The Impact of Trade Wars on Firms in Third Countries*

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Abstract

Bilateral trade shocks can reallocate demand and reshape competition across multiple origins and destinations, spilling over to firms in third countries that are not directly exposed. We develop a non–parametric general–equilibrium trade model that point–identifies destination–specific own–price demand elasticities, cross–origin cross–price demand elasticities, and external returns to scale. These parameters enable an exact decomposition of firm export responses, tracing how foreign price movements create winners and losers within a bystander economy and how these gains and losses translate into employment, investment, and allocative efficiency. Using administrative data covering the universe of Italian firms, we find that the 2018–2019 US–China trade war generated net export opportunities on average, albeit with substantial heterogeneity across firms. The largest gains accrued to more productive firms in sectors with stronger economies of scale, enhancing overall allocative efficiency. More broadly, our framework can be used to study within– and between–firm responses to shocks that shift relative prices across countries.

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1 Introduction

After decades of free trade, the 2018–2019 US–China trade war marked a turn toward protectionism. Over two years, the US raised average tariffs on several Chinese goods from less than 3% to over 20%, with China imposing comparable tariffs in response.[1] Beyond their effects on the two countries directly involved, US–China tariff changes reallocated global demand toward countries producing close substitutes, with significant implications for bystander economies (Fajgelbaum et al., 2024; Mayr-Dorn et al., 2023; Utar et al., 2023; Cavalcanti et al., 2025; Chen et al., 2025). A central question is how firms in third countries adjusted to these tariff changes and the resulting aggregate and distributional outcomes. This question is key not only for understanding the US–China trade war, but also for anticipating the effects of future protectionist measures (Helpman, 2025).

In this paper, we develop a non–parametric general equilibrium trade model with heterogeneous firms and use it to study the effects of a major bilateral trade conflict—the 2018–2019 US–China trade war—on firms in a third country, Italy. Our framework is motivated by the fact that bilateral trade shocks affect third–country firms through multiple, potentially offsetting channels, making their net effects ex ante ambiguous. Higher US tariffs on Chinese goods may divert expenditure toward alternative suppliers, increasing demand for close substitutes from other origins. However, Chinese producers may redirect exports to third markets, intensifying competition faced by third–country firms (Benguria and Saffie, 2024; Iyoha et al., 2024; Jiao et al., 2024). These forces extend beyond direct competitors: exporters of substitutes may gain, while exporters of complements may lose. Such effects—potentially amplified or dampened by scale economies—vary across firms, products, and destinations and interact with firms' initial export portfolios. As a result, the net impact on third–country firms is ambiguous ex ante.

In our model, household preferences are described by a three–level nested aggregator: at the top level, households consume a homogeneous good and differentiated goods made by domestic and foreign firms; at the middle level, foreign goods are aggregated across origins and product categories; at the bottom level, firm–level varieties are aggregated within each product–origin pair. This structure governs competition without imposing ex–ante substitution or complementarity patterns within nests (Adao et al., 2017; Arkolakis et al., 2019; Lind and Ramondo, 2023b). Moreover, we allow for external economies of scale by letting a firm's marginal cost depend on the total export quantity of its product from the same country, without restricting the sign of the scale effect (Lashkaripour and

[1] By the end of 2019, nearly two–thirds of US–China trade—about $450 billion—was subject to new tariffs (Fajgelbaum et al., 2020).

Lugovskyy, 2023; Bartelme et al., 2025). Finally, firms are heterogeneous in productivity and product appeal, face export entry costs, and may exert market power (Atkeson and Burstein, 2008; Alviarez et al., 2023).

Our model complements and extends standard trade frameworks in several important ways. While canonical models are well suited for quantifying aggregate gains from trade (Arkolakis et al., 2012), they typically rely on strong assumptions—such as a single elasticity of substitution, constant marginal production costs, and parametric distributions that integrate out firm heterogeneity (Imbs and Mejean, 2015; Bas et al., 2017)—that limit their ability to characterize how trade shocks differentially affect firms across products and destinations. By relaxing these restrictions, our framework nests standard Armington–, Ricardian–, and Melitz–type models as special cases, while enabling a granular analysis of firm–level export responses: We identify destination–specific own–price demand elasticities, cross–origin cross–price elasticities, and external scale economies in exports,[2] which allow us to identify both winners and losers from trade shocks and trace the channels through which these effects operate, rather than focusing solely on aggregate gains.[3]

The model decomposes intensive–margin changes in firm–level export revenues into five components: (i) destination–specific general–equilibrium changes (destination effect); (ii) changes in import tariffs levied by a given destination on domestic products (own–demand effect); (iii) changes in total quantity of domestic exports of a product across all destinations (scale effect); (iv) changes in prices faced by households in that destination for the same product from other origins (cross–demand effect); and (v) changes in unobservables, such as firm productivity and product appeal. This decomposition sheds light on the fact that firms located in third countries are more exposed to bilateral trade shocks when their exports are concentrated in key destination markets, disproportionately oriented toward tariff–targeted products, subject to external economies of scale, or highly substitutable for—or complementary to—products supplied by other origin countries. An analogous decomposition applies to extensive–margin adjustments.[4]

We apply our framework to the case of Italy, which provides an ideal laboratory for

[2]These three objects constitute the structural parameters we directly bring to the data. Other relevant forces are absorbed into fixed effects or the residual term. While the model could be extended to disentangle additional mechanisms—such as productivity or labor–market dynamics—this would require richer data and stronger assumptions.

[3]We show that, while average effects of the trade war are well approximated by standard trade models that abstract from economies of scale and cross–demand effects, these models substantially understate the heterogeneity in gains and losses across firms. This has important implications for the evaluation and targeting of trade and industrial policies.

[4]However, our model estimates reveal no significant extensive–margin responses. This may reflect the fact that the shock was not big enough to trigger firm entry into or exit from export markets, or that such adjustments require more time to unfold than is captured in our sample period.

studying the impact of the trade war on third–country firms, given that both the US and China are major destinations for Italian exports and that the US–China trade war was unrelated to Italian firms' performance, facilitating identification of the model primitives. We estimate the model by combining two administrative datasets covering the universe of Italian limited companies from 2014 to 2019: customs records on firm–product–level exports to the EU and non–EU destinations, and balance sheet data on domestic sales, employment, and investment. These data are complemented by product–level information on 2018–2019 US and Chinese tariffs from Fajgelbaum et al. (2024).[5]

Our analysis yields four main insights. First, the estimated elasticities reveal substantial heterogeneity in market responses to price changes induced by the US–China trade war. Demand for Italian products is more than twice as elastic in the US as in China, making Italian export revenues highly sensitive to US tariffs on EU imports. Cross–price elasticities also vary systematically across destinations: in the US, Italian products substitute for Chinese and other EU goods, whereas in China they complement US and EU goods but substitute for goods from other origins. These patterns imply that Italian exporters benefited from US tariffs on Chinese imports while incurring losses from Chinese tariffs on US goods, although the latter effect is quantitatively modest. We also find strong evidence of positive external economies of scale in Italian exports—particularly in food, chemicals, and leather goods—which amplify demand shocks faced by Italian firms. While identifying the underlying sources of these scale economies is beyond the scope of the paper, we provide suggestive evidence that they are stronger in sectors with greater knowledge diffusion and spillovers (proxied by the number of active firms) and with greater access to advanced technologies (proxied by a higher share of high–tech production).

Second, while the trade war created net export opportunities for the average Italian firm, it also generated winners and losers, with roughly one–fifth of firms experiencing a decline in exports. Aggregating the model–predicted export changes attributable to the trade war, we find an average increase in export revenues of about 2.5%—consistent with Fajgelbaum et al. (2024)[6]—and a standard deviation of 7.6%. At the sector and province level, the largest gains accrued to consumer goods, food and beverages, and fuels and

[5] Using these data, we document that about three–quarters of Italian exports in 2017 involved products later targeted by US or Chinese reciprocal tariffs. Over time, exports of targeted products rose, while those of untargeted goods declined. We also draw on survey–based measures of firms' self–assessed exposure to the US–China tariffs, collected by the Bank of Italy in 2018. Only 13% of firms reported any impact on export sales, yet these firms were disproportionately large, accounting for 46% of sales, 39% of employment, and 30% of investment among respondents. Overall, the evidence suggests that the US–China trade war reallocated demand toward Italian products, with highly heterogeneous firm–level responses.

[6] Fajgelbaum et al. (2024) place Italy in the left tail of countries with net export gains, suggesting that our estimates provide a conservative lower bound relative to gains in other bystander countries.

lubricants, and were concentrated in northern provinces.

Third, we show that the average Italian firm experienced an increase in its export revenues not only to the US—consistent with Italian goods partially substituting for Chinese ones—but also to other markets. We estimate that the scale channel accounts for roughly three–quarters of the variation in export revenue changes. In other words, changes in total export quantities induced by the US–China trade war were the main drivers of firm–level export growth, while destination, own–demand, and cross–origin demand effects jointly explain the remaining share.[7]

Fourth, correlating changes in export revenues with ex–ante firm–level characteristics shows that gains were concentrated among firms that were initially more productive, exhibited higher investment intensity, and offered a broader range of products. Turning to domestic outcomes, we estimate that a 2.5% increase in export revenues translated into a 1.6% rise in labor expenditure and a 0.7% increase in capital investment, consistent with the literature finding that the US–China trade war acted as a positive labor demand shock in bystander economies (Mayr-Dorn et al., 2023; Cavalcanti et al., 2025; Chen et al., 2025). These patterns suggest improvements in allocative efficiency, as more productive and more investment–intensive firms expanded relative to others.

Overall, our findings contribute to understanding the global reallocation effects of the 2018–2019 US–China trade war and add a structural interpretation of the underlying mechanisms and their within–country distributional consequences. Our model can also be used to quantify firm–level responses in other countries and to other trade shocks, including sanctions, export controls, and other protectionist measures.

Related literature. Our work contributes to the literature on the effects of trade wars. Several studies have examined the implications of the 2018–2019 US–China trade war for the US and Chinese economies (Amiti et al., 2019, 2020; Flaaen and Pierce, 2019; Cavallo et al., 2021; Chor and Li, 2024; Farrokhi and Soderbery, 2024; Jiao et al., 2024). By contrast, evidence on the effects of trade wars on bystander countries remains more limited. The closest paper to ours in this respect is Fajgelbaum et al. (2024). Our analysis differs from and complements theirs in two key ways. First, conceptually, we focus on firm–level responses rather than country–level outcomes, which allows us to examine within–country distributional effects in bystander economies. Second, methodologically, while Fajgelbaum et al. (2024) adopt a revealed–preference approach to infer substitution patterns and economies of scale from observed export responses, our non–parametric

[7] In addition, we find that import dynamics from emerging markets, including China, are uncorrelated with scale economies or changes in firm–level exports, and therefore do not pose a threat to our identification strategy.

framework achieves point identification of key structural parameters. This enables us to disentangle the relative importance of different channels in shaping firm–level behavior.

Our work is also related to Utar et al. (2023), who document that Mexican firms increased exports to the US in response to the trade war. Our contribution is to recover the underlying substitution patterns and scale forces that govern firms' responses in third markets, and to quantify how these shocks transmit to the domestic economy. Our paper is also related to Mayr-Dorn et al. (2023), Cavalcanti et al. (2025), and Chen et al. (2025), who examine trade diversion effects of the 2018–2019 US–China trade war on Vietnam, Brazil, and Mexico, respectively. Like us, they rely on firm– and product–level export data; however, their focus is primarily on labor market outcomes, whereas we emphasize firm–level heterogeneity in trade responses and the implications for domestic outcomes.

We also contribute to the literature on quantitative trade models and structural gravity. Standard models assume gross substitutability across goods, constant marginal costs, and a single elasticity of substitution within an industry (Eaton and Kortum, 2002; Anderson and Van Wincoop, 2003; Arkolakis et al., 2012; Caliendo and Parro, 2015). While this framework is powerful for quantifying gains from trade with minimal data (Arkolakis et al., 2012), it is prone to bias. Bas et al. (2017) show that in heterogeneous–firm models with selection, the aggregate trade elasticity is not constant and depends on the full distribution of firm–level fundamentals, while Imbs and Mejean (2015) show that estimating a single elasticity on aggregate data imposes a homogeneity restriction, attenuating macro elasticities relative to the distribution of underlying sectoral elasticities. Similarly to Adao et al. (2017), Arkolakis et al. (2019), and Lind and Ramondo (2023b), our non–parametric framework allows for rich patterns of complementarity and substitution. We add to this literature by introducing a model that produces a full matrix of bilateral own– and cross–price elasticities across origin–product–destination triplets and by showing how these elasticities can be identified directly from firm–product–destination responses to tariff shocks.

Finally, on the supply side, scale economies have been increasingly studied empirically and quantitatively, mainly in the context of industrial policy (Lashkaripour and Lugovskyy, 2023; Bartelme et al., 2025). We estimate comparable external economies of scales as in the literature using a different framework and strategy. We treat the scale elasticity as a reduced–form object, estimated jointly with demand elasticities using tariff variation, and use it to quantify how trade shocks can be dampened or amplified at the firm level.

The paper unfolds as follows. Section 2 introduces our data. Section 3 presents the model. Section 4 discusses identification and estimation. Section 5 shows the results. Section 6 inspects firm–level responses and the underlying mechanisms. Section 7 concludes.

2 Data, Summary Statistics, and Preliminary Evidence

This section introduces our data sources, summarizes the 2018–2019 tariff changes between the US and China, and offers descriptive evidence on Italian firms' exposure to them.

2.1 Data Sources

Our analysis combines information on the international and domestic activities of Italian firms with product–level trade and tariff data. We introduce each data source below.

2.1.1 Firm–Level Data

Information on the activities of Italian firms comes from two main data sources: customs records and balance sheet statements on limited, non-financial companies (CERVED).

From the customs data, we extract export values and quantities (in kilograms) at the firm–product–country–year level. All extra–European transactions are included, while intra–European transactions are recorded only if they exceed a minimum threshold.[8] Product codes are expressed at the 6–digit level of the 2012 Harmonized System (HS) nomenclature. We use customs data for the 2014–2019 period.[9] These data allow us to examine firms' short–run adjustments in international trade activities—namely export flows and entry into new markets—in response to the US–China tariff escalation.

Balance sheet information on the universe of limited liability companies in Italy comes from CERVED.[10] These data include standard company accounts, such as total sales, gross labor costs, expenditures on tangible materials, fixed assets, and investments. We link them with social security records, which provide information on firms' employment, and with firm registry data, which report the postcode of each firm's headquarters in Italy, allowing us to identify their province of origin. Social security data distinguish between manual workers, clerks, and managers for each firm,[11] while the registry also provides the primary industry of activity of each firm according to the 2–digit NACE classification. Estimates of total factor productivity and markups for firms in CERVED

[8]Thresholds are set by individual member states so that reported trade covers at least 97% of total dispatch value (intra-EU exports). These thresholds may vary across member states and over time.

[9]The sample ends in 2019 to avoid confounding effects from the COVID-19 pandemic, which began to affect global trade flows in early 2020.

[10]Firms not included are mainly financial and real estate companies together with small businesses, such as sole proprietorship or household producers. CERVED data form the basis for the Italian segment of Moody's Orbis. See Akcigit et al. (2023) for additional details.

[11]We classify clerks and managers as white–collar workers, and manual workers as blue–collar workers See also Section 6.2.

come from Ciapanna et al. (2024). As for the customs data, balance sheet information refers to the period 2014–2019. We use balance sheet data to investigate whether changes in international trade strategies influenced domestic outcomes—employment, investment, and productivity—among Italian firms.

Unique firm tax identifiers enable unambiguous matching of firms across the customs and balance sheet data for the years 2014–2019. For data cleaning, we follow the procedure recommended by Kalemli-Özcan et al. (2024) when working with the Moody's Orbis database. Specifically, we drop firm–year observations with non–positive or missing values for labor costs, turnover, cost of goods sold, or tangible fixed assets. Additionally, we exclude outliers in terms of turnover growth rates, defined as observations in the bottom or top 1% of the distribution. To ensure that our sample reflects firms with actual economic activity in Italy, we retain only those that filed at least one balance sheet declaration between 2014 and 2019. This procedure excludes very small firms exempt from filing balance sheets, as well as foreign firms with an office in Italy but that do not carry out economic activity there.[12]

Finally, we complement these data with a survey conducted by the Bank of Italy among approximately 4,500 representative firms headquartered in Italy with at least 20 employees. This survey, known as the "*Sondaggio Congiunturale sulle Imprese Industriali e dei Servizi*" (SONDTEL), collects qualitative information on firms' economic performance during the current year. In 2019, it also included questions on whether firms' intra– and extra–European exports were affected by the US–China trade war. For surveyed firms, we link survey responses to administrative customs and balance sheet data and use these responses to provide anecdotal evidence on firms' perceptions of the trade war.

2.1.2 Product–Level Data

We supplement the Italian firm–level data with information on tariffs and trade flows by product at the country–pair level. From Fajgelbaum et al. (2024), we obtain data on product–level import tariffs imposed by the US on China and the corresponding retaliatory tariffs imposed by China on US goods. These data are reported monthly for 2018 and 2019 at the 8– or 10–digit HS level, which we aggregate to the annual level and harmonize to the 2012 6–digit HS nomenclature to match our customs data. The dataset also includes "byproduct" tariff changes imposed by the US and China on other trading partners (see Section 2.2.1 for details). The 2018–2019 tariff changes provide exogenous variation in

[12]After merging the customs data with CERVED, we find that approximately 5% of firms present in the customs records never appear in CERVED. In any given year, these firms account for less than 10% of total export values.

product–level demand (Mayr-Dorn et al., 2023; Utar et al., 2023; Cavalcanti et al., 2025; Chen et al., 2025), which we exploit to estimate Italian firms' responses.

Using the CEPII BACI dataset, we construct product–level export unit prices—measured as export value divided by quantity (in kilograms)—for all country pairs between 2014 and 2019. Products are classified according to the 2012 6–digit HS nomenclature. These data allow us to analyze price responses to the US–China trade war beyond Italy.

2.2 Summary Statistics

This section provides background on the changes in the structure of US and Chinese tariffs between 2018 and 2019 and presents descriptive statistics for the sample of Italian firms obtained by merging the datasets described above.

2.2.1 Overview of Tariff Changes during the 2018–2019 US–China Trade War

Between 2018 and 2019, the US administration imposed tariffs on roughly two–thirds of goods imported from China (measured at 2017 import values), raising average tariffs from 3% to 21%, with substantial heterogeneity across sectors (Appendix Figure A.1, top panel). The main products targeted included solar panels, washing machines, iron, steel, and aluminum. China responded with retaliatory tariffs of similar magnitude, targeting approximately 60% of US exports to China, though focused on different sectors—primarily agricultural products (Appendix Figure A.1, bottom panel). As Fajgelbaum et al. (2020) note, this abrupt escalation represented the most dramatic increase in tariff barriers since the end of World War II.

Beyond the bilateral dispute, the US–China trade war triggered "byproduct" tariff adjustments affecting other trade partners. The US imposed some tariffs on goods from the EU and the Rest of the World (RoW), though much smaller than those on China and concentrated in industrial supplies such as machinery and metals (Appendix Figure A.2). In turn, the EU and RoW raised tariffs on US imports (Appendix Figure A.3). Concurrently, China reduced its MFN tariffs on imports from the EU and RoW by roughly 1.5 percentage points (Appendix Figure A.4). As argued by Bown et al. (2019), these MFN tariff reductions were intended to strengthen trade linkages with non–US partners and partially offset the disruptions caused by the bilateral dispute.

In sum, the 2018–2019 US–China tariff escalation marked a major shift in global trade policy, generating substantial product–level demand variation that we exploit to study Italian firms' responses. Although these changes spilled over to other countries, the resulting tariff adjustments were smaller and more narrowly targeted, highlighting the central role of the US–China tensions in reshaping global trade patterns (Freund et al., 2024).

2.2.2 Firm Characteristics and Export Exposure to the Trade War

The cleaned matched sample used in our analysis includes 617,689 unique firms. Over the sample period, about 22% of them reported positive export flows at the product–destination country level in at least one year.[13]

In 2017, prior to the imposition of any new tariffs, Italian exports were primarily concentrated in the motor vehicle, pharmaceutical, agri–food, and mechanical sectors. Approximately 77% of Italian exports (by value) consisted of products that were later targeted by either US tariffs on China or Chinese tariffs on the US, as shown in Appendix Table A.3. Within this set of products, direct exports to the United States and China accounted for 7.1% and 2.8% of total export values, respectively, making them the two largest non–EU destination markets for Italian exporters.

Appendix Figure A.5 traces the evolution of Italian exports for two groups of products: those targeted by US tariffs on Chinese imports or by Chinese tariffs on US imports ("targeted products") and those not affected by reciprocal tariffs between the two countries ("untargeted products"). Overall, export values of targeted products have grown over time, while exports of untargeted products have declined. These patterns become even more pronounced after the US–China tariffs were first implemented in 2018.[14]

Survey responses shows that these aggregate statistics conceal considerable heterogeneity at the firm level. In 2019, firms were asked the following question: *"The US administration has been introducing tariffs on imports for over a year, primarily targeting goods from the Chinese market. How have these protectionist measures and the retaliatory actions taken by the affected countries influenced or will influence the following aspects of your business?"* Possible answers included: (1) not affected, (2) affected sales to the US market, (3) affected sales to the EU market, and (4) affected sales to non–EU markets.

As shown in Appendix Table A.4, only 13% of firms reported any impact on sales. Although these shares may appear low, the affected firms were disproportionately large, representing roughly 23% of export revenues, 46% of total sales, 39% of employment, and 30% of investment among survey respondents.

[13] In line with the existing literature (Bernard and Jensen, 1999; Bernard et al., 2007), Appendix Table A.1 shows that exporters outperform non–exporters in several dimensions, including sales, employment, and input expenditure. Consequently, although exporters are a minority of firms, they account for a disproportionate share of economic activity (Appendix Table A.2).

[14] The increase in export values for targeted goods after 2018 is further confirmed using a simple event–study analysis. See Appendix B for details.

These findings provide preliminary evidence of substantial firm–level heterogeneity in exposure and responses to the US–China trade war, particularly by firm size—a pattern we explore further in Section 6, where we also disentangle the underlying drivers.

3 Theory

This section introduces a non–parametric multi–country general–equilibrium model that disentangles the margins and channels through which heterogeneous firms respond to trade shocks, summarized in Proposition 1. Although our empirical application focuses on the US–China trade war, the model is general enough to accommodate a wide range of trade shocks, including sanctions and export controls.

3.1 Economic Environment

The world economy consists of $\mathcal{N}$ countries, indexed by j (origin) and n (destination), each populated by a representative household. Households consume a composite basket of differentiated domestic and foreign goods, as well as a homogeneous good. Differentiated goods are produced by heterogeneous domestic and foreign firms using capital and labor, potentially under non–constant returns to scale. Firms differ in both total factor productivity and product appeal. The homogeneous good is produced by representative firms under constant returns to scale. Labor is inelastically supplied by households, whereas the total capital stock available to firms is country–specific and exogenously determined. Differentiated goods are traded internationally subject to tariffs, while the homogeneous good is freely traded. In each country, the government collects tariff revenue and redistributes it to households in a lump–sum fashion.

3.1.1 Preferences

Household preferences in country n are given by:

$$c_n = Q_U(\{Q_n^H, Q_n^F, Q_n^O\}, \zeta_n); \; Q_n^F = Q_M(\{q_{j\omega n}\}, \xi_{j\omega n}); \; q_{j\omega n} = Q_L(\{q_{f(j)\omega nt}\}, \phi_{f(j)\omega n}). \tag{1}$$

Let c_n denote total consumption in country n. Consumption is a nested homothetic aggregator of domestic and foreign varieties. The upper–level aggregator (Q_U) combines domestic differentiated goods (Q_n^H), foreign differentiated goods (Q_n^F), and the homogeneous good (Q_n^O). The middle–level aggregator (Q_M) combines foreign differentiated goods across origins and product categories, where $q_{j\omega n}$ denotes the quantity of product ω exported from origin j to destination n. The lower–level aggregator (Q_L) combines firm–level varieties within a given product–origin pair, with $q_{f(j)\omega n}$ denoting the quantity of product ω exported by firm f from origin j to destination n. Let ζ_n, $\xi_{j\omega n}$, and $\phi_{f(j)\omega n}$ indicate preference shifters of the upper, middle, and lower nest, respectively. All aggregators are assumed to be differentiable and increasing in their arguments. We impose no restrictions on complementarity or substitutability within each nest, similarly to other non–parametric trade models (Adao et al., 2017; Arkolakis et al., 2019; Lind and Ramondo, 2023b; Adao et al., 2024).[15] Instead, these patterns will be estimated from the data in Section 5.

Our three–level nesting structure resembles multilevel demand systems used in international trade (Broda and Weinstein, 2006; Hottman et al., 2016). Our contribution is to preserve the economic content of this nesting—clarifying who competes with whom and mapping micro shocks to trade flows—without imposing parametric structures such as CES or translog. Rather than restricting cross–price elasticities to depend on trade shares and a few substitution parameters, we allow for arbitrary substitution and complementarity patterns within each nest, potentially varying by destination.

Equation (1) implies that a firm selling product ω from origin j to destination n competes neither with other products (its own or those of other firms) nor with domestic producers of the same product in country n. The first feature rules out strategic complementarities across goods and is standard in international trade. The second is necessary because firm–product–level domestic sales are unobserved (Broda and Weinstein, 2006).

Households in country n face the following budget constraint:

$$c_n = w_n\, L_n + T_n + \Pi_n. \tag{2}$$

Let w_n denote wages, while L_n is the household's (inelastic) labor supply. T_n represents lump–sum government transfers, and Π_n denotes aggregate profits of domestic firms. Firms are domestically owned, so aggregate profits Π_n accrue to households in country n.

[15] In line with their work, we impose no parametric structure on demand and work with local log–linear representations of equilibrium conditions in terms of demand elasticities. Our main departure lies in the level of disaggregation and the nesting structure: Adao et al. (2017) work at the factor–sector level, while Arkolakis et al. (2019) and Adao et al. (2024) focus on variety–level demand within a single nest. In contrast, we distinguish explicitly between (i) domestic versus foreign differentiated goods, (ii) foreign products by origin and HS category, and (iii) firm–level varieties within each product–origin pair.

3.1.2 Technology, Trade, and Market Structure

Firm f in country j producing differentiated product ω faces marginal costs:

$$c_{f(j)\omega} = c(w_j, i_j, z_{f(j)}, q_{j\omega}). \tag{3}$$

Let w_j and i_j denote the rental rates of labor and capital, which firms take as given. Let $z_{f(j)}$ be firm–level total factor productivity, and $q_{j\omega}$ total export quantity of product ω from country j. We assume marginal costs are differentiable in all arguments, increasing in input prices and decreasing in productivity. Dependence on aggregate product–level export quantities introduces Marshallian external economies of scale. We leave this term unspecified, allowing for increasing, decreasing, or constant returns to scale.[16]

Shipping product ω from origin j to destination n entails ad–valorem tariffs. We denote $\tau_{j\omega n}$ the import tariff rate applied by country n on product ω from country j. We impose $\tau_{j\omega n} > 1$ if $j \neq n$ and $\tau_{j\omega n} = 1$ if $j = n$.

The price charged by firm f selling product ω from origin j to destination n is:

$$p_{f(j)\omega n} = \mu_{f(j)\omega n}\, \tau_{j\omega n}\, c_{f(j)\omega}. \tag{4}$$

Let $\mu_{f(j)\omega n}$ denote markups. This price formulation nests several standard market structures, including variable markups under imperfect competition (Atkeson and Burstein, 2008), constant markups under monopolistic competition (Melitz, 2003), and unit markups under perfect competition (Eaton and Kortum, 2002).

The representative firm producing the homogeneous good faces marginal costs which depend only on capital and labor rental rates:

$$c_j = c(w_j, i_j). \tag{5}$$

We assume homogeneous goods producers are perfectly competitive, operate under constant returns to scale, and face no trade costs. As a result, the price of the homogeneous good is equalized across countries, and we normalize it to one (numéraire).

[16] For generality, we let firms differ in product appeal, as per Equation (1), and productivity, as per Equation (3). However, we do not aim to disentangle their contribution for firm growth (Hottman et al., 2016).

3.1.3 Firm Entry and Market Clearing

The mass of firms selling product ω from origin j to destination n is determined by the free–entry condition:

$$\mathbb{E}_{z,\phi}\left[\pi_{f(j)\omega n}\right] = F_{j\omega n}. \tag{6}$$

Let $\pi_{f(j)\omega n}$ indicate gross profits of firm f exporting product ω from country j to destination n. $F_{j\omega n}$ are entry costs that firms must pay to export product ω from country j to destination n, which we are paid in terms of the homogeneous good. The expectation is taken over the distribution of the two dimensions of heterogeneity among differentiated goods producers: total factor productivity ($z_{f(j)}$) and product appeal ($\phi_{f(j)\omega}$). We assume that all potential producers of differentiated goods are ex–ante homogeneous, with all heterogeneity realizing only upon entry. The mass of domestic producers in each country is exogenous. In each country, labor, capital, and differentiated goods markets must clear:

$$L_j = \sum_{f(j)\in\mathcal{F}_j} l_{f(j)}, \qquad K_j = \sum_{f(j)\in\mathcal{F}_j} k_{f(j)}, \qquad y_{j\omega} = \sum_{n\in\mathcal{N}_j} q_{j\omega n}. \tag{7}$$

Let $\mathcal{F}_j$ be the set of active firms in country j, and $\mathcal{N}_j$ the set of their export destinations. Firm f in country j demands labor $l_{f(j)}$ and capital $k_{f(j)}$. The total endowments of labor L_j and capital K_j available to firms in country j are exogenously given. We denote by $y_{j\omega}$ the total production of product ω in country j, net of its domestic households' consumption.

Governments fund lump–sum transfers to households with tariff revenue:

$$T_n = \sum_{j\in\mathcal{I}_n} \sum_{\omega\in\mathcal{O}_{jn}} \tau_{j\omega n}\, p_{j\omega n} q_{j\omega n}. \tag{8}$$

Let $\mathcal{I}_n$ be the set of countries from which buyers in country n purchase foreign products, $\mathcal{O}_{jn}$ the set of products exported from j to n, and $p_{j\omega n}q_{j\omega n}$ the export value of product ω from country j to destination n.

3.2 Export Responses to Trade Shocks

This section characterizes firm–level responses to international trade shocks along both the intensive margin (changes in export revenues for incumbent firms) and the extensive margin (changes in the number of active exporters). Derivations are in Appendix C.1.

3.2.1 Intensive Margin

Solving the households' problem yields the following expression for the export revenues of firm f when selling product ω from origin j to destination n:

$$r_{f(j)\omega n} = s_{f(j)\omega n}(\{p_{f(j)\omega n}\}, \phi_{f(j)\omega n}) \cdot s_{j\omega n}(\{p_{j\omega n}\}, \xi_{j\omega n}) \cdot s_n^F(\{p_n^H, p_n^F, p_n^0\}, \zeta_n) \cdot E_n. \tag{9}$$

In each period, households in country n allocate a fraction s_n^F of their total expenditure E_n to differentiated foreign goods. This expenditure is then divided across imported products ω, with $s_{j\omega n}$ denoting the share of country n's spending on product ω sourced from origin j. Within each origin–product pair, spending is distributed across firms proportionally to their market share $s_{f(j)\omega n}$. Each share depends on the relevant set of prices and preference shifters implied by the structure of households' preferences in Equation (1).

Taking the logarithmic differences of Equation (9) for any incumbent firm f exporting product ω from origin j to destination n delivers the following intensive–margin changes in export revenues (and suppressing function arguments for brevity):

$$\mathrm{d}\ln r_{f(j)\omega n} = \mathrm{d}\ln s_{f(j)\omega n} + \mathrm{d}\ln s_{j\omega n} + \mathrm{d}\ln s_n^F E_n. \tag{10}$$

Tariff changes between the US and China affect the export revenues of third–country firms through both direct and indirect channels. To fix ideas, consider an increase in US import tariffs on Chinese steel. This policy directly impacts Italian steel exporters by changing their market share in the US ($s_{j\omega n}$): if US buyers view Italian and Chinese steel as substitutes (complements), Italian exporters face higher (lower) demand (Fajgelbaum et al., 2024). Beyond this direct channel, export revenues may also adjust through general–equilibrium effects. First, aggregate US expenditure on foreign steel ($s_n^F E_n$) may adjust, proportionally affecting all foreign suppliers. Second, within Italy, firm–level export market shares ($s_{f(j)\omega n}$) may change, for example due to the entry or exit of exporters in response to changes in US demand for Italian steel. Ripple effects beyond the US are also possible: if Chinese exporters redirect exports away from the US, Italian firms could face intensified or reduced competition abroad,[17] making the overall effects of the US–China trade war on Italian firms ex–ante ambiguous.

[17] In line with this mechanism, Jiao et al. (2024) find that Chinese exports to the EU rose in response to the 2018–2019 US–China trade war, whereas there was little change in other markets.

Expressing $\mathrm{d}\ln s_{j\omega n}$ in terms of its components, we can rearrange Equation (10) as:[18]

$$\mathrm{d}\ln \tilde{r}_{j\omega n} = \kappa_n + \varepsilon_{j\omega n}\,\mathrm{d}\ln p_{j\omega n} + \sum_{\omega\in\mathcal{O}_{kn},\,k\notin\{j,n\}} \varepsilon_{k\omega n}\,\mathrm{d}\ln p_{k\omega n} + u_{j\omega n}. \tag{11}$$

The left–hand side of Equation (11) represents the change in aggregate export revenues of product ω from origin j to destination n.[19] This formulation clarifies that, because US–China tariffs do not discriminate across producers of the targeted products, firms within a given product–destination market are affected in the same way in expectation.[20] The term κ_n $(=\mathrm{d}\ln s^F_n E_n)$ captures instead destination–specific general–equilibrium adjustments in foreign expenditure.[21] The parameters $\varepsilon_{j\omega n}$ and $\varepsilon_{k\omega n}$ denote the own– and cross–price elasticities of the middle–nest market shares $s_{j\omega n}$ with respect to middle–nest prices, denoted by $p_{j\omega nt}$. Finally, $u_{j\omega n}$ captures changes in middle–nest market shares due to changes in unobservables.

Equation (11) captures the same export responses to the US–China trade war as Equation (10), but further decomposes changes in middle–nest market shares into own– and cross–price effects. Consider again an increase in US import tariffs on Chinese steel. The cross–price elasticity between Italian and Chinese products determines how changes in Chinese steel price directly affects Italian exporters to the US. Cross–price elasticities between Italian and other non–Chinese products capture additional effects faced by Italian exporters in response to price adjustments beyond China. Finally, the own–price elasticity governs changes in exports resulting from adjustments in Italian steel export prices.

Equation (11) can be further manipulated to disentangle price adjustments into its tariff and aggregate quantity components. Middle–nest price changes can be written as:

$$\mathrm{d}\ln p_{j\omega n} = \mathrm{d}\ln \tau_{j\omega n} + \psi_{j\omega}\mathrm{d}\ln q_{j\omega} + \nu_{j\omega n}. \tag{12}$$

Let $\mathrm{d}\ln \tau_{j\omega n}$ denote changes in tariffs imposed by country n on products ω from origin j, and $\mathrm{d}\ln q_{j\omega}$ the total change in export quantity of product ω from origin j. The parameter

[18] We use the property that $\mathrm{d}\ln f(x,y) = \varepsilon_{f,x}\,\mathrm{d}\ln x + \varepsilon_{f,y}\,\mathrm{d}\ln y$, where $\varepsilon_{f,x}$ and $\varepsilon_{f,y}$ are the elasticities of $f(x,y)$ with respect to x and y. Notice that we abstract from any high–order general–equilibrium effects that changes in revenues of Italian exporters generate on global consumption allocation, implicitly assuming that firm–level revenue changes do not propagate into global reallocations in a quantitatively meaningful way.

[19] To see this, let $\tilde{r}_{j\omega n} = \sum_{f\in\mathcal{O}_{jn}} r_{f(j)\omega n}$, where $\mathcal{O}_{jn}$ is the set of firms that export product ω from j to n, and note that $s_{f(j)\omega n} = r_{f(j)\omega n}/\tilde{r}_{j\omega n}$. Hence, $\mathrm{d}\ln r_{f(j)\omega n} - \mathrm{d}\ln s_{f(j)\omega n} = \mathrm{d}\ln \tilde{r}_{j\omega n}$.

[20] The same logic applies to other trade–related shocks, such as sanctions targeting specific countries or subsidies for particular goods. By contrast, shocks affecting firms asymmetrically already ex–ante would alter firm–level market shares $s_{f(j)\omega n}$.

[21] Such changes may occur for reasons other than tariff changes, including fluctuations in bilateral exchange rates between countries and changes in households' income.

$\psi_{j\omega}$ captures the elasticity of middle–nest prices with respect to total exported quantity and is informative about external returns in export supplies: $\psi_{j\omega} < 0$ indicates increasing external economies of scale, $\psi_{j\omega} > 0$ reflects decreasing external economies of scale, and $\psi_{j\omega} = 0$ corresponds to constant economies of scale. Finally, $\nu_{j\omega n}$ captures changes in unobserved shifters, including firms' productivity, markups, and appeal.

Substituting Equation (12) inside Equation (11) yields the final formulation of the equation we use to identify intensive–margin export responses:

$$\mathrm{d}\ln \tilde{r}_{j\omega n} = \kappa_n + \varepsilon_{j\omega n}\,\mathrm{d}\ln \tau_{j\omega n} + \varepsilon_{j\omega n}\,\psi_{j\omega}\,\mathrm{d}\ln q_{j\omega} + \sum_{\omega \in \mathcal{O}_{knt},\, k \notin \{j,n\}} \varepsilon_{k\omega n}\,\mathrm{d}\ln p_{k\omega n} + v_{j\omega n}. \tag{13}$$

Returning to the steel tariff example, during the 2018–2019 trade war the US raised import tariffs not only on Chinese steel but also on steel from the EU, including Italy (see Section 2.2.1). In addition to the effects discussed above, Equation (13) distinguishes between the direct impact of tariffs and the role of economies of scale in driving changes in the revenues of Italian steel exporters to the US. We do not decompose changes in the middle–nest price index for other origins, $\mathrm{d}\ln p_{k\omega n}$ for $k \notin \{j, n\}$, because our data cover only Italian exporters, preventing credible identification of scale economies outside Italy. In principle, with customs data for multiple countries, we could disentangle the impact of tariffs from scale economies in each origin country. However, the observed changes in export prices from other origins do respond to US–China tariffs, as clarified by Equation (12).

3.2.2 Extensive Margin

Under the assumption that firms are ex–ante homogeneous and all shocks are realized only upon entry, Equations (6) and (9) imply that the number of firms exporting product ω from origin j to destination n ($N_{j\omega n}$) is pinned down by the following equality:

$$\frac{s_{j\omega n}\, s_n^F\, E_n}{N_{j\omega n}} = F_{j\omega n}. \tag{14}$$

Following the same steps as for the intensive margin, we derive an expression governing extensive–margin export responses—i.e., changes in the number of firms exporting product

ω from origin j to destination n:

$$\mathrm{d}\ln N_{j\omega n} = \kappa_n + \varepsilon_{j\omega n}\,\mathrm{d}\ln\tau_{j\omega n} + \varepsilon_{j\omega n}\,\psi_{j\omega}\,\mathrm{d}\ln q_{j\omega} + \sum_{\omega\in\mathcal{O}_{knt},\,k\notin\{j,n\}} \varepsilon_{k\omega n}\,\mathrm{d}\ln p_{k\omega n} + \nu_{j\omega n}. \tag{15}$$

Notation follows Equation (13), with the distinction that all variables now refer to extensive–margin changes. Notice we assume that entry costs do not change over time, i.e., $\mathrm{d}\ln F_{j\omega n} = 0$. While restrictive, this assumption fits our context: we study a two–year long horizon during which ad–valorem tariff changes arguably did not directly affect entry costs.

3.3 Decomposition of Export Responses

The total change in firm–level export revenues can be defined as the weighted average of product–destination–specific export revenue changes:

$$\mathrm{d}\ln r_{f(j)} = \sum_{n\in\mathcal{N}_f}\sum_{\omega\in\Omega_{fn}} \theta_{f(j)\omega n}\,\mathrm{d}\ln\tilde{r}_{j\omega n}. \tag{16}$$

Let $\theta_{f(j)\omega n}$ denote the share of firm f's export revenues from selling product ω to destination n at baseline—i.e., before the shock is realized—, and $\mathrm{d}\ln\tilde{r}_{j\omega n}$ the change in product–destination–specific export revenues from Equation (13). We define $\mathcal{N}_f$ as the set of destinations served by firm f and Ω_{fn} as the set of products it exports to destination n.

Applying the Olley and Pakes (1996) decomposition to Equation (16), we can break down changes in a firm's total export revenues into two parts. The first part measures the average change in export revenues across all product–destination pairs offered by firm f, and is the same for all firms that export the same set of products to the same destinations over time. The second part is a covariance term that links a firm's initial export exposure to changes in product–destination–specific export revenues, reflecting reallocation across products and destinations within the firm.

The next proposition presents the decomposition, which constitutes the central outcome of our model and serves as the main tool for disentangling and quantifying the various channels through which the US–China trade war triggered firm–level export responses in a bystander country such as Italy.

Proposition 1. *Firm–level total export revenue changes can be decomposed as follows:*

$$\mathrm{d}\ln r_{f(j)} = \underbrace{\mathbb{E}\left[\mathrm{d}\ln\tilde{r}_{j\omega n}\right]}_{\textit{Mean Term}} + \underbrace{\mathrm{cov}\left(\theta_{f(j)\omega n},\,\mathrm{d}\ln\tilde{r}_{j\omega n}\right)}_{\textit{Covariance Term}}. \tag{17}$$

Using Equation (13), we can rewrite the Mean Term as:

$$\mathbb{E}\left[\mathrm{d}\ln\tilde{r}_{j\omega n}\right] = \underbrace{\mathbb{E}\left[\kappa_n\right]}_{\text{Destination Effect}} + \underbrace{\mathbb{E}\left[\varepsilon_{j\omega n}\,\psi_{j\omega}\,\mathrm{d}\ln q_{j\omega}\right]}_{\text{Scale Effect}}$$
$$+ \underbrace{\mathbb{E}\left[\varepsilon_{j\omega n}\,\mathrm{d}\ln\tau_{j\omega n}\right]}_{\text{Own–Demand Effect}} + \underbrace{\mathbb{E}\left[\sum_{\omega\in\mathcal{O}_{knt},\,k\notin\{j,n\}}\varepsilon_{k\omega n}\,\mathrm{d}\ln p_{k\omega n}\right]}_{\text{Cross–Demand Effect}} + \underbrace{\mathbb{E}\left[\nu_{j\omega n}\right]}_{\text{Residual}}, \tag{18}$$

and the Covariance Term as:

$$\operatorname{cov}\left(\theta_{f(j)\omega n}, \mathrm{d}\ln\tilde{r}_{j\omega n}\right) = \underbrace{\operatorname{cov}\left(\theta_{f(j)\omega n}, \kappa_n\right)}_{\text{Destination Effect}} + \underbrace{\operatorname{cov}\left(\theta_{f(j)\omega n}, \varepsilon_{j\omega n}\,\psi_{j\omega}\,\mathrm{d}\ln q_{j\omega}\right)}_{\text{Scale Effect}}$$
$$+ \underbrace{\operatorname{cov}\left(\theta_{f(j)\omega n}, \varepsilon_{j\omega n}\,\mathrm{d}\ln\tau_{j\omega n}\right)}_{\text{Own–Demand Effect}} + \underbrace{\sum_{\omega\in\mathcal{O}_{knt},\,k\notin\{j,n\}}\operatorname{cov}\left(\theta_{f(j)\omega n}, \varepsilon_{k\omega n}\,\mathrm{d}\ln p_{k\omega n}\right)}_{\text{Cross–Demand Effect}}$$
$$+ \underbrace{\operatorname{cov}\left(\theta_{f(j)\omega n}, \nu_{j\omega n}\right)}_{\text{Residual}}. \tag{19}$$

Appendix C.2 provides the analytical expressions for the Mean and Covariance terms.

Proposition 1 shows that both the mean and covariance terms can be broken down into five quantifiable components. These components depend on the model's structural parameters, which are estimated, and on changes in equilibrium variables, which are observed in the data. The first captures destination–specific general–equilibrium adjustments, common to all firms and products, and is informative about general equilibrium effects and aggregate macroeconomic forces. The second reflects changes in total export quantity, and is informative about external economies of scale affecting firms' export revenues. The third isolates changes in destination–imposed import tariffs on a firm's exported products, shedding light on own–price demand elasticities. The fourth captures changes in the prices paid by consumers in each destination for the same product sourced from other origins, revealing substitution and complementarity patterns. The final component is a residual term, tracking changes in productivity and product appeal over time.

To fix ideas, consider again the case of the US raising import tariffs on products from China and the EU. Proposition 1 highlights that the Italian firms most affected (in absolute terms) are those whose exports are concentrated (*i*) in the US, (*ii*) in products targeted by US tariffs, (*iii*) in products subject to economies of scale, and (*iv*) in products strongly substitutable for, or complementary to, those from other origins.

3.4 Pass–Through to Domestic Outcomes

The labor and capital shares of firm f, located in country i, at time t can be written as:

$$\frac{w_j l_{f(j)}}{r_{f(j)}} = \frac{\vartheta_j}{\mu_{f(j)}}, \qquad \frac{i_j k_{f(j)t}}{r_{f(j)}} = \frac{\chi_j}{\mu_{f(j)}}. \tag{20}$$

Here, $r_{f(j)t}$ denotes total firm–level sales. The parameters θ_i and χ_j are the output elasticities of labor and capital, respectively, which we assume to be constant across all firms within a country–year. Finally, $\mu_{f(j)}$ denotes firm–level markups. Taking the log difference of Equation (20) delivers the following pass–through equations:

$$\mathrm{d}\ln w_j l_{f(j)} = \mathrm{d}\ln \frac{\vartheta_j}{\mu_{f(j)}} + \mathrm{d}\ln r_{f(j)t}, \qquad \mathrm{d}\ln i_j k_{f(j)} = \mathrm{d}\ln \frac{\chi_j}{\mu_{f(j)}} + \mathrm{d}\ln r_{f(j)t}. \tag{21}$$

Equation (21) highlights that input expenditures adjust proportionally to both the ratio of input elasticities to markups and to changes in total sales (Autor et al., 2020). This equation establishes a direct link between firm–level sales changes—induced, e.g., by the US–China trade war—and expenditure on domestic labor and capital investment.

3.5 Discussion

We conclude this section by discussing possible extensions of our model.

3.5.1 Import Responses

A natural extension is to allow firms to adjust to trade shocks not only through exports, but also through imports. During the US–China trade war, Chinese exporters may have redirected goods to third markets, including Italy, potentially at lower prices. Such cheaper inputs could lower Italian firms' marginal costs and raise their exports. Our model can accommodate this channel. Let imports be a firm–specific aggregator of imported varieties (Antras et al., 2017). Marginal production costs can be expressed as:

$$c_{f(j)\omega} = c(w_j, i_j, m_{f(j)}, z_{f(j)}, q_{j\omega}). \tag{22}$$

Notation follows from Equation (3), except now $m_{f(j)}$ denotes firm–specific import costs. If lower input prices from China reduce $m_{f(j)}$, they affect marginal costs in the same way as higher productivity and enter the error term of Equation (13). Therefore, the estimated coefficients can be interpreted as conditional on import choices being already made.[22]

3.5.2 Labor Market Frictions

We assume frictionless labor markets and a representative agent, implying wage equalization within a country. In practice, however, labor mobility is limited, temporary trade shocks are not immediately absorbed by wages, and their effects vary by skill (Dix-Carneiro, 2014; Caliendo et al., 2019). The baseline model represents one extreme, with perfectly flexible and spatially equalized wages. At the opposite extreme, wages could be firm–specific—due to monopsony power or bilateral bargaining—so wage changes would enter the error term of Equation (13) similarly to productivity shocks. Intermediate cases, such as sector–level wages, can be captured by fixed effects aggregated above the firm level.

3.5.3 Capital Accumulation

To keep the model parsimonious, we assume capital supply is exogenous. This lets us quantify how trade shocks transmit to domestic labor and capital while abstracting from accumulation and transitional dynamics. A simple extension would allow households to save in risk–free bonds, with savings contributing to next period's capital (net of depreciation), which is rented to firms. If firms take capital price as given, this yields the same estimating equation as Equation (13).

4 Estimation and Identification

This section discusses the mapping between the model and the data, and the identification and estimation of the structural parameters that govern firm–level export responses to the US–China trade war.

4.1 Estimating Equations and Estimation Sample

To quantify firm–level responses to the US–China trade war, we need to estimate the own- and cross–price elasticities and the scale–economies parameter in Equations (13) and (15). In our baseline results, we assume that price elasticities are destination–specific and scale economies are constant across products, and we inspect heterogeneity later in Section 5.

[22] The evidence suggests that import reallocation played a limited role in shaping Italian export responses during the 2018–2019 US–China trade war. Specifically, we do not find any systematic relationship between firms' export responses and their exposure to (or changes in) imports from China (see Section 6).

Under these restrictions, our main estimating equation for intensive–margin responses becomes:

$$\mathrm{d}\ln\tilde{\pi}_{j\omega n} = \kappa_n + \varepsilon_n \,\mathrm{d}\ln\tau_{j\omega n} + \varepsilon_n\,\psi\,\mathrm{d}\ln q_{j\omega} + \sum_{\omega\in\mathcal{O}_{knt},\,k\notin\{j,n\}} \varepsilon_{kn}\,\mathrm{d}\ln p_{k\omega n} + v_{j\omega n}. \tag{23}$$

We estimate Equation (23) having Italy as the only origin. We classify all other countries into four groups: the US, China, the EU (excluding Italy), and the Rest of the World (RoW). Our sample covers 4,910 6-digit HS products. Tariff changes $\mathrm{d}\ln\tau_{j\omega n}$ are nonzero only for Italy's trade with the US and China (see Section 2.2.1), and are zero for trade with the EU and the RoW. Changes in all variables are measured over the 2017-2019 period—as tariffs remained largely unchanged before 2017.

Estimation is performed via weighted-stacked Generalized Method of Moments (GMM). For each destination, we define the relevant moment conditions and then stack them across destinations, using the number of exporters in each product–destination cell as weights. We estimate Equation (23) using long differences between 2019 and 2017, and cluster standard errors by firm–product. We follow the same procedure when applying Equation (15) to the data, except that no weighting is needed to estimate the parameters governing extensive–margin responses.

Finally, regarding the pass–through to domestic outcomes, we use output elasticities—allowed to vary at the 2-digit NACE level—and firm–level markups in Equation (21) using estimates from Ciapanna et al. (2024), which are based on a production-function approach à la De Loecker and Warzynski (2012) and the same data sources as ours.[23]

4.2 Identification

Identification of the own–price elasticity in Equation (23) hinges on the tariff changes faced by Italian exporters during the 2018–2019 US–China trade war being uncorrelated with unobserved shocks to their revenues. As discussed in Section 2.2.1, this assumption is plausible because these tariff changes were effectively a "byproduct" of the US–China dispute, rather than policy measures enacted in response to the export performance of bystander countries in general, or Italy in particular. Moreover, as tariffs are not firm–

[23] We use their estimates rather than producing our own for two reasons. First, in Equation (3), firm–level output depends on total export quantity, a feature not easily accommodated by standard production-function estimators (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015). Extending these methods to account for external economies of scale in export quantity is beyond the scope of our paper. Second, firm–level markups in Equation (21) represent weighted averages of product–destination–specific markups, which would require additional model assumptions to estimate. Relying on external estimates thus avoids imposing further structure.

specific but represent aggregate shifters, they do not directly affect firm–level markups entering in $v_{j\omega n}$ and thus do not introduce potential endogeneity.[24]

Our demand system in Equation (1) allows for the possibility that changes in middle–nest export prices of Italian competitors ($\mathrm{d}\ln p_{k\omega n}$) correlate with unobservable shocks to Italian exporters' performance ($\nu_{j\omega n}$). Such correlation may arise, for example, if exporters' performance shocks are correlated within products across countries. However, the structure of our model clarifies that this channel operates only through changes in the middle–nest market share—and, consequently, prices—of Italian exporters, which are directly controlled for in Equation (23). This feature therefore alleviates concerns about omitted–variable bias in the identification of cross–price elasticities.

Endogeneity concerns emerge when estimating the parameter governing external economies of scale if changes in Italy's total product–level export quantities ($\mathrm{d}\ln q_{j\omega}$) correlate with unobserved shocks to firms' export revenues for that product in a given destination. This may occur, for instance, if revenue shocks in a major market—say, the US—are sufficiently large to affect total Italian exports of that product. To address this concern, we introduce the following instrument:

$$\mathrm{d}\ln\min\{\tau_{US\rightarrow CN,\omega},\tau_{CN\rightarrow US,\omega}\}. \tag{24}$$

We instrument changes in Italy's product–level total export quantity with changes in the minimum tariff rate applied between the US and China for each 6–digit HS product. This instrument captures the lower bound of tariff–induced changes in product–level prices between the two countries and the associated reallocation of global demand and supply across these products.

The exclusion restriction requires that US–China bilateral tariff changes affect Italian exports solely through this exogenous reallocation. This assumption is plausible because US–China tariffs were largely driven by political and strategic considerations unrelated to the export performance of third countries (Mayr-Dorn et al., 2023; Utar et al., 2023; Fajgelbaum et al., 2024; Cavalcanti et al., 2025; Chen et al., 2025). The same logic applies when estimating the equation for extensive–margin responses, which we omit for brevity.

[24]For example, in the oligopolistic market structure of Atkeson and Burstein (2008), firm–level markups are an increasing and convex function of firms' market shares. A uniform tariff applied to all firms proportionately leaves the market share distribution unchanged and thus does not change firm–level markups.

5 Estimation Results

This section presents the estimates derived from our model. It also discusses their robustness as well as heterogeneous effects.

5.1 Baseline Estimates

Figure 1 illustrates the four estimated components of Equation (23): own–price and scale-economy elasticities (Panel A), cross–price elasticities (Panel B), and destination fixed effects (Panel C). Full estimates are reported in column (1) of Appendix Table A.5.

The left figure of Panel A illustrates substantial heterogeneity in own–price demand elasticities across destinations, with estimates consistent with the literature (Broda and Weinstein, 2006; Head and Mayer, 2014; Fontagné et al., 2022; Boehm et al., 2023). US demand for Italian products is more than twice as elastic as Chinese demand, implying that Italian exports were more sensitive to US tariff increases than to Chinese MFN tariff reductions. The right figure documents positive scale economies, which further amplify the impact of direct demand shocks. Quantitatively, our estimates fall within the range of 0.1–0.3 reported in the literature (Lashkaripour and Lugovskyy, 2023; Bartelme et al., 2025).

Panel B highlights heterogeneity in cross–price elasticities. Italian products act as substitutes (positive cross–price elasticity) for Chinese goods in the US market, and also for EU goods, though the latter effect is only significant at the 10% level. The pattern reverses for exports to China: Italian goods complement (negative cross–price elasticity) US and EU goods but substitute for RoW goods. Toward the EU and RoW, Italian products generally behave as substitutes for all other origins.

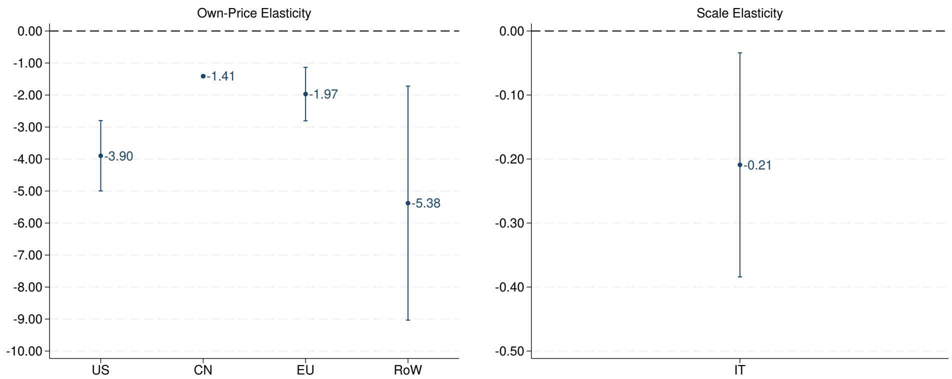
Panel C shows that other destination–specific general–equilibrium adjustments between 2017 and 2019 slightly raised export revenues to the US and, to a lesser extent, the EU. There is no evidence of substantial changes toward China or the RoW.

The last column of Appendix Table A.5 shows that the parameters governing extensive–margin responses are noisily estimated, and no clear pattern emerges regarding how own–price, cross–price, or scale elasticities shape firms' entry. At most, we observe modest entry into China and exit from the EU and RoW, driven by destination–specific adjustments. Plausible explanations are that the tariff changes were too small to trigger extensive–margin responses, or that such responses take longer to materialize than our sample period allows.[25] We therefore focus on intensive–margin responses in what follows.

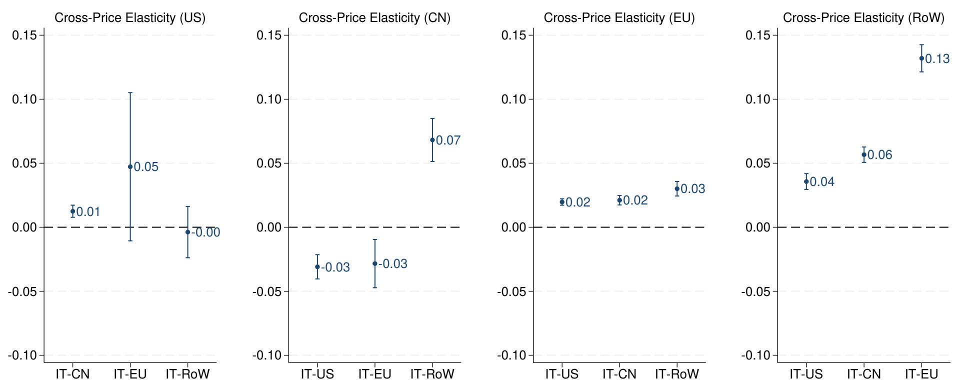
[25] The 2025 wave, with much higher tariff rates, may yield different outcomes.

Figure 1. Intensive–Margin Baseline Estimates

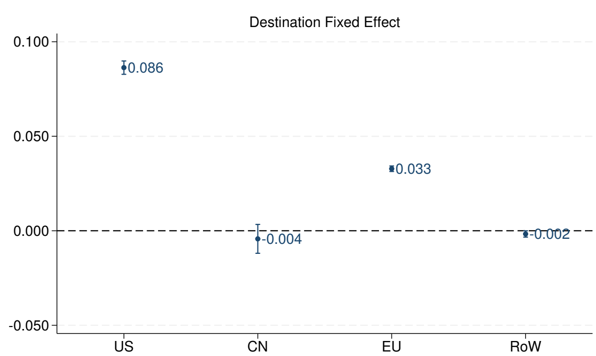
Panel A



Panel B



Panel C



Notes: The figure shows the four estimated components of Equation (23): own–price and scale economies elasticities (Panel A), cross–price elasticities (Panel B), and destination fixed effects (Panel C). Point estimates and 95% confidence intervals are shown. Standard errors are clustered by firm and product.

5.2 Model Fit

In Equation (1), we have four sets of moment conditions, one for each product–destination pair. While tariff and price changes are product–destination specific, total export quantity is common across destinations. In other words, the system is over–identified, allowing us to assess the validity of our instrument. Reassuringly, the p–value for our baseline estimates in Figure 1 is 0.62, indicating that we cannot reject the hypothesis that our over–identification restrictions hold.

As an additional check of model fit, we compute the share of explained variance for the full model, as well as for restricted models that omit scale economies and cross–price elasticities, akin to a canonical trade model (Head and Mayer, 2014). Appendix Table A.6 reports results pooling export revenue changes across all destinations. The full model accounts for roughly two-thirds of the total outcome variance, whereas the restricted models, which set scale and cross–price elasticities to zero, explain only roughly one–sixth or one–tenth. Remarkably, omitting scale economies produces the largest drop in explanatory power, suggesting they are a key driver of firm–level export responses. We return to this issue in Section 6, which confirms this interpretation.

Appendix Table A.7 presents the same decomposition for each destination separately. Even at this level, the restricted models perform substantially worse than the full model on average, indicating that the substitution structure imposed by standard trade models may be too restrictive and fail to capture important channels through which firms adjusted their exports in response to the US–China trade war. In this regard, our results support the findings of Imbs and Mejean (2015) and Bas et al. (2017).

5.3 Robustness

Columns (2)–(5) of Appendix Table A.5 assess the robustness of the baseline results reported in column (1). In column (2), we show that the baseline estimates are robust to clustering standard errors by firm rather than by firm–product. In column (3), we control for the lagged change in the outcome variable between 2014 and 2016 to ensure that our estimates capture the response to the tariff treatment rather than pre–existing trends in export revenues. Reassuringly, the baseline estimates remain largely unchanged after accounting for outcome pre–trends. In column (4), we replace our baseline instrument in Equation (24) with the change in US product–level import tariffs on Chinese goods ($\mathrm{d}\ln\tau_{US\to CN,\omega}$). Once again, the estimates are fundamentally unchanged.

Finally, in column (5) we use the change in export quantity, rather than export revenues, as the outcome variable. Our model implies that the export quantity of firm f selling product ω from origin j to destination n at time t is given by:

$$q_{f(j)\omega n} = s_{f(j)\omega n}(p_{f(j)\omega n}, \phi_{f(j)\omega n}) \cdot s_{j\omega n}(p_{j\omega n}, \xi_{j\omega n}) \cdot s_n^F(p_n^H, p_n^F, p_n^0, \zeta_n) \cdot \frac{E_n}{P_n}. \tag{25}$$

The key difference from Equation (9) is that real income, rather than nominal income, is used to determine export quantities. Therefore, we follow the same strategy as in Section 3.2.1 to obtain an estimating equation for intensive–margin export quantity responses. In practice, we estimate Equation (23) with changes in export quantity rather than changes in export value as the outcome variable. This approach allows us to disentangle whether changes in export revenues are driven primarily by price adjustments, quantity adjustments, or a combination of both.

Comparing the estimates in columns (1) and (5) shows that the signs of the coefficients governing export revenue responses are consistent with those of export quantity responses, indicating that revenues changed because of quantities changes instead of price movements.

5.4 Heterogeneity

Our baseline estimates allow own– and cross–price elasticities to vary only by destination. We adopt this benchmark for clarity and to ensure computational feasibility of the GMM routine. However, Equation (13) also permits elasticities to vary by product. To investigate this source of heterogeneity, Appendix Table A.8 tests whether cross–price elasticities and scale economies differ across product types. Columns (1)–(2) interact these elasticities with an indicator for whether products are intermediate or final according to the Broad Economic Categories (BEC) classification. Columns (3)–(4) distinguish differentiated from homogeneous goods using the classification proposed by Rauch (1999). Column (5) interacts the scale elasticity with an indicator for whether firms are headquartered in the Center–North, using the South and Islands as the omitted group.

The results provide three key insights. First, there is no detectable heterogeneity in cross–price elasticities between final and intermediate goods (column 1), but positive scale economies are entirely driven by intermediate products (column 2). Second, as expected, substitution patterns are stronger for homogeneous goods (column 3), and scale economies appear larger for these goods, though the estimates are noisy (column 4). Third, scale economies are stronger for firms located in the Center–North (column 5), consistent with the notion that Italian firms tend to cluster production in industrial districts in these regions (Di Giacinto et al., 2023).

6 Aggregation

This section uses the structural estimates to decompose firm–level responses according to Proposition 1, evaluate the pass–through of export revenue changes to domestic outcomes, and examine changes in allocative efficiency among Italian firms.

Our results show that the 2018–2019 US–China trade war enabled incumbent Italian exporters to expand in foreign markets, particularly in the US. Economies of scale amplified the initial demand shifts triggered by reciprocal tariffs between the US and China and account for most of the observed changes in firm–level export revenues. While the average effect is positive, the gains were unevenly distributed: some firms benefited substantially, whereas others experienced declines in export revenues. These changes were mirrored in firm–level employment and investment decisions. Overall, the firms that were initially more productive captured the largest gains, suggesting that allocative efficiency in Italy improved over the 2017–2019 period.

6.1 Firm–Level Export Revenue Change Decomposition

Using Equation (16), we compute firm–level changes in total export revenue as a weighted average of destination–specific changes. Initial export shares ($\theta_{f(j)\omega n}$) come from 2017 data, while product–destination–specific changes ($\mathrm{d}\ln\tilde{r}_{j\omega n}$) are obtained from Equation (23), and capture the effects of the 2018–2019 US–China trade war as predicted by our model.

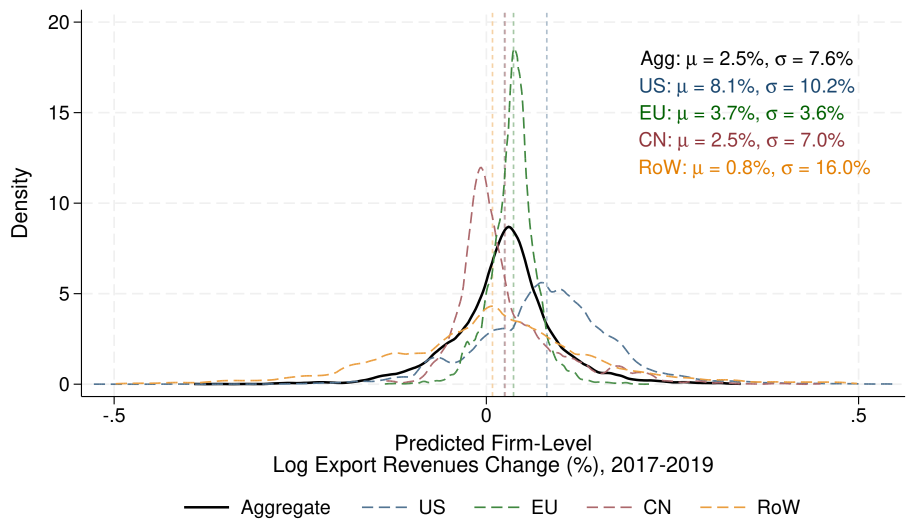
6.1.1 Distribution of Export Revenue Changes across Firms

Figure 2 shows the distribution of export revenue changes across firms, both pooled across destinations and broken down by destination. Overall, the 2018–2019 US–China trade war generated short–run net export opportunities for Italian firms, with average export revenues rising by 2.5% over the period.[26] Most of this gain stemmed from increased sales to the US, consistent with Italian exports substituting for Chinese products. Exports to the EU and China—and, to a lesser extent, to the RoW—also expanded, consistent with the presence of external increasing returns to scale in Italian exports. The growth in exports to China is noteworthy: given the complementarity between Italian and US goods in the Chinese market, one would expect Italian exports to fall when import tariffs reduce US sales to China. The observed increase therefore implies that external scale economies were sufficiently strong to more than offset this negative channel.

[26] This finding is consistent with Fajgelbaum et al. (2024), who also show that Italy lies toward the lower end of the distribution among net winners.

These average effects, however, mask substantial heterogeneity: the standard deviation of pooled export revenue changes is 7.6%, highlighting that the trade war created both winners and losers among Italian exporters.

Figure 2. Distribution of Firm–Level Export Revenue Changes



Notes: The figure shows the distribution of predicted export revenue changes across Italian firms between 2017 and 2019, both pooled across destinations and disaggregated by destination. Firm–level export revenue changes are computed using Equation (16).

Appendix Figure A.6 aggregates firm–level export revenue changes to the sector level, using the BEC classification. All sectors experienced growth in export revenues, with the largest increases concentrated in consumer goods, food and beverages, and fuels and lubricants. Appendix Figure A.7 highlights substantial heterogeneity across Italian provinces: most gains accrued to northern provinces, though some provinces in the center–south and islands also benefited.[27] Appendix Figure A.8 further decomposes province–level changes by export destination. Interestingly, provinces did not uniformly gain or lose across destinations. The Pearson (Spearman) correlation between province–level export revenue changes toward the US and China is –17% (–14%), indicating divergence, while changes toward the EU and RoW are more aligned, with correlations of 46% (42%).

6.1.2 Mechanisms Inspection: Demand, Scale Economies, and Competition

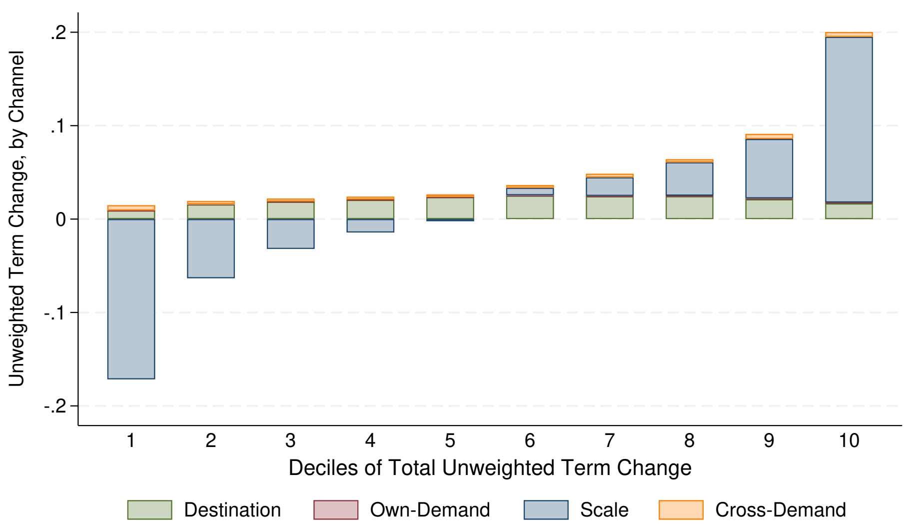
We compute the contributions of each channel driving firm–level export revenue changes resulting from the US–China trade war, as highlighted in Proposition (1). Unweighted

[27]This finding is consistent with Borin et al. (2025), who show that Italian northern local labor markets have a higher export exposure to the US than those in the center and south.

mean changes account for roughly four–fifths of the observed variation in export revenues, while covariance terms collectively explaining the remaining one–fifth.

Figure 3 presents the decomposition of unweighted mean export revenue changes from Proposition (1). It shows the average contribution of the unweighted term across deciles of its total change, broken down into four components: destination–specific, own–demand, scale, and cross–demand effects. Across deciles, the scale economy channel explains roughly three–quarters of the total variation in unweighted mean export revenue changes. This suggests that changes in product–level export quantities to any destination induced by the US–China trade war were the primary drivers of firm–level export revenue changes for both winners and losers. The remaining one–quarter is explained collectively by destination, own–demand, and cross–demand effects, which consistently pushed export revenues up across all deciles, though their impact is dominated by scale economies.

Figure 3. Decomposition of Firm–Level Export Revenue Changes (Mean Change)

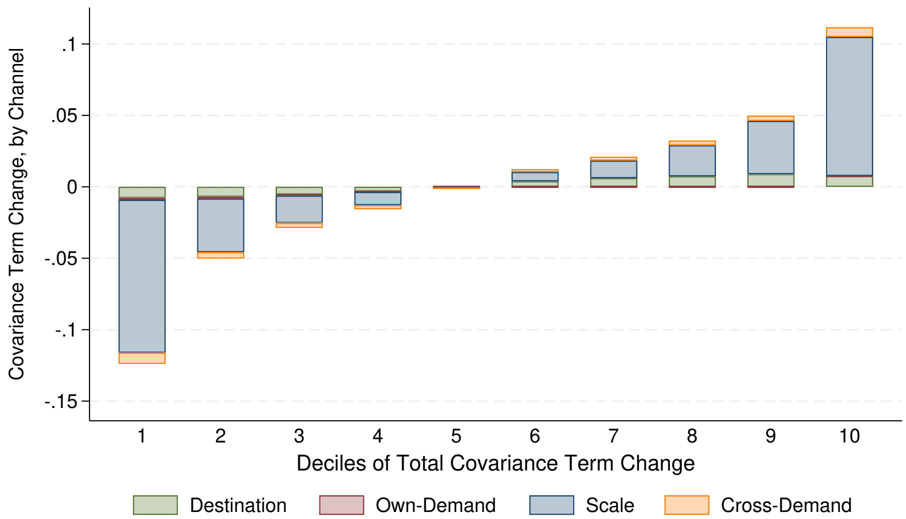


Notes: The figure shows the decomposition of unweighted mean export revenue changes from Proposition (1). It displays the average change of the unweighted term across deciles of its total change, broken down into four components: destination–specific, own–demand, scale, and cross–demand effects. The unweighted mean component explains about four–fifths of the total observed change in export revenues in the data.

A similar pattern emerges when decomposing mean export revenue changes across destinations, as shown in Appendix Figure A.9, except for exports to China. Here, the increase in export revenues was entirely driven by the own–demand channel, reflecting Chinese MFN tariff cuts toward non–US countries. In contrast, reductions in exports to China were largely explained by cross–demand effects, due to the complementarity between Italian exports and those from the US and EU, as highlighted in Figure 1.

Figure 4 presents the same decomposition as Figure 3, but for the covariance term. As with the unweighted term, the scale economies channel largely determines the direction of changes in the covariance term across deciles, accounting for roughly two-thirds of its total change. Unlike the unweighted mean changes, however, all four channels move in the same direction, jointly contributing either to increases or decreases in export revenues.

Figure 4. Decomposition of Firm–Level Export Revenue Changes (Covariance Terms)



Notes: The figure shows the decomposition of the covariance term of export revenue changes from Proposition (1). It displays the average change of the covariance term across deciles of its total change, broken down into four components: destination–specific, own–demand, scale, and cross–demand effects. The covariance term component explains about one–fifth of the total observed change in export revenues in the data.

When decomposing mean export revenue changes across destinations, scale economies again appear to be the main driver of changes in the covariance term, with the exception of exports to China, as shown in Appendix Figure A.10. As in Appendix Figure A.9, increases in export revenues to China are driven by the own–demand channel, while reductions are primarily due to cross–demand effects.

Overall, the quantitative results in Figures 2, 3, and 4 indicate that Italian firms responded to the US–China trade war not only by adjusting exports to these two countries, reflecting changes in the international competitive landscape, but also by increasing exports to the EU and RoW, consistent with scale economies in Italian exports operating across destinations.

6.1.3 Inspecting Economies of Scale

The results above underscore the importance of positive external economies of scale in explaining changes in Italian exporters' revenues, both for winners and losers. What drives these scale effects? To investigate this, we re–estimate Equation (23) separately for each 2–digit HS product code, and then relate the resulting product–specific scale elasticity estimates to various mechanisms highlighted in the literature.

Specifically, we regress the estimated product–specific scale elasticities on several potential drivers of external scale economies: (i) the average number of firms producing that product across Italian provinces in 2017, capturing the potential for knowledge spillovers among geographically proximate firms (Redding, 2022); (ii) the share of high–tech products within that HS category,[28] proxying for knowledge intensity and opportunities for know–how diffusion (Lind and Ramondo, 2023a); (iii) average labor productivity across firms producing those products in 2017, reflecting that more productive workers may transmit knowledge when moving across firms (Chaney and Ossa, 2013); (iv) average investment–to–value–added and materials–to–employment ratios across those firms in 2017, capturing that investment– and material–intensive sectors typically exhibit high fixed costs and low marginal costs, a classic source of increasing returns (Alvarez, 2017); and (v) the share of imports sourced from emerging markets, capturing the role of cheaper inputs in supporting scale expansion (De Loecker et al., 2016).[29]

Appendix Table A.9 shows moments of the distribution of the estimated external economies of scale. Economies of scale tend to be larger in the food industry (beverages and spirits, dairy products, and cereal–, flour–, starch–, or milk–based preparations), in the chemical sector (including cosmetics, perfumery, pigments, and paints) and in leather goods (such as handbags, wallets, and belts). As shown in Table 1, product groups characterized by a greater number of active firms and a higher share of high–tech production display stronger scale economies. This pattern is consistent with knowledge diffusion facilitated by geographic proximity and access to advanced technologies. In contrast, there is no empirical evidence supporting the other proposed channels.

The absence of a correlation between scale economies and imports from emerging markets, including China, is noteworthy and indicates that access to cheaper inputs is not a major driver of scale economies in our sample. Appendix Figure A.11 corroborates this result by regressing the model–predicted change in export revenues from Equation (23) on firms' share of imports from China in 2017 (left panel) and on the change in imports from China between 2017 and 2019 (right panel). In both cases, changes in export revenues are

[28] We classify products as high– or low–tech following the Eurostat definition (see `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries`).

[29] Emerging markets are defined according to the MSCI classification (see `https://www.msci.com/indexes/index-resources/market-classification`). In an alternative specification, we replace the import share from MSCI markets with the import share from China. The results in Appendix Table 1 are substantially unaffected.

unrelated to exposure to Chinese inputs, suggesting that Italian firms did not benefit from direct access to cheaper Chinese inputs during the 2018–2019 US–China trade war.

Table 1. Drivers of External Economies of Scale

VARIABLES	(1) Scale Elasticity (HS2)
Number of Firms, 2017	-0.17***
	(0.05)
Share of High–Tech Products, 2017	-0.16***
	(0.05)
Labor Productivity, 2017	-0.00
	(0.06)
Investment over Value Added, 2017	-0.02
	(0.06)
Materials over Number of Employees, 2017	-0.06
	(0.07)
Import Share from Emerging Markets, 2017	0.07
	(0.05)
Constant	-0.21***
	(0.05)
Observations	73

Notes: Each observation corresponds to a 2–digit HS product. The dependent variable is the scale elasticity estimated from Equation (23) for each 2–digit HS product code. *Number of Firms, 2017* denotes the average number of firms producing that product across Italian provinces in 2017. *Share of High–Tech Products, 2017* measures the share of high–tech products within that HS category. *Labor Productivity, 2017* is the average labor productivity among firms producing those products in 2017. *Investment over Value Added, 2017* and *Materials over Number of Employees, 2017* correspond to the average investment–to–value–added and materials–to–employment ratios for firms producing each 2–digit HS product in 2017. *Import Share from Emerging Markets, 2017* measures the share of imports sourced from emerging economies. All variables are standardized to have a mean of zero and a standard deviation of one within the sample. Standard errors in parentheses are heteroskedasticity–robust. Significance levels: *** 0.01, ** 0.05, * 0.1.

6.2 Role of Firms' Characteristics

Figure 2 shows that some firms expanded while others contracted in response to the 2018–2019 US–China trade war. A natural question is whether these gains and losses were related to initial firms' characteristics. Table 2 addresses this question by regressing the model–predicted change in export revenues between 2017 and 2019 on several firm–level characteristics measured in 2017. All variables are standardized to have a mean of zero and a standard deviation of one within the sample.

Table 2. Inspecting Firm–Level Export Revenue Changes

	(1)	(2)	(3)	(4)	(5)
VARIABLES	d Log Exp	d Log Exp	d Log Exp	d Log Exp	d Log Exp
Log TFP	0.70***	0.68***	0.61***	0.57***	0.66***
	(0.18)	(0.17)	(0.17)	(0.19)	(0.20)
Log Employment		0.37***	0.41***	0.42***	0.06
		(0.14)	(0.14)	(0.15)	(0.19)
Log Share of White Collar Employees			0.94***	0.96***	0.57*
			(0.28)	(0.29)	(0.33)
Log Investment per Employee				0.40**	0.43**
				(0.20)	(0.20)
Log Number of Exp Products					0.62***
					(0.20)
Log Number of Exp Destinations					0.05
					(0.25)
Observations	3,124	3,124	3,119	2,978	2,978

Notes: Each observation corresponds to a firm. The dependent variable is the model–predicted change in export revenues between 2017 and 2019. *Log TFP* denotes the log of firm–level total factor productivity in 2017, computed following Ciapanna et al. (2024). *Log Employment* is the log of the number of employees in 2017, while *Log Share White Collar* is the log of the share of white collar workers (clerks and managers) relative to the number of employees in 2017. *Log Investment per Employee* measures the log of investment per employee in the same year. *Log Number of Exported Products* is the log of the number of products exported by each firm in 2017, and *Log Number of Export Destinations* is the log of the number of destinations to which each firm exported in 2017. All variables are standardized to have a mean of zero and a standard deviation of one within the sample. Standard errors reported in parentheses are heteroskedasticity–robust. Significance levels: *** 0.01, ** 0.05, * 0.1.

Column (1) shows that firms with higher initial productivity experienced larger subsequent increases in export revenues. Columns (2)–(5) sequentially add controls for employment, share of white collar workers,[30] investment per employee, number of exported products, and number of export destinations. The results in the last column suggest that export revenue gains are concentrated among firms that were initially more productive, had more skilled labor force, exhibited higher investment intensity, and offered a broader range of products.

Interestingly, the positive correlation between changes in export revenues and initial productivity survives after controlling for all other firm characteristics. This pattern suggests that the 2018–2019 US–China trade war not only generated net export opportunities

[30] Clerks and managers are white–collar employees; manual workers are classified as blue–collar.

for Italian firms but also improved allocative efficiency à la Olley and Pakes (1996). This finding is further supported by Appendix Figure A.12, which shows that initially more productive firms expanded their export revenues to every destination more than less productive firms.

6.3 Effects on Domestic Outcomes

Using Equation (21), Table 3 reports the model–implied changes in domestic labor expenditure and capital investment resulting from the change in total export sales induced by the 2018–2019 US–China trade war. For reference, the first row presents the model–predicted change in firms' export revenues, while the second and third rows display the implied responses of labor expenditure and investment. On average, firms experienced a 2.5% increase in export revenues (Figure 2), which translated into a 1.6% increase in labor expenditure and a 0.7% increase in capital investment. For comparison, the observed changes in the data over the same period were 7.6% for labor expenditure and 0.2% for capital investment. Thus, the model explains roughly one-fifth of the observed growth in labor expenditure, while slightly over–predicting capital investment.

Table 3. Pass–Through to Employment and Investment

Predicted Log Outcome Change	Mean	Q5	Q25	Q50	Q75	Q95
Export Revenues	2.5%	-9.9%	-1.1%	2.7%	6.0%	14.1%
Labor Expenditure	1.6%	-6.4%	-0.6%	1.6%	3.8%	9.2%
Capital Investment	0.7%	-2.9%	–0.3%	0.8%	1.8%	4.3%

Notes: The table reports the distribution of firm–level export revenue changes between 2017 and 2019 predicted by our model in response to US–China trade war, along with the corresponding changes in labor expenditure and investment, computed using Equation (21). Estimates of output elasticities and markups are drawn from Ciapanna et al. (2024), who assume a Cobb-Douglas production function in labor and capital. For reference, observed changes in the data during the same period were 7.6% for labor expenditure and 0.2% for capital investment.

To further assess the relationship between changes in export revenues and domestic outcomes, Appendix Figure A.13 plots the correlation between firm–level changes from 2017 to 2019 in several domestic outcomes and the model–predicted changes in export revenues using Equation (23). We find that export–revenue growth translated into both wage growth and higher employment. The increase in total employment reflected growth in both white– and blue–collar positions, with the latter exhibiting a stronger response to export–revenue growth. Growth in firms' total sales closely matched export dynamics, indicating that increases in export revenue did not crowd out domestic sales. Taken together, these results indicate that the trade war operated as a positive aggregate demand shock for domestic factor inputs.

6.4 Comparison to Canonical Trade Models

Lastly, we compare the predictions of our benchmark model with those implied by alternative specifications consistent with standard theoretical frameworks (Arkolakis et al., 2012; Head and Mayer, 2014). Relative to canonical trade models, a key advantage of our framework is that it allows for Marshallian external economies of scale and unrestricted cross–price elasticities.

To quantitatively assess the bias induced by standard models, we construct counterfactual firm–level export revenues using Equation (13), abstracting from economies of scale ($\psi_{j\omega} = 0$) and cross–demand effects ($\epsilon_{k\omega n} = 0 \; \forall k \neq j$).

We find that, while average effects are well approximated by the restricted models, the heterogeneity in gains and losses across firms is substantially underestimated relative to the benchmark. Appendix Figure A.14 reports the distribution of export revenue changes across firms, pooled across destinations, under the benchmark model and the restricted specifications. The restricted models predict that the average Italian exporter benefited from the 2018–2019 US–China trade war by about 2.5–2.7% over the period, in line with the benchmark model. However, the dispersion of outcomes is markedly smaller: the standard deviation of pooled export revenue changes declines from 7.6% in the benchmark model to 1.6% when abstracting from economies of scale, and to 1.1% when additionally shutting down cross–demand effects. While the trade war generated both winners and losers among Italian exporters, restricted models fail to capture the extent of heterogeneity across firms with implications for the evaluation and targeting of industrial policy (Bartelme et al., 2025).[31]

7 Conclusion

In this paper, we develop a multi–country general equilibrium trade model to disentangle the channels through which third–country firms were affected by the 2018-2019 US-China trade war, including adjustments in demand, foreign competition, and scale economies. We estimate the model using administrative data on the universe of Italian firms' export and domestic activities, combined with detailed information on 2018–2019 US–China tariffs.

[31] These findings are consistent with the explained variance of each model reported in Appendix Tables A.6 and A.7.

Importantly, our framework is general and can be readily applied to study firm–level responses in other countries or to alternative trade shocks, such as sanctions or export controls.

We find that the trade war generated net export gains for Italian firms overall, but the benefits were highly uneven. Many firms experienced losses, while those in sectors with stronger scale economies—often concentrated in the Center–North—captured the largest gains. By benefiting the most productive firms, tariff–induced adjustments not only raised aggregate exports but also improved resource allocation across the economy.

What do our results imply for the recent wave of U.S. import tariffs announced on April 2, 2025? A back-of-the-envelope calculation based on our estimated elasticities suggests that firm–level export revenues of Italian exporters to the US could decline through multiple channels. As a first approximation, an own–price demand elasticity of -3.9 implies that raising US import tariffs on EU goods from 1.5% to 15% would reduce export revenues by roughly 48% within two years.[32] However, because the US is imposing even higher tariffs on China and other countries, substitution effects toward alternative suppliers could partially offset these reductions. Moreover, these direct negative demand effects would be particularly pronounced in sectors characterized by positive scale economies—such as the food industry, chemical sector, and leather goods. Policymakers may therefore wish to devote specific attention to firms operating in these sectors, as output and employment losses could be especially severe.

These findings provide guidance for policymakers seeking to support firms and workers most exposed to trade disruptions. Trade wars may create short–term opportunities for some bystander countries, but they also heighten volatility and widen the gap between winners and losers. Looking ahead, there are several directions our work could take. First, further disentangling the underlying drivers of external economies of scale would help clarify which types of policies may most effectively increase economic resilience. Second, a comprehensive assessment of the firm-level effects of the 2025 "Liberation Day" tariffs would provide a valuable complement to existing model–based simulations (Ignatenko et al., 2025), but would require access to updated firm–level data. We leave these important questions for future research.

[32] A 15% US import tariff rate on most EU goods was agreed upon by the US and the EU in their August 2025 "Framework Agreement" (European Commission, 2025).

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Appendix

The Impact of Trade Wars on Firms in Third Countries: Evidence from Italy

Francesco Paolo Conteduca, Marco Errico, Fabrizio Leone, Ludovic Panon, and Giacomo Romanini

A Tables and Figures

Appendix Table A.1. Summary Statistics by Trade Status

	Export Values	Import Values	Sales	Labor Cost	Employment	Materials
Others		22.71	1835.10	338.93	11.40	1374.47
		(1038.00)	(53804.19)	(3206.57)	(112.21)	(47632.48)
Exporters	2776.02	2202.43	13837.33	1792.66	36.81	11176.29
	(36933.03)	(45094.92)	(1.9e+05)	(22956.27)	(510.46)	(1.7e+05)

Note: Columns report export values, import values, total sales, labor costs, number of employees, and materials (goods and services). Nominal values are expressed in Euros. We report averages first and standard deviation in parentheses below. We distinguish between non–exporters, i.e., those that never export, and exporting firms, i.e., those that export at least once during our sample period.

Appendix Table A.2. Summary Statistics by Trade Status

	Firms	Sales	Labor Cost	Employment	Materials
Others	78.1%	32.1%	40.2%	52.5%	30.5%
Exporters	21.9%	67.9%	59.8%	47.5%	69.5%

Note: Columns report the average share of total number of firms, sales, labor costs, number of employees, and materials (goods and services). We distinguish between non–exporters, i.e., those that never export, and exporting firms, i.e., those that export at least once during our sample period.

Appendix Table A.3. Export Exposure to US–China Tariffs (2017)

	Exp Share to US	Exp Share to CN	Exp Share to EU	Exp Share to RoW	Total
Untargeted	2.6%	0.5%	10.8%	9.3%	23.2%
Targeted	7.1%	2.8%	37.6%	29.3%	76.8%

Note: The table reports the aggregate export shares (based on 2017 export values) of Italian firms by product type and destination market. We distinguish between products involved in the 2018–2019 US–China tariffs—either targeted by US tariffs on China or by Chinese tariffs on the US—and those never subject to tariffs. Shares in the table sum to one.

Appendix Table A.4. Summary Statistics by Survey Answer

Affected	Firms	Exports	Sales	Employment	Investment
No	86.9%	76.8%	53.1%	60.6%	70.0%
Yes	13.1%	23.2%	46.9%	39.4%	30.0%

Note: The first column indicates whether firms reported that their sales were affected by the US–China trade war in the 2019 SONDTEL survey (see Section 2.2.2 for additional details). The remaining columns show the share of total export values, sales, number of employees, and investment accounted for by each group.

Appendix Table A.5. Estimation Results - Baseline

	Baseline (1)	Alt. SE (2)	Pre-Trends (3)	Alt. IV (4)	Quantity (5)	Ext. Margin (6)
Scale el.	-0.209**	-0.210*	-0.202**	-0.254**	-0.168	-1.281
	(0.106)	(0.117)	(0.096)	(0.110)	(0.128)	(1.667)
Intercept (US)	0.086***	0.086***	0.088***	0.086***	0.035***	0.011
	(0.002)	(0.002)	(0.003)	(0.002)	(0.005)	(0.012)
Own-price el. (US)	-2.898***	-2.892***	-2.935***	-2.473***	-4.610***	0.763
	(0.668)	(0.787)	(0.664)	(0.647)	(1.316)	(0.813)
Cross-price el. IT-CN (US)	0.012***	0.012***	0.013***	0.012***	0.007	-0.022
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.032)
Cross-price el. IT-RoW (US)	-0.004	-0.004	-0.003	-0.005	-0.053**	0.001
	(0.012)	(0.012)	(0.011)	(0.011)	(0.025)	(0.039)
Cross-price el. IT-EU (US)	0.047	0.048	0.046	0.051*	0.031	-0.064
	(0.035)	(0.038)	(0.033)	(0.028)	(0.069)	(0.051)
Intercept (CN)	-0.004	-0.004	-0.004	-0.005	-0.069***	0.044***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.010)	(0.008)
Own-price el. (CN)	-0.411***	-0.408***	-0.415***	-0.410***	-0.519***	0.074**
	(0.022)	(0.028)	(0.022)	(0.022)	(0.043)	(0.030)
Cross-price el. IT-US (CN)	-0.031***	-0.031***	-0.032***	-0.031***	-0.049***	-0.011
	(0.006)	(0.005)	(0.006)	(0.006)	(0.012)	(0.009)
Cross-price el. IT-RoW (CN)	0.068***	0.069***	0.068***	0.070***	0.096***	-0.005
	(0.010)	(0.010)	(0.010)	(0.010)	(0.022)	(0.013)
Cross-price el. IT-EU (CN)	-0.028**	-0.028**	-0.028**	-0.026**	-0.056**	0.005
	(0.011)	(0.012)	(0.011)	(0.011)	(0.023)	(0.011)
Intercept (EU)	0.033***	0.033***	0.033***	0.033***	-0.005	-0.124***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.011)
Own-price el. (EU)	-0.970*	-0.964*	-0.995**	-0.846**	-2.379	0.660
	(0.508)	(0.545)	(0.487)	(0.372)	(1.906)	(1.342)
Cross-price el. IT-US (EU)	0.020***	0.020***	0.020***	0.019***	0.018***	0.018
	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)	(0.022)
Cross-price el. IT-RoW (EU)	0.030***	0.030***	0.030***	0.031***	0.021*	-0.032
	(0.003)	(0.003)	(0.003)	(0.003)	(0.011)	(0.065)
Cross-price el. IT-CN (EU)	0.021***	0.021***	0.021***	0.020***	0.014**	-0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.030)
Intercept (RoW)	-0.002	-0.002	-0.002	-0.007***	-0.050***	-0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)
Own-price el. (RoW)	-4.379**	-4.359*	-4.512**	-4.634**	-5.910	-0.144
	(2.223)	(2.413)	(2.132)	(2.007)	(4.522)	(0.418)
Cross-price el. IT-US (RoW)	0.036***	0.035***	0.036***	0.020***	0.026***	0.011
	(0.004)	(0.004)	(0.004)	(0.004)	(0.010)	(0.015)
Cross-price el. IT-CN (RoW)	0.057***	0.057***	0.057***	0.064***	0.039***	0.040
	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.039)
Cross-price el. IT-EU (RoW)	0.132***	0.132***	0.132***	0.161***	0.124***	-0.018
	(0.006)	(0.007)	(0.007)	(0.007)	(0.017)	(0.017)
Observations	365,781	365,781	365,781	366,122	355,187	14,245

Note: Each observation corresponds to a firm–product–destination tuple. Products are classified according to the 6-digit 2012 HS nomenclature. There are four destinations: the US, China, the EU (excluding Italy), and the rest of the world (RoW). Column (1) reports the estimates of Equation (23). Column (2) shows the estimates with standard errors clustered by firm. Column (3) presents the estimates controlling for the lagged change in the outcome between 2014 and 2016. Column (4) reports estimates using the change in product–level US import tariffs on Chinese products as instrument. Column (5) presents estimates using export quantity as the outcome variable. Column (6) shows the estimates of the extensive margin. Standard errors in parentheses are clustered by firm and product, except in column (2). Significance levels: *** 0.01, ** 0.05, * 0.1.

Appendix Table A.6. Share of Explained Variance (Pooled)

Full Model	No Scale Elasticity	Neither Scale nor Cross-Price Elasticities
57.1%	14.0%	11.4%

Note: The first column shows the share of the outcome variable variance in Equation (23) explained by the full model. The second column shows the share of variance explained by a restricted model without scale economies. The last column shows the share of variance explained by a restricted model without scale economies and cross–price elasticities.

Appendix Table A.7. Share of Explained Variance (by Destination)

Region	Full Model	No Scale Elasticity	Neither Scale nor Cross-Price Elasticities
US	42.6%	7.2%	4.3%
CN	23.1%	21.8%	19.4%
EU	23.7%	5.1%	-
RoW	85.7%	13.1%	-

Note: The first column shows the share of the outcome variable variance in Equation (23) explained by the full model, distinguishing for each destination. The second column shows the share of variance explained by a restricted model without scale economies. The last column shows the share of variance explained by a restricted model without scale economies and cross–price elasticities.

Appendix Table A.8. Estimation Results - Heterogeneity

	Cross Intermediate (1)	Scale Intermediate (2)	Cross Differentiated (3)	Scale Differentiated (4)	Scale Center-North (5)
Scale el.	-1.200	0.648***	0.006	-0.412	-0.131**
	(1.003)	(0.244)	(0.050)	(0.274)	(0.054)
Scale el. × Intermediate		-5.854***			
		(2.087)			
Scale el. × Differentiated				0.347	
				(0.235)	
Scale el. × North					-0.185***
					(0.057)
Intermediate	-0.041***	-0.006			
	(0.014)	(0.011)			
Differentiated			-0.024***	-0.046***	
			(0.007)	(0.011)	
North					-0.025***
					(0.003)
Intercept (US)	0.107***	0.132***	0.112***	0.126***	0.109***
	(0.008)	(0.005)	(0.007)	(0.012)	(0.004)
Own-price el. (US)	-0.152	-0.625***	-4.240***	-17.493**	-2.729***
	(0.139)	(0.188)	(0.740)	(8.740)	(0.677)
Cross-price el. IT-CN (US)	0.018***	0.011**	0.039***	0.028***	0.014***
	(0.003)	(0.005)	(0.004)	(0.007)	(0.003)
Cross-price el. IT-CN × Intermediate (US)	-0.011				
	(0.007)				
Cross-price el. IT-CN × Differentiated (US)			-0.048***		
			(0.007)		
Cross-price el. IT-RoW (US)	0.007	0.148***	0.018*	-0.028	-0.012
	(0.011)	(0.025)	(0.011)	(0.019)	(0.010)
Cross-price el. IT-EU (US)	-0.001	0.034*	-0.042	0.127**	0.081***
	(0.034)	(0.017)	(0.029)	(0.056)	(0.018)
Intercept (CN)	0.026***	0.043***	0.012	0.029***	0.018***
	(0.008)	(0.009)	(0.008)	(0.011)	(0.006)
Own-price el. (CN)	-0.312***	-0.373***	-0.460***	-0.485***	-0.407***
	(0.051)	(0.028)	(0.023)	(0.023)	(0.021)
Cross-price el. IT-US (CN)	-0.024***	-0.024***	0.067***	-0.028***	-0.029***
	(0.007)	(0.007)	(0.019)	(0.006)	(0.006)
Cross-price el. IT-US × Intermediate (CM)	-0.006				
	(0.012)				
Cross-price el. IT-US × Differentiated (CN)			-0.108***		
			(0.020)		
Cross-price el. IT-RoW (CN)	0.067***	0.063***	0.072***	0.075***	0.069***
	(0.011)	(0.012)	(0.010)	(0.010)	(0.010)
Cross-price el. IT-EU (CN)	-0.015	-0.022	-0.025**	-0.028**	-0.025**
	(0.014)	(0.014)	(0.012)	(0.012)	(0.011)
Intercept (EU)	0.034***	0.141***	0.032***	0.032***	0.056***
	(0.001)	(0.053)	(0.001)	(0.001)	(0.003)
Own-price el. (EU)	-0.153	-2.478	32.217	-2.871	2.040*
	(0.129)	(1.548)	(260.664)	(2.073)	(1.165)
Cross-price el. IT-US (EU)	0.020***	0.021	0.026***	0.023***	0.020***
	(0.002)	(0.017)	(0.002)	(0.002)	(0.002)
Cross-price el. IT-RoW (EU)	0.030***	0.130**	0.039***	0.019**	0.032***
	(0.003)	(0.053)	(0.003)	(0.007)	(0.003)
Cross-price el. IT-CN (EU)	0.020***	-0.083	0.026***	0.041***	0.022***
	(0.002)	(0.052)	(0.002)	(0.005)	(0.002)
Intercept (RoW)	-0.000	0.058***	0.002*	-0.003**	0.022***
	(0.001)	(0.007)	(0.001)	(0.001)	(0.003)
Own-price el. (RoW)	-0.723	-0.735**	126.213	-11.886	-3.045***
	(0.604)	(0.291)	(1020.255)	(8.512)	(0.907)
Cross-price el. IT-US (RoW)	0.039***	0.090***	0.048***	0.030***	0.035***
	(0.004)	(0.009)	(0.004)	(0.009)	(0.004)
Cross-price el. IT-CN (RoW)	0.055***	0.162***	0.048***	0.066***	0.060***
	(0.004)	(0.016)	(0.004)	(0.013)	(0.004)
Cross-price el. IT-EU (RoW)	0.125***	0.080***	0.107***	0.126***	0.134***
	(0.006)	(0.013)	(0.006)	(0.010)	(0.007)
Observations	364,496	364,496	345,253	345,253	365,781

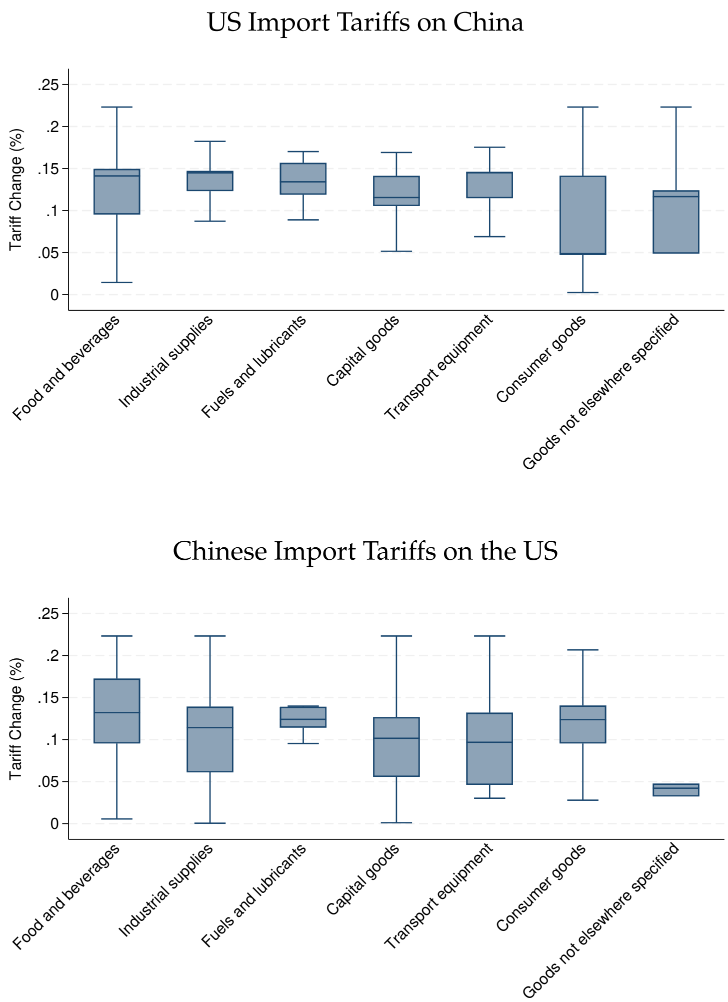
Note: The sample is the same as in Appendix Table A.5. Each column reports estimates of Equation (23) with interactions to explore heterogeneity in cross–price or scale elasticities. Column (1) interacts cross–price elasticities (Italy–China in the US, Italy–US in China) with a Broad Economic Categories (BEC) indicator for intermediate goods. Column (2) interacts this BEC indicator with the scale elasticity. Column (3) interacts the same cross–price elasticities with a Rauch (1999) indicator for differentiated products. Column (4) interacts this indicator with the scale elasticity. Column (5) interacts the scale elasticity with a binary indicator for whether firms are headquartered in the center-north (south and islands are the omitted group). Significance levels: *** 0.01, ** 0.05, * 0.1.

Appendix Table A.9. Distribution of External Economies of Scale

Percentile	Q5	Q25	Q50	Q75	Q95
	–1.24	–0.32	–0.26	–0.15	–0.10

Notes: The table reports the moments of the distribution of the estimated external economies of scale at the 2-digit HS product level.

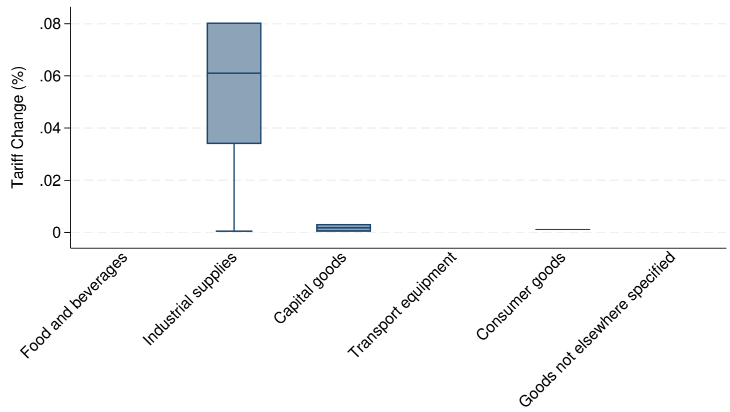
Appendix Figure A.1. US–China Tariff Changes



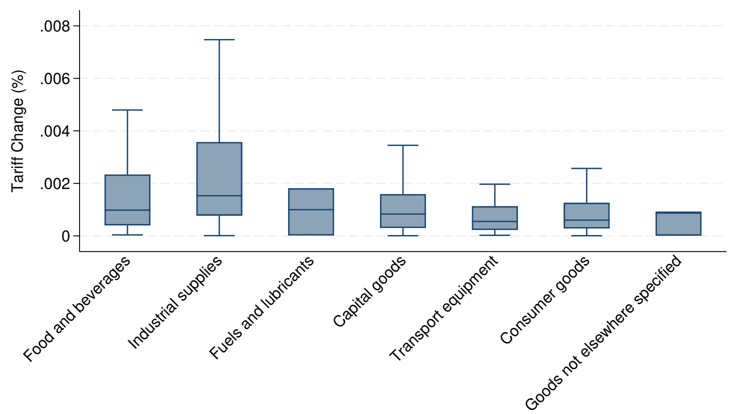
Notes: The figure shows changes in import tariffs imposed by the US on China (top panel), and changes in import tariffs imposed by China on the US (bottom panel). Each box represents the 25th, 50th (median), and 75th percentiles, while the whiskers indicate the 10th and 90th percentiles.

Appendix Figure A.2. US Tariff Changes on the European Union and Rest of the World

US Import Tariffs on the EU



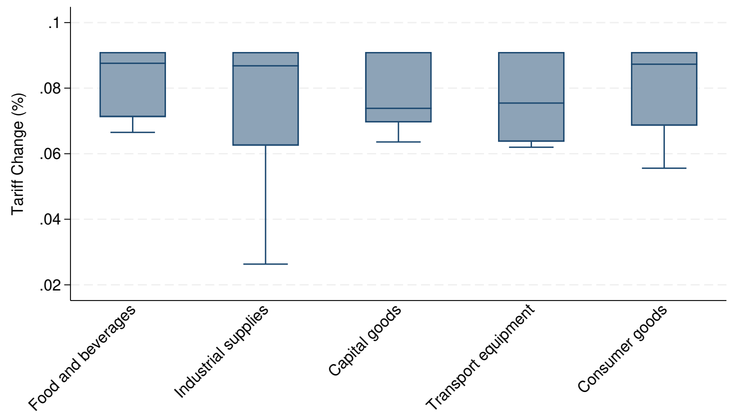
US Import Tariffs on RoW



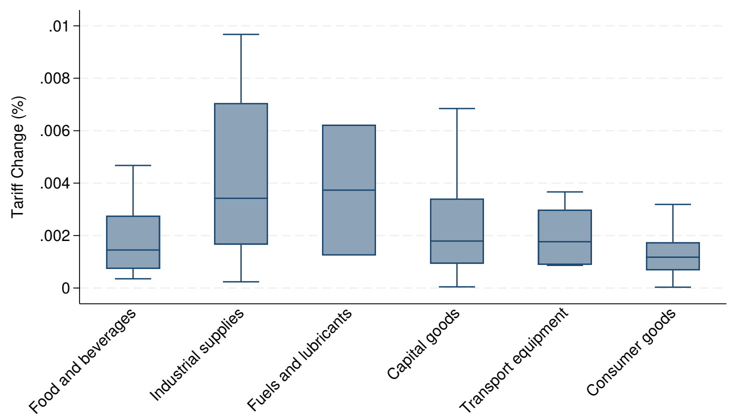
Notes: The figure shows changes in import tariffs imposed by the US on the EU (top panel) and the Rest of the World (bottom panel). Each box represents the 25th, 50th (median), and 75th percentiles, while the whiskers indicate the 10th and 90th percentiles.

Appendix Figure A.3. EU and RoW Tariff Changes on the US

EU Import Tariffs on the US

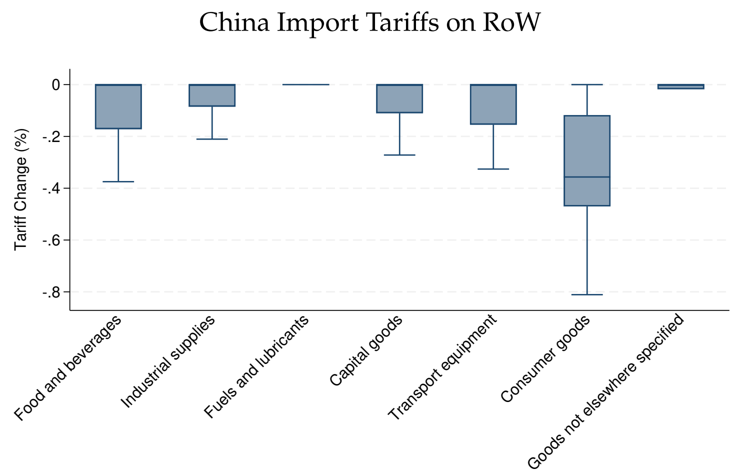


RoW Import Tariffs on the US



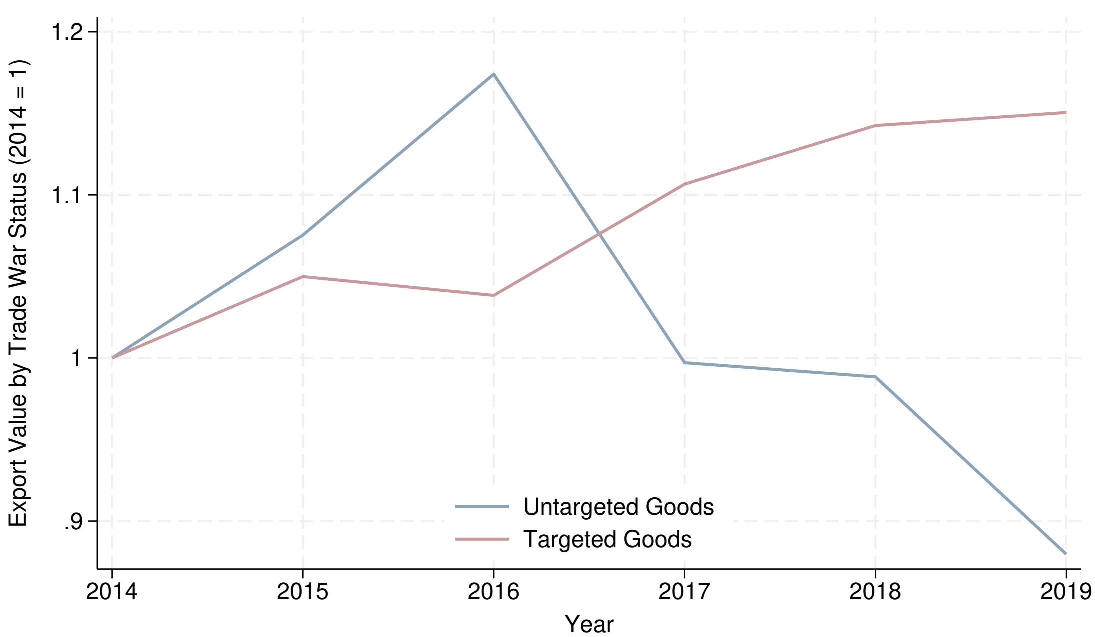
Notes: The figure shows changes in import tariffs imposed by the EU (top panel) and the Rest of the World (bottom panel) on the US. Each box represents the 25th, 50th (median), and 75th percentiles, while the whiskers indicate the 10th and 90th percentiles.

Appendix Figure A.4. China Tariff Changes on Rest of the World



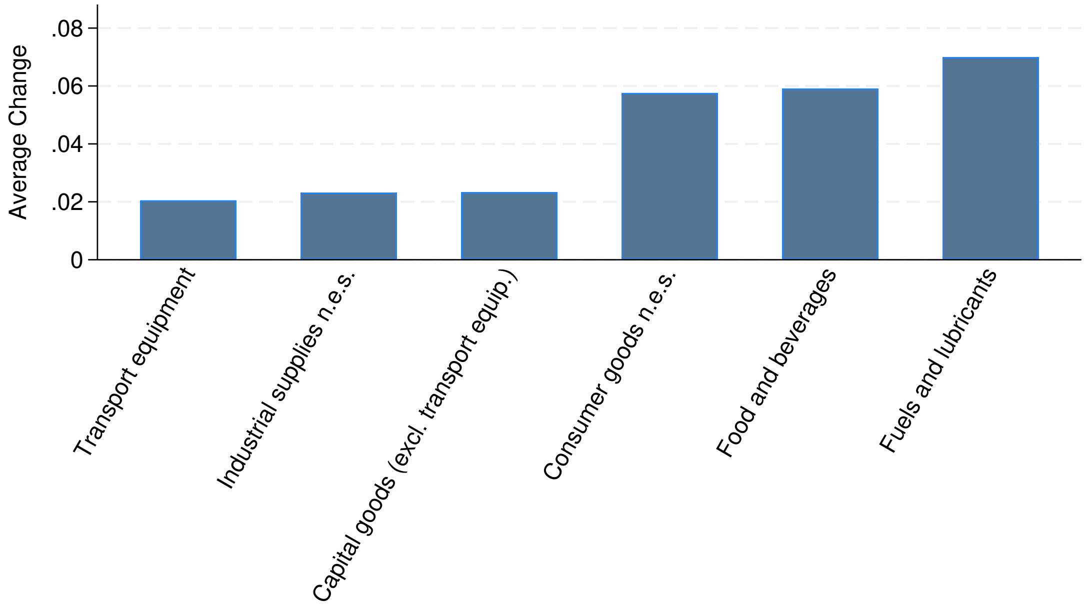
Notes: The figure shows changes in (MFN) import tariffs imposed by China on the Rest of the World. Each box represents the 25th, 50th (median), and 75th percentiles, while the whiskers indicate the 10th and 90th percentiles.

Appendix Figure A.5. Trends in Export Values by Type of Product



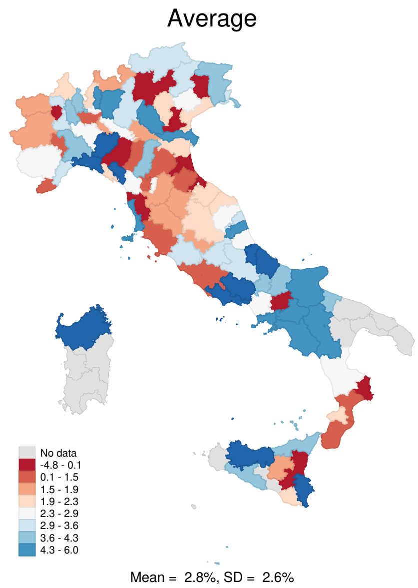
Notes: The figure shows the evolution of export values for two groups of products: those ultimately targeted by US tariffs on Chinese imports or by Chinese tariffs on US imports ("Targeted Goods") and those not affected by reciprocal tariffs between the two countries ("Untargeted Goods"). Both series are normalized to 1 in 2014.

Appendix Figure A.6. Distribution of Export Revenue Changes across Sectors



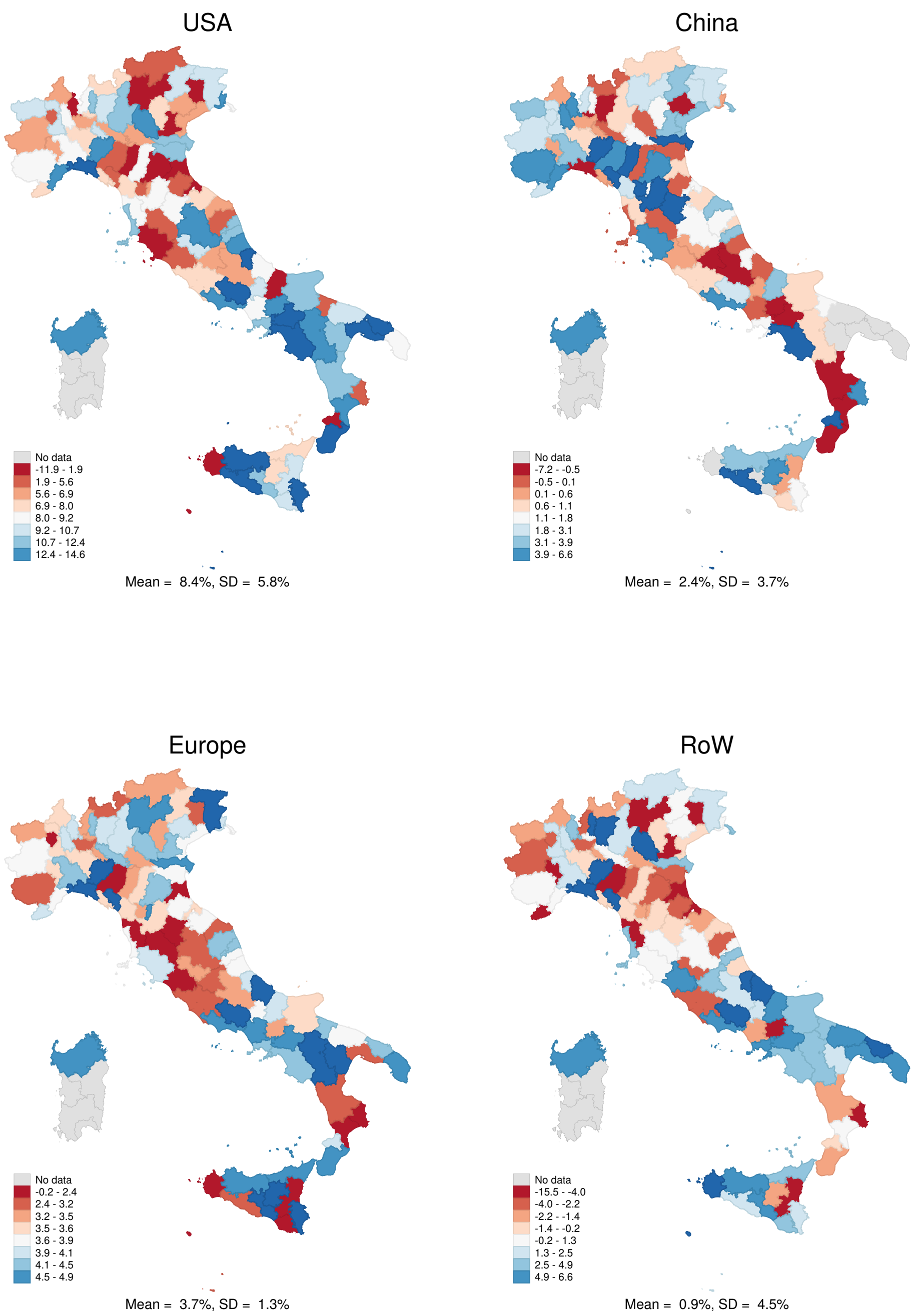
Notes: The figure shows the distribution of predicted export revenue changes across sectors between 2017 and 2019. Sectors are defined according to the Broad Economic Categories (BEC) classification. Sector-level changes are computed by aggregating firm–level export revenue changes using Equation (16).

Appendix Figure A.7. Distribution of Export Revenue Changes across Provinces



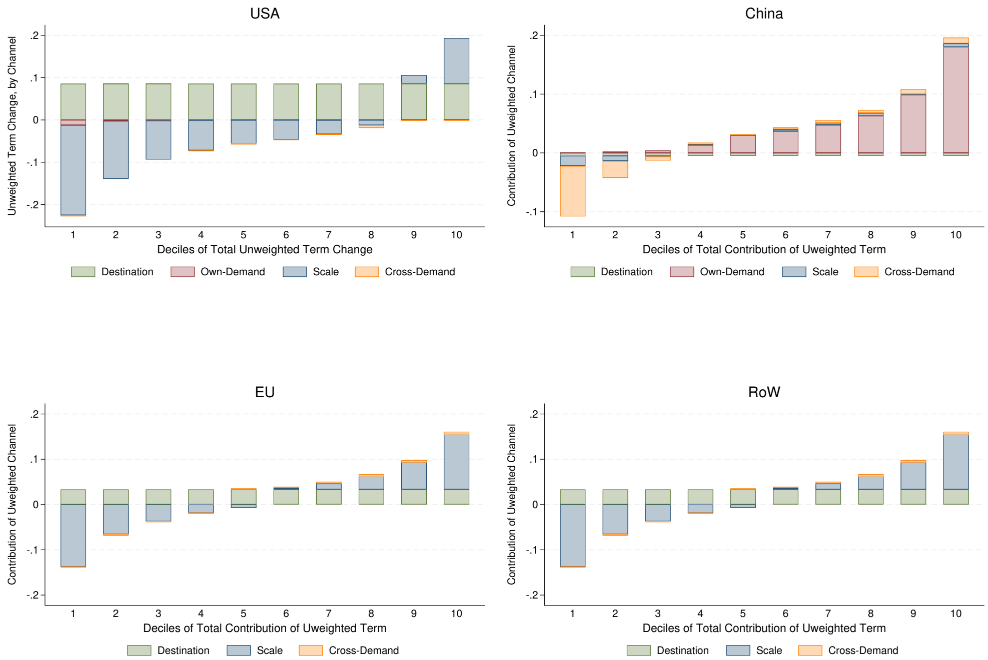
Notes: The figure shows the distribution of predicted export revenue changes across provinces between 2017 and 2019. province–level changes are computed by aggregating firm–level export revenue changes using Equation (16). We assign firms to the province in which they are headquartered.

Appendix Figure A.8. Distribution of Export Revenue Changes across Provinces



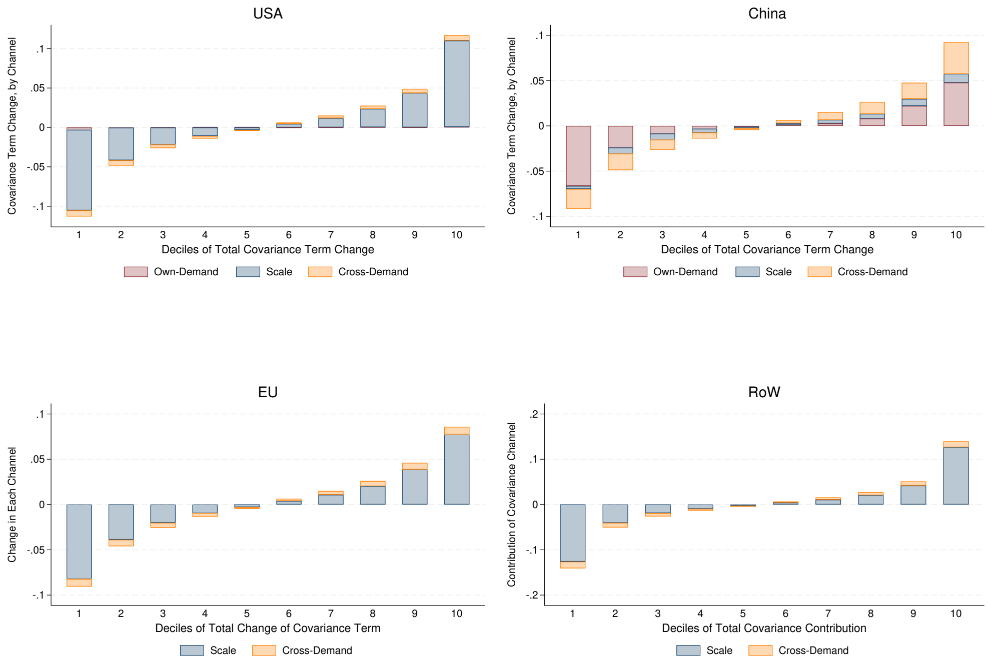
Notes: The figure shows the distribution of predicted export revenue changes across provinces by destination between 2017 and 2019. Province-destination-level changes are computed by aggregating firm-destination-level export revenue changes using Equation (16). We assign firms to the province in which they are headquartered.

Appendix Figure A.9. Decomposition of Firm–Level Export Revenue Changes (Mean Change)



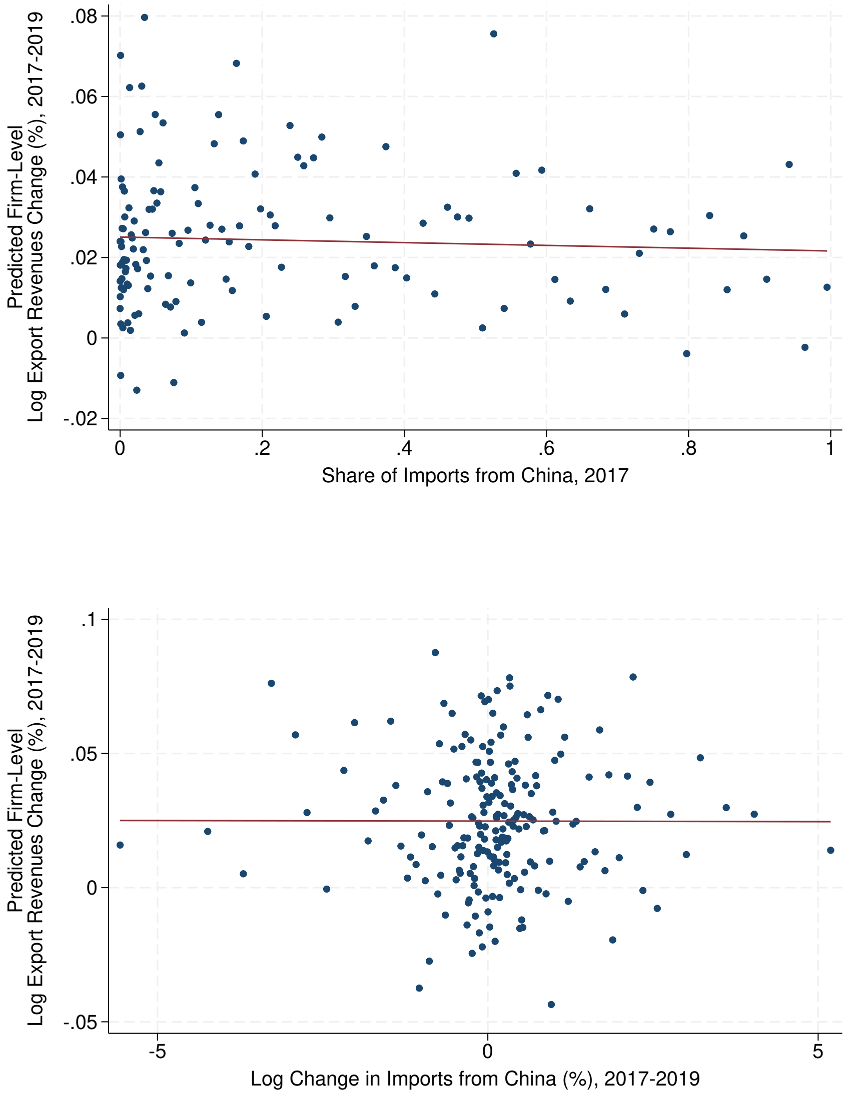
Notes: The figure shows the decomposition of unweighted mean export revenue changes by destination country from Proposition (1). It displays the average change of the unweighted term across deciles of its total change, broken down into four components: destination–specific, own–demand, scale, and cross–demand effects. There is no own–price effect for the EU and the Rest of the World, as they did not change import tariffs on Italian goods during the period under analysis.

Appendix Figure A.10. Decomposition of Firm–Level Export Revenue Changes (Mean Change)



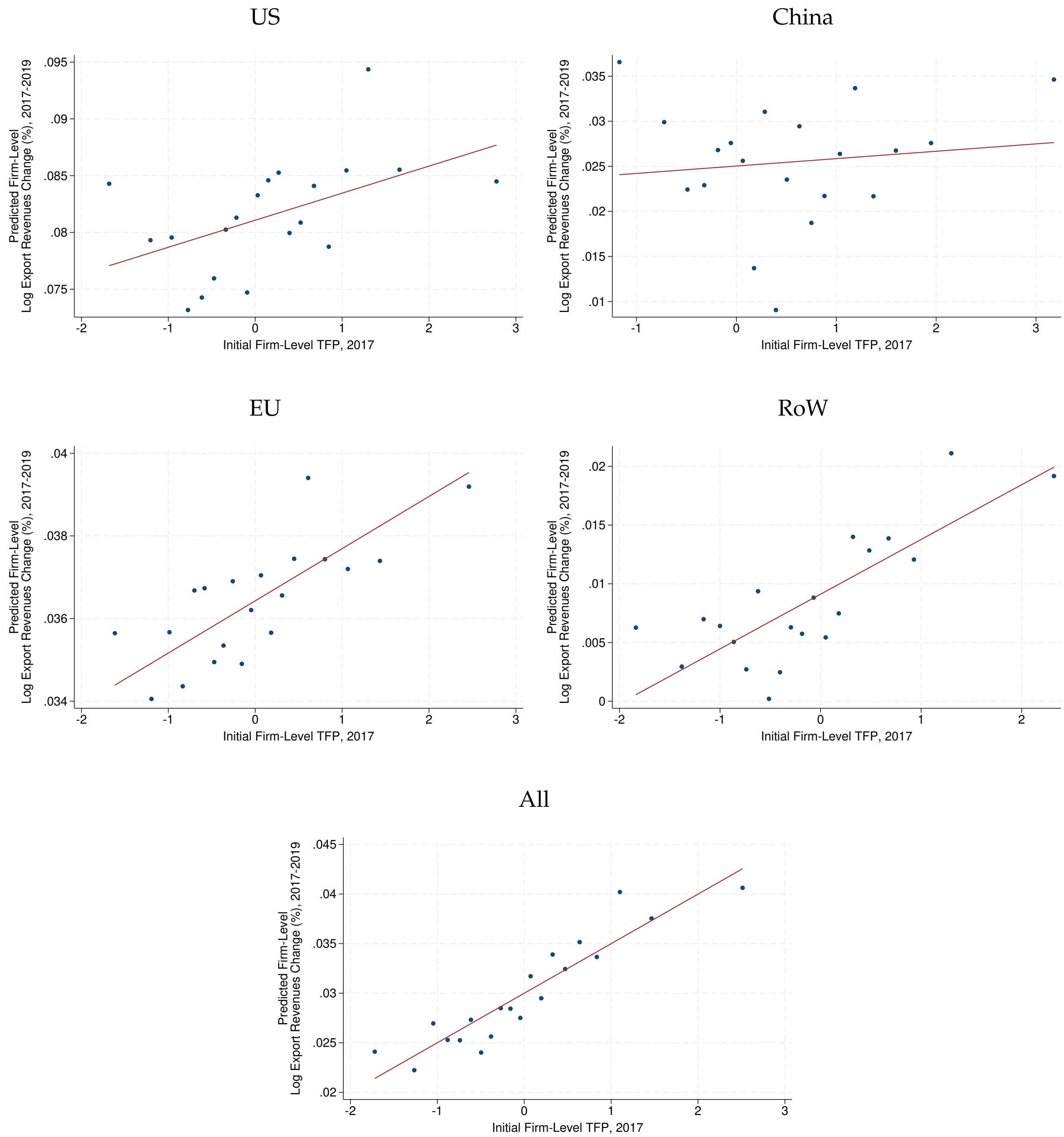
Notes: The figure shows the decomposition of the covariance term of export revenue changes by destination country from Proposition (1). It displays the average change of the covariance term across deciles of its total change, broken down into four components: destination–specific, own–demand, scale, and cross–demand effects. There is no own–price effect for the EU and the Rest of the World, as they did not change import tariffs on Italian goods during the period under analysis. In this case, since the destination channel is the same for all firms exporting to a given country, the covariance between firm exposure and destination–specific changes is always zero and therefore omitted from the plot.

Appendix Figure A.11. Correlation between Log Export Changes and Imports from China



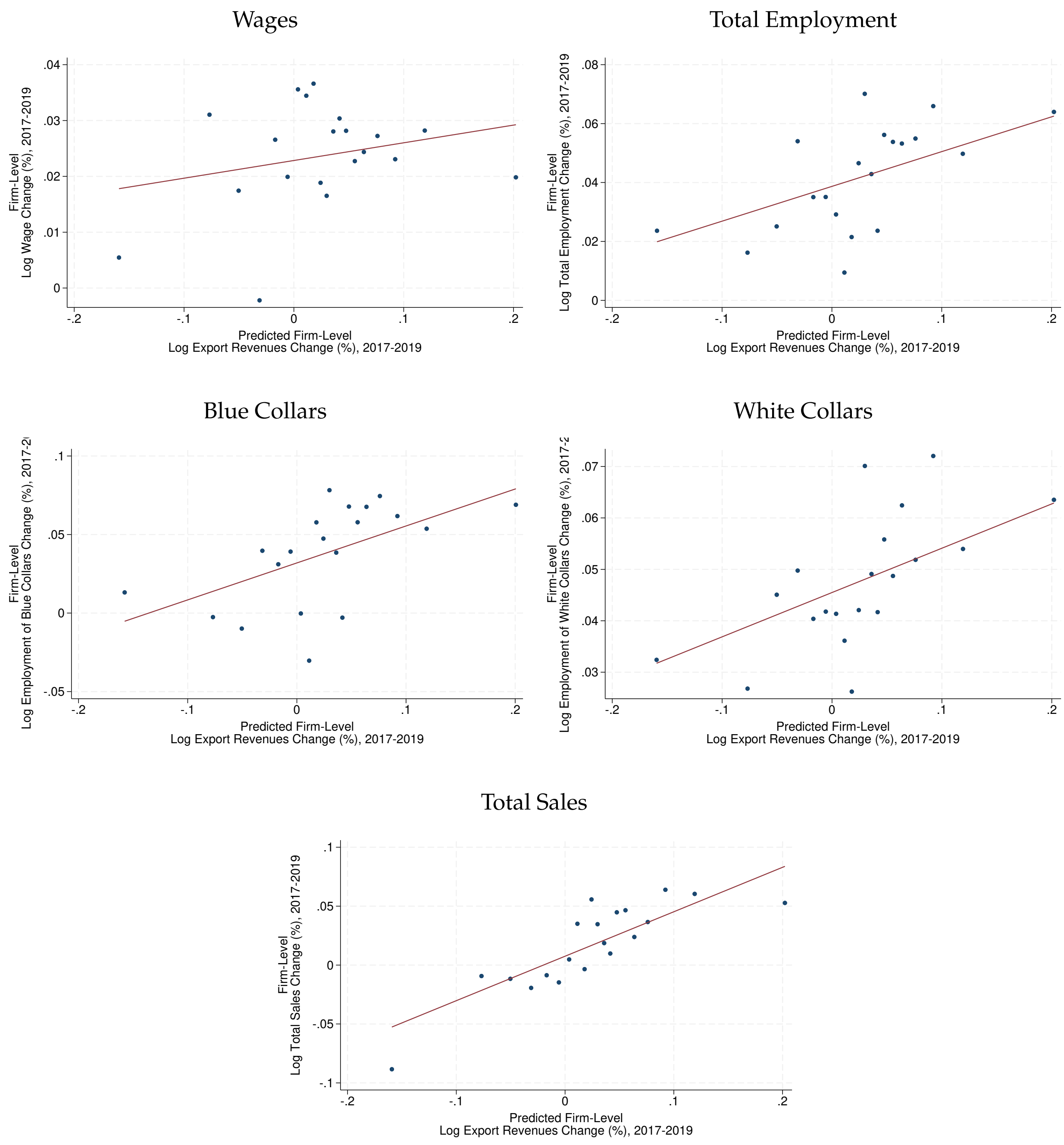
Notes: The figure shows the scatterplot and linear fit between model–predicted firm–level log export revenue changes between 2017 and 2019 against firm–level share of imports from China in 2017 (top panel) and the log change in imports from China between 2017 and 2019 (bottom panel).

Appendix Figure A.12. Allocative Efficiency



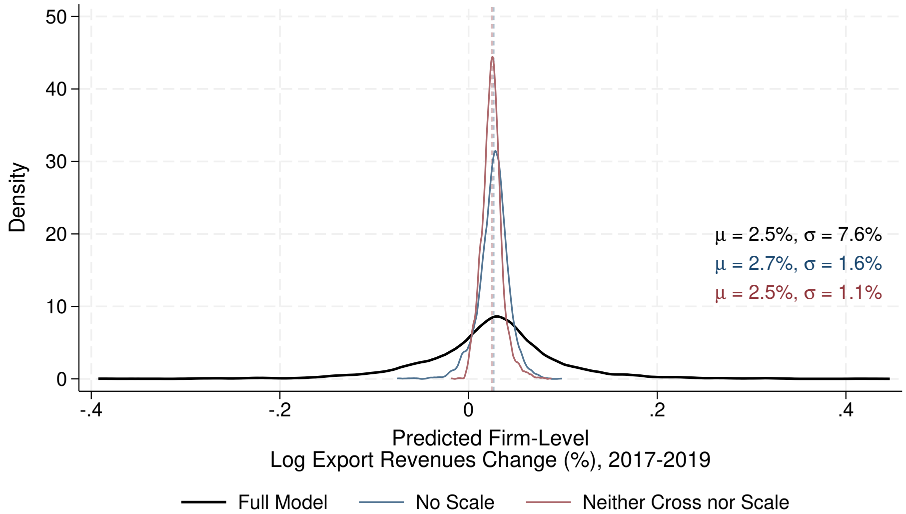
Notes: The figure presents binscatter plots of model–predicted changes in firm–level export revenues against firms' initial TFP in 2017. The first four panels display destination–specific predicted changes—namely, toward the US, China, EU, and RoW—, while the final panel shows the average predicted change across all destinations. We standardize TFP to have mean zero and unit variance in the sample.

Appendix Figure A.13. Correlation of Firm–Level Outcomes with Predicted Changes in Export Revenues



Notes: The figure presents binscatter plots of the correlation between changes in firm–level outcomes from 2017 to 2019 in the data and the model–predicted changes in firm–level export revenues. The outcomes examined include wages, total employment, blue–collar employment, white–collar employment, and total sales.

Appendix Figure A.14. Distribution of Firm–Level Export Revenue Changes across Models



Notes: The figure shows the distribution of predicted export revenue changes across Italian firms between 2017 and 2019 pooled across destinations. The black line represents the distribution in the benchmark model; the blue (red) line represents the distribution under no economies of scale (and cross–demand effects). Firm–level export revenue changes are computed using Equation (16).

B Preliminary Evidence on Firm–Level Export Responses

Using an event-study design, this Appendix provides additional evidence on the potential positive demand effects of the 2018–2019 US–China trade war for Italian exporters. We estimate the following equation:

$$\log Exports_{fpt} = \beta\big(Treated_p \times Post_t\big) + FE_{fp} + FE_t + \varepsilon_{fpt}. \tag{B.1}$$

The dependent variable is the logarithm of export value of firm f in product class p and year t, aggregated across all destinations. Product classes are divided into two groups: those eventually targeted by either US tariffs on China or Chinese tariffs on the US (treatment group), and those never involved (control group). $Treated_p$ is an indicator variable equal to one for products in the first group, while $Post_t$ is an indicator variable equal to one for years 2018 and later. FE_{fp} and FE_t denote firm–product-class and year fixed effects, respectively, while ε_{fpt} is the error term. We cluster standard errors by product class and year.

The coefficient β captures the differential response of firm–level exports in product classes affected by the US–China trade war after 2018 relative to unaffected products.[33] It is identified after accounting for time–invariant firm–product characteristics and aggregate time trends.

Appendix Table B.10 reports the estimates of Equation (B.1). Column (1) indicates that, after 2018, Italian firms increased export values in products affected by the US–China trade war relative to unaffected products by approximately 28%. Column (2) shows that this result is robust to controlling for firm size, measured as the logarithm of the number of employees. Columns (3) and (4) further confirm robustness when controlling for 2-digit NACE industry trends and province trends, capturing common sectoral and regional patterns in export values.

Overall, Appendix Table B.10 provides preliminary evidence that the 2018–2019 US–China trade war generated net export opportunities for Italian firms. This finding is consistent with Fajgelbaum et al. (2024), who place Italy in the left tail of countries with net export gains, suggesting our results provide a lower bound relative to the gains realized in other bystander countries. However, the results in Appendix Table B.10 do not provide insights on the underlying mechanisms driving the increase in exports, differently from

[33]We estimate Equation (B.1) at the annual level for the 2014-2019 period. Since most tariff changes occurred in 2018, we abstract from cohort-specific effects (De Chaisemartin and d'Haultfoeuille, 2023). Moreover, with only two post-treatment periods, we focus on a pooled specification rather than a dynamic one.

the analysis in the main text.

Appendix Table B.10. Preliminary Evidence on Firm–Level Responses to the US–China Trade War

	(1)	(2)	(3)	(4)
	Log Exports$_{fpt}$	Log Exports$_{fpt}$	Log Exports$_{fpt}$	Log Exports$_{fpt}$
$Treated_p \times Post_t$	0.28**	0.29**	0.24**	0.27***
	(0.09)	(0.09)	(0.08)	(0.09)
Observations	520,436	477,268	477,264	476,976
Controls	No	Yes	No	No
Firm-Product Class FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Industry-Year FE	No	No	Yes	No
Province-Year FE	No	No	No	Yes

Note: An observation is a firm–product class-year tuple. The dependent variable is the logarithm of total export value of firm f in product class p and year t. Product classes are divided into two groups: those eventually targeted by either US tariffs on China or Chinese tariffs on the US, which form the treatment group, and those never involved, which serve as the control group. $Treated_p$ is an indicator variable equal to one for products in the first group, while $Post_t$ is an indicator variable equal to one for years 2018 and later. Controls include the logarithm of the number of employees of firm f in year t. Industries are defined using 2-digit NACE codes. Standard errors in parentheses are clustered by product class and year. Significance levels: *** 0.01, ** 0.05, * 0.1.

C Mathematical Appendix

C.1 Estimating Equation

Our model implies that middle-nest prices can be expressed as:

$$p_{j\omega n} = p(w_j, i_j, \tau_{j\omega n}, q_{j\omega}, \{\mu_{f(j)\omega n}, z_{f(j)}, \phi_{f(j)\omega n}\}). \tag{C.2}$$

Taking logs and differentiating Equation (C.2) yields:

$$\mathrm{d}\ln p_{j\omega n} = \varepsilon_{p,w}\,\mathrm{d}\ln w_j + \varepsilon_{p,i}\,\mathrm{d}\ln i_j + \varepsilon_{p,\tau}\mathrm{d}\ln \tau_{j\omega n} + \psi_{j\omega}\mathrm{d}\ln q_{j\omega} + \varepsilon_{p,\xi}\,\mathrm{d}\ln \xi_{j\omega n}. \tag{C.3}$$

The term $\xi_{j\omega n}$ contains the three firm–product–destination–specific terms in the right-most curly bracket in Equation (C.2). Two observations are worth noting. First, $\mathrm{d}\ln c(w_j, i_j) = \varepsilon_{p,w}\,\mathrm{d}\ln w_j + \varepsilon_{p,i}\,\mathrm{d}\ln i_j = 0$. This follows from the fact that the homogeneous good is produced using only capital and labor, under perfect competition and constant returns to scale, and is freely traded. Its price is therefore normalized to one (numéraire) and held fixed over time. Second, we assume that all firms face the same ad–valorem tariffs, which implies complete pass–through in the middle nest, i.e., $\varepsilon_{p,\tau} = 1$.

We can now derive our estimating equation. Consider again Equation (10):

$$\mathrm{d}\ln r_{f(j)\omega n} = \mathrm{d}\ln s_{f(j)\omega n} + \mathrm{d}\ln s_{j\omega n} + \mathrm{d}\ln s_n^F E_n. \tag{C.4}$$

The share of country n's spending on product ω from origin j $s_{j\omega n}$ is a function of a vector of prices and a preference shifter, i.e.:

$$s_{j\omega n} = s_{j\omega n}\left(\{p_{j\omega n}\}, \xi_{j\omega n}\right). \tag{C.5}$$

Totally differentiating this equation yields:

$$\begin{aligned}
\mathrm{d}s_{j\omega n} &= \sum_k \frac{\partial s_{j\omega n}}{\partial p_{k\omega n}}\mathrm{d}p_{k\omega n} + \frac{\partial s_{j\omega n}}{\partial \xi_{j\omega n}}\mathrm{d}\xi_{j\omega n} \\
&= \sum_k \frac{\partial s_{j\omega n}}{\partial p_{k\omega n}}\frac{s_{j\omega n}p_{k\omega n}}{s_{j\omega n}p_{k\omega n}}\mathrm{d}p_{k\omega n} + \frac{\partial s_{j\omega n}}{\partial \xi_{k\omega n}}\frac{s_{j\omega n}\xi_{j\omega n}}{s_{j\omega n}\xi_{j\omega n}}\mathrm{d}\xi_{j\omega n} \\
&= \frac{1}{s_{j\omega n}}\sum_k \varepsilon_{k\omega n}\mathrm{d}\ln p_{k\omega n} + \frac{1}{s_{j\omega n}}\varepsilon^{\xi}_{j\omega n}\mathrm{d}\ln \xi_{j\omega n} \\
&= \frac{1}{s_{j\omega n}}\left(\varepsilon_{j\omega n}\mathrm{d}\ln p_{j\omega n} + \sum_{\omega\in\mathcal{O}_{kn}, k\notin\{j,n\}} \varepsilon_{k\omega n}\mathrm{d}\ln p_{k\omega n}\right) + \frac{1}{s_{j\omega n}}\varepsilon^{\xi}_{j\omega n}\mathrm{d}\ln \xi_{j\omega n},
\end{aligned} \tag{C.6}$$

where $\varepsilon_{j\omega n}$ is the elasticity of the middle–nest market shares with respect to middle–nest prices. Rearranging, we obtain:

$$\mathrm{d}\ln s_{j\omega n} = \varepsilon_{j\omega n}\mathrm{d}\ln p_{j\omega n} + \sum_{\omega\in\mathcal{O}_{kn},k\notin\{j,n\}} \varepsilon_{k\omega n}\mathrm{d}\ln p_{k\omega n} + \varepsilon^{\xi}_{j\omega n}\mathrm{d}\ln\xi_{j\omega n}. \tag{C.7}$$

Starting from Equation (C.4), we thus get:

$$\begin{aligned}
\mathrm{d}\ln r_{f(j)\omega n} &= \mathrm{d}\ln s_{f(j)\omega n} + \mathrm{d}\ln s_{j\omega n} + \mathrm{d}\ln s^F_n E_n \\
\mathrm{d}\ln r_{f(j)\omega n} - \mathrm{d}\ln s_{f(j)\omega n} &= \mathrm{d}\ln s_{j\omega n} + \mathrm{d}\ln s^F_n E_n \\
\mathrm{d}\ln r_{f(j)\omega n} - \mathrm{d}\ln s_{f(j)\omega n} &= \varepsilon_{j\omega n}\mathrm{d}\ln p_{j\omega n} + \sum_{\omega\in\mathcal{O}_{kn},k\notin\{j,n\}} \varepsilon_{k\omega n}\mathrm{d}\ln p_{k\omega n} + \varepsilon^{\xi}_{j\omega n}\mathrm{d}\ln\xi_{j\omega n} + \mathrm{d}\ln s^F_n E_n \\
\mathrm{d}\ln r_{f(j)\omega n} - \mathrm{d}\ln s_{f(j)\omega n} &= \varepsilon_{j\omega n}\mathrm{d}\ln p_{j\omega n} + \sum_{\omega\in\mathcal{O}_{kn},k\notin\{j,n\}} \varepsilon_{k\omega n}\mathrm{d}\ln p_{k\omega n} + \varepsilon^{\xi}_{j\omega n}\mathrm{d}\ln\xi_{j\omega n} + \kappa_n \\
\mathrm{d}\ln \tilde{r}_{j\omega n} &= \varepsilon_{j\omega n}\mathrm{d}\ln p_{j\omega n} + \sum_{\omega\in\mathcal{O}_{kn},k\notin\{j,n\}} \varepsilon_{k\omega n}\mathrm{d}\ln p_{k\omega n} + \varepsilon^{\xi}_{j\omega n}\mathrm{d}\ln\xi_{j\omega n} + \kappa_n,
\end{aligned} \tag{C.8}$$

where the second row subtracts firm–level export market shares from the left–hand side, the third row applies Equation (C.7), the fourth row defines $\kappa_n = \mathrm{d}\ln s^F_n E_n$ and the final row uses the fact that, by definition of market shares:

$$s_{f(j)\omega n} = \frac{r_{f(j)\omega n}}{\sum_f r_{f(j)\omega n}} = \frac{r_{f(j)\omega n}}{\tilde{r}_{j\omega n}}.$$

Defining $\nu_{j\omega n} = \varepsilon_{p,\xi}\,\mathrm{d}\ln\xi_{j\omega n}$ in Equation (C.3) yields Equation (12). Using the expression for prices in the previous expression leads to our final estimating equation:

$$\mathrm{d}\ln \tilde{r}_{j\omega n} = \varepsilon_{j\omega n}\mathrm{d}\ln p_{j\omega n} + \sum_{\omega\in\mathcal{O}_{kn},k\notin\{j,n\}} \varepsilon_{k\omega n}\mathrm{d}\ln p_{k\omega n} + \varepsilon^{\xi}_{j\omega n}\mathrm{d}\ln\xi_{j\omega n} + \kappa_n. \tag{C.9}$$

C.2 Proposition 1 Details

The Mean Term in Proposition 1 can be written as:

$$\mathbb{E}\left[\mathrm{d}\ln\tilde{r}_{j\omega n}\right] = \frac{1}{|\mathcal{N}_f||\Omega_{fn}|}\sum_{n\in\mathcal{N}_f}\sum_{\omega\in\Omega_{fn}}\mathrm{d}\ln\tilde{r}_{j\omega n}. \tag{C.10}$$

This expression clarifies that the expectation is taken across products and destinations within each firm. The Covariance Term in Proposition 1 can be written as:

$$\begin{aligned}\operatorname{cov}\left(\theta_{f(j)\omega n}, \mathrm{d}\ln \tilde{r}_{j\omega n}\right) =& \frac{1}{|\mathcal{N}_f||\Omega_{fn}|}\sum_{n\in\mathcal{N}_f}\sum_{\omega\in\Omega_{fn}}\theta_{f(j)\omega n}\,\mathrm{d}\ln \tilde{r}_{j\omega n} \\ & - \left(\frac{1}{|\mathcal{N}_f||\Omega_{fn}|}\sum_{n\in\mathcal{N}_f}\sum_{\omega\in\Omega_{fn}}\theta_{f(j)\omega n}\right)\left(\frac{1}{|\mathcal{N}_f||\Omega_{fn}|}\sum_{n\in\mathcal{N}_f}\sum_{\omega\in\Omega_{fn}}\mathrm{d}\ln \tilde{r}_{j\omega n}\right).\end{aligned} \tag{C.11}$$

This expression clarifies that the covariance operator is also firm–specific and taken across products and destinations.