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Abstract

This paper examines the impact of safeguard import tariffs on market diversity in Ecuador from 2015 to 2017. Using firm-level data, we estimate the effects of tariffs on revenue and market shares in the Manufacturing and Wholesale & Retail (W&R) sectors with a Quantile Treatment Effect on the Treated (QTT) estimator. We also assess firm exit probabilities and pass-through effects on prices through a difference-in-differences approach. By linking firm-level QTT estimates to industry-level diversity measures, we construct counterfactual revenue distributions to quantify the effect on market concentration. We find that tariffs disproportionately reduced revenue and market shares for smaller firms, significantly increasing exit rates and reducing market diversity, with stronger effects in W&R. While tariffs did not generate broad inflationary pressures, they induced short-term pass-through effects that further strained smaller firms. These sector-specific price responses reinforced market consolidation, accelerating the decline in market diversity.

JEL classifications: D40, F13, F14, O4, O24, O54
Keywords: Market structure, Trade policy, Protectionism, Emerging markets, Latin America

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1. Introduction

Protectionist measures such as import tariffs can shape competitive incentives and firm dynamics in fundamental ways (Caliendo and Parro, 2022; Chen et al., 2009; De Loecker and Goldberg, 2014; Melitz, 2003; Tybout, 2000; Goldberg and Pavcnik, 2016). Yet, their impact on *market diversity*—beyond the traditional focus on productivity or markups—remains largely unexplored. Following Ahern et al. (2024), we define market diversity in terms of both the number of firms in a market (*richness*) and the distribution of market shares across firms (*evenness*). This paper examines how safeguard import tariffs influence these dimensions of diversity.

The effect of protection on diversity is not clear ex ante. On the one hand, as argued by Tybout (2000), in an industry with limited imports, protection may cause domestic firms to exploit their market power by *reducing production* and increasing their markups. On the other hand, if the industry has substantial import penetration, protection may increase the market size for domestic firms, leading them to *expand*. Although markups may increase in either case,[1] since firms' scale may change in either direction, it is not clear how diversity is affected.

To empirically assess these effects, we exploit the broad-based safeguard import tariffs implemented in Ecuador between 2015 and 2017. These tariffs were enacted in response to the sharp decline in oil prices at the end of 2014 and were initially imposed in March 2015. The policy affected more than one-third of all imports, covering approximately 3,000 10-digit headings, including intermediate inputs, capital goods, and consumer goods (Grijalva et al., 2022). This setting provides an ideal scenario for evaluating the impact of trade policy on diversity, as the policy was unexpected, following a decade-long oil boom, and it was extended again unexpectedly following a strong earthquake that affected the coast of Ecuador in April 2016. Also, since the safeguards were implemented under Article XVIII of the WTO, Ecuador's trading partners did not retaliate.

Using firm-level data, we analyze how these safeguards reshaped the distribution of firms' revenues and market shares, and their impact on firm exit. If safeguards disproportionately harm smaller firms, evenness declines; if they also increase exit rates, richness declines, both of which erode market diversity.

Our empirical approach combines a difference-in-differences design with the Quantile Treatment Effect on the Treated (QTT) estimator developed by Callaway and Li (2019). This allows us to capture heterogeneous effects across the firm-size distribution, extending prior work on trade policy and distributional impacts (e.g., Iacovone et al., 2013). We further construct counterfactual revenue distributions to quantify the net effect on industry-level diversity (Ahern et al., 2024). Finally, we examine whether changes in market structure translate into increased market power by assessing the pass-through of safeguard-induced cost increases to final prices.

Our results show that safeguard import tariffs disproportionately reduced revenue and market shares for smaller firms, particularly in Wholesale & Retail (W&R), while leaving larger firms largely unaffected. Revenue and market share losses ranged from 10% to 30% among small importer-

[1] Autor et al. (2020) show that trade openness can lead to markups increasing or decreasing, depending on the size of the affected firms.

exporters. Value chain exposure also had a negative effect on smaller firms in both Manufacturing and W&R, particularly those below the 35th percentile of the revenue distribution. Meanwhile, large manufacturing firms gained market share, reinforcing market concentration.

At the industry level, these firm-level shifts translated into a decline in market diversity that intensified over time. While part of this change reflects firm exit rather than direct safeguard effects, we find a strong correlation between reduced balanced diversity and increased dominance diversity, suggesting that safeguards accelerated market concentration.

Although we find no evidence of broad inflationary effects, we identify short-run sector-specific price responses. In 2015, a 1% increase in input exposure raised inflation by 0.81% in Manufacturing and 0.47% in W&R. By 2016, these effects had dissipated, becoming negative (though insignificant) in 2017. These results suggest that firms initially passed on higher costs to consumers, but this capacity weakened as markets adjusted. While safeguard tariffs did not trigger widespread inflation, they imposed price pressures that compounded the challenges faced by smaller firms, further consolidating market power.

Relation to the Literature

This paper contributes to the literature on trade protection and industry diversity by examining how safeguard import tariffs influence firm-level revenue and market shares, as well as industry-level diversity. While most studies focus on trade openness and its effects on productivity and markups (Bernard et al., 2007; Chen et al., 2009; De Loecker et al., 2016; De Loecker and Van Biesebroeck, 2018), we extend the analysis by considering the distributional consequences of protectionism. Using the Quantile Treatment Effect on the Treated (QTT) estimator (Callaway and Li, 2019), we assess how safeguard import tariffs reshape market structure across the firm-size distribution and introduce a new method to link firm-level effects to aggregate diversity measures (Athey and Imbens, 2006).

This study connects to a well-established literature on how trade policies influence market concentration and firm dynamics (Autor et al., 2017, 2020; De Loecker et al., 2016; De Loecker and Van Biesebroeck, 2018). Since Kumar (1985) first argued that international trade should be incorporated into measures of market concentration, researchers have examined how trade liberalization affects firm entry, exit, and market power. In Latin America, Rodríguez-Castelán et al. (2023) show that informal firms are more likely to exit when exposed to international competition, while Iacovone et al. (2013) find that smaller firms suffer disproportionately from exposure to Chinese imports. Although trade liberalization is often associated with increased competition and firm exits, the effects of trade protection are not necessarily symmetric (Furceri et al., 2021). Furthermore, Furceri et al. (2021) show that protectionist policies can lead to highly uneven outcomes across firms. Recent studies on the U.S. trade war have reinforced this view, highlighting how tariffs reshape firm behavior and industry structure in complex ways (Amiti et al., 2019; Cavallo et al., 2021; Fajgelbaum et al., 2020; Flaaen and Pierce, 2019).

We also contribute to research on industry concentration and firm diversity by examining how temporary import restrictions alter market composition through input costs and firm-level responses (Davies and Geroski, 1997; Kambhampati and Kattuman, 2009). These authors provide decompositions that allow the mapping of changes in market shares to changes in concentration. We contribute to this literature by linking the full distribution of firm-level market sales and market shares to the dynamics of industry-level diversity in the context of a causal analysis.

Prior studies have explored how changes in firm-level market shares affect industry concentration, but few have analyzed these shifts through the lens of input acquisition. We extend this approach by linking trade protection to both output and input channels, building on the concept of effective protection (Corden, 1966, 1971). Additionally, this paper adds to the growing literature on how trade policies propagate through value chains, influencing firms beyond those directly affected by import restrictions (Barattieri and Cacciatore, 2023; Bown et al., 2021; Handley et al., 2020a; Konings and Vandenbussche, 2013).

Methodologically, we apply the QTT estimator (Callaway and Li, 2019) to capture heterogeneous effects of tariffs on firm sales and market shares across the distribution. This allows us to pinpoint which segments of the market experience the greatest disruptions. To quantify the broader impact of these shifts, we construct counterfactual revenue distributions, following Athey and Imbens (2006), and extend insights from Davies and Geroski (1997) and Kambhampati and Kattuman (2009). By integrating distributional analysis with measures of overall industry diversity, we provide a clearer picture of how trade protection reshapes market structure.

The paper closest to this study is Uribe-Terán et al. (2025). These authors use the same dataset as this paper to evaluate the effect of Ecuador's safeguard import tariffs on firms' performance. We expand their analysis to show that the negative scale effects that they find are concentrated on a subset of firms, mainly smaller, less productive ones, thus leading to industry-level changes in diversity.

The paper is organized as follows. Section 2 defines market diversity and its components. Section 3 presents a simple model of firm-level market share determination. Section 4 describes the policy context and dataset. Section 5 outlines our identification strategy, exposure measures, and the QTT approach. Section 6 presents the results, while Section 7 discusses robustness checks. Section 8 concludes.

2. Market Diversity

Traditionally, research on industry structure has focused on *market concentration* (e.g., Davies and Geroski, 1997; Caves, 1998). Recently, however, Ahern et al. (2024) introduced the concept of *market diversity*, which provides a broader perspective of industry structure by explicitly incorporating the two key drivers of concentration: the number of active firms (*richness*) and the distribution of market shares among them (*evenness*). A more diverse market corresponds to lower concentration.

The analysis of market diversity offers a more nuanced view of industry structure through two related measures that differ in how they weigh richness and evenness. The first, *balanced diversity*, assigns equal importance to each dimension (Ahern et al., 2024) and is formally defined as:

$$D = \exp\left(-\sum_{i=1}^{N} \alpha_i \ln \alpha_i\right), \tag{1}$$

where α_i represents the market share of firm i and N is the total number of firms in the market.

The second measure, *dominance diversity*, disregards the number of firms and instead focuses entirely on the distribution of market shares. Thus, for instance, a market with only two firms but equal market shares would have high dominance diversity, despite its low richness. This measure is the inverse of the Herfindahl-Hirschman Index (HHI) and is defined as:

$$D^2 = \left(\sum_{i=1}^{N} \alpha_i^2\right)^{-1} = \frac{1}{HHI}, \tag{2}$$

where α_i is again the market share of firm i.

By analyzing these two measures, we obtain a more comprehensive picture of how trade policy influences industry structure. While balanced diversity captures both firm entry and relative market positioning, dominance diversity isolates shifts in market share concentration, highlighting the extent to which protectionist policies affect the competitive balance.

3. A Simple Model of Market Share Determination

In this section, we present a simple partial-equilibrium model of monopolistic competition to illustrate how tariffs may disproportionately affect smaller firms, thereby reducing overall market diversity. We assume a continuum of firms, each producing a differentiated variety by combining a local input z_i and an imported input x_i. Because imported inputs are difficult to substitute, z_i and x_i are treated as perfect complements. Firms differ in a productivity parameter $\varphi_i > 0$, which measures how efficiently the imported input is used. The production function is

$$q_i(z_i, x_i) \;=\; \min\{\, z_i,\; \varphi_i\, x_i\}.$$

Cost minimization (conditional on producing q_i) implies $z_i^* = q_i$ and $x_i^* = q_i/\varphi_i$. Hence, the total cost function is

$$c_i(q_i, \varphi_i, w, w^*) \;=\; \left(w + \frac{(1+\tau)\, w^*}{\varphi_i}\right) q_i,$$

where w is the price of the local input, w^* is the price of the imported input, and τ is a safeguard import tariff on that input.

Each variety faces an isoelastic demand curve characterized by $q_i(p_i) = \delta_i \, p_i^{-\varepsilon}$, where δ_i is a demand shifter and $\varepsilon > 1$. Profit maximization yields

$$p_i \;=\; \frac{\varepsilon}{\varepsilon - 1}\Big[w + \tfrac{(1+\tau)\,w^*}{\varphi_i}\Big], \qquad q_i \;=\; \delta_i\Big(\tfrac{\varepsilon-1}{\varepsilon}\Big)^{\varepsilon}\Big[w + \tfrac{(1+\tau)\,w^*}{\varphi_i}\Big]^{-\varepsilon}.$$

In this framework, smaller (less productive) firms are more vulnerable to tariffs, losing market share and thus reducing overall market evenness. We formalize these observations in the following theorems.

Theorem 1 (Tariff pass-through)**.** *Tariff pass-through is proportional to markups but heterogeneous across firms. Less productive firms (low φ_i) raise prices more when tariffs increase.*

Proof. Differentiate p_i with respect to τ:

$$\frac{\partial p_i}{\partial \tau} \;=\; \frac{\varepsilon}{\varepsilon - 1}\,\frac{w^*}{\varphi_i}.$$

Because $\frac{\varepsilon}{\varepsilon-1}$ is the markup factor, higher markups lead to stronger pass-through. The cross-derivative with respect to φ_i is negative, so more productive firms (larger φ_i) experience smaller price increases. ∎

Theorem 1 implies that even with imperfect competition, we may observe imperfect pass-through from tariffs to prices if we can only measure the average effect across firms.

Theorem 2 (Output reductions)**.** *A tariff increase reduces quantities sold, with a stronger percentage decline for larger ε and for less productive firms.*

Proof. Differentiate q_i with respect to τ:

$$\frac{\partial q_i}{\partial \tau} \;=\; -\,\varepsilon\,\frac{w^*}{\varphi_i\,w + (1+\tau)\,w^*}\;q_i \;<\; 0.$$

When ε is larger, demand is more elastic, so higher tariffs lead to sharper output contractions. Firms with lower φ_i (less productive) face larger percentage reductions in q_i. ∎

Since more productive firms have lower prices, they sell larger quantities and thus experience smaller output losses when tariffs rise. Smaller firms, by contrast, lose sales more sharply. This heterogeneity alters market shares, as stated next.

Theorem 3 (Market-share effects)**.** *A tariff hike reduces market share for smaller (less productive) firms, whereas larger firms maintain or expand theirs.*

Proof. Let α_i be firm i's market share. Its percentage change with respect to τ satisfies

$$\frac{\frac{\partial \alpha_i}{\partial \tau}}{\alpha_i} \;=\; \frac{1}{q_i}\,\frac{\partial q_i}{\partial \tau} \;-\; \frac{1}{Q}\sum_j \frac{\partial q_j}{\partial \tau}.$$

By Theorem 2, $\frac{1}{q_i}\frac{\partial q_i}{\partial \tau}$ is more negative for less productive firms. The term $\frac{1}{Q}\sum_j \frac{\partial q_j}{\partial \tau}$ is the average drop in total output. Thus, a firm whose production falls faster than the overall market, loses market share, while more productive firms (lower price, smaller decline in output) lose less and often gain share. ■

From Theorem 3, we conclude that higher tariffs shift the distribution of sales toward larger producers, thereby diminishing the evenness of market shares and ultimately reducing market diversity.

4. Background and Data

This section provides an overview of Ecuador's reliance on capital controls and safeguard tariffs since adopting the US dollar, focusing on the surcharges introduced after the sharp decline in oil prices (Broz et al., 2016; Grijalva et al., 2022). We discuss why these measures can be considered exogenous, highlighting the limited role of private-sector lobbying and the rapid policy response (Uribe-Terán et al., 2025). Finally, we describe our dataset, which merges administrative records from COMEX, the Central Bank of Ecuador, the Superintendencia de Compañías, and the Internal Revenue Service.

4.1. Background

Given its heavy dependence on oil revenue, Ecuador has historically responded to oil price declines by restricting imports.[2] The first short-lived import safeguards were introduced in 2009 following the 2008 financial crisis.[3] In response to the sharp drop in oil prices at the end of 2014, the government introduced import surcharges in early 2015. These safeguard tariffs, affecting nearly 38% of trade subheadings and 31% of total imports in 2014, were implemented in March 2015 and initially set to expire by mid-2016 (Uribe-Terán et al., 2025). However, after a major earthquake in April 2016, they were extended and gradually phased out by mid-2017. The adoption of these safeguards complied with WTO and Cartagena Agreement guidelines, ensuring a temporary, nondiscriminatory measure aimed at stabilizing the balance of payments without provoking retaliation.[4] The surcharges were imposed as *ad valorem* rates of 5%, 15%, 25%, and 45%, with higher rates applied to consumption goods and lower rates to raw materials and capital goods.

A potential concern for sectoral analysis is whether the policy disproportionately targeted specific industries. Uribe-Terán et al. (2025) show that it did not. The safeguards were product-focused rather than sector-focused, with consumption goods facing an average tariff of 45% and inputs across sectors averaging 15%. While the policy did not differentiate by industry, actual exposure varied significantly.

[2] Ecuador has used the US dollar as its official currency since 2000, eliminating exchange rate adjustments and monetary policy as tools for responding to economic shocks (Broz et al., 2016).

[3] See Grijalva et al. (2022) for an account of Ecuador's trade policy under dollarization.

[4] See Grijalva et al. (2022) for a detailed discussion of the provisions that enabled the safeguards.

The safeguards were a reactive measure to the economic downturn caused by falling oil prices and, as argued by Grijalva et al. (2022), were not driven by private-sector lobbying. Decisions were made by Ecuador's Foreign Trade Committee (*Comité de Comercio Exterior* - COMEX) and the Ministry of Finance, with a focus on fiscal revenue and controlling import volumes. Moreover, the policy was enacted within five months of the oil price decline. These factors support our identification strategy, treating the safeguards as exogenous.

Grijalva et al. (2022) provide further evidence supporting this view. Based on qualitative analysis of interviews with more than 20 key public and private sector actors, they conclude that private-sector influence on trade policy in Ecuador is limited compared to other countries. Lobbying efforts are primarily directed at infrastructure and fuel subsidies rather than trade policy. They also find that trade policy between 2007 and 2017 was supply-driven, with the President playing a direct role in decision-making. The rapid enactment of the safeguards and minimal private-sector involvement further support their exogeneity. Nevertheless, to account for potential firm-level heterogeneity, in our empirical analysis, we control for economic sector, firm size, and whether a firm belongs to an economic group.

4.2. Data

Our dataset covers the period 2013–2017 and focuses on two sectors: Manufacturing and Wholesale & Retail (W&R). This time frame provides a pre-policy baseline (2013–2014) against which to assess the effects of the safeguards during their implementation (2015–2017). We analyze both sectors to compare our results with prior studies that focused exclusively on Manufacturing and to examine a sector—W&R—that plays a critical role in developing economies.[5]

The dataset integrates four primary sources of administrative records. First, we compile COMEX resolutions issued between 2015 and 2017 to reconstruct the nominal safeguard import tariffs enforced during that period. Second, we obtain transaction-level import and export data from the Central Bank of Ecuador (BCE), including 10-digit Harmonized Tariff Schedule (HTS) codes and firms' fiscal identification numbers (RUC). We also use BCE's input-output tables to construct sector-level price deflators, including a *manufacturing goods price index* based on total consumption and an *imported goods price index* based on total imported component consumption. Total consumption accounts for both intermediate and final demand in local markets.

Firms' balance-sheet data, derived from tax returns, come from the *Superintendencia de Compañías* (SuperCías). Additionally, the Transactions Annex (*Anexo Transaccional*) from Ecuador's Internal Revenue Service (SRI) for 2014 and 2015 provides firm-to-firm transaction data, allowing us to map value chains and compute industry-level technical coefficients (ISIC 4-digit classification). Information on economic groups and large corporations is also obtained from the SRI.[6]

To ensure a stable pre-policy baseline, we construct a balanced panel of firms active in both 2013 and 2014, allowing us to isolate firm entry and exit effects during the baseline period. However,

[5] The dataset is the same as in Uribe-Terán et al. (2025), except that Agriculture is excluded from this study.
[6] See Uribe-Terán et al. (2025) for a more detailed dataset description.

	Economic Sector					
	Manufacturing			Wholesale & Retail		
	Local	Importer-exporter	Total	Local	Importer-exporter	Total
2013-2014	$1,713$	$1,066$	$2,779$	$4,770$	$2,914$	$7,684$
2015	$1,535$	$1,021$	$2,556$	$4,093$	$2,731$	$6,824$
2016	$1,385$	977	$2,362$	$3,570$	$2,560$	$6,130$
2017	$1,276$	945	$2,221$	$3,226$	$2,429$	$5,655$

Table 1: Distribution of Firms by Year, Economic Sector and Trade Status This table presents the distribution of firms in our estimation sample, categorized by year, economic sector, and trade status. We build a perfectly balanced panel for 2013 and 2014, allowing for attrition in the subsequent years. Observations with negative values for sales, value added, wages, material costs, or capital were excluded. Firms are classified as importers-exporters if their imports or exports accounted for more than 5% of their total sales in 2014; those that did not meet this criterion are considered local firms.

since firm turnover is central to market diversity, we allow for attrition during the policy period. For exporting firms, we only consider sales in the domestic market.

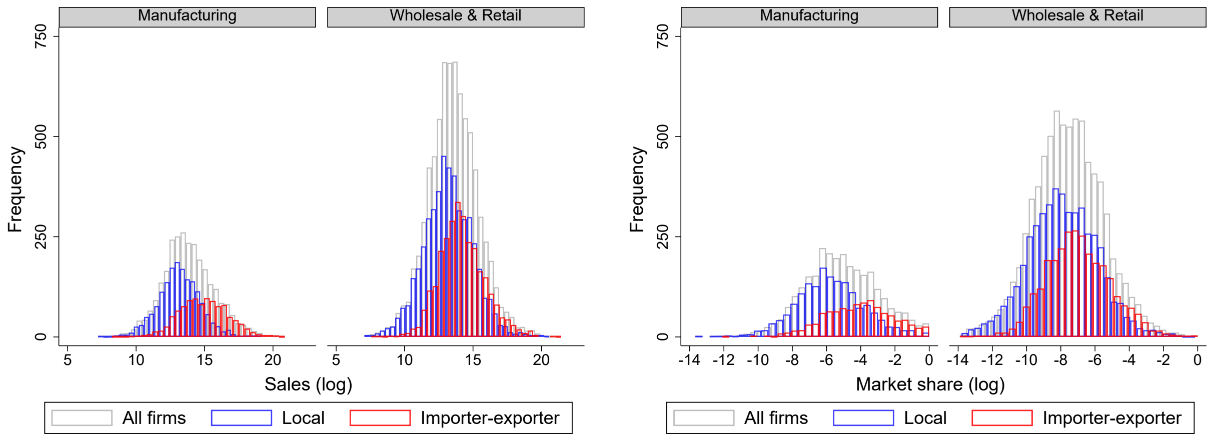
Despite relying on administrative data, some inconsistencies require cleaning. We exclude firms reporting negative sales, value added, wages, material costs, or capital. Table 1 presents the final distribution of firms by year and trade status. Our dataset includes 12,697 observations in Manufacturing, with a balanced panel of 2,556 firms per year, 2,221 of which survived by 2017. For W&R, we have 33,977 observations, with 7,684 firms per year in the balanced panel, of which 5,655 survived by 2017.

Table 1 also shows that the majority of firms operates locally, while importer-exporters represent around 40% of all firms. This distinction is crucial, as safeguard tariffs affected not only direct importers but also firms along the value chain. By including local firms, we provide a comprehensive analysis of the policy's broader economic impact.

Our identification strategy evaluates the effect of safeguard tariffs across the full distribution of firms. Figure 1 presents the revenue (Panel 1a) and market share (Panel 1b) distributions for Manufacturing and W&R firms in 2014, just before the safeguards. The full sample (light gray) is compared to local firms (blue) and importer-exporters (red). The distributions show that importer-exporters, while fewer in number, tend to have significantly higher revenues and market shares, consistent with prior findings (e.g., Muûls and Pisu, 2009).

Next, we analyze diversity. Figure 2 shows percentage changes in balanced diversity and dominance diversity between 2015 and 2017, relative to 2014. Both measures indicate a significant decline, particularly in W&R, where diversity drops by nearly 30%. In Manufacturing, diversity also falls, but only by about 10-15%, with dominance diversity even increasing slightly in 2015. The larger decline in balanced diversity for Manufacturing and dominance diversity for W&R suggests differences in the mechanisms driving concentration.

Figure 3 provides further evidence of the determinants of diversity by tracking market shares and firm counts over time. Market shares rise in both sectors, but the increase is more pronounced



(a) Revenue **(b)** Market share

Figure 1: Pre-policy Distributions of Revenue and Market Share by Economic Sector and Trade Status This figure presents the distributions of revenue (Panel 1a) and market share (Panel 1b) in logarithms for the year 2014, categorized by economic sector—Manufacturing and W&R. We show the distributions for all firms (gray), local firms (blue), and importer-exporter firms (red). Market shares are calculated for firms within each ISIC 4-digit level. For clarity, in the figures we have excluded the bottom and top 5% of firms in the distributions. All firms are included in the estimations.

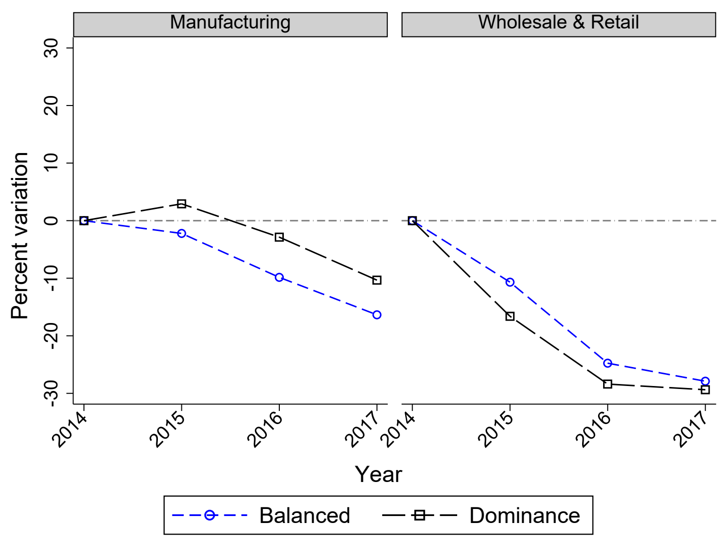


Figure 2: Evolution of industry diversity by economic sector. This figure shows the evolution of diversity within economic sectors. We present the percentage changes in aggregate diversity measures for each year from 2015 to 2017, using 2014 as the baseline. The diversity measures are calculated following the methodology of Ahern et al. (2024). In both cases, the averages are weighted by sales to emphasize the impact of larger firms. Industries are defined at the four-digit level of the ISIC-v4 codes.

in W&R, exceeding 25%. Meanwhile, firm counts decline in both sectors, with W&R experiencing a nearly 30% drop. These trends align with the diversity measures and highlight sectoral differences in how market structure evolved in response to the introduction of the safeguards.

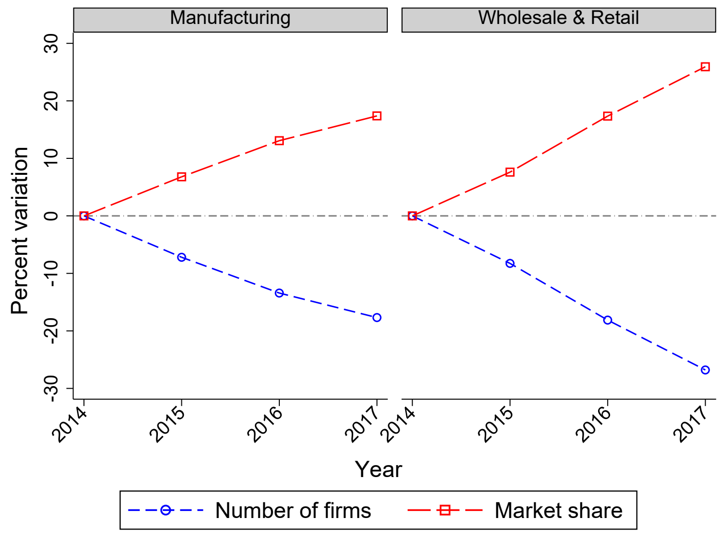


Figure 3: Evolution of market shares and firm count by economic sector. This figure illustrates the evolution of market shares and the number of firms across economic sectors over time. We present the percentage changes in these aggregates for each year relative to 2014. Market shares and firm counts are calculated within each industry, categorized according to the four-digit level of the ISIC-V4 codes.

5. Identification Strategy

We now turn to our identification strategy. We first define industry- and firm-level exposure to safeguard import tariffs, ensuring that these measures are exogenous. We then present three models to estimate the effects of the policy: i) a quantile treatment effects estimator for revenue and market share distributions, ii) a probit model for firm exit probabilities, and iii) a two-way fixed-effects estimator for pass-through effects on prices.

5.1. Measures of Safeguard Exposure

Our identification approach constructs exogenous treatment variables that capture different channels through which import restrictions affect market competition. Following Corden (1971); Amiti and Konings (2007a); Handley et al. (2020b); Uribe-Terán et al. (2025), we define two industry-level measures of *potential* exposure and one firm-level measure of *direct* output exposure.

First, safeguard import tariffs *protect* domestic production from import competition. We measure this effect with industry-level *cumulative output exposure* ($\tau^p_{j,t}$) for industry j at time t:

$$\tau^p_{j,t} = \frac{1}{(t-2014)M_{j,0}} \sum_{s=2015}^{t} \sum_{m=1}^{12} \sum_{\ell=1}^{I_{j,m,0}} \tau_{\ell,m,s} M_{\ell,j,m,0}, \tag{3}$$

where $M_{j,0}$ represents total industry imports in 2014 (pre-policy), $\tau_{\ell,m,s}$ is the safeguard tariff on product ℓ, and $M_{\ell,j,m,0}$ denotes imports of good ℓ by industry j in month m. Aggregating these tariffs over time normalizes exposure by pre-policy imports, eliminating potential endogeneity.

Second, tariffs raise production costs by increasing input prices. We capture this through *cumulative input exposure* ($\tau^x_{j,t}$), which accounts for indirect exposure via upstream purchases:

$$\tau^x_{j,t} = \sum_k \omega_{j,k,0} \cdot \tau^p_{k,t}, \tag{4}$$

where $\omega_{j,k,0}$ is the share of purchases by industry j from industry k, using 2014 data to avoid contamination from endogenous firm responses.

Finally, for importing firms, we define firm-level *direct output exposure* ($\tau^d_{i,j,t}$) as:

$$\tau^d_{i,j,t} = \frac{1}{(t-2014)M_{i,j,0}} \sum_{s=2015}^{t} \sum_{m=1}^{12} \sum_{\ell=1}^{I_{i,j,m,0}} \tau_{\ell,m,s} M_{\ell,i,j,m,0}, \tag{5}$$

analogous to equation (3), but at the firm level. This measure applies only to firms with positive imports.

Our industry-level measures assume firms operate within single industries; but multi-product firms could be misclassified. Although we lack direct product-level data, analysis of firms' export behavior (Appendix Table 4) suggests that most firms in our sample specialize in a single product, mitigating this concern.

5.2. Quantile Treatment Effects on the Treated (QTT)

Ideally, we would estimate industry-level difference-in-differences (DiD) regressions using diversity measures as dependent variables. However, aggregating at the industry level severely reduces statistical power, particularly in a small economy like Ecuador. Instead, following Davies and Geroski (1997) and Kambhampati and Kattuman (2009), we link industry-level diversity to firm-level outcomes. Rather than focusing on overall diversity, we estimate causal effects on its components, *evenness* (market share distribution) and *richness* (number of firms).

Market share effects require analyzing the entire distribution, as an average treatment effect (ATE) alone is uninformative about whether small or large firms are most affected. We employ the *Quantile Treatment Effect on the Treated* (QTT) estimator from Callaway and Li (2019), which estimates:

$$QTT(q) = F^{-1}_{Y_{1,t}|D=1}(q) - F^{-1}_{Y_{0,t}|D=1}(q), \tag{6}$$

where $F^{-1}_{Y_{1,t}|D=1}(q)$ is the empirical quantile of outcome Y for treated firms, and $F^{-1}_{Y_{0,t}|D=1}(q)$ is the counterfactual.

Since counterfactual distributions are unobservable, we rely on two assumptions from Callaway and Li (2019): the *Conditional Distributional Difference-in-Differences Assumption* (analogous to parallel trends) and the *Copula Stability Assumption*, which requires that the dependence structure between pre-policy and post-policy market shares remains stable. The latter assumption necessitates at least three time periods for identification.

Given that our exposure measures are continuous, we construct binary treatment variables based on quantiles of the exposure distributions:

$$\hat{\tau}^{\iota}_{j,t} = \mathbf{1}\left[\tau^{\iota}_{j,t} > F^{-1}_{\iota,t}(q)\right].$$

where $\iota = \{p, x\}$ and $F^{-1}_{\iota,t}(q)$ is the q-quantile of exposure.

5.3. Firm Exit: Probit Difference-in-Differences

To assess how tariffs affect firm survival, we estimate a probit model of firm exit:

$$d_{i,j,t} = \Phi(\theta_t + \boldsymbol{\beta}_t \boldsymbol{\tau}_{i,j,t} + \boldsymbol{\nu}_t \mathbf{X}_{i,j,0} + \epsilon_{i,j,t}), \tag{7}$$

where $d_{i,j,t} = 1$ if firm i in industry j exits in period t, and $\mathbf{X}_{i,j,0}$ contains pre-policy controls. Because we track a balanced panel, our analysis focuses only on firm exits, not entries. Exposure effects vary by firm type.[7] We use our continuous exposure measures in this specification.

5.4. Two-Way Fixed-Effects Estimator for Price Pass-Through

Finally, we estimate a two-way fixed-effects model to examine whether safeguard import tariffs are passed on to consumers through higher prices, following Uribe-Terán et al. (2025). The model accounts for firm-level, industry-level, and sector-level exposure:

$$\frac{\Delta z_{s,t}}{z_{s,0}} = \alpha_t + \beta_t\, \tau^{d}_{i,j,s,t} + \theta_t\, \tau^{x}_{j,s,t} + \boldsymbol{\gamma}_t\, \mathbf{X}_{i,j,s,0} + \varepsilon_{i,j,s,t}, \tag{8}$$

where $z_{s,t}$ is the sector-level price index, replicated for all firms in sector s to exploit firm-level variation in tariff exposure. The term $\tau^{d}_{i,j,s,t}$ captures firm-level direct tariff exposure, while $\tau^{x}_{j,s,t}$ represents industry-level input exposure. The vector $\mathbf{X}_{i,j,s,0}$ contains firm-level pre-policy controls.

We limit the sample to importer-exporters, as they are most likely to experience—and potentially pass on—cost increases from the tariffs. By linking firm-level, industry-level, and sector-level exposures to price indexes, this specification provides a comprehensive view of how tariff shocks propagate through the economy.

6. Results

In this section, we present the results of the estimations discussed in Section 5. Our analysis examines how safeguard import tariffs affect revenue distribution, market shares, firm exit probability, and aggregate market diversity in the Manufacturing and W&R sectors. We also assess whether firms' market power influences the pass-through of tariffs to prices. The results suggest

[7] Importer-exporters experience both direct and value chain exposure, while local firms are affected only through their value chains. Manufacturing firms may experience both protection and higher input costs, whereas W&R firms are primarily affected by input costs.

that direct tariff exposure drove price increases in Manufacturing. In W&R, price effects were primarily linked to supply chain adjustments, and they decreased over time.

6.1. Quantile Treatment Effects

To estimate the Quantile Treatment Effects, we partition our sample into various sub-samples. This step is essential for accurately identifying the relevant markets and ensuring that our estimation strategy, which relies on propensity score matching, is applied to homogeneous groups.

We begin by dividing the sample into two economic sectors: Manufacturing and W&R. These sectors differ significantly in firm composition. The Manufacturing sector primarily consists of importer-exporters and local firms in import-competing industries, which tend to be more productive. In contrast, firms in W&R are mainly importers and local firms operating in non-import-competing industries, typically exhibiting lower average productivity (Uribe-Terán et al., 2025).

Within each sector, we further classify firms into two groups: importer-exporters and local firms. The first group includes firms that imported in 2014, regardless of whether they also exported. The second group comprises firms that did not engage in importing or exporting activities in 2014, irrespective of whether they operated in import-competing or non-import-competing industries.

For these four groups, we use the following covariates to perform propensity score matching: labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects at the ISIC 2-digit level, and dummy variables for firm size based on revenue categories in the CAN classification. All control variables are fixed at the baseline. To ensure the quality of the matched sample, we assess balance following Rubin (2001).[8] We first present results for importer-exporter firms and then examine the outcomes for local firms.

6.1.1. Effects on Importer-Exporters

Following the insights of Uribe-Terán et al. (2025), based on Corden (1966, 1971) and Amiti and Konings (2007b), importer-exporter firms can be affected by trade policy through two different channels: directly, and indirectly through the value chain if they source their inputs locally from other importing firms (input exposure). However, Uribe-Terán et al. (2025) show that importer-exporters' performance is not significantly affected by input exposure, and that the entire effect stems from direct exposure. Moreover, the QTT methodology only allows us to consider one treatment at a time. Taking both factors into consideration, we focus solely on direct exposure.

Figure 4 presents the results on revenues and market shares of importer-exporters in the Manufacturing sector for 2015-2017, while Figure 5 does the same for firms in the W&R sector. Our estimations show that there are no significant effects of safeguard import tariffs on the distribution of revenues and market shares for the Manufacturing sector over the three years that the policy was in place.

[8] See Appendix C for a detailed explanation of the propensity score testing.

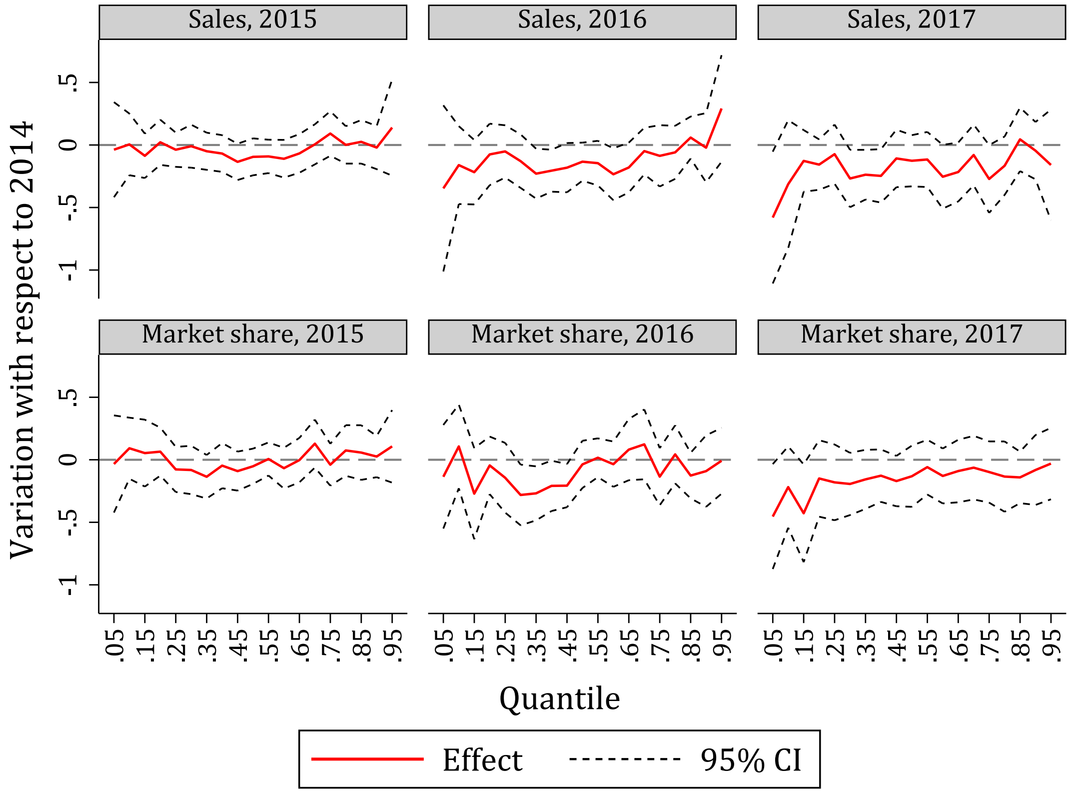


Figure 4: Effects of Direct Exposure to Safeguards of Importer-exporters in Manufacturing This figure shows the estimated effects of direct exposure to safeguard import tariffs on sales (revenue) and market shares for importer-exporter firms in the manufacturing sector. Because the outcome variables are measured in logarithms, the coefficients correspond to percentage variations. The values correspond to the estimation of equation (6) across 20 quantiles. We estimate the propensity scores following Firpo (2007), conditioning on labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects (ISIC 2-digit level), and dummy variables that identify firms' size in terms of sales according to the CAN classification. All control variables are fixed at baseline. Standard errors are estimated using bootstrap with 100 replications. The dashed lines represent 95% confidence intervals.

In contrast, there are significant effects in the W&R sector, and these effects are not uniformly distributed across the firms' distribution, confirming the relevance of our estimation approach. First, small firms in the W&R sector are negatively affected, while large firms are not. In 2015, firms located in quantiles 5 to 35 experience significant reductions in revenue, ranging from approximately 16% at quantile 5 to 14% at quantile 35. The effect is accentuated in 2016, when it becomes significant up to quantile 45, ranging from a 20% decline at quantile 5 to a 10.4% decline at quantile 45. As shown in Figure 5, however, these effects are not monotonic. The most pronounced negative effect occurs at quantile 15, with a revenue reduction of 31%. The effects on firms up to quantile 40 persist and remain significant even in 2017. In that year, the negative effect for firms located at the lower end of the distribution is about 30% on average, while for firms in quantiles 25 to 40, the effects hover around 15%.

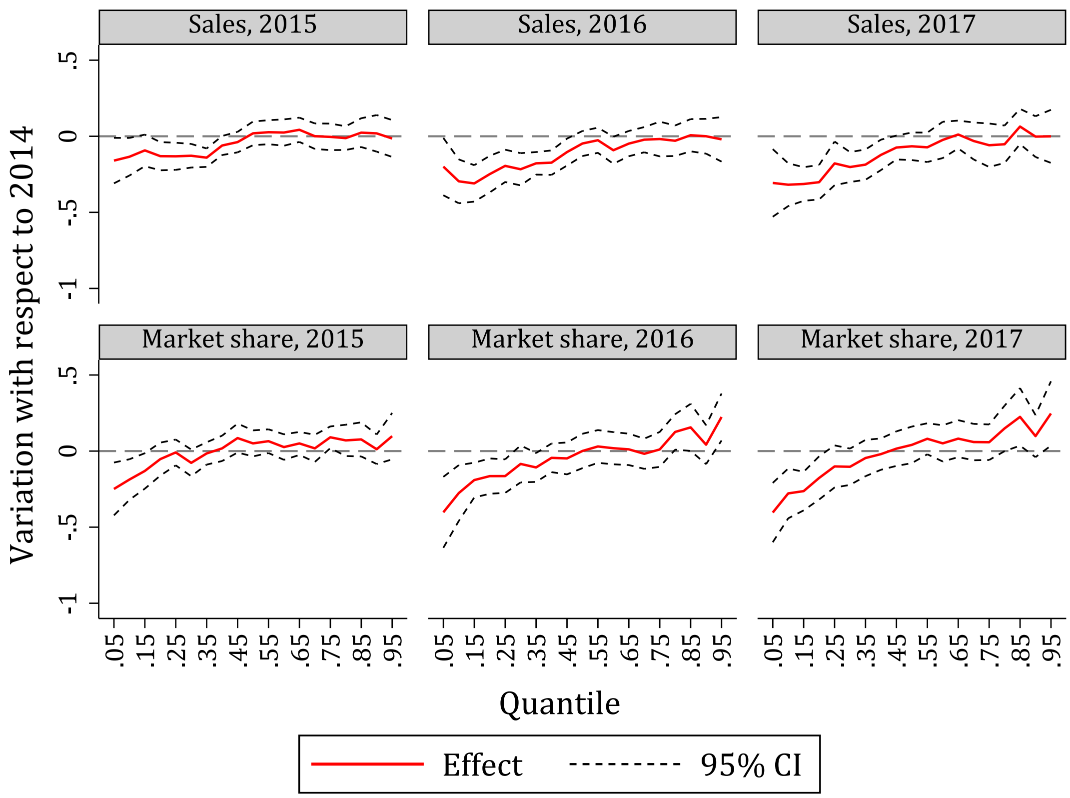


Figure 5: Effects of Direct Exposure to Safeguards of Importer-exporters in Wholesale & Retail
This figure shows the estimated effects of direct exposure to safeguard import tariffs on sales (revenue) and market shares for importer-exporter firms in wholesale & retail. Because the outcome variables are measured in logarithms, the coefficients correspond to percentage variations. The values correspond to the estimation of equation (6) across 20 quantiles. We estimate the propensity scores following Firpo (2007), conditioning on labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects (ISIC 2-digit level), and dummy variables that identify firms' size in terms of sales according to the CAN classification. All control variables are fixed at baseline. Standard errors are estimated using bootstrap with 100 replications. The dashed lines represent 95% confidence intervals.

These shifts in firms' revenue affect the distribution of market shares. In general, we find that revenue reductions imply that small firms lose market participation, while larger firms' market shares remain unchanged relative to the baseline. In 2015, the negative effects on market shares are concentrated at the lower end of the distribution, with contractions ranging from 24.9% at quantile 5 to 13.1% at quantile 15. The effects are stronger in 2016; the market share for firms in quantile 5 falls by 40.3%, and the effects remain significant up to quantile 35, which registers a 10.7% reduction in market share.

Consistent with the effect on revenue, the impact on market share appears to be temporary for quantiles near the median. By 2017, significant losses in market shares are found only in quantiles 5 to 20, ranging from 40.4% to 17.7%. Interestingly, in this year, firms that already held a large fraction of the market at baseline experience significant gains in market share. Specifically, firms located in quantiles 85 to 95 register increases of about 23% on average.

These results suggest that small importer-exporter firms in Manufacturing exhibit greater resilience than their counterparts in the W&R sector. This difference may stem from Manufacturing firms' higher productivity and stronger market positions. Additionally, firms in this sector may have been better able to adjust prices to accommodate cost increases, mitigating the impact of safeguard tariffs on their revenues and market shares.

In contrast, small firms in W&R face greater challenges. The competitive nature of this sector limits their ability to pass cost increases onto consumers, making them more vulnerable to negative revenue shocks. As a result, the negative scale effect reported by Uribe-Terán et al. (2025) appears to be concentrated among smaller firms. The reduction in revenue leads to significant declines in their market participation, and by 2017, this decline translates into a redistribution of market shares, with larger firms capturing a greater share of the market. Consequently, market concentration increases, particularly by 2017, as the competitive pressures in the sector drive further consolidation.

6.1.2. Effects on Local Firms

Safeguard import tariffs impact outcomes through different channels depending on whether firms are in the Manufacturing or W&R sectors. Local firms in Manufacturing may belong to import-competing or non-import-competing industries. Import-competing industries are *protected* by safeguard import tariffs, whereas non-import-competing industries are mainly affected by tariffs through their effect on the value chain. In contrast, there are no import-competing industries within W&R, and thus, all the effects on local firms in this sector occur through the value chain (input exposure) (Uribe-Terán et al., 2025).

We find no significant effects on local manufacturing firms through output exposure.[9] Therefore, we focus on the input exposure effects on local firms in both sectors. Figure 6 presents the results for Manufacturing, and Figure 7 for W&R. Negative effects on the revenue of small firms are present in both sectors, although for W&R the effects are more pronounced and affect a larger portion of the distribution.

In 2015, the effect on revenue in the Manufacturing sector was not significant. However, by 2016, the revenue reduction affected firms located in the lower tail of the distribution up to percentile 35. At quantile 5, the revenue reduction is 76.6%, decreasing to 39.9% for firms at quantile 10. The magnitude of the effect then reduces monotonically, reaching a contraction of 23.3% at quantile 35.

By 2017, the revenue reduction for firms at quantile 5 is 94.4%, followed by a 46.0% contraction for firms at quantile 10, and a reduction of 28.6% at quantile 35. Hence, the effects become stronger in the last year of the policy. During this year, larger firms experience an increase in their revenue: firms at quantile 85 increase it by 28.7%, firms at quantile 90 by 42.1%, and firms at quantile 95 by 76.4%.

Turning to the effect on market share, as expected given the results on revenue in 2015, there are no effects on the distribution of market shares in the Manufacturing sector in this year. By 2016,

[9] These results are presented in Figure 11 in the Appendix.

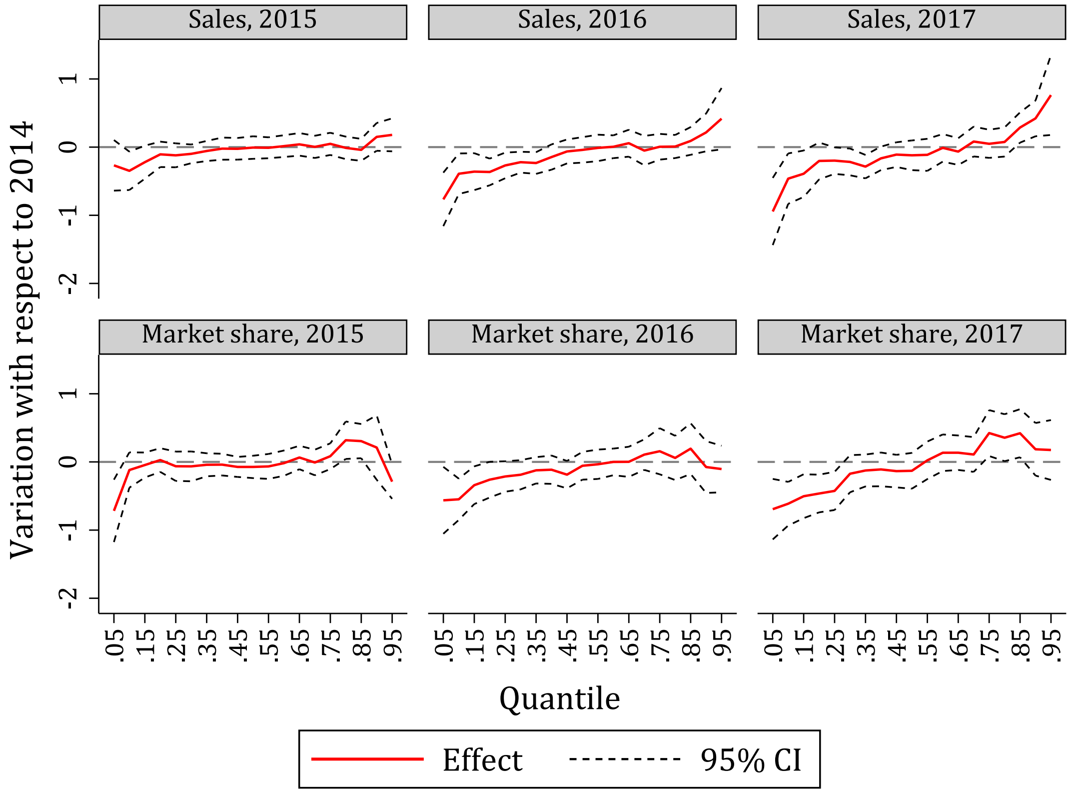


Figure 6: Effects of Input Exposure to Safeguards of Local Firms in Manufacturing This figure shows the estimated effects of input exposure to safeguard import tariffs on sales (revenue) and market shares for local firms in Manufacturing. Because the outcome variables are measured in logarithms, the coefficients correspond to percentage variations. The values correspond to the estimation of equation (6) across 20 quantiles. We estimate the propensity scores following Firpo (2007), conditioning on labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects (ISIC 2-digit level), and dummy variables that identify firms' size in terms of sales according to the CAN classification. All control variables are fixed at baseline. Standard errors are estimated using bootstrap with 100 replications. The dashed lines represent 95% confidence intervals.

however, we observe significant results: quantiles 5 to 15 experience a reduction in market shares, ranging from 56.3% at quantile 5 to 34.1% at quantile 15. In 2017, the negative effect extends up to quantile 25 and becomes stronger for quantiles 5 to 15, now ranging from a 69.3% to a 50.3% reduction. The revenue contraction at quantile 25 is 42.5%. Interestingly, the increase in revenue among larger firms translates into significant gains in market shares only for quantiles 75 to 85, where the increase in market shares ranges from 35.5% to 42.4%.

Consider next the effects on W&R. Revenue contraction is much more generalized for firms in this sector. In 2015, the fall in revenue affects quantiles 5 to 45, with reductions ranging from 28.3% to 10.2%. The effect becomes stronger in 2016, affecting quantiles 5 to 55, and even showing significant reductions for quantiles 75 and 80. This year the reduction in revenue goes from 43.1% to 9.5%. By 2017, the effect is present at quantiles 5 to 70, with revenue reductions varying between 42.6% and 11.9%.

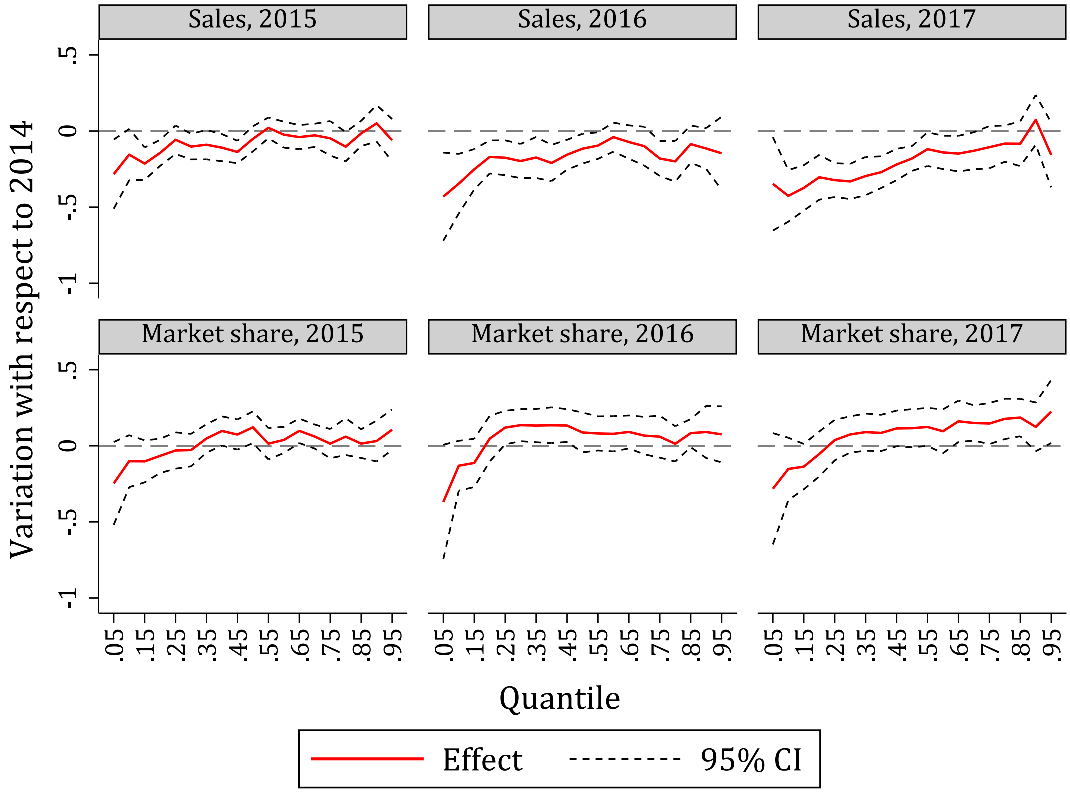


Figure 7: Effects of Input Exposure to Safeguards of Local Firms in Wholesale & Retail This figure shows the estimated effects of input exposure to safeguard import tariffs on sales (revenue) and market shares for local firms in Wholesale & Retail. Because the outcome variables are measured in logarithms, the coefficients correspond to percentage variations. The values correspond to the estimation of (6) across 20 quantiles. We estimate the propensity scores following Firpo (2007), conditioning on labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects (ISIC 2-digit level), and dummy variables that identify firms' size in terms of sales according to the CAN classification. All control variables are fixed at baseline. Standard errors are estimated using bootstrap with 100 replications. The dashed lines represent 95% confidence intervals.

Turning to market shares in W&R, in 2015 there are no significant effects. Interestingly, by 2016, the reduction in revenue does not affect market shares at the extremes of the distribution. On the contrary, we observe a significant increase in market shares for firms located at quantiles 30 to 45, with increases ranging from 12.0% to 13.5%. By 2017, this increase in market shares shifts to the right end of the distribution and there are significant increases in market shares between quantiles 65 and 95, ranging from 14.7% to 22.5%.

The heterogeneity in the results provides interesting insights about the effect of safeguards on the firms' distribution of revenue and market share. First, the impact of safeguards through input exposure is much more harmful than its direct effects. The mechanism for this result is documented in Uribe-Terán et al. (2025). Specifically, large importers see an increase in their market power, and thus are able to pass through the additional costs to their customers. Not all customers can bear this increase in production costs, so smaller producers reduce their scale. The effects are smaller among Manufacturing firms and are not entirely present during the first year of policy implementation.

As time goes by, however, the effect strengthens and affects almost all the less resilient retailers. These smaller firms, both in the Manufacturing and W&R sectors, reduce their scales, leading to a shift in market shares. However, while in Manufacturing the smaller firms are the ones that lose market participation, in W&R it is the larger firms that manage to capture the market lost by smaller competitors.

6.2. Effects on Firms' Exit Probability

We now estimate the impact of safeguard import tariffs on firms' exit probability by applying equation (7) to importer-exporters and local firms in the Manufacturing and W&R sectors. For importer-exporters, we include both direct and input exposure as treatments.[10] For local firms, we include both input and output exposure in Manufacturing, while in W&R, we consider only input exposure. The estimates are presented in Table 2.

Uribe-Terán et al. (2025) conducted a similar analysis focusing exclusively on direct and input effects for importer-exporters. They found no significant impact of direct exposure on exit probability but observed a significant effect of input exposure, particularly from 2017 to 2019.

A potential explanation for these findings is that, while direct exposure primarily affects firm performance, input exposure gradually increases the likelihood of exit due to the cumulative effects of sustained tariffs. As tariffs persist, firms may struggle to continue passing increased costs to consumers. Higher prices can lead to reduced demand or push consumers toward competitors sourcing inputs differently. This results in margin compression, forcing firms to either absorb higher costs or accept declining revenues. Initially, firms may rely on inventories, financial reserves, or short-term strategies to mitigate cost increases. However, as these buffers deplete, rising input costs begin to erode profitability, potentially driving weaker firms out of the market (Uribe-Terán et al., 2025).

Our findings confirm this pattern when analyzing importer-exporters within economic sectors. However, in Manufacturing, the peak increase in exit probability occurs in 2016 rather than 2017. Specifically, a 1% increase in input exposure is associated with a 0.96% higher probability of exit. In W&R, our results align with Uribe-Terán et al. (2025), with a significant effect emerging in 2017, where a 1% increase in input exposure raises the probability of exit by 0.75%. We find no significant effects for local firms.

These results suggest that importer-exporters are more vulnerable to input exposure in terms of market exit risk. The earlier peak in Manufacturing implies that firms in this sector may have faced immediate pressure from rising input costs, while retailers were able to delay the impact until

[10] Unlike our approach in estimating Quantile Treatment Effects (QTE), we include both direct and input exposure for importer-exporters in this model. While this may seem inconsistent, Uribe-Terán et al. (2025) show that although input exposure does not significantly affect firm performance, it does explain increases in exit probability from 2017 onward. Based on these findings, we incorporate both types of exposure into our exit probability estimation for importer-exporters.

	Change in outcomes between t and 2014								
	Direct Exposure			**Input exposure**			**Output exposure**		
	2015	**2016**	**2017**	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
				Panel A: Manufacturing					
Panel A.1: Importer-exporters									
Marginal Effect	−0.040	−0.001	0.061	0.372	0.963 **	0.645			
	(0.118)	(0.116)	(0.114)	(0.307)	(0.424)	(0.514)			
Mean	0.042	0.083	0.114	0.042	0.083	0.114			
Observations	1066	1066	1066	1066	1066	1066			
Panel A.2: Locals									
Marginal Effect				0.097	−0.032	0.421	0.071	−0.043	−0.075
				(0.242)	(0.438)	(0.502)	(0.067)	(0.094)	(0.117)
Mean				0.104	0.191	0.255	0.104	0.191	0.255
Observations				1713	1713	1713	1713	1713	1713
				Panel B: Wholesale and Retail					
Panel B.1: Importer-exporters									
Marginal Effect	−0.007	0.048	0.035	0.328	0.416	0.750 **			
	(0.027)	(0.032)	(0.045)	(0.229)	(0.315)	(0.361)			
Mean	0.063	0.121	0.166	0.063	0.121	0.166			
Observations	2914	2914	2914	2914	2914	2914			
Panel B.2: Locals									
Marginal Effect				0.113	0.435	0.626			
				(0.195)	(0.293)	(0.404)			
Mean				0.142	0.252	0.324			
Observations				4770	4770	4770			

Table 2: Effects of Safeguard Import Tariffs on Firms' Exit Probability This table presents the marginal effects of safeguard import tariffs on firms' exit probabilities, categorized by economic sector and trade status. Panel A displays the estimations for firms in the Manufacturing sector, while Panel B shows the estimations for firms in Wholesale & Retail. Within each panel, subpanels (1) present estimations for importer-exporters, and subpanels (2) for local firms. If more than one exposure measure is shown, it indicates that the estimation equation included all relevant measures simultaneously. The estimations are conditioned on labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects (ISIC 2-digit level), and dummy variables identifying firms' size based on sales according to the CAN classification. All control variables are fixed at baseline. Standard errors are estimated using the delta method.

2017. The lack of significant effects for local firms suggests that businesses not directly engaged in importing were less affected by safeguard import tariffs in terms of exit probability.

6.3. Overall Effect on Market Diversity

Our results thus far indicate significant revenue declines among small firms and increased exit probabilities, particularly for importer-exporters. Both findings suggest a reduction in market diversity due to safeguard import tariffs. However, translating these effects into variations in diversity is not straightforward. To address this, we follow Ahern et al. (2024) and Athey and Imbens (2006) by constructing counterfactual revenue distributions based on our estimates, leveraging the Copula Stability Assumption from our identification strategy.

Formally, let $y^{qtt}_{i,t}(q)$ denote firm i's counterfactual revenue at time t, where i belongs to quantile q of the baseline revenue distribution. Given the quantile treatment effect $\Delta^{qtt}y_t(q)$ from equation (6), counterfactual revenue under treatment is:

$$y^{qtt}_{i,t}(q) = y_{i,0}(q) + \Delta^{qtt}y_t(q), \tag{9}$$

where $y_{i,0}(q)$ represents firm i's revenue in the baseline year, 2014. With $\Delta^{qtt}y_t(q)$ estimated, we compute counterfactual market shares and apply equations (1) and (2) to derive balanced and dominance diversity indices.

Equation (9) captures all causal effects relevant to a firm. For a treated local firm in Manufacturing, this includes both input and output exposure. However, exposure can have opposing effects depending on firm type. Direct exposure negatively impacts importer revenues, while output exposure benefits producers of import-competing goods. Therefore, our diversity estimates reflect the *net* impact of safeguard tariffs.

Figure 8 presents deviations in balanced diversity from 2014 levels. Each point represents an industry (ISIC 4-digit aggregation), with vertical lines indicating 95% confidence intervals estimated via bootstrapping. The results show a widespread decline in market diversity. In Manufacturing, the negative effect is significant for fewer than 25 of 125 industries in 2015, but it expands to more than half by 2016. In W&R, nearly all industries experience a significant decline from the outset. By 2017, the magnitude of these effects intensifies, although a few Manufacturing industries exhibit increases in diversity.

While many distributional estimates are individually insignificant, the aggregation of results reveals a significant decline in overall market diversity. This occurs because most distributional effects—–though not always significant—–consistently indicate revenue losses for smaller firms. When aggregated, these effects translate into a systematic reduction in diversity.

These findings suggest that safeguard import tariffs contribute to a less competitive environment by disproportionately harming smaller firms. The resulting decline in diversity implies increased market concentration, which could reduce innovation and raise consumer prices.

As discussed in Section 2, balanced diversity reflects both the number of firms and the distribution of market shares. Given the significant exit probability effects, balanced diversity is the more appropriate measure for our analysis. To assess robustness, we compare changes in balanced and dominance diversity. Figure 9 illustrates this relationship, showing a strong correlation between the two measures. However, dominance diversity estimates tend to lie above the 45-degree line, implying that it overstates positive effects and understates diversity losses.

This discrepancy arises because dominance diversity does not account for firm exits, focusing only on the distribution of market shares among surviving firms. Consequently, it may underestimate the true decline in diversity. Balanced diversity, by incorporating both firm exits and market share concentration, provides a more comprehensive measure of changes in market structure.

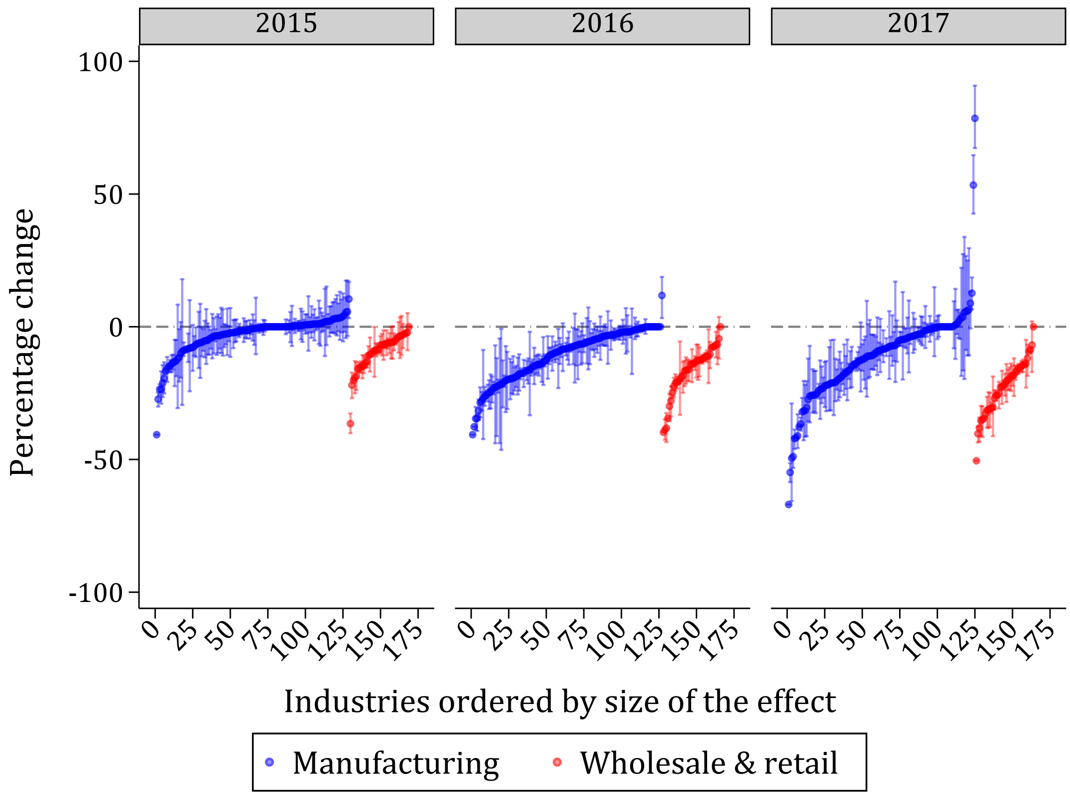


Figure 8: Effects of Safeguards on Market Diversity This figure shows the distribution of the causal effects of safeguard import tariffs on industry-level balanced diversity, with industries ordered by the magnitude of the effect and grouped by economic sector. To estimate these effects, we start with the firm-level revenue distribution at baseline and then incorporate the effects triggered by direct, input, and output exposure to safeguards. This estimation is conditional on economic sector, trade status, and whether the firm was affected by each type of exposure. Dots represent the point estimates, and vertical lines represent 95% confidence intervals. Standard errors are estimated using bootstrap with 100 replications. For presentation purposes, we have excluded percentage variations that exceed 100%; however, there is only one industry in the Wholesale & Retail sector that shows a variation higher than 100% in 2017.

6.4. Pass-Through Effects on Prices

We focus on importer-exporters, as they are the firms directly affected by the safeguards. To measure the extent of pass-through, we construct two price indices that reflect the pricing behavior of firms in the Manufacturing and W&R sectors. These indices capture how firms interact with local and international markets and respond to tariff-induced cost changes.

For the Manufacturing sector, we assume firms produce goods using both domestic and imported inputs, with imported goods serving exclusively as production inputs rather than being sold directly in local markets. Once manufactured, these goods are sold to firms or households. Based on this structure, we develop a *manufacturing price index*, representing the average price at which firms in industry k within sector s sell to customers up in the value chain.

This index is built using input-output data on total consumption of manufactured goods, measured in both current and constant prices. Firm-level balance sheet data, classified by four-digit

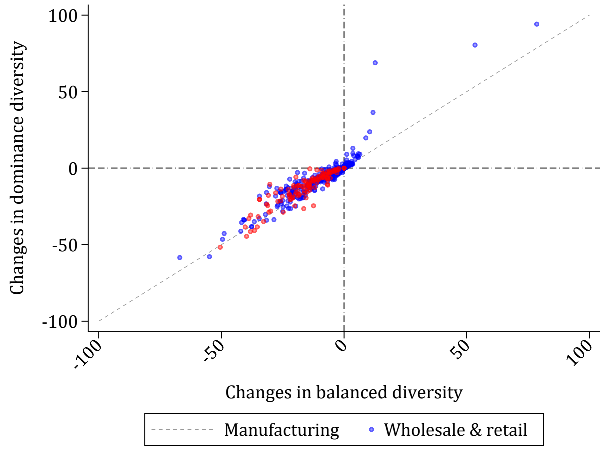


Figure 9: Correlation between Effects on Alternative Diversity Measures This figure shows the correlation between the effects on diversity measured using dominance diversity and balanced diversity, with data pooled across all years (2015 to 2017). Each dot represents a point estimate for an industry, and the diagonal line represents the 45-degree line of perfect equality between the two measures. For clarity, we have excluded percentage variations that exceed 100%; however, only one industry in the Wholesale & Retail sector shows a variation higher than 100% in 2017.

ISIC codes, are linked to aggregate input-output tables based on CPC codes. Consequently, the outcome variable varies only at the sector level, while the treatment variables, direct and input exposure, depend on firm- and industry-level differences. Formally, let p^l_s denote the price index of manufactured goods for sector s:

$$p^l_{s,t} = \frac{y_{s,t}}{y_{s,0}},$$

where $y_{s,t}$ represents total sales in sector s at time t, and $t = 0$ marks the base year.

In contrast, analyzing pass-through in W&R requires a different approach, as ISIC codes do not directly match with CPC codes used for manufacturing. W&R firms act as intermediaries rather than producers, reselling imported goods to local firms or households. To capture this, we construct a *firm-level imported goods price index*, based on each firm's unique basket of imported goods, identified at the 10-digit HTS code level and mapped to input-output data via an HTS-CPC linkage.

Because firms' imported goods may belong to multiple economic sectors, we construct firm-specific price indices by weighting sectoral price deflators from the input-output table according to the share of each HTS code in a firm's total imports. Unlike the manufacturing price index, which is uniform across firms in the same sector, this imported goods price index varies at the firm level, reflecting differences in import composition. Additionally, since these indices are derived from input-output tables, they measure local market prices for imported goods rather than the international purchase prices paid by firms. Formally, we compute:

$$p^m_{s,j,t} = \sum_{\ell=1}^{I_{j,t}} m_{\ell,s,j,t} \frac{y^m_{s,t}}{y^m_{s,0}},$$

where $I_{j,t}$ is the number of imported goods firm j purchases at time t, $m_{\ell,s,j,t}$ is the share of good ℓ in firm j's total imports within sector s, and $y^m_{s,t}$ represents total local market sales of imported goods from sector s at time t.

We expect the pass-through effect to materialize primarily through input exposure in both sectors. Firms with market power can raise markups in response to higher costs induced by tariffs. Since input exposure reflects these increased costs, firms more reliant on affected inputs face greater cost growth. If they hold sufficient market power, they can pass on these additional costs to customers through higher prices.

	Effect on Prices of Imported Components					
	Manufacture			**Wholesale & Retail**		
	2015	**2016**	**2017**	**2015**	**2016**	**2017**
Panel A: Direct Exposure						
Merginal Effect	0.008	0.016	0.170	0.026	0.034	0.011
	(0.029)	(0.051)	(0.129)	(0.022)	(0.057)	(0.050)
Panel B: Input Exposure						
Merginal Effect	0.810 **	0.645	−2.146	0.474 **	0.567 *	−0.401
	(0.317)	(1.005)	(3.168)	(0.211)	(0.276)	(0.497)

Table 3: Effects of Safeguards on Prices This table presents the marginal effects of safeguard import tariffs on inflation in the Manufacturing and Wholesale & Retail sectors. Panel A reports estimates for the impact of firms' direct exposure to safeguard tariffs, while Panel B examines the effects transmitted through the value chain. The regressions control for labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects at the ISIC 2-digit level, and firm size dummies based on sales following the CAN classification. All control variables are fixed at baseline. Standard errors are clustered at the ISIC 3-digit level.

Table 3 presents our results. Columns (1) to (3) report estimates for Manufacturing from 2015 to 2017, while columns (4) to (6) show results for W&R. Panel A reports the effects of direct exposure, and Panel B shows the impact of input exposure. Our findings indicate significant price effects in both sectors, but only in 2015. A 1% increase in input exposure raised inflation by 0.81% in Manufacturing and 0.47% in W&R. However, this effect disappeared by 2016 and turned negative——though not statistically significant——by 2017.

This pattern suggests that in the first year of tariff implementation, firms with market power exploited the inelasticity of short-run demand to increase prices. Consumers and firms purchasing imported goods or inputs had limited immediate substitutes, enabling cost pass-through. However, as shown by Uribe-Terán et al. (2025), importer sales declined sharply in 2016 and 2017, suggesting that demand eventually adjusted. Over time, buyers likely substituted away from higher-priced imports, eroding firms' ability to pass costs onto consumers, thereby eliminating the pass-through effect in later years.

7. Robustness

Our identification strategy at the distributional level relies on two key assumptions: the Conditional Distributional Difference-in-Differences Assumption and the Copula Stability Assumption (Callaway and Li, 2019). While the former is standard in difference-in-differences (DiD) estimations, the latter imposes a potentially strong restriction on the data-generating process. In simple terms, the Copula Stability Assumption requires that treatment does not alter the ranking of affected units. In this section, we assess the influence of these assumptions on our results by modifying our modeling strategy and adopting alternative estimation approaches.

First, we employ the Changes-in-Changes (CIC) framework introduced by Athey and Imbens (2006). Unlike the QTT estimator, which requires at least three periods, CIC requires only two periods and does not rely on panel data, fully relaxing the Copula Stability Assumption. However, CIC imposes its own restriction: treatment effects must be monotonic in unobservables and remain constant over time in longitudinal datasets.

Second, we use the Quantile Difference-in-Differences (QDID) estimator, also proposed by Athey and Imbens (2006), to construct counterfactual distributions. Unlike QTT and CIC, QDID assumes a linear relationship between the outcome and treatment at each quantile of the distribution. The conventional DiD estimator at the mean is a particular case of QDID. However, Athey and Imbens (2006) note that QDID has key limitations: it assumes additive separability between treatment and unobservables and requires that the distribution of unobservables is identical across all subpopulations.

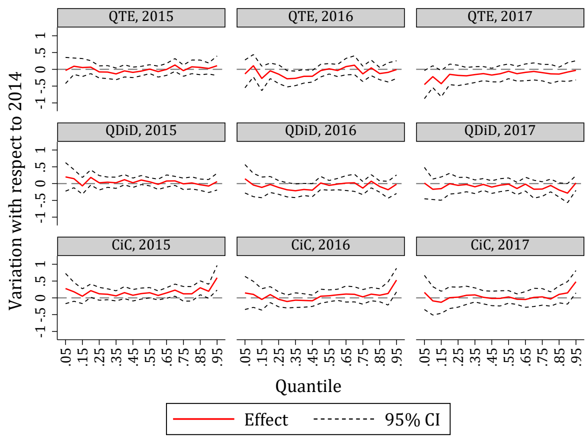
More broadly, both CIC and QDID impose constraints on the use of covariates. They allow only for continuous unit-level covariates (in our case, firm-level characteristics) and automatically incorporate unit and time fixed effects. Estimation relies on residuals to infer distributional effects, reducing the flexibility to include covariates beyond simple linear relationships.

Figure 10d presents alternative estimates of the impact of safeguard import tariffs on market shares, comparing QDID (panels a and c) and CIC (panels b and d) for direct exposure and input exposure in Manufacturing (Panel A) and Wholesale & Retail (Panel B).[11] Our findings show that QDID estimates are generally insignificant, which may reflect attenuation bias due to model misspecification. This outcome is likely due to the estimator's reliance on the linearity within quantiles assumption and the constraints on incorporating covariates. By contrast, CIC estimates closely align with QTE results, despite limitations in covariate inclusion. Differences emerge primarily at the extremes of the distribution, particularly among firms in the lower and upper quantiles.

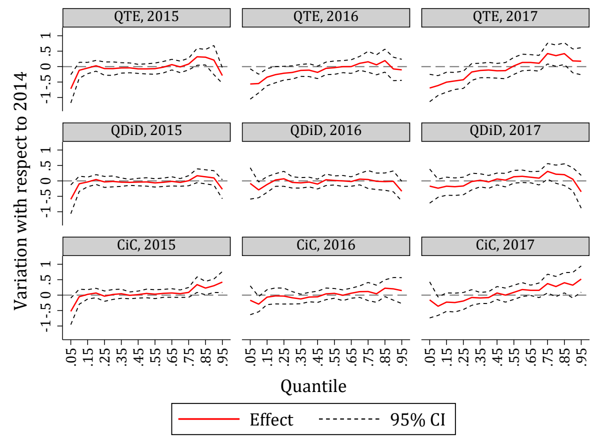
These robustness checks confirm that while alternative methodologies introduce some variation——particularly in significance levels and effect magnitudes at specific quantiles——the core patterns remain consistent. The negative impact of safeguard import tariffs on small firms and market diversity is evident across estimation strategies, reinforcing the validity of our main findings.

[11] Appendix results include robustness checks for output exposure of manufacturing firms and revenue effects.

Panel A: Manufacturing

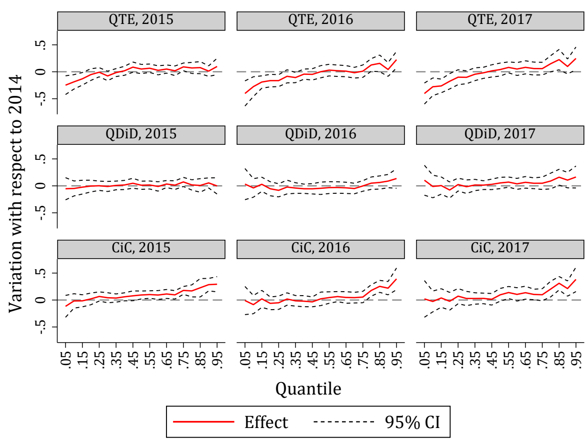


(a) Direct exposure

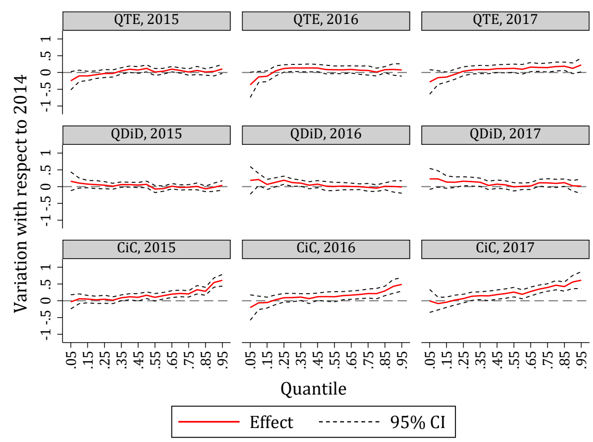


(b) Input exposure

Panel B: Wholesale & Retail



(c) Direct exposure



(d) Input exposure

Figure 10: Alternative Estimates of the Distributional Effects of Safeguards on Market Shares
This figure presents the estimated effects of safeguard import tariffs on the distribution of market shares, categorized by economic sector and exposure measures (direct and input), across three alternative methodologies. The QTE approach follows Callaway and Li (2019), while QDiD and CiC refer to Quantile Difference-in-Difference and Changes-in-changes, both developed by Athey and Imbens (2006). The QTE estimates account for labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects (ISIC 2-digit), and firm size dummies based on the CAN sales classification. In contrast, QDiD and CiC estimates are conditional on labor costs, material costs, capital stock, firm-level fixed effects, and time fixed effects. All control variables are fixed at baseline. Standard errors are bootstrapped with 100 replications, and the dashed lines indicate 95% confidence intervals.

8. Conclusion

This paper examines the effects of safeguard import tariffs on market diversity, focusing on their distributional impacts on firm revenue, market share, and exit probability in the Manufacturing and W&R sectors. Our findings provide key insights into how trade policy interventions shape competitive dynamics.

First, safeguard import tariffs disproportionately harm smaller firms, particularly in W&R. These firms experience significant revenue declines, which erode their market shares and weaken their competitive position. The negative scale effect, previously highlighted in the literature (e.g., Uribe-Terán et al., 2025), is most pronounced among smaller firms that struggle to pass on increased costs. This forces reductions in their scale of operations and market participation. In contrast, larger firms, particularly in Manufacturing, demonstrate greater resilience, often maintaining or even expanding their market shares despite tariff-induced cost increases. This sectoral divergence underscores the role of firm size and industry characteristics in determining the impact of trade policy.

Second, we find that input exposure, rather than direct exposure, significantly increases the probability of firm exit for importer-exporters. In Manufacturing, this effect peaks in 2016, while in W&R, it is strongest in 2017. This pattern suggests that firms may initially absorb cost increases but eventually succumb to rising input costs, particularly as short-term mitigation strategies (e.g., inventory buffers or financial reserves) become exhausted. In contrast, we find no significant effects on the exit probability of local firms, suggesting that non-importers may be less vulnerable to safeguard tariffs, possibly due to their greater flexibility in adjusting to domestic market conditions.

Third, our counterfactual revenue distribution analysis highlights the broader market implications of these firm-level effects. The decline in market diversity stems from both the exit of smaller firms and the shrinking market shares of surviving small firms. This dynamic leads to increased market concentration, consolidating power within a smaller group of large firms. While this consolidation may offer short-term advantages to these firms, it raises concerns about long-term inefficiencies, as reduced competition could limit innovation and drive up consumer prices.

Our analysis of pass-through effects reveals that firms with market power, particularly in sectors with inelastic demand, initially pass on tariff-induced cost increases through higher prices. However, over time, consumers and businesses adjust their purchasing behavior, limiting firms' ability to sustain price hikes. This finding highlights the complex interaction between demand elasticity, market structure, and cost absorption strategies, emphasizing the nuanced effects of tariffs on pricing and competition.

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A. Effects of Output Exposure on Local Firms in Manufacturing

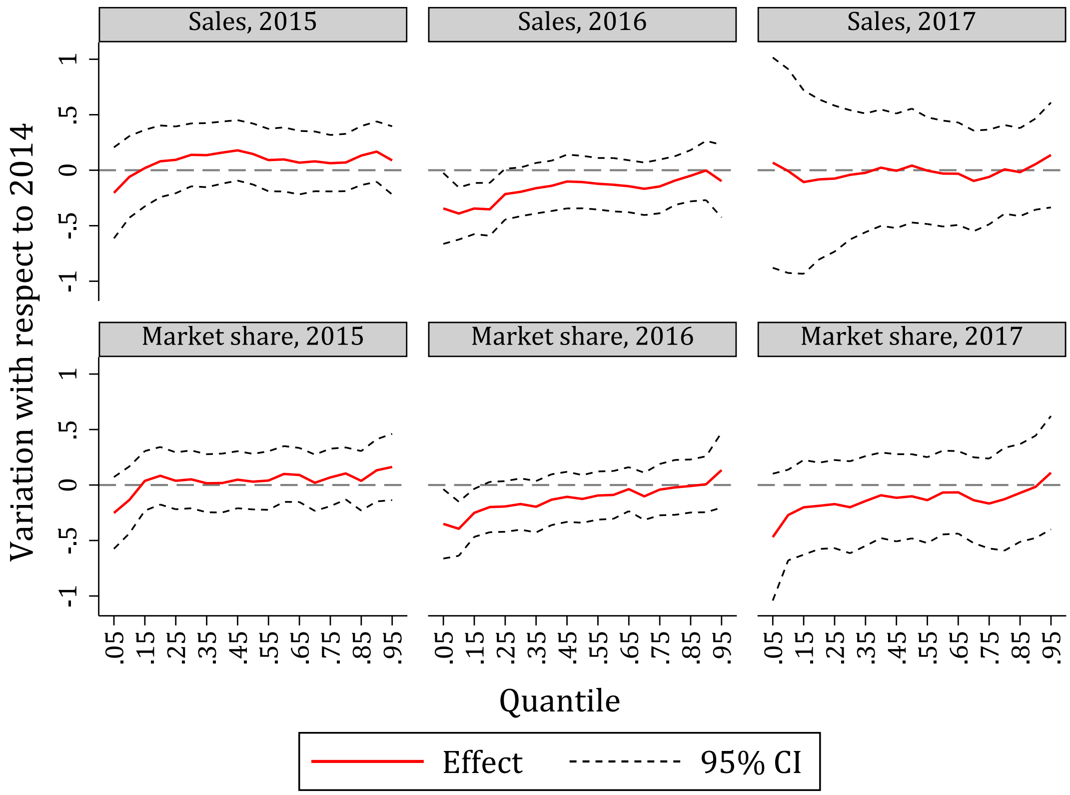
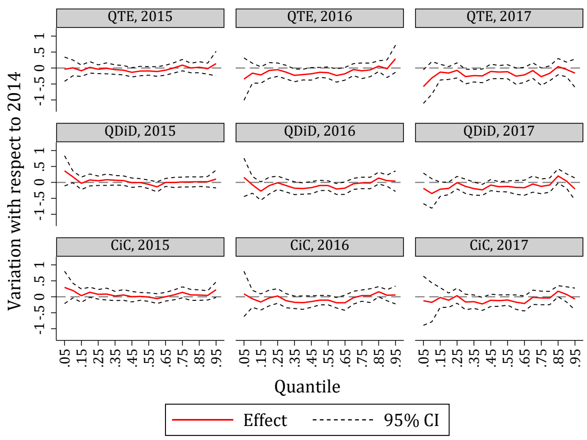


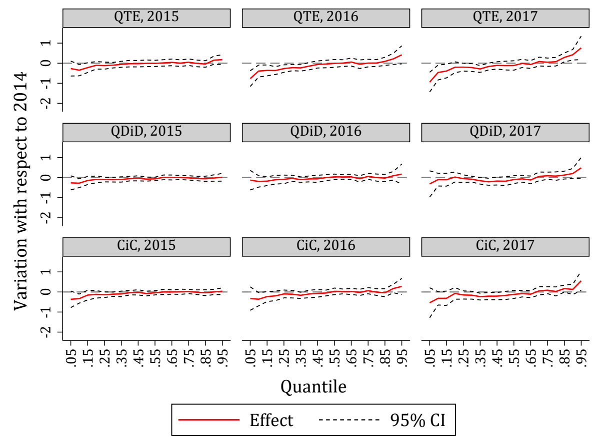
Figure 11: Effects of Output Exposure to Safeguards of Local Firms in Manufacturing This figure shows the estimated effects of output exposure to safeguard import tariffs on sales and market shares for local firms in manufacturing. Because the outcome variables are measured in logarithms, the coefficients correspond to percentage variations. The values correspond to the estimation of (6) across 20 quantiles. We estimate the propensity scores following Firpo (2007), conditioning on labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects (ISIC 2-digit level), and dummy variables that identify firms' size in terms of sales according to the CAN classification. All control variables are fixed at baseline. Standard errors are estimated using bootstrap with 100 replications. The dashed lines represent 95% confidence intervals.

B. Complementary Robustness Analysis

Panel A: Manufacturing

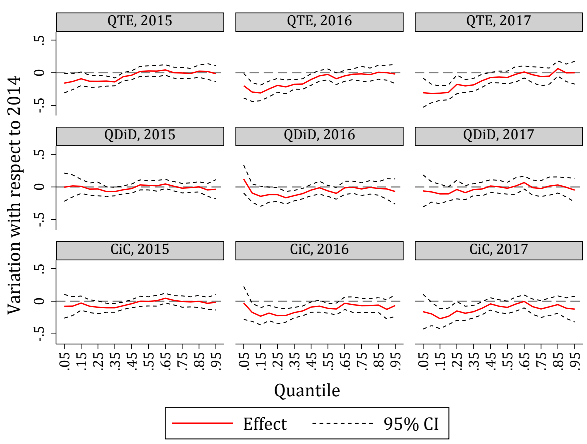


(a) Direct exposure

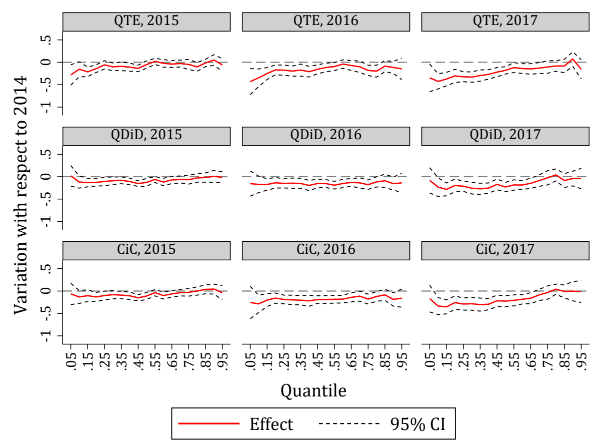


(b) Input exposure

Panel B: Wholesale & Retail

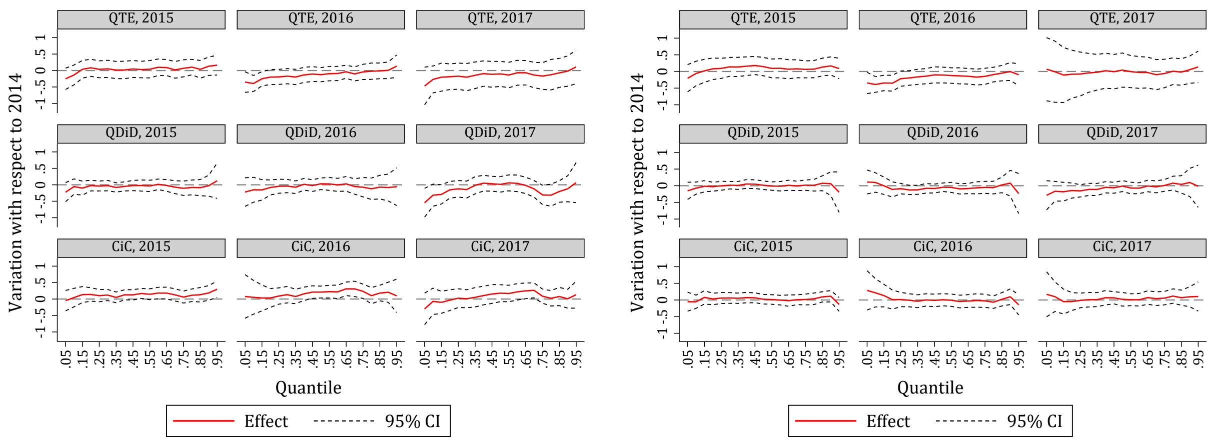


(c) Direct exposure



(d) Input exposure

Figure 12: Alternative Estimates of the Distributional Effects of Safeguards on Sales This figure presents the estimated effects of safeguard import tariffs on the distribution of sales, categorized by economic sector and exposure measures (direct and input), across three alternative methodologies. The QTE approach follows Callaway and Li (2019), while QDiD and CiC refer to Quantile Difference-in-Difference and Changes-in-changes, both developed by Athey and Imbens (2006). The QTE estimates account for labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects (ISIC 2-digit), and firm size dummies based on the CAN sales classification. In contrast, QDiD and CiC estimates are conditional on labor costs, material costs, capital stock, firm-level fixed effects, and time fixed effects. All control variables are fixed at baseline. Standard errors are bootstrapped with 100 replications, and the dashed lines indicate 95% confidence intervals.



(**a**) Market share (**b**) Sales

Figure 13: Alternative Estimates of the Distributional Output Exposure Effects of Safeguards on Manufacturing This figure shows the estimated effects of safeguard import tariffs on the distributions of market shares and sales, based on firms' output exposure in the manufacturing sector across three alternative methodologies. The QTE approach follows Callaway and Li (2019), while QDiD and CiC refer to Quantile Difference-in-Difference and Changes-in-changes, both developed by Athey and Imbens (2006). The QTE estimates account for labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects (ISIC 2-digit), and firm size dummies based on the CAN sales classification. In contrast, QDiD and CiC estimates are conditional on labor costs, material costs, capital stock, firm-level fixed effects, and time fixed effects. All control variables are fixed at baseline. Standard errors are bootstrapped with 100 replications, and the dashed lines indicate 95% confidence intervals.

C. Propensity Score Matching

This appendix provides further details on the Propensity Score Matching (PSM) procedure used to estimate the Quantile Treatment Effects (QTE). This method is essential for invoking the *Conditional Distributional Difference-in-Differences Assumption*, a key component for identification. Callaway and Li (2019) apply PSM following Firpo (2007), estimating propensity scores using a logistic specification:

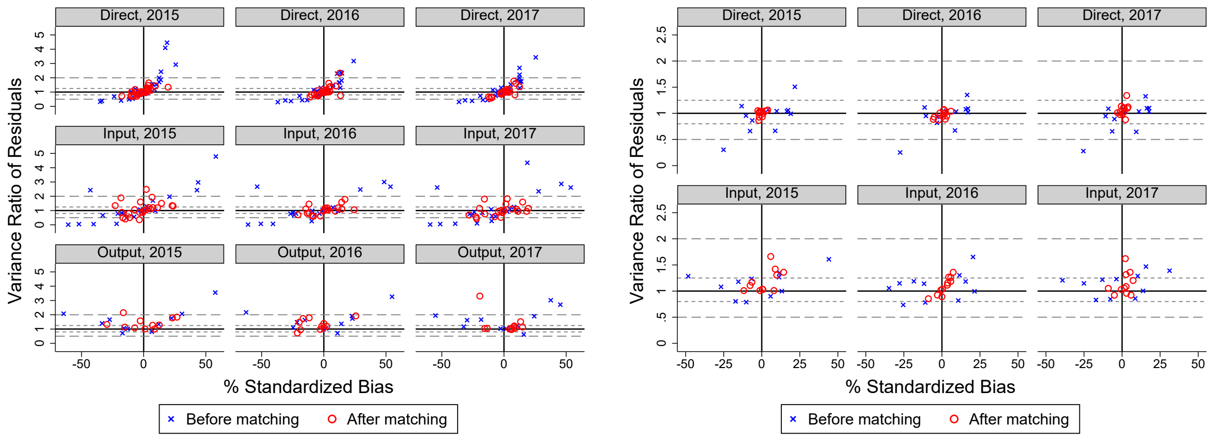
$$p(X) = \frac{1}{1 + e^{-\beta_0 + \mathbf{X}\boldsymbol{\beta}}}, \tag{10}$$

where X represents the vector of covariates, β_0 is the intercept, and $\boldsymbol{\beta}$ is the vector of coefficients.

Once propensity scores are estimated, matches are made using the nearest neighbor algorithm. As with any PSM method, identifying causal effects requires three key assumptions: i) unconfoundedness, meaning potential outcomes are independent of treatment assignment given covariates; ii) common support, ensuring sufficient overlap in propensity scores across treated and untreated units; and iii) correct model specification, ensuring that propensity scores are accurately estimated.

Given the exogeneity of the policy design, we are confident that unconfoundedness holds once we control for relevant covariates. Equation (10) is estimated including labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects (ISIC 2-digit level), and firm size dummies based on CAN sales classification, all fixed at baseline (2014). Under this specification, more than 95% of observations satisfy the common support condition, and the logistic model appears correctly specified.

To assess balance in the matched sample, we follow Rubin (2001), which evaluates balance in two dimensions: i) the standardized bias of the means for each covariate and ii) the variance ratio of covariates orthogonal to the propensity score. This approach ensures balance along the first two moments of the distribution for each covariate.



(**a**) Manufacturing (**b**) Wholesale & Retail

Figure 14: Balance of Samples before and after Matching This figure illustrates the balance of the different samples used in the QTE estimations, focusing on the first two moments: the mean and the variance. The horizontal axis represents the standardized bias of the means for each covariate used in estimating the propensity score, while the vertical axis displays the variance ratio of the covariates (orthogonal to the propensity score) before and after matching (Rubin, 2001). The horizontal lines mark thresholds for evaluating the variance ratios: variables with ratios between $[0.5, 0.8]$ and $[1.25, 2]$ are considered *of concern*, while those with ratios below 0.5 or above 2 are classified as *bad*. The covariates used to estimate the propensity scores include labor costs, material costs, capital stock, geographic fixed effects, industry-level fixed effects (ISIC 2-digit), and firm size dummies based on the CAN sales classification.

Figure 14 presents the results graphically for each sample. A perfectly balanced sample should exhibit zero standardized mean bias, with a variance ratio close to 1. Ideally, all variables should align at the center of the black cross in the graph. In random samples, bias should be minimal, and acceptable variance ratios range from 0.8 to 1.25. Ratios between [0.5, 0.8] and [1.25, 2] are considered *of concern*, while values below 0.5 or above 2 are classified as *bad*.

Overall, the balance of matched samples is acceptable, though some covariates are classified as *bad*, particularly in Manufacturing for output exposure and in W&R for input exposure. However, given the large number of fixed effects in the PSM model, we are not overly concerned, as imbalance may stem from one of these fixed effects. Importantly, in all samples, PSM significantly reduces both standardized bias and variance ratio compared to the unmatched sample.

D. Analysis of Firms' Market Participation and Product Scope

We define markets using four-digit International Standard Industrial Classification (ISIC) codes, a standard approach in the trade literature. However, this method may present limitations if firms operate across multiple markets by producing a diverse portfolio of products.

Although we lack complete data on firms' full product portfolios, we do have information on the exported products of exporting firms. In this appendix, we analyze the number of products exported and the number of markets in which exporters operate, then compare these distributions to those of non-exporting firms.

Table 4 provides an overview of these statistics. The first panel categorizes firms by trade status, distinguishing importers, importer-exporters, local firms in import-competing industries, and local firms in non-import-competing industries. The second panel presents the distribution of exporting firms based on the number of markets they serve, measured at the ISIC four-digit level and matched with Harmonized Tariff Schedule (HTS) codes. The third panel classifies firms by the number of products they export, following the same breakdown. The fourth panel reports the average export value in millions of USD for firms in each product category, while the final panel presents distribution statistics for the revenue of non-exporting firms.

Out of more than 10,000 firms active in 2014, only 360 are exporters. Among these, approximately 64 percent operate in more than one market; however, these firms account for less than 3 percent of the total firm sample. In terms of exported products, about 78 percent of exporters sell more than one product, yet they represent only 2.9 percent of the total sample on average.

Despite the small number of exporting firms, particularly multiproduct exporters, these firms tend to be significantly larger than non-exporters. Firms exporting a single product report average exports of 5.4 million USD over the 2014–2017 period. This figure rises to 9.5 million USD for firms exporting between two and five products and reaches 26.7 million USD for firms exporting more than 20 products.

Comparing these figures to non-exporters, we find that the median revenue for non-exporting firms over the same period is 785,000 USD, substantially lower than the average exports of the smallest exporters. If anything, the average revenue of non-exporters is comparable to the average exports of firms exporting a single product, and 75 percent of the revenue distribution for non-exporters lies below the average exports of these single-product exporters. In fact, 79.3 percent of non-exporting firms generate less than 5.4 million USD, the average export value of firms operating in only one market.

These observations suggest that the patterns observed among exporters are not representative of the broader population of firms in the economy. Although we do not have precise data on the product scope of non-exporters, it is likely that most firms in Ecuador operate in a single market. Therefore, the market definition used in our estimations, based on four-digit ISIC codes, should not pose concerns regarding the validity of our analysis.

	Year			
	2014	**2015**	**2016**	**2017**
Panel A: Firms by Trade Status				
Importers	3,620	3,417	3,230	3,084
Importer-exporters	360	335	307	290
Local, import competing	1,532	1,372	1,238	1,141
Local, non-import competing	4,951	4,256	3,717	3,361
Total	10,463	9,380	8,492	7,876
Panel B: Firms by Number of Markets with Participation				
1 market	130	151	127	88
2 to 5 markets	146	151	134	132
6 to 10 markets	43	36	28	32
11 to 20 markets	16	12	11	15
More than 20 markets	25	10	35	40
Panel C: Firms by Number of Products Exported				
1 product	80	100	79	48
2 to 5 products	146	141	118	115
6 to 10 products	58	61	65	53
11 to 20 products	31	34	25	32
More than 20 products	45	24	48	59
Panel D: Average Exports by Number of Products Exported				
1 product	6.83	6.89	4.60	3.18
2 to 5 products	9.32	8.63	9.18	10.96
6 to 10 products	13.89	10.39	9.92	9.56
11 to 20 products	17.78	19.09	18.14	22.51
More than 20 products	21.32	24.5	30.41	30.44
Panel E: Sales Distribution of Non-exporters				
Median	0.76	0.79	0.77	0.82
Mean	6.00	6.19	6.12	6.67
75th percentile	2.55	2.68	2.6	2.81
90th percentile	8.09	8.4	8.44	9.17
95th percentile	17.19	17.56	17.76	19.34

Table 4: Summary Statistics of Firms by Trade Status, Market Participation, and Product Scope This table presents summary statistics of firms in Ecuador from 2014 to 2017. **Panel A** shows the number of firms by trade status: importers, importer-exporters, local firms operating in import-competing industries, and local firms in non-import-competing industries. **Panel B** displays the number of firms based on the number of markets in which they participate, categorized as 1 market, 2 to 5 markets, 6 to 10 markets, 11 to 20 markets, and more than 20 markets. Markets are defined using the four-digit ISIC classification code matched with Harmonized Tariff Schedule (HTS) codes. **Panel C** presents the number of firms by the number of products exported, using the same categorical breakdown. **Panel D** reports the average exports (in million USD) for firms within each product category over the specified years. **Panel E** provides distribution statistics (in million USD) for the revenue of non-exporting firms, including the median, mean, and selected percentiles. The data illustrate the differences in market participation and product scope between exporters and non-exporters, highlighting that exporters, especially those with a larger number of products, tend to have significantly higher export values.