginal cost (index)	31,087	4.969	1.773	1.194	10.04
Price markup	31,087	2.192	1.347	1.014	6.952

Notes: this tables shows the summary statistics of the variables used in the plant-level analysis.

B Data Appendix

B.1 Construction of the Capital Series

Earlier studies tried to re-construct capital stock series applying the perpetual inventory method (PIM) to the first year of capital stock data reported by the plant (**?**; Javorcik and Poelhekke (2017)). However this imputation method crucially relies on the capital value self-reported by the plant the first year this data is available, which is not necessarily accurate.[17] One potential advantage of using PIM is that purchase and sales data might be more accurate relative to self-reported value of the stock, requiring an appropriate calculation of market values and depreciations. However, PIM needs to rely on measures of capital depreciation, which are difficult to accurately estimate. To mitigate such tradeoff, we have adopted a hybrid strategy. We first clean the self-reported adopting an algorithm which keeps only observations that fulfil a battery of tests, which are described below. Then, we apply the PIM only to fill the gaps between the missing observations and reapply the same battery of tests to ensure consistency of the series.

In order to avoid relying on depreciation rates, we tried to preserve the self-reported original values by the plant as much as possible and applied the PIM only to fill gaps. In this paper self-reported capital series were object of an extensive cleaning algorithm aimed at mitigating measurement errors. One problem with the reported series is that in some years, there are plants were characterised by implausible large values of capital. Studying the behaviour of the stock within plants reveals that in some circumstances plants reported values in different units. The phenomenon is somewhat more frequent in 1996 and 2006, when the BPS conducted a wider economic census that collected information in units rather than in thousand Rupiah. For instance, in 2006 the number of surveyed firms increased by 40%. The increase in coverage required hiring inexperienced enumerators that were more likely to make mistakes, which contributed to increase measurement errors.

Our algorithm consists first in replacing zero or negative values as missing observations

[17] In particular, there is no a priori reason to believe that the quality of the self-reported capital stock the first year is necessarily better than the value in other years.

and then applying a two-steps procedure based on capital-labor ratios (KL). For each year, we compute the average KL in each 4-digit KBLI sector over the whole sample, but excluding the years in which the average and total values of the capital stock exhibited suspicious jumps, i.e. 1996, 2000, 2003, 2006, 2009 and 2014. An observation is dropped is the ratio of plant-KL to the sector average KL is below 0.02 or larger than 50. We experiment with stricter thresholds which result in too many observations dropped. Then, in a second step we compare a plant KL in a given year with the average value of the KL within the same plant but in the other years of observation. An observation is dropped if the ratio of plant-year-KL to the plant average KL is below 0.2 or larger than 5. Plants are dropped from the sample in case the cleaning procedure results in all missing values of self-reported capital. When a plant has some but not all valid observations for self-reported capital stock, then missing values are replaced by applying a forward/backward perpetual inventory method (PIM). Being only a fraction of the total observations, we rely less on estimates of depreciation rates. We follow Arnold and Javorcik (2009) and assume that the annual depreciation rate for buildings is 3.3%, for machinery 10%, and for vehicles and other fixed assets 20%. For land, we assumed no depreciation.

Previous studies focus on the first year of observation of a plant, without assessing the plausibility of the data point. Since PIM series are very sensitive to the choice of the initial observation, especially with relatively short time series, the resulting capital stock could be severely mis-measured. Moreover, information on purchases and sales of capital equipment, which is subject to the same measurement errors of the reported capital. For such a reason, after filling missing values with the PIM we re-apply the two stages check described above in order to minimise the possibility of mis-measurement. As a final test, we compute plant level growth rates of KL and we check that it is reasonably distributed (Figure B1). Figure B2 compares original and clean capital stock series.

Figure B1: Plants' growth rate distribution of capital-labor ratio.

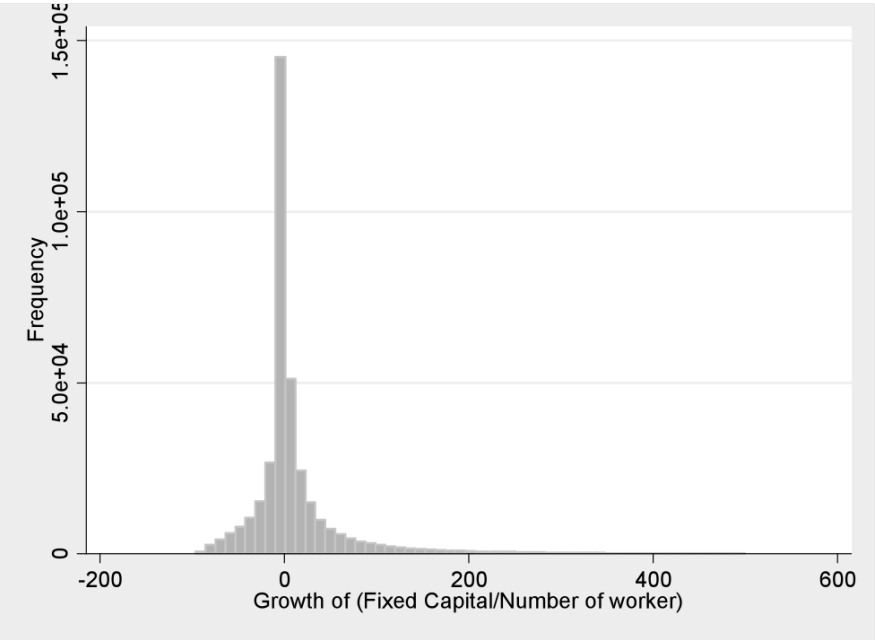
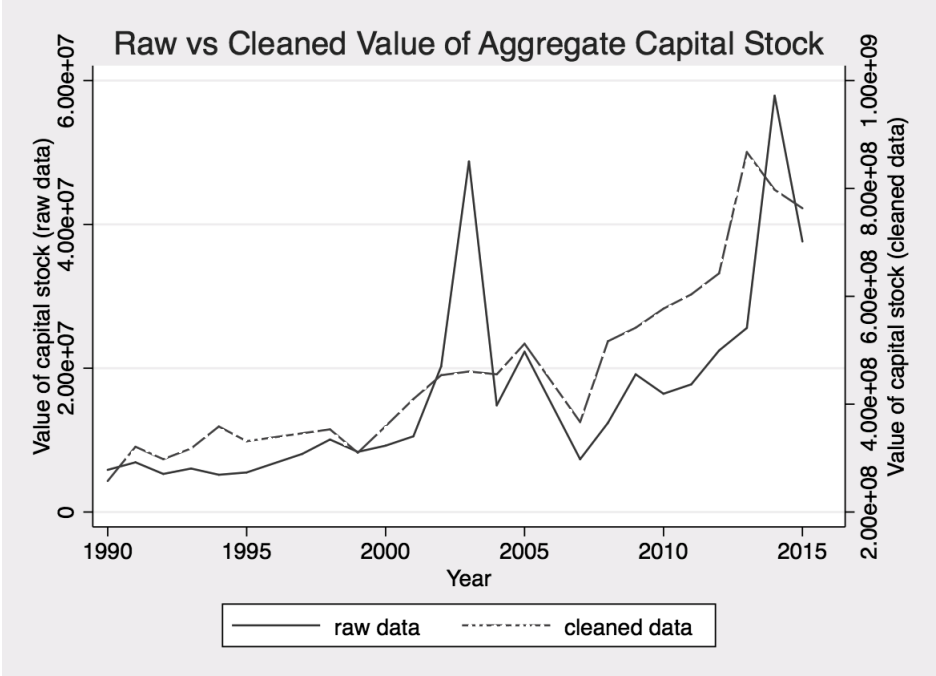


Figure B2: Comparison of Aggregate Nominal Capital Stock Series.



B.2 Products and Intermediate Inputs Data Cleaning Algorithm

This section describes the algorithm we use to clean the product and intermediate inputs files.

- We first go through the KKI publications and list coding and descriptions of each material in all years of the sample. If we find discrepancies for some year, we use coding and description that appears more frequently.
- We correct manually spelling mistakes in the descriptions and coding when there was an obvious coding mistake (e.g. we replace code 0123456789 with 123456789. This resulted in the adjustment of more than 300 entries.
- When the use of an input is expressed in different units across plants or in different years within a plant, we converted units and the corresponding corresponding values using the relevant conversion tables.
- After computing average unit prices by dividing value with quantities, we compute yearly price growth. If the price grow by more than a factor of 10 or decreases more than by a factor of 1/10, we drop the observation.

B.3 Construction of plant level Price indices

The derivation of plant-specific price indices from product-level and input-level price data closely follows Eslava et al. (2004) and **?**. Specifically, we use plant-level Tornqvist indices exploiting information on 9-digit products produced and inputs used by each plant:

$$\pi_{jt} = \prod_{p=1}^{n} \left(\frac{P_{pjt}}{P_{pj,t-1}} \right)^{.5(s_{pjt}+s_{pj,t-1})} \pi_{j,t-1}$$

where P_{pjt} is the price of good p and s_{pjt} is the share of this good in total product market sales of plant j in period t. Therefore, the growth of π_{jt} is the product of each plant's price growth, each weighted with the average share of sales or expenditure in t and $t-1$.

Wee set $\pi_{jt} = 100$ in 2006. For plants entering after 2006, we follow Eslava et al. (2004) and **?** and use the 5-digit industry average of the plant price indices as a starting

values. When price growth data are missing, we replace it with an average of product or inputs price changes within the same 5-digit industry.

C Estimation Appendix

C.1 Dynamic Panel Estimator

We follow Blundell and Bond (2000) and assume that the productivity term ω_{ft} follows an AR(1) process:

$$\omega_{ft} = \bar{\omega}_f + \rho^{\omega}\omega_{ft-1} + \eta_{ft}$$

where η_{ft} is a MA(0) productivity shock.

Our objective is estimating $\boldsymbol{\beta}$. The dynamic representation of the model is

$$\begin{aligned} q_{ft} &= f\left(k_{ft}, l_{ft}, m_{ft}; \boldsymbol{\beta}\right) \\ &+\rho^{\omega}\Big(q_{ft-1} - f\left(k_{ft-1}, l_{ft-1}, m_{ft-1}; \boldsymbol{\beta}\right)\Big) \\ &+ \epsilon_{ft} - \rho^{\omega}\epsilon_{ft-1} + \bar{\omega}_f + \eta_{ft} \end{aligned} \tag{12}$$

We assume that the error term ϵ_{ft} includes a component reflecting shocks common to all producers (u_t), a time-invariant firm-specific shifter (u_f), and an i.i.d. error term capturing measurement errors (ε_{ft}):

$$\epsilon_{ft} = u_t + u_f + \varepsilon_{ft}$$

We define the following terms:

$$u_t^* \equiv u_t - \rho^{\omega}u_t$$

$$u_f^* \equiv u_f - \rho^{\omega}u_f + \bar{\omega}_f$$

$$\varepsilon^*_{ft} \equiv \varepsilon_{ft} - \rho^{\omega}\varepsilon_{ft-1}$$

Then, we can rewrite (12) as

$$\begin{aligned} q_{ft} &= f\left(k_{ft}, l_{ft}, m_{ft}; \boldsymbol{\beta}\right) \\ &+\rho^{\omega}\Big(q_{ft-1} - f\left(k_{ft-1}, l_{ft-1}, m_{ft-1}; \boldsymbol{\beta}\right)\Big) \\ &+ u^*_t + u^*_f + \varepsilon^*_{ft} + \eta_{ft} \end{aligned} \tag{13}$$

where η_{ft} is MA(0) and ε^*_{ft} is MA(1).

As in Blundell and Bond (2000), we further assume that $E[\Delta\tilde{x}_{ft}u^*_f] = 0$, where $\tilde{x}_{ft} = \{k_{ft}, l_{ft}, m_{ft}\}$, and $E[\Delta q_{f2}u^*_f] = 0$

Letting $w_{ft} = \varepsilon^*_{ft} + \eta_{ft}$, which is thus MA(1), and defining $x_{ft} = (q_{ft}, \tilde{x}_{ft})$, we can write the following moment conditions:[18]

$$E[x_{ft-s}\Delta w_{ft}] = 0,\ s \geq 3$$

$$E[\Delta x_{ft-s}(u^*_f + w_{ft})] = 0,\ s = 2$$

As in Blundell and Bond (2000), we allow for serially correlated measurement errors and include year dummies to minimize the possibility of correlation across plants in the idiosyncratic shocks.

After the estimation, for each industry we run two diagnostic tests: the Arellano–Bond test for serial correlation in the first-differenced errors, and the Sargan test of overidentifying restrictions. We cannot reject the null hypothesis of no serial correlation in the first-differenced errors at an order greater than 1 for all industries; based on the Sargan test, we cannot reject the null hypothesis of valid overidentifying restrictions in all but one industry.[19]

[18] These are the same moment conditions used by Yeh et al. (2022).

[19] As it is customary, we use a threshold of 5% p-value to evaluate the Sargan test. If we were to use a 1% threshold, we would never reject the null hypothesis.

The parameters of the production functions $\hat{\boldsymbol{\beta}}$ are estimated with the Generalized Method of Moments (GMM). We calculate standard errors with the sandwich estimator, which are thus robust to heteroskedasticity.[20]

C.2 Markup Calculation

To calculate the markuo, we follow De Loecker and Warzynski (2012) and consider the dual cost minimization of a firm producing output with capital, labor and materials, $Q = F(K, L, M)$. Unlike in the main text, where we consider labor cost minimization *conditional* on the optimality conditions of the other production factors, here we consider a more general optimization problem and focus on intermediate materials.

As in De Loecker and Warzynski (2012), we assume intermediate materials to be a static input and that plants are price takers in the materials market.

The Lagrangian is:

$$\mathcal{L} \equiv WL + P^M M + P^K K - \lambda\big(F(K, L, M) - Q\big)$$

where $W$is the real wage, P^M the real price of materials, P^K the real price of capital, and λ the Lagrangian multiplier.

The first order conditions for materials are

$$P^M = \lambda \cdot F'_M = \lambda \cdot F'_M \cdot \frac{PQ}{PQ} \cdot \frac{M}{M} = \frac{\lambda}{P} \cdot \frac{F'_M M}{Q} \cdot \frac{PQ}{M}$$

Rearranging, we get the well-known expression for the price markup:

$$\mu \equiv \frac{P}{\lambda} = \theta^M \cdot s_M^{-1}$$

where $\theta^M \equiv \frac{F'_M M}{Q}$ and $s_M \equiv \frac{PQ}{P^M M}$.

Notice that conditional on the assumptions of materials being a static input sourced in a perfectly competitive market, the expression for the markup holds irrespective of

[20] The cost of robust standard errors is that by relaxing the assumption of i.i.d. residuals, one cannot compute the Sargan test for the validity of over-identifying restrictions.

market power in the input market.

D Examples of QT in Manufacturing

- **(31) Food Products**: Lower-grade wheat, often with lower protein content, produces weaker dough that breaks more easily during processing, requiring a larger quantity to maintain product consistency in pasta manufacturing.
- **(32) Beverages**: Low-quality hops with inconsistent bitterness levels necessitate larger quantities to achieve the desired flavor profile in beer production.
- **(33) Tobacco Products**: Inferior tobacco leaves, often with uneven burning properties, require higher volumes to produce cigarettes that burn evenly and maintain consistent flavor.
- **(34) Textiles**: Lower-quality cotton, with shorter or weaker fibers, results in frequent thread breakage during spinning, requiring larger quantities to produce the same amount of yarn.
- **(35) Wearing Apparel, Except Footwear**: Low-grade wool with uneven fibers produces more waste during weaving, requiring additional material to create a finished garment of the same quality.
- **(36) Leather and Fur Products**: Poor-quality leather with uneven surfaces and imperfections leads to greater waste during cutting, necessitating larger amounts to produce goods like shoes and bags.
- **(37) Footwear, Except Rubber or Plastic**: Low-quality rubber for soles deteriorates faster under stress, requiring thicker or additional layers to ensure durability.
- **(38) Wood and Cork Products, Except Furniture**: Inferior plywood with more knots and defects has lower structural integrity, requiring thicker panels to achieve the same strength.

- **(39) Furniture and Fixtures, Except Primarily of Metal**: Low-grade wood with visible imperfections results in higher wastage during manufacturing and requires additional material for repairs or refinishing.

- **(40) Paper and Paper Products**: Lower-quality pulp produces weaker paper prone to tearing, necessitating additional material to achieve the required durability for products like packaging.

- **(41) Printing, Publishing, and Allied Industries**: Low-quality ink with uneven pigmentation requires more layers to achieve consistent print quality, increasing consumption per print job.

- **(42) Industrial Chemicals**: Low-grade polyethylene, with inconsistent molecular structure, reduces flexibility and strength, requiring higher quantities to achieve the desired properties in plastic products.

- **(43) Other Chemical Products**: Impure adhesives require larger volumes to achieve the same bond strength, increasing material usage in construction and manufacturing.

- **(44) Petroleum Refineries**: Lower-quality lubricants break down more quickly under high stress, necessitating larger quantities to maintain machinery performance.

- **(45) Miscellaneous Products of Petroleum and Coal**: Low-grade bitumen in road construction deteriorates faster, requiring thicker layers to achieve the same durability.

- **(46) Rubber Products**: Low-quality synthetic rubber in tire manufacturing wears out more quickly, requiring thicker treads to maintain lifespan.

- **(47) Plastic Products**: Inconsistent quality plastics result in higher defect rates during molding, requiring greater input to produce a set number of defect-free products.

- **(48) Pottery, China, and Earthenware**: Poor-quality clay with impurities leads to cracking during firing, requiring more material to produce the same number of finished pieces.

- **(49) Glass and Glass Products**: Impure silica produces glass prone to breakage, requiring thicker sheets to meet strength requirements.

- **(50) Other Non-Metallic Mineral Products**: Low-grade cement with poor binding properties requires higher volumes to ensure adequate strength in construction applications.

- **(51) Basic Iron and Steel**: Low-quality steel with impurities has lower tensile strength, necessitating thicker or additional beams in structural applications to meet safety standards.

- **(52) Non-Ferrous Metals**: Copper with impurities reduces electrical conductivity, requiring longer or thicker wires to achieve the same performance in electrical systems.

- **(53) Fabricated Metal Products, Except Machinery and Equipment**: Aluminum alloys with lower purity have weaker structural properties, requiring more material to achieve the same weight-bearing capacity.

- **(54) Machinery, Except Electrical**: Poor-quality ball bearings with uneven surfaces wear out faster, requiring manufacturers to use larger quantities to meet durability expectations.

- **(55) Electrical Machinery, Apparatus, Appliances, and Supplies**: Low-quality silicon in semiconductors produces chips with higher defect rates, increasing the amount of silicon needed to produce functional units.

- **(56) Transport Equipment**: Low-quality aluminum alloys in aerospace applications require thicker parts to achieve the necessary structural integrity, increasing material usage.

- **(57) Professional and Scientific Instruments**: Optical lenses with imperfections scatter light, requiring larger lenses or additional material to compensate for the reduced performance in scientific instruments.
- **(58) Other Manufactured Goods**: Inferior textiles used in safety gear, like fireproof suits, require additional layers to provide the same level of protection, increasing material consumption.

E Proofs

E.1

A simple microfundation for the reduced form $\tilde{p}_f(\tau_m) = \tau p_f^* + \tau_m$ is batch shipping with per-shipment PSI costs. Suppose the plant needs $\bar{x}_{fm}$ units over the period and orders in shipments of size s_m, so the number of shipments is $\bar{x}_{fm}/s_m$. Each shipment entails a fixed PSI/compliance cost F_m and the firm pays an inventory/working-capital carrying rate κ on the delivered unit value τp_f^*. With batch ordering, average inventory is $s_m/2$, so average delivered cost per unit is

$$\tilde{p}_f(s_m) = \tau p_f^* + \frac{F_m}{s_m} + \kappa(\tau p_f^*)\frac{s_m}{2}.$$

Minimizing over s_m yields $s_m^* = \sqrt{2F_m/(\kappa\tau p_f^*)}$ and the minimized per-unit delivered price

$$\tilde{p}_f(\tau_m) = \tau p_f^* + \sqrt{2\kappa(\tau p_f^*)F_m} \equiv \tau p_f^* + \tau_m,$$

so τ_m is a reduced-form per-unit equivalent of per-shipment PSI costs.

E.2 Proof of Proposition 1

Fix $M_m = \bar{M}_m$. Let $y_f \equiv b x_{fm}$ and $y_d \equiv a x_{dm}$. Then (4) becomes $\bar{M}_m = (y_d^{\frac{\theta-1}{\theta}} + y_f^{\frac{\theta-1}{\theta}})^{\frac{\theta}{\theta-1}}$ and the corresponding cost is $\tilde{p}_f(\tau_m)x_{fm} + p_d x_{dm} = (\tilde{p}_f(\tau_m)/b)y_f + (p_d/a)y_d$. Define quality-adjusted prices $\pi_f \equiv \tilde{p}_f(\tau_m)/b$ and $\pi_d \equiv p_d/a$.

(i) Import share. Standard CES cost minimization yields the efficiency-unit demand ratio

$$\frac{y_f}{y_d} = \left(\frac{\pi_f}{\pi_d}\right)^{-\theta}.$$

Since $x_{fm} = y_f/b$ and $x_{dm} = y_d/a$, we obtain

$$\frac{x_{fm}}{x_{dm}} = \frac{a}{b}\left(\frac{\pi_f}{\pi_d}\right)^{-\theta} = \frac{a}{b}\left(\frac{\tilde{p}_f(\tau_m)\,a}{p_d\,b}\right)^{-\theta}. \tag{14}$$

Because $d\tilde{p}_f/d\tau_m > 0$ and $\theta > 1$, (14) implies $d(x_{fm}/x_{dm})/d\tau_m < 0$, hence $d\theta_{fm}/d\tau_m < 0$.

(ii) Total physical quantity. Let $T_m = x_{fm} + x_{dm}$. Using $y_f = r\, y_d$ where $r \equiv y_f/y_d = (\pi_f/\pi_d)^{-\theta}$, the composite implies $\bar{M}_m = y_d\,(1 + r^{\frac{\theta-1}{\theta}})^{\frac{\theta}{\theta-1}}$ so $y_d(r) = \bar{M}_m\,(1 + r^{\frac{\theta-1}{\theta}})^{-\frac{\theta}{\theta-1}}$ and $y_f(r) = r\, y_d(r)$.

Therefore

$$T_m(r) = \frac{y_f(r)}{b} + \frac{y_d(r)}{a} = y_d(r)\left(\frac{r}{b} + \frac{1}{a}\right).$$

Differentiating yields

$$\frac{dT_m}{dr} = \frac{y_d(r)}{1 + r^{\frac{\theta-1}{\theta}}}\left(\frac{1}{b} - \frac{r^{-1/\theta}}{a}\right).$$

Under CES demands, $r^{-1/\theta} = \pi_f/\pi_d = (\tilde{p}_f/b)/(p_d/a) = (\tilde{p}_f/p_d)(a/b)$, hence

$$\frac{1}{b} - \frac{r^{-1/\theta}}{a} = \frac{1}{b}\left(1 - \frac{\tilde{p}_f(\tau_m)}{p_d}\right).$$

Thus $dT_m/dr < 0$ if and only if $\tilde{p}_f(\tau_m) > p_d$. Since $r = (\pi_f/\pi_d)^{-\theta}$ is decreasing in π_f and π_f is increasing in $\tilde{p}_f(\tau_m)$, we have $dr/d\tau_m < 0$. Therefore, when $\tilde{p}_f(\tau_m) > p_d$,

$$\frac{dT_m}{d\tau_m} = \frac{dT_m}{dr}\frac{dr}{d\tau_m} > 0.$$

(iii) Average unit value. By definition, $\bar{p}_m = p_d(1 - \theta_{fm}) + \tilde{p}_f(\tau_m)\theta_{fm}$. Differentiating,

$$\frac{d\bar{p}_m}{d\tau_m} = \theta_{fm}\frac{d\tilde{p}_f(\tau_m)}{d\tau_m} + (\tilde{p}_f(\tau_m) - p_d)\frac{d\theta_{fm}}{d\tau_m}.$$

From part (i), $d\theta_{fm}/d\tau_m < 0$. Hence $d\bar{p}_m/d\tau_m < 0$ provided the negative composition term dominates the direct price term, i.e.

$$(\tilde{p}_f(\tau_m) - p_d)\left|\frac{d\theta_{fm}}{d\tau_m}\right| > \theta_{fm}\frac{d\tilde{p}_f(\tau_m)}{d\tau_m}.$$

Under $\tilde{p}_f(\tau_m) = \tau p_f^* + \tau_m$, $d\tilde{p}_f/d\tau_m = 1$, which gives the stated simplified condition.

E.3 Proof of Proposition 2

The choice of n_H is continuous and characterized by the first-order condition

$$\frac{\partial \pi(n_F, a(n_H); \tau_m)}{\partial a(n_H)} \cdot a'(n_H) = G'(n_H). \tag{15}$$

Define

$$F(n_H, \tau_m) \equiv \pi_a(n_F^*(\tau_m), a(n_H); \tau_m)\ a'(n_H) - C'(n_H),$$

where $\pi_a \equiv \partial \pi / \partial a$.

At the optimum, $F(n_H^*(\tau_m), \tau_m) = 0$.

Differentiate implicitly:

$$\frac{dn_H^*}{d\tau_m} = -\frac{F_\tau}{F_{n_H}}. \tag{16}$$

Step 1: $F_{n_H} < 0$ (second-order condition). Using $a'(n_H) > 0$, $a''(n_H) \leq 0$, and $C''(n_H) > 0$, and assuming π is concave in a (so $\pi_{aa} \leq 0$),

$$F_{n_H} = \pi_{aa}\,(a')^2 + \pi_a\, a'' - C'' < 0.$$

Thus the denominator in (16) is negative.

Step 2: $F_\tau > 0$ under (9). We have

$$F_\tau = \left[\frac{\partial \pi_a}{\partial \tau_m} + \frac{\partial \pi_a}{\partial n_F}\frac{dn_F^*}{d\tau_m}\right] a'(n_H).$$

A sufficient condition is $\partial \pi_a / \partial \tau_m > 0$ evaluated at the optimum, which is exactly (9). Intuitively, higher PSI shifts the firm's sourcing toward domestic inputs (Proposition 1), increasing the marginal benefit of improving domestic effectiveness. Since $a'(n_H) > 0$, this implies $F_\tau > 0$.

Step 3: Sign of $dn_H^*/d\tau_m$. With $F_\tau > 0$ and $F_{n_H} < 0$, (16) implies

$$\frac{dn_H^*}{d\tau_m} > 0.$$

E.4 Proof of Proposition 3

Step 1 (Domestic demand increases). By Proposition 1(i), an increase in τ_m raises the delivered import price $\tilde{p}_f(\tau_m)$ and reduces the import share within type m (assuming the substitution effect dominates any income effect), shifting expenditure toward domestic producers. Let $D_m^d(\tau_m)$ denote total domestic expenditure on type m. Then

$$\frac{dD_m^d}{d\tau_m} > 0.$$

Step 2 (Cutoff falls). A domestic producer with productivity φ charges the constant-markup price

$$p(\varphi) = \frac{\tilde{\sigma}}{\tilde{\sigma}-1}\frac{w}{\varphi},$$

and earns operating profits

$$\pi(\varphi;\tau_m) = \frac{1}{\tilde{\sigma}} r(\varphi;\tau_m) - f,$$

where revenue satisfies

$$r(\varphi;\tau_m) \propto D_m^d(\tau_m)\left(\frac{p(\varphi)}{P_m^d}\right)^{1-\tilde{\sigma}},$$

with P_m^d the domestic CES price index and $\tilde{\sigma} > 1$. The cutoff productivity φ_m^* is defined by the zero-profit condition

$$\pi(\varphi_m^*;\tau_m) = 0 \quad \Longleftrightarrow \quad \frac{1}{\tilde{\sigma}} r(\varphi_m^*;\tau_m) = f.$$

Since $r(\varphi;\tau_m)$ is proportional to $D_m^d(\tau_m)$, Step 1 implies that for any fixed φ, $r(\varphi;\tau_m)$ increases with τ_m. Therefore, to restore equality at the cutoff, φ_m^* must fall:

$$\frac{d\varphi_m^*}{d\tau_m} < 0,$$

establishing (i).

Step 3 (Mass of producers increases). The mass of active domestic producers is

$1 - G(\varphi_m^*)$, which increases when the cutoff falls:

$$\frac{d}{d\tau_m}\big(1 - G(\varphi_m^*)\big) = -g(\varphi_m^*)\frac{d\varphi_m^*}{d\tau_m} > 0,$$

establishing (ii), where g is the density of G.

Step 4 (Average quality falls). Quality is increasing in productivity by (11):

$$q(\varphi) = q_{\min}\left(\frac{\varphi}{\varphi_{\min}}\right)^{\eta}, \qquad \eta > 0.$$

Hence lowering the cutoff shifts the conditional distribution of φ toward lower values, reducing average quality:

$$\bar{q}_m^d(\tau_m) = E[q(\varphi) \mid \varphi \geq \varphi_m^*(\tau_m)], \qquad \frac{d\bar{q}_m^d}{d\tau_m} < 0.$$

To make this explicit, assume for illustration that G is Pareto with shape parameter $k > 0$:

$$G(\varphi) = 1 - \left(\frac{\varphi_{\min}}{\varphi}\right)^{k}, \qquad \varphi \geq \varphi_{\min}.$$

Then, provided $k > \eta$,

$$\bar{q}_m^d(\tau_m) = E[q(\varphi) \mid \varphi \geq \varphi_m^*] = q_{\min}\frac{k}{k-\eta}\left(\frac{\varphi_m^*}{\varphi_{\min}}\right)^{\eta},$$

which is strictly increasing in φ_m^*. Since $d\varphi_m^*/d\tau_m < 0$, it follows that $d\bar{q}_m^d/d\tau_m < 0$, establishing (iii).