

The Impact of Trade Wars on Firms in Third Countries*

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Abstract

Bilateral trade shocks affect firms in third countries by redirecting demand and reallocating competition across markets, creating winners and losers. We propose a tractable trade model with heterogeneous firms to decompose firm-level export responses as a function of destination-specific changes in demand, own-price and cross-price elasticities, and external economies of scale. Using the 2018–2019 US–China trade war as a source of exogenous variation and data on the universe of Italian firms, we show how bilateral trade shocks occurring elsewhere identify these primitives for third countries. On average, the US–China trade war created a 2.5% export gain, albeit with substantial heterogeneity across firms. The external economies of scale channel accounts for three-quarters of changes in export performance.

Keywords: Firm heterogeneity, reallocation, scale economies, trade wars.

JEL classifications: D21, D22, E65, F13, F14.

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1 Introduction

Recent bilateral trade disruptions have reshaped global trade patterns (Freund et al., 2024; Alfaro and Chor, 2025). Despite evidence that bilateral trade shocks—e.g., arising from tariff changes, sanctions, or export controls—affect third countries that are not directly involved (Fajgelbaum et al., 2024), little is known about the mechanisms driving firms’ responses in third countries. Understanding these channels and quantifying their role is all the more important in a context where global economic integration is increasingly being challenged (Gopinath et al., 2025), and where such disruptions may have aggregate implications through reallocations across firms (Melitz, 2003; Hsieh and Klenow, 2009).

In this paper, we propose a tractable trade model with heterogeneous firms—free of functional-form restrictions on preferences and technology—to quantify the drivers of firm-level export responses to a major bilateral trade shock, the 2018–2019 US–China trade war, focusing on firms in a third country, Italy. The US–China trade war provides an ideal quasi-experimental setting, as it marked a turn toward protectionism after decades of free trade, reshuffling global demand and creating spillovers for bystander economies (Mayr-Dorn et al., 2023; Cavalcanti et al., 2025; Chen et al., 2025; Utar et al., 2025). Italy is a well-suited laboratory for this analysis: both the US and China are major export destinations, and the trade war was exogenous to Italian firms’ performance, facilitating the identification of the model’s primitives.

Our framework is motivated by the fact that bilateral trade shocks affect third-country firms through multiple, potentially offsetting channels. Higher US tariffs on Chinese goods may divert expenditure toward alternative suppliers, increasing demand for close substitutes from other origins. At the same time, 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 effects extend beyond direct competitors: firms exporting substitute goods to those being tariffed may benefit, while exporters of complementary goods may lose. Such effects—potentially amplified or dampened by the presence of scale economies—vary across firms, products, and destinations and interact with firms’ initial export portfolios. As a result, the net impact on firms in third countries is unclear ex ante. The theoretical framework we propose disciplines these mechanisms and allows us to quantify their relative importance. Importantly, our model is tractable and can be readily used to quantify firm-level responses in other countries and to other trade shocks, including sanctions, export controls, and other protectionist measures.

In our model, household preferences are described by a three-level nested aggregator: at the top level, households consume differentiated goods made by domestic and foreign

firms; at the middle level, foreign goods are aggregated across origins; 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 of producing a good depend on the total export quantity of that product from the same country, without restricting the sign of the scale effect (Lashkaripour and 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).

The model delivers gravity equations that decompose firm-level changes in export revenues at the intensive margin into five components: (i) origin–destination-specific changes (bilateral 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);¹ (iv) changes in prices faced by households in that destination for the same product from other origins (cross–demand effect); and (v) a residual capturing changes in unobservables, such as firm productivity and product appeal. This decomposition highlights that firms in third countries are more exposed to bilateral trade shocks when they export products affected by tariff changes, that exhibit external economies of scale, or that are highly substitutable for—or complementary to—goods from alternative origins.²

Identification of the price elasticities relies on the assumption that US–China tariff changes, along with other foreign price movements, are uncorrelated with changes in unobserved exporter characteristics in the third country of interest. Identification of the parameter governing external economies of scale is achieved by leveraging exogenous variation in product-level global demand induced by the US–China trade war.

We estimate these parameters by combining two administrative datasets covering the universe of Italian limited companies from 2014 to 2019: customs records on firms’ exports to the EU and non-EU destinations, and balance-sheet data on domestic sales, employment, and investment. We complement these data with product-level information on 2018–2019 US and Chinese tariffs from Fajgelbaum et al. (2024).³

¹We identify the parameter governing the presence of external economies of scale, not variation in their intensity.

²An analogous decomposition applies at the extensive margin. 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.

³Using 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

Our analysis yields four main insights. First, there is substantial heterogeneity in export responses to price changes induced by the US–China trade war. Demand for Italian products is more elastic in the US than in China, making Italian export revenues highly sensitive to US tariffs on EU imports. Cross–price elasticities also vary 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 and suffered losses from Chinese retaliatory 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 which amplify demand shocks faced by Italian firms, thus confirming the presence of scale economies documented in other settings (Bartelme et al., 2025).⁴

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)—and a standard deviation of 7.6%.⁵

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.⁶ We also 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.

Fourth, correlating changes in export revenues with ex–ante firm–level characteristics shows that gains were concentrated among firms that were initially more productive. We also find that export growth is positively correlated with increases in wages, employment,

of untargeted goods declined.

⁴Various explanations may underlie external scale economies. While identifying and disentangling such drivers 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).

⁵Fajgelbaum 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.

⁶We show 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 the interpretation of our results.

and investment at the firm level, consistent with evidence that the US–China trade war acted as a positive demand shock in bystander economies (Mayr-Dorn et al., 2023; Cavalcanti et al., 2025; Chen et al., 2025). These patterns point to improvements in allocative efficiency, as more productive and investment-intensive firms expanded relative to others.

Overall, our framework delivers a structural interpretation of the mechanisms driving the global reallocation effects of the 2018–2019 US–China trade war, and can be readily applied to analyze similar firms’ export responses well beyond this specific setting.

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 framework achieves point identification of key structural parameters. This enables us to disentangle the relative importance of different channels in shaping firm-level behavior and supports their finding that Italy ranked as a net export beneficiary of the trade war.

Our work relates to recent work on bystanders by 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. Their focus, however, is primarily on labor market outcomes, whereas we emphasize firm-level heterogeneity in trade responses. Our work is also closely related to Utar et al. (2025), who document that Mexican firms increased exports to the US in response to the trade war. Our contribution is to develop a theoretical framework that permits recovering 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.

We also contribute to the literature on quantitative trade models and structural gravity (Eaton and Kortum, 2002; Anderson and Van Wincoop, 2003; Arkolakis et al., 2012; Head and Mayer, 2014; Caliendo and Parro, 2015). While canonical models are well suited for quantifying aggregate gains from trade (Arkolakis et al., 2012), they typically rely

on restrictive assumptions—such as a single elasticity of substitution, constant marginal production costs, and parametric distributions that integrate out firm heterogeneity—that limit their ability to characterize how trade shocks differentially affect firms across products and destinations.⁷ We relax these assumptions and develop a framework that nests Armington–, Ricardian–, and Melitz–type models as special cases, while permitting a granular analysis of firm–level export responses. The model delivers a firm–level gravity equation that identifies destination–specific own–price elasticities, cross–origin cross–price elasticities, and external economies of scale in exports. This structure allows us to characterize the winners and losers from trade shocks and to trace the underlying channels, rather than focusing solely on aggregate outcomes. As in [Adao et al. \(2017\)](#), [Arkolakis et al. \(2019\)](#), and [Lind and Ramondo \(2023b\)](#), our framework accommodates rich patterns of substitution and complementarity. Crucially, the model’s parameters can be estimated in a single step from firm–product–destination responses to trade shocks, relying solely on this gravity equation.

Finally, on the supply side, recent papers have contributed to the empirical and quantitative revival of scale economies, mainly in the context of industrial policy ([Lashkaripour and Lugovskyy, 2023](#); [Bartelme et al., 2025](#)). We estimate comparable external economies of scale using a different framework and strategy. We estimate the scale elasticity jointly with demand elasticities using tariff variation, and use it to quantify how trade shocks can be dampened or amplified at the firm level. Our finding that the presence of scale economies drive firms’ export responses to a major bilateral shock echoes [Defever and Ornelas \(2026\)](#), who show that removing Chinese quotas in US and European markets boosted Chinese textile and clothing exports to unaffected third countries. Our results rationalize these patterns through external economies of scale.

The remainder of the paper is organized as follows. [Section 2](#) presents our theoretical framework. [Section 3](#) describes the data and provides preliminary evidence about Italian firms’ exposure to the 2018–2019 US–China trade war. [Section 4](#) outlines the identification and estimation of the model primitives. [Section 5](#) reports the estimation results. [Section 6](#) analyzes firm–level responses and quantifies the relative importance of the underlying channels. [Section 7](#) presents additional results, and [Section 8](#) concludes.

⁷While this framework is powerful for quantifying gains from trade with minimal data, 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 assuming a single elasticity generates downward bias in substitutability when the underlying sectoral elasticities are heterogeneous.

2 Theory

This section presents a tractable model of international trade—free of functional-form restrictions on preferences and technology—that disentangles the margins and channels through which heterogeneous firms respond to trade shocks, as summarized in [Proposition 1](#). While our empirical application focuses on Italian firms affected by the US–China trade war, the framework is sufficiently general to study firm responses in any country and to a wide range of trade shocks, such as sanctions and export controls.

2.1 Economic Environment

The economy consists of \mathcal{N} countries, indexed by j (origin) and n (destination), each populated by a representative household. Households consume both domestic and foreign goods. Foreign goods are produced by heterogeneous firms that differ in total factor productivity (TFP) and product appeal. Firms may sell multiple products across multiple destinations, and can operate under non-constant external returns to scale. Export decisions are assumed to be separable across products and destinations.

2.1.1 Preferences

Let c_n denote total consumption in country n . Consumption is a nested aggregator of domestic and foreign varieties. Household preferences in country n are given by:

$$\begin{aligned} c_n &= Q_U(Q_n^H, \{Q_{n,\omega}^F\}; \zeta_n), \\ Q_{n,\omega}^F &= Q_M(\{q_{j\omega n}\}; \xi_{j\omega n}), \\ q_{j\omega n} &= Q_L(\{q_{f(j)\omega n t}\}; \phi_{f(j)\omega n}), \end{aligned} \tag{1}$$

where the upper-level aggregator (Q_U) combines domestic (Q_n^H) and foreign ($Q_{n,\omega}^F$) products. The middle-level aggregator (Q_M) combines a given foreign differentiated products across origins, where $q_{j\omega n}$ denotes the quantity of product ω exported from origin j to destination n .⁸ 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 homogeneous of degree one, differentiable, and increasing in their arguments.

⁸Since our framework is meant to study firm-level export responses, we do not take a stand on the structure of Q_n^H .

Equation (1) implies that a firm selling product ω from origin j to destination n directly competes neither with other products $v \neq \omega$ (its own or those of other firms) nor with 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).

Our three–level nesting structure resembles multilevel demand systems commonly used in international trade (Broda and Weinstein, 2006; Hottman et al., 2016). We preserve the economic content of this structure—clarifying who competes with whom and how firm–level shocks map into trade flows—without imposing parametric assumptions such as constant elasticity of substitution (CES) or Cobb–Douglas. Instead, we allow for flexible patterns of substitution and complementarity within each nest, which may vary across destinations, and estimate these patterns directly from the data, in the spirit of recent non–parametric trade models (Adao et al., 2017; Arkolakis et al., 2019; Lind and Ramondo, 2023b; Adao et al., 2024).⁹

2.1.2 Technology, Trade, and Market Structure

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

$$c_{f(j)\omega} = c(w_j, z_{f(j)}, q_{j\omega}), \quad (2)$$

where w_j denotes the price of domestic production inputs, which is common to all firms and taken as given.¹⁰ Let $z_{f(j)}$ be firm–level TFP,¹¹ and $q_{j\omega}$ total export quantity of product ω from country j . We assume marginal costs are homogeneous of degree one and differentiable in all arguments. Dependence on aggregate product–level export quantities $q_{j\omega}$ introduces export–specific external economies of scale. We leave this term unspecified, allowing for increasing, decreasing, or constant returns to scale. This flexibility further distinguishes our model from canonical trade models, which typically assume constant re-

⁹Our main departure from this literature 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.

¹⁰Our approach does not require specifying the composition of the domestic input bundle. For simplicity, one can interpret w_j as the domestic wage for a homogeneous labor input, although the framework also allows for multiple domestic inputs. More generally, the model can accommodate richer input market structures that imply sector– or firm–specific input costs.

¹¹For generality, we let firms differ in product appeal, as per Equation (1), and productivity, as per Equation (2). However, we do not aim to disentangle their contribution for firm performance (Hottman et al., 2016).

turns to scale or impose a specific functional form for non-constant returns (Lashkaripour and Lugovskyy, 2023; Bartelme et al., 2025).

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:

$$p_{f(j)\omega n} = \mu_{f(j)\omega n} \tau_{j\omega n} c_{f(j)\omega}, \quad (3)$$

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

Using Equation (2) and Equation (3), we can write middle-nest prices as:

$$p_{j\omega n} = p(w_j, \tau_{j\omega n}, q_{j\omega}, \tilde{\xi}_{j\omega n}), \quad \tilde{\xi}_{j\omega n} = \{\mu_{f(j)\omega n}, z_{f(j)}, \phi_{f(j)\omega n}\}, \quad (4)$$

which depend on domestic production costs (w_j), country-pair product-level tariffs ($\tau_{j\omega n}$), the total export quantity of the origin-product pair ($q_{j\omega}$), and the joint distribution of firm-level TFP, markups and demand shifters ($\tilde{\xi}_{j\omega n}$).

2.1.3 Firm Entry

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

$$\mathbb{E}_{z, \phi} \left[\pi_{f(j)\omega n} \right] = F_{j\omega n}, \quad (5)$$

where $\pi_{f(j)\omega n}$ 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 . The expectation is taken over the distribution of the two dimensions of firm heterogeneity: TFP ($z_{f(j)}$) and product appeal ($\phi_{f(j)\omega}$). We assume that firms are ex-ante homogeneous, with all heterogeneity realizing only upon entry.

2.2 Export Responses to Trade Shocks

This section introduces the firm-level gravity equations that govern export 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 B.1](#).

2.2.1 Intensive Margin

Our demand system implies the following equilibrium expression for the export revenues of firm f when selling product ω from origin j to destination n :

$$r_{f(j)\omega n} = s_{f(j)\omega n}(\{p_{f(j)\omega n}\}, \Phi_{f(j)\omega n}) \cdot s_{j\omega n}(\{p_{j\omega n}\}, \zeta_{j\omega n}) \cdot s_n^F(\{p_n^H, p_n^F\}, \zeta_n) \cdot E_n. \quad (6)$$

Households in country n allocate a fraction s_n^F of their total expenditure E_n to 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 \(1\)](#).

Consider a product–specific trade shock that affects $s_{j\omega n}$ either through changes in $p_{j\omega n}$ —such as bilateral tariffs imposed by n on product ω from j —or through changes in $p_{k\omega n}$ —such as tariffs imposed by n on the same product ω from a different origin $k \neq j$.¹² Totally differentiating [Equation \(6\)](#) for firm f exporting product ω from origin j to destination n yields the following intensive–margin change in export revenues (suppressing function arguments for brevity):¹³

$$d \ln r_{f(j)\omega n} = d \ln s_{f(j)\omega n} + d \ln s_{j\omega n} + d \ln s_n^F E_n, \quad (7)$$

where $d \ln s_{j\omega n}$ captures changes in firms' export revenues directly due to the trade shock, while $d \ln s_{f(j)\omega n}$ and $d \ln s_n^F E_n$ capture changes due to concurrent adjustments in costs, markups, or overall demand. Since [Equation \(7\)](#) pertains to the intensive margin, $d \ln s_{f(j)\omega n}$ is only defined for incumbent firms. We will analyze firm entry and exit below.

Because product–specific trade shocks affect all firms within a given product–destination symmetrically ex ante, it is useful to express firms' average export revenue changes as:¹⁴

$$d \ln \tilde{r}_{j\omega n} = \kappa_n + \varepsilon_{s,p}^j d \ln p_{j\omega n} + \sum_{k \notin \{j,n\}} \varepsilon_{s,p}^k d \ln p_{k\omega n} + u_{j\omega n}, \quad (8)$$

¹²From the perspective of a third country, the US–China trade war is a shock to $s_{j\omega n}$ via changes in $p_{k\omega n}$.

¹³We focus on direct effects on firm revenues and abstract from indirect equilibrium feedback effects.

¹⁴We use the property that $d \ln f(x, y) = \varepsilon_{f,x} d \ln x + \varepsilon_{f,y} d \ln y$, where $\varepsilon_{f,x}$ and $\varepsilon_{f,y}$ denote the elasticities of f with respect to x and y , respectively.

where we have decomposed $d \ln s_{j\omega n}$ into its underlying components. The left-hand side of Equation (8) represents the average change in export revenues of product ω from origin j to destination n .¹⁵ The term $\kappa_n (= d \ln s_n^F E_n)$ captures instead destination-specific adjustments in foreign expenditure.¹⁶ The parameters $\varepsilon_{s,p}^j$ and $\varepsilon_{s,p}^k$ denote the own- and cross-price elasticities of the middle-nest market shares $s_{j\omega n}$ with respect to middle-nest prices. These elasticities could vary at the origin-product-destination level. The sign of the cross-price elasticities is left unrestricted, allowing for both substitution and complementarity patterns in demand. Finally, $u_{j\omega n}$ captures changes in middle-nest market shares due to changes in unobservables, including TFP and product appeal.

Using Equation (4), changes in middle-nest prices can be written as:

$$d \ln p_{j\omega n} = \kappa_j + d \ln \tau_{j\omega n} + \varepsilon_{p,q} d \ln q_{j\omega} + \varepsilon_{p,\tilde{\xi}} d \ln \tilde{\xi}_{j\omega n}, \quad (9)$$

where $\varepsilon_{p,x}$ denotes the elasticity of $p_{j\omega n}$ with respect to component x , and $\kappa_j \equiv \varepsilon_{p,w} d \ln w_j$. The latter is satisfied assuming that changes in domestic input costs shift export prices uniformly across all products and destinations within origin j , and therefore constitute an origin-specific price shifter κ_j .¹⁷ Equation (9) also exploits the fact that, because ad valorem tariffs apply uniformly to all firms within a given product-destination, homogeneous-of-degree-one aggregators such as Equation (4) imply that $\varepsilon_{p,\tau} = 1$ to a first-order approximation.¹⁸

Using Equation (9), we can rewrite Equation (8) to obtain the final gravity equation we use to identify intensive-margin export responses:

$$d \ln \tilde{r}_{j\omega n} = \kappa_{j,n} + \varepsilon_{s,p}^j d \ln \tau_{j\omega n} + \varepsilon_{s,p}^j \varepsilon_{p,q} d \ln q_{j\omega} + \sum_{k \notin \{j,n\}} \varepsilon_{s,p}^k d \ln p_{k\omega n} + v_{j\omega n}, \quad (10)$$

¹⁵This average is the same for all firms within the same product-destination cell. It reflects the fact that shocks to middle-nest market shares—such as the US-China trade war for third-country firms—do not discriminate across firms and represent a common shock ex ante.

¹⁶Such changes may occur for reasons other than the product-specific tariff changes, including fluctuations in bilateral exchange rates between countries and changes in households' income.

¹⁷The assumption is standard in the trade literature (Arkolakis et al., 2012). In canonical models with linear technology, homogeneous labor as the only input, and wages taken as given by firms, $\varepsilon_{p,w} = 1$, and wage changes are passed through one-for-one into all product-destination prices. At the other extreme, wages may be firm-specific—for example, due to monopsony power—in which case wage variation would enter the residual in Equation (9), similarly to productivity shocks. Intermediate cases, such as sector-level wages, can be accommodated through sectoral fixed effects.

¹⁸This holds exactly in any model where tariff changes do not reallocate market shares across firms, and to a first-order approximation when such reallocation effects are limited. For example, in Melitz (2003) and Atkeson and Burstein (2008), it applies as long as the set of active firms remains unchanged, or if the number of incumbents is large when entry and exit are allowed. Empirically, this term captures “byproduct” tariff changes imposed by the US and China on other trading partners. See Section 3.2 for details.

where $\kappa_{j,n} = \kappa_j + \kappa_n$ and $v_{j\omega n} = u_{j\omega n} + \varepsilon_{s,p}^j \varepsilon_{p,\tilde{\xi}} \text{d} \ln \tilde{\xi}_{j\omega n}$. We do not decompose changes in the middle–nest price index for other origins because our data cover only one bystander country (Italy), preventing credible identification of scale economies outside our context.¹⁹

2.2.2 Extensive Margin

Under the assumption that firms are ex–ante homogeneous and all shocks are realized only upon entry, Equation (5) and Equation (6) imply that the number of firms exporting product ω from origin j to destination n ($N_{j\omega n}$) is given by:

$$\frac{s_{j\omega n} s_n^F E_n}{N_{j\omega n}} = F_{j\omega n}. \quad (11)$$

We assume that entry costs do not change over time, i.e., $\text{d} \ln F_{j\omega n} = 0$. This assumption fits our context: we focus on a two–year long horizon during which ad–valorem tariff changes arguably did not directly affect entry costs. Following the same steps as for the intensive margin, we derive the gravity equation governing extensive–margin export responses—i.e., changes in the number of firms exporting product ω from origin j to destination n :

$$\text{d} \ln N_{j\omega n} = \tilde{\kappa}_{j,n} + \tilde{\varepsilon}_{s,p}^j \text{d} \ln \tau_{j\omega n} + \tilde{\varepsilon}_{s,p}^j \tilde{\varepsilon}_{p,q} \text{d} \ln q_{j\omega} + \sum_{k \notin \{j,n\}} \tilde{\varepsilon}_{s,p}^k \text{d} \ln p_{k\omega n} + \tilde{v}_{j\omega n}. \quad (12)$$

Notation follows Equation (10), with all variables now carrying a tilde to reflect the fact that they also account for extensive–margin adjustments in the number of active firms.

2.3 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:

$$\text{d} \ln r_{f(j)} = \sum_{n \in \mathcal{N}_f} \sum_{\omega \in \Omega_{fn}} \theta_{f(j)\omega n} \text{d} \ln \tilde{r}_{j\omega n}, \quad (13)$$

with $\theta_{f(j)\omega n}$ denoting 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 $\text{d} \ln \tilde{r}_{j\omega n}$ the change in product–destination–specific export revenues from Equation (10). 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 .

¹⁹In principle, with customs data for multiple countries, one could disentangle the impact of tariffs from scale economies in each origin country.

We decompose Equation (13) in order to 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 of 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.²⁰

The next proposition presents the decomposition, the key tool for disentangling and quantifying the channels through which trade shocks affect firm–level exports.

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

$$\mathrm{d} \ln r_{f(j)} = \underbrace{\mathbb{E} [\mathrm{d} \ln \tilde{r}_{j\omega n}]}_{\text{Mean Term}} + \underbrace{\mathrm{cov}(\theta_{f(j)\omega n}, \mathrm{d} \ln \tilde{r}_{j\omega n})}_{\text{Covariance Term}}. \quad (14)$$

Using Equation (10), we can rewrite the Mean and Covariance terms as:

$$\begin{aligned} \mathbb{E} [\mathrm{d} \ln \tilde{r}_{j\omega n}] &= \underbrace{\mathbb{E} [\kappa_{j,n}]}_{\text{Bilateral Effect}} + \underbrace{\mathbb{E} [\varepsilon_{s,p}^j \varepsilon_{p,q} \mathrm{d} \ln q_{j\omega}]}_{\text{Scale Effect}} \\ &+ \underbrace{\mathbb{E} [\varepsilon_{s,p}^j \mathrm{d} \ln \tau_{j\omega n}]}_{\text{Own–Demand Effect}} + \underbrace{\mathbb{E} \left[\sum_{k \notin \{j,n\}} \varepsilon_{s,p}^k \mathrm{d} \ln p_{k\omega n} \right]}_{\text{Cross–Demand Effect}} + \underbrace{\mathbb{E} [v_{j\omega n}]}_{\text{Residual}}, \end{aligned} \quad (15)$$

$$\begin{aligned} \mathrm{cov}(\theta_{f(j)\omega n}, \mathrm{d} \ln \tilde{r}_{j\omega n}) &= \underbrace{\mathrm{cov}(\theta_{f(j)\omega n}, \kappa_{j,n})}_{\text{Bilateral Effect}} + \underbrace{\mathrm{cov}(\theta_{f(j)\omega n}, \varepsilon_{s,p}^j \varepsilon_{p,q} \mathrm{d} \ln q_{j\omega})}_{\text{Scale Effect}} \\ &+ \underbrace{\mathrm{cov}(\theta_{f(j)\omega n}, \varepsilon_{s,p}^j \mathrm{d} \ln \tau_{j\omega n})}_{\text{Own–Demand Effect}} + \underbrace{\sum_{k \notin \{j,n\}} \mathrm{cov}(\theta_{f(j)\omega n}, \varepsilon_{s,p}^k \mathrm{d} \ln p_{k\omega n})}_{\text{Cross–Demand Effect}} \\ &+ \underbrace{\mathrm{cov}(\theta_{f(j)\omega n}, v_{j\omega n})}_{\text{Residual}}. \end{aligned} \quad (16)$$

Appendix B.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 coming from our gravity Equation (10). 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 origin–destination–

²⁰This decomposition is similar in spirit to Olley and Pakes (1996)'s decomposition used to understand the drivers of changes in aggregate productivity.

specific adjustments, common to all firms and products, and is informative about aggregate bilateral effects. 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-specific 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 [Proposition 1](#) in the context of third-country firms' responses to an increase in US import tariffs on Chinese goods. Firms most affected in absolute terms are those whose exports are concentrated (i) in the US market, (ii) in products targeted by US "byproduct" import tariffs (see [Section 3.2](#)), (iii) in products exhibiting economies of scale, and (iv) in products that are close substitutes for, or complements to, goods supplied by other origins. The net effect on firm-level export revenues depends on the sign and relative strength of these channels.

3 Data

This section introduces our data sources and offers descriptive evidence on Italian firms' exposure to the 2018–2019 US–China trade war. Additional details are in [Appendix C.1](#).

3.1 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.

3.1.1 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). Unique firm tax identifiers enable unambiguous matching of firms across the customs and balance sheet data.

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.²¹

²¹Thresholds 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.

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 to avoid confounding effects from the COVID-19 pandemic. These data allow us to examine firms’ 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.²² These data include standard 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, while the registry also provides the primary industry of activity of each firm according to the 2–digit NACE classification. Estimates of TFP for firms in CERVED 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 in a reduced–form way whether changes in international trade strategies influenced domestic outcomes—employment, investment, and productivity—among Italian firms.

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.

3.1.2 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

²²Firms not included are mainly financial and real estate companies together with small businesses, such as sole proprietorship or household producers. See [Akcigit et al. \(2023\)](#) for additional details.

Section 3.2 for details). The 2018–2019 tariff changes provide exogenous variation in product–level demand (Mayr-Dorn et al., 2023; Utar et al., 2025; 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.

3.2 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 (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 (Figure A.1, bottom panel). Machinery, electrical equipment, intermediate industrial goods, and consumer goods were also covered by new tariffs.

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 (Figure A.2). In turn, the EU and RoW raised tariffs on US imports (Figure A.3). Concurrently, China reduced its MFN tariffs on imports from the EU and RoW by roughly 1.5 percentage points (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 with the US.

In sum, the 2018–2019 US–China tariff escalation generated substantial product–level demand reallocation across countries (Freund et al., 2024; Alfaro and Chor, 2025). This will be used to identify the mechanisms driving Italian firms’ export responses.

3.3 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.²³

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 [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 two of the largest non–EU destination markets for Italian exporters.

[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 2018.²⁴

Survey responses show 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 [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.

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.

²³In line with the existing literature ([Bernard and Jensen, 1999](#); [Bernard et al., 2007](#)), [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 ([Table A.2](#)).

²⁴Although we do not aim to provide a causal interpretation to the estimates, the increase in export values for targeted goods after 2018 is further confirmed using a simple event–study analysis. See [Appendix C.2](#) for additional details.

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 [Equation \(10\)](#) and [Equation \(12\)](#). In our baseline results, we assume that price elasticities are destination-specific ($\varepsilon_{s,p}^i = \varepsilon_n^i$ for $i \in \{j, k\}$) and scale economies are constant across products ($\varepsilon_{p,q} = \varepsilon_q$), and we inspect heterogeneity later in [Section 5](#). Under these restrictions, our main estimating equation for intensive-margin responses becomes:

$$d \ln \tilde{r}_{j\omega n} = \kappa_{j,n} + \varepsilon_n^j d \ln \tau_{j\omega n} + \varepsilon_n^j \varepsilon_q d \ln q_{j\omega} + \sum_{k \notin \{j,n\}} \varepsilon_n^k d \ln p_{k\omega n} + v_{j\omega n}. \quad (17)$$

We estimate [Equation \(17\)](#) having Italy as the only origin, so $\kappa_{j,n}$ is *de facto* a destination fixed effect. 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 $d \ln \tau_{j\omega n}$ are nonzero only for Italy’s trade with the US and China (see [Section 3.2](#)), 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.

Estimation is performed via weighted-stacked Generalized Method of Moments (GMM). We define the relevant moment conditions at the product–destination level and then stack them for all exporters within a given product–destination cell. We estimate [Equation \(17\)](#) using long differences between 2019 and 2017, and cluster standard errors by firm–product. We follow the same procedure when applying [Equation \(12\)](#) to the data, except that no stacking across exporters is needed to estimate the parameters governing extensive-margin responses.

4.2 Identification

[Equation \(17\)](#) allows to estimate a vector of destination-specific own-price elasticities, a matrix of destination-specific cross-price elasticities, and a parameter governing external economies of scale. The US–China trade war constitutes an ideal exogenous shock to identify these primitives in bystander economies not directly involved in the dispute.

Identification of the US- and China-specific own-price elasticity hinges on the “byproduct” 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 3.2](#), this assumption is plausible because US tariff increases on certain European products and China’s MFN cuts applied to all non-US partners were largely a byproduct of the US–China dispute, rather than policy responses to the export performance of bystander countries in general, or Italy in particular. Identification of the EU- and RoW-specific own-price elasticities instead comes from the over-identifying restrictions implied by the model. [Equation \(17\)](#) delivers four sets of moment conditions, one for each destination market. Since the scale elasticity is common across destinations, these additional moments allow us to recover the EU- and RoW-specific own-price elasticities.

Our demand system in [Equation \(1\)](#) allows for the possibility that changes in middle-nest export prices of Italian competitors ($d \ln p_{k\omega n}$) correlate with unobservable shocks to Italian exporters’ performance. 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 \(17\)](#). 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 ($d \ln q_{j\omega}$) 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:

$$d \ln \min\{\tau_{US \rightarrow CN, \omega}, \tau_{CN \rightarrow US, \omega}\}. \quad (18)$$

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. Intuitively, 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.²⁵ The exclusion restriction requires that US–China bilateral tariff changes affect the total quantity of Italian exports solely through this exoge-

²⁵In [Section 5.3](#), we show that our results are robust to using changes in US tariffs on Chinese products as an instrument, i.e., only the first set of tariffs in [Equation \(18\)](#).

nous reallocation. This assumption is plausible because US–China tariffs were driven by considerations unrelated to the export performance of third countries (Fajgelbaum et al., 2024). The same logic applies when estimating extensive–margin equations.

A final concern when identifying the external scale economy elasticity is that, if firms are non–atomistic within an HS6 product category, changes in aggregate export quantities could mechanically reflect changes in the largest exporter’s activity. This concern appears limited. The correlation between the largest firm’s revenue changes and total export quantity changes in our data is just 3.2%, indicating that total export movements reflect sector–level activity rather than the behavior of a few dominant firms.

5 Estimation Results

This section presents the estimates derived from our model.

5.1 Baseline Estimates

Figure 1 illustrates the four estimated components of Equation (17): 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 Table A.5.

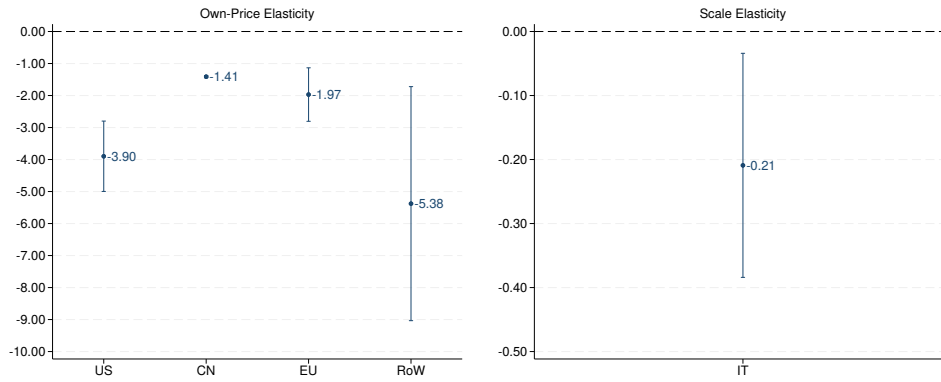
The left panel of Panel A shows substantial heterogeneity in own–price demand elasticities across destinations, with estimates ranging from 1.4 to 5.3, in line with the existing literature (Broda and Weinstein, 2006; Head and Mayer, 2014; Fontagné et al., 2022; Boehm et al., 2023). US demand for Italian products is more elastic than Chinese demand. The right figure documents the existence of positive scale economies, which amplify the direct impact of demand shocks. Quantitatively, our estimates fall within the range of 0.1–0.3 reported by Lashkaripour and Lugovskyy (2023) and 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.²⁶

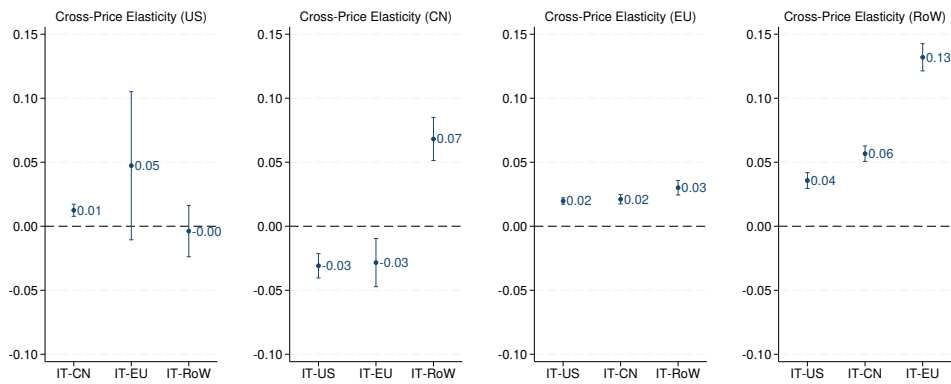
²⁶Using data for Brazil, Cavalcanti et al. (2025) instead provide evidence consistent with Brazilian and US products being substitutes for Chinese consumers. The difference with our result likely reflects differences in export composition between Italy and Brazil.

Figure 1. Intensive-Margin Baseline Estimates

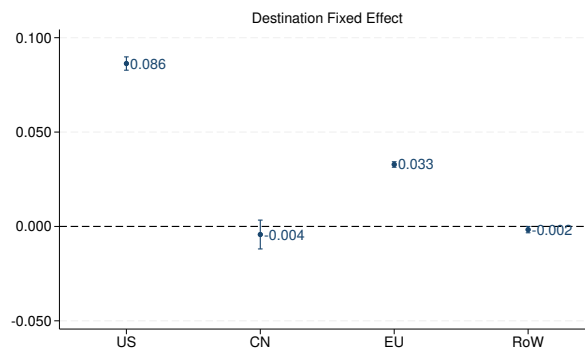
Panel A



Panel B



Panel C



Notes: The figure shows the four estimated components of Equation (17): 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.

Panel C shows that other destination-specific 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 [Table A.5](#) shows that the parameters governing extensive-margin responses are noisily estimated, and no clear pattern emerges. If anything, 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.²⁷ We therefore focus on intensive-margin responses in what follows.

5.2 Model Fit

In [Figure 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](#)). [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.

[Table A.7](#) presents the same decomposition for each destination separately. Even at this level, the restricted models perform worse than the full model, indicating that the substitution structure imposed by standard trade models may fail to capture important margins of firms' export responses to trade shocks. In this regard, our results echo the findings of [Imbs and Mejean \(2015\)](#) and [Bas et al. \(2017\)](#) that allowing for heterogeneity in price elasticities is crucial for obtaining correct aggregate predictions from gravity models.

²⁷The 2025 wave of US tariffs may yield different outcomes, as the tariff increases were much higher.

5.3 Robustness

Columns (2)–(5) of [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 \(18\)](#) with the change in US product–level import tariffs on Chinese goods ($d \ln \tau_{US \rightarrow CN, \omega}$). 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. 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 changes in revenues were positively correlated with changes in quantities.

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 \(10\)](#) also permits elasticities to vary by product. To investigate this source of heterogeneity, [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 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 Firm–Level Outcomes

This section uses the structural estimates to decompose firm–level responses according to [Proposition 1](#) and evaluate the pass–through of export revenue changes to domestic outcomes.

6.1 Distribution of Export Revenue Changes across Firms

Using [Equation \(13\)](#), we compute firm–level changes in total export revenue as a weighted average of product–destination–specific changes. Initial export shares ($\theta_{f(j)\omega n}$) come from 2017 data, while product–destination–specific changes ($d \ln \tilde{r}_{j\omega n}$) are obtained from [Equation \(17\)](#), and capture the effects of the 2018–2019 US–China trade war as predicted by our model.

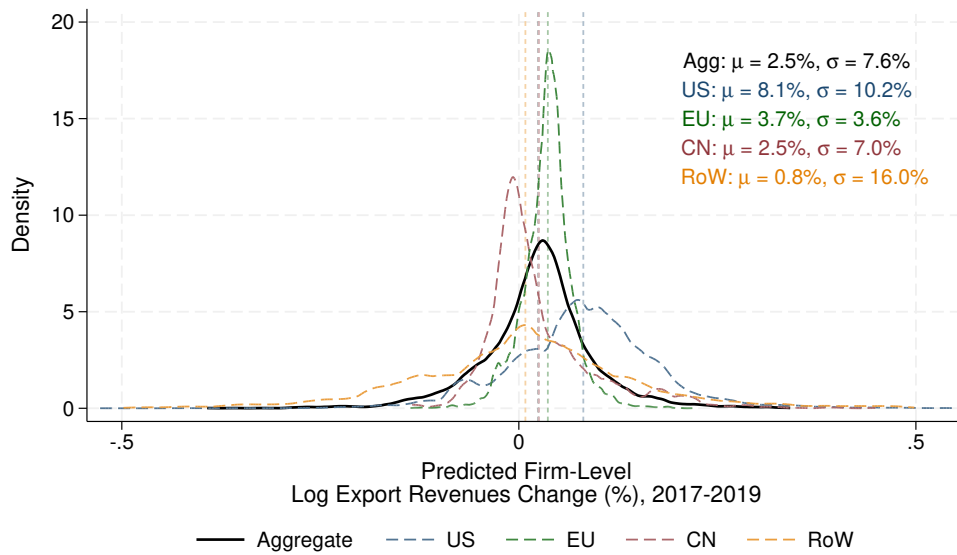
[Figure 2](#) shows the distribution of export revenue changes across firms, both pooled across destinations and broken down by destination. Overall, the 2018–2019 US–China trade war generated short–run net export opportunities for Italian firms, with average export revenues rising by 2.5% over the period.²⁸ Average gains are higher in 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.

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 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. [Figure A.7](#) highlights substantial heterogeneity across Italian provinces: most gains ac-

²⁸This finding is consistent with [Fajgelbaum et al. \(2024\)](#), who also show that Italy lies toward the lower end of the distribution among net winners.

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 (13).

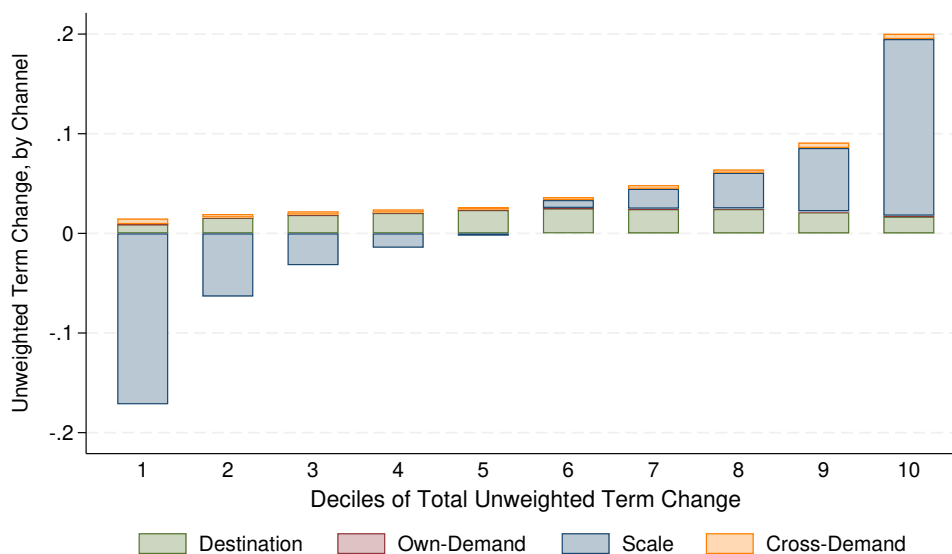
crued to northern provinces, though some provinces in the center-south and islands also benefited.²⁹ Figure A.8 further decomposes province-level changes by export destination. Interestingly, provinces did not uniformly gain or lose across destinations. The Pearson (Spearman) correlation between province-level 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%).

6.2 Mechanism: Demand, Scale Economies, and Competition

Figure 3 presents the decomposition of the unweighted mean component from Proposition 1, which accounts for 80% of total changes in firm-level export revenues. 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

²⁹This 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.

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.

cross-demand effects, which consistently pushed export revenues up across all deciles, though their impact is dominated by scale economies.

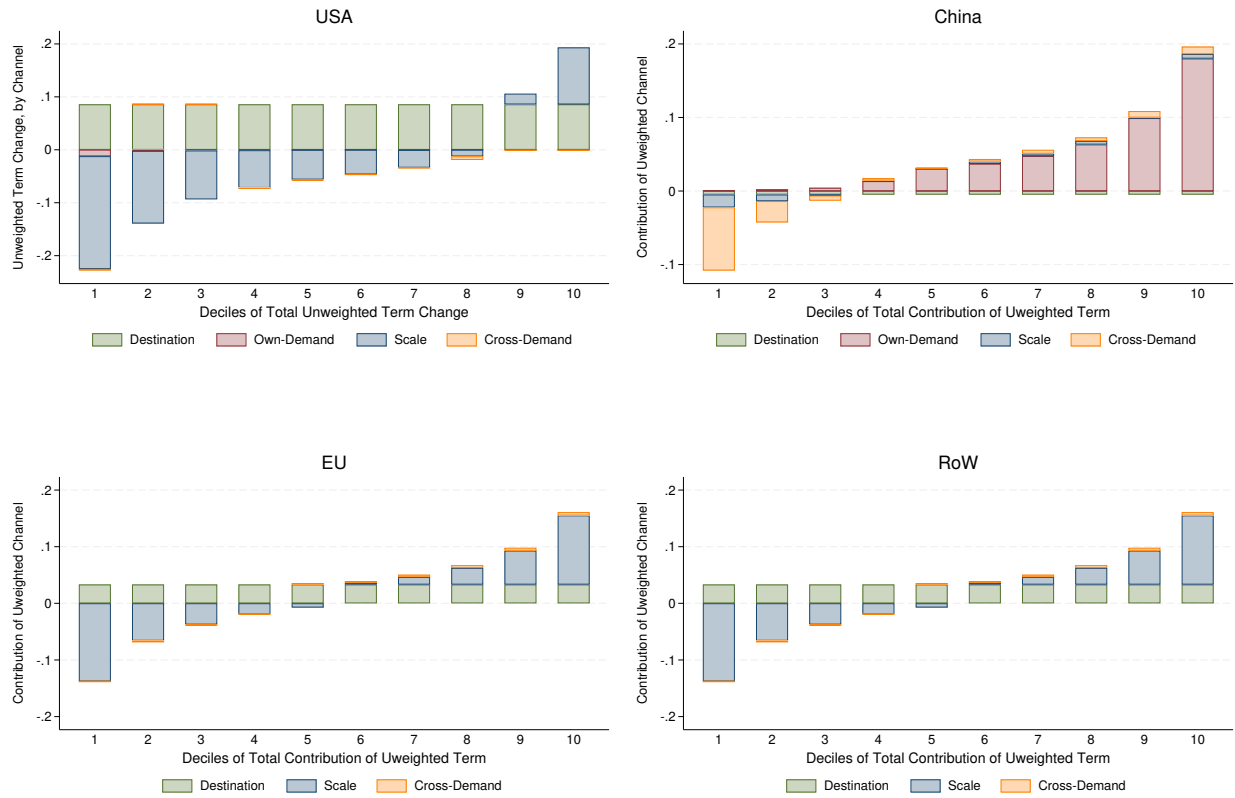
A similar pattern emerges when decomposing mean export revenue changes across destinations, as shown in Figure 4, except for exports to China. Here, the increase in export revenues was entirely driven by the own-demand channel, reflecting Chinese MFN tariff cuts toward all non-US countries. In contrast, reductions in exports to China were largely explained by cross-demand effects, due to the complementarity between Italian exports and those from the US, as highlighted in Figure 1.

Figure A.9 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.³⁰

Overall, the quantitative results in Figure 2 and Figure 3 indicate that Italian firms responded to the US-China trade war not only by adjusting exports to these two countries,

³⁰When 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 Figure A.10. As in Figure 4, increases in export revenues to China are driven by the own-demand channel, while reductions are primarily due to cross-demand effects.

Figure 4. Decomposition of Firm–Level Export Revenue Changes by Destination (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.

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. Our finding that the presence of scale economies drives firms’ export responses to a major bilateral shock echoes Defever and Ornelas (2026), who show that removing Chinese quotas on textiles and clothing in US and European markets increased Chinese exports to third countries where policy was unchanged. Our results rationalize these patterns through external economies of scale.

6.3 Role of Firm–Level 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 1 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 1. Inspecting Firm–Level Export Revenue Changes

Dependent variable:	d Log Model–Predicted Exports				
	(1)	(2)	(3)	(4)	(5)
Log TFP	0.70*** (0.18)	0.68*** (0.17)	0.61*** (0.17)	0.57*** (0.19)	0.66*** (0.20)
Log Employment		0.37*** (0.14)	0.41*** (0.14)	0.42*** (0.15)	0.06 (0.19)
Log Share of White Collar Employees			0.94*** (0.28)	0.96*** (0.29)	0.57* (0.33)
Log Investment per Employee				0.40** (0.20)	0.43** (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 2017. *Log Number of Exp Products* is the log of the number of products exported by each firm in 2017, and *Log Number of Exp Destinations* is the log of the number of destinations to which each firm exported in 2017. The number of observations changes across columns due to missing values in some of the controls. 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.³¹ Columns (2)–(5) sequentially add controls for employment, share of white collar workers,³² investment per employee, number of ex-

³¹Our measure of productivity is closer to revenue–based TFP (TFPR) than physical productivity (TFPQ), as we deflate revenues using sectoral price indices rather than firm–level prices. Still, TFPR is positively correlated with TFPQ (Foster et al., 2008) and is informative for cross–sectional comparisons.

³²Clerks and managers are white–collar employees; manual workers are classified as blue–collar.

ported 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. The positive correlation between changes in export revenues and initial productivity survives after controlling for all other firm characteristics.

Overall, this pattern suggests that the 2018–2019 US–China trade war not only generated net export opportunities for Italian firms but also improved allocative efficiency. This finding is further supported by [Figure A.11](#), which shows that initially more productive firms expanded their export revenues to every destination more than less productive firms.

6.4 Implications for Domestic Outcomes

An interesting question is whether changes in export revenues induced by the 2018–2019 US–China trade war translated into changes in domestic activities for Italian firms.

We adopt a reduced–form approach and assess the relationship between changes in export revenues and domestic outcomes by projecting firm–level changes from 2017 to 2019 in several observed domestic outcomes onto the model–predicted firm–level changes in export revenues from [Equation \(17\)](#). This allows us to shed light on how US–China trade war–induced demand shocks are correlated with the domestic operations of Italian firms.³³

[Figure A.12](#) plots these correlations. We find that export–revenue growth is associated with wage growth, higher employment, and more investment. The increase in total employment reflects gains in both white– and blue–collar positions, with the latter exhibiting a stronger response to export–revenue growth. Growth in firms’ total sales closely tracks export dynamics, indicating that increases in export revenue did not crowd out domestic sales. Taken together, these results provide suggestive evidence that the trade war acted as a positive aggregate demand shock for domestic factor inputs.

7 Discussion

In this section, we discuss how our model compares to canonical trade models and provide additional insights on the drivers of economies of scale.

³³Providing a structural answer to this question is feasible in our context but requires imposing additional assumptions on firms’ production function.

7.1 Comparison to Canonical Trade Models

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 performance of our framework versus standard models, we construct counterfactual firm-level export revenues using Equation (10), abstracting from economies of scale ($\varepsilon_{p,q} = 0$) and cross-demand effects ($e_{s,p}^k = 0, \forall k \neq j$).

Figure A.13 reports the distribution of export revenue changes across firms, pooled across destinations, under the benchmark model and the restricted specifications. 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. 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.³⁴

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).

7.2 Inspecting External Economies of Scale

Our previous results underscore the importance of positive external economies of scale in explaining changes in Italian exporters' revenues, both for winners and losers. What explains the presence of scale effects? To investigate this, we re-estimate Equation (17) separately for each 2-digit HS product code,³⁵ 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

³⁴These findings are consistent with the explained variance of each model reported in Table A.6 and Table A.7.

³⁵Table A.9 shows moments of the distribution of the estimated external economies of scale as the 2-digit HS product code level. 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).

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,³⁶ 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).³⁷

As shown in Table A.10, product groups characterized by a greater number of active firms and a higher share of high-tech production display stronger scale economies. This is consistent with knowledge diffusion facilitated by geographic proximity and access to advanced technologies. There is no empirical evidence supporting the other 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.³⁸ Figure A.14 corroborates this result by regressing the model-predicted change in export revenues from Equation (17) 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 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.

8 Conclusion

In this paper, we provide a tractable model of international trade that disentangles the margins and channels through which heterogeneous firms respond to trade shocks. The

³⁶We 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).

³⁷Emerging 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 Table A.10 are unaffected.

³⁸Our framework can be readily extended to incorporate import decisions. If firms choose imports before deciding on exports, Equation (2) can be modified to include a firm-specific aggregator of imported varieties, following Antras et al. (2017). Changes in this import aggregator affect marginal costs in a manner similar to productivity shocks and enter the error term of Equation (10). In a way, the estimated coefficients could be interpreted as if import decisions were already made.

model delivers gravity equations that decompose firm-level changes in export revenues at the intensive margin into destination-specific demand shifts, own- and cross-price demand effects, and production cost changes arising from the presence of external economies of scale in exports. Importantly, our framework does not impose restrictions on the sign and magnitude of these effects, which are estimated from the data. We estimate the model using administrative data covering the universe of Italian firms, exploiting the 2018–2019 US–China trade war as a source of exogenous variation in product-level global demand, which allows us to recover the model primitives in a transparent way. However, 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 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 US 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 38% within two years.³⁹ However, because the US is imposing even higher tariffs on China and other countries, substitution effects toward alternative suppliers could partially offset these reductions, and cross-price elasticities could play a larger role in explaining both average and distributional effects.

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 simulations (Ignatenko et al., 2025; Federico et al., 2025), but would require access to updated firm-level data. We leave these important questions for future research.

³⁹A 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

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A Tables and Figures

Table A.1. Summary Statistics by Trade Status

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

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.

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.

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 SONDEL survey (see [Section 3.3](#) for additional details). The remaining columns show the share of total export values, sales, number of employees, and investment accounted for by each group.

Table A.5. Estimation Results - Baseline

	Baseline	Alt.	Pre-	Alt.	Quantity	Ext.
	(1)	SE	Trends	IV	(5)	Margin
	(1)	(2)	(3)	(4)	(5)	(6)
Scale el.	-0.209** (0.106)	-0.210* (0.117)	-0.202** (0.096)	-0.254** (0.110)	-0.168 (0.128)	-1.281 (1.667)
Intercept (US)	0.086*** (0.002)	0.086*** (0.002)	0.088*** (0.003)	0.086*** (0.002)	0.035*** (0.005)	0.011 (0.012)
Own-price el. (US)	-2.898*** (0.668)	-2.892*** (0.787)	-2.935*** (0.664)	-2.473*** (0.647)	-4.610*** (1.316)	0.763 (0.813)
Cross-price el. IT-CN (US)	0.012*** (0.003)	0.012*** (0.003)	0.013*** (0.003)	0.012*** (0.003)	0.007 (0.007)	-0.022 (0.032)
Cross-price el. IT-RoW (US)	-0.004 (0.012)	-0.004 (0.012)	-0.003 (0.011)	-0.005 (0.011)	-0.053** (0.025)	0.001 (0.039)
Cross-price el. IT-EU (US)	0.047 (0.035)	0.048 (0.038)	0.046 (0.033)	0.051* (0.028)	0.031 (0.069)	-0.064 (0.051)
Intercept (CN)	-0.004 (0.005)	-0.004 (0.005)	-0.004 (0.005)	-0.005 (0.005)	-0.069*** (0.010)	0.044*** (0.008)
Own-price el. (CN)	-0.411*** (0.022)	-0.408*** (0.028)	-0.415*** (0.022)	-0.410*** (0.022)	-0.519*** (0.043)	0.074** (0.030)
Cross-price el. IT-US (CN)	-0.031*** (0.006)	-0.031*** (0.005)	-0.032*** (0.006)	-0.031*** (0.006)	-0.049*** (0.012)	-0.011 (0.009)
Cross-price el. IT-RoW (CN)	0.068*** (0.010)	0.069*** (0.010)	0.068*** (0.010)	0.070*** (0.010)	0.096*** (0.022)	-0.005 (0.013)
Cross-price el. IT-EU (CN)	-0.028** (0.011)	-0.028** (0.012)	-0.028** (0.011)	-0.026** (0.011)	-0.056** (0.023)	0.005 (0.011)
Intercept (EU)	0.033*** (0.001)	0.033*** (0.001)	0.033*** (0.001)	0.033*** (0.001)	-0.005 (0.003)	-0.124*** (0.011)
Own-price el. (EU)	-0.970* (0.508)	-0.964* (0.545)	-0.995** (0.487)	-0.846** (0.372)	-2.379 (1.906)	0.660 (1.342)
Cross-price el. IT-US (EU)	0.020*** (0.002)	0.020*** (0.002)	0.020*** (0.002)	0.019*** (0.001)	0.018*** (0.005)	0.018 (0.022)
Cross-price el. IT-RoW (EU)	0.030*** (0.003)	0.030*** (0.003)	0.030*** (0.003)	0.031*** (0.003)	0.021* (0.011)	-0.032 (0.065)
Cross-price el. IT-CN (EU)	0.021*** (0.002)	0.021*** (0.002)	0.021*** (0.002)	0.020*** (0.002)	0.014** (0.007)	-0.006 (0.030)
Intercept (RoW)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.007*** (0.001)	-0.050*** (0.003)	-0.032*** (0.004)
Own-price el. (RoW)	-4.379** (2.223)	-4.359* (2.413)	-4.512** (2.132)	-4.634** (2.007)	-5.910 (4.522)	-0.144 (0.418)
Cross-price el. IT-US (RoW)	0.036*** (0.004)	0.035*** (0.004)	0.036*** (0.004)	0.020*** (0.004)	0.026*** (0.010)	0.011 (0.015)
Cross-price el. IT-CN (RoW)	0.057*** (0.004)	0.057*** (0.004)	0.057*** (0.004)	0.064*** (0.004)	0.039*** (0.009)	0.040 (0.039)
Cross-price el. IT-EU (RoW)	0.132*** (0.006)	0.132*** (0.007)	0.132*** (0.007)	0.161*** (0.007)	0.124*** (0.017)	-0.018 (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 (17). 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. The number of observations changes across columns due to missing values in some of the controls. Standard errors in parentheses are clustered by firm and product, except in column (2). Significance levels: *** 0.01, ** 0.05, * 0.1.

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 \(17\)](#) 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.

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 \(17\)](#) 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.

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

Note: The sample is the same as in Table A.5. Each column reports estimates of Equation (17) 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). The number of observations changes across columns due to missing values in some of the controls. Significance levels: *** 0.01, ** 0.05, * 0.1.

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

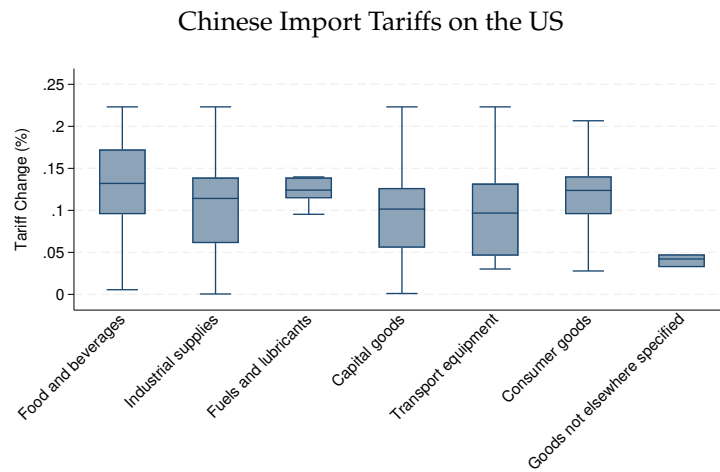
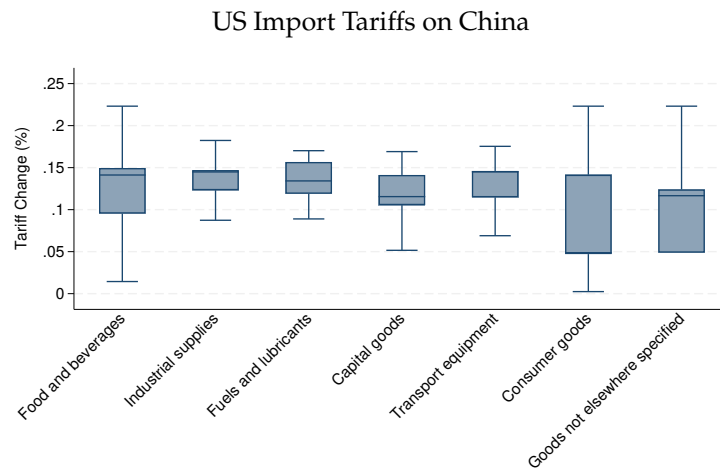
Notes: The table reports the moments of the distribution of the estimated external economies of scale at the 2-digit HS product level.

Table A.10. Drivers of External Economies of Scale

Dependent variable:	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

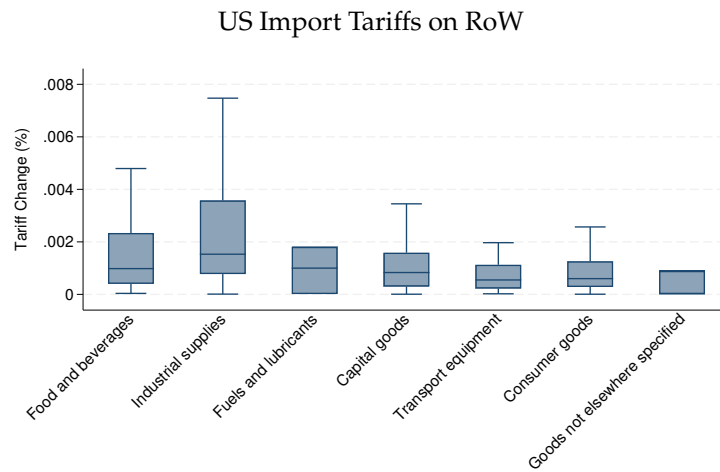
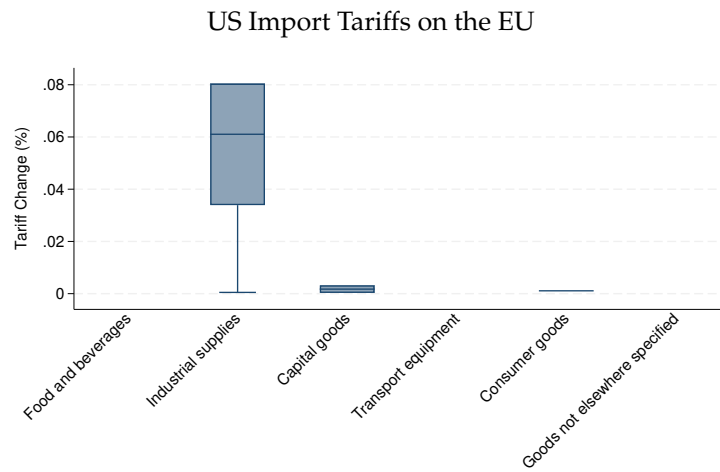
Notes: Each observation corresponds to a 2-digit HS product. The dependent variable is the scale elasticity estimated from Equation (17) for each 2-digit HS product code. *Number of Firms, 2017* denotes the average number of firms producing that product across Italian provinces in 2017. *Share of High-Tech 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.

Figure A.1. US–China Tariff Changes



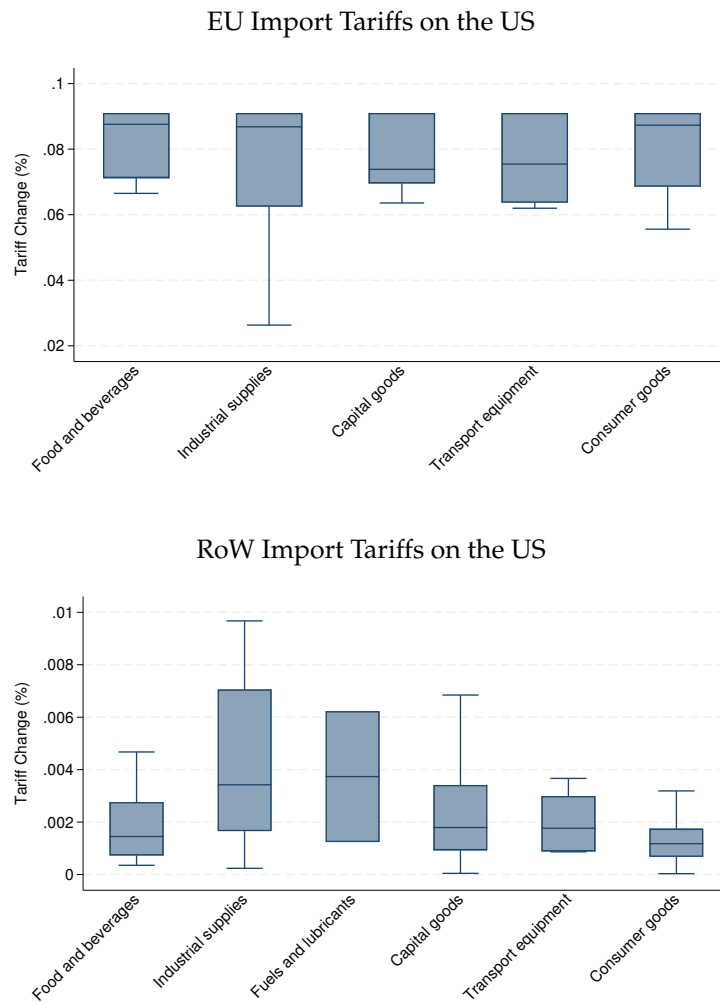
Notes: The figure shows changes in import tariffs imposed by the US on China (top panel), and changes in import tariffs imposed by China on the US (bottom panel). Each box represents the 25th, 50th (median), and 75th percentiles, while the whiskers indicate the 10th and 90th percentiles.

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



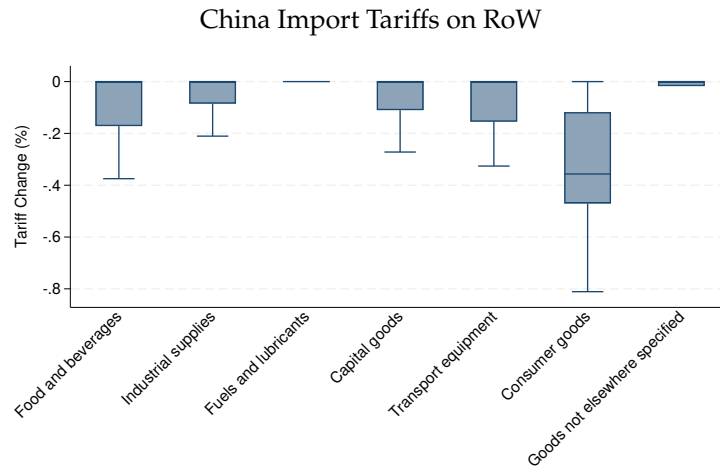
Notes: The figure shows changes in import tariffs imposed by the US on the EU (top panel) and the Rest of the World (bottom panel). Each box represents the 25th, 50th (median), and 75th percentiles, while the whiskers indicate the 10th and 90th percentiles.

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



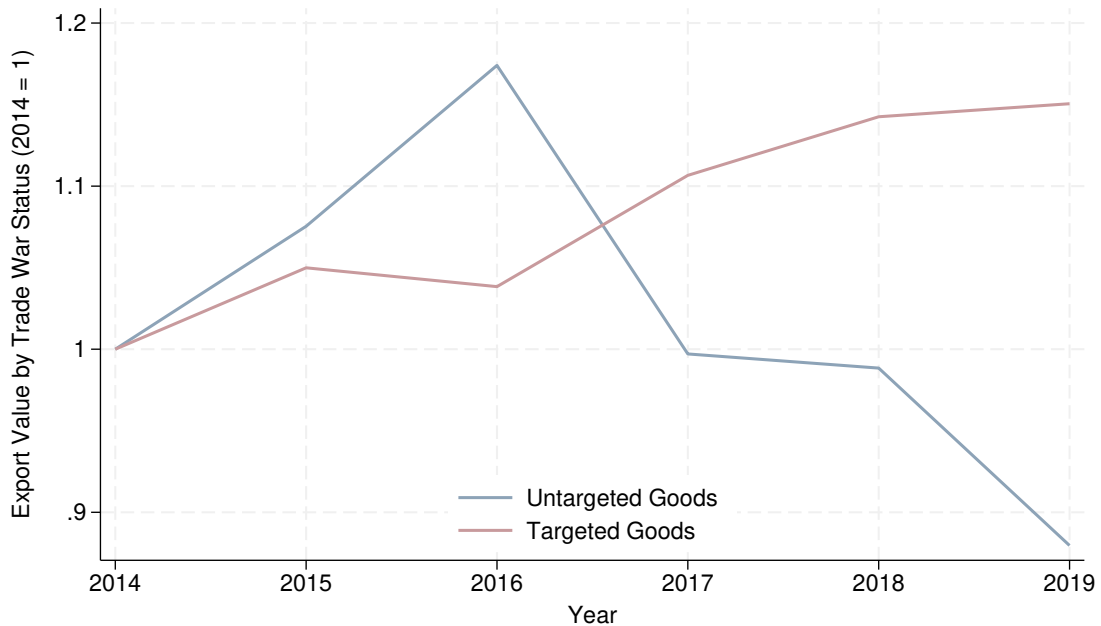
Notes: The figure shows changes in import tariffs imposed by the EU (top panel) and the Rest of the World (bottom panel) on the US. Each box represents the 25th, 50th (median), and 75th percentiles, while the whiskers indicate the 10th and 90th percentiles.

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



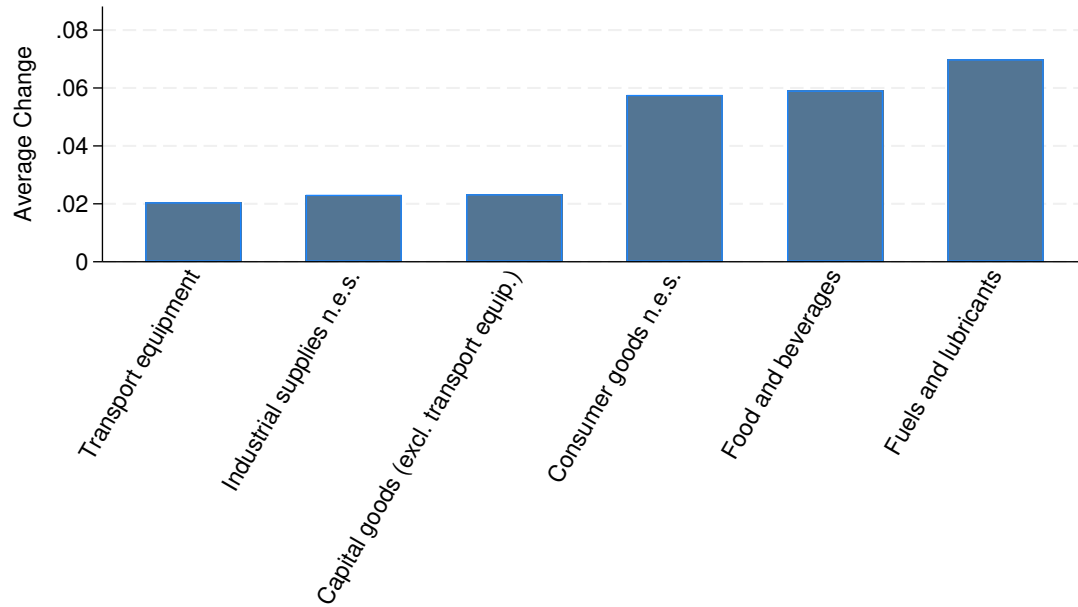
Notes: The figure shows changes in (MFN) import tariffs imposed by China on the Rest of the World. Each box represents the 25th, 50th (median), and 75th percentiles, while the whiskers indicate the 10th and 90th percentiles.

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



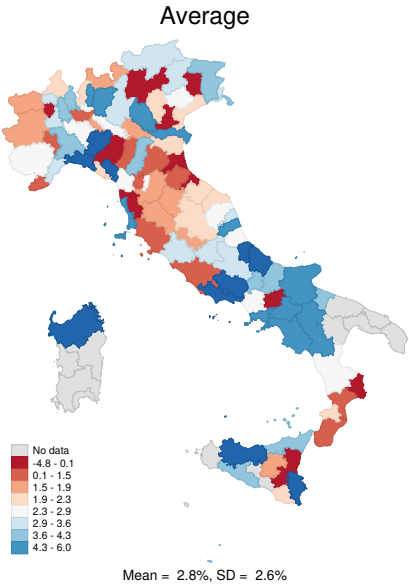
Notes: The figure shows the evolution of export values for two groups of products: those ultimately targeted by US tariffs on Chinese imports or by Chinese tariffs on US imports (“Targeted Goods”) and those not affected by reciprocal tariffs between the two countries (“Untargeted Goods”). Both series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

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



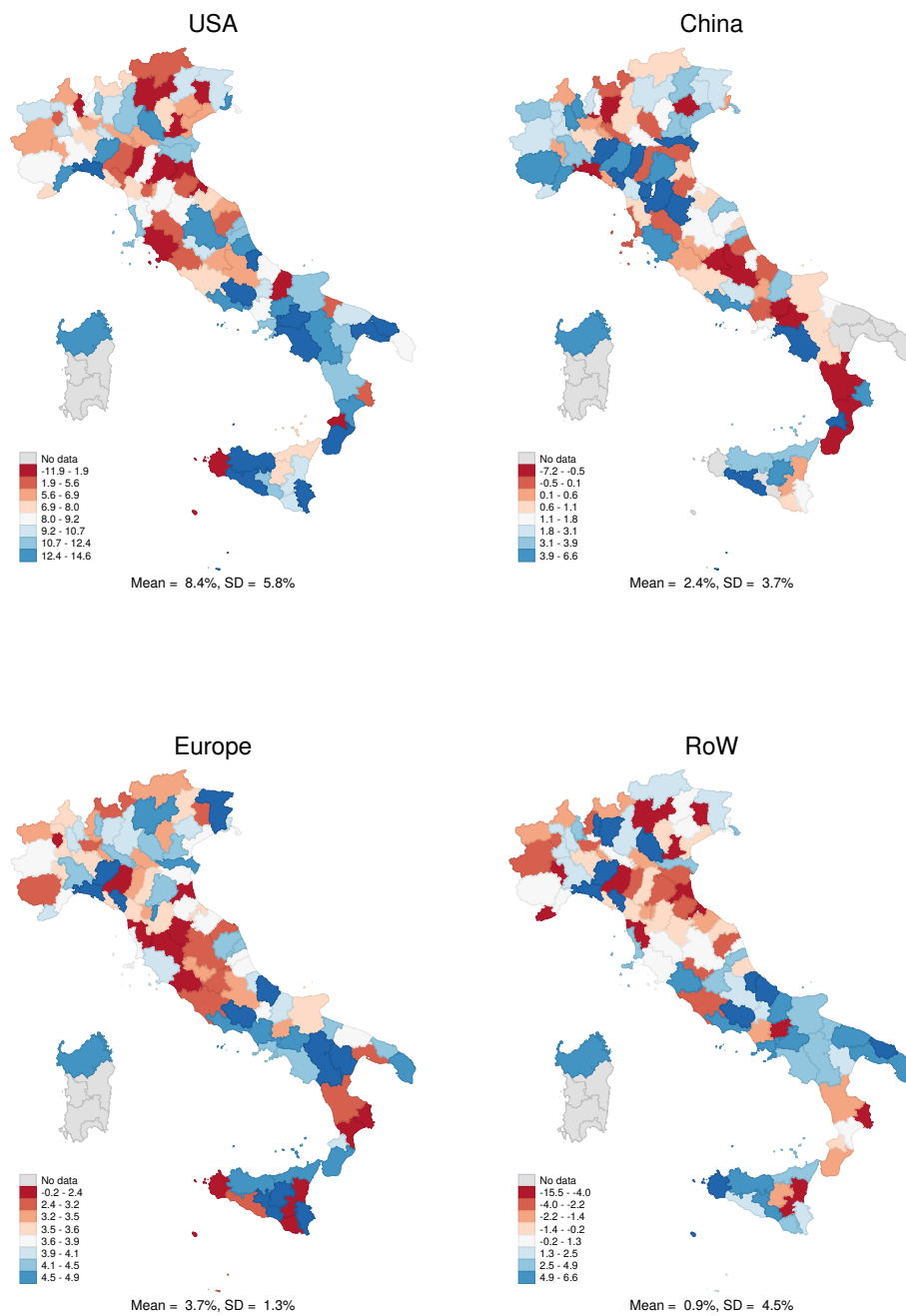
Notes: The figure shows the distribution of predicted export revenue changes across sectors between 2017 and 2019. Sectors are defined according to the Broad Economic Categories (BEC) classification. Sector-level changes are computed by aggregating firm-level export revenue changes using [Equation \(13\)](#).

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



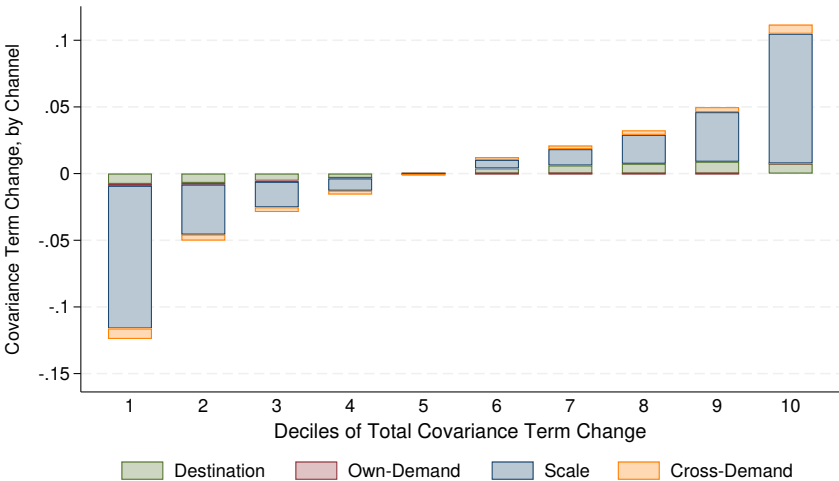
Notes: The figure shows the distribution of predicted export revenue changes across provinces between 2017 and 2019. province-level changes are computed by aggregating firm-level export revenue changes using Equation (13). We assign firms to the province in which they are headquartered.

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



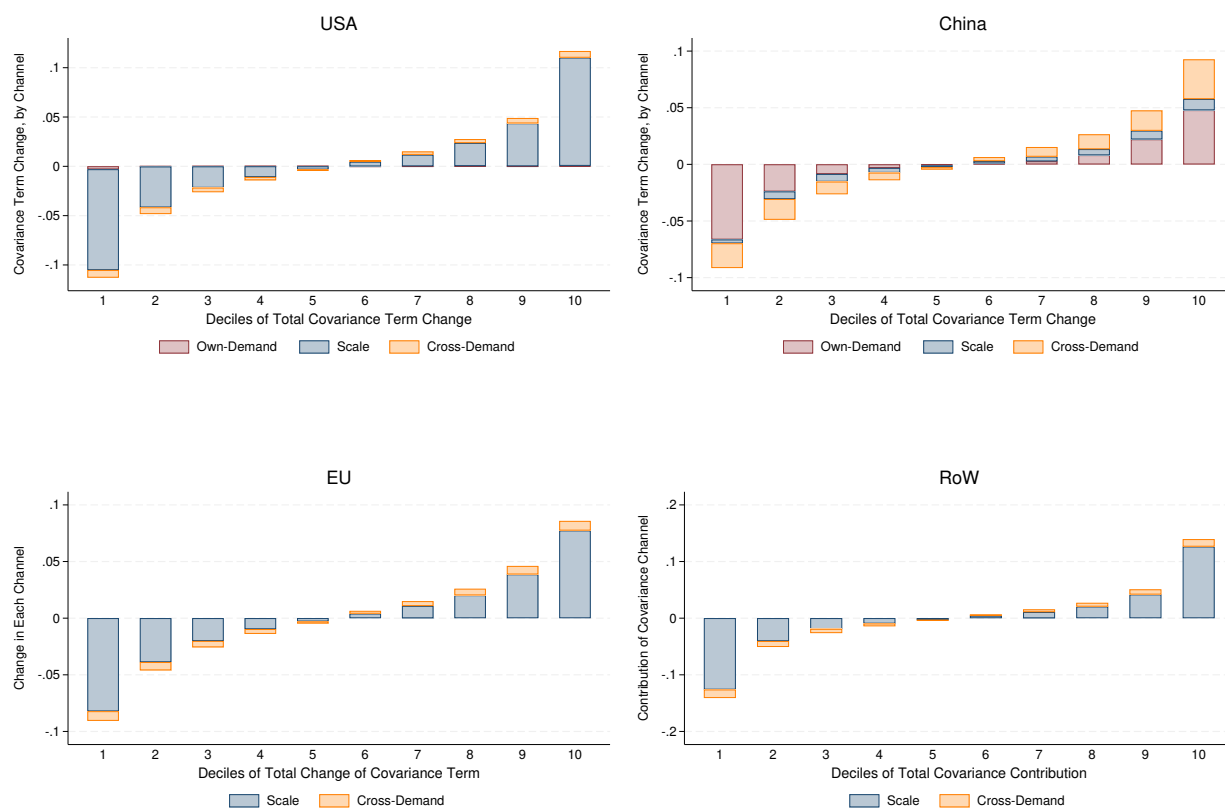
Notes: The figure shows the distribution of predicted export revenue changes across provinces by destination between 2017 and 2019. Province–destination–level changes are computed by aggregating firm–destination–level export revenue changes using Equation (13). We assign firms to the province in which they are headquartered.

Figure A.9. Decomposition of Firm-Level Export Revenue Changes (Covariance Term)



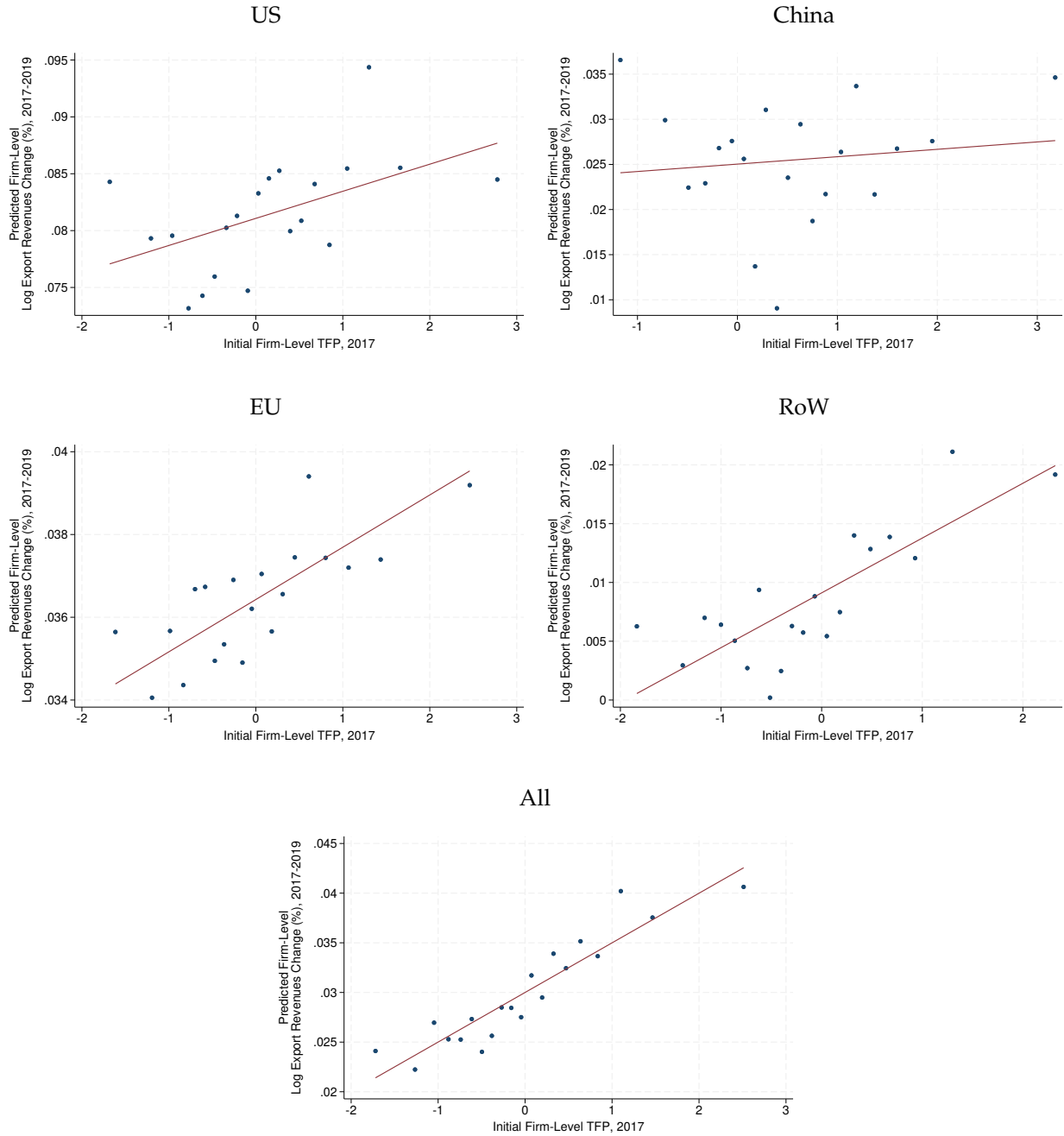
Notes: The figure shows the decomposition of the covariance term of export revenue changes from Proposition 1. It displays the average change of the covariance term across deciles of its total change, broken down into four components: destination-specific, own-demand, scale, and cross-demand effects.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

Figure A.10. Decomposition of Firm-Level Export Revenue Changes (Covariance Term)



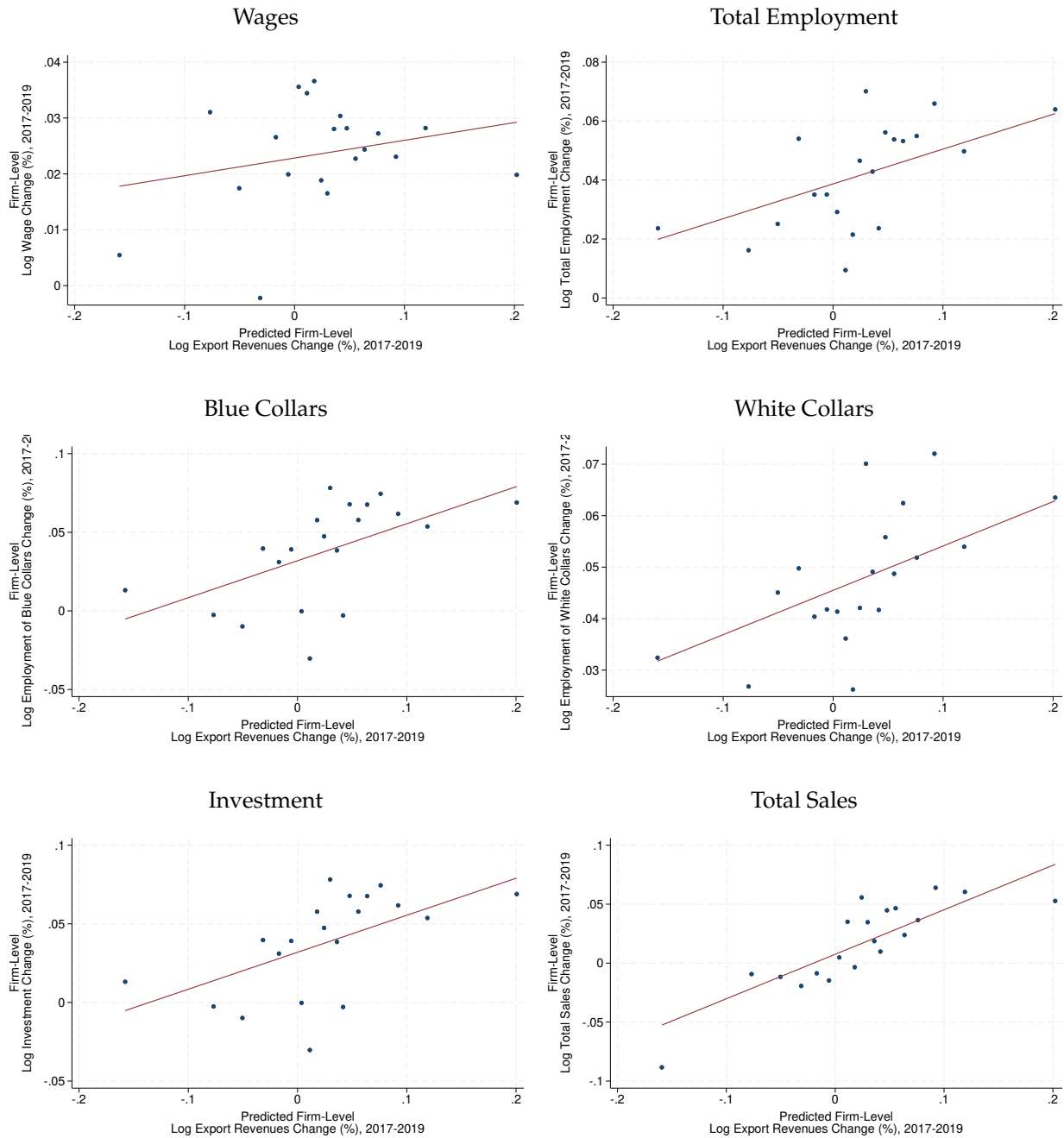
Notes: The figure shows the decomposition of the covariance term of export revenue changes by destination country from Proposition 1. It displays the average change of the covariance term across deciles of its total change, broken down into four components: destination-specific, own-demand, scale, and 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.

Figure A.11. Allocative Efficiency



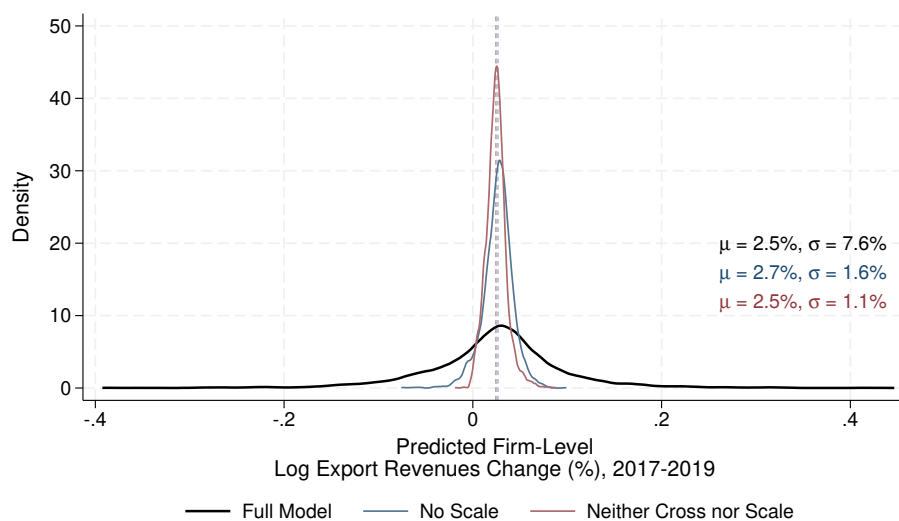
Notes: The figure presents binscatter plots of model-predicted changes in firm-level export revenues against firms' initial TFP in 2017. The first four panels display destination-specific predicted changes—namely, toward the US, China, EU, and RoW—, while the final panel shows the average predicted change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

Figure A.12. Correlation of Firm-Level Outcomes with Predicted Changes in Export Revenues



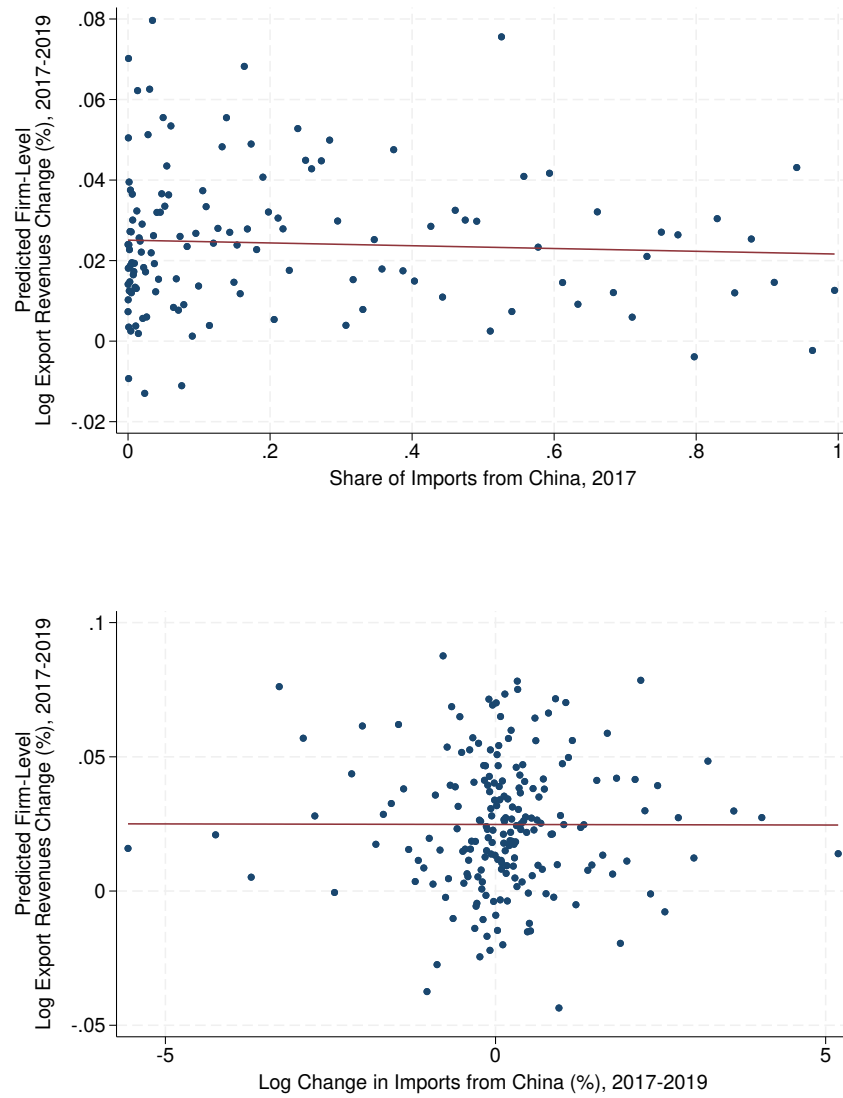
Notes: The figure presents binscatter plots of the correlation between changes in firm-level outcomes from 2017 to 2019 in the data and the model-predicted changes in firm-level export revenues. The outcomes examined include wages, total employment, blue-collar employment, white-collar employment, investment,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

Figure A.13. 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 \(13\)](#).

Figure A.14. 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).

B Theoretical Appendix

B.1 Derivation of Intensive–Margin Estimating Equation

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.:

$$s_{j\omega n} = s_{j\omega n}(\{p_{k\omega n}\}, \zeta_{j\omega n}). \quad (\text{B.1})$$

Totally differentiating this equation yields:

$$\begin{aligned} ds_{j\omega n} &= \sum_k \frac{\partial s_{j\omega n}}{\partial p_{k\omega n}} dp_{k\omega n} + \frac{\partial s_{j\omega n}}{\partial \zeta_{j\omega n}} d\zeta_{j\omega n} \\ &= \sum_k \frac{\partial s_{j\omega n}}{\partial p_{k\omega n}} \frac{s_{j\omega n} p_{k\omega n}}{s_{j\omega n} p_{k\omega n}} dp_{k\omega n} + \frac{\partial s_{j\omega n}}{\partial \zeta_{j\omega n}} \frac{s_{j\omega n} \zeta_{j\omega n}}{s_{j\omega n} \zeta_{j\omega n}} d\zeta_{j\omega n} \\ &= s_{j\omega n} \sum_k \varepsilon_{s,p}^k d \ln p_{k\omega n} + \frac{1}{s_{j\omega n}} \varepsilon_{s,\zeta} d \ln \zeta_{j\omega n} \\ &= s_{j\omega n} \left(\varepsilon_{s,p}^j d \ln p_{j\omega n} + \sum_{k \notin \{j,n\}} \varepsilon_{s,p}^k d \ln p_{k\omega n} \right) + s_{j\omega n} \varepsilon_{s,\zeta} d \ln \zeta_{j\omega n}, \end{aligned} \quad (\text{B.2})$$

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

$$d \ln s_{j\omega n} = \varepsilon_{s,p}^j d \ln p_{j\omega n} + \sum_{k \notin \{j,n\}} \varepsilon_{s,p}^k d \ln p_{k\omega n} + \varepsilon_{s,\zeta} d \ln \zeta_{j\omega n}. \quad (\text{B.3})$$

Starting from Equation (7), we thus get:

$$\begin{aligned} d \ln r_{f(j)\omega n} &= d \ln s_{f(j)\omega n} + d \ln s_{j\omega n} + d \ln s_n^F E_n \\ d \ln r_{f(j)\omega n} - d \ln s_{f(j)\omega n} &= d \ln s_{j\omega n} + d \ln s_n^F E_n \\ d \ln r_{f(j)\omega n} - d \ln s_{f(j)\omega n} &= \varepsilon_{s,p}^j d \ln p_{j\omega n} + \sum_{k \notin \{j,n\}} \varepsilon_{s,p}^k d \ln p_{k\omega n} + \varepsilon_{s,\zeta} d \ln \zeta_{j\omega n} + d \ln s_n^F E_n \\ d \ln r_{f(j)\omega n} - d \ln s_{f(j)\omega n} &= \varepsilon_{s,p}^j d \ln p_{j\omega n} + \sum_{k \notin \{j,n\}} \varepsilon_{s,p}^k d \ln p_{k\omega n} + \varepsilon_{s,\zeta} d \ln \zeta_{j\omega n} + \kappa_n \\ d \ln \tilde{r}_{j\omega n} &= \varepsilon_{s,p}^j d \ln p_{j\omega n} + \sum_{k \notin \{j,n\}} \varepsilon_{s,p}^k d \ln p_{k\omega n} + \varepsilon_{s,\zeta} d \ln \zeta_{j\omega n} + \kappa_n, \end{aligned} \quad (\text{B.4})$$

where the second row subtracts firm-level export market shares from the left-hand side, the third row applies [Equation \(B.3\)](#), the fourth row defines $\kappa_n = d \ln s_n^F E_n$ 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 $v_{j\omega n} = \varepsilon_{p,\xi} d \ln \tilde{\zeta}_{j\omega n}$. Using [Equation \(9\)](#) leads to our final formulation of [Equation \(10\)](#).

B.2 Proposition 1 Details

The Mean Term in [Proposition 1](#) can be written as:

$$\mathbb{E}[d \ln \tilde{r}_{j\omega n}] = \frac{1}{|\mathcal{N}_f| |\Omega_{fn}|} \sum_{n \in \mathcal{N}_f} \sum_{\omega \in \Omega_{fn}} d \ln \tilde{r}_{j\omega n}. \quad (\text{B.5})$$

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:

$$\begin{aligned} \text{cov}(\theta_{f(j)\omega n}, d \ln \tilde{r}_{j\omega n}) &= \frac{1}{|\mathcal{N}_f| |\Omega_{fn}|} \sum_{n \in \mathcal{N}_f} \sum_{\omega \in \Omega_{fn}} \theta_{f(j)\omega n} d \ln \tilde{r}_{j\omega n} \\ &\quad - \left(\frac{1}{|\mathcal{N}_f| |\Omega_{fn}|} \sum_{n \in \mathcal{N}_f} \sum_{\omega \in \Omega_{fn}} \theta_{f(j)\omega n} \right) \left(\frac{1}{|\mathcal{N}_f| |\Omega_{fn}|} \sum_{n \in \mathcal{N}_f} \sum_{\omega \in \Omega_{fn}} d \ln \tilde{r}_{j\omega n} \right). \end{aligned} \quad (\text{B.6})$$

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

C Empirical Appendix

C.1 Data Cleaning

After merging customs and balance sheet data, 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.⁴⁰

C.2 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:

$$\log Exports_{fpt} = \beta(Treated_p \times Post_t) + FE_{fp} + FE_t + \varepsilon_{fpt}. \quad (C.7)$$

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.⁴¹ It

⁴⁰After 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.

⁴¹We estimate [Equation \(C.7\)](#) 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.

Table C.11. Preliminary Evidence on Firm–Level Responses to the US–China Trade War

Dependent variable:	Log Exports _{<i>fpt</i>}	Log Exports _{<i>fpt</i>}	Log Exports _{<i>fpt</i>}	Log Exports _{<i>fpt</i>}
$Treated_p \times Post_t$	0.28** (0.09)	0.29** (0.09)	0.24** (0.08)	0.27*** (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.

is identified after accounting for time–invariant firm–product characteristics and aggregate time trends.

Table C.11 reports the estimates of Equation (C.7). 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, Table C.11 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 Table C.11 do not provide insights on the underlying mechanisms driving the increase in exports, differently from the analysis in the main text.