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Gain without Pain?

Non-Tariff Measures, Plants' Productivity and Markups

Massimiliano Calì
Marco Le Moglie
Giorgio Presidente

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Abstract

This paper studies how productivity and markups respond to non-tariff measures. The analysis uses a novel time-varying data set on all non-tariff measures applied to imported products by Indonesia. Price and quantity information is used to disentangle the impact of non-tariff measures on plants' technical efficiency and markups. The findings show that on average, non-tariff measures generate fewer distortions than import tariffs do. However, while specific non-tariff measures increase the quality of the products on which they are applied, others act as barriers to trade similar to import tariffs. These results suggest that to gauge their impacts and guide policy making, non-tariff measures should not be bundled together in empirical analyses.

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The authors may be contacted at mcali@worldbank.org, marco.lemoglie@unicatt.it, and giopresidente@gmail.com.

Gain without Pain? Non-Tariff Measures, Plants' Productivity and Markups[☆]

Massimiliano Calì[a], Marco Le Moglie[b], Giorgio Presidente[c,*]

[a] *World Bank*
[b] *Catholic University of the Sacred Heart*
[c] *Oxford Martin School, Oxford University and World Bank*

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[*] Corresponding author.

Email addresses: mcali@worldbank.org (Massimiliano Calì), marco.lemoglie@unicatt.it (Marco Le Moglie), giorgio.presidente@oxfordmartin.ox.ac.uk (Giorgio Presidente)

1. Introduction

The economic impact of trade reforms has been one of the most studied topics in economics in the last decades (e.g. Pavcnik (2002); Amiti and Konings (2007); Caliendo and Parro (2015); De Loecker et al. (2016)). The empirical literature has mainly focused on the changes in import tariffs across the 1980s and 1990s, as tariffs were the main trade policy instrument for most of the 20th century.

Modern trade policy, however, has become more complex. Greater product sophistication and increasing public concern around health and safety have resulted in the proliferation of non-tariff measures (NTMs).[1] By 2017, NTMs were applied to goods covering around 60 percent of import values in developing countries and over 80 percent in high-income countries (UNCTAD and World Bank, 2018). In the same year, data from the *Global Trade Alert* suggest that import tariffs accounted for just 20 percent of all trade policy measures adopted globally.

Despite their extensive use, little systematic evidence exists on the economic impact of NTMs. The few existing studies on the topic use aggregate measures of NTMs, which lump highly heterogeneous regulations together (Kee et al., 2009; Webb et al., 2020), or focus on one-off liberalization of a specific NTM, usually quotas (Khandelwal et al., 2013; Harrigan and Barrows, 2009), which however represent only around 2 percent of all applied NTMs (UNCTAD and World Bank, 2018). An important reason behind the paucity of evidence is the difficulty in collecting sufficiently comprehensive and detailed data on NTMs (Goldberg and Pavcnik, 2016).

To help fill this gap, we build the first available time-varying dataset on all NTMs applied to the universe of goods produced in Indonesia from 2008 to 2015. We exploit the experience of Indonesia because it fits remarkably well the general pattern of trade policy over the past three decades: import tariffs liberalization since the 1990s and a contemporaneous increase the application of NTMs (Patunru and Rahardja, 2015).

Our novel dataset improves on existing NTM data in three crucial aspects. First, instead of looking at industry aggregates or categories of goods (e.g. food *vs* durable), we focus on ten-digit *Harmonized System* (HS-10 digits) products. Second, we exploit the most disaggregate available classification of NTMs to assign narrowly defined measures

[1] 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 trade in goods, changing quantities traded, or prices or both"*.

to each product.[2] Third, we analyze changes in the application of NTMs year by year, which allows us to build a time-varying dataset and apply panel data methods.[3] A further advantage of using Indonesian data is the availability of price and quantity information, which allows us to disentangle the impact of NTMs on plants' physical productivity and price markups.

This paper makes three main contributions. First, it examines the net impact of NTMs on plants' performance and compares it with the impact of import tariffs. Our findings suggest that NTMs across all categories have on average a neutral impact on manufacturing plants. Hence NTMs in Indonesia appear to create less distortion than import tariffs, which consistently with the literature we find to reduce competition and productivity (e.g. Amiti and Konings (2007); De Loecker et al. (2016)). We interpret the neutral impact of NTMs as the result of two countervailing effects. One the one hand, some of the measures boost plants' performance by increasing the quality of the goods on which NTMs are applied. On the other hand, NTMs can have a negative impact on performance due to an increase in trade compliance costs. The extent to which these two effects are at play differs significantly across NTM types.

To explore the heterogeneity of impact of NTMs, we go beyond their average net effects and study specific measures, which is the paper's second main contribution. This is important as different types of NTMs are likely to have highly heterogeneous effects according to the objective (explicit or otherwise) they fulfill. On the one hand, NTMs' *raison d'etre* should be to increase domestic welfare by addressing market failures, such as negative externalities or information asymmetries. For instance, a country might impose sanitary standards on imported products, or require certain foreign goods to satisfy fabrication and performance requirements in order to be commercialized domestically. To the extent that the main outcome of such measures is the increase in products' safety and/or quality, this may benefit the productivity of producers using such goods as intermediate inputs. On the other hand, NTMs may also generate compliance costs for foreign producers thereby increasing the costs of sourcing imported goods. This may be particularly evident for those measures which violate one of the key principles of WTO

[2]The UNCTAD classification can be found at UNCTAD's web page.

[3]We observe large variation in the application of NTMs across products and over time. For instance, the average HS-10 digit product in Indonesia is subject to 2.7 changes in the application of NTMs over the period 2008-15.

rules, i.e. not restricting trade unnecessarily.

We focus on two types of NTMs to tease out such heterogeneity. The first is *anti-pest treatment requirements* (APT), which we use as an example of "virtuous NTM". Most countries apply this type of measure to eliminate a potential negative externality in agricultural products, i.e. the presence of plant and animal pests or disease-causing organisms. The second type of NTM is *pre-shipment inspections* (PSI), which we deem an example of "protectionist NTM". This measure requires the goods to be inspected at the port of departure. Only a handful of mostly low-income countries applies PSI, typically to ensure that the import declaration lists the correct classification of the goods to be imported as a way of detecting improper importing activities. Unlike APT, PSI appear redundant in a country like Indonesia, where the customs agency applies a risk management system aiming to detect suspicious shipment at the border.[4] In the absence of clear benefits, the bulk of the effect of this measure is likely to be the increased compliance costs for imports.

The analysis leverages the unusual richness of Indonesia's manufacturing data to decompose firms' revenue-total factor productivity (TFPR) into quantity-total factor productivity (TFPQ) and markup. The results of the analysis are in line with our priors linked to the different features of these NTMs. The introduction of APT on a plant's inputs results in an increase in both the plant's technical efficiency and its markup, consistently with an increase in the quality of imported inputs. On the other hand, the application of PSI on inputs reduces the markup and the TFPR of the plant. When applied on the same product produced by the plant, the PSI increases the markup, in line with the increased protection for domestic producers.

We are able to explore in detail the mechanism behind the negative effects of input PSI on plants' performance. This enables the paper to provide a third contribution by unveiling the difference in impacts between PSI and import tariffs, and adding to the literature on fixed trade cost, trade lumpiness, and the behavior of inventories and markups (e.g. Alessandria et al. (2010)). We find that by increasing the cost of imported goods, tariffs trigger a switch from imported to domestically-produced inputs, which translates in lower technical efficiency. Unlike tariffs, however, PSI generate non-monetary fixed costs per-shipment. These costs are related to the uncertainty around the timing of the

[4] Consistently with this view, Indonesian Customs do not take into account the outcome of the PSI in their decision whether to inspect the shipment at the border.

inspection outcome. The evidence suggests that instead of switching to less suitable domestic inputs, producers impacted by PSI prefer to smooth the risk of shipping delays by importing larger quantities less frequently. As this strategy increases inventory costs, producers lower markups to increase sales and reduce inventories. As a result, applying PSI on inputs lowers TFPR through lower markups, rather than technical efficiency (TFPQ).

This paper relates to the literature on the economic impact of trade reforms. The bulk of this literature focuses on changes in import tariffs as a result of unilateral trade liberalization (Amiti and Konings, 2007; De Loecker et al., 2016; Pavcnik, 2002), WTO accession (Handley and Limao, 2015; Brandt et al., 2017) or trade agreements (Caliendo and Parro, 2015; McCaig and Pavcnik, 2018). The paper contributes to this literature by providing novel evidence on the impact of NTMs on plants, both in aggregate and for narrowly-defined measures, and comparing their effect to import tariffs.

The paper also adds to the literature by disentangling the impact of trade instruments on TFPR between the impact on TFPQ and on markups. Our results suggest that this decomposition is important. Looking at TFPR risks to underestimate the distortions created by tariffs, as they tend to have countervailing impacts on markups and technical efficiency.

This paper is related as well to the literature studying the interaction between price and inventory decisions in retailing firms. In the framework developed by Aguirregabiria (1999), the existence of stockout probabilities and per shipment costs generate an inverse relationship between inventories and markups. Hornok and Koren (2015) document that fixed costs per-shipment are associated with less frequent and larger shipments. Alessandria et al. (2010) present evidence that per-shipment costs induce shipment delays, leading importers to import infrequently and hold additional inventory, which generates costs.

The rest of the paper is organized as follows. Section 2 introduces the data and the institutional framework; Section 3 describes the empirical methodology; Section 4 presents the main results comparing the impact of NTMs to import tariffs. Section 5 provides examples of "virtuous" and "protectionist" NTMs, and Section 6 concludes.

2. Data

We gather information from several sources. This section presents the essential features of the data, focusing on our novel NTM dataset. Summary statistics of all variables used in the analysis are presented in Table 1. Details on all sources and variables' construction are presented in Appendix B.

2.1. NTMs in Indonesia: Institutional Background

The overall responsibility to determine rules over products sold in Indonesia lies with the Ministry of Trade (MoT). However, different government institutions are also responsible to determine NTMs for specific products. For instance, agricultural products are usually subject to NTMs applied by the Ministry of Agriculture and the Ministry of Health, including the food and drug agency (BPOM). These NTMs typically aim to protect consumer safety from risks such as plant and animal diseases through sanitary and phyto-sanitary (SPS) measures. Similarly, the Ministry of Industry regulates NTMs aiming to ensure consumer protection from risks linked to the use of manufacturing goods through technical barriers to trade (TBT).

Overall, 13 government institutions (ministries and agencies) have issued regulations on NTMs in Indonesia during our period of analysis (2008-15). As a result many products are subject to multiple NTMs. In our data, an average of 2.6 NTMs are applied to the universe of HS-10 digit products in 2008-15; and 5.4 for products with at least 1 NTM applied. These span a wide range of NTMs. Using the most refined NTM classification of UNCTAD at the 3-digit level, Indonesia applied 56 individual NTM types to the universe of its products in the 2008-15 period.[5]

The Indonesian government has been increasing the use of NTMs over the period of analysis through relatively frequent changes in their application across HS-10 digit products. To the extent that NTMs mainly fulfill the objective of addressing market failures in trade, such changes should be less subject to the kind of regulatory capture typical of import tariffs (Grossman and Helpman, 1992). This would allow to use this

[5]UNCTAD classifies NTMs by assigning codes according to different levels of aggregation. The first level corresponds to six macro-categories: i) SPS; ii) TBT, iii) pre-shipment inspections and other formalities (INSP); iv) non-automatic licensing, quotas and other quantitative controls (QC); v) price controls (PC), and vi) other NTMs (OTH). The next categories are defined according to digits, with 2- and 3-digits.

variation across time and products identify the effects of NTMs on the performance of firms more cleanly than in the case of tariffs. However, it is also plausible to conjecture that the government may indeed use some NTMs to protect domestic producers from import competition, which would threaten the validity of the analysis. We cannot rule out this hypothesis, as we do not observe the real motives of the Indonesian government in setting NTMs. Hence, in the Section 3.1 we discuss several ways in which we address potential threats to the identification.

2.2. "Virtuous" vs. *"Protectionist" NTMs*

NTMs are highly heterogeneous measures with different aims and likely different effects. To guide our analysis, we make one central distinction between NTMs. We ask whether they are likely to breach a key principle of WTO rules, i.e. not restricting trade unnecessarily (Cadot et al., 2012). While NTMs' *raison d'etre* is to increase domestic welfare by addressing market failures, they can also distort trade unnecessarily in the process of fulfilling a legitimate policy objective, or even without fulfilling one.

Establishing whether a measure is strictly necessary to achieve a "legitimate policy objectives" is challenging, as policy-makers may have different definitions - even within the same country - of what "legitimate" means. One hint on its "legitimacy" is given by how widespread the application of the measure is across countries. An NTM that is used by most countries is more likely to be necessary than one that is used only by a handful of countries.

We focus on OECD countries, which tend to have more transparent trade policy, and compute the share of OECD countries that apply each of the 2-digit NTMs applied by Indonesia during the period of our analysis. We take data from UNCTAD's *TRAINS* dataset on NTMs applied by 34 OECD countries in 2015.

We restrict the analysis to the most common groups of applied NTMs in Indonesia, i.e. SPS, TBT and INSP. We focus in particular on SPS to identify possible "virtuous" NTMs, for two reasons. First, SPS measures address threats to the health and safety of consumers stemming from high-risk products, including food and medical products. The legitimacy of such first-order policy objectives may be more difficult to challenge than that of other NTM categories. Second, the application of SPS on agricultural products and drugs makes them a less suitable instrument to protect the manufacturing sector than the other categories of NTMs.[6] Within the SPS group, we take the 2-digit NTMs which are applied by at least 95 percent of OECD countries. This returns a list of 7 measures, among which we select APT (coded as A5 in the data) as an example of "virtuous" NTM.[7] This measure aims to eliminate a particularly important potential externality in agricultural products, i.e. the presence of plant and animal pests or disease-causing organisms in the final product. As a result, the measure is applied widely across countries and requires different types of treatment which can be applied during production or as a post-production process. For instance, citrus fruits must undergo disinfection processes as treatment to kill bacteria and viruses in order to be commercialized.

At the other end of the spectrum, PSI (coded as C1 in the data) is the NTM applied by the least number of OECD countries among the NTMs applied by Indonesia. Only one OECD country (New Zealand) applies it *erga omnes* and only on protected animal species, i.e. Red Pandas and African Hunting Dogs. PSI requires the goods to be inspected at the port of departure typically to ensure that the import declaration lists the correct classification of the goods to be imported as a way of detecting improper importing activities. Unlike APT, this type of measure appears redundant in a country like Indonesia, where the customs agency applies a risk management system aiming to detect suspicious shipment at the border. Indeed, Indonesian Customs do not take into account the outcome of the PSI in their assessment of the risk of the shipment at the border.

In the absence of clear benefits, the bulk of the effect of this measure is likely to be the increased compliance costs for imports. Such costs are particularly relevant in the case of Indonesia, as only two State-Owned Enterprises have the authority (granted by the MoT) to perform PSI for the Indonesian government. Anecdotal evidence suggests that such limited supply of inspection agencies increases the uncertainty around the time it takes to comply with such procedure. Thus, PSI can increase the cost of trade not only through the monetary costs of compliance for the importer, but also by increasing

[6] The results in Calì et al. (2021) for Indonesia and in Wood et al. (2019) for China confirm that TBT represent a greater barrier to imports than SPS.

[7] The other measures are: Prohibitions/restrictions of imports for sanitary and phytosanitary reasons; Tolerance limits for residues and restricted use of substances; Labelling, marking and packaging requirements; Hygienic requirements related to sanitary and phyto-sanitary conditions; Other requirements relating to production or post-production processes; Conformity assessment related to sanitary and phytosanitary conditions.

the uncertainty of the import process. We take PSI as an example of "protectionist" NTMs.

2.3. NTM Data Construction

The original information on NTMs comes from the *TRAINS* database collected by the *Economic Research Institute for ASEAN and East Asia* (ERIA) and UNCTAD. This data is based on official regulations that were in effect by January 2015 with an in-force date by January 2016. The building block of our explanatory variables are dummies taking value 1 if in a given year, the Indonesian government applied an NTM on an HS-10 digit product. Since we consider the universe of HS-10 digit products, if a particular NTM is not in our data, then it means that the Indonesian government never applied it.[8]

The resulting yearly panel at HS-10 digits code starts in January 2008 and ends in December 2015. We adjust the data in a number of ways. First, when the same NTM appeared multiple times for an individual product, we verified whether the corresponding regulations effectively introduced a new measure. Forty percent of repeated NTM codes corresponded to regulation updating an older one, in which case we do not consider it as a separate measure (as the original ERIA dataset does). Second, we adjust the date of entry into force of certain measures when their associated regulation (as recorded in January 2015) was in fact an update of earlier regulations.[9] In such cases, we also record whether there are changes in the list of products the NTM regulation applies to. Finally, as the dataset is based on the coding of data collected in January 2015, there may be concerns about measures that were in force during part of the period of analysis but eventually eliminated before January 2015. To address these concerns, we check for such instances through the *Global Trade Alert* data, which records both trade restrictive and trade liberalizing measures for all countries since 2009.[10]

To link the NTM dataset to our panel of manufacturing plants, we follow the literature on trade reforms.[11] We build two types of variables. The first is an NTM output measure,

[8] Given that our focus is on the effect on imports of NTMs imposed by the Indonesian government, we exclude from our analysis bilateral contingent measures and measures imposed by the exporting country.

[9] In those cases we attribute the date of entry into force of the measure as that of the first regulation.

[10] The dataset can be accessed at its own web page.

[11] Our methodology closely follows Amiti and Konings (2007) and De Loecker et al. (2016).

NTM_{it}^{out}, corresponding to the share of HS-10 digit products subject to at least one NTM within the corresponding five digit industry i in the manufacturing plant-level data, in year t (see sections 2.4 and Appendix B.1 for details on the manufacturing data).

Based on the output NTM variable, we compute the input NTM measure, NTM_{it}^{in}. To that end we construct input-output (IO) tables from the plant-level data. For each five digit industry i, input NTM is defined as the weighted sum of output NTM in each five digit supplying industry k:

$$NTM_{it}^{in} = \sum_{k} w_{ij} NTM_{kt}^{out}$$

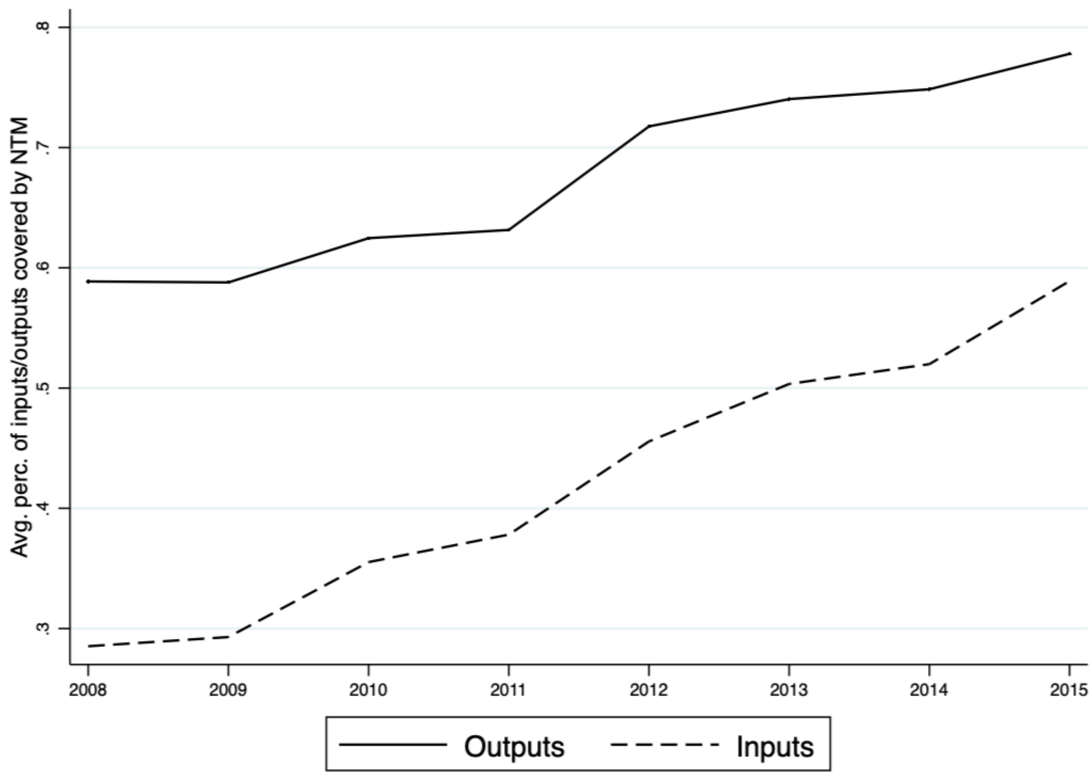
where w_{ik} is the share of k in total input value in industry i. Our approach results in much more granular IO tables to construct upstream linkages, compared with the trade reforms literature (Javorcik, 2004; Bourlès et al., 2013). In particular, the weights w_{ik} are obtained from detailed base year information on nine digits raw inputs used by each plant (see sections 2.4 and Appendix B.1). While this data would allow us to compute plant level input NTM variable, we prefer to aggregate the plant level information at the five digit level to minimize measurement error.[12] The results of the analysis below are qualitatively similar when using plant- instead of industry-specific input NTMs although the estimates are less precise, consistently with the larger noise in the data (results available from the authors upon request).

The evolution of output NTM in our sample is depicted by the solid line in Figure 1. The figure suggests a widespread and increasing incidence of NTMs for Indonesian manufacturing plants. Over the years of the sample, the share of products subject to NTM went from 60 to almost 80 percent. The increasing incidence of NTMs for Indonesian plants is also reflected in our measure of input NTM. In Figure 1, the dashed line represents the average share of intermediate inputs subject to at least one NTM. The share of inputs used by plants subject to NTMs went from less than 30 percent in 2008 to 60 percent in 2015. The higher incidence of output NTM presented in Figure 1 suggests that final consumption goods are more likely to be subject to NTMs than intermediate goods, although the gap shrinks considerably over time.

[12]The input data at the plant level appears to be quite noisy with several examples of plants changing their input mix frequently over the years. The aggregation across plants at the five digit industry allows to smooth this variability.

Finally, we complete the trade policy data with import tariff data collected by the UNCTAD TRAINS dataset. This records yearly Most Favored Nations (MFN) import tariff at the HS-10 digit product level.

Figure 1: Trends in Outputs and Inputs Covered by NTMs



Note: The figure shows the yearly average share of outputs (solid line) and inputs (dashed line) covered by at least one NTM in each plant.

2.4. Manufacturing Data

Plant-level 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 1996 and 2006 and it is very close to a census in the remaining years, hence ensuring high representatives even at the provincial level. Plants are grouped into five digits industries following the definition in the *Klasifikasi Baku Lapangan Usaha Indonesia* (KBLI), a classification mostly compatible with ISIC coding.

Our data include information on quantities and values of the products produced, and raw inputs (domestic and imported) used by each plant. These are both defined at a highly granular level, namely nine digits *Klasifikasi Komoditi Indonesia* (KKI), a more detailed classification based on KBLI. In our sample, each plant produces on average 2 products and 25% of the plants produce more than one product. On average, each plant uses four different varieties of raw inputs. The drawback of the high level of detail in materials' data is that sometimes there are coding mistakes by the reporters. Appendix B.2 describes in detail the methodology we use to clean the data. After computing unit prices by dividing value with quantities, we use them to construct plant-level price deflators (see Appendix B.5).

One challenge of the *Statistik Industri* data is the lack of complete series of capital stock. 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 (Amiti and Konings, 2007; 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.[13] 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 depreciation. 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, which is described in Appendix Appendix B.3.

2.5. Estimating Productivity and Markup Measures

Our main dependent variables are estimates of plant-level productivity and markup. Unlike most existing studies using industry-level price indexes to deflate nominal variables, the granularity of our data allows us to calculate plant-specific output and input price indexes. This allows us to mitigate the bias deriving by inputs' price heterogeneity across plants and to disentangle technical efficiency (TFPQ) and markups.[14]

To estimate plant-level production function parameters, we follow the control function approach and timing assumptions of Ackerberg et al. (2015), which are useful to mitigate

[13]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.

[14]Foster et al. (2008) discuss the bias arising when using plant revenue deflated by industry deflators. De Loecker et al. (2016) extend the analysis in the contest of unobserved variation in input prices.

the simultaneity bias affecting simple OLS coefficients.[15] We slightly modify the standard estimator to allow for the presence of adjustment costs in materials.[16] Then, using the estimated production functions, we calculate plant-level markups based on a model of profit maximization by firms, as in De Loecker and Warzynski (2012). Finally, we combine our estimates of TFPQ and markup to obtain a measure of revenue-total factor productivity (TFPR), which in many existing studies is considered the main productivity variable. The details of our estimator are provided in Appendix C.

3. Empirical Identification

Our main empirical strategy consists in regressing plant-level outcomes on output and input NTMs, by using the following linear model:

$$Y_{jit} = \alpha_0 + \alpha_1 NTM_{it}^{out} + \alpha_2 NTM_{it}^{in} + \gamma \mathbf{X}_{it} + u_{st} + u_{rt} + u_j + \epsilon_{jt} \tag{1}$$

where Y_{jit} is one of the outcome variables described in Section 2.5, of plant j operating in a 5-digit industry i, at time t . The coefficients of interest are α_1 and α_2 which measure, respectively, the impact of NTMs imposed on the products produced (NTM_{it}^{out}) and the intermediate inputs (NTM_{it}^{in}) used by a plant. The vector $\mathbf{X}_{it}$ includes output and input tariffs. We add controls for tariffs because of the potential correlation between NTMs and MFN import tariffs. On the one hand, import duties can have a significant impact on plants' performance (Amiti and Konings, 2007). On the other hand, NTMs might be used as an alternative tool to restrict trade and so they might be correlated with tariffs. Appendix Figure A1 summarizes graphically the correlation between tariffs and NTMs between 2008 and 2015. The figure depicts tariffs and the percentage of products covered by at least one NTM, both of them averaged at the 5-digit industry-level. The figure suggests the two variables are positively correlated, at least in our sample (correlation coefficient = 0.38).[17]

In (1), we include 2-digit industry-year fixed effects (u_{st}) to control for demand and

[15]Control function approaches to production functions' estimation have been introduced by Olley and Pakes (1996) and Levinsohn and Petrin (2003).

[16]Allowing for materials' adjustment costs turns out to be important in our case. This is discussed in Appendix Appendix C.

[17]For the sake of a clearer exposition, only products with tariffs smaller that 50% are considered, since they represent the 99% of the entire sample.

Table 1: Summary Statistics

	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
(a): Plant-level sample					
Number of plants	–	15,550	0	15,550	15,550
Output tariff	62,212	0.092	0.085	0	2.749
Input tariff	62,212	0.051	0.029	8.61e-05	0.523
Output NTM	62,212	0.716	0.405	0	1
Input NTM	62,212	0.424	0.187	0	1
Pre-shipment inspections (output)	62,212	0.456	0.453	0	1
Pre-shipment inspections (input)	62,212	0.152	0.114	0	0.716
Anti-pest treatment (output)	62,212	0.002	0.031	0	0.771
Anti-pest treatment (input)	62,212	0.005	0.014	0	0.252
TFPQ (log)	62,212	6.334	3.905	-0.094	19.38
Markup (log)	62,212	1.168	1.079	-1.591	4.181
TFPR (log)	62,212	7.502	4.289	-1.524	23.29
Price deflator (index)	42,383	4.679	0.912	4.77e-07	19.89
Real inventories of raw inputs (log)	42,383	10.66	3.044	-0.179	28.04
Real sales (log)	42,383	14.40	2.119	-1.581	31.80
Employment (log)	42,383	4.246	1.210	2.197	10.52
Real inventories of finished products (log)	36,588	11.12	2.925	-0.639	29.94
(b): Plant-inputs sample					
Import tariff	68,736	0.057	0.032	0	0.400
Pre-shipment inspections	68,736	0.202	0.401	0	1
Anti-pest treatment	68,736	0.003	0.050	0	1
Average input price (log)	68,736	3.134	2.414	-14.06	19.14
Import/domestic switching dummy	68,736	0.009	0.096	0	1
Share of imported inputs	68,736	0.065	0.231	0	1
(c): Customs data sample					
Number of importers	–	3,983	0	3,983	3,983
Import exposed to pre-shipment inspections (% imported value)	13,453	0.002	0.061	0	5.686
Number of shipments (log)	13,453	1.243	1.027	0	2.485
Value per shipment (log)	13,453	8.108	5.316	0	18.68

Note: The table shows summary statistics for the plant-level sample (Panel a), the plant-inputs sample (Panel b) and the custom data sample (Panel c).

supply trends that might be correlated with the decision of imposing NTMs. To control for geographic trends related to local development, we include region-year fixed effects (u_{rt}).

Unlike in previous studies looking at the impact of NTMs, we are able to exploit the time-varying nature of our data and include in (1) plant fixed effects (u_f). These absorb both observable and unobservable time invariant plant-level heterogeneity. Finally, we cluster standard errors at the five-digit industry level to match the variation in the trade policy variables.

3.1. Threats to the empirical identification

Our identification relies on the assumption that conditional on all the time-varying and time-invariant controls, NTMs (and also tariffs) are exogenous to plants' performance or outcomes. This assumption is plausible to the extent that introducing or eliminating NTMs is a national government decision, which individual plants cannot affect.

There are two potential threats to this assumption. On the one hand, some firms or industries might be able to lobby the government, directly or indirectly. On the other hand, the government could be interested in protecting specific industries for example as they ensure large levels of employment. To the extent that these characteristics are related to the plants' performance, the issue could result in biased estimates.

We tackle the concern in four different ways. First, in all regressions we include 2-digit industry-year fixed effects which should also capture eventual changes in lobbying activity over time. The 2-digit industry classification is suitable for that objective as it roughly matches the classification around which sectoral business associations are organized (e.g. textile, garments, processed food, etc.).

It could also be the case that lobbying may occur at a finer level of sectoral disaggregation than 2-digit industry. To control for such a possibility, we exploit the empirical finding in Bombardini and Trebbi (2012) that industry concentration is a key determinant of lobbying activity on trade policy. We compute the base year value of the (revenue-based) Herfindahl-Hirschman Index in each 5-digit industry and interact it with year effects. Such a control should purge the estimates from potential bias at the most refined level of industry aggregation allowed by our empirical specification.

Third, we test whether 5-digit industry trends predict subsequent changes in NTMs. To do so, we regress the probability of observing any type of NTMs in a 5-digit industry during the period 2008-2015, on the average rate of change between 2004 and 2007 of four industry-level performance measures, i.e. total output, employment, TFPQ and markups. We use them as separate regressors and all at once.[18] As a further robustness test, we use the NTM probability only in the first year of the NTMs database (i.e., 2008). The results of these tests are presented in the Appendix Table A1. Odd columns show the simple correlation between dependent and independent variables, while even columns add 2-digit industry fixed effects. Virtually, all the coefficients of the performance measures are statistically indistinguishable from zero, thus providing further evidence against the possible violation of our identifying assumption.[19]

Finally, after presenting our baseline estimates in the following sections, we check that the results still hold whenever we exclude large plants - defined as those producing more than 10 percent of a 5-digit industry's output - or politically connected plants, as they might affect government's decision on the application of NTMs.[20]

4. Impact of NTMs *vs* Import Tariffs on Performance

Table 2 presents the estimated coefficients of Equation 1 for three dependent variables: TFPQ, markup and TFPR. We do not find any evidence of a statistically significant impact of the aggregate NTM variables on productivity and markups.

The muted impact of NTMs contrasts with the effect of import tariffs, which in line with previous studies have a negative effect on firms' performance. The coefficient of output tariffs on TFPQ (column 1) is negative, although not statistically significant at conventional levels. On the contrary, output tariffs have a positive and significant impact on markups (column 2). This can be interpreted as a competition effect: by lowering competitive pressure from imports, output tariffs allow plants to charge higher markups, while allowing their inefficiencies to increase. The combination of these 2 effects on TFPQ and markup results in a negative but not significant effect of tariffs on TFPR. The lack of significance might be due to the countervailing effect on TFPQ and markup.

[18] All these variables are taken in logarithmic scale.

[19] These results are robust to the use of different time definitions of both the dependent and independent variables, as well as to the use of an intensive measure of NTM introduction in the referring period. Results of such robustness tests are available upon request.

[20] Politically connected plants are those being identified as having connections with the Suharto regime by Mobarak and Purbasari (2006). There are 246 such plants in our dataset.

On the other hand, input tariffs are associated to a large reduction in both TFPQ and markup (columns 1-2). As a result, input tariffs have a negative and statistically significant effect on TFPR (column 3). Our evidence is thus similar to Amiti and Konings (2007) in that we find a larger detrimental impact on productivity for input tariffs than for output tariffs. Our decomposition of TFPR shows that tariffs harm technical efficiency through both channels, but in the case of output tariffs the effect is offset by the countervailing impact on markups.

For robustness, Appendix Tables A2 and A3 report the coefficients obtained when excluding the largest and politically connected plants, respectively. In Table A2, the output tariff coefficient of markup is no longer statistically significant. However, all other coefficients are in line with those presented in the main analysis, including the NTMs coefficients that are still not statistically significant.

Based on the estimated coefficients in Table 2, Table 3 displays the average marginal effect of NTMs and import tariffs as opposed to the marginal effects as in Table 2.[21] On average, NTMs do not appear to have any significant cumulative (i.e. the sum of output- and input-NTMs) impact on plants' performance. To the extent that the imposition of NTMs increases trade-related compliance costs, the zero net effect could reflect some countervailing positive impact of NTMs on performance. Such positive impact would be consistent with the role of NTMs in addressing market failures of trade, which would translate into an increase in the quality of and/or the demand for the products subject to the NTM. However, the zero net effect could also be the result of very low compliance costs associated with negligible externalities. In the next section we will shed further light on these effects for two specific categories of NTMs.

In fact, NTMs might still have non neutral impacts on welfare, which we are unable to observe in our data. For instance, quality and safety standards might have a beneficial impact on consumers' utility. This is different to the case of import tariffs, which have a negative impact on TFPQ and TFPR, and unlike NTMs, they should not have any positive impact on consumers.

However, the evidence in Table 3 concerns the *net* impact of all NTMs combined. In fact, as discussed in Section 2, NTMs are a highly diverse set of measures, whose

[21]The calculation of the average impact is based on (1) and it is calculated as follows: Average impact of NTMs = $\hat{\alpha_1} \times NT\bar{M}^{out} + \hat{\alpha_2} \times NT\bar{M}^{in}$, where $NT\bar{M}^{out}$ and $NT\bar{M}^{in}$ are, respectively, the sample averages of the output and input NTM variable.

economic effects are likely to be very heterogeneous. Hence, the next section focuses on specific NTMs trying to tease out some of this heterogeneity. This approach is also more policy relevant than considering the aggregated NTM, as policy-makers consider the benefits and costs of individual NTMs.

5. A Tale of Two NTMs

An analysis of the impact of all individual NTMs applied by Indonesia (47 at 2-digit level) is impractical and well beyond the scope of this paper. Instead, in this section we provide two examples of NTMs with markedly different degrees of policy legitimacy. As explained in section 2.2, we focus on APT as an example of "virtuous NTM" and on PSI as an example of "protectionist NTM". This allows us to show the different effects of NTMs and as well as to describe in a detailed way the channels of impact.

5.1. Anti-Pest Treatments

Table 4 reports the results of estimating Equation 1 while replacing the aggregate NTM output and input variables with the corresponding variables on APT. To avoid omitted variable bias, we control as well for the aggregate NTM variables excluding APT. None of the coefficients on the output measure is statistically significant. On the other hand the input APT has a positive and statistically significant effects on TFPQ, markup and TFPR. These results are consistent with APT increasing the quality of inputs, which allows plants to produce more efficiently and increase the margins on the sale of the final product.

The lack of significance of the output APT coefficient may simply reflect its limited application on manufacturing products. In fact, only a few plants produce products that require APT. At the same time, such products are used as intermediate inputs by a larger number of plants. Indeed, the mean values of the input APT measure is almost double the size of the output measure (Table 1). This ensures greater variation of the input- relative to the output-APT measure.

Similarly to the general case analyzed in the previous section, we test the robustness of the results with respect to the exclusion of the largest and politically connected plants. Appendix tables A4 and A5 show the results are robust to these tests.

Overall, these results confirm the hypothesis that APT may be considered as an example of a virtuous measure. The compliance costs that it might generate appear to

Table 2: Impact of NTMs *vs* Import Tariffs

	(1) TFPQ	(2) Markup	(3) TFPR
Output NTM	0.008	-0.064	-0.057
	(0.029)	(0.111)	(0.125)
Input NTM	0.044	0.100	0.144
	(0.080)	(0.134)	(0.190)
Output tariff	-0.280	0.262*	-0.0184
	(0.197)	(0.158)	(0.279)
Input tariff	-1.112***	-0.804**	-1.915***
	(0.402)	(0.389)	(0.600)
Observations	59,791	59,791	59,791
R-squared	0.981	0.694	0.955
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of NTMS and import tariffs, applied either to output or inputs, on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. *Output NTM* is the share of HS-10 digits products subject to at least one NTM within the corresponding five digit industry. For each five digit industry, *Inputs NTM* is the weighted sum of output NTM in all five digit supplying industries. *Output tariff* is the average tariff rate in the 5 digit industry of a plant. *Inputs tariff* is the weighted average of the tariffs rates applied to the inputs used by a plant. The coefficients are obtained by the estimation of Equation 1. All specifications include plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Impact of NTMs *vs* Import Tariffs: Average Marginal Effects

	(1) TFPQ	(2) Markup	(3) TFPR
Impact of NTMs	0.028	-0.005	0.022
	(0.038)	(0.025)	(0.137)
Impact of tariffs	-0.083***	-0.017	-0.099***
	(0.017)	(0.114)	(0.032)

Note: This table shows the average marginal effect of NTMS and import tariffs on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. The average marginal effects are computed from the estimates showed in Table 2. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

be compensated by the higher quality of the products it applies to. When the latter are used as inputs, they increase the productivity and markup of the final products.

5.2. Pre-Shipment Inspections

Table 5 reports the results of estimating Equation 1 with a specific focus on PSI. Output PSI does not have a significant impact on TFPQ (column 1), but it has a positive and significant impact on markups (column 2). This is consistent with the hypothesis that compliance with the inspection is costly for foreign producers. As a result, the marginal cost of commercializing the product increases and so does its sale price. This creates a cost advantage for domestic producers, which allows them to charge a higher markup. Column (3) suggests that when a PSI is imposed on an imported product, the plants producing the same product domestically experience an increase in TFPR. The results in columns (1) and (2) indicate that this is the result of higher margins due to reduced competition, rather than higher technical efficiency.This interpretation is also consistent with the reduction in imports associated with the imposition of PSI documented in in Table 7.

The second row of Table 5 reports the coefficients of input PSI. While input PSI do not have an impact on TFPQ, the coefficients in columns (2) and (3) show that they have a negative impact on markups, which translates into a negative impact on TFPR.

Table 4: Impact of Anti-Pest Treatments (APT)

	(1) TFPQ	(2) Markup	(3) TFPR
Anti-pest treatment (output)	-0.126	-0.353	-0.479
	(0.219)	(0.298)	(0.297)
Anti-pest treatment (input)	3.756***	5.478**	9.235***
	(0.885)	(2.167)	(2.559)
Observations	59,791	59,791	59,791
R-squared	0.981	0.695	0.955
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of anti-pest treatments (APT), applied either to output or inputs, on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. *Output APT* is the share of HS-10 digits products subject to at least one APT within the corresponding five digit industry. For each five digit industry, *Inputs APT* is the weighted sum of output APT in all five digit supplying industries. The coefficients are obtained by the estimation of Equation 1. All specifications include controls for other NTMs and import tariffs applied on plant's outputs and inputs, plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Before turning to explore the mechanisms behind the observed impact of PSI on productivity and markups, we check the robustness of the results to a battery of tests. First, we exclude the largest and politically connected plants (Appendix Tables A6 and A7, respectively) and once again the results remain unchanged. An additional concern for both the results in tables 4 and 5 is that the difference in effects is not intrinsically due to the different categories of NTM, but rather to the characteristics of products to which the NTMs are applied. While industry-year effects should mitigate the concern, we check the robustness of our findings explicitly in Appendix tables A8 and A9. Table A8 assesses the impact of APT exclusively on plants subjects to PSI, while Table A9 assesses the impact of PSI exclusively on plants subject to APT. The results are broadly consistent in such specifications, although the impact of PSI on plants subjects to APT is less precisely estimated due to the much lower number of observations.[22]

5.3. Mechanisms behind the impact of PSI on plants

The reduced-form effects of PSI on plants' performance suggests that the measure increases the costs of trade. The negative effect should dominate in the absence of a countervailing positive impact of PSI through the resolution of a market failure. In order to better understand what would happen to the dynamics of the plants in that case, we explore in more detail the mechanisms behind the estimates in Table 5.

Our hypothesis goes as follows. When a PSI is applied to an imported product, it increases the uncertainty around the time to complete the import procedure as the timing of the inspection itself is uncertain.[23] Shipment delays might disrupt production chains and generate monetary costs. From the perspective of a producer utilizing the product as an input, it would be safer to purchase the same product from domestic producers. However, the quality or suitability of the domestic input might be inferior to the imported one. To edge against shipping delays, the importer can follow an alternative strategy: increasing inventories to build a buffer of the imported input. However, heavier inventories entail higher storage costs, which induce plants to empty inventories as quickly as possible. To empty out inventories, one common strategy is running "promotions" (Aguirregabiria, 1999), i.e. lowering markups to increase sales.

[22]Recall that APT is applied to a limited number of plants.

[23]This problem is amplified by the artificial limited supply of authorized inspection agencies in Indonesia as explained above.

Table 5: Pre-Shipment Inspections (PSI)

	(1)	(2)	(3)
	TFPQ	Markup	TFPR
Pre-shipment inspections (output)	0.056	0.330**	0.386**
	(0.060)	(0.155)	(0.184)
Pre-shipment inspections (input)	-0.052	-0.906**	-0.958*
	(0.206)	(0.398)	(0.534)
Observations	59,791	59,791	59,791
R-squared	0.981	0.694	0.955
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of pre-shipment inspections (PSI), applied either to output or inputs, on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. *Output PSI* is the share of HS-10 digits products subject to at least one PSI within the corresponding five digit industry. For each five digit industry, *Inputs PSI* is the weighted sum of output PSI in all five digit supplying industries. The coefficients are obtained by the estimation of Equation 1. All specifications include controls for other NTMs and import tariffs applied on plant's outputs and inputs, plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

To test such hypothesis, we first check whether or not the application of PSI on imported inputs induces plants to switch towards domestically produced inputs. To that end we exploit highly disaggregated plant-level data on the use of intermediate inputs at 9 digit-level. Importantly, the data allows to distinguish between domestically sourced and imported inputs. More specifically, we estimate the following linear model:

$$Y_{jmt} = \delta_0 + \delta_1 Input\, PSI_{mt} + \Gamma \mathbf{X}_{mt} + u_{it} + u_{rt} + u_{jm} + \epsilon_{jmt} \tag{2}$$

In Equation 2, Y_{jmt} is an outcome variable for input m used by plant j at time t. The variable $Input\, PSI_{mt}$ is a dummy taking value 1 if PSI is applied on an intermediate input m at time t. The vector $\mathbf{X}_{mt}$ includes import tariffs and dummy variables for whether NTMs other than those under analysis are applied to input m.[24] We also include 5-digit industry-year fixed effects (u_{it}) that control for differences in competition and other industry-level confounders, and region-year fixed effects (u_{rt}). Plant-input fixed effects are denoted by u_{jm}. Standard errors are clustered at the plant-level.

Table 6 presents the estimates for Equation (2).[25] The dependent variable in column (1) is a dummy variable taking value 1 if a plant switches from an imported to a domestic variety of a given 9-digit input. The dummy takes value 1 if the imported quantity of an input decreases and the domestic quantity of the same input increases.

The coefficients in column (1) suggest that while PSI does not induce plants to switch to domestic inputs, import tariffs do. The results in column (1) are also supported by those in column (2), where the dependent variable is the share of imported quantity of an input over the total use of the same input (i.e., imported plus domestically sourced).

This switch to domestic inputs induced by tariffs may help explain the negative impact of tariffs on TFPQ, as domestically produced inputs may be of lower-quality than imported inputs. This is supported by the result in column (3), which suggests that import tariffs are associated with a reduction of the average unit price of the used inputs. Consistent with the view that PSI does not affect the quality of inputs used by the plants, the coefficients of PSI are not significant on the dependent variables presented in Table 6.

Why do import tariffs and PSI applied on imported inputs induce two different

[24] Also in this specification, we use aggregate 1-digit categories of NTMs.

[25] The number of observations is higher in such specification, due to the fact that each plant utilizes multiple inputs.

Table 6: Evidence from Intermediate Inputs Data

	(1) Pr(switch)	(2) Share Imp. Inp.	(3) Avg. Inp. Price
Input PSI	-0.000	-0.001	-0.054
	(0.003)	(0.004)	(0.045)
Import tariff	0.153***	-0.170***	-6.835***
	(0.043)	(0.057)	(0.709)
Observations	138,464	138,464	138,464
R-squared	0.354	0.830	0.704
Plant-input FE	yes	yes	yes
5-digit ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of pre-shipment inspections (PSI) applied to inputs, on plant's probability of switching to domestic inputs (col. 1), share of imported inputs (col. 2) and average input price (col. 3) in the years between 2008 and 2015. *Input PSI* is a dummy taking value 1 if a NTM is applied on an intermediate input m at time t. The coefficients are obtained by the estimation of Equation 2. All specifications include controls for other NTMs and import tariffs applied on plant's inputs, plant-input fixed effects, 5-digit industry-year fixed effects and region-year fixed effect. Standard errors are robust to heteroskedasticity and clustered at the plant level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

responses by plants? To answer the question, we notice that the two trade policy instruments generate different cost structures. From an importer's perspective, PSI generates both a monetary and a likely larger non-monetary fixed cost per shipment, due to the increased risk of shipping delay. Rather than switching to domestic inputs, the uncertainty cost can be "smoothed" by an alternative strategy, i.e. importing less frequently larger quantities.

This strategy on the other hand, is not effective in reducing the cost increase of tariffs, as they generate monetary costs proportional to the quantity imported. The absence of an available smoothing strategy may make switching to domestic inputs a more likely choice, even at the expense of inputs' quality.

To test this hypothesis, we turn to monthly customs' data (see Appendix B.4 for details on the data). For each importer and year, we regress the (log) number of annual shipments and their (log) value on the share of imports exposed to PSI.[26] Customs data only provide information on the values of traded goods, but not additional information on the importer.[27] Therefore, we can only control for importer fixed effect and year fixed effect. The results - presented in Table 7 - are consistent with our hypothesis. In particular we find strong evidence that within a year, the application of PSI is associated with a lower number of shipments (column 1), but with shipment of higher value on average (column 2). For comparison, we report the impact of import tariffs as well. Unlike PSI, import tariffs on do not appear to significantly affect the frequency and value of shipment, although both coefficients are large and negative.

The strategy of importing higher value shipments less frequently should impact plants' inventories of raw inputs, a hypothesis supported by the results in Table 8. The coefficient in column (1) suggests that PSI on inputs increases inventories.[28] This is consistent with the notion that higher inventories help buffering against the greater uncertainty of input supply generated by PSI.[29] Inventory costs increase with the length of time the input lies in stock. Therefore, plants can lower markup to increase sales and reduce inventories. Consistent with this view, the coefficient of input PSI on sales in

[26]We express the shares as a fraction of the total value of imports in the first available observation. We then drop the first observation to avoid issues of endogeneity.

[27]Due to such data limitations we cannot link customs and SI data.

[28]The lower number of observations relative to Table 5 is due to missing data on inventories.

[29]Inventories are expressed as (log) averages of beginning- and end-of-the-year values of raw inputs, deflated by the plant-level input price index.

Table 7: Evidence from Customs' Office Data

	(1) N. Ship.	(2) Val. per Ship.
Input PSI	-0.303***	0.189***
	(0.016)	(0.071)
Input tariff	-0.816	-12.164
	(1.355)	(11.637)
Observations	13,035	13,035
R-squared	0.863	0.789
Other NTMs	yes	yes
Importer FE	yes	yes
Year FE	yes	yes

Note: This table shows the effect of inputs exposure to pre-shipment inspections (PSI) on the plant's average number of shipments (col. 1) and the average value per shipment (col. 2), both in logarithmic scale, in the years between 2014 and 2018. *Input PSI* is the share of the total value of imported goods covered by PSI. The impact of import tariffs is measured analogously. All specifications include controls for other NTMs applied on plant's inputs, importer fixed effects and year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the importer level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

column (2) of Table 8 is positive, but not significant.[30] As sales may react with a lag to lower prices, column 3 regresses next period' sales on PSI. The coefficient becomes positive and significant. Having expressed inventories in logs allows us to compare the elasticities. Consistent with the idea that lower markups have the objective to boost sales and empty out inventories, we find that the increase in sales is of similar magnitude as the increase in inventories.

To further corroborate the mechanism just described in Appendix Table A10, we provide two further tests. First, the coefficient of input PSI showed in column (1) shows that the application of this type of NTM on inputs does not have any impact on inventories of finished goods, which should be only partially impacted by restrictions on intermediate materials. Second, in column (2) of Appendix Table A10, we show that input PSI does not have any impact on employment, consistent with the idea that the increase in sales may not be related to a successful growth strategy of the plant.

6. Conclusions

This paper builds a novel NTM dataset on all NTMs applied to the universe of goods produced in Indonesia from 2008 to 2015 and uses the data to explore the impact of NTMs in a large panel of manufacturing plants. The results suggest that on average NTMs do not harm plants' performance, whether through the input or the output channel. To the extent that some of the benefits of NTMs in addressing market failures may not be fully captured by the plant-level outcomes, NTMs might even have a net positive impact on welfare. This is different to the case of import tariffs, which have a negative impact on productivity and - unlike NTMs - they also do not appear to have any positive impact on consumers.

This average neutral effect of NTMs masks a wide heterogeneity across individual NTMs. To tease out some of this heterogeneity, the paper focuses on two specific measures (APT and PSI), which we argue differ markedly in terms of how necessary they are to achieve legitimate policy objectives. In line with our hypothesis, the application of APT on imported inputs has a positive impact on TFPR through increases in markup, which we interpret as a sign of quality improvement linked to the measure. On the other hand, the results for PSI suggest that this acts mainly as an import barrier,

[30]Sales are the log of total production minus the yearly change in inventories of finished products, deflated by the plant-level output price deflator.

Table 8: Pre-Shipment Inspections (PSI): Inventory and Sales Behavior

	(1)	(2)	(3)
	Raw invent	Sales	Sales (t+1)
Pre-shipment inspections (output)	0.003	-0.042	-0.075
	(0.079)	(0.093)	(0.094)
Pre-shipment inspections (input)	0.582**	0.336	0.519**
	(0.285)	(0.291)	(0.243)
Observations	40,102	40,102	38,309
R-squared	0.927	0.908	0.906
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of pre-shipment inspections (PSI), applied either to output or inputs, on plant's raw materials inventory (col. 1), sales (col. 2) and next period' sales (col. 3) in the years between 2008 and 2015. *Output PSI* is the share of HS-10 digits products subject to at least one PSI within the corresponding five digit industry. For each five digit industry, *Inputs PSI* is the weighted sum of output PSI in all five digit supplying industries. The coefficients are obtained by the estimation of Equation 1. All specifications include controls for other NTMs and import tariffs applied on plant's outputs and inputs, plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

reducing competition, raising markup in the output markets, and increasing the cost of sourcing the imported inputs. We provide evidence that PSI induces plants to import larger quantities less frequently, in order to edge against the uncertainty generated by the inspection. At the same time, the larger inventories prompt plants to lower markups to increase sales and absorb inventory costs.

This type of analysis underscores the importance of moving beyond the aggregate NTM variables that much of the literature has focused on. Besides capturing the large heterogeneity in the economic effects of NTMs, focusing on the individual measures allows to inform directly the trade policy debate, which centres around specific rather than aggregate NTMs. We have proposed some methods to start identifying different types of individual measures on the basis of their *ex ante* legitimacy. We view additional systematic ways of classifying NTMs and further empirical analyses as a fruitful avenue for future research.

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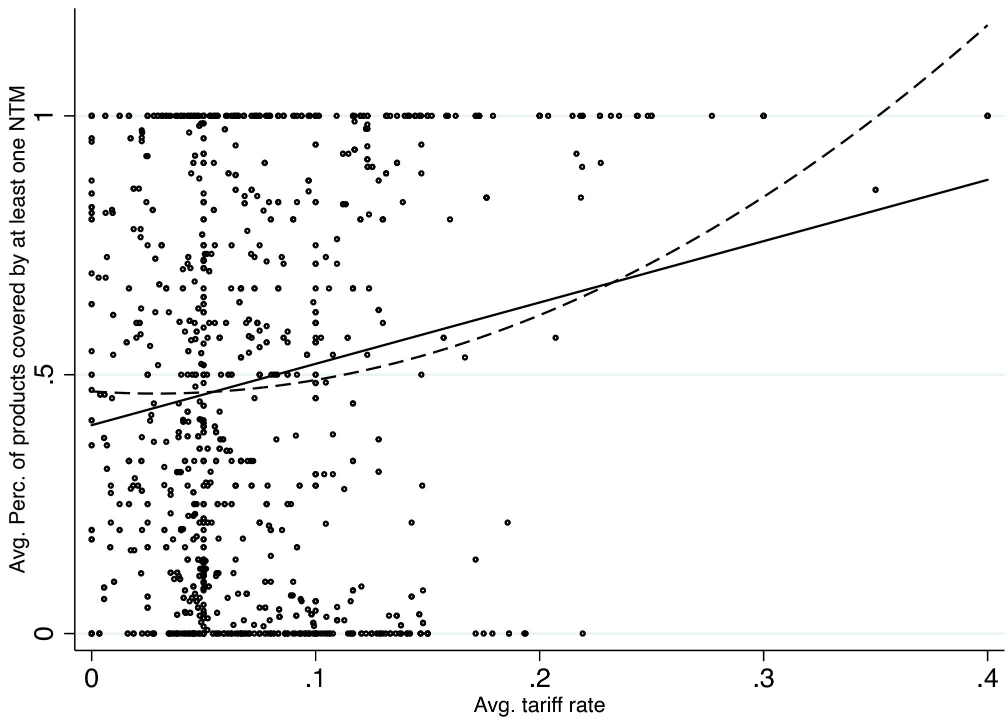
Appendix A. Additional Figures and Tables

Figure A1: Correlation Between NTMs and Import Tariffs.



Note: The figure shows the yearly correlation between the average percentage of products covered by at least one NTM in each 5-digit industry and the average import tariff rate at the same industry level, for all the years between 2008-2015, together with linear (black line) and quadratic interpolations (black dashed line).

Table A1: Impact of Industry's Performance on the Introduction of NTMs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Pr(NTM)	Pr(NTM)	Pr(NTM)	Pr(NTM)	Pr(NTM)	Pr(NTM)	Pr(NTM)	Pr(NTM)	Pr(NTM)	Pr(NTM)
(a): At least one NTM between 2008 and 2015										
Output (Ln)	0.015	0.011							-0.008	0.003
	(0.013)	(0.012)							(0.015)	(0.016)
Employment (Ln)			0.043*	0.030					0.054**	0.029
			(0.024)	(0.022)					(0.027)	(0.027)
TFPQ (Ln)					-0.019	0.025			-0.042	0.016
					(0.026)	(0.025)			(0.044)	(0.045)
Markups (Ln)							0.002	0.060	0.033	0.060
							(0.033)	(0.039)	(0.043)	(0.050)
Observations	282	282	270	270	286	286	284	284	266	266
R-squared	0.006	0.161	0.015	0.175	0.003	0.162	0.000	0.162	0.025	0.182
Sec2digits FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
(b): At least one NTM in 2008										
Output (Ln)	-0.011	0.001							-0.021	0.017
	(0.018)	(0.018)							(0.023)	(0.025)
Employment (Ln)			0.020	0.009					0.039	-0.013
			(0.032)	(0.033)					(0.040)	(0.041)
TFPQ (Ln)					0.011	0.047			0.029	0.091*
					(0.035)	(0.043)			(0.043)	(0.048)
Markups (Ln)							0.033	0.027	0.075	0.037
							(0.062)	(0.070)	(0.063)	(0.077)
Observations	282	282	270	270	286	286	284	284	266	266
R-squared	0.001	0.175	0.001	0.175	0.000	0.176	0.001	0.176	0.012	0.202
Sec2digits FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Note: This table shows the effect of changes between 2004 and 2007 at the 5-digit industry level in total output (columns 1–2), employment (columns 3–4), TFPQ (columns 5–6), Markups (columns 7–8), and all these variables together (columns 9–10), on the probability of observing at least one NTM within the period 2008-2015 (Panel a), or in 2008 (Panel b). Even columns include also 2-digit industry fixed effects. Standard errors are robust to heteroskedasticity. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A2: Impact of NTMs *vs* Import Tariffs: Excluding Large Plants

	(1) TFPQ	(2) Markup	(3) TFPR
Output NTM	0.004	-0.082	-0.077
	(0.030)	(0.117)	(0.134)
Input NTM	0.071	0.131	0.202
	(0.084)	(0.147)	(0.206)
Output tariff	-0.349	0.240	-0.109
	(0.244)	(0.202)	(0.351)
Input tariff	-1.173**	-0.843*	-2.017***
	(0.467)	(0.429)	(0.699)
Observations	57,816	57,816	57,816
R-squared	0.982	0.693	0.955
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of NTMS and import tariffs, applied either to output or inputs, on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. *Output NTM* is the share of HS-10 digits products subject to at least one NTM within the corresponding five digit industry. For each five digit industry, *Inputs NTM* is the weighted sum of output NTM in all five digit supplying industries. *Output tariff* is the average tariff rate in the 5 digit industry of a plant. *Inputs tariff* is the weighted average of the tariffs rates applied to the inputs used by a plant. The coefficients are obtained by the estimation of Equation 1. The estimation sample excludes the industries with large plants i.e. producing more than ten percent of output in a five digit industry. All specifications include plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A3: Impact of NTMs *vs* Import Tariffs: Excluding Politically Connected Plants

	(1) TFPQ	(2) Markup	(3) TFPR
Output NTM	0.007	-0.066	-0.059
	(0.029)	(0.111)	(0.126)
Input NTM	0.0437	0.101	0.144
	(0.080)	(0.134)	(0.189)
Output tariff	-0.283	0.261*	-0.0223
	(0.198)	(0.157)	(0.280)
Input tariff	-1.121***	-0.803**	-1.924***
	(0.402)	(0.389)	(0.598)
Observations	59,701	59,701	59,701
R-squared	0.981	0.693	0.955
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of NTMS and import tariffs, applied either to output or inputs, on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. *Output NTM* is the share of HS-10 digits products subject to at least one NTM within the corresponding five digit industry. For each five digit industry, *Inputs NTM* is the weighted sum of output NTM in all five digit supplying industries. *Output tariff* is the average tariff rate in the 5 digit industry of a plant. *Inputs tariff* is the weighted average of the tariffs rates applied to the inputs used by a plant. The coefficients are obtained by the estimation of Equation 1. The estimation sample excludes politically connected plants. All specifications include plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A4: Impact of Anti-Pest Treatments (APT): Excluding Large Plants

	(1) TFPQ	(2) Markup	(3) TFPR
Anti-pest treatment (output)	-0.179	-0.331	-0.510
	(0.230)	(0.277)	(0.318)
Anti-pest treatment (input)	3.942***	5.842***	9.785***
	(0.932)	(1.945)	(2.357)
Observations	57,816	57,816	57,816
R-squared	0.982	0.694	0.955
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of anti-pest treatments (APT), applied either to output or inputs, on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. *Output APT* is the share of HS-10 digits products subject to at least one APT within the corresponding five digit industry. For each five digit industry, *Inputs APT* is the weighted sum of output APT in all five digit supplying industries. The coefficients are obtained by the estimation of Equation 1. The estimation sample excludes the industries with large plants i.e. producing more than ten percent of output in a five digit industry. All specifications include controls for other NTMs and import tariffs applied on plant's outputs and inputs, plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A5: Impact of Anti-Pest Treatments (APT): Excluding Politically Connected Plants

	(1) TFPQ	(2) Markup	(3) TFPR
Anti-pest treatment (output)	-0.126	-0.350	-0.476
	(0.218)	(0.298)	(0.297)
Anti-pest treatment (input)	3.749***	5.475**	9.224***
	(0.885)	(2.162)	(2.554)
Observations	59,701	59,701	59,701
R-squared	0.981	0.694	0.955
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of anti-pest treatments (APT), applied either to output or inputs, on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. *Output APT* is the share of HS-10 digits products subject to at least one APT within the corresponding five digit industry. For each five digit industry, *Inputs APT* is the weighted sum of output APT in all five digit supplying industries. The coefficients are obtained by the estimation of Equation 1. The estimation sample excludes politically connected plants. All specifications include controls for other NTMs and import tariffs applied on plant's outputs and inputs, plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A6: Pre-Shipment Inspections (PSI): Excluding Large Plants

	(1) TFPQ	(2) Markup	(3) TFPR
Pre-shipment inspections (output)	0.051	0.356**	0.407**
	(0.065)	(0.167)	(0.201)
Pre-shipment inspections (input)	-0.046	-1.017**	-1.064*
	(0.232)	(0.437)	(0.596)
Observations	57,816	57,816	57,816
R-squared	0.982	0.694	0.955
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of pre-shipment inspections (PSI), applied either to output or inputs, on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. *Output PSI* is the share of HS-10 digits products subject to at least one PSI within the corresponding five digit industry. For each five digit industry, *Inputs PSI* is the weighted sum of output PSI in all five digit supplying industries. The coefficients are obtained by the estimation of Equation 1. The estimation sample excludes the industries with large plants i.e. producing more than ten percent of output in a five digit industry. All specifications include controls for other NTMs and import tariffs applied on plant's outputs and inputs, plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A7: Pre-Shipment Inspections (PSI): Excluding Politically Connected Plants

	(1) TFPQ	(2) Markup	(3) TFPR
Pre-shipment inspections (output)	0.058	0.330**	0.388**
	(0.060)	(0.155)	(0.184)
Pre-shipment inspections (input)	-0.051	-0.904**	-0.954*
	(0.206)	(0.398)	(0.533)
Observations	59,701	59,701	59,701
R-squared	0.981	0.694	0.955
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of pre-shipment inspections (PSI), applied either to output or inputs, on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. *Output PSI* is the share of HS-10 digits products subject to at least one PSI within the corresponding five digit industry. For each five digit industry, *Inputs PSI* is the weighted sum of output PSI in all five digit supplying industries. The coefficients are obtained by the estimation of Equation 1. The estimation sample excludes politically connected plants. All specifications include controls for other NTMs and import tariffs applied on plant's outputs and inputs, plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A8: Impact of Anti-Pest Treatments (APT): Plants Subject to PSI only

	(1) TFPQ	(2) Markup	(3) TFPR
Anti-pest treatment (output)	-0.085	-0.369	-0.453
	(0.203)	(0.285)	(0.304)
Anti-pest treatment (input)	3.755***	5.400**	9.155***
	(0.862)	(2.105)	(2.528)
Observations	55,539	55,539	55,539
R-squared	0.980	0.697	0.951
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of anti-pest treatments (APT), applied either to output or inputs, on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. *Output APT* is the share of HS-10 digits products subject to at least one APT within the corresponding five digit industry. For each five digit industry, *Inputs APT* is the weighted sum of output APT in all five digit supplying industries. The coefficients are obtained by the estimation of Equation 1. All specifications include controls for other NTMs and import tariffs applied on plant's outputs and inputs, plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A9: Pre-Shipment Inspections (PSI): Plants subject to APT Only

	(1) TFPQ	(2) Markup	(3) TFPR
Pre-shipment inspections (output)	0.0430	0.154	0.197
	(0.0950)	(0.181)	(0.235)
Pre-shipment inspections (input)	-0.189	-1.382	-1.571
	(0.307)	(0.836)	(1.039)
Observations	17,762	17,762	17,762
R-squared	0.725	0.669	0.727
Plant FE	yes	yes	yes
2-dig ind-year FE	yes	yes	yes
Region-year FE	yes	yes	yes
5-dig HH-year FE	yes	yes	yes
Other NTMs	yes	yes	yes

Note: This table shows the effect of pre-shipment inspections (PSI), applied either to output or inputs, on plant's TFPQ (col. 1), markup (col. 2) and TFPR (col. 3) in the years between 2008 and 2015. *Output PSI* is the share of HS-10 digits products subject to at least one PSI within the corresponding five digit industry. For each five digit industry, *Inputs PSI* is the weighted sum of output PSI in all five digit supplying industries. The coefficients are obtained by the estimation of Equation 1. All specifications include controls for other NTMs and import tariffs applied on plant's outputs and inputs, plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A10: Pre-Shipment Inspections (PSI): Placebo Tests

	(1)	(2)
	Finish invent	Employment
Pre-shipment inspections (output)	-0.049	-0.020
	(0.100)	(0.039)
Pre-shipment inspections (input)	-0.009	0.032
	(0.271)	(0.076)
Observations	34,460	40,102
R-squared	0.924	0.962
Plant FE	yes	yes
2-dig ind-year FE	yes	yes
Region-year FE	yes	yes
5-dig HH-year FE	yes	yes
Other NTMs	yes	yes

Note: This table shows the effect of pre-shipment inspections (PSI) applied to inputs, on plant's finished product inventory (col. 1) and employment (col. 2) in the years between 2008 and 2015. *Inputs PSI* are the share of plant's inputs covered by PSI. The coefficients of output PSI are not significant and omitted from the Table. The coefficients are obtained by the estimation of Equation 1. All specifications include controls for other NTMs and import tariffs applied on plant's outputs and inputs, plant fixed effects, 2-digit industry-year fixed effects and macro region-year fixed effect. The Herfindahl-Hirschman Index is computed for each 5-digit industry in the base year and interacted with year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix B. Data Appendix

Appendix B.1. Details on Product/Industry Concordances

The KBLI classification has been adjusted to be consistent over the whole sample, ranging from 2008 to 2015. One issue is that in converting codes from KBLI rev.3 to KBLI rev.4, some industries are split in more than one industry, or vice-versa. For such reason, we only keep those KBLI codes that have an unambiguous one to one mapping across the two revisions.[31]

To link HS-10 digit products to KBLI industries, we first build a correspondence between HS-10 and nine digit KKI. Then, we map KKI products to the relative five digit KBLI. Based on these NTM-output measures, we compute an input-NTM measure. For each five digit industry, we compute the weighted sum of output-NTMs in supplying industries. The weights are obtained from plant-product level information on nine digit varieties of raw materials used by each plant, and then aggregated at the five digit-level.[32] In particular, we compute for each plant and year the share of expenditure on each nine digit input. Using our correspondence between KKI and HS-10, we link NTMs to such shares. Instead of using time-varying shares, we use 2006-2007 averages to mitigate the concern that changes in NTMs affect the inputs used by the plant, which might bias the estimate of their impact. We include 2006 in the base period because that was a census year, which helps maximising the size and representativeness of the sample.

Appendix B.2. Product and Raw Materials' Cleaning Algorithm

This section describes the algorithm we use to clean the raw materials' file.

- 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.

[31] We experiment with a looser conversion including more industries, but that does not change our main results.

[32] Our methodology closely follows Amiti and Konings (2007) and De Loecker et al. (2016).

- When the use of a material 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 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.

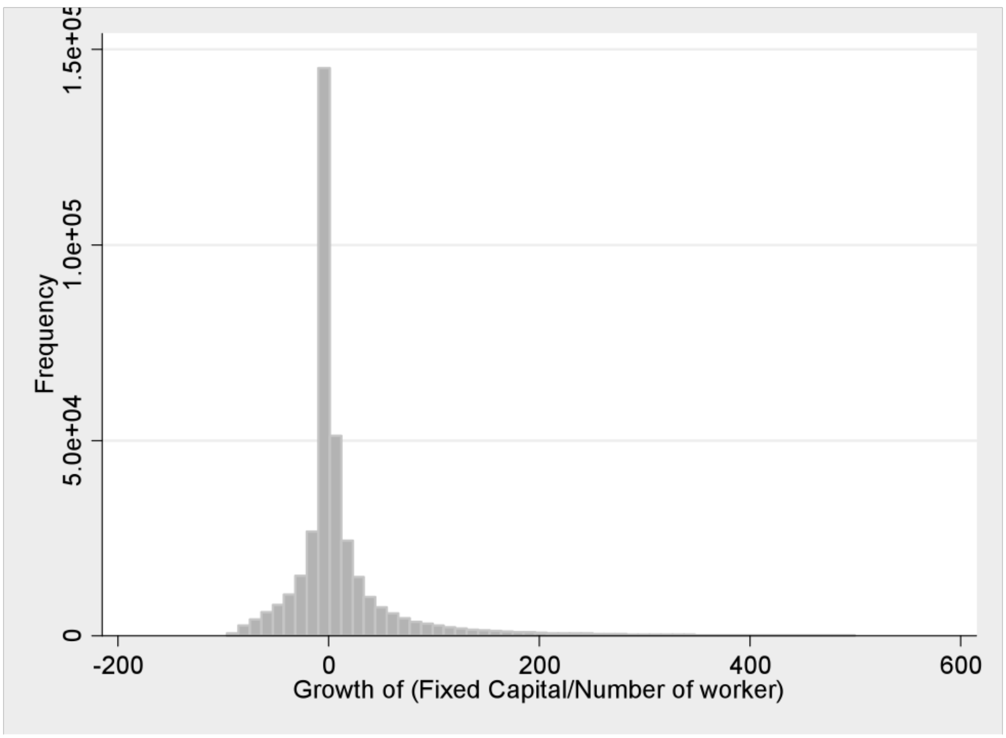
Appendix B.3. Construction of Indonesian Capital Series

To construct consistent series for the capital stock, we apply the following algorithm. We first clean the self-reported values by 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 re-apply the same battery of tests to ensure consistency of the series. We are able to obtain different capital deflators depending on the type of asset. We distinguish general price deflators from machinery and equipment, vehicles, and buildings. For all deflators, 2010 is used as a base year.

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 important 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 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.

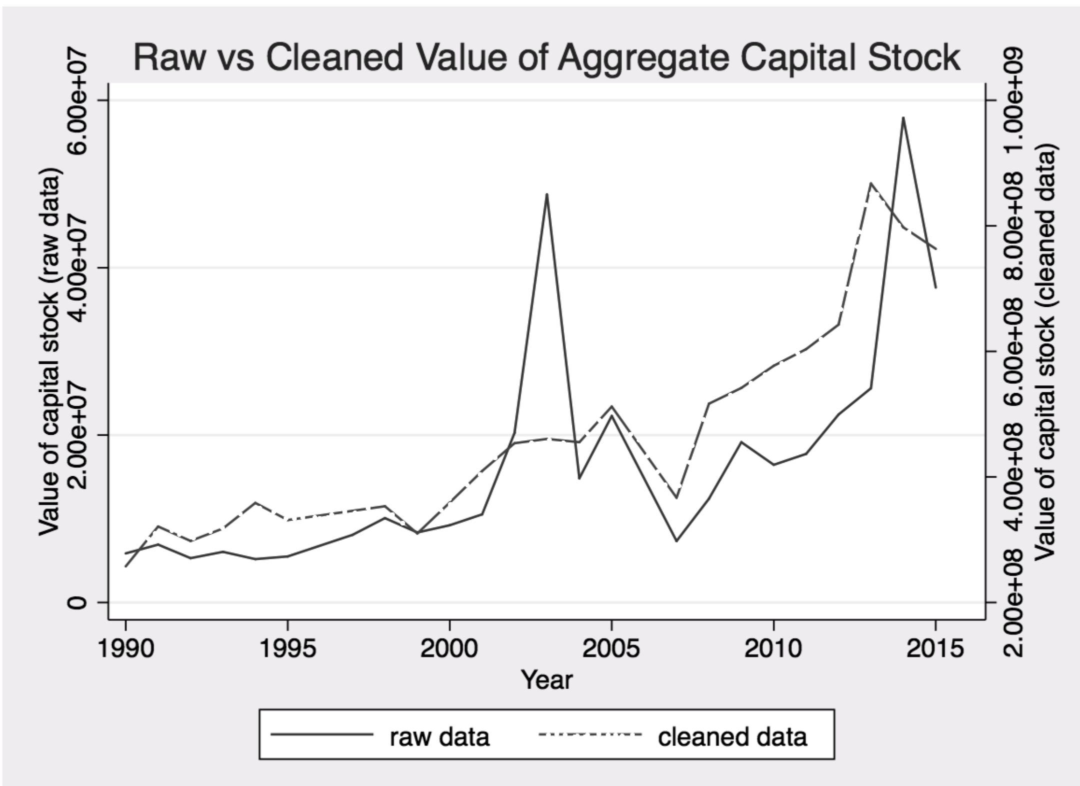
When a plant has some but not all valid observations for self-reported capital stock, then missing values are replaced by applying a forward/backward perpetual inventory method (PIM). Being only a fraction of the total observations, we rely less on estimates of depreciation rates. We follow Arnold and Javorcik (2009) and assume that the annual depreciation rate for buildings is 3.3 percent, for machinery 10 percent, and for vehicles and other fixed assets 20 percent. 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 A2). Figure A3 compares original and clean capital stock series.

Figure A2: Plants' growth rate distribution of capital-labor ratio.



Note: The figure shows the distribution of plant-level growth rates of the capital-labor ratio.

Figure A3: Comparison of Aggregate Nominal Capital Stock Series.



Note: The figure shows the capital stock series before and after applying our cleaning algorithm.

Appendix B.4. Customs' Data

We have data on the universe of Indonesian plants importing and exporting from 2014 to 2018.[33] The monthly data are collected by custom offices and record values imported and exported aggregated at the plant level from 10-digit Harmonized System (HS) products, as well as whether each product is subject to NTMs. We aggregate information up to the plant level and calculate the share of imported products subject to NTMs, using the import value of each product in the first twelve months of business of each plant as weights. Unfortunately customs' data do not provide the plant identifier that would otherwise allow us to link them with SI data.

Appendix B.5. Construction of Plant-level Price indices

The derivation of plant-specific price indices from product-level price data closely follows Eslava et al. (2004) and Mertens (2019).

These are 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 in t and $t-1$. Wee set $\pi_{jt} = 100$ in 2008,which is the first year of observation in the data. For plants entering after 2008, we follow Eslava et al. (2004) and Mertens (2019) and use the 5-digit industry average of the plant price indices as a starting value. We follow the same method to construct inputs' price indices. When price growth data are missing, we replace it with an average of product or inputs price changes within the same 2-digit industry and region. The latter dimension helps accounting for geographical differences that can affect output and input prices.

Appendix C. Estimation Appendix

We assume that in each period t, plant j produces output Q_{jt} with the following production function:

[33] It should be noticed that the Customs' sample spans a different time period compared to the SI data on plants and intermediate inputs, which includes the years 2008-2015.

$$Q_{jt} = \min\left\{\gamma_e E_{jt}, F(K_{jt}, L_{jt}, M_{jt}) \cdot \Omega_{jt}\right\} \tag{C.1}$$

where E_{jt} is energy consumption, K_{jt} the capital stock, L_{jt} labor and $M_{jt} = \{M^d_{jt}, M^i_{jt}\}$ are domestic and imported raw materials, respectively. The term Ω_{jt} represents Hicks-neutral productivity. The production function (C.1) is a structural value added specification (De Loecker and Scott (2016)) in which capital, labor and materials are allowed to be characterised by some degree of substitution and energy is a perfect complement to the combination of the other inputs. Most existing structural value added specifications include raw materials (possibly including energy) in the first argument of the *min* operator, therefore considering them proportional to output. Proportionality is equivalent to assuming that plants never change the materials' intensity of production. However, that would not be appropriated in our framework, for two reasons. First, as emphasised by the literature on per-shipment costs, the latter might induce shipment delays or trigger substitution between imported and domestic materials. In turn, changes in materials' mix is likely to affect the whole production process, which involves adjustment in capital and labor. The second reason is that Indonesia is often characterised by poor transportation infrastructure, which combined with a high geographical heterogeneity can result in road closures, disruption in naval shipment or technical failure of a materials' supplier's transportation equipment (Calì et al., 2019). Therefore, it seems appropriate to allow for some degree of adjustment costs for raw materials and consider energy a more flexible input.[34]

Given (C.1), a profit maximising plant would set

$$Q_{jt} = \gamma_e E_{jt} = F(K_{jt}, L_{jt}, M_{jt}) \cdot \Omega_{jt} \tag{C.2}$$

Appendix C.1. Recovering Production Function Parameters

This section describes the estimator used to recover the production function parameters. As in Mertens (2019), we exploit product-level information on quantities and prices to construct plant-level deflators which we use to deflate revenues. Unlike most of the existing literature, however, we are also able to construct plant-level inputs' deflators by exploiting information on price and quantities of each raw material used in production

[34] Notice that in absence of such adjustment costs, our specification would still be valid.

by the plant.[35] This is a strong advantage over previous studies such as Mertens (2019) and De Loecker et al. (2016) that do not have plant-level materials' deflators. Using plant-specific price indices allows us to overcome the bias that would otherwise arise using revenues and materials' expenditure deflated by industry price indices.[36]

Given that we observe quantities for products and materials, an alternative approach could have been using output and input quantity directly in our estimation routine. However, following such a strategy would pose aggregation issue due that plants often report the same products and inputs in different units, which would introduce considerable noise.[37] Moreover, since quantity output and input data are available for only 63% of the plants, using plant-specific deflators to derive quasi-quantities allows us to maximise the size of the sample.[38]

One problem we still face, common to all existing studies estimating production functions, is that we do not observe physical capital. Since different plants might use capital assets of different qualities, using expenditure to estimate productivity would result in biased estimates. We address the issue by using asset type-specific price indices to deflate the value of the capital stock (see Section 2) and estimating the production function parameters by 2-digit industries separately, as the homogeneity of capital equipment within such industries gives less scope for capital price variation.[39]

In our empirical application, we use a flexible trans-log specification $f(\cdot)$. We estimate the logged version of production function (C.2):

$$q_{jt} = f\left(k_{jt}, l_{jt}, m^d_{jt}, m^i_{jt}; \boldsymbol{\beta}\right) + \omega_{jt} + \epsilon_{jt} \tag{C.3}$$

Recall that ω_{jt} represents the log of Hicks-neutral productivity, which is known by plants' managers but not by us. The variable ϵ_{jt} is an i.i.d. error term that captures factors such as measurement errors.

[35]Appendix Appendix B.5 describes in detail the procedure used to construct such deflators, which follows closely Mertens (2019) and Eslava et al. (2004).

[36]This would be equivalent to assume that all plants have the same product within an industry, or that they use materials of identical quality.

[37]See Section Appendix B.2 for details on our cleaning procedure.

[38]See Section Appendix B.5 for the details of how we impute deflators when price and quantity data are missing.

[39]We do not have a sufficient number of observations to robustly estimate the parameters by three or more digits industries.

We are interested in estimating the vector of the production function parameters $\boldsymbol{\beta}$. To recover unbiased and consistent estimates of firms' production function (C.3), we need to address the well-known simultaneity problem deriving from the fact that ω_{jt} is correlated to labor and materials' input (but not to capital, which is chosen one period ahead). We build on the methodology of Ackerberg et al. (2015). In particular, we make the following timing assumptions concerning inputs' decisions: i) capital k_{jt} is chosen at $t-1$; ii) l_{jt}, m^d_{jt} and m^i_{jt} are chosen in $t-b$ after observing ω_{jt}, and iii) energy e_{jt} is chosen at $t-a$, with $1 < b < a$.

Our timing assumptions differ from most of the existing literature, which typically assumes materials to be completely flexible inputs. We depart from that assumption in order to allow for materials' adjustment costs. We use our timing assumption to specify an energy demand function,

$$e_{jt} = \tilde{h}(\omega_{jt}, k_{jt}, l_{jt}, m^d_{jt}, m^i_{jt}, \boldsymbol{\theta}_{jt}) \tag{C.4}$$

The vector $\boldsymbol{\theta}_{jt}$ includes variables that affect plant-level demand for energy. Calì et al. (2019) show that due a variegated landscape differences in the quality of infrastructures, the cost of energy distribution is heterogeneous across Indonesian regions. Therefore, we include a full set of location dummies in $\boldsymbol{\theta}_{jt}$. We also include year dummies which captures time varying factors common to all plants in a given industry. Assuming that the energy consumption function of the plant, $\tilde{h}$ is monotonically increasing and invertible in ω, we obtain a control function that proxies for unobserved productivity,

$$\omega_{jt} = h(e_{jt}, k_{jt}, l_{jt}, m^d_{jt}, m^i_{jt}, \boldsymbol{\theta}_{jt}) \tag{C.5}$$

where $h \equiv \tilde{h}^{-1}$. One additional advantage of our approach is that in our data, we directly observe the quantity of electricity consumed.[40] That makes our estimator less subject to bias. To see this, consider an exogenous shock to energy prices. If we were to use energy expenditures rather than actual quantities, depending on the elasticity of electricity consumption to energy prices, the increase in prices might result in an increase of energy expenditures and lead us to erroneously conclude that unobserved productivity increased based on (C.5).

[40]For energy types different from electricity we convert in KhW equivalents using standard conversion factors.

Adding $h(\cdot)$ to (C.3), we get

$$q_{jt} = f\big(k_{jt}, l_{jt}, m^d_{jt}, m^i_{jt}; \boldsymbol{\beta}\big) + h(e_{jt}, k_{jt}, l_{jt}, m^d_{jt}, m^i_{jt}, \boldsymbol{\theta}_{jt}) + \epsilon_{jt} \tag{C.6}$$

We follow Ackerberg et al. (2015) by approximating the right-hand-side of (C.6) with a third-order polynomial in all its elements, except for the elements of $\boldsymbol{\theta}$, which we enter linearly.[41] From the first stage, we obtain expected output $\hat{q}_{j,t}$ and the residulas $\hat{\epsilon}_{j,t}$.[42]

The next step is specifying a law of motion for productivity ω_{jt}. We assume that ω_{jt} follows Markov process that can be shifted by plant managers' action:

$$\omega_{jt} = g\big(\omega_{j,t-1}, \boldsymbol{\Gamma}_{j,t-1}\big) + \xi_{jt} \tag{C.7}$$

In (C.7), ξ_{jt} denotes the innovation to productivity and the vector $\boldsymbol{\Gamma}$ includes variables controlled by plants' managers that influence the expected future value of productivity and state variables which determine differences in productivity dynamics across plants.[43] In our framework, these are dummy variables for the decision to exporting and importing, import tariffs, and NTMs.[44]

Current expected productivity is then expressed as a function of the data and parameters,

$$\omega(\boldsymbol{\beta})_{jt} = \hat{q}_{j,t} - f\big(k_{jt}, l_{jt}, m^d_{jt}, m^i_{jt}; \boldsymbol{\beta}\big) \tag{C.8}$$

To estimate $\boldsymbol{\beta}$, we form moments based on the innovation ξ_{jt} in the law of motion (C.7),

$$\xi(\boldsymbol{\beta})_{jt} = \omega(\boldsymbol{\beta})_{jt} - E\big[\omega(\boldsymbol{\beta})_{jt} | \omega(\boldsymbol{\beta})_{j,t-1}, \boldsymbol{\Gamma}_{j,t-1}\big] \tag{C.9}$$

[41] This approach is similar to Mertens (2019).

[42] It should be noticed that in the first stage, none of the production function parameters are identified, because they enter both $f(\cdot)$ and $h(\cdot)$.

[43] For instance, in De Loecker et al. (2016), which study the impact of trade reforms, $\boldsymbol{\Gamma}$ included export dummies and import tariffs; De Loecker (2007) includes export quotas; Doraszelski and Jaumandreu (2013) include R&D expenditure, and Konings and Vanormelingen (2015) include measures of workforce training.

[44] To ease the exposition, all productivity and markup estimates presented in the main text, including those in Table 4 and 5, are obtained including the general output and input NTMs in $\boldsymbol{\Gamma}$. We obtain very similar results if we estimate productivity and markups including separately APT for Table 4 and PSI for 5 in $\boldsymbol{\Gamma}$. The tables are available upon request.

The moments that identify the parameters are:

$$E\left[\xi(\boldsymbol{\beta})_{jt}\mathbf{M}_{jt}\right] = 0 \tag{C.10}$$

where the vector $\mathbf{M}_{jt}$ includes current capital, lagged domestic and imported materials, lagged labor, and lagged electricity consumption. It should be noticed that materials, labor and electricity consumption are all significantly correlated within plants over time, which justify their inclusion in (C.10) as instruments.[45]

Equipped with the estimated production function parameters, $\hat{\boldsymbol{\beta}}$, we recover TFPQ by taking the residual:

$$TFPQ_{it} \equiv \hat{\omega}_{jt} = \hat{q}_{jt} - f\left(k_{jt}, l_{jt}, m^d_{jt}, m^i_{jt}; \hat{\boldsymbol{\beta}}\right) \tag{C.11}$$

Appendix C.2. Deriving Markups From Plants' Cost Minimisation

Following De Loecker and Warzynski (2012), we derive an expression for plants' markup as a function of the elasticity of $F(\cdot)$ with respect to labor (a static production input) and the plant's revenue cost shares for labor and energy consumption.

Cost minimisation with respect to labor, which we consider a static input, implies the following first order condition:[46]

$$\frac{\partial \mathcal{L}_{jt}}{\partial L_{jt}} = W_{jt} - \tilde{\lambda}_{jt}\frac{\partial F(K_{jt}, L_{jt}, M_{jt}) \cdot \Omega_{jt}}{\partial L_{jt}} = 0$$

where $\mathcal{L}$ is plant's j Lagrangian, W_{jt} wages and $\tilde{\lambda}_{jt}$ the Lagrangian multiplier. Rearranging terms and multiplying both sides of the previous equation by $\frac{L_{jt}}{Q_{jt}}$, we obtain

$$\frac{\partial F(K_{jt}, L_{jt}, M_{jt}) \cdot \Omega_{jt}}{\partial L_{jt}}\frac{L_{jt}}{Q_{jt}} = \frac{1}{\tilde{\lambda}_{jt}}\frac{W_{jt}L_{jt}}{Q_{jt}}$$

Following De Loecker and Warzynski (2012), we define the plant's markup over the marginal cost of output λ_{jt} as

[45] In particular, in a regression regression of current on past electricity consumption - our proxy variable for productivity - including plant, 2-digit industry-year and region-year fixed effects, the autoregressive coefficient is 0.17 and significant at the 99 percent.

[46] What matters for the consistency of the model, is that labor is chosen in each period t, as opposed to capital, which is chosen in $t-1$.

Section Appendix C.1 will discuss the implication of potential presence of labor adjustment costs.

$$\tilde{\mu}_{jt} \equiv \frac{P_{jt}}{\tilde{\lambda}_{jt}}$$

where P_{jt} is the price of output produced by the firm. The previous equation yields an expression of plants' markup depending on the elasticity of output with respect to the variable input, β_l, and the inverse of the revenue share of expenditure on L_{jt}:

$$\tilde{\mu}_{jt} = \frac{\partial F(K_{jt}, L_{jt}, M_{jt}) \cdot \Omega_{jt}}{\partial L_{jt}} \frac{L_{jt}}{Q_{jt}} \frac{P_{jt} Q_{jt}}{W_{jt} L_{jt}}$$

As discussed in De Loecker and Scott (2016), $\tilde{\lambda}_{jt}$ expresses the marginal cost of an additional unit of $F(\cdot)$, but the total marginal cost of producing output, λ_{jt}, is given by

$$\lambda_{jt} = \tilde{\lambda}_{jt} + \frac{P_{Et}}{\gamma_e}$$

where P_{Et} denotes the price of energy. Therefore, the correct expression of plant's j markup is given by

$$\mu_{jt} = \frac{\partial F(K_{jt}, L_{jt}, M_{jt}) \cdot \Omega_{jt}}{\partial L_{jt}} \frac{L_{jt}}{Q_{jt}} \frac{P_{jt} Q_{jt}}{W_{jt} L_{jt} + P_{Et} E_{jt}} \tag{C.12}$$

We can use μ_{jt} to decompose revenue-total factor productivity (TFPR) :

$$TFPR_{it} \equiv \frac{P_{it} Q_{it}}{\lambda_{it} F\big(K_{it}, L_{it}\big)} = \mu_{it} \times TFPQ_{it} \tag{C.13}$$

Finally, we use the estimated production function parameters to compute (C.12) and (C.13). In our application, we drop the top and bottom one percent of the TFPQ and markups' estimates in order to avoid outliers driving our findings, although results are consistent if we do not trim the distributions.