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Abstract

Understanding producers' selection into exporting and its consequences for micro-founded gravity estimation calls for an in-depth analysis of the interplay between aggregate exports and the distribution of producers' productivity. Yet, knowledge about such interplay is still rather limited from both a theoretical and an empirical standpoint. We supplement this knowledge by studying how different moments of the distribution of producers' productivity affect the trade elasticity, and in turn how shocks that alter those moments in different ways may have different impacts on aggregate exports. We first show that, to obtain an unbiased measure of that elasticity, gravity regressions have to account not only for the share of producers that export, but also for their productivity premium relative to all producers. This is particularly important when the share is small and the premium is large, that is, when aggregate exports are driven by few overperforming `superstar exporters'. We then assess how aggregate exports react to shocks entailing the same change in the first moment of the distribution of producers' productivity, but different changes in its higher moments. Our empirical results confirm that taking into full consideration the productivity premium of exporters and the occurrence of `superstar exporters' is crucial to correctly explain and predict the response of aggregate exports to different productivity shocks.

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It Takes (More Than) a Moment: Estimating Trade Flows with Superstar Exporters.*

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Abstract

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1 Introduction

Gravity models are the most popular tool used to explain and predict international trade flows. Their basic structure relates bilateral exports to the characteristics of the origin country, those of the destination country and distance-related bilateral trade costs. In this relation, a key parameter with far-reaching welfare implications is the trade elasticity, which measures the percentage reduction in exports associated with a percentage increase in trade costs (Arkolakis et al., 2012; Melitz and Redding, 2015). There are several theoretical foundations for such structure and alternative empirical approaches to estimating the trade elasticity depending on the specification of export demand and supply. Essential features of both macro-founded and micro-founded gravity models with representative firms are country size and balanced trade (Anderson, 2011; Fally, 2015). Micro-founded gravity models with heterogeneous firms emphasize the decomposition of aggregate exports into the number of exporters ('extensive margin of trade') and the value of exports per exporter ('intensive margin of trade'). In these models, which also include fixed export costs, the number of exporters is a fraction of the number of producers in the origin country as only the most productive producers self-select into exporting (Helpman et al., 2008; Melitz, 2003). While understanding the self-selection and its consequences for gravity estimation naturally calls for an in-depth analysis of the interplay between aggregate exports and the productivity distribution of producers, knowledge about such interplay is still rather limited from both a theoretical and an empirical standpoints (di Giovanni et al., 2014).

The aim of this paper is to further this knowledge by studying how different moments of the distribution of producers' productivity affect the trade elasticity, and in turn how microeconomic shocks that alter those moments in different ways have different impacts on aggregate exports. In doing so, it argues that the estimation procedure of micro-founded gravity models put forth by Helpman et al. (2008) has to be enriched to account not only for the share of producers that export as they already stress, but also for the productivity premium of exporters relative to all producers. We call the former share the 'extensive margin of selection' and the latter premium the 'intensive margin of selection'. The smaller the share and the larger the premium, the more aggregate exports are driven by few overperforming 'superstar exporters'. Our results show that neglecting the intensive margin of selection biases gravity estimation and, therefore, taking into full consideration the occurrence of 'superstar exporters' is crucial in order to correctly explain and predict the response of aggregate exports to different productivity shocks.

The importance of the specific parametrization of the distribution of producers' productivity for gravity estimation within the canonical framework by Melitz (2003) is well-known since initial applications by Chaney (2008) and Helpman et al. (2008). The former shows that, when producers' productivity is assumed to follow an unbounded Pareto distribution, conditional on the fixed export costs, aggregate exports respond to changing trade costs only at the extensive margin with a constant trade elasticity determined by the distribution's parameter reflecting producers' heterogeneity. Helpman et al. (2008) argue that this is not consistent with the observation that the trade elasticity varies across countries. In addition, if no upper bound ('technology frontier') is assumed in the support of the Pareto distribution, the absence of trade flows between several country pairs in the data cannot be explained. More recently, Fernandes et al. (2023) highlight that the analysis of a cross-country firm-level export dataset reveals that adjustment mostly happens at the intensive margin, and this has to be taken into account to better evaluate the welfare effect of trade liberalization.

The shortcomings of gravity predictions based on the unbounded Pareto distribution have lead to exploring alternative assumptions. Head et al. (2014), Bas et al. (2017) and Fernandes et al. (2023) demonstrate that using the Log-normal instead of the Pareto distribution generates variations in the trade elasticity across country pairs. Helpman et al. (2008) and Melitz and Redding (2015) obtain similar results by allowing for an upper truncation in the Pareto distribution. In both cases, variable trade elasticity is shown to have important implication for the analysis of the welfare effects of trade shocks. In addition, Helpman et al. (2008) show that the introduction of a technology frontier, obtained by imposing an upper bound in the support of the productivity distribution, is not only needed to generate the zeros observed in bilateral trade flows. It is also instrumental in the unbiased estimation of the marginal impact of distance between countries on their exports to one another through the implied inclusion of a selection term in the gravity model. Estimation disregarding countries that do not trade with each other gives up important information contained in the data, and leads to biased estimates as a result. Overall, the parametrization of the productivity distribution turns out to be fundamental for the estimation of trade elasticities as well as for the assessment of how shocks are transmitted from the micro to the macro levels.

With respect to the existing literature, we innovate in several respects. First, we refine the estimation procedure by Helpman et al. (2008) based on a gravity model with heterogeneous firms without imposing any specific assumptions on the productivity distribution. The only regularity conditions required are that the distribution is continuous differentiable and has an upper-truncated support to allow for the possibility of zero trade flows. We show that the model leads to an empirical specification telling the researcher how to take into due account the information contained in the zeros of bilateral trade flows. It also suggests how to control for the extensive and intensive margins of selection, in order to achieve an unbiased estimation of the marginal impact of bilateral distance on bilateral exports as well as a precise evaluation of the overall impact of bilateral trade costs on bilateral trade flows. In particular, we demonstrate the importance of controlling for the bilateral productivity premium of exporters. Omitting this control generates a downward bias in the estimated marginal impact of bilateral distance. This is confirmed empirically by running the refined and the original Helpman et al. (2008) procedures on BACI data at (6 digit) product level.[1]

Second, while the estimation of the marginal impact of bilateral distance on bilateral exports does not rely on any specific assumption about the distribution of producers' productivity, the measurement of the overall elasticity of trade flows to trade costs requires to take a stance on the parametrization of that distribution. Following the literature, we consider two alternatives, a bounded Pareto and a double-truncated Log-normal distributions. The finite upper bound of the support generates variable bilateral trade elasticities, which converge to those in Bas et al. (2017) as the bound goes to infinity. In principle, quantifying the impact of shocks that change the shape of the distribution of producers' productivity across sectors and countries faces a tough empirical hurdle. The reason is that linking firms' productivity with their export performance ideally requires matched firm-level export and balance sheet data harmonized across countries, which is something hardly available. For example, while reporting firm-level exports from several countries, the World Bank's Exporter Dynamics Database used by Fernandes et al. (2023) is not matched with data allowing for firm-level productivity estimation. To overcome this hurdle, we leverage the CompNet database, which includes sectoral statistics about the empirical moments of the distribution of producers' productivity for a sample of EU countries. Estimating bilateral

[1] The omission of the exporters' productivity premium also biases the estimation of the origin country's fixed effect, which captures its systematic ability to export across destinations (Head and Mayer, 2014). In structural gravity models, the fixed effect corresponds to a multilateral resistance term combining the origin scale of production with its distance-weighted access to world demand (Anderson, 2011; Costinot et al., 2011). In the absence of a structural interpretation, it encompasses all the unobservable features of the origin country that shift its exports to all destinations (Anderson and Yotov, 2012).

trade elasticities across sectors, we find that they are consistent with the predictions of the refined gravity model, according to which they should be decreasing functions of the upper bound of the producers' productivity distribution and increasing functions of the lower bound of the exporters' productivity distribution. Although the data supports a preference for the Log-normal over the Pareto distributions, the trade elasticities exhibit similar behaviors under the two alternatives. Intuitively, the trade elasticity is high when the upper bound of producers' productivity is low and the lower bound of exporters' productivity is high because the set of exporters consists of few superstar firms that are quite similar to each other. In this case, a small increase in trade costs leads to a large decrease in bilateral exports as there is little scope for reallocation of foreign market shares among such exporters.

Third, our analysis leads to a deeper understanding of the impact of shocks to the distribution of producers' productivity on aggregate trade flows. Specifically, we show how various moments of the distribution matter for aggregate exports. By perturbating the values of the Pareto and Log-normal distributions' parameters calibrated on the CompNet moments, we study how different changes in the location and the shape of the distributions translate into different responses in aggregate exports and their margins. All in all, the simulation results highlight that identical increases in average productivity can result in very different increases in exports depending on the exact parameters (and the associated moments) of the productivity distribution that generate those increases. In particular, exports rise more if, for a given increase in average productivity, the density on the upper tail grows. For example, while the same rise in the average productivity of producers may be obtained by either shifting density from the left to the right tail or by increasing the upper bound of the support, in the former case export growth is smaller than in the latter. Moreover, when the initial share of exporters is large (small), higher average productivity generates a smaller (larger) increase in trade with most adjustment occurring at the extensive (intensive) margin.

The rest of the paper is organized in eight sections. Section 2 presents the model and derives its gravity equation. Section 3 discusses the omissions that lead to biased estimation. Section 4 and 5 respectively detail the unbiased estimation strategy and the data used for its implementation. Section 6 estimates the overall trade elasticity of bilateral trade flows to bilateral trade costs. Section 7 describes the simulation analysis and its results. Section 8 concludes.

2 Gravity and Superstar Exporters

Head and Mayer (2014) define general gravity as comprising the set of models yielding bilateral trade equations that can be expressed as the product of a 'gravitational' constant, an origin-specific variable capturing the 'capabilities' of the country of origin as an exporter to all destinations, a destination-specific variable capturing the 'capabilities' of the destination country as an importer from all origins, and an origin-destination-specific 'dyadic' variable capturing the bilateral accessibility of the destination country to the origin country by combining bilateral trade costs with the so-called 'trade elasticity', that is, the elasticity of bilateral trade flows to bilateral trade costs. In this section we use a standard trade model with monopolistic competition and heterogeneous firms to show in detail how firm heterogeneity affects general gravity and the estimation of the corresponding bilateral trade equations, with the aim of going beyond what Helpman et al. (2008) have already highlighted.

2.1 Model Setup

Consider the same setup as in Helpman et al. (2008). The world consists of N countries indexed by $i = 1, ..., N$. There are several sectors and every country consumes and produces a continuum of products in each sector. We focus on a generic sector and we leave the leave the sectoral index implicit for parsimonious notation. We will make it explicit later on after presenting the data panel in Section 5 when needed for clarity.

Country i's sectoral preferences are captured by the (sub-)utility function

$$u_i = \left[\int_{\omega \in \Omega_i} x_i(\omega)^{\frac{\varepsilon-1}{\varepsilon}} d\omega \right]^{\frac{\varepsilon}{\varepsilon-1}} \tag{1}$$

where Ω_i is the set of available products, $x(\omega)$ is the consumption of product ω in that set, and $\varepsilon > 1$ is the constant elasticity of substitution between products, which is common across countries. Let E_i denote the expenditures of country i and P_i denote the exact price index associated with utility (1)

$$P_i = \left[\int_{\omega \in \Omega_i} \hat{p}_i(\omega)^{1-\varepsilon} d\omega \right]^{\frac{1}{1-\varepsilon}}$$

where $\hat{p}_i(\omega)$ is the price of product ω. Utility maximization implies that the demand for product ω is given by

$$x_i(\omega) = \hat{p}_i(\omega)^{-\varepsilon} A_i \tag{2}$$

where A_i is a demand shifter defined as $A_i \equiv E_i P_i^{\varepsilon-1}$.

Each product is supplied by one and only one firm under monopolistic competition. Some products are produced domestically, others are imported. We use M_i to denote the measure ('number') of products that are domestically produced and thus also the number of country i's producers. The production technology is linear with constant (total factor) productivity varying across firms. Indexing firms by their productivity, the implied marginal cost of a firm with productivity y is m_i/y where $m_i > 0$ is the unit cost of the input bundle. Firm productivity follows a continuous differentiable distribution with c.d.f. $F_i(y)$ over the support $[y_{L,i}, y_{H,i}]$ with $0 \leq y_{L,i} < y_{H,i} < \infty$. Hence, differently from Helpman et al. (2008), we allow the firm productivity distribution to vary across countries.

Producers bear only production costs when selling in their domestic market but face additional trade costs when exporting. These costs, which are specific to the country of origin (i) and the country of destination (n), have two components: a fixed component $m_i f_{ni}$ and a variable proportional component τ_{ni} affecting the delivered marginal $m_i \tau_{ni}/y$ with $f_{ni} > 0$ ($f_{ii} = 0$) and $\tau_{ni} > 1$ ($\tau_{ii} = 1$). Under monopolistic competition, firm profit is maximized by mark-up pricing

$$p_{ni}(y) = \frac{\varepsilon}{\varepsilon - 1} \frac{m_i \tau_{ni}}{y} \tag{3}$$

and maximized profit evaluates to

$$\pi_{ni}(y) = \left(\frac{\varepsilon}{\varepsilon - 1} \right)^{1-\varepsilon} \left(\frac{m_i \tau_{ni}}{y} \right)^{1-\varepsilon} \frac{A_n}{\varepsilon} - m_i f_{ni} \tag{4}$$

Given that $f_{ii} = 0$ implies $\pi_{ii}(y) > 0$ whatever the value of y may be, all firms produce and sell in their domestic market. However, due to $f_{ni} > 0$ for $n \neq i$, $\pi_{ni}(y) \geq 0$ holds only for a subset of them that find it profitable to export to country n. As $\pi_{ni}(y)$ is an increasing function of y, this subset consists of firms with productivity larger than or equal to the cutoff level

$$y_{ni}^{*}=\frac{\varepsilon}{\varepsilon-1}\tau_{ni}\left(f_{ni}\right)^{\frac{1}{\varepsilon-1}}\left(m_{i}\right)^{\frac{\varepsilon}{\varepsilon-1}}\left(\frac{\varepsilon}{A_{n}}\right)^{\frac{1}{\varepsilon-1}} \tag{5}$$

as implied by the zero profit condition

$$\pi_{ni}(y_{ni}^{*})=\left(\frac{\varepsilon}{\varepsilon-1}\right)^{1-\varepsilon}\left(\frac{m_{i}\tau_{ni}}{y_{ni}^{*}}\right)^{1-\varepsilon}\frac{A_{n}}{\varepsilon}-m_{i}f_{ni}=0 \tag{6}$$

Then, as a result of selection into exporting, aggregate exports from i to n evaluate to $X_{ni} = M_i \int_{y_{ni}^*}^{y_{H,i}} r_{ni}(y)dF_i(y)$ where $r_{ni}(y) = p_{ni}(y)x_{ni}(y)$ is firm export revenues.

2.2 Gravity Equation

Using (2) and (3), aggregate bilateral exports can be rewritten as

$$X_{ni}=\left(\frac{\varepsilon}{\varepsilon-1}\right)^{1-\varepsilon}\left(m_{i}\right)^{1-\varepsilon}M_{i}A_{n}\left(\tau_{ni}\right)^{1-\varepsilon}V_{ni} \tag{7}$$

with

$$V_{ni}=\begin{cases}\int_{y_{ni}^{*}}^{y_{H,i}}y^{\varepsilon-1}dF_{i}(y) & \text{for } y_{ni}^{*}\geq y_{L}\\ 0 & \text{otherwise}\end{cases} \tag{8}$$

Assuming that $y_{ni}^* \leq y_{H,i}$ holds so that there is indeed selection into exporting, V_{ni} can be decomposed in a country-specific component Θ_i and a country-pair-specific component S_{ni}^{-1} such that $V_{ni} = \Theta_i S_{ni}^{-1}$. The country-specific component is defined as the output weighted producer productivity

$$\Theta_{i}\equiv\int_{y_{L,i}}^{y_{H,i}}y^{\varepsilon-1}dF_{i}(y) \tag{9}$$

and corresponds to $(\varepsilon-1)$-th moment of the firm productivity distribution. The country-pair specific component is then defined as

$$S_{ni}^{-1}\equiv\begin{cases}\frac{\int_{y_{ni}^{*}}^{y_{H,i}}y^{\varepsilon-1}dF_{i}(y)}{\int_{y_{L,i}}^{y_{H,i}}y^{\varepsilon-1}dF_{i}(y)} & \text{for } y_{ni}^{*}\geq y_{L}\\ 0 & \text{otherwise}\end{cases}.$$

After introducing $F_i^*(y) \equiv F_i(y)/F_i^*(y_{ni}^*)$ to denote the c.d.f. of the productivity distribution of exporters to n over the support $[y_{L,i}, y_{ni}^*]$, the denominator term

$$\int_{y_{ni}^{*}}^{y_{H,i}}y^{\varepsilon-1}dF_{i}(y)=(1-F_{i}(y_{ni}^{*}))\int_{y_{ni}^{*}}^{y_{H,i}}y^{\varepsilon-1}dF_{i}^{*}(y)$$

can be interpreted as the share of producers that export times their output weighted productivity. For $y_{ni}^* \geq y_L$, we can rewrite

$$S_{ni}^{-1}=\underbrace{(1-F_{i}(y_{ni}^{*}))}_{\text{Extensive margin of export selection } (W_{ni})}\times\underbrace{\frac{\int_{y_{ni}^{*}}^{y_{H,i}}y^{\varepsilon-1}dF_{i}^{*}(y)}{\int_{y_{L,i}}^{y_{H,i}}y^{\varepsilon-1}dF_{i}(y)}}_{\text{Intensive margin of export selection } (\widetilde{Y}_{ni}^{*})} \tag{10}$$

where the ratio measures the relative productivity of exporters with respect to producers. Then S_{ni} can be seen as the export-selection 'dyadic filter' one has to apply to V_{ni} in order to obtain the component of country i's exporter capabilities $\Theta_i = S_{ni}V_{ni}$ that is a function of the properties of the productivity distribution. This filter is needed because, due to the presence of V_{ni} in (7), exports X_{ni} conflate the implications of such properties and those of selection into exporting through the share of exporters and their relative productivity. After separating the two types of implications, aggregate bilateral exports (7) evaluate to

$$X_{ni} = \left(\frac{\varepsilon}{\varepsilon - 1}\right)^{1-\varepsilon} (m_i)^{1-\varepsilon} M_i \Theta_i A_n (\tau_{ni})^{1-\varepsilon} S_{ni}^{-1} \tag{11}$$

where $(m_i)^{1-\varepsilon} M_i \Theta_i$ captures country i's exporter capabilities, A_n captures n's importer capabilities and $(\tau_{ni})^{1-\varepsilon} S_{ni}^{-1}$ results from trade costs (through $(\tau_{ni})^{1-\varepsilon}$) and export selection (through S_{ni}^{-1}). In particular, equation (11) shows that bilateral exports increase with the origin country's absolute output-weighted average productivity of producers as well as with its exporters' share and their output-weighted average productivity premium relative to producers. Henceforth, we will refer to exporters' share as the 'extensive margin of export selection' ($W_{ni} \equiv 1 - F_i(y_{ni}^*)$) and to their productivity premium as the 'intensive margin of export selection' ($\widetilde{Y}_{ni}^* \equiv S_{ni}^{-1} W_{ni}^{-1}$), as highlighted in expression (10). A higher productivity cutoff decreases the extensive margin and increases the intensive one.

The gravity equation (11) can be implemented empirically by extending the procedure developed by Helpman et al. (2008) for a bounded Pareto distribution of firm productivity to the general case of a double truncated continuous differentiable distribution. Before doing that, however, it is important to highlight that the exporters' share and premium depend on various parameters of the productivity distribution that, among other things, regulate the thickness and the shape of its right tail. To see this let us consider two parametrizations of $F_i(y)$ that will come in handy later on.

2.3 Parametrization

To evaluate Θ_i and S_{ni}^{-1} , we need to make some functional form assumption on $F_i(y)$ as $\Theta_i \equiv \int_{y_{L,i}}^{y_{H,i}} y^{\varepsilon-1} dF_i(y)$ and $\Theta_i S_{ni}^{-1} \equiv \int_{y_{ni}^*}^{y_{H,i}} y^{\varepsilon-1} dF_i(y)$ correspond to the $(\varepsilon-1)$-th raw moments of the productivity distributions of producers and exporters repectively. Two common assumptions, which are both analitically convenient and empirically relevant, are that firm productivity Y follows a bounded Pareto or a double-truncated Log-normal distributions.

2.3.1 Pareto Distribution

Under the bounded Pareto assumption, we have

$$F_i(y) = \frac{1 - \left(\frac{y_{L,i}}{y}\right)^{k_i}}{1 - \left(\frac{y_{L,i}}{y_{H,i}}\right)^{k_i}}$$

over the support $[y_{L,i}, y_{H,i}]$ with country-specific scale and shape parameters $y_{M,i} > 0$ and $k_i > 0$. In this case, under the regularity condition $k_i > \varepsilon - 1$, the computation of the $(\varepsilon - 1)$-th raw moments gives

$$\Theta_i = \frac{k_i}{k_i - \varepsilon + 1} (y_{L,i})^{\varepsilon-1} \frac{1 - \left(\frac{y_{L,i}}{y_{H,i}}\right)^{k_i-\varepsilon+1}}{1 - \left(\frac{y_{L,i}}{y_{H,i}}\right)^{k_i}}$$

and

$$S_{ni}^{-1} \equiv \Theta_i^{-1} \frac{k_i}{k_i - \varepsilon + 1} \left(y_{ni}^*\right)^{\varepsilon - 1} \frac{1 - \left(\frac{y_{ni}^*}{y_{H,i}}\right)^{k_i - \varepsilon + 1}}{1 - \left(\frac{y_{ni}^*}{y_{H,i}}\right)^{k_i}}$$

for $y_L \leq y_{ni}^* \leq y_H$. Moreover, we can write

$$W_{ni} = \frac{\left(\frac{y_{H,i}}{y_{ni}^*}\right)^{k_i} - 1}{\left(\frac{y_{H,i}}{y_{L,i}}\right)^{k_i} - 1}. \tag{12}$$

2.3.2 Log-Normal Distribution

In contrast, under the Log-normal assumption, we have

$$F_i\left(y\right) = 1 - \frac{\Phi(y_{H,i}) - \Phi(y)}{\Phi(y_{H,i}) - \Phi(y_{L,i})}$$

where $\Phi\left(\cdot\right)$ is the c.d.f. of the standard normal distribution. Computing the $(\varepsilon - 1)$-th raw moments then leads to

$$\Theta_i \equiv \int_{y_{L,i}}^{y_{H,i}} y^{\varepsilon - 1} dF_i(y) = e^{(\varepsilon-1)\mu_i + \frac{1}{2}(\varepsilon-1)^2\sigma_i^2} \frac{\Phi\left(\left(\varepsilon - 1\right)\sigma_i - \frac{\ln y_{L,i} - \mu_i}{\sigma_i}\right) - \Phi\left(\left(\varepsilon - 1\right)\sigma_i - \frac{\ln y_{H,i} - \mu_i}{\sigma_i}\right)}{\Phi\left(\frac{\ln y_{H,i} - \mu_i}{\sigma_i}\right) - \Phi\left(\frac{\ln y_{L,i} - \mu_i}{\sigma_i}\right)}$$

and

$$S_{ni}^{-1} \equiv \Theta_i^{-1} e^{(\varepsilon-1)\mu_i + \frac{1}{2}(\varepsilon-1)^2\sigma_i^2} \frac{\Phi\left(\left(\varepsilon - 1\right)\sigma_i - \frac{\ln y_{ni}^* - \mu_i}{\sigma_i}\right) - \Phi\left(\left(\varepsilon - 1\right)\sigma_i - \frac{\ln y_{H,i} - \mu_i}{\sigma_i}\right)}{\Phi\left(\frac{\ln y_{H,i} - \mu_i}{\sigma_i}\right) - \Phi\left(\frac{\ln y_{ni}^* - \mu_i}{\sigma_i}\right)}$$

for $y_L \leq y_{ni}^* \leq y_H$, where$\mu_i$ and σ_i^2 are the mean and variance of the Normal distributed random variable $X = \ln Y$. Moreover, we can write

$$W_{ni} = \frac{\Phi(y_{H,i}) - \Phi(y_{ni}^*)}{\Phi(y_{H,i}) - \Phi(y_{L,i})}. \tag{13}$$

3 Export Selection and Biased Estimation

An important insight by Helpman et al. (2008) is that estimating the gravity equation on samples of countries that have only positive trade flows between them produces biased results because it gives up important information contained in the data. In particular, the bias derives from the fact that, in a world of heterogeneous firms, zero trade flows tell something about export selection. In this respect, we want to show here that it is crucial to take into account not only the extensive margin of selection as Helpman et al. (2008) already do, but also its intensive margin. That is, not only the share of exporters that self-select from a given origin into a given destination, but also their productivity relative to producers in that origin.

To make this point, we first recall the approach by Helpman et al. (2008), which relies on equation (7), and then we introduce an extended approach based on equation (11). In the process, we will also show that a country-pair-specific trade elasticity naturally arises when the productivity distribution is defined over a finite support, irrespective of its exact parametrization, which qualifies the conclusions drawn by Bas, Mayer and Thoenig (2017).

3.1 Extensive Margin of Selection

Let us refer to Helpman et al. (2008) as simply HMR (2008) henceforth. They propose to estimate a microfounded gravity equation like (7) in log term as

$$x_{ni} = \alpha_0 + \lambda_i + \chi_n - \gamma d_{ni} + w_{ni} + u_{ni} \tag{14}$$

where χ_n and λ_i are the origin and destination fixed effects corresponding to $(m_i)^{1-\varepsilon} M_i$ and A_n respectively. The iceberg trade costs τ_{ni} is operationalized as embedding both observed distance-related trade barriers D_{ni} between the trade partners and an unobserved trade cost u_{ni} such that $\tau_{ni}^{\varepsilon-1} = D_{ni}^{\gamma} e^{u_{ni}}$ holds with $d_{ni} = \ln D_{ni}$.[2] The term that distinguishes (14) from a standard gravity regression is $w_{ni} = \ln W_{ni}$, which implements $\ln V_{ni}$ as the share of exporters with W_{ni} equal to zero in the case of no trade flows. By omitting w_{ni}, the standard gravity regression confounds the effects of trade barriers on average exports per exporter with their effects on the proportion of exporting firms. Moreover, selection into exporting induces a correlation between the observed distance-related barriers d_{ni} and the unobserved trade cost u_{ni} as in a the standard selection model with omitted variables.

To obtain unbiased estimates of (14), HMR (2008) suggest a two stage procedure. The first stage estimates the selection equation for the probability of observing positive bilateral trade flows. In particular, it uses a probit model to estimate the probability that the most productive producers (i.e. those at the 'technology frontier' $y_{H,i}$) earn positive export profits $\pi_{ni}(y_{H,i}) > 0$. By (4), this is equivalent to the probability ρ_{ni} that $z_{ni} = \ln Z_{ni} > 0$ holds for the latent variable $Z_{ni} \equiv \left(\frac{\varepsilon}{\varepsilon-1}\right)^{1-\varepsilon} \left(\frac{m_i \tau_{ni}}{y}\right)^{1-\varepsilon} \frac{A_n}{\varepsilon} / (m_i f_{ni})$, which can be expressed in terms of origin fixed effects, destination fixed effects and dyadic terms. Though z_{ni} is unobserved, the presence or the absence of bilateral exports implies $z_{ni} > 0$ or $z_{ni} = 0$ respectively. Moreover, for any continuous differentiable productivity distribution, larger z_{ni} implies larger bilateral exports.

The second stage estimates (14) only for positive bilateral trade flows by including the appropriate corrections. In particular, the first-stage probit provides consistent estimates for both w_{ni} and u_{ni} to be used in the second-stage regression

$$x_{ni} = \alpha_0 + \lambda_i + \chi_n - \gamma d_{ni} + \hat{z}_{ni} + \hat{z}_{ni}^2 + \hat{z}_{ni}^3 + IMR_{ni} + \eta_{ni} \quad \forall x_{ni} > 0. \tag{15}$$

with $\hat{z}_{ni} = \Phi^{-1}(\hat{\rho}_{ni})$ being the predicted latent variable, where $\Phi(\cdot)$ is the c.d.f. of the standard normal distribution and $\hat{\rho}_{ni}$ is the predicted probability of observing positive bilateral trade flows from the first-stage probit. $IMR_{ni} = \phi(\widehat{z}_{nit})/\Phi(\widehat{z}_{nit})$ is the Inverse Mills Ratio, which is a standard Heckman correction for sample selection required by the fact that zero trade flows are excluded from the estimation of (15). It addresses the bias generated by the correlation between the observed distance-related barriers d_{ni} and the unobserved trade cost u_{ni}. However, IMR_{ni} does not deal with the bias generated by confounding the effects of trade barriers on the exporters' average exports and share. This is what the inclusion of w_{ni} in (14) is meant to do. In this respect, to avoid making specific assumptions on the parametrization of $F_i(y)$, in (15) w_{ni} is approximated by a polynomial function of the latent variable $\hat{z}_{ni}$. Hence, it is the joint inclusion of IMR_{ni} and $\hat{z}_{ni} + \hat{z}_{ni}^2 + \hat{z}_{ni}^3$ that neutralizes the biases associated with the extensive margin of selection.[3]

[2]Hence, the marginal impact of distance between countries on their exports to one another (γ) is different from the price elasticity of export demand ($\varepsilon - 1$).

[3]Given that we do not make any specific assumption on the parametrization of $F_i(y)$, the share of exporters has no particular functional form. That is why a polynomial is used to approximate w_{nit} .

3.2 Intensive Margin of Selection

Equation (11) differs from equation (7) in that the former uses the decomposition $V_{ni} = \Theta_i S_{ni}^{-1}$ with $S_{ni}^{-1} = W_{ni}\widetilde{Y}_{ni}^{*}$, where W_{ni} is again the share of producers that export ('extensive margin of selection ') and $\widetilde{Y}_{ni}^{*}$ is their relative productivity with respect to all producers ('intensive margin of selection'). This has two implications for the empirical specification of the gravity equation. First, the origin fixed effect now includes also the $(\varepsilon - 1)$-th moment (Θ_i) of producers'productivity. Hence, the origin country's exporter capabilities increase with the relative density of the upper tail of the producers' productivity distribution. The more so the larger the demand elasticity ε as larger elasticity magnifies the output shares of producers in the upper tail. Second, and foremost, the additional dyatic term $\widetilde{Y}_{ni}^{*}$ requires the microfounded gravity equation (14) to be extended to

$$x_{ni} = \alpha_0 + \lambda_i + \chi_n - \gamma d_{ni} + w_{ni} + \widetilde{y}_{ni}^{*} + u_{ni}. \tag{16}$$

with $\widetilde{y}_{ni}^{*} = \ln \widetilde{Y}_{ni}^{*}$. The inclusion of the intensive margin of selection in addition to its extensive margin (through w_{ni}) is relevant as neglecting $\widetilde{y}_{ni}^{*}$ can introduce bias into the estimation of the coefficients. First, $\widetilde{y}_{ni}^{*}$ is likely to be positively correlated with total exports: keeping producers' productivity constant, higher exporters' relative productivity increases average exports per exporter and thus total exports. Second, $\widetilde{y}_{ni}^{*}$ may exhibit positive or negative correlation with distance. On the one hand, distant markets are more accessible to more productive firms, leading to a positive correlation between the numerator of $\widetilde{y}_{ni}^{*}$ and d_{ni} as greater distance results in higher export cutoff and thus higher exporters' productivity. On the other hand, also the correlation between the denominator of $\widetilde{y}_{ni}^{*}$ and d_{ni} may be positive as anything that shifts the support or the density of the producers' productivity distribution to the right makes them more likely to access more distant markets. The result could be a negative correlation of $\widetilde{y}_{ni}^{*}$ with distance. The sign of the resulting bias in the estimated γ would then depend on which effect dominates.[4] Finally, the omission of $\widetilde{y}_{ni}^{*}$ may also generate an overestimation of the origin fixed effect λ_i as long as this would include not only producers' productivity Θ_i, but also the aggregation of bilateral exporters' productivity premia across destinations. In combination with a bias in γ, the bias in the origin fixed effect would then distort the quantitative assessment of the effects of counterfactual experiments (such as hypothetical trade liberalization).

To better understand the difference between specifications with and without the extensive margin of selection $\widetilde{y}_{ni}^{*}$, it is useful to consider two numerical examples of the behavior of S_{ni}^{-1} when firm productivity follows the bounded Pareto and the double truncated Log-normal distribution presented in sections 2.3.1 and 2.3.2 respectively.

The corresponding results, obtained simulating an economy with 10,000 firms and demand elasticity $\varepsilon = 4.5$, are reported in the two panels of Figure 1a. The curves appearing in the two panels plot S_{ni}^{-1} on the vertical axis against the associated $W_{n,i}$ on the horizontal axis. Both variables range between 0 and 1: when no producer exports, both the exporters' share and their relative productivity are equal to 0 ($S_{ni}^{-1} = W_{n,i} = \widetilde{y}_{ni}^{*} = 0$); when all producers export both the exporters' share and their relative productivity are equal to 1 ($S_{ni}^{-1} = W_{n,i} = \widetilde{y}_{ni}^{*} = 1$). The green 45-degree line represents the relation between the two variables when one neglects the intensive margin of selection (i.e., when $S_{ni}^{-1} = W_{n,i}$ is assumed to always hold). Thus, the vertical distance between the curves and 45-degree line measures what changes between considering or not considering $\widetilde{y}_{ni}^{*}$.

[4] Signing the bias would be even more complicated if one did not properly control for the share of exporters w_{ni} as advised by HMR (2008), given that the error term could then be correlated also with $\widetilde{y}_{ni}^{*}$. See Appendix C.1 for a more detailed discussion and tests for the origin of the the omitted variable bias.

[Figure 1 about here.]

The longest distance appears for intermediate values of $W_{n,i}$ and it is due to the concavity of the relation between S_{ni}^{-1} and $W_{n,i}$. Such concavity derives from the fact that, as the exporters' share rises from 0, the first producers that start to export are the most productive ones leading to a steep rise in the exporters's relative productivity. However, as the exporters' share keeps on rising, the additional producers that start to export are less and less productive. Under the Pareto assumption, more dispersion in the productivity distribution (smaller k_i) is associated with more pronounced concavity as it comes with a higher density of more productive firms. In contrast, under the Log-normal assumption, more dispersion has an ambiguous impact of concavity as it somes with higher density of both less and more productive firms. Differently, more elastic demand (larger ε) increases concavity under both assumptions as it makes productivity difference between firms more consequential for their relative output levels.

4 Estimation Strategy

To implement the extended gravity regression (16), we need estimates for the unobserved trade cost u_{ni}, the exporters' share w_{ni} and their productivity premium $\widetilde{y}^*_{ni}$. While for u_{ni} and w_{ni} we follow HMR (2008), without relying on specific parametrizations of the productivity distribution, for the new variable $\widetilde{y}^*_{ni}$ we propose a novel estimation procedure.

4.1 Unobserved Trade Cost and Exporters' Share

To retrieve the control variable for the share of exporters and unobserved trade cost, for any given period t we estimate the probability of observing positive trade flows $\rho_{nit} > 0$ between i and n conditional on a vector of controls $\mathbf{x}_{nit}$. This is achieved by running the probit model

$$\rho_{nit} = Pr(Exp_{nit} = 1|\mathbf{x}_{nit}) = \Phi\left(a_0 + a_{1,nt} - a_{2,it} + a_3 \ln \tau_{nit} - a_4 C_{ni}\right), \tag{17}$$

where the dependent variable Exp_{nit} is a dummy equal to 1 if country i exports a strictly positive amount of goods to country n in year t,and 0 otherwise; a_0, $a_{1,nt}$ and $a_{2,it}$ are a constant, a time-varying destination fixed effect, and a time-varying origin fixed effect respectively; and C_{ni} is the selection variable (which will be excluded from extended gravity regression): we consider religious proximity as a variable that predicts the existence of trade flows between country pairs but is uncorrelated with export intensity. Finally, we specify the bilateral iceberg trade cost τ_{nit} as

$$\tau_{nit} = \exp\left(\gamma \ln dist._{ni} + \delta_1 C.B._{ni} + \delta_2 C.L._{ni} + \delta_3 C.T._{ni} + \delta_4 RTA_{nit}\right), \tag{18}$$

including a (time-invariant) measure of geographic distance ($dist._{ni}$), a time-varying indicator for the existence of a Regional Trade Agreement (RTA_{nit}), and the usual set of (time-invariant) dummy variables capturing different dimensions of proximity between trading partners: common border ($C.B._{ni}$), common language ($C.L._{ni}$), and colonial ties ($C.T._{ni}$).

Then, as already discussed in Section 3.1, the predicted probability $\hat{\rho}_{nit}$ from (17) allows us to compute the inverse Mills ratio IMR_{ni} and the third-order polynomial $\hat{z}_{ni} + \hat{z}^2_{ni} + \hat{z}^3_{ni}$ that deal with the biases associated with the extensive margin of selection.

4.2 Exporters' Productivity Premium

Turning to the bias associated with the intensive margin of selection, it is addressed in specification (16) by the inclusion of $\widetilde{y}^*_{ni} = \ln \widetilde{Y}^*_{ni}$, where $\widetilde{Y}^*_{ni}$ is the the ratio of exporters' to producers' output-weighted average productivities. This is also the ratio of the $(\varepsilon-1)$-th raw moments of the corresponding productivity distributions and can therefore be computed by combining three pieces of information: the elasticity of substitution ε, the productivity of exporters to destination n, and a proxy for the higher moments of the distribution of producers' productivity.

Consider a producer in origin country i exporting its product j to destination country n in period t. To estimate the elasticity of substitution ε, we define a first order linear approximation of the demand function (Forlani et al., 2016). As ε is constant, the markup $\theta=\varepsilon/(\varepsilon-1)$ is also constant and common across firms. We can then express the value of exports x_{jnit} as a function of exported quantity q_{jnit}, product-destination-time specific demand shocks λ_{jnt} and an i.i.d. error term η_{jnit} as

$$x_{jnit}=\frac{1}{\theta}\ln q_{jnit}+\frac{1}{\theta}\lambda_{jnt}+\eta_{jnit}. \tag{19}$$

By running this regression, the elasticity of substitution can then be computed from the estimated markup. A source of concern, however, is that the estimation of θ may be biased by demand and other unobserved shocks (due to, e.g., trade policy, selection, etc.) potentially correlated with the exported quantity. To address this concern and minimize the potential bias arising from different sources of endogeneity, we estimate (19) in double difference (Arkolakis et al., 2018)

$$\Delta_{mnt}\Delta_{jni}x_{jnit}=\frac{1}{\theta}\Delta_{mnt}\Delta_{jni}\ln q_{jnit}+\Delta_{mnt}\Delta_{jni}\eta_{jnit}, \tag{20}$$

where Δ is the difference operator. The term Δ_{mnt} is the mean-difference over destination n, time t and industry m product j belongs to, which controls for asymmetric demand shocks at destination-industry level. The term Δ_{jni} is the mean-difference over product j, origin i and destination n, which eliminates product heterogeneity arising from destination-specific demand shocks λ_{jnt}. [5]

As for exporters' productivity, a consistent estimate can be obtained exploiting information on the unit values of the exported products.[6] In light of equation (3), the exporter's price (p_{jnit}) is a function of trade costs (τ_{jnit}), marginal cost (m_{jit}/y_{jnit}) and a constant markup ($\theta=\varepsilon/(\varepsilon-1)$), where we have assumed that the firm draws from $F^i(y)$ a destination-specific productivity level y_{jnit}. We can thus define a linear polynomial approximation of the export price as

$$\ln p_{jnit}=\beta_1\ln q_{jnit}+\beta_2\ln T_{jnit}+\phi(\ln T_{jnit},\ln q_{jnit})+I_{it}+I_{jnt}+\xi_{jnit}+\eta_{jnit}, \tag{21}$$

where T_{jnit} is the bilateral tariff on product j, $\phi(\cdot,\cdot)$ is a second order polynomial in tariff and quantity, I_{jnt} is a product-destination fixed effect, and I_{it} is an origin fixed effect. The former fixed effect capture asymmetric demand shocks across destinations, while the latter captures asymmetric technological shocks across origins. The term η_{jnit} is an error that includes (the log of) firm-product marginal cost m_{jit}/y_{jnit}. The term ξ_{jnit} is a control variable for possible bias from sample selection, which deals with the fact that unobserved factors determining the existence of a positive trade flow ($x_{jnit}>0$) may enter the error term (see Appendix C.2 for details).

[5] In addition, estimates from (19) can be biased by unobserved factors affecting firm selection in the destination. This issue can be addressed by augmenting (19) with the inclusion of a selection term ξ_{jnit}. See Appendix C.2 for details on double difference and selection.

[6] We exploit the heterogeneity in the exported quantity to identify markups and differences in the unit values across destination to calculate the exporters' productivity.

Regression (21) delivers the estimated origin-year fixed effects $\hat{I}_{it}$, which we use to as a lower bound estimate of producers' output-weighted average productivity.[7] It also allows us to compute the exporter's productivity from the residual. Specifically, assuming that in the error anything but $\ln(m_{jit}/y_{jit})$ is noise, we can use the estimated residual $\hat{\eta}_{jnit}$ to recover the estimated marginal cost as $\hat{m}_{jit}/\hat{y}_{jnit} = \exp(\hat{\eta}_{jnit})$. If we normalize the estimated marginal cost by its maximum $\exp(\hat{\eta}_{j0it}) = \max_n \exp(\hat{\eta}_{jnit})$ across destinations, we can get rid of $\hat{m}_{jit}$ and obtain $\hat{y}_{jnit}/\hat{y}_{j0it} = \exp(\hat{\eta}_{j0it})/\exp(\hat{\eta}_{jnit})$ with $\hat{y}_{j0it} = \min_n \hat{y}_{jnit}$ and $\hat{y}_{jnit}/\hat{y}_{j0it} \geq 1$. We then use the estimated elasticity $\hat{\varepsilon}$ from (20) to compute the empirical $(\hat{\varepsilon}-1)$-th raw moment of the exporters' normalized productivity distribution, which we use to proxy their output-weighted average productivity. With J exporters, such moment evaluates to $J^{-1}\sum_j^J (\hat{y}_{jnit}/\hat{y}_{j0it})^{\hat{\varepsilon}-1}$. The estimate $\widehat{\widetilde{Y}}^*_{nit}$ of the exporters' productivity premium is finally computed as

$$\widehat{\widetilde{Y}}^*_{nit} = \frac{J^{-1}\sum_j^J \left(\exp(\hat{\eta}_{j0it})/\exp(\hat{\eta}_{jnit})\right)^{\hat{\varepsilon}-1}}{\hat{I}_{it}^{\hat{\varepsilon}-1}}. \tag{22}$$

4.3 Extended Gravity Regression

Equipped with IMR_{nit}, $\hat{z}_{ni}$ and $\widehat{\widetilde{Y}}^*_{nit}$, we have all the controls needed for the different sources of bias: unobserved trade cost, exporters' extensive margin of selection and extensive margin of selection respectively.

In particular, we estimate the following gravity model in logarithmic terms (Anderson and Yotov, 2012; Imbs and Mejean, 2015):

$$\begin{aligned} x_{nit} \quad = \quad & \lambda_{it} + \chi_{nt} + \gamma \ln dist_{ni} + \delta_1 C.B._{ni} + \delta_2 C.L._{ni} + \delta_3 C.T._{ni} + \\ & \delta_4 RTA_{nit} + \beta_1 \widehat{\widetilde{y}}^*_{nit} + IMR_{nit} + \hat{z}_{ni} + \hat{z}^2_{ni} + \hat{z}^3_{ni} + \eta_{nit}, \ \forall x_{ni} > 0 \end{aligned} \tag{23}$$

with $\widehat{\widetilde{y}}^*_{nit} = \ln \widehat{\widetilde{Y}}^*_{nit}$, origin-year fixed effect λ_{it} and destination-year fixed effect χ_{nt}. The crucial difference with respect to HMR (2008) is the inclusion of exporters' (log) productivity premium $\widehat{\widetilde{y}}^*_{nit}$.

5 Data

We consider 22 manufacturing sectors, indexed $s = 1, ..., 32$, and estimate all the equations sector-by-sector on a panel of 50 countries over the period 2001-2012. Running the regressions separately across sectors reduces the number of parameters to be estimated from each regression compared with a pooled regression with sector-country-year fixed effects. This approach overcomes the incidental parameter problem facilitating the convergence of the probit regression (17).

For our empirical analysis, we mainly use three data sources: BACI and CEPII for the gravity variables, and CompNet for the productivity distributions.

BACI - The BACI data include the value and quantities traded between country pairs at the product level (HS2002 6-digit) for the period 2002-2012 (Gaulier and Zignago, 2010).

[7] Due to Jensen's inequality, we have $\hat{I}_i^{\varepsilon-1} = \left(\int_{y_{L,i}}^{y_{H,i}} y dF_i(y)\right)^{\varepsilon-1} = \int_{y_{L,i}}^{y_{H,i}} y^{\varepsilon-1} dF_i(y)$.

Only strictly positive trade flows are recorded. We consider the bilateral trade flows for 50 countries, including the subset of 16 countries also available in CompNet.[8] Values are expressed in thousands current USD (f.o.b. values), while quantities in tons.

It is important to underline that products are classified by BACI according to the HS 2002 product classification, while CompNet defines sectors based on the NACE rev.2 classification. Thus, we need to harmonize classifications and link trade data (HS) with CompNet data (NACE). For this we use the conversion tables mapping from HS 2002 to HS 2007 (at 6-digits). Then, the HS 2007 classification is converted into the CPA 2008 classification, whose first two digits correspond to the first two digits of the NACE rev.2 classification. With this mapping at hand, we can link each HS 6-digit products to a NACE rev.2 two-digit sector. Table 1 reports trade data by NACE sector.

[Table 1 about here.]

For estimation, we define a sector s at the NACE rev.2 two-digit level and a product j associated within the sector at the HS 6-digit level. We then assume that each product j exported from location i can be considered as a unique product supplied by a single monopolistic competitive firm in sector s. In other words, we make the Armington assumption that a HS 6-digit product produced in country i is imperfectly substitutable with the same HS 6-digit product produced in country n, and further assume that some firm has monopolistic power on that product.

We employ the BACI data at two different levels of aggregation. As described in Section 4.2, data at product level on values and quantities are used to estimate the elasticity of substitution through regression (20) and the exporters' productivity premium through regression (21). Then, we aggregate the HS 6-digit product-level data on values within the same NACE rev.2 two-digit sector and we employ the sectoral export value to estimate the sectoral gravity equations (15) and (16) as well as the sectoral selection equation (17).

CEPII - The Gravity Database from CEPII (Conte et al., 2022) provides information on distance, religion, language, common border, colonial ties, and common religion for country pairs.[9] In addition, we obtain information on regional trade agreements (RTA) from Egger and Larch (2008), which we exploit to measure the existence of an RTA between country pairs by a dummy variable taking value 1 in year t if the two countries have a valid RTA in that year. Lastly, we integrate additional information for bilateral tariffs at HS 6-digit product by computing the (simple) average applied tariffs from the TRAINS database.

CompNet - CompNet is the result of a joint effort of several European institutions that use firm-level data to generate a harmonized cross-country database with various indicators of competitiveness.[10] CompNet indicators are computed following the so-called "distributed micro-data approach" developed by Bartelsman et al. (2013), whose basic idea is to apply a common

[8] Table 29 in Appendix B reports the list of countries. BACI allows to construct the database to estimate the bilateral gravity model. Aggregated (sector) trade data includes 646,800 observations (29,400 per sector).

[9] As a measure of geographical *Distance* we use the geodesic distance calculated with the great circle formula, which is based on latitudes and longitudes of the most populated city. *Language* is a dummy variable equal to 1 when the origin and the destination country share the same official or primary language. *Colony* is a dummy variable equal to 1 if the two countries were linked by colonial ties in the past. *Border* is a dummy variable equal to 1 if the two countries share a common border. *Religious proximity* is an index computed as the product of the shares of Catholics, Protestants and Muslims in the two countries: it measures a sort of religious proximity and is bounded between 0 and 1.

[10] The CompNet network was launched by the European System of central Banks (ESCB) in 2012. As reported in CompNet Task Force (2018) "The interplay between actors enables CompNet to: (i) include in the dataset indicators demanded by policy makers and researchers; (ii) address the two most common problems regarding cross-country firm-level data, namely, lack of comparability across countries and confidentiality concerns."

protocol on national firm-level data to produce aggregate statistics that are at the same time cross-country harmonized and firm-level based. This approach has some important merits. First, it allows cross-country analyses based on firm-level data without violating confidentiality issues that are particularly strong when dealing with firms. Second, thanks to its operational flexibility, it can provide novel figures on aggregate statistics, for example not only the mean but also a rich set of statistical moments of the distribution of a given firm-level indicator.

In this paper, we use the IV$^{\text{th}}$ vintage of the CompNet *"20E sample"*, which includes country-sector-year level data generated from a sample of firms with at least 20 employees. It is an unbalanced panel dataset containing information for 16 European countries (Belgium, Croatia, Estonia, Finland, France, Germany, Hungary, Italy, Lithuania, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden, over the period 2001-2012. In order to improve the representativeness of the underlying data, the *"20E sample"* comes with a weighting scheme, based on the total number of firms by country-year-sector-size class, with weights computed using the Eurostat Structural Business Statistics (SBS).[11]

The "20E sample" has some drawbacks. First, it does not provide a full and correct representation of a country's productive system that in many European economies is populated by a large majority of very small firms. To some extent, this is a minor issue in our case since we aim at studying export performance, and exporting is well-known to be an activity for more productive and relatively larger firms as most exports are generated by large firms (Mayer and Ottaviano, 2007). As an example, in the case of Italy, which is a country with an exceptionally highly fragmented productive system, the exporting firms with less than 20 employees are only 2 percent of the total number of firms with 0-19 employees and make up for about 10 per cent of total exports (despite being 75 per cent of the total number of exporters). Restricting the analysis to manufacturing, as we do, makes their relevance even more marginal. Second, due to the way some of the firm-level datasets are built, there are potential sample biases in favor of more productive firms so that, even after weighting, aggregate values (by country or sector) may sometimes report non-negligible differences with respect to the Eurostat official statistics. We will address this second concern by including a rich set of fixed effects aimed at controlling for unobservable systematic sample differences across countries, sectors, years and their combinations. The alternative to the "20E sample" is the sample built on data covering all firm size classes. In CompNet this is named the "Full sample". While having a larger coverage, this alternative dataset presents other more serious limitations: a reduced number of countries and sectors, a representativeness that is quite limited for some countries and often very distorted in the smaller size classes because the aggregate figures are computed on a restricted sample of very highly productive micro and small firms.

From CompNet we retrieve various indicators on total factor productivity (TFP) at the country-sector-year level. Importantly for our purposes, CompNet includes information not only on the mean but also on additional moments moments of the TFP distribution and the values of various percentiles (e.g., 10$^{\text{th}}$ or 90$^{\text{th}}$) for each country-sector-year cell. This rich set of moments allows us to compute the relevant parameters of the Pareto and Log-Normal distribution, that will be used to perform the counterfactual analysis.

Table 2 reports the average value of different TFP statistics (mean, standard deviation, skewnees and median) by country, whereas Table 3 shows the sample size composition by country. *Obs.* reports the number of observations (CompNet cells) by country. The other three columns report information on the underlying firms' population that is used to construct aggregated statistics. *Mean* is the average number of firms. For example, the Italian statistics are computed

[11] Additional details are reported in Appendix B.

using (on average) 1176 firms. *Max* and *Min.* report the maximum and minimum number of observational units (firms) used to construct the CompNet aggregated statistics (*Min* is greater than 10 by construction).

[Table 2 about here.]

[Table 3 about here.]

6 Estimation Results

We report here the results obtained by applying the empirical approach outlined in Section 4 to the dataset described in Section 5. We first discuss the estimates related to the unobserved trade cost and share of exporters from the probit regression (17), which we need to control for the extensive margin of selection. We then turn to the estimated exporters' productivity premium (22), which is needed to control for the intensive margin of selection. Finally, we report the estimation results from the extended gravity equation (23), where both selection margins are controlled for, and we compare them those derived from the application of HMR (2008) to our data.

6.1 Unobserved Trade Costs and Exporters' Share

We proceed as described in Section 4.1. As a first step, we estimate the selection equation (17) by running the following Probit model for each sector s:

$$\begin{aligned}\rho(s)_{nit} &= \alpha_0 + \alpha_1 \ln distance_{ni} + \alpha_2 C.B._{ni} + \alpha_3 C.L._{ni} + \alpha_4 C.T._{ni} + \\ &\quad \alpha_5 RTA_{nit} + \delta_6 R.P._{ni} + \mathbf{\Gamma}_{it} + \mathbf{\Gamma}_{nt} + u_{nit}, \end{aligned} \tag{24}$$

where the dependent variable is a dummy equal to 1 for any strictly positive trade flow from country i to country n in year t, and zero otherwise, Γ_{nt} and Γ_{it} are a sets of fixed effects at the destination-year and origin-year levels. Their purpose is to capture any unobserved time-varying country-specific factor affecting the probability to observe positive trade flows. In particular, Γ_{it} controls for fixed export costs that are common across all destinations for origin i, while Γ_{nt} controls for fixed trade barriers that destination j imposes to all origins. We cluster robust standard errors at origin-year level.

Table 4 reports the estimated coefficients by sector. Most of the coefficients have the expected sign. The coefficient of $\ln Dist.$ is always negative and statistically significant, ranging from -1.37 to -0.868. The coefficients of the proximity indicators (common border, colonial ties, and common language) are positive when statically significant. Also the RTA coefficient is positive when it is statistically significant (15 cases). Out of 22 sectoral estimates, religion proximity $R.P.$ (the excluded variable) is positive in 19 cases and statistically significant in 12. The lack of significance and, in few cases, the negative coefficient of $R.P.$ can be due to the fact that religion proximity is highly correlated with the two measures of physical distance and common language. [12]

[12] Compared to HMR (2008), our estimation strategy differs in one important aspect, leaving aside differences in the sample (number of countries and time span). This has to do with the treatment of the sectoral dimension, which we purposely maintain separate by running sector-by-sector regressions.

Once more, the predicted probability $\hat{\rho}_{nit}$ from (24) allows us to compute the inverse Mills ratio IMR_{ni} and the third-order polynomial in the latent variable $\hat{z}_{ni}$ that allow us to deal with the biases due to the extensive margin of selection.

[Table 4 about here.]

6.2 Exporters' Productivity Premium

Table 5 reports the estimated demand elasticities ε_s obtained by running the double difference regression (20) sector by sector. The sectoral estimates range between 2.7 (Printing and Publishing - 18) and 8.64 (Tobacco - 12) with an average value of 4.85, which is consistent with most of the estimates in the international trade literature.[13] Results are robust to the inclusion of different type of controls (such as HS 6 digit tariffs) and linear selection to account for $x_{jnit} > 0$ as described in Appendix E.[14]

[Table 5 about here.]

For each sector, Table 6 reports the estimation results from the price equation (21) with product-destination-time (I_{jnt}) and exporter-time fixed effects (I_{it}).[15] The selection term ξ_{jnit} is positive and statistically significant across sectors, suggesting the existence of a positive correlation between prices and unobserved shocks that affect the probability to observe trade flows (such as demand or quality shocks). Furthermore, we observe a positive correlation between tariffs and export prices across most sectors, and a negative correlation between quantity and price.

[Table 6 about here.]

To check whether the normalized residuals from (21) can be taken as a meaningful measure of exporters' productivity, Table 7 reports the correlation across sectors between the log of bilateral unit values at fob value (UV_{nist}) and the log of the average normalized bilateral residuals at the numerator of expression (22). Consistently with our framework, one would expect unit values to be negatively correlated with the exporters' productivity as higher firm productivity leads to lower export prices. Columns 1 to 4 show that across sectors average normalized residuals are indeed negatively correlated with unit values, and this finding is robust to the inclusion of different type of fixed effects controlling for unobserved demand and supply shocks. Similar results also hold when we control for the distance between origin and destination.[16]

[Table 7 about here.]

The last item we need in order to obtain is the exporters' productivity premium (22) is the origin-country fixed effects $\hat{I}_{it}$, which we estimate from (21) as a measure of producers' productivity. One would expect that producers' productivity is positively correlated with both total exports and average exporters' productivity. [17] Thus, as a sanity check, we regress the

[13] For instance, Arkolakis et al. (2018) report an estimated value of 4.8.

[14] See Table 5 in Appendix E.

[15] As a robustness check for unobserved demand shocks, we also estimate (21) by double differencing the variables. The empirical model is described by (C-5) in Appendix C.2. The estimation results are reported in Table 25. The correlation between exporters' productivity (numerator of Eq.22) derived from the price equation in levels and with double difference is 0.87.

[16] We obtain similar results by using product level information. When we regress the export price for HS product p_{jni} on estimated firm productivity ($\hat{y}_{jnit}$), we observe a negative correlation that is robust to the inclusion of different set of fixed effect and selection term ξ_{jnit}. Thse results are available upon request.

[17] Average exporter productivity by sourcing country is defined as the mean of the numerator of Eq. 22 across products and destinations.

log of total sectoral exports $\ln(exp)_{ist}$ and the log of sectoral average exporter productivity across products and destination on the estimated origin fixed effects. Table 8 shows that the fixed effects $\hat{I}_{ist}$ are positively correlated with both total exports (columns 1 to 3) and average exporters' productivity (columns 4 to 6). It suggests that the estimated origin-year fixed effects from regression (21) may be taken as a reasonable measure of producers' productivity.

[Table 8 about here.]

6.3 Extended Gravity Regression

For each sector, we implement (23) through the following linear model without the constant term:

$$\begin{aligned} \ln x(s)_{nit} \;=\;& \alpha_0 + \delta_1 \ln distance_{ni} + \delta_2 Language_{ni} + \delta_3 Colony_{ni} + \delta_4 Border_{ni} + \\ & \delta_5 RTA_{nit} + IMR_{nit} + \nu(\widehat{z}_{nit}) + \ln \widehat{\widetilde{y}}(s)^*_{nit} + \mathbf{\Lambda}_{it} + \mathbf{\Lambda}_{nt} + e_{nit}, \end{aligned} \tag{25}$$

where $\mathbf{\Lambda}_{it}$ is a set of fixed effects at the origin-year level, $\mathbf{\Lambda}_{nt}$ is a set of fixed effects at the destination-year level, and crucial controls consist of the inverse Mills ratio IMR_{nit}, the third-order polynomial $v(\hat{z}_{nit})$ is the latent variable $\hat{z}_{nit}$, and the exporters' productivity premium $\widehat{\widetilde{y}}(s)^*_{nit}$. .

[Table 9 about here.]

The estimation results are shown in Table 9. As expected, the estimated coefficient of $\ln(Dist_{ni})$ is always negative and statistically significant. It varies between -0.847 and -1.597 across sectors, indicating that a 1% increase in distance is linked to a reduction in trade levels ranging from 0.85% to 1.6%. Compared with Helpman et al. (2008), the coefficient is bigger, which is consistent with the idea that gravity models at the sector level generate larger estimates than those at the aggregate level (Redding and Weinstein, 2019).

All the other coefficients have the expected sign with the exclusion of RTA, which is negative and statistically significant in 6 out of 22 sectors. Focusing on the crucial controls, IMR_{nit} is positive and significant for most sectors, highlighting the importance of unobserved trade costs for the creation of a trade link; conversely, the polynomial expansion $v(\widehat{z}_{nit})$ is statistically significant in few cases, possibly suggesting that the main implications of selection are captured by $\ln \widehat{\widetilde{y}}(s)^*_{nit}$.[18] The coefficient of the latter is indeed statistically significant for all the regressions. A higher level of trade is associated with observations with a large exporters' productivity premium, that is, a large productivity gap between exporters and producers. Analyzing the positive trade flows, an increase of 10% in the productivity premium raises the average exports between 0.3% (sector 29) and 1% (sector 32).

6.4 Intensive vs. Extensive Margins of Selection

The inclusion of $\ln \widehat{\widetilde{y}}(s)^*_{nit}$ in our extended gravity estimation is not only important to appreciate the role of the intensive margin of export selection, but also to overcome possible biases

[18] We can substitute both IMR and $\nu(\widehat{z}_{nit})$ with alternative control variables. Firstly, we can substitute IMR with the average micro level selection (C-5), i.e., the mean value of ξ_{jint} across products. Secondly, we can control for the share of exporting firms by the share of exported products from i to n rather than by $\nu(\widehat{z}_{nit})$. In both cases, the estimation produces even smaller distance parameters; in addition the selection control variable is negatively correlated with trade while the share of exporting firm is positively correlated. These results are available upon request as the main aim of the baseline analysis is to compare our results with those in Helpman et al. (2008).

in the parameters' estimates. To see this, it is useful to compare the estimation results from the extended gravity regression with those obtained from the application of the approach proposed by Helpman et al. (2008). In Section 3.2 (and Appendix C.1), we already discussed the theoretical reasons why one may be concerned that neglecting the intensive margin of selection might engender a negative bias in the estimated distance coefficient and a positive bias in the estimated origin fixed effect, with potential relevant consequences for counterfactual analysis. We hereby check to what extent these concerns find confirmation in our data.

Table 10 reports the distance parameter estimated from four alternative gravity specifications (columns 1 to 4). All specifications are estimated on the sample of positive trade flows only, in log terms, and using OLS. The table compares the estimated distance parameter from the extended specification of Table 9 (column 4, Model D) with those from three alternative specifications: (i) a specification without correction for the extensive and intensive margins of selection (Model A); (ii) a specification correcting only for the intensive margin through $\widehat{\widetilde{y}}(s)^*_{nit}$ (Model B); and (iii) a specification *à la* HMR (2008) controlling only for the extensive margin of selection through the third-order polynomial in the latent variable $\hat{z}_{ni}$ (Model C).

Compared with the three alternatives, for all sectors the extended gravity specification (column 4) yields a systematically smaller distance coefficient (columns 4 vs. 1, 2, and 3). In most cases, the sole adjustment for $\widehat{\widetilde{y}}(s)^*_{nit}$ attenuates the upward bias in the estimated distance parameter estimation associated with no correction (columns 2 vs. 1). This attenuation is similar to the one produced by specification *à la* HMR (2008) (columns 3 vs. 1). Testing whether the differences in the distance parameter's estimates are statistically significant shows that our extended gravity specification generates smaller coefficients that the specification *à la* HMR (2008) for all sectors, with a negative bias that ranges from -0.007 to -0.1 (column 7).[19]

[Table 10 about here.]

Turning to the origin fixed effect, Table 11 reports the test for the statistical difference between the average estimated fixed effects from the extended gravity (25) and the specification *à la* HMR (2008). The test is performed on both the full sample of countries and on the sample of CompNet countries only. The estimates from our model are systematically lower than those obtained from applying HMR (2008). This is in line with the expected impact of omitting the exporters' premium discussed in Section 3.2: the omission conflates producers' productivity with the average effect across destinations of bilateral expoters' productivity premia.[20]

[Table 11 about here.]

To investigate the potential consequences of biased estimation for counterfactual analysis, we use the fitted values of the gravity equation to make predictions about the changes in trade flows due to changes in distance-related trade frictions. According to the theory developed in Section 2, as trade frictions fall, new trade relations are created, the share of exporters increases, and their productivity premium decreases as less productive marginal firms start exporting. Hence, when the exporters' productivity premium is also taken into account, one should expect to see a smaller increase in bilateral trade from lower trade frictions for two reasons: (a) the negative bias in the estimated distance coefficient due to the omitted exporters' premium $\widehat{\widetilde{y}}(s)^*_{nit}$, and (b) the reduction in average exports per firm due to smaller $\widehat{\widetilde{y}}(s)^*_{nit}$.

For tighter comparison with HMR (2008), we evaluate the importance of the omitted variable bias while keeping $\widehat{\widetilde{y}}(s)^*_{nit}$ unchanged. In particular, assuming that the distance between each

[19] With respect to Helpman et al. (2008) we use not only different data in terms of country and time coverage, but we additionally exploit cross-sector variation to identify the heterogeneity of distance coefficients.

[20] The test by sector leads to the same conclusion. The correspoding results are available upon request.

country pairs decreases by 10 percentage points (i.e., $\ln (dist)'_{ni} - \ln(dist)_{ni} = \ln 0.9$), we compute the changes in trade flows and the implied elasticities to trade frictions, assuming that the share of exporters varies, while the number of trade linkages and the exporters' premium are unaffected.[21]

Table 12 reports summary statistics for trade growth and the implied elasticites for the gravity regression *à la* HMR (2008) as baseline and our extended regression. Sample averages show that both the trade variations ($\ln \hat{x}' - \ln \hat{x}$) and the elasticities ($|\ln \hat{x}' - \ln \hat{x}| \,/\, |\ln dist' - \ln dist|$) are smaller in the extended than in the baseline regressions, reflecting the downward bias in the distance parameter estimation. Despite being relatively small for the trade variation (Panel A), the difference is statistically significant in both cases.

[Table 12 about here.]

7 Bilateral Trade Elasticities

Evaluating the elasticity of trade flows to distance while keeping $\widehat{\widetilde{y}}(s)^*_{nit}$ constant is useful for comparison with HMR (2008). However, it falls short of a fully fledged characterization of the actual trade elasticity needed for simulating the effects of counterfactual changes in trade costs on trade flows as $\widehat{\widetilde{y}}(s)^*_{nit}$ responds to changes in distance. Such characterization is what we will now pursue by restricting the analysis to the parametrizations of firm productivity introduced in Section 2.3. We will then use the resulting trade elasticities for some simulation exercises.

7.1 Pareto vs. Log-Normal

By definition, total exports can be expressed as the product of two factors: the number of exporters ('extensive margin of trade' - EM, which we previously called the 'extensive margin of selection') and average exports per exporter ('intensive margin of trade' - IM). The trade elasticity combines the elasticities of the two margins to the variable component τ_{ni} of trade costs. Assuming that firm productivity follows either a bounded Pareto distribution (see Section 2.3.1) or a truncated Log-normal distribution (see Section 2.3.2), the bilateral trade elasticity implied by the theoretical model of Section 2 is country-pair specific.[22]

Under Pareto, the elasticities of the extensive and intensive margins of trade are

$$\eta(P)^{EM,\tau}_{ni} = -k_i \frac{y^k_{H,i}}{y^k_{H,i} - y^{*k}_{ni}}$$

and

$$\eta(P)^{IM,\tau}_{ni} = k_i \frac{y^{*k}_{ni}}{y^k_{H,i} - y^{*k}_{ni}} - (k_i - \varepsilon + 1) \frac{y^{*k-\varepsilon+1}_{ni}}{y^{k-\varepsilon+1}_{H,i} - y^{*k-\varepsilon+1}_{ni}},$$

which sum up to the elasticity of total export

$$\eta(P)^{\tau}_{ni} = -k_i - (k_i - \varepsilon + 1) \left(\frac{y^{*k_i-\varepsilon+1}_{ni}}{y^{k_i-\varepsilon+1}_{H,i} - y^{*k_i-\varepsilon+1}_{ni}} \right), \tag{26}$$

which is the 'trade elasticity' we are after.

Three remarks are in order. First, the trade elasticity $\eta(P)^{\tau}_{ni}$ is origin-destination specific and this is due to the finite upper bound of the support. For $y_{H,i} \to \infty$, the right hand side

[21] Additional details are presented in Appendix C.3.

[22] See Appendix A for detailed derivations.

of (26) converges (in absolute value) to the shape parameter k_i and it is thus specific to the origin only. This happens as the elasticities of the extensive and intensive margins go to k_i in absolute value and zero respectively. Hence, for $y_{H,i} \to \infty$, the trade elasticity coincides with the extensive margin elasticity. Second, for finite $y_{H,i}$, the intensive and extensive margin elasticities, and thus the trade elasticity are all country-pair specific. Moreover, in absolute value, the latter is a decreasing function of the upper bound $y_{H,i}$ and an increasing function of the export cutoff y^*_{ni}. Therefore, for $y_{H,i} \to \infty$, the trade elasticity $\eta(P)^\tau_{ni}$ converges in absolute value to k_i from above. In other words, the trade elasticity is always larger with bounded that unbounded Pareto and the gap shrinks are the upper bound grows. Third, as τ_{ni} increases, the extensive margin elasticity captures the negative impact of trade costs on the exporters' share. In turn, the intensive margin elasticity captures two effects that are channeled through the output-weighted average productivity of exporters: higher trade costs increase their unweighted average productivity, which promotes exports; on the other hand, it decreases the output shares of the most productive exporters as the least productive ones stop exporting, which hampers exports, the more so the smaller the demand elasticity ε.

Analogously, under Log-normal, the elasticities of the extensive and intensive margins of trade are

$$\eta(LN)^{EM,\tau}_{ni} = -\frac{1}{\sigma_i}\frac{\phi(y^*_{0,ni})}{\Phi(y_{0,H,i}) - \Phi(y^*_{0,ni})}$$

and

$$\eta(LN)^{IM,\tau}_{ni} = \frac{1}{\sigma_i}\frac{\phi(y^*_{0,ni})}{\Phi(y_{0,H,i}) - \Phi(y^*_{0,ni})} - \frac{1}{\sigma_i}\left[\sigma_i(\varepsilon-1) + \frac{\phi(y^*_{0,ni} - (\varepsilon-1)\sigma_i)}{\Phi(y_{0,H,i} - (\varepsilon-1)\sigma) - \Phi(y^*_{0,ni} - (\varepsilon-1)\sigma_i)}\right],$$

where $\Phi(\cdot)$ is the c.d.f. of a standard normal, $\phi(\cdot)$ is the corresponding density function, and we have defined $y_{0,\cdot} \equiv [\ln(y_\cdot) - \mu_i]/\sigma_i$ for $y_\cdot \in \{y_{H,i}, y_{L,i}, y^*_{ni}\}$, with the two elasticities summing up to the 'trade elasticity'

$$\eta(LN)^\tau_{ni} = -(\varepsilon-1) - \frac{1}{\sigma_i}\left(\frac{\phi(y^*_{0,ni} - (\varepsilon-1)\sigma_i)}{\Phi(y_{0,H,i} - (\varepsilon-1)\,\sigma_i) - \Phi(y^*_{0,ni} - (\varepsilon-1)\sigma_i)}\right). \tag{27}$$

The same remarks as for the Pareto apply to the Log-normal with an important exception: for $y_{H,i} \to \infty$, the right hand side of (27) remains country-pair specific with its denominator converging to $1 - \Phi(y^*_{0,ni} - (\varepsilon-1)\sigma_i)$. Otherwise, with finite upper bound $y_{H,i}$, under both Pareto and Log-normal the theoretical model predicts that, given $y_{H,i}$, as exporting becomes less selective (i.e. y^*_{ni} falls) due to lower trade costs (i.e. smaller τ_{ni}), the sensitivity of trade flows to trade costs decreases.

7.2 Theoretical and Empirical Moments

According to expressions (26) and (27), the quantification of the trade elasticity requires empirical estimates of the demand elasticity ε, the bilateral trade cutoff y^*_{ni}, and the distribution parameters: k_i and $y_{H,i}$ under Pareto; μ_i, σ_i and $y_{H,i}$ under Log-normal. As we have already estimated the demand elasticity (see Table 5), we focus here on the rest.

For the export cutoff y^*_{ni} we consider the observed percentiles of TFP reported in CompNet. Specifically, we take the percentage of products not exported from i to n (in a sector-year pair) and proxy y^*_{ni} by the corresponding TFP percentile. For instance, if we see from BACI that i exports 20% of its products to n , then the 80^{th} percentile of TFP identifies the productivity cutoff for exporting to n. A higher share of exported products is thus associated with a lower cutoff.[23]

Turning to the distribution parameters, the ideal data for their estimation would consist of harmonized firm-level information across a large set of countries. As such data is unfortunately unavailable, we exploit alternative information from the CompNet dataset.[24]

A unique feature of CompNet is that, for each triplet country-sector-year, it reports key empirical moments of producers' productivity, including mean, standard deviation, skewness, and various percentiles. We can then use the method of moments to recover the distribution parameters from those sample statistics by identifying the parameters' values for which the moments' theoretical definitions are equal to the corresponding observed statistics.

Computation is more challenging the larger the number of parameters is. For unbounded Pareto or untruncated Log-normal, there are only two parameters to be computed (k_i and $y_{L,i}$ or μ_i and σ_i respectively) and these can be obtained as the solution of a system of two equations in two unknowns as in Head (2013).[25] For bounded Pareto or double-truncated Log-normal, the parameters are three or four (k_i, $y_{L,i}$ and $y_{H,i}$ or μ_i, σ_i, $y_{L,i}$ and $y_{H,i}$ respectively) and solving the system is more challenging not only because there are more equations, but also because of non-linearities in the truncated moments. Nonetheless, due to the presence of some zero bilateral trade flows in our data and the purpose of characterizing bilateral trade elasticities, the bounded or truncated distributions are our target. We will report also results for unbounded Pareto or untruncated Log-normal for comparison only.

Consider a generic observation defined in CompNet by the triplet country-sector-year $\chi = (i, s, t)$. To compute the parameters, we exploit the properties of the moments function, the functional forms of the distributions, and the information on the sample mean m_χ, variance v_χ, and skewness s_χ of productivity. The computation relies on the fact that the mean, variance and skewness are related to the first three raw moments $\zeta(1)_\chi$, $\zeta(2)_\chi$ and $\zeta(3)_\chi$ as follows:

$$
\begin{aligned}
m_\chi &= \zeta(1)_\chi \\
v_\chi &= \zeta(2)_\chi - (\zeta(1)_\chi)^2 \\
s_\chi &= \frac{\zeta(3)_\chi - 3\zeta(1)_\chi v_\chi - (\zeta(1)_\chi)^3}{(v_\chi)^{\frac{3}{2}}}.
\end{aligned}
$$

For bounded Pareto, this system of equations can numerically solved for k_i, $y_{L,i}$ and $y_{H,i}$ after replacing the theoretical moments with the corresponding empirical ones ($\widehat{\zeta}(1)_\chi$, $\widehat{\zeta}(2)_\chi$, $\widehat{\zeta}(2)_\chi$):

$$
\begin{aligned}
\hat{\zeta}(1)_\chi &= \frac{k_\chi}{k_\chi - 1}(y_{L,\chi}) \frac{1 - \left(\frac{y_{L,\chi}}{y_{H,\chi}}\right)^{(k_\chi - 1)}}{1 - \left(\frac{y_{L,\chi}}{y_{H,\chi}}\right)^{k_\chi}} \qquad (28) \\
\hat{\zeta}(2)_\chi &= \frac{k_\chi}{k_\chi - 2}(y_{L,\chi})^2 \frac{1 - \left(\frac{y_{L,\chi}}{y_{H,\chi}}\right)^{(k_\chi - 2)}}{1 - \left(\frac{y_{L,\chi}}{y_{H,\chi}}\right)^{k_\chi}} \\
\hat{\zeta}(3)_\chi &= \frac{k_\chi}{k_\chi - 3}(y_{L,\chi})^3 \frac{1 - \left(\frac{y_{L,\chi}}{y_{H,\chi}}\right)^{(k_\chi - 3)}}{1 - \left(\frac{y_{L,\chi}}{y_{H,\chi}}\right)^{k_\chi}}
\end{aligned}
$$

[23] We round the share of non-exported products to the closer percentile observed in CompNet. For instance, if 34% (36%) of products are not exported, we use the 30^{th} (40^{th}) percentile.

[24] Details in Appendix C.4. The drawback of this approach is that we can compute trade elasticities only for the CompNet countries.

[25] See Eq. C-8 and Eq. C-9 in Section C.4.

For double-truncated Log-normal, we face some additional problems. First, we have four parameters to estimate, but CompNet provides only the first three empirical moments. To obtain a fourth equation, we therefore use the 90^{th} percentile.[26] Second, the resulting system of four equations in four unknowns is not only non-linear, but it also includes the Log-normal c.d.f., which is a non-elementary functions. Following Bowling et al. (2009), we linearly approximate this c.d.f. as

$$\Phi(y) \approx \left[1 + e^{-0.07056 y_0^3 + 1.5976 y_0}\right]^{-1}, \tag{29}$$

where the maximum approximation error is $\pm.0001414$ when $y_0 \equiv [\ln y - \mu] / \sigma = \pm 1.47$. We then numerically solve the following system:

$$\begin{aligned}
\hat{\zeta}(1)_\chi &= e^{(\mu_\chi + 0.5\sigma_\chi^2)} \frac{\Phi(y_{0,H,\chi} - \sigma_\chi) - \Phi(y_{0,L,\chi} - \sigma_\chi)}{\Phi(y_{H,\chi}) - \Phi(y_{L,\chi})} \\
\hat{\zeta}(2)_\chi &= e^{(2\mu_\chi + 2\sigma_\chi^2)} \frac{\Phi(y_{0,H,\chi} - 2\sigma_\chi) - \Phi(y_{0,L,\chi} - 2\sigma_\chi)}{\Phi(y_{H,\chi}) - \Phi(y_{L,\chi})} \\
\hat{\zeta}(3)_\chi &= e^{(3\mu_\chi + \frac{9}{2}\sigma_\chi^2)} \frac{\Phi(y_{0,H,\chi} - 3\sigma_\chi) - \Phi(y_{0,L,\chi} - 3\sigma_\chi)}{\Phi(y_{H,\chi}) - \Phi(y_{L,\chi})} \\
0.90 &= \frac{\Phi(y_{0,p90,\chi}) - \Phi(y_{L,\chi})}{\Phi(y_{H,\chi}) - \Phi(y_{L,\chi})}
\end{aligned} \tag{30}$$

with $y_{0,\cdot} \equiv [\ln(y_\cdot) - \mu_\chi] / \sigma_\chi$, where $\ln(y_{p90,\chi})$ is the log of the 90^{th} percentile of TFP and $\Phi(y)$ is approximated and substituted by (29). Numerically solving systems (28) and (30) for each country-sector-year χ yields two vectors of estimated parameters $\hat{S}_{\chi,P} = [\hat{k}_\chi, \hat{y}_{L,\chi}, \hat{y}_{H,\chi}]$ and $\hat{S}_{\chi,LN} = [\hat{\mu}_\chi, \hat{\sigma}_\chi, \hat{y}_{L,\chi}, \hat{y}_{H,\chi}]$ for Pareto and Log-normal respectively.[27]

Table 13 reports the average value of the computed parameters for both the bounded and unbounded Pareto and both the truncated and untrunctated Log-normal distributions (for CompNet countries only) [28] In the lower part, it also reports the average value of the estimated elasticities for both distributions, $\hat{\eta}(P)^\tau_{ni}$ and $\hat{\eta}(LN)^\tau_{ni}$, together with the average share of exporters and the log of the bilateral cutoff $\hat{y}^*_{ni}$. For Log-normal, we can observe that the average elasticity is -4.39 (median= -4.03), which is in line with the literature (Bas et al., 2017, report a median value of -4.79 and a mean of -4.97), and that the truncated Log-normal parameters are larger than the corresponding untruncated ones.

For the bounded Pareto, the dispersion parameter k is on average equal to 1.42, which is close to the findings of Head et al. (2014) (1.81 for French and 1.37 for Chinese exporters to Japan for the truncated distributions). For the unbounded Pareto, the dispersion parameter k_u is larger and equals 3.25. The implied average elasticity is $\widehat{\eta}(P) = -4.44$ (median$=-4.05$) which is not that different from its Log-normal counterpart.

[Table 13 about here.]

7.3 Trade Elasticity and Selection

With the estimated trade elasticties $\hat{\eta}(P)^\tau_{ni}$ and $\hat{\eta}(LN)^\tau_{ni}$ at hand, we can assess whether they behave as predicted by the theory. According to (26) and (27), they should be decreasing

[26] We use the ninetieth percentile to better approximate the right tail. The use of median would not affect our final results.

[27] The solution of systems (28) and (30) recalls a Simulated Method of Moments. However, we do not compute a variance-covariance matrix nor we test the statistical significance of the vectors $\hat{S}_{P,\chi}$ and $\hat{S}_{LN,\chi}$.

[28] In Appendix E, Tables 28 and 27 report the correlation between the different estimated parameters and distribution percentiles. They show to what extent bounded (truncated) and unbounded (untruncated) parameter estimates are correlated between them and with the observed top and low percentiles of observed TFP.

functions of the upper bound $y_{H,i}$ and increasing functions of the export cutoff y^*_{ni}. We check whether this is the case by regressing them on the estimated bilateral cutoff $\hat{y}^*_{ni}$ and on the exporters' share as both (12) and (13) show that it is an increasing function of $y_{H,i}$. The regression results would be consistent with the theoretical predictions if elasticities were decreasing in the exporters' share and increasing in the export cutoff.

The estimation sample includes all CompNet countries with positive bilateral trade flows for which we estimated the distribution parameters. The specifications allow for batteries of fixed effects. The regression results, reported in Table 14 and 15, show that both $\hat{\eta}(P)^{\tau}_{ni}$ and $\hat{\eta}(LN)^{\tau}_{ni}$ are indeed positively correlated with the export cutoff and negatively with the exporters' share.[29] Most coefficients are significant at 1% level, with different combination of fixed effects. Interpreting the results, if the exporters' share increases by 10 percentage points, the average elasticity decreases by 3% under Log-normal and 4.5% under Pareto. In other words, when it is exporting is more selective, the bilateral elasticity is larger and exports are more sensitive to variations in trade costs.

[Table 14 about here.]

[Table 15 about here.]

Figure 2 depicts the correlation of the predicted bilateral trade elasticity under bounded Log-normal with the share of exported products between country pairs. It shows that, as the share increases, the elasticity converges to the sector-specific upper bound $-(\varepsilon_s - 1)$. Moreover, as the exporters' share rises, the variability of the elasticity across destinations decreases.

[Figure 2 about here.]

Figure 3 compares the relations between the trade elasticity and the exporters' share under Pareto and Log-normal. It does so by focusing on a subset of countries and a sector that will be used for counterfactual simulation in the next section. In particular, it reports the bilateral trade elasticities under Pareto and Log-normal for sector NACE 26 (Computer electronic and optical products), for which $k_u > \varepsilon - 1$ mostly holds, and four countries (France, Hungary, Italy and Poland). While in all four cases the trade elasticity decreases as the exporters' share rises, in absolute value $\widehat{\eta}_{ni}(LN)$ is smaller than $\widehat{\eta}_{ni}(P)$, the more so the closer the share is to 1 (see also Table 13).[30]

[Figure 3 about here.]

8 Moments and Shocks

The theoretical model and the estimation results highlight the importance of accounting for both margins of export selection to obtain unbiased estimates of the gravity model (Section 6.4) and of the trade elasticity (Section 7). However, the analysis at the aggregate level may not fully capture the implications of export selection among heterogeneous producers for the extent to which micro-level shocks propagate at the aggregate level or variations in different moments of the productivity distribution affect aggregate trade flows.

[29] Hence, there is also a negative correlation between the export cutoff and the exporters' share.

[30] Parameters are computed for each country-sector-year triplet, the parameter k_{ist} varies across origins, sectors, and years, while ε_s is sector specific. Thus, as the share approaches 1, the elasticity becomes sector specific in the Log-normal case and country-sector-year specific in the Pareto case (see equations (26) and (27)).

8.1 Simulation Framework

To investigate how different types of shocks to the firm productivity distribution affect aggregate trade flows, we consider a country trading with the rest of the world and focus on two sectors in a given year. The country is Italy (i) in 2010 (t) and the two sectors (s) are Computer electronic and optical products (NACE 26) and Machinery and equipment n.e.c. (NACE 28). These are sectors with different demand elasticities.

The responses of trade flows to different shocks are simulated based on the Log-normal gravity model (Eq.11 with Section 2.3.2), which we parameterize as reported in Table 16. For each sector, we proceed as follows:

1. We create a sample with the same number of firms with more than 10 employees as reported in CompNet. We assume that the composite input price is $m = 1$. We lift elasticity ε from the estimates reported in Table 5.

2. We randomly assign to each firm a productivity level y from a double truncated Log-normal distribution with the estimated parameters $\hat{S}_{\chi,LN} = [\hat{\mu}_{\chi}, \hat{\sigma}_{\chi}, \hat{y}_{L,\chi}, \hat{y}_{H,\chi}]$ where the triplet χ consists of $i = Italy$, $s = 26$ *or* 28 and $t = 2010$.

3. We assign values to the demand shifter $A_{n,i}$, the fixed trade cost $f_{n,i}$ and the variable trade cost $\tau_{n,i}$ as random draws by assuming: $\tau_{n,i} = 1 + t$ with $t \sim U[0.01, 1]$; $f_{n,i} = \tau_{n,i}^{1-\varepsilon} + u$ with $u \sim U[0.01, 1]$ (which implies that the condition on $\tau_{n,i} \cdot f_{n,i}^{\frac{1}{\varepsilon-1}}$ to obtain positive trade flows is satisfied (Melitz and Redding, 2015)); $A_n = f_{n,i} \cdot l$ with $l \sim LN(0, 1)$ for sector 26 and $l \sim 1000LN(0, 1)$ for sector 28. In this way we make all the characteristics associated with the destination market random.

4. We compute the export cutoff productivity $y^*_{n,i}$ using (5) together with trade flows from i to n as well as their extensive and intensive margins.[31]

5. We introduce different productivity shocks to country i and compute the implied changes in total exports from i and n, as well as the associated adjustments at the extensive and intensive margins.

6. We replicate the above five steps $10,000$ times randomizing over the trade costs ($f_{n,i}$ and $\tau_{n,i}$) and the demand shifter (A_n), while keeping all other parameters constant. In other words, we replicate the same industrial structure and the same productivity shocks under different conditions in the export market.[32]

7. We compute the average variation across the replications. The outcome can be considered as the average effect of the productivity shocks across different (randomized) destination markets.

[Table 16 about here.]

8.2 Simulation Results

We perform two types of exercises. First, to learn about the implications of shocking different distribution parameters, we separately let μ_i, σ_i and $y_{H,i}$ increase by 1% with respect to the estimated $\hat{\mu}_{\chi}$, $\hat{\sigma}_{\chi}$ and $\hat{y}$. Second, to see whether identical increases in average productivity have

[31] See Appendix D for additional details.

[32] We only consider simulations for which the extensive margin is strictly positive (between 0.05 and 0.95) in order to isolate the effects of productivity shocks on trade from the effects on potential market selection.

different impacts on trade flows depending on which distribution parameter is shocked, we look into the effects of mean preserving shocks.

8.2.1 Comparative Statics

Before presenting the results, it is useful to clarify what changing different parameters entails. The same percentage variation in μ_i, σ_i or $y_{H,i}$ implies a different transformation in the shape of the Log-normal distribution. Larger μ_i shifts the distribution to the right for given bounds of the support, thus making higher productivity draws more likely. Larger σ_i spreads out the distribution, making both low and high productive draws more likely. Which ones become relatively more likely depends on the specific asymmetry between the lower and upper bounds of the support. Larger $y_{H,i}$ extends the upper bound, thereby advancing the technology frontier. While average productivity (D-1) increases with μ_i and $y_{H,i}$, its relation with σ_i is ambiguous as it depends on the link between the bounds of the support and the thickening of the distribution's tails.[33]

Tables 17 and 18 show the average changes in exports (both in total and by margin) obtained from separately increasing μ_i, σ_i and $y_{H,i}$ by 1% in sectors NACE 26 and 28 respectively. After reporting the associated changes on average productivity, their rows are divided in three panels. Panel A considers all successful replications, while Panels B and C refer to all replications with a pre-shock exporters' share above and below the median value of about 50% respectively.

As for the columns, Case (1) is about a 1% increase in μ_i, which approximately corresponds to a 0.3% increase in average TFP in both sectors. This shock leads to average increases in exports of 1% in sector 26 and 0.7% in sector 28 (Panel A). Both margins react, though the extensive margin reacts more and this asymmetry is mostly due to the replications with a pre-shock exporters' share below 50% (Panel C vs. B). Case (2) concerns a 1% increase in σ_i. In contrast with case (1), in Panel A average TFP decreases by about 0.1% and 0.5% in sectors 26 and 28 respectively.[34] Also exports decrease at both the extensive and intensive margins, with the former reacting more. Exports actually increase (though only slightly) at the intensive margin for the replications with a pre-shock exporters' share below 50% (Panel C). Trade falls because, given the estimated bounds of the productivity support, increased dispersion makes it relatively more likely to observe low productive firms on the left tail with export volumes. Finally, case (3) refers to a 1% increase in $y_{H,i}$. This shock raises the average productivity by 4% and 5% in sectors 26 and 28 respectively (Panel A). Once more, exports increase more at the extensive than at the intensive margins (Panel A). This outcome is driven by the replications with exporters' share below 50% (Panel C) as for the others the adjustment at the intensive margin dominates (Panel B).

In all the cases, the rise in trade determined by the same growth in productivity is decreasing in the pre-shock exporters' share as the expansion at the intensive margin does not compensate for the limited scope for further expansion at the extensive margin.

[Table 17 about here.]

[Table 18 about here.]

For comparison, we repeat the same exercise for the bounded Pareto. Focusing on sector 26 for parsimony, we consider a productivity distribution for Italian firms with initial parameter

[33] See Appendix D for additional details.

[34] That average TFP falls depends on the selected sectors and year. For example, if we considered sector 28 in 2007, we would have $\widehat{S}_{LN} = [\mu_i = -1.69, \sigma_i = 0.45, y_{L,i} = 0.04, y_{H,i} = 0.72]$, and a 1% increase in σ_i would lead to a 0.6% increase inaverage productivity.

values $k_i = 3.88$, $y_{L,i} = 2.73$ and $y_{H,i} = 11.13$. Holding all other parameters constant, we investigate two cases: (1) a 1% increase in the shape parameter k_i, and (2) a 1% increase in the support's upper bound $y_{H,i}$. Table 19 reports the results of the corresponding simulations. In Case (1), a 1% increase in k_i is associated with 0.27% and 1.3% average reductions in productivity and total trade respectively. As with the Log-normal, the reduction in total trade is larger if the initial share of exporters is below 50% (Panel C). Conversely, if the share is above 50%, total trade increases (Panel B). In both situations, changes are positive at the intensive margin and negative at the extensive margin given that larger k_i implies a smaller share of exporters with higher productivity. In Case (2), an increase in the upper bound $y_{H,i}$ leads to 0.034% and 0.6% increases in productivity and total trade respectively. As the initial share of exporters rises above 50%, the adjustment at the intensive margin becomes dominant, but the increase in total trade gets smaller (Panel B and C).

[Table 19 about here.]

8.2.2 Mean Equivalent Shocks

The above simulation exercises shed light on the reactions of productivity and trade flows to the same percentage increase of the different distribution parameters. This is informative in terms of comparative statics, but it is hard to gain any additional insight by comparing the outcomes of the different shocks as these do not have a common metric.

To make progress on this front, we now restrict our attention to shocks that still originate from changes in different parameters, but cause the same common increase in average productivity. In particular, for the Log-normal, we focus on changes in μ_i, σ_i, or $y_{H,i}$ that generate the same 1% increase in average TFP. We then investigate whether the reactions of trade flows vary depending on the specific parameter we shock. In other words, we want to answer the following question: is the response of exports indifferent to the source of average productivity growth?

To compute the changes in μ_i, σ_i or $y_{H,i}$ leading to a 1% increase in average productivity, we consider the latter's total differential. For example, to recover the change in μ_i generating 1% TFP growth, we use the following approximation:

$$\frac{\Delta E(y)}{E(y)} = \frac{\partial E(y)}{\partial \mu_i}\frac{\Delta \mu_i}{E(y)} + \tilde{o} = 0.01$$

or equivalently

$$\frac{\partial E(y)}{\partial \mu_i}\frac{\mu_i}{E(y)}\frac{\Delta \mu}{\mu_i} + \tilde{o} = 0.01$$

where $E(y)$ refers to expression (D-1) in Appendix D. As $\tilde{o} \approx 0$ holds for small productivity changes, we can then rewrite

$$\Delta \mu = 0.01 * \mu \left(\eta(LN)_{y,\mu}\right)^{-1}$$

with $\eta(LN)_{y,\mu} \equiv \partial \ln E(y)/\partial \ln \mu_i$.[35]

Table 20 reports the simulation results for sector 26 and shows that the effects of a 1% increase in average TFP indeed vary depending on the origin of the shock. In particular, to produce a 1% increase in productivity, μ_i has to increase by 2.9%, while σ_i has to decrease by 5.4%. In both cases, exports rise on average by 2.5% (Panel A) and the contribution of the extensive margin is more important than the contribution of the intensive margin, which

[35] We apply the same approach to compute the variations in σ_i and $y_{H,i}$ that increase TFP by 1%. The derivatives of average productivity with respect to these parameters can be obtained from Appendix A. In particular, the elasticity of (D-1) is equal to the elasticity of the intensive margin with $\beta = 1$ after substituting the cutoff y^* with the lower bound y_L.

is almost negligible if the pre-shock exporters' share is below 50% (Panels B vs. C). These outcomes can be better appreciated by looking at Figure 4. The figure is drawn for sector 26 and shows that, as the pre-shock exporters' share increases, the rise in exports due to a 1% increase in average productivity is less pronounced (green line). At the same time, the increase in the extensive margin shrinks (orange line) while that of the intensive expands (blue line) but not enough to compensate. Similar considerations can be made on sector 28 (see Table 21).

Turning to the upper bound, to obtain 1% productivity growth in sector 26, $y_{H,i}$ has to rise by 1.6%. The associated increase in exports is 6.5%, which is much larger than the increases computed for the changes in σ_i and μ_i. As before, the smaller the pre-shock exporters' share, the larger the rise in exports and the bigger the role of the intensive margin (Panels B vs. C). Similar patterns can be observed for sector 28 (see Table 21).

Overall, the simulation results highlight that identical increases in average productivity can result in very different increases in exports depending on the exact parameters (and the associated moments) of the productivity distribution that generate the increases in average TFP. In particular, exports rise more if, for a given increase in average productivity, the density on the upper tail grows.

[Figure 4 about here.]

[Table 20 about here.]

[Table 21 about here.]

We conclude by investigating the effects of mean equivalent shocks to productivity for the bounded Pareto. We again focus on sector 26 for parsimony and consider the same initial parameter values as in the previous section ($k_i = 3.88$, $y_{L,i} = 2.73$, $y_{H,i} = 11.13$). Table 22 reports simulation results for a 1% increase in average TFP, which is achieved by either (1) a 3.90% reduction in k_i or (2) a 57.9% rise in $y_{H,i}$. While both shocks increase total trade, the latter has a stronger impact (17.8% vs. 9.6%) through a larger adjustment of the intensive margin that more than compensates the smaller response of the extensive margin. Compared with the Log-normal finding in Table 20, the increase in $y_{H,i}$ generates a larger increase in total trade. However, a 1% growth in average productivity is achieved through a much larger increase in the upper bound (58% vs. 1.6%). For both shocks, the growth in total trade is smaller when the initial share of exporters is above 50%. The simulations for bounded Pareto confirm that identical changes in average TFP can have different effects on total exports depending on how the shocks at their origin affect the higher moments of the productivity distribution.

[Table 22 about here.]

9 Conclusion

Understanding producers' selection into exporting and its consequences for micro-founded gravity estimation calls for an in-depth analysis of the interplay between aggregate exports and the distribution of producers' productivity. Yet, knowledge about such interplay is still rather limited from both a theoretical and an empirical standpoints.

We have furthered this knowledge by studying how different moments of the distribution of producers' productivity affect the trade elasticity, and in turn how shocks that alter those moments in different ways have different impacts on aggregate exports.

We have shown that, in order to obtain an unbiased of that elasticity, gravity regressions have to account not only for the share of producers that export, but also for their productivity premium relative to all producers. The smaller the former and the larger the latter, the more aggregate exports are driven by few overperforming ‘superstar exporters’.

Our empirical findings show that taking into full consideration the occurrence of ‘superstar exporters’ is crucial if one wants to correctly explain and predict the response of aggregate exports to shocks changing the distribution of producers’ productivity in diffferent ways.

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A Elasticity

In this section, we derive the elasticity of trade flows w.r.t. to distance (trade elasticity) and w.r.t distribution's parameters (Pareto and Log-normal). In doing that, we disentangle the trade elasticity between extensive and intensive margin.

To calculate elasticities, we start from the formula of the generalized gravity model of trade as in Eq. 11, assuming an upper truncation y_H in the productivity distribution, i.e., [36]

$$X_{ni} = \left(\frac{\varepsilon}{\varepsilon-1}\right)^{1-\varepsilon} (m_i)^{1-\varepsilon} M_i^e (\tau_{ni})^{1-\varepsilon} \; A_n s^x_{ni} \ddot{y}_{ni},$$

where $s^x_{ni} = Pr(y > y^*_{n,i})$ and $\ddot{y}_{ni} = E\left[Y^{\varepsilon-1} \mid y^* \leq Y \leq y_H\right]$ are the bilateral elements which define the extensive and intensive margin of trade, respectively. The functional form for the the share of exporting firms (s^x_{ni}) and the $(\varepsilon-1)$-th moment of exporters productivity ($\ddot{y}_{ni}$) will depend on the assumption on productivity distribution. We can demonstrate that bilateral trade elasticity arises also assuming Pareto distribution with an upper truncation (Bas et al., 2017). In addition, the elasticity formula are used in the counterfactual simulation described in Section xxx. [37]

We can write the elasticity η with respect to a generic distribution parameter v or iceberg trade cost τ as follows

$$\eta^{X,v}_{ni} = \frac{\partial X}{\partial v}\frac{v}{X} \quad = \quad \frac{\partial s^x_{ni}}{\partial v}\frac{v}{s^x_{ni}} + \frac{\partial \ddot{y}_{ni}}{\partial v}\frac{v}{\ddot{y}_{ni}} = \eta^{EM,v}_{ni} + \frac{\partial \ddot{y}_{ni}}{\partial v}\frac{v}{\ddot{y}_{ni}} \tag{A-1}$$

$$\eta^{X,\tau}_{ni} = \frac{\partial X}{\partial \tau}\frac{\tau}{X} \quad = \quad \frac{\partial s^x_{ni}}{\partial \tau}\frac{v}{s^x_{ni}} + \frac{\partial \ddot{y}_{ni}}{\partial \tau}\frac{\tau}{\ddot{y}_{ni}} + (1-\varepsilon) = \eta^{EM,\tau}_{ni} + \underbrace{\frac{\partial \ddot{y}_{ni}}{\partial v}\frac{v}{\ddot{y}_{ni}} + (1-\varepsilon)}_{\eta^{IM,\tau}_{ni}} \tag{A-2}$$

where $\eta^{EM,\cdot}_{ni}$ and $\eta^{EM,\cdot}_{ni}$ are the bilateral elasticities for the extensive (EM) and intensive (IM) margin. Depending on the productivity distribution, the functional form of EM and IM will vary.

Pareto - Assuming that productivity is distributed as a double truncated Pareto, the extensive margin EM (share of exporting firms) is defined as the probability to observe a value of y above the productivity cutoff y^*, i.e.

$$EM(P)_{ni} = s^x = Pr(Y > y^*_{ni}) = \frac{\left(\frac{y_L}{y^*}\right)^k - \left(\frac{y_L}{y_H}\right)^k}{1 - \left(\frac{y_L}{y_H}\right)^k}, \tag{A-3}$$

where y_L and y_H are the lower and the upper bound of the distribution, respectively. If we divide total export (Eq. 11) by the number of exporters, the intensive margin (IM) of trade is defined as follows

$$IM(P)_{ni} = X_{ni}/(M_i^e * s^x_{ni}) = \Gamma\tau^{1-\varepsilon}\ddot{y}_{ni} = \Gamma\tau^{1-\varepsilon}_{ni}\frac{k_i}{k_i-\varepsilon+1} y^{*(\beta)} \left(\frac{1-\frac{y^{*(k_i-\beta)}}{y_H^{k_i-\beta}}}{1-\frac{y^{*(k_i)}}{y_H^{k_i}}}\right), \tag{A-4}$$

where $\Gamma = \left(\frac{\varepsilon}{\varepsilon-1}\right)^{1-\varepsilon} (m_i)^{1-\varepsilon} A_n$ and $\beta = \varepsilon - 1$.

[36] We could derive the same elasticities using Eq. 11 and applying Pareto or LogNormal to Θ_i and S^{-1}_{ni}.

[37] More precisely, the derivative of $\ddot{y}_{ni}$ allows us to compute the total differential of the average productivity, so that we can calculate the variation in the distribution parameters (by approximation) that produces an $x\%$ variation in the average productivity.

Log-normal - Using the same definition of margins as in Eq. A-3 and Eq. A-4, the trade margins assuming double truncated Log-normal are

$$EM(LN)_{ni} = \frac{\Phi(y_{H0}) - \Phi(y_0^*)}{\Phi(y_{H0}) - \Phi(y_{L0})} \tag{A-5}$$

$$IM(LN)_{ni} = \Gamma\tau^{1-\varepsilon} e^{\beta\mu_i + \frac{1}{2}\beta^2\sigma_i^2} \frac{\Phi\left(\beta\sigma_i - y_0^*\right) - \Phi\left(\beta\sigma_i - y_{H0}\right)}{\Phi\left(y_{H0}\right) - \Phi\left(y_0^*\right)} \tag{A-6}$$

where Φ is the cdf of a standard normal, and $\Phi(x_0) = \Phi(\frac{ln(x)-\mu}{\sigma})$ with $x = y_H,\ y_L,\ y_{ni}^*$.

A.1 Trade Elasticity - Pareto

To calculate the trade elasticity, we start from the definition of productivity cutoff (Eq. 5) where $y_{ni}^* = r\tau_{ni}$: we plug the cutoff in Eq. A-3 and we compute the derivative with respect to τ. [38] Assuming Pareto distribution, we obtain the extensive margin elasticity, i.e.,

$$\eta(P)_{ni}^{EM,\tau} = -k\frac{y_H^k}{y_H^k - y_{ni}^{*k}}. \tag{A-7}$$

Similarly, we take the derivative of Eq. A-4 with respect to τ to compute intensive margin elasticity

$$\eta(P)_{ni}^{IM,\tau} = k\frac{y_{ni}^{*k}}{y_H^k - y_{ni}^{*k}} - (k-\beta)\frac{y_{ni}^{*k-\beta}}{y_H^{k-\beta} - y_{ni}^{*k-\beta}}, \tag{A-8}$$

where $\beta = \varepsilon - 1$. Notice that, Eq. A-8 is positive if k is large enough. Using Eq. A-2 and combining Eq. A-7 with Eq. A-8, the trade elasticity is defined as follows,

$$\boxed{\eta(P)_{ni}^{\tau} = \eta(P)_{ni}^{EM,\tau} + \eta(P)_{ni}^{IM,\tau} = -k - (k-\varepsilon+1)\left(\frac{y_{ni}^{*k-\varepsilon+1}}{y_H^{k-\varepsilon+1} - y_{ni}^{*k-\varepsilon+1}}\right).} \tag{A-9}$$

The first term of Eq. A-8 simplifies with Eq. A-7 and become $-k$: the reduction in the extensive margin due to an increase in trade cost is partially compensated by an increase in the average exports of surviving firms (due to less competition). This reduction is independent on the bilateral cutoff y_{ni}^*. However, an increase in trade cost reduces exports in function of the distance between the upper truncation (technology frontier) and the cut-off: the smaller the distance (denominator Eq. A-9) the larger is the reduction in trade. In other words, if the cut-off for destination n is relatively high compared to technological frontier in country i, an increase in trade costs will reduce export by a larger amount compared to a situation where the export activity is much more feasible for a larger share of domestic firms. Thus, trade elasticity varies across destinations even if we assume Pareto distribution; conversely, untruncated Pareto generates a constant trade elasticity, i.e., $y_H \to \infty$ then $\eta_{x,\tau} = -k$ (Bas et al., 2017; Chaney, 2008).

A.2 Parameter Elasticity - Pareto

In this section, we define the elasticity of trade with respect of Pareto parameters. Using Eq. A-1, we start to compute the elasticity with respect to parameter k. We begin from the extensive

[38] From Eq. 5, we observe that $r^{-1} = \frac{\varepsilon-1}{\varepsilon}\frac{1}{(f_{ni})^{\frac{1}{\varepsilon-1}}}\left(\frac{1}{m_i}\right)^{\frac{\chi}{\varepsilon-1}+1}\left(\frac{1}{m_n}\right)^{\frac{1-\chi}{\varepsilon-1}}\left(\frac{A_n}{\varepsilon}\right)^{\frac{1}{\varepsilon-1}}$. Thus $\frac{\partial y^*}{\partial \tau}\frac{\tau}{y^*} = 1$

margin elasticity (Eq. A-3) , i.e.,

$$\eta(P)_{ni}^{EM,k} = \frac{\partial s_{ni}^{x}}{\partial k}\frac{k}{s_{ni}^{x}} = k\left[\frac{\overline{y}^{*k} ln(\overline{y}^{*}) - \overline{y}_{H}^{k} ln(\overline{y}_{H})}{\overline{y}^{*k} - \overline{y}_{H}^{k}} + \frac{\overline{y}_{H}^{k} ln(\overline{y}_{H})}{1-\overline{y}_{H}^{k}}\right], \tag{A-10}$$

where $\overline{y^{*}} = y_L/y_{ni}^{*}$ and $\overline{y_H} = y_L/y_H$. Then, we define the elasticity of the $(\varepsilon-1)$-th moment of exporters productivity $(\ddot{y}_{ni})$ as follows,

$$\frac{\partial \ddot{y}_{ni}^{*}}{\partial k}\frac{k}{\ddot{y}_{ni}^{*}} = k\left[-\frac{\beta}{k-\beta} + \frac{y_{ni}^{*k-\beta}}{y_{H}^{k-\beta} - y_{ni}^{*k-\beta}} ln\left(y_H/y_{ni}^{*}\right) - \frac{y_{ni}^{*k}}{y_{H}^{k} - y_{ni}^{*k}} ln\left(y_H/y_{ni}^{*}\right)\right]. \tag{A-11}$$

with $\beta = \varepsilon - 1$. Combining Eq. A-10 and Eq. A-11, we obtain export elasticity with respect to dispersion parameter k,

$$\boxed{\eta(P)_{ni}^{X,k} = k\left[\frac{\overline{y}^{*k} ln(\overline{y}^{*})(1-\overline{y}_{H}^{k}) - \overline{y}_{H}^{k} ln(\overline{y}_{H})(1-\overline{y}^{*k})}{(\overline{y}^{*k} - \overline{y}_{H}^{k})(1-\overline{y}_{H}^{k})} - \frac{\beta}{k-\beta} + \frac{y_{ni}^{*k-\beta} y_{H}^{k-\beta}(y_{H}^{k} - y_{ni}^{*k})}{(y_{H}^{k-\beta} - y_{ni}^{*k-\beta})(y_{H}^{k} - y_{ni}^{*k})} ln\left(y_H/y_{ni}^{*}\right)\right]} \tag{A-12}$$

Using the same approach, we define the trade elasticity versus the upper truncation y_H, namely the technology frontier. First, we provide the formula for the extensive margin

$$\eta(P)_{ni}^{EM,y_H} = \frac{\partial s_{ni}^{x}}{\partial y_H}\frac{y_H}{s_{ni}^{x}} = k\left[\frac{(y_{ni}^{*k} - y_{L}^{k})y_{H}^{k}}{(y_{H}^{k} - y_{ni}^{*k})(y_{H}^{k} - y_{L}^{k})}\right]. \tag{A-13}$$

Second, we derive the elasticity of the $(\varepsilon-1)$-th moment of exporters productivity

$$\frac{\partial \ddot{y}_{ni}^{*}}{\partial y_H}\frac{y_H}{\ddot{y}_{ni}^{*}} = (k-\beta)\frac{y_{ni}^{*k-\beta}}{y_{H}^{k-\beta} - y_{ni}^{*k-\beta}} - k\frac{y_{ni}^{*k}}{y_{H}^{k} - y_{ni}^{*k}}, \tag{A-14}$$

where with $\beta = \varepsilon - 1$. Combining Eq. A-13 and Eq. A-13, we obtain the elasticity of trade w.r.t. the technology frontier y_H, i.e.,

$$\boxed{\eta(LN)_{ni}^{X,y_H} = (k-\beta)\frac{y_{ni}^{*k-\beta}}{y_{H}^{k-\beta} - y_{ni}^{*k-\beta}} - k\frac{y_{L}^{K}}{y_{H}^{K} - y_{L}^{K}}} \tag{A-15}$$

A.3 Trade Elasticity - Log-Normal

Similarly to the Pareto case, we depart from the definition of productivity cutoff and we plug it in Eq. A-5 and we compute the derivative with respect to τ. Assuming Log-normal distribution, the elasticity of the extensive margin with respect to iceberg trade cost is

$$\eta(LN)_{ni}^{EM,\tau} = -\frac{1}{\sigma}\frac{\phi(y_0^{*})}{\Phi(y_{H0}) - \Phi(y_0^{*})}. \tag{A-16}$$

Similarly, we take the derivative of Eq. A-6 with respect to τ to compute the intensive margin elasticity

$$\eta(LN)_{ni}^{IM,\tau} = (1-\varepsilon) - \frac{1}{\sigma}\left(\frac{\phi(y_0^{*} - \beta\sigma)}{\Phi(y_H - \beta\sigma) - \Phi(y_0^{*} - \beta\sigma)} - \frac{\phi(y_o^{*})}{\Phi(y_{H0}) - \Phi(y_0^{*})}\right), \tag{A-17}$$

where Φ is the cdf of a standard normal, and $\Phi(x_0) = \Phi(\frac{ln(x)-\mu}{\sigma})$ with $x = y_H,\ y_L,\ y_{ni}^{*}$. Combining Eq. A-16 and Eq. A-17, we obtain the bilateral trade elasticity under Log-normal assumption, namely

$$\boxed{\eta(LN)^{\tau}_{ni} = \eta(LN)^{EM,\tau}_{ni} + \eta(LN)^{IM,\tau}_{ni} = (1-\varepsilon) - \frac{1}{\sigma}\left(\frac{\phi(y_0^* - \beta\sigma)}{\Phi(y_H - \beta\sigma) - \Phi(y_0^* - \beta\sigma)}\right).} \tag{A-18}$$

Similarly to Eq. A-9, the trade elasticity of the extensive margin cancels out with the first element of Eq. A-17. Also in this case trade elasticity is bilateral and depend on the cutoff and productivity distribution parameters (Bas et al., 2017).

A.4 Parameter Elasticity - Log-Normal

Finally, we define the elasticity of trade with respect of Log-normal parameters μ σ and y_H.

$$\eta(LN)^{EM\mu}_{ni} = \frac{\partial s^x_{ni}}{\partial \mu}\frac{\mu}{s^x_{ni}} = \frac{\mu}{\sigma}\left(\frac{\phi(y_{H0}) - \phi(y_{L0})}{\Phi(y_{H0}) - \Phi(y_{L0})} - \frac{\phi(y_{H0}) - \phi(y_0^*)}{\Phi(y_{H0}) - \Phi(y_0^*)}\right),$$

$$\frac{\partial \ddot{y}^*_{ni}}{\partial \mu}\frac{\mu}{\ddot{y}^*_{ni}} = \frac{\mu}{\sigma}\left(\beta + \frac{\phi(\beta\sigma - y_0^*) - \phi(\beta\sigma - y_{H0})}{\Phi(\beta\sigma - y_0^*) - \Phi(\beta\sigma - y_{H0})} - \frac{\phi(y_0^*) - \phi(y_{H0})}{\Phi(y_{H0}) - \Phi(y_0^*)}\right)$$

where $\beta = \varepsilon - 1$, $x_0 = \frac{ln(x)-\mu}{\sigma}$ with $x = y_H,\ y_L,\ y^*_{ni}$. Then, trade elasticity w.r.t. μ parameter is

$$\begin{aligned}
\eta(LN)^{X,\mu}_{ni} &= \frac{\partial s^x_{ni}}{\partial \mu}\frac{\mu}{s^x_{ni}} + \frac{\partial \ddot{y}^*_{ni}}{\partial \mu}\frac{\mu}{\ddot{y}^*_{ni}} \\
&= \frac{\mu}{\sigma}\left(\beta + \frac{\phi(y_{H0}) - \phi(y_{L0})}{\Phi(y_{H0}) - \Phi(y_{L0})} + \frac{\phi(\beta\sigma - y_0^*) - \phi(\beta\sigma - y_{H0})}{\Phi(\beta\sigma - y_0^*) - \Phi(\beta\sigma - y_{H0})}\right)
\end{aligned} \tag{A-19}$$

If we consider dispersion parameter σ, the elasticity of the extensive margin and of the $(\varepsilon - 1)$-th moment are respectively

$$\eta(LN)^{EM,\sigma}_{ni} = \frac{\partial s^x_{ni}}{\partial \sigma}\frac{\sigma}{s^x_{ni}} = \left(\frac{y_{H0}\phi(y_{H0}) - y_{L0}\phi(y_{L0})}{\Phi(y_{H0}) - \Phi(y_{L0})} - \frac{y_{H0}\phi(y_{H0}) - y_0^*\phi(y_0^*)}{\Phi(y_{H0}) - \Phi(y_0^*)}\right),$$

$$\frac{\partial \ddot{y}^*_{ni}}{\partial \sigma}\frac{\sigma}{\ddot{y}^*_{ni}} = \sigma^2\beta^2 + \frac{(\beta\sigma^2 + y_0^*)\phi(\beta\sigma - y_0^*) - (\beta\sigma^2 + y_{H0})\phi(\beta\sigma - y_{H0})}{\Phi(\beta\sigma - y_0^*) - \Phi(\beta\sigma - y_{H0})} - \frac{y_0^*\phi(y_0^*) - y_{H0}\phi(y_{H0})}{\Phi(y_{H0}) - \Phi(y_0^*)}$$

Then, trade elasticity w.r.t. σ parameter is

$$\begin{aligned}
\eta(LN)^{X,\sigma}_{ni} &= \frac{\partial s^x_{ni}}{\partial \sigma}\frac{\sigma}{s^x_{ni}} + \frac{\partial \ddot{y}^*_{ni}}{\partial \sigma}\frac{\sigma}{\ddot{y}^*_{ni}} \\
&= \sigma^2\beta^2 + \frac{(\beta\sigma^2 + y_0^*)\phi(\beta\sigma - y_0^*) - (\beta\sigma^2 + y_{H0})\phi(\beta\sigma - y_{H0})}{\Phi(\beta\sigma - y_0^*) - \Phi(\beta\sigma - y_{H0})} + \frac{y_{H0}\phi(y_{H0}) - y_{L0}\phi(y_{L0})}{\Phi(y_{H0}) - \Phi(y_{L0})}
\end{aligned} \tag{A-20}$$

Finally we consider the upper truncation y_H. We compute the elasticity with respect to variations in the technology frontier. The extensive margin elasticity is

$$\eta(LN)^{EM,y_H}_{ni} = \frac{\partial s^x_{ni}}{\partial y_H}\frac{y_H}{s^x_{ni}} = \frac{1}{\sigma}\left(\frac{\phi(y_H)}{\Phi(y_H) - \Phi(y_0^*)} - \frac{\phi(y_H)}{\Phi(y_H) - \Phi(y_L)}\right),$$

while the elasticity of the $(\varepsilon - 1)$-th moment is

$$\frac{\partial \ddot{y}^*_{ni}}{\partial y_H}\frac{y_H}{\ddot{y}^*_{ni}} = \frac{1}{\sigma}\left(\frac{\phi(\beta\sigma - y_H)}{\Phi(\beta\sigma - y_0^*) - \Phi(\beta\sigma - y_H)} - \frac{\phi(y_H))}{\Phi(y_H) - \Phi(y_0^*)}\right).$$

Then, trade elasticity w.r.t. y_H parameter is

$$\begin{aligned}\eta(LN)_{ni}^{X,y_H} &= \frac{\partial s_{ni}^x}{\partial y_H}\frac{y_H}{s_{ni}^x} + \frac{\partial \ddot{y}_{ni}^*}{\partial y_H}\frac{y_H}{\ddot{y}_{ni}^*} \\ &= \frac{y_H}{\sigma}\left(\frac{\phi(\beta\sigma - y_H)}{\Phi(\beta\sigma - y_0^*) - \Phi(\beta\sigma - y_H)} - \frac{\phi(y_H)}{\Phi(y_H) - \Phi(y_L)}\right)\end{aligned} \quad \text{(A-21)}$$

B Data

CompNet - From CompNet database (IVth vintage), we have excluded Austria and Malta because there are not sector level information. We consider in our analysis 21 manufacturing sectors (Nace rev.2 2-digit classification). After excluding Tobacco (12) and Petroleum (19) the sectors included in the analysis are: Food products (10), Beverages (11), Textile (13), Wearing Apparel (14), Leather (15) Wood and products of wood and cork except furniture (16), Paper and paper products (17), Printing and reproduction of record media (18), Chemicals and pharmaceutical products (20), Basic pharmaceutical products (21), Rubber and plastic products (22), Other non metallic and mineral products (23), Basic metals (24), Fabricated metal products, except machinery and equipment (25), Computer electronic and optical products (26), Electrical equipment (27), Machinery and equipment n.e.c. (28), Motor vehicles trailers and semitrailers (29), Other transport equipment (30), Furniture (31), and other manufacturing (32).

TFP in CompNet is a residual of a value added-based Cobb-Douglas production function with Hicks-neutral technical change and the estimation relies on the proxy variable approach (Levinsohn and Petrin, 2003; Olley and Pakes, 1996) and the Wooldridge methodology (Wooldridge, 2009). [39] Each production function is estimated at country-sector level and includes year dummies. Given that the dependent variable is the value added deflated with sectoral deflators, the estimated TFP is a "revenue based" indicator of efficiency and not a pure measure of technical efficiency.

We clean CompNet data as follows. We eliminate country-sector-year cells for which the underlying sample size is smaller than 10 firms. We also eliminate extreme observations that are identified in the following way: we compute a coefficient of deviation (CoD) using the 10^{th} and the 90^{th} percentile of TFP distribution (i.e. $CoD = \frac{TFP_{p90} - TFPp10}{TFP_{p90} + TFPp10}$) and we drop observations with a value of CoD above the 99^{th} or below the 1^{st} percentile. As a result, the empirical analysis is based on an unbalanced sample of 3,131 observations disaggregated at the level of country, year, and manufacturing sectors. The sample is unbalanced because some CompNet countries report missing observations.[40]

C Methodology

C.1 Omitted variable bias: exporters heterogeneity $\widetilde{y}_{ni}^*$

We can think to estimate a simplified version of gravity model (Eq. 16), i.e.,

$$x_{ni} = \gamma \ln dist_{ni} + \delta_y \widetilde{y}_{ni}^* + w_{ni} + \eta_{ni}, \quad \text{(C-1)}$$

where δ_y is the direct effect of exporters' heterogeneity on trade. However, if we do not observe $\widetilde{y}_{ni}^*$, we would estimate the following model:

[39] For more details see Galuscak and Lizal (2011); Lopez-Garcia, P. and CompNet Task Force (2014).
[40] For example, data start in 2005 for Poland and in 2006 for Portugal.

$$x_{ni} = \gamma \ln dist_{ni} + w_{ni} + u_{ni}. \tag{C-2}$$

The consequence of estimating Eq. C-2 instead of Eq. C-1 is to obtain a biased estimate of γ due to unobserved element $\widetilde{y}^*_{ni}$ embedded in the error term u_{ni}. If $Cov(\ln dist, \widetilde{y}^*_{ni}) \neq 0$, the bias depends on the correlation between distance and exporters' heterogeneity plus the omitted effect of $\widetilde{y}^*_{ni}$ on trade. We could express the missing term as

$$\widetilde{y}^*_{ni} = \delta_{yt} \ln dist_{ni} + \eta(1)_{ni}$$

where the effect of distance on heterogeneity is defined by $\delta_{yt} = Cov(\ln dist, \widetilde{y}^*_{ni})/Var(\ln dist)$. Thus, the OLS estimator of γ in Eq. C-2 would be:

$$\begin{aligned}
\widehat{\gamma} &= \frac{Cov[x, \ln dist]}{Var(\ln dist)} \\
&= \frac{Cov\left[(\gamma \ln dist + \delta_y \widetilde{y}^* + \eta_{ni}), \ln dist\right]}{Var(\ln dist)} \\
&= \underbrace{\frac{Cov(\gamma \ln dist, \ln dist)}{Var(\ln dist)}}_{\gamma \cdot 1} + \frac{Cov(\delta_y \widetilde{y}^*, \ln dist)}{Var(\ln dist)} + \underbrace{\frac{Cov(\eta, \ln dist)}{Var(\ln dist)}}_{=0} \\
&= \gamma + \underbrace{\delta_y \frac{Cov(\widetilde{y}^*, \ln dist)}{Var(\ln dist)}}_{OVB = \delta_y \delta_{yt}}
\end{aligned}$$

where $\frac{Cov(\widetilde{y}^*, \ln dist)}{Var(\ln dist)}$ is the coefficient of a regressions of distance on average exporters' heterogeneity. The sign of the bias will depend on the correlation that exporters' heterogeneity has with total trade and distance. The estimation results suggest a negative bias (see Table 11).

On the one hand, the omitted term $\widetilde{y}^*_{ni}$ is positively correlated with trade flows ($\delta_y > 0$). Once controlled for the share of exporters, we would expect that an increase in the efficiency of exporting firms (compared to producers) will raise the exports, *ceteris paribus*. Independently on the assumption on productivity distribution, the exports are increasing in $\widetilde{y}^*_{ni}$. The estimated coefficient of $\widetilde{y}^*_{ni}$ supports this hypothesis (Table 9).

On the other hand, we may expect both sign for the correlation δ_{yt}. Given that $\widetilde{y}^*_{ni}$ is made by the efficiency of both exporters and producers (numerator and denominator of Eq. 22), the direction of the correlation will depend on how distance relates with these two elements.

First, higher distance allows only firms at the tail of the distribution to be exporters. Given that cutoff is increasing in τ, the covariance between $\ln dist_{ni}$ and $\widetilde{y}^*_{ni}$ is expected positive through the numerator: a higher cutoff raises the average productivity of active exporters as the extensive margin shrinks.

However, high trade cost implies that only the most efficient countries are able to reach far destinations: if $y^*_{ni} > y_{H,i}$ no trade exists from i to n. Then, a large τ might be associated with a large denominator of $\widetilde{y}^*_{ni}$ so that we would observe exports only for the most efficient countries. If technologically advance countries (with high $y_{H,i}$) can reach far markets, the denominator of Eq. 22 dominates and the correlation between distance and exporters' heterogeneity is negative.

We can observe the negative correlation between distance and $\widetilde{y}^*_{ni}$ (i.e., $\delta_{yt} < 0$) from the example reported Figure 6. Assume we have two countries: A, and B which differ in term of technology and markets of destination. In particular country A serves market 1 for which the cutoff point is 2 while country B serves markets 2 where the cutoff is 2.5. Remember that cutoff is linear in distance $\partial y^*/\partial \tau = 1$ (see Eq.5). Firms in country B are more efficient than those ine country A ($\overline{y}_A = 0.89$, $\overline{y}_B = 1.28$). Assuming $\varepsilon = 2$, if A exports to 1 and B exports to the distant market 2, exporters heterogeneity $\widetilde{y}^*_{ni}$ is larger for A (2.73) than B (2.68). Whether, countries similar to A systematically export only to 1 while country as B in both markets we will observe a negative correlation between distance and $\widetilde{y}^*_{ni}$ through country size (denominator).

[Figure 5 about here.]

Data analysis supports the idea of a negative correlation. Table 30 shows the existing correlation of $\ln dist_{ni}$ with both the log of the estimated exporters heterogeneity $\widehat{\widetilde{y}}(s)^*_{nist}$ (C and the estimated bilateral productivity $\widehat{y}_{nist}$ (numerator Eq. 22). Exporters heterogeneity is negatively correlated with distance (Col.(1) to Col.(4)) while (as expected) the bilateral productivity (numerator of Eq.22) is positively correlated with distance.

For this reason, we regress the estimated country efficiency, i.e., the fixed effects $\widehat{I}_{ist}$ from Eq.21 on the the average distance of markets from country i. We compute the trade distance for each sourcing country i as a weighted mean where weights are the share of trade that country i has with country n in a given sector s,

$$Weighted\ Distance_{ist} = \sum_{n}^{N} \frac{Export_{nist}}{Tot.Export_{ist}} Distance_{ni} \tag{C-3}$$

Table 31 shows that it exists a negative correlation between producers productivity and the average distance of destination markets served by country i. Correlations hold also if we control for the average share of exported products by country i. The results are in line with the observed negative bias in the gravity models reported in Table 10. [41]

C.2 Product level estimation

The aim if this section is to provide technical details about product level estimations described in Section 4.2. We assume that each product j (defined at HS 6-digit level) exported from location i can be considered as a single variety produced by a monopolistic competitive firm. We implicitly assume that a each country generates a specific feature for product j, making it a unique variety for which a firm located in country i has some monopolistic power.

Double difference - To obtain robust and unbiased estimates of the markups θ from the micro level export equation, we double difference Eq. 19 in both quantities and export value (Forlani et al., 2016). We aim at eliminating unobserved demand shocks λ and other unobserved factors that might bias the estimates (Arkolakis et al., 2018). First, we difference with respect to the average export per destination to eliminate any systematic correlation between trading partners (constant over time):

$$\Delta_{jni} x_{jnit} = x_{jnit} - \frac{1}{T_{jni}} \sum_{t} x_{jnit}$$

where T_{jni} is the number of positive trade by product-origin-destination; in other word, we compute the average export across year by origin-destination and products. We demean bilateral exports over time to eliminate any constant factors which are countries-product specific.

[41] Similarly in HMR (2008), the impact of trade frictions in the standard gravity equation (without correction) are skewed upwards due to their conflation of the actual impact of these costs (distance, etc,) with their indirect influence on the share of exporting firms

Second, we eliminate idiosyncratic demand shocks by destination. We take a second difference across destination, industry, and time. Industry m includes all HS1996 6-digit products that belong to a given NACE rev.2 3-digit code to eliminate potential correlation of demand shocks across products that belong to the same industry m within the same broad sector s (Nace rev.2 2-digit). Thus, the second difference is

$$\Delta_{mnt}\Delta_{jni}x_{jnit} = \Delta_{jni}x_{jnit} - \frac{1}{I_{jnm}}\sum_{i}\Delta_{jni}x_{jnit},$$

where I_{jnm} is the number of sourcing countries to destination n for product j belonging to industry m. This double difference procedure defines Eq. 20. With the same approach, we difference also selection term ξ_{jnit} derived from Eq. C-5.

The price equation Eq. 21 can be derived in double difference. It is defined as follows

$$\begin{aligned}\Delta_{mnt}\Delta_{jni}\ln p_{jnit} \quad = \quad & \beta_1\Delta_{mnt}\Delta_{jni}\ln q_{jnit} + \beta_2\Delta_{mnt}\Delta_{jni}\ln T_{jnit} + \\ & \Delta_{mnt}\Delta_{jni}\ln q^2_{jnit} + \Delta_{mnt}\Delta_{jni}\ln T^2_{jnit} + \\ & \Delta_{mnt}\Delta_{jni}\ln q_{jnit} * \ln T_{jnit} + \Delta_{mnt}\Delta_{jni}\ln q^2_{jnit} * \ln T^2_{jnit} + \\ & \mathbf{I}_{it} + \Delta_{mnt}\Delta_{jni}\xi_{jnit} + \Delta_{mnt}\Delta_{jni}\eta_{jnit}\end{aligned} \tag{C-4}$$

where ξ_{jnit} is the linear selection term and $\mathbf{I}_{it}$ (not in difference) are the exporting country - time fixed effects.

Micro level selection - The entry probability is estimated using a linear probability model, with $\pi_{jnit} = 1$ if a positive trade flow is observed, otherwise zero, i.e.,

$$\pi_{jnit} = \ln\tau_{nit} + I_{jnt} + I_{jit} + \nu_{jnit} \tag{C-5}$$

where I_{jit} and I_{jnt} are exporter-product-time and importer-product-time fixed effects: they aim at capturing any unobserved asymmetric country-products shocks affecting the probability to observe positive trade flows. The term τ_{nit} is the iceberg trade costs defined as in Eq. 18 (plus religion proximity), and ν_{nijt} is the i.i.d. error term. Selection variable ξ_{jnit} is a linear function of predicted term $\widehat{\pi}_{jnit}$ from the OLS estimates i.e., $\xi_{jnit} = \widehat{\pi}_{jnit} - 1$ (Berman et al., 2019; Olsen, 1980). Linear selection is preferred to non-linear models (probit) and inverse Mill's Ratio due to the large number of parameters and sample size that would make difficult the convergence of maximum likelihood. Results from selection equation are reported in Table 23 in Appendix E.

C.3 Trade Liberalization - Counterfactual

For the counterfactual exercise on trade liberalization, we follow the approach of Helpman et al. (2008). First of all, we assume that unobserved trade cost are not affected by a variation in distance given that we could not observe if a country pair would trade with new trade cost $\ln dist'$. The best estimator for unobserved trade cost is still given by the inverse mills ratio from Eq.24 considering the initial level of distance $\ln dist$.

Thus, if we observe a positive trade flow, i.e., $p_{nit} = 1$, the estimator for the share of exporter $\widehat{z}'$ after a variation in trade cost is given by $\widehat{z}'_{nit} = \Phi(\widehat{\rho}'_{nit}) + \frac{\phi(\widehat{z}_{nit})}{\Phi(\widehat{z}_{nit})}$. We can notice that $\ln dist'$. is used to compute $\widehat{z}'_{nit}$ (control for share of exporter) but not to compute inverse mills ratio (i.e., the selection term that controls for unobserved trade costs). The new value of $\widehat{z}'_{nit}$ and distance $\ln dist'$ (with the old value of IMR and exporters' heterogeneity) can be used to compute changes in trade flows after a variation on trade costs. We could model exporter heterogeneity to account also variation in distance, however we keep it as unaffected to appreciate the effect of the bias in distance parameter γ on a the counterfactual exercise. For each sector s, the overall effect on trade is given by the predicted value of the second stage with the new values, namely:

$$\begin{aligned} x'_{nit} &= \widehat{\lambda}_{it} + \widehat{\chi}_{nt} + \widehat{\gamma'}_1 \ln dist'_{ni} + \widehat{\delta}_2 C.B._{ni} + \widehat{\delta}_3 C.L._{ni} + \widehat{\delta}_4 C.T._{ni} + \\ & \widehat{\delta}_5 RTA_{nit} + \widehat{\beta}_0 IMR_{nit} + \widehat{z'}_{nit} + \widehat{z'^2}_{nit} + \widehat{z'^3}_{nit} + \widehat{\beta}_1 \widetilde{\hat{y}}^*_{nit}. \end{aligned} \quad \text{(C-6)}$$

C.4 Parameters' calculation

In this section we presents details on the calculations of parameters for bounded distributions and the methodology used to compute parameters for the unbounded distributions.

Unbounded distributions - The unbounded Pareto distribution is made up of two parameters, the scale parameter y_L and the shape parameter k. The unbounded Log-normal depends on the parameters μ and σ. In both cases these values can be computed at the country-sector-year level. To this purpose we use two sample moments that we can compute from the data: the sample mean (m) and the sample variance (v). Both sample mean and variance are in function of both parameters (y_L and k for Pareto and μ and σ for Log-normal) so that we can calculate parameters as a solution of a system of two equations in two unknowns. Following Head (2013), the scale and the shape parameters of the unbounded Pareto distribution are defined as follows Head (2013):

$$\begin{aligned} k_u &= 1 + \sqrt{1 + m^2/v} \\ y_L &= m(k-1)/k.. \end{aligned} \quad \text{(C-7)}$$

while in the case of unbounded Log-Normal parameters, we use the following expressions

$$\begin{aligned} \mu_u &= \ln m - \sigma^2/2 \\ \sigma_u &= \sqrt{\ln(m^2 + v) - 2\ln m}. \end{aligned} \quad \text{(C-8)}$$

Alternatively in the case of Log-normal, we could compute μ and σ using the properties of two specific Log-Normal moments, that is the median and *mean-to-median ratio*. More precisely, we know that the median (TFP(P50)) of a Log Normally distributed random variable is equal to e^{μ}, while the *mean-to-median ratio* (a measure of dispersion, Dis) is defined as $e^{\sigma^2/2}$. Taking the logs of the two sample moments, we can derive μ and σ as follows:

$$\ln TFP(P50) = \ln e^{\mu} = \mu \quad \text{(C-9)}$$

$$\ln \frac{mean}{TFP(P50)} = \ln mean - \ln TFP(P50) = \ln e^{\sigma^2/2} = \frac{1}{2}\sigma^2 \quad \text{(C-10)}$$

so that $\mu = \ln TFP(P50)$ and $\sigma = \sqrt{2(\ln mean - \mu)}$. It must be noticed that the two approaches provide parameters that are highly correlated: μ's are correlated at 0.99, while σ's at 0.86.

Bounded distributions - Using the moments of productivity distribution from CompNet we aim to compute parameters which describes a theoretical distribution that could fit with the firms' observed productivity.The systems defined in (28) and (30) do not allow closed form solutions. We need to compute two vectors of parameters $S_P^o = [k^o, y_L^o, y_H^o]$ and $S_{LN}^o = [\mu^o, \sigma^o, y_L^o, y_H^o]$ which are the solutions for the Pareto and Log-normal systems, respectively. In order to compute parameters, we look for a numerical solution. We apply the same alghortim to solve both systems.

1. We define a system for each country i, sector s, and year t. For each triple $\chi = i, s, t$, we compute the predicted moments $\widehat{\zeta}_{ist}$ using the sample mean m_{ist}, variance v_{ist}, and skewness s_{ist}.

2. With the three predicted moments $\widehat{\zeta}_{ist}$ (and the value of ninety-nineth percentile for Log-normal system), we look for the numerical solutions of systems 28 and 30.

3. The vectors of solutions S_P^o and S_{LN}^o minimize the squared distances η between the predicted moments $\widehat{\zeta}$ and the theoretical moments. For a generic country i, the solutions S_P^o and S_{LN}^o minimize $(e_{P,1}, e_{P,2}, e_{P,3})$ and $(e_{LN,1}, e_{LN,2}, e_{LN,3}, e_{LN,4})$, respectively:

$$\begin{aligned}
\left(\widehat{\zeta(1)}_i - \tfrac{k_i}{k_i-1}\left(y_{L,i}\right)\frac{1-\left(\frac{y_{L,i}}{y_{H,i}}\right)^{(k_i-1)}}{1-\left(\frac{y_{L,i}}{y_{H,i}}\right)^{k_i}}\right)^2 &= e_{P,1}\\
\left(\widehat{\zeta(2)}_i - \tfrac{k_i}{k_i-2}\left(y_{L,i}\right)^2\frac{1-\left(\frac{y_{L,i}}{y_{H,i}}\right)^{(k_i-2)}}{1-\left(\frac{y_{L,i}}{y_{H,i}}\right)^{k_i}}\right)^2 &= e_{P,2}\\
\left(\widehat{\zeta(3)}_i - \tfrac{k_i}{k_i-3}\left(y_{L,i}\right)^3\frac{1-\left(\frac{y_{L,i}}{y_{H,i}}\right)^{(k_i-3)}}{1-\left(\frac{y_{L,i}}{y_{H,i}}\right)^{k_i}}\right)^2 &= e_{P,3}
\end{aligned}$$

$$\begin{aligned}
\left(\widehat{\zeta(1)}_i - e^{(\mu+0.5\sigma^2)}\frac{\Phi(\frac{\ln(y_H)-\mu}{\sigma}-\sigma)-\Phi(\frac{\ln(y_L)-\mu}{\sigma}-\sigma)}{\Phi(y_H)-\Phi(y_L)}\right)^2 &= e_{LN,1}\\
\left(\widehat{\zeta(2)}_i - e^{(2\mu+2\sigma^2)}\frac{\Phi(\frac{\ln(y_H)-\mu}{\sigma}-2\sigma)-\Phi(\frac{\ln(y_L)-\mu}{\sigma}-2\sigma)}{\Phi(\ln(y_H))-\Phi(\ln(y_L))}\right)^2 &= e_{LN,2}\\
\left(\widehat{\zeta(3)}_i - e^{(3\mu+\frac{9}{2}\sigma^2)}\frac{\Phi(\frac{\ln(y_H)-\mu}{\sigma}-3\sigma)-\Phi(\frac{\ln(y_L)-\mu}{\sigma}-3\sigma)}{\Phi(\ln(y_H))-\Phi(\ln(y_L))}\right)^2 &= e_{LN,3}\\
\left(0.90 - \frac{\Phi(\frac{\ln(y_{p90})-\mu}{\sigma})-\Phi(\ln(y_L))}{\Phi(\ln(y_H))-\Phi(\ln(y_L))}\right)^2 &= e_{LN,4}
\end{aligned}$$

where $\Phi(\ln(y))$ is the cdf of a standard normal, i.e., $\Phi(\frac{\ln y-\mu_i}{\sigma_i})$

4. We solve the systems with the optimization functions in Mata environment for Stata using the Davidon–Fletcher–Powell algorithm.

5. The results may be affected by the initial values of parameters. For this reasons, for each country/sector/year observation we randomly select ten different sets of initial values for parameters. We solve each system ten times with different set of initial values each time. Initial parameters value for k, μ, and σ are selected in a neighborhood of the unbounded parameters solutions u (Eq. C-8 and Eq. C-9): e.g., starting value for k=$k_u*(1+\delta)$ where δ is drawn from a uniform in the interval $[-1;+1]$. Staring values for upper and lower bounds (y_L and y_H) are defined in a similar way, i.e., in a neighborhood of the tenth and the ninetieth percentile for the lower and upper bounds, respectively. Therefore, for each

system we can generate potentially ten vectors solutions $S^o(j)$ with $j = [1, .., 10]$. [42]

6. We perform a first selection of the solutions. We do not consider solutions that violate distributions' properties: we eliminate solutions with negative k and σ, solutions with negative lower bound, and solutions with an upper bound smaller than the lower bound.

7. Finally among the realistic solutions we need to select a vectors $S^o(j)$. Among the different vectors j of solutions $S(j)^o_P$ and $S(j)^o_{LN}$, that we can obtain with different starting values for parameters, we select the vector j that generate the smaller (mean) error η, i.e.,

$$\begin{array}{lcr} min \ \ \frac{1}{3}\sum_i^3 e_{P,i} & \rightarrow & S(j)_P[k^o, y_L^o, y_H^o] \\ min \ \ \frac{1}{4}\sum_i^4 e_{LN,i} & \rightarrow & S(j)_{LN}[\mu^o, \sigma^o, y_L^o, y_h^o] \end{array}$$

D Counterfactual Simulation

The expected value of a random variable distributed according to a truncated Log Normal is equal to

$$E\left[Y \mid y_L \leq Y \leq y_H\right] = e^{\mu_i + \frac{1}{2}{}^2\sigma_i^2} \frac{\Phi\left(\sigma_i - \frac{\ln y_L - \mu_i}{\sigma_i}\right) - \Phi\left(\sigma_i - \frac{\ln y_H - \mu_i}{\sigma_i}\right)}{\Phi\left(\frac{\ln y_H - \mu_i}{\sigma_i}\right) - \Phi\left(\frac{\ln y_L - \mu_i}{\sigma_i}\right)} \quad \text{(D-1)}$$

Figure 7 gives us the intuition of a parameter's variation for the Log-normal distribution. We simulate a productivity distribution for 10000 firms and we introduce the three shocks separately. As in the counterfactual simulation, we consider a double truncated Log-normal with the following parameters of sector 26 year 2010 μ=1.57, σ= 0.83, $y_L = 1.32$, $y_H = 6.23$. Differently from the counterfactual simulation, we introduce a 10% shock in order to have a more intuitive graph.

The continuous line represents the baseline distribution, while the dotted curves the new distributions after the shocks. We can notice that an increase in μ shifts the distribution on the right (fatter right tail), while a 10% increase in σ widens the distribution (it is more likely to observe both low and high productive firms). Depending on the truncation points, the average productivity increases or decreases whether it is more likely to observe high productive or low productive firms, respectively. Finally, an increase in the upper bound y_H makes only the right tail longer meaning an upward shift in the technology frontier. [43]

[Figure 6 about here.]

If we assume truncated Pareto distribution, the expected value is defined as

$$E\left[Y \mid y_L \leq Y \leq y_H\right] = e^{\mu_i + \frac{1}{2}{}^2\sigma_i^2} \frac{\Phi\left(\sigma_i - \frac{\ln y_L - \mu_i}{\sigma_i}\right) - \Phi\left(\sigma_i - \frac{\ln y_H - \mu_i}{\sigma_i}\right)}{\Phi\left(\frac{\ln y_H - \mu_i}{\sigma_i}\right) - \Phi\left(\frac{\ln y_L - \mu_i}{\sigma_i}\right)} \quad \text{(D-2)}$$

E Additional Tables

[Table 23 about here.]

[Table 24 about here.]

[42] Notice that we do not reach a solution every time we start computation of a system with a different set of initial values. Algorithm does not necessarily converge.

[43] In these three cases, the sample mean increases by 3.4% with a μ, by -1.6% with σ, and by +6% with y_H.

[Table 25 about here.]

[Table 26 about here.]

[Table 27 about here.]

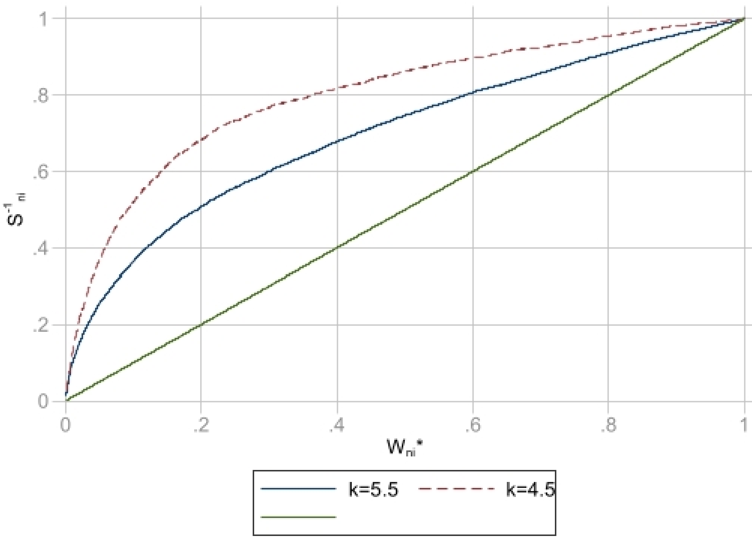
[Table 28 about here.]

[Table 29 about here.]

[Table 30 about here.]

[Table 31 about here.]

(a) Pareto



(b) LogNormal

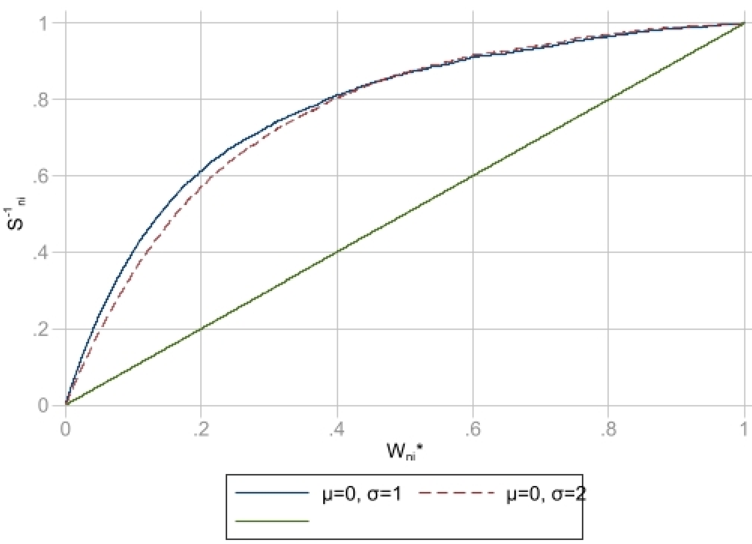


Figure 1: Numerical exercise: S_{ni}^{-1} vs. W_{ni}.

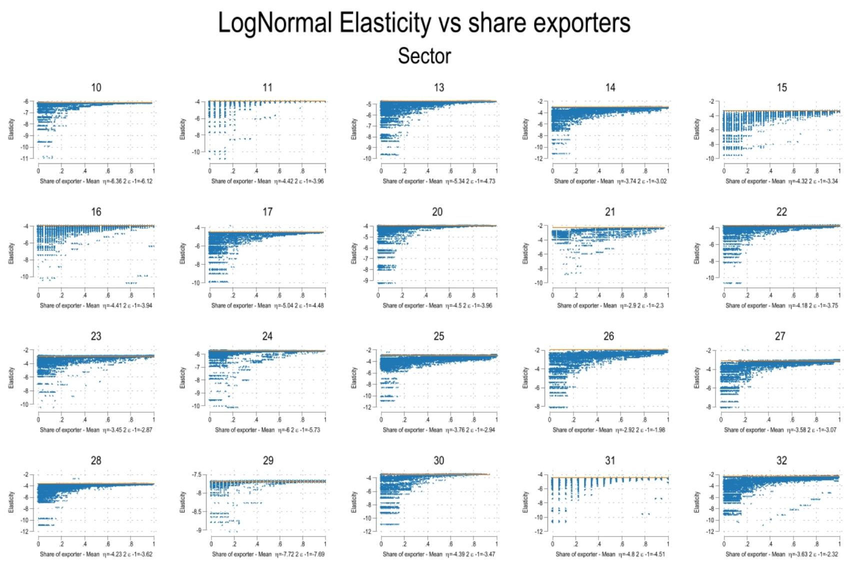


Figure 2: Elasticity

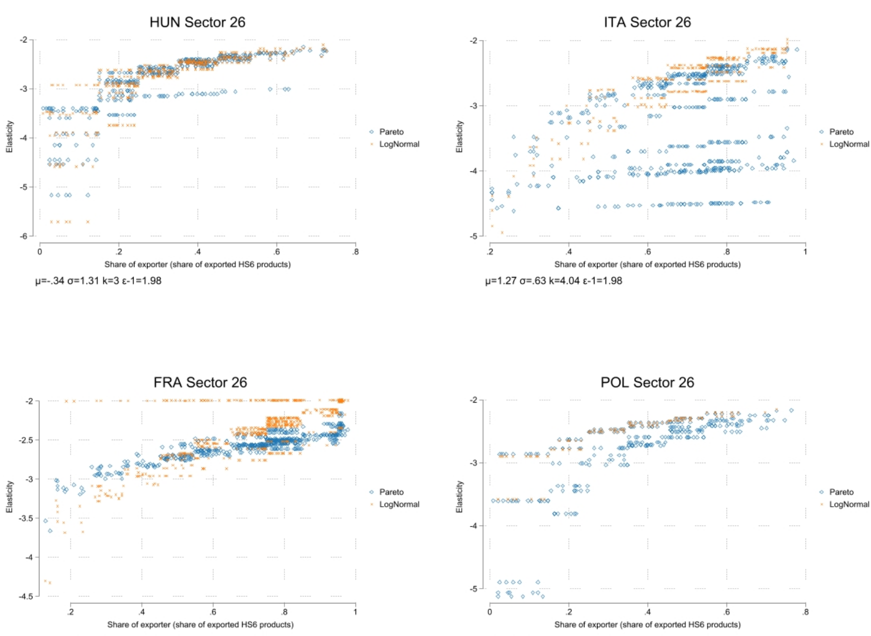
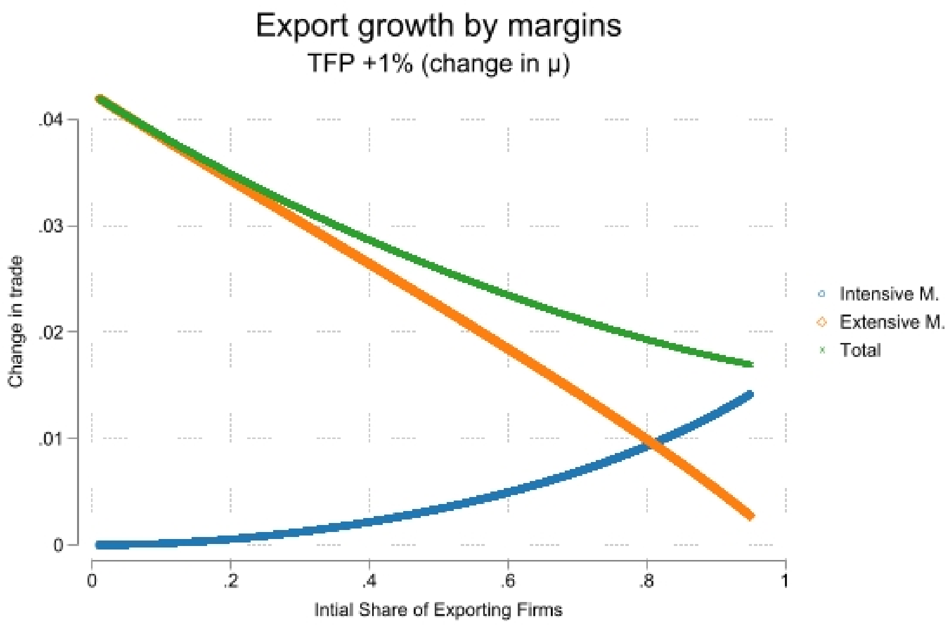


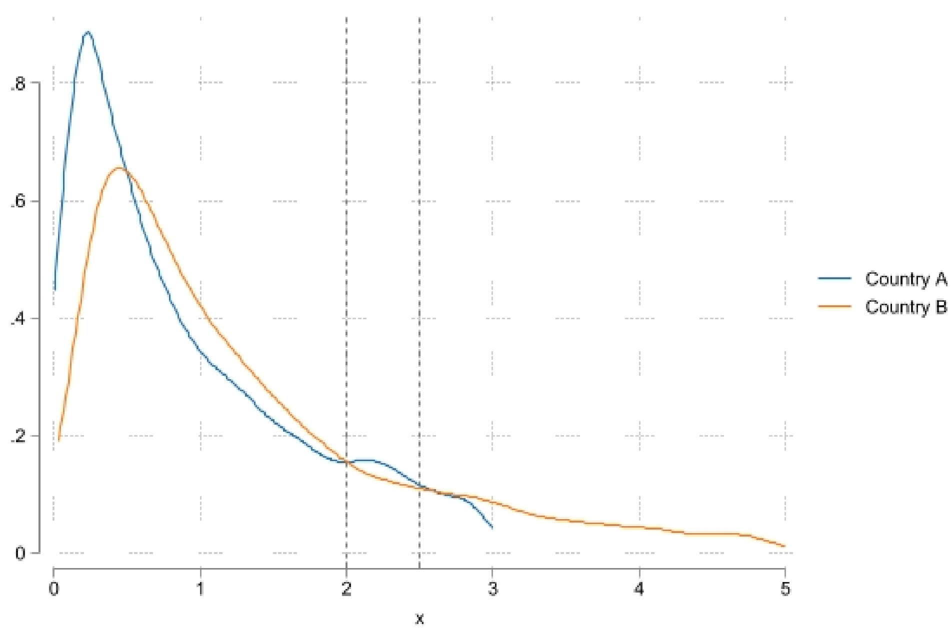
Figure 3: LogNormal and Pareto trade elasticity vs exporters' share

Figure 4: Correlation exporter fixed effects - total exports



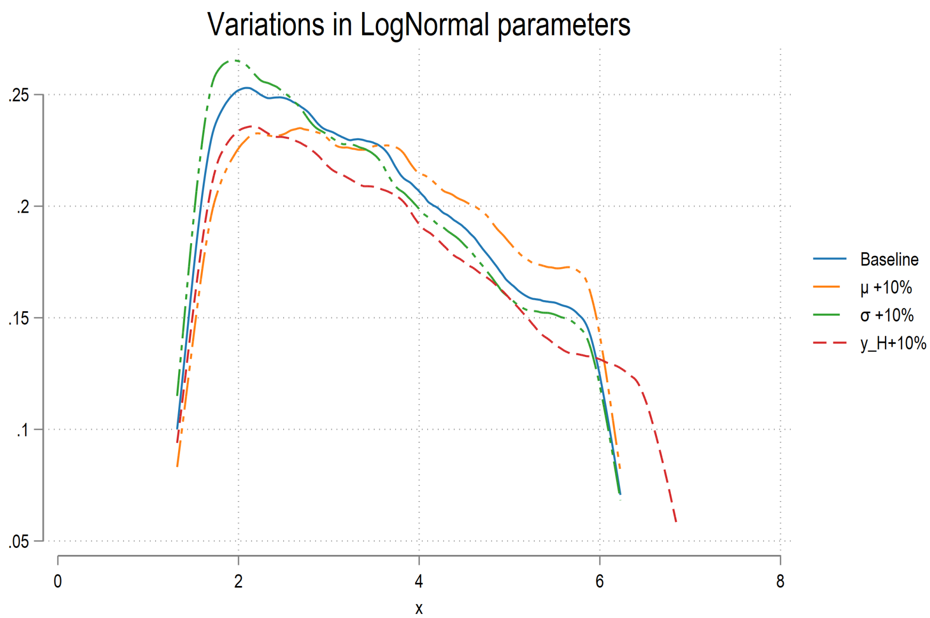
Source: authors' elaborations.

Figure 6: Producers and Exporters Productivity



Country A: $[\mu = 0, \sigma = 1.5, y_L = 0.001, y_H = 3]$. Country B: $[\mu = 0, \sigma = 1, y_L = 0.001, y_H = 5]$. Cutoff $y^*_{A1} = 2$, $y^*_{B2} = 2.5$ $\varepsilon = 2$

Figure 7: TFP distributions: parameters shocks



Productivity distribution simulated for 10000 observations. LogNormal parameters, μ=-1.75, σ=0.46, a=0.04, b=0.65 (Italy, year 2010, sector 28 (NACE rev.2).)

Table 1: Gravity data - Aggregated Level (Sector) [a]

Sector	Log(Export)	Log(Quantity)	Share of positive trade
10	8.770	8.574	0.953
11	5.420	6.220	0.799
12	2.799	3.414	0.482
13	7.766	6.081	0.954
14	7.367	4.549	0.944
15	6.169	3.766	0.890
16	6.141	6.599	0.868
17	6.919	7.136	0.887
18	1.743	0.999	0.415
20	9.110	8.868	0.957
21	6.648	4.299	0.837
22	7.830	6.671	0.943
23	7.080	7.204	0.919
24	8.129	8.403	0.881
25	7.872	6.412	0.945
26	8.831	4.789	0.964
27	8.664	6.350	0.957
28	9.103	6.984	0.962
29	7.826	6.545	0.895
30	7.173	5.220	0.868
31	5.859	5.288	0.856
32	7.685	4.677	0.952
Total	7.041	6.064	0.869

[a] Source: BACI-CEPII. Log (Export): average log of exports (in th euros, fob), by sector. Log (Quantity): average log of exported quantity (in tons), by sector. Share of positive trade: average share of positive trade flows by sector. Sector: NACE rev.2

Table 2: TFP statistics (averages) - CompNet[a]

Country	Mean	St.Dev	Skewness	Median
Belgium	-0.956	10.480	1.650	-1.088
Croatia	-0.546	0.405	1.281	-0.697
Estonia	0.147	0.843	0.915	0.040
Finland	-0.123	4.011	1.439	-0.232
France	-1.529	0.271	1.432	-1.622
Germany	0.003	1.041	1.786	-0.145
Hungary	0.494	1.499	1.843	0.252
Italy	-0.404	0.458	1.675	-0.524
Lithuania	0.876	2.620	1.366	0.688
Poland	0.276	2.038	1.844	0.106
Portugal	0.923	4.982	1.979	0.761
Romania	0.088	1.077	2.082	-0.165
Slovakia	-0.063	1.275	1.953	-0.272
Slovenia	0.311	0.878	1.185	0.199
Spain	-0.197	0.664	2.034	-0.367
Total	-0.103	2.122	1.645	-0.259

[a] Source: CompNet (IVth Vintage). Each column reports the average value by country of a TFP statistic (in log term) computed from micro-level data. Mean: average firms' TFP St.Dev: firms' TFP standard deviation.

Table 3: Sample Size - CompNet[a]

		Number of firms per statistics		
Country	Obs.	Mean	Min	Max
Belgium	200	150.4	15	572
Croatia	92	69.8	11	255
Estonia	154	36.9	11	106
Finland	224	91.7	11	383
France	250	734.0	11	3449
Germany	240	486.1	50	2178
Hungary	189	169.5	14	667
Italy	198	1176.1	210	4152
Lithuania	175	79.4	11	272
Poland	144	410.1	11	1560
Portugal	122	264.6	11	1135
Romania	178	353.2	48	1435
Slovakia	214	73.3	11	281
Slovenia	208	48.1	11	176
Spain	252	435.2	38	1975
Total	2840	327.9	11	4152

[a] Source: CompNet (IVth Vintage). Obs. Number of observations by country. Number of firms per statistics: number of micro-level observations (firms) used to calculate aggregated TFP statistics. Mean: average number of firms per statistics. Min: minimum number of firms per statistics. Max: max number of firms per statistics.

Table 4: Gravity Model - First Stage (2001-2012) [a]

Sector (NACE rev.2)	10	11	12	13	14	15	16	17	18	20	21
$\ln(Dist_{ni})$	-0.912***	-0.895***	-0.929***	-1.370***	-1.003***	-1.020***	-1.088***	-1.193***	-1.157***	-1.135***	-0.868***
	(0.0758)	(0.0434)	(0.0317)	(0.0960)	(0.0707)	(0.0475)	(0.0555)	(0.0551)	(0.0348)	(0.0817)	(0.0415)
$C.L._{ni}$	1.257***	0.526***	0.383***	0.643***	0.888***	0.267**	0.842***	0.673***	0.531***	0.712***	1.150***
	(0.127)	(0.0931)	(0.0563)	(0.144)	(0.147)	(0.105)	(0.0858)	(0.110)	(0.0629)	(0.159)	(0.111)
$C.T._{ni}$		0.204	0.406***			0.818**	0.632***	-0.0978	0.484***		1.087***
		(0.140)	(0.0743)			(0.368)	(0.209)	(0.290)	(0.0818)		(0.171)
$C.B._{ni}$		2.115***	0.458***				0.235		0.796***		0.446***
		(0.479)	(0.0753)				(0.327)		(0.0847)		(0.159)
RTA_{nit}	-0.0192	0.0710	-0.0168	0.558***	0.305***	0.169***	0.132**	0.240***	-0.0685	0.531***	0.151**
	(0.0892)	(0.0509)	(0.0441)	(0.0881)	(0.0982)	(0.0565)	(0.0543)	(0.0599)	(0.0484)	(0.0835)	(0.0620)
$R.P._{ni}$	-0.409***	0.504***	0.236***	-0.293*	0.378***	0.214**	0.111	0.530***	0.462***	0.392***	0.0259
	(0.122)	(0.0951)	(0.0642)	(0.151)	(0.138)	(0.0949)	(0.106)	(0.0963)	(0.0682)	(0.119)	(0.0852)
Cons	9.426***	7.852***	12.38***	13.52***	6.895***	8.801***	9.141***	10.24***	14.78***	10.68***	9.719***
	(0.879)	(0.498)	(0.404)	(1.071)	(0.782)	(0.576)	(0.645)	(0.666)	(0.439)	(0.990)	(0.551)
Obs	7,072	22,911	28,616	7,911	8,872	15,936	19,656	14,271	27,832	6,731	16,915
Pseudo R^2	0.471	0.574	0.511	0.504	0.556	0.585	0.581	0.548	0.57	0.517	0.556
Sector (NACE rev.2)	22	23	24	25	26	27	28	29	30	31	32
$\ln(Dist_{ni})$	-1.158***	-1.193***	-1.129***	-1.022***	-1.029***	-1.247***	-1.222***	-0.937***	-0.961***	-1.138***	-0.917***
	(0.0595)	(0.0609)	(0.0550)	(0.0535)	(0.0836)	(0.0954)	(0.0804)	(0.0562)	(0.0444)	(0.0521)	(0.0795)
$C.L._{ni}$	0.894***	0.759***	1.241***	0.819***	1.294***	1.401***	1.192***	0.795***	0.721***	1.034***	0.817***
	(0.163)	(0.119)	(0.114)	(0.184)	(0.409)	(0.363)	(0.277)	(0.102)	(0.107)	(0.124)	(0.189)
$C.T._{ni}$		0.815*	0.162					0.107	0.584**	0.389	
		(0.469)	(0.281)					(0.170)	(0.264)	(0.328)	
$C.B._{ni}$								1.809***	1.232***		
								(0.440)	(0.348)		
RTA_{nit}	0.387***	0.0949	0.435***	0.342***	0.556***	0.500***	0.665***	0.262***	-0.0593	0.106	0.455***
	(0.0768)	(0.0739)	(0.0608)	(0.0775)	(0.103)	(0.0924)	(0.108)	(0.0669)	(0.0502)	(0.0648)	(0.0900)
$R.P._{ni}$	0.0554	-0.242**	0.0179	0.154	0.654***	0.248	0.514***	0.394***	0.352***	0.0995	0.364***
	(0.124)	(0.102)	(0.103)	(0.121)	(0.165)	(0.159)	(0.144)	(0.107)	(0.0759)	(0.0930)	(0.135)
Cons	8.772***	10.38***	11.89***	9.865***	9.051***	11.38***	12.01***	10.09***	7.876***	8.306***	8.375***
	(0.810)	(0.760)	(0.768)	(0.674)	(0.972)	(1.016)	(1.038)	(0.664)	(0.509)	(0.584)	(0.891)
Obs	9,921	11,141	15,290	8,619	5,235	6,579	4,996	16,187	17,345	18,148	7,007
Pseudo R^2	0.599	0.584	0.594	0.587	0.562	0.625	0.547	0.611	0.546	0.628	0.547

[a] Probit Model. Each column represents a different estimation. Dependent variable is a dummy equal one if it exists a positive trade flows between country-pairs at time t, otherwise zero. Importer-Year and Exporter-Year fixed effects included. *Dist*: distance; *C.L.*: common language; *C.B.*: common border; *C.T.*: colonial ties; *RTA*: regional trade agreement; *R.P.*: reglious proximity. Missing coefficients occur if variables perfectly predicts zeros or ones. Number of reported observations changes across sectors: observations are dropped if zeros or ones are perfectly predicted by origin-year or destination-year fixed effects. Standard errors are clustered at exporter-year level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 5: Elasticity estimation (2001-2012) [a]

Sector (NACE rev.2)	$1/\theta$	S.E.	Obs	R2	θ	ε
10	.859***	(.0015)	1682545	.802	1.17	6.97
11	.798***	(.0037)	159691	.739	1.26	4.87
12	.889***	(.0061)	23921	.802	1.13	8.64
13	.826***	(.0027)	1815950	.721	1.22	5.58
14	.751***	(.0062)	1054493	.595	1.36	3.77
15	.77***	(.0056)	284415	.605	1.31	4.19
16	.797***	(.0032)	314660	.723	1.26	4.88
17	.818***	(.0022)	645814	.776	1.23	5.40
18	.64***	(.0137)	7559	.546	1.58	2.73
20	.798***	(.002)	3064543	.744	1.26	4.87
21	.697***	(.0042)	268048	.488	1.45	3.24
22	.79***	(.0029)	967394	.701	1.27	4.66
23	.742***	(.0026)	920454	.678	1.35	3.82
24	.851***	(.002)	1563562	.806	1.18	6.61
25	.747***	(.0033)	1481124	.625	1.35	3.88
26	.665***	(.0048)	924278	.482	1.55	2.81
27	.754***	(.0036)	1313518	.622	1.34	3.97
28	.784***	(.0022)	2937118	.612	1.29	4.51
29	.885***	(.0025)	534490	.748	1.14	8.33
30	.776***	(.0039)	299075	.566	1.30	4.38
31	.819***	(.0032)	224341	.729	1.23	5.39
32	.699***	(.0045)	702295	.527	1.45	3.21

[a] OLS estimation of equation 20. Estimantion sample inlcudes only observations with positive trade flows $x_{jnit} > 0$. Each row refers to an estimation. Robust standard errors are clustered at exporter-destination level and are reported in parenthesis. Column ε reports the estimated elasticity Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 6: Price equation (2001-2012) [a]

Sector (NACE rev.2)	10	11	12	13	14	15	16	17	18	20	21
$\ln T$	.051***	-4.8e-03	-.044	.099***	.114***	.07***	.032	.065***	.414***	.147***	.313***
	(.009)	(.0203)	(.0437)	(.017)	(.0322)	(.0228)	(.0251)	(.02)	(.1435)	(.0153)	(.0444)
$\ln q$	-.166***	-.142***	-.139***	-.177***	-.147***	-.138***	-.234***	-.253***	-.302***	-.246***	-.246***
	(.0028)	(.0107)	(.0136)	(.0034)	(.0067)	(.0079)	(.0046)	(.0034)	(.034)	(.0027)	(.0086)
$(\ln T)^2$	-.011***	-6.8e-03	.015	-.038***	-.041***	-.026***	-.014	-.023***	-.144**	-.043***	-.061***
	(.0025)	(.0049)	(.01)	(.0056)	(.0107)	(.007)	(.0085)	(.0067)	(.0613)	(.0058)	(.0172)
$(\ln q)^2$	5.2e-03***	-3.4e-04	7.4e-03***	6.8e-03***	9.7e-04	1.6e-03	9.3e-03***	.012***	.01**	8.1e-03***	4.5e-05
	(2.7e-04)	(.0012)	(.0015)	(4.5e-04)	(9.2e-04)	(.0012)	(4.4e-04)	(3.1e-04)	(.0047)	(2.7e-04)	(.0012)
$\ln T \cdot \ln q$	-3.6e-03***	-7.3e-05	4.4e-03	-3.3e-04	3.6e-03	2.4e-03	-1.5e-03	-6.4e-03**	-.028	-.011***	-.044***
	(.0011)	(.0028)	(.0076)	(.002)	(.0033)	(.0038)	(.0038)	(.0026)	(.0299)	(.0017)	(.0067)
$(\ln T \cdot \ln q)^2$	1.3e-04***	2.4e-04***	-2.6e-04	2.2e-04**	7.5e-05	1.3e-04	-9.2e-05	2.3e-04*	-5.0e-05	4.2e-04***	1.3e-03***
	(3.7e-05)	(8.1e-05)	(2.7e-04)	(9.5e-05)	(1.8e-04)	(1.7e-04)	(1.6e-04)	(1.3e-04)	(.0025)	(7.9e-05)	(4.3e-04)
ξ	.373***	.627***	.479***	.502***	.679***	.622***	.351***	.4***	1.31***	.483***	.939***
	(.0136)	(.0321)	(.0636)	(.018)	(.0345)	(.0357)	(.0241)	(.0195)	(.3239)	(.0152)	(.0427)
Obs	1659379	158952	23356	1785642	1038704	282713	312498	642592	7415	3030851	263870
R^2	.696	.711	.836	.653	.62	.593	.704	.683	.551	.745	.72
Sector (NACE rev.2)	22	23	24	25	26	27	28	29	30	31	32
$\ln T$	.121***	.068***	.14***	.056***	.03	.048**	.038**	.035*	3.9e-03	-.069***	.084***
	(.0159)	(.0218)	(.0151)	(.0188)	(.0259)	(.0213)	(.0184)	(.0178)	(.0252)	(.0265)	(.0236)
$\ln q$	-.204***	-.3***	-.216***	-.215***	-.249***	-.191***	-.202***	-.123***	-.154***	-.148***	-.213***
	(.0042)	(.0046)	(.003)	(.0046)	(.0064)	(.0045)	(.0035)	(.0039)	(.0062)	(.0075)	(.008)
$(\ln T)^2$	-.041***	-.027***	-.037***	-.022***	-.017	-.025***	-.01	-.012**	-.015*	9.5e-03	-.038***
	(.0056)	(.0071)	(.0057)	(.0068)	(.011)	(.0078)	(.0076)	(.0058)	(.0083)	(.0088)	(.0096)
$(\ln q)^2$	7.6e-03***	.01***	9.6e-03***	5.8e-03***	5.3e-03***	4.4e-03***	6.0e-03***	5.8e-03***	7.2e-04	2.9e-03***	6.3e-03***
	(5.3e-04)	(4.8e-04)	(2.9e-04)	(5.5e-04)	(8.2e-04)	(6.0e-04)	(4.5e-04)	(3.6e-04)	(7.5e-04)	(8.8e-04)	(.0011)
$\ln T \cdot \ln q$	-2.3e-03	-4.1e-03	-.01***	1.5e-03	-3.7e-03	3.0e-03	7.4e-03***	9.0e-05	-4.3e-03	.013***	4.7e-03
	(.0024)	(.0026)	(.0017)	(.003)	(.0037)	(.0029)	(.0022)	(.0021)	(.0044)	(.0043)	(.0041)
$(\ln T \cdot \ln q)^2$	-4.8e-05	2.8e-04***	1.2e-04*	-4.3e-04***	1.3e-04	-1.7e-04	-5.2e-04***	3.2e-05	2.8e-04	-3.2e-04	-5.3e-04**
	(1.3e-04)	(1.0e-04)	(6.6e-05)	(1.5e-04)	(2.0e-04)	(1.6e-04)	(1.3e-04)	(7.0e-05)	(2.1e-04)	(2.2e-04)	(2.3e-04)
ξ	.46***	.565***	.415***	.564***	1.04***	.646***	.78***	.381***	.836***	.336***	.931***
	(.0176)	(.0192)	(.0172)	(.0214)	(.0302)	(.0206)	(.021)	(.0267)	(.0351)	(.0354)	(.0298)
Obs	965842	915547	1549591	1474381	907642	1309664	2923610	533371	293146	224227	693379
R^2	.556	.76	.802	.658	.658	.64	.538	.526	.75	.494	.734

[a] OLS estimation of price equation 21. Estimantion sample inlcudes only observations with positive trade flows $x_{jnit} > 0$. The estimation includes origin-year and product-destination-year fixed effects. T: bilateral tariff for product j at time t. q: exported quantity j, from i to n at time t. ξ is the linear selection term (see Appendix C.2). Robust standard errors are clustered at origin-destination level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 7: Unit values and exporters heterogeneity[a]

	(1) $\ln(UV_{nist})$	(2) $\ln(UV_{nist})$	(3) $\ln(UV_{nist})$	(4) $\ln(UV_{nist})$	(5) $\ln(UV_{nist})$	(6) $\ln(UV_{nist})$	(7) $\ln(UV_{nist})$	(8) $\ln(UV_{nist})$	(9) $\ln(UV_{nist})$
$\ln \widehat{y}_{nist}$	-.2646***	-.2664***	-.3313***	-.268***	-.2592***	-.2697***	-.2715***	-.3342***	-.2731***
	(.0053)	(.0053)	(.0045)	(.0053)	(.0051)	(.0051)	(.005)	(.0041)	(.0051)
$\ln Dist_{ni}$						.259***	.2588***	.2593***	.2589***
						(.0066)	(.0066)	(.0064)	(.0066)
Cons.	2.239***	2.241***	2.334***	2.243***	2.231***	.1054*	.1097**	.1948***	.1111**
	(.0094)	(.0094)	(.0083)	(.0094)	(.0072)	(.0557)	(.0556)	(.054)	(.0556)
Obs.	516892	516892	516892	516892	516892	516892	516892	516892	516892
R^2	.655	.659	.757	.661	.681	.667	.672	.769	.673
					Fixed Effect				
Origin	✓								
Destination	✓					✓			
Sector	✓	✓				✓	✓		
Year	✓		✓			✓		✓	
Origin x Year		✓		✓			✓		✓
Destination x Year		✓		✓			✓		✓
Sector x Origin			✓					✓	
Sector x Destination			✓					✓	
Sector x Year				✓	✓				✓
Origin x Destination					✓				

[a] Source: OLS estimation from BACI. Each column represents a regression with a different combination of fixed effects. Dependent variable is the log of unit value of exports from i to n for each NACE sector s, i.e., $\ln(UV_{nist}) = \ln\left(\frac{Export_{nist}}{Quantity_{nist}}\right)$. $\widehat{y}_{nist} = \frac{1}{J(s)}\sum_j^J exp(\widehat{y}_{jnist})$ is the average value across products of normalized residuals (numerator of Eq.22). $\ln Dist_{ni}$ the log if distance between country pairs. Standard errors are clustered at exporter-importer level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 8: Country Average Efficiency[a]

	(1) $\ln(exp)_{ist}$	(2) $\ln(exp)_{ist}$	(3) $\ln(exp)_{ist}$	(4) $\ln \widehat{y}_{ist}$	(5) $\ln \widehat{y}_{ist}$	(6) $\ln \widehat{y}_{ist}$
$ln\widehat{I}_{ist}$	2.454***	2.444***	1.267***	.2216***	.2341***	.0677
	(.3862)	(.4016)	(.1688)	(.0665)	(.0687)	(.0633)
Cons.	11.72***	11.73***	12.51***	1.468***	1.46***	1.57***
	(.2552)	(.2654)	(.1115)	(.044)	(.0455)	(.0419)
Obs.	13192	13192	13192	13164	13164	13164
R^2	.8259	.8277	.9824	.5189	.5334	.7145
				Fixed Effects		
Origin	✓	✓		✓	✓	
Sector	✓			✓		
Year	✓		✓	✓		✓
Sector x Year		✓			✓	
Origin x Sector			✓			✓

[a] Source: OLS estimation from BACI. Each column represents a regression with a different combination of fixed effects. Dependent variable in Col. (1) to (3) is $\ln(exp)_{ist}$, the log of total export by sourcing country i Dependent variable in Col (4) to (6), $\widehat{y}_{ist} = \frac{1}{J(s)}\frac{1}{N}\sum_n^N\sum_j^J exp(\widehat{y}_{jnist})$ is the average value across products and destinations of normalized residuals (numerator of Eq.22). $\widehat{I}_{ist}$ are fixed effects from the estimation of Eq.21. Standard errors are clustered at exporter level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 9: Gravity Model - Second Stage (2001-2012) [a]

Sector (Nace 2-digit)	10	11	12	13	14	15	16	17	18	20	21
$\ln(Dist_{ni})$	-1.225***	-1.100***	-1.330***	-1.244***	-1.297***	-1.137***	-1.516***	-1.606***	-1.232***	-1.344***	-0.845***
	(0.0306)	(0.0404)	(0.0788)	(0.0291)	(0.0348)	(0.0326)	(0.0341)	(0.0316)	(0.0542)	(0.0260)	(0.0277)
$C.L._{ni}$	0.227***	0.255***	0.358***	0.366***	0.673***	0.408***	0.460***	0.510***	0.564***	0.165***	0.415***
	(0.0431)	(0.0559)	(0.0805)	(0.0377)	(0.0491)	(0.0511)	(0.0513)	(0.0517)	(0.0676)	(0.0403)	(0.0511)
$C.T._{ni}$	0.641***	0.681***	0.152*	0.445***	0.593***	0.607***	0.708***	0.406***	0.178**	0.504***	0.460***
	(0.0481)	(0.0549)	(0.0916)	(0.0418)	(0.0529)	(0.0517)	(0.0527)	(0.0460)	(0.0710)	(0.0388)	(0.0546)
$C.B._{ni}$	0.741***	1.034***	0.473***	0.276***	0.365***	0.751***	0.396***	0.220***	1.002***	0.373***	0.507***
	(0.0406)	(0.0839)	(0.0896)	(0.0424)	(0.0499)	(0.0576)	(0.0521)	(0.0442)	(0.0742)	(0.0402)	(0.0621)
RTA_{nit}	0.163***	0.105*	0.138*	0.296***	-0.0148	-0.135***	-0.148***	0.00239	-0.220***	0.313***	0.111**
	(0.0493)	(0.0589)	(0.0816)	(0.0397)	(0.0458)	(0.0465)	(0.0520)	(0.0451)	(0.0710)	(0.0406)	(0.0436)
$\widehat{z}_{nit}$	0.197	1.275***	2.337***	1.966***	0.314	1.963***	1.263***	1.830***	1.511***	2.708***	0.806**
	(0.624)	(0.345)	(0.513)	(0.557)	(0.460)	(0.354)	(0.325)	(0.399)	(0.356)	(0.646)	(0.357)
$\widehat{z}^2_{nit}$	0.244	-0.195*	-0.555***	-0.476***	0.0334	-0.512***	-0.122	-0.361***	-0.382***	-0.665***	-0.0143
	(0.204)	(0.110)	(0.180)	(0.172)	(0.147)	(0.114)	(0.101)	(0.124)	(0.126)	(0.197)	(0.115)
$\widehat{z}^3_{nit}$	-0.0426**	0.00909	0.0397**	0.0407**	-0.00711	0.0465***	-0.00518	0.0250**	0.0332**	0.0554***	-0.0163
	(0.0204)	(0.0110)	(0.0194)	(0.0166)	(0.0147)	(0.0115)	(0.00982)	(0.0120)	(0.0139)	(0.0189)	(0.0118)
IMR_{nit}	1.086***	1.358***	1.605***	1.227***	0.914***	1.673***	1.621***	1.583***	1.610***	2.378***	1.139***
	(0.254)	(0.137)	(0.179)	(0.278)	(0.226)	(0.166)	(0.145)	(0.168)	(0.118)	(0.330)	(0.158)
$\ln\widehat{\widehat{y}}(s)^*_{nit}$	0.0400***	0.0412***	0.0641***	0.0691***	0.0634***	0.105***	0.0551***	0.0585***	0.0759***	0.0661***	0.107***
	(0.00281)	(0.00510)	(0.00409)	(0.00304)	(0.00450)	(0.00529)	(0.00449)	(0.00398)	(0.00961)	(0.00318)	(0.00644)
Obs.	27,997	22,672	14,006	27,914	27,610	25,830	24,826	25,958	11,963	28,072	24,488
R^2	0.984	0.963	0.913	0.983	0.978	0.970	0.968	0.973	0.915	0.987	0.976

Sector (NACE rev.2)	22	23	24	25	26	27	28	29	30	31	32
$\ln(Dist_{ni})$	-1.453***	-1.460***	-1.467***	-1.408***	-1.020***	-1.174***	-1.131***	-1.455***	-1.143***	-1.414***	-1.003***
	(0.0245)	(0.0270)	(0.0339)	(0.0251)	(0.0213)	(0.0211)	(0.0218)	(0.0334)	(0.0365)	(0.0293)	(0.0223)
$C.L._{ni}$	0.383***	0.305***	0.164***	0.397***	0.284***	0.441***	0.335***	0.336***	0.229***	0.642***	0.469***
	(0.0433)	(0.0459)	(0.0509)	(0.0409)	(0.0377)	(0.0442)	(0.0415)	(0.0480)	(0.0577)	(0.0449)	(0.0526)
$C.T._{ni}$	0.482***	0.535***	0.594***	0.670***	0.505***	0.643***	0.566***	0.242***	0.703***	0.337***	0.545***
	(0.0427)	(0.0477)	(0.0467)	(0.0442)	(0.0454)	(0.0461)	(0.0461)	(0.0797)	(0.0623)	(0.0412)	(0.0399)
$C.B._{ni}$	0.541***	0.617***	0.229***	0.296***	0.332***	0.289***	0.323***	0.260***	0.448***	0.571***	0.530***
	(0.0461)	(0.0416)	(0.0474)	(0.0410)	(0.0487)	(0.0477)	(0.0448)	(0.0833)	(0.0648)	(0.0499)	(0.0495)
RTA_{nit}	0.0188	-0.225***	0.168***	-0.0403	-0.0585*	0.110***	-0.0351	0.307***	-0.235***	-0.0845	-0.0235
	(0.0336)	(0.0402)	(0.0454)	(0.0358)	(0.0323)	(0.0374)	(0.0332)	(0.0503)	(0.0610)	(0.0543)	(0.0392)
$\widehat{z}_{nit}$	0.259	0.801**	0.510	0.707	0.779	1.786***	0.685	1.613***	2.340***	2.033***	-0.211
	(0.392)	(0.363)	(0.452)	(0.474)	(0.610)	(0.566)	(0.595)	(0.378)	(0.460)	(0.303)	(0.507)
$\widehat{z}^2_{nit}$	0.111	-0.123	0.140	-0.0413	-0.0975	-0.446**	-0.0438	-0.236**	-0.391***	-0.416***	0.243
	(0.120)	(0.113)	(0.139)	(0.145)	(0.186)	(0.174)	(0.187)	(0.118)	(0.142)	(0.0952)	(0.159)
$\widehat{z}^3_{nit}$	-0.0201*	0.00804	-0.0284**	-0.00355	0.00339	0.0404**	-0.00393	0.00838	0.0168	0.0293***	-0.0330**
	(0.0116)	(0.0109)	(0.0135)	(0.0140)	(0.0178)	(0.0168)	(0.0183)	(0.0116)	(0.0139)	(0.00937)	(0.0156)
IMR_{nit}	0.991***	0.962***	1.068***	1.299***	1.384***	1.476***	1.397***	1.678***	2.090***	1.941***	0.878***
	(0.177)	(0.160)	(0.203)	(0.230)	(0.303)	(0.247)	(0.249)	(0.159)	(0.216)	(0.116)	(0.226)
$\ln\widehat{\widehat{y}}(s)^*_{nit}$	0.0672***	0.0927***	0.0557***	0.0708***	0.0959***	0.0819***	0.0649***	0.0322***	0.0889***	0.0476***	0.102***
	(0.00359)	(0.00449)	(0.00264)	(0.00424)	(0.00585)	(0.00398)	(0.00370)	(0.00179)	(0.00406)	(0.00369)	(0.00547)
Obs.	27,442	26,797	25,535	27,646	28,230	27,878	28,159	25,299	25,125	24,579	27,964
R^2	0.986	0.982	0.979	0.986	0.988	0.988	0.990	0.977	0.963	0.975	0.984

[a] OLS regression. Dependent variable: log of export value (Exp> 0). Importer-Year and Exporter-Year fixed effects included. Standard errors are clustered at exporter-year level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 10: Gravity Model - Distance coefficient comparison [a]

	Distance γ				Test difference γ			
Sector	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
	A	B	C	D	A-B	A-C	C-D	Obs.
10	-1.349***	-1.259***	-1.308***	-1.225***	-.0902***	-.0409***	-.083***	
	(.0168)	(.0169)	(.0169)	(.017)	(.0082)	(.0089)	(.0077)	28005
11	-1.22***	-1.187***	-1.127***	-1.101***	-.0335***	-.0933***	-.0265***	
	(.0215)	(.0215)	(.0232)	(.0232)	(.0054)	(.0245)	(.0046)	23482
12	-1.385***	-1.296***	-1.427***	-1.323***	-.0886***	.0426	-.1039***	
	(.0376)	(.0371)	(.0693)	(.0683)	(.0142)	(.0896)	(.0204)	14166
13	-1.382***	-1.279***	-1.33***	-1.244***	-.1032***	-.0516***	-.0861***	
	(.0158)	(.0157)	(.0161)	(.0159)	(.0085)	(.0139)	(.0077)	28051
14	-1.362***	-1.328***	-1.324***	-1.298***	-.0344***	-.0376***	-.0263***	
	(.0174)	(.0173)	(.0174)	(.0174)	(.0055)	(.0111)	(.0048)	27740
15	-1.245***	-1.16***	-1.198***	-1.137***	-.0845***	-.0464**	-.0617***	
	(.0188)	(.0185)	(.0195)	(.0192)	(.0085)	(.0154)	(.0077)	26167
16	-1.633***	-1.574***	-1.556***	-1.512***	-.0588***	-.0773***	-.0436***	
	(.0198)	(.0198)	(.0212)	(.0212)	(.0065)	(.0221)	(.0055)	25525
17	-1.759***	-1.674***	-1.665***	-1.606***	-.0848***	-.094***	-.0587***	
	(.0199)	(.0199)	(.0206)	(.0205)	(.0083)	(.0172)	(.0067)	26080
18	-1.072***	-1.049***	-1.234***	-1.222***	-.0233***	.1622**	-.0126*	
	(.0299)	(.0299)	(.0419)	(.0417)	(.0062)	(.0546)	(.0057)	12202
20	-1.451***	-1.353***	-1.436***	-1.344***	-.098***	-.0153	-.0919***	
	(.016)	(.016)	(.0161)	(.0162)	(.0079)	(.0109)	(.0076)	28135
21	-.9549***	-.8867***	-.8951***	-.8448***	-.0682***	-.0598***	-.0504***	
	(.0198)	(.0196)	(.0206)	(.0204)	(.0088)	(.0157)	(.0081)	24596
22	-1.556***	-1.493***	-1.495***	-1.453***	-.0627***	-.0608***	-.0419***	
	(.0146)	(.0144)	(.0148)	(.0146)	(.0071)	(.0106)	(.0056)	27719
23	-1.581***	-1.487***	-1.537***	-1.461***	-.0936***	-.0438***	-.0762***	
	(.0157)	(.0157)	(.0159)	(.0159)	(.0079)	(.0111)	(.0071)	27027
24	-1.746***	-1.606***	-1.574***	-1.468***	-.1404***	-.1722***	-.1061***	
	(.0208)	(.0209)	(.0214)	(.0214)	(.0101)	(.0202)	(.0085)	25908
25	-1.482***	-1.433***	-1.442***	-1.409***	-.0485***	-.0404***	-.0327***	
	(.0148)	(.0146)	(.0148)	(.0146)	(.0065)	(.0096)	(.0051)	27774
26	-1.049***	-1.021***	-1.045***	-1.02***	-.0271***	-.0041	-.0243***	
	(.0149)	(.0148)	(.0149)	(.0148)	(.0054)	(.0086)	(.0048)	28347
27	-1.25***	-1.199***	-1.215***	-1.175***	-.0504***	-.035***	-.0396***	
	(.0145)	(.0143)	(.0146)	(.0143)	(.0067)	(.0095)	(.0057)	28140
28	-1.22***	-1.147***	-1.192***	-1.132***	-.0728***	-.0272**	-.0602***	
	(.0139)	(.0137)	(.0139)	(.0137)	(.0075)	(.0084)	(.0065)	28277
29	-1.618***	-1.52***	-1.524***	-1.456***	-.0983***	-.0941***	-.0681***	
	(.0203)	(.0201)	(.021)	(.0209)	(.0092)	(.0163)	(.0074)	26308
30	-1.332***	-1.213***	-1.234***	-1.143***	-.1192***	-.0982***	-.091***	
	(.0251)	(.0249)	(.0257)	(.0255)	(.0103)	(.0182)	(.009)	25531
31	-1.488***	-1.462***	-1.421***	-1.412***	-.0261***	-.0667***	-.0096**	
	(.0174)	(.0172)	(.0181)	(.018)	(.005)	(.0188)	(.0037)	25165
32	-1.044***	-1.012***	-1.029***	-1.003***	-.0319***	-.0144*	-.0262***	
	(.015)	(.0148)	(.015)	(.0148)	(.0055)	(.0071)	(.0048)	27997

[a] OLS regression. Columns 1 to 4 report distance coefficient for the gravity model estimation ($X_{ni} > 0$) under four different models. (A) no correction for selection, share of exporters, and exporters heterogeneity (No Corr). (B) Only correction for exporters heterogeneity $(\widehat{\widetilde{y}}(s)^*_{nit})$. (C) HMR model 2008. (D) All corrections: Eq.23 (HMR+$\widehat{\widetilde{y}}(s)^*_{nit}$). Standard errors are clustetred at exporter-importer level and are reported in parenthesis. Columns 5 to 7 report the test for the statistical difference of distance coefficient between models. (A-B): No Corr. vs $\widehat{\widetilde{y}}(s)^*_{nit}$. (A-C): No Corr. vs HMR. (C-D): HMR vs $\widehat{\widetilde{y}}(s)^*_{nit}$. Standard errors are clustered at exporter-importer level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 11: Gravity Model - Exporter fixed effect comparison [a]

	Obs	$\widehat{\lambda}$	HMR fixed effects	Mean comparison	St.Err.	t-stat	P-Val
All Countries	13200	18.864	19.601	-0.737	0.004	-198.4	0
CompNet Countries	4284	18.823	19.511	-.689	0.006	-112.9	0

[a] Test on the equality of means (unpair variance) between fixed effects λ from Eq.23 and fixed effects from HMR model (2008). Mean comparison - H_0: Diff = 0

Table 12: Trade Liberalization - Counterfactual Analysis [a]

Panel A			Mean	S.D.	Min	Max	Obs
$\ln \widehat{x'} - \ln \widehat{x}$	Baseline HMR		0.140	0.020	0.094	0.175	541822
$\ln \widehat{x'} - \ln \widehat{x}$	Augmented		0.134	0.019	0.089	0.169	541783
	Diff	0.006***(.0000135)					
Panel B			Mean	S.D.	Min	Max	Obs
$\frac{\lvert \ln \widehat{x'} - \ln \widehat{x} \rvert}{\lvert \ln dist' - \ln dist \rvert}$	Baseline HMR		1.329	0.190	0.895	1.664	541822
$\frac{\lvert \ln \widehat{x'} - \ln \widehat{x} \rvert}{\lvert \ln dist' - \ln dist \rvert}$	Augmented		1.273	0.182	0.845	1.606	541783
	Diff	0.056***(.0001399)					

[a] Average trade growth and trade elasticity due to a reduction of 10% in distance. Diff: t-test for mean difference. Bootstrapped standard errors reported in parenthesis.

Table 13: Descriptive Statistics - Distributions' Parameters and Elasticity[a]

	Lognormal (Bounded)				Pareto (Bounded)		
	μ_b	σ_b	y_L	y_H	k_b	y_H	y_L
Mean	-2.666	1.326	0.5922	7.166	1.482	1.191	6.78
SD	5.813	1.583	0.7916	11.09	0.905	3.754	12.83
Obs	2305	2305	2305	2305	2722	2722	2722
	Lognormal (unbounded)				Pareto (unbounded)		
	μ_u	σ_u	P1	P99	k_u	y_L	
Mean	-0.237	0.275	1.769	10.71	3.255	3.528	
SD	1.638	0.154	15.55	60.96	0.5532	27.97	
Obs.	2784	2784	2784	2784	2784	2784	
	$\widehat{\eta}(LN)_{ni}$	$\widehat{\eta}(P)_{ni}$	Share	$\ln(\widehat{y}_{ni})$			
Mean	-4.391	-4.44	0.370	-0.093			
SD	1.431	1.37	0.329	1.866			
Obs.	104999	125976	197568	141904			

[a] Source: our calculation from CompNet and BACI database. Bounded parameters are the the solutions of Eq. 28 and 28 (subscritpt b). Unbounded parameters are the solutions of Eq. C-8 and C-9 (subscritpt u). P1 and P99 are the average value of the 1st and 99th percentile of TFP reported in CompNet. $\widehat{\eta}(LN)_{ni}$ (b.): estimated LogNormal elasticity with bounded distribution. $\widehat{\eta}(P)_{ni}$ (un.): estimated Pareto elasticity with unbounded distribution. Share: share of exported HS6 digit products. $\ln(\widehat{y}_{ni})$: log of bilateral TFP cutoff.

Table 14: Elasticity Analysis - Cutoff[a]

	(1)	(2)	(3)	(4)
Panel A			$\widehat{\eta}(LN)$	
$\ln(y^*_{ni})$	-.029***	-.007**	-.517***	-.026***
	(.0046)	(.0034)	(.0283)	(.0045)
Cons	-4.38***	-4.37***	-4.47***	-4.38***
	(.007)	(6.6e-04)	(.0066)	(.007)
Obs	104607	104607	104607	104607
R^2	.76	.779	.821	.765
	(1)	(2)	(3)	(4)
Panel B			$\widehat{\eta}(P)$	
$\ln(y^*_{ni})$	-.054***	-.043***	-.5***	-.117***
	(.004)	(.0039)	(.027)	(.005)
Cons	-4.45***	-4.44***	-4.52***	-4.46***
	(.007)	(6.6e-04)	(.0062)	(.014)
Obs.	125976	125976	125976	125976
R^2	.77	.789	.85	.713
			Fixed Effects	
	Origin, Destination, Sector, Year	Origin X Destination, Sector, Year	Origin x Sector, Destination, Year	Destination x Sector, Origin, Year

[a] OLS estimation. Sample: CompNet countries with positive bilateral trade flows. $\ln(y^*_{ni})$: log of the bilateral TFP cutoff between country pairs. Standard errors are clustered at exporter-importer level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 15: Elasticity Analysis - Extensive Margin [a]

	(1)	(2)	(3)	(4)
Panel A			$\widehat{\eta}(LN)$	
Share Exported Products	1.35***	1.36***	1.26***	1.36***
	(.047)	(.0488)	(.0513)	(.0359)
Cons	-4.96***	-4.96***	-4.92***	-4.96***
	(.0199)	(.0211)	(.0216)	(.023)
Obs	104607	104607	104607	104607
R^2	.78	.789	.827	.757
	(1)	(2)	(3)	(4)
Panel B			$\widehat{\eta}(P)$	
Share Exported Products	1.34***	1.37***	1.2***	1.31***
	(.046)	(.0574)	(.0503)	(.0371)
Cons	-5.02***	-5.03***	-4.96***	-5***
	(.0199)	(.0248)	(.0212)	(.0235)
Obs	125976	125976	125976	125976
R^2	.789	.798	.855	.762
			Fixed Effects	
	Origin, Destination, Sector, Year	Origin X Destination, Sector, Year	Origin x Sector, Destination, Year	Destination x Sector, Origin, Year

[a] OLS estimation. Sample: CompNet countries with positive bilateral trade flows. Share Exported Products: share of exported HS6 digit products between country pairs. Standard errors are clustered at exporter-importer level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 16: Simulations parameters - Summary Data [a]

Variable	Sector 26	Sector 28	Descripition
M_1^e	$M^e_{Ita,26} = 578$	$M^e_{Ita,28} = 3344$	Number of firms with more than 10 employees in 2010 (Source: CompNet).
ε	$\varepsilon_{26} = 2.16$	$\varepsilon_{28} = 4.51$	Elasticity of Substitution. Table5
m_1	1	1	Input cost index in country 1
χ_1	1	1	Share of fixed input cost at Home.
$\tau_{n,i} = 1 + t_{n,i}$	$t_{n,i} \sim U[0.01, 1]$	$t_{n,i} \sim U[0.01, 1]$	Iceberg trade cost
$f_{n,i} = \tau_{n,i}^{1-\varepsilon} + u$	$u \sim U[0.01, 1]$	$u \sim U[0.01, 1]$	$f_{n,i}$ fixed cost to export to n from i.
$A_n = f_{n,i} \cdot l$	$l \sim LN(0, 1)$	$l \sim 10000 \cdot LN(0, 1)$	A_n market size at destination.
$\widehat{S}_{ist,LN}$	$[1.57, 0.833, 1.32, 6.23]$	$[-1.066, 0.881, 0.0134, 0.345]$	Distribution paramters $[\mu, \sigma, y_L, y_H]$

[a] Source: our calculation from CompNet database. Reference Year 2010

Table 17: Counterfactual Simulation: variation in the LogNormal parameters (1% increase) - Trade variation - Sector 26 [a]

	(1)		(2)		(3)	
	μ		σ		y_H	
Δ TFP Mean (Eq.D-1)	0.349%		-0.182%		0.615%	
Panel A	All		All		All	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.0096	0.0024	-0.0039	0.0003	0.0397	0.0692
Δ Int.Margin	0.0014	0.0013	-0.0003	0.0005	0.0103	0.0008
Δ Ext.Margin	0.0081	0.0037	-0.0036	0.0008	0.0291	0.0690
Panel B	$Share_0 > 50\%$		$Share_0 > 50\%$		$Share_0 > 50\%$	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.0074	0.0009	-0.0037	0.0003	0.0148	0.0017
Δ Int.Margin	0.0026	0.0010	-0.0006	0.0005	0.0111	0.0005
Δ Ext.Margin	0.0048	0.0019	-0.0030	0.0009	0.0036	0.0021
Panel C	$Share_0 < 50\%$		$Share_0 < 50\%$		$Share_0 < 50\%$	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.0115	0.0016	-0.0041	0.0002	0.0614	0.0892
Δ Int.Margin	0.0004	0.0004	0.00002	0.0000	0.0097	0.0004
Δ Ext.Margin	0.0111	0.0019	-0.0041	0.0002	0.0513	0.0886

[a] Note: μ=1.57, σ= 0.83, y_L = 1.32, y_H = 6.23 (Italy, Sector 26, Year 2010). Firms=578. Δ is computed as $\frac{x_1-x_0}{x_0}$ Mean: mean of variations. St.Dev.: standard deviatiation of variations. *Panel A* reports the variations for all the succesful replications (7027), *Panel B* reports the variations for all the replications with an initial share of exporting firms above the 50%, and *Panel C* reports the variations for all the replications with an initial share of exporting firms below the 50%. Median share of exporting firms ($Share_0$: 47%. Replications=10000

Table 18: Counterfactual Simulation: variation in the LogNormal parameters (1% increase) - Trade variation - Sector 28 [a]

	(1)		(2)		(3)	
	μ		σ		y_H	
Δ TFP Mean	0.3%		-0.48%		0.711%	
Panel A	All		All		All	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.007	0.001	-0.009	0.000	0.050	0.058
Δ Int.Margin	0.001	0.001	-0.001	0.001	0.023	0.003
Δ Ext.Margin	0.006	0.002	-0.008	0.001	0.026	0.058
Panel B	$Share_0 > 50\%$		$Share_0 > 50\%$		$Share_0 > 50\%$	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.007	0.000	-0.009	0.000	0.031	0.001
Δ Int.Margin	0.002	0.001	-0.002	0.001	0.026	0.001
Δ Ext.Margin	0.004	0.001	-0.007	0.001	0.005	0.002
Panel C	$Share_0 < 50\%$		$Share_0 < 50\%$		$Share_0 < 50\%$	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.008	0.001	-0.009	0.000	0.063	0.073
Δ Int.Margin	0.001	0.000	0.000	0.000	0.021	0.002
Δ Ext.Margin	0.007	0.001	-0.009	0.000	0.041	0.073

[a] Note: μ=-1.066, σ= 0.881, y_L = 0.0134, y_H = 0.345 (Italy, Sector 28, Year 2010). Firms=3344. Δ is computed as $\frac{x_1-x_0}{x_0}$ Mean: mean of variations. St.Dev.: standard deviatiation of variations. *Panel A* reports the variations for all the succesful replications (9121), *Panel B* reports the variations for all the replications with an initial share of exporting firms above the 50%, and *Panel C* reports the variations for all the replications with an initial share of exporting firms below the 50%. Median share of exporting firms ($Share_0$: 47%. Replications=10000

Table 19: Counterfactual Simulation: variation in the Pareto parameters (1% increase) - Trade variation - Sector 26 [a]

	(1)		(2)	
	k (increase)		y_H	
Δ TFP Mean (Eq.D-2)	-0.271%		0.034%	
Panel A	All		All	
	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	-0.013	0.011	0.006	0.005
Δ Int.Margin	0.006	0.001	0.004	0.001
Δ Ext.Margin	-0.018	0.010	0.002	0.003
Panel B	$Share_0 > 50\%$		$Share_0 > 50\%$	
	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.003	0.002	0.002	0.000
Δ Int.Margin	0.007	0.000	0.002	0.000
Δ Ext.Margin	-0.004	0.002	0.000	0.000
Panel C	$Share_0 < 50\%$		$Share_0 < 50\%$	
	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	-0.016	0.010	0.007	0.005
Δ Int.Margin	0.006	0.001	0.004	0.001
Δ Ext.Margin	-0.021	0.009	0.003	0.003

[a] Note: $k = 3.88; y_L = 2.73; y_H = 11.13$ (Italy, Sector 26, Year 2010). Firms=578. Δ is computed as $\frac{x_1 - x_0}{x_0}$ Mean: mean of variations. St.Dev.: standard deviatiation of variations. *Panel A* reports the variations for all the succesful replications (6327), *Panel B* reports the variations for all the replications with an initial share of exporting firms above the 50%, and *Panel C* reports the variations for all the replications with an initial share of exporting firms below the 50%. Median share of exporting firms ($Share_0$: 14%. Replications=10000

Table 20: Counterfactual Simulation: variation in the average TFP (1% increase) - Trade variation - Sector 26 [a]

	(1)		(2)		(3)	
	$\Delta\mu = +2.87\%$		$\Delta\sigma = -5.42\%$		$\Delta y_H = +1.62\%$	
Panel A	All		All		All	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.028	0.007	0.023	0.002	0.065	0.113
Δ Int.Margin	0.004	0.004	0.002	0.003	0.017	0.001
Δ Ext.Margin	0.023	0.011	0.021	0.005	0.048	0.112
Panel B	$Share_0 > 50\%$		$Share_0 > 50\%$		$Share_0 > 50\%$	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.021	0.003	0.021	0.002	0.024	0.003
Δ Int.Margin	0.007	0.003	0.004	0.003	0.018	0.001
Δ Ext.Margin	0.014	0.005	0.018	0.005	0.006	0.003
Panel C	$Share_0 < 50\%$		$Share_0 < 50\%$		$Share_0 < 50\%$	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.033	0.005	0.024	0.001	0.103	0.146
Δ Int.Margin	0.001	0.001	0.000	0.000	0.016	0.001
Δ Ext.Margin	0.032	0.006	0.024	0.001	0.086	0.144
	Change in the TFP statitics					
Δ St.Dev	.0004 [-.0017 .0025]		-.0058 [-.0078 -.0035]		.0194 [.0188 .0202]	
Δ Skew	-0.139 [-1.07 1.41]		-.129 [-3.054 20.70]		.044 [-1.501 1.045]	

[a] Note: μ=1.57, σ= 0.83, $y_L = 1.32$, $y_H = 6.23$ (Italy, Sector 26, Year 2010). Firms=578. Δ is computed as $\frac{x_1 - x_0}{x_0}$ Mean: mean of variations. St.Dev.: standard deviatiation of variations. *Panel A* reports the variations for all the succesful replications (7087), *Panel B* reports the variations for all the replications with an initial share of exporting firms above the 50%, and *Panel C* reports the variations for all the replications with an initial share of exporting firms below the 50%. Median share of exporting firms ($Share_0$: 47%. Replications=10000

Table 21: Counterfactual Simulation: variation in the average TFP (1% increase) - Trade variation - Sector 28 [a]

	(1) $\Delta\mu = +3.45\%$		(2) $\Delta\sigma = -2.08\%$		(3) $\Delta y_H = +1.39\%$	
Panel A	All		All		All	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.025	0.003	0.020	0.001	0.070	0.081
Δ Int.Margin	0.004	0.003	0.002	0.002	0.032	0.004
Δ Ext.Margin	0.020	0.006	0.018	0.003	0.037	0.081
Panel B	$Share_0 > 50\%$		$Share_0 > 50\%$		$Share_0 > 50\%$	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.022	0.001	0.019	0.000	0.043	0.001
Δ Int.Margin	0.008	0.003	0.004	0.002	0.036	0.002
Δ Ext.Margin	0.014	0.003	0.015	0.002	0.007	0.003
Panel C	$Share_0 < 50\%$		$Share_0 < 50\%$		$Share_0 < 50\%$	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.026	0.002	0.020	0.001	0.089	0.101
Δ Int.Margin	0.002	0.001	0.000	0.000	0.030	0.002
Δ Ext.Margin	0.025	0.004	0.020	0.001	0.057	0.100
	Change in the TFP empirical moments					
Δ St.Dev	-.003 [-.004 -.002]		-.007 [-.0077 -.0067]		.0166 [.0165 .0168]	
Δ Skew	-0.192 [-1354 1964]		-1.32 [-7200 852.4]		.614 [-51.3 25.5]	

[a] Note: μ=-1.066, σ= 0.881, y_L = 0.0134, y_H = 0.345 (Italy, Sector 28, Year 2010). Firms=3344. Δ is computed as $\frac{x_1-x_0}{x_0}$ Mean: mean of variations. St.Dev.: standard deviatiation of variations. *Panel A* reports the variations for all the succesful replications (9121), *Panel B* reports the variations for all the replications with an initial share of exporting firms above the 50%, and *Panel C* reports the variations for all the replications with an initial share of exporting firms below the 50%. Median share of exporting firms ($Share_0$: 47%. Replications=10000

Table 22: Counterfactual Simulation: variation in the average TFP (1% increase) - Pareto - Sector 26 [a]

	(1) $\Delta k = -3.90\%$		(2) $\Delta y_H = +57.9\%$	
Panel A	All		All	
	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.096	0.072	0.178	0.142
Δ Int.Margin	0.013	0.019	0.120	0.059
Δ Ext.Margin	0.083	0.093	0.048	0.069
Panel B	$Share_0 > 50\%$		$Share_0 > 50\%$	
	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.037	0.007	0.059	0.006
Δ Int.Margin	0.022	0.003	0.057	0.005
Δ Ext.Margin	0.015	0.010	0.002	0.001
Panel C	$Share_0 < 50\%$		$Share_0 < 50\%$	
	Mean	St.Dev	Mean	St.Dev
Δ Total Trade	0.107	0.073	0.202	0.144
Δ Int.Margin	0.011	0.020	0.133	0.056
Δ Ext.Margin	0.096	0.096	0.057	0.072
	Change in the TFP empirical moments			
Δ St.Dev	0.041 [.029 .049]		0.127 [.0388 .299]	
Δ Skew	-0.139 [-.0464 .0004]		0.316 [.0526 .9117]	

[a] Note: $k = 3.88; y_L = 2.73; y_H = 11.13$ (Italy, Sector 26, Year 2010). Firms=578. Δ is computed as $\frac{x_1-x_0}{x_0}$ Mean: mean of variations. St.Dev.: standard deviatiation of variations. *Panel A* reports the variations for all the succesful replications (6327), *Panel B* reports the variations for all the replications with an initial share of exporting firms above the 50%, and *Panel C* reports the variations for all the replications with an initial share of exporting firms below the 50%. Median share of exporting firms ($Share_0$: 14%). Replications=10000

Table 23: Selection Equation - Product Level (2001-2012) [a]

Sector (NACE rev.2)	10	11	12	13	14	15	16	17	18	20	21
$\ln dist$	-3.6e-03	.012*	3.1e-04	2.3e-03	.011	6.0e-03	8.7e-03	3.3e-03	3.9e-03	-6.8e-03	7.6e-04
	(.0053)	(.0065)	(.0046)	(.0069)	(.0069)	(.0087)	(.0073)	(.0101)	(.0062)	(.0069)	(.0065)
C.L.	.02	9.1e-03	-.011	-.017	-.012	-8.6e-03	-6.6e-03	-1.7e-03	.01	8.2e-03	6.7e-03
	(.0212)	(.0255)	(.0156)	(.0199)	(.021)	(.0291)	(.0262)	(.0301)	(.0148)	(.022)	(.0167)
C.T.	4.9e-03	.032	9.3e-03	.029	.024	.029	.022	.101**	.012	.033	.032
	(.0329)	(.0642)	(.0456)	(.0569)	(.0647)	(.0734)	(.0332)	(.0507)	(.031)	(.0352)	(.0232)
C.B.	-.02	.02	5.9e-03	-.026	.022	-.027	-.013	.015	-.035	.019	.029
	(.0196)	(.0244)	(.0176)	(.0225)	(.0303)	(.0343)	(.0227)	(.0451)	(.0294)	(.0452)	(.0234)
RTA	.123***	.134***	.088***	.117***	.095***	.117***	.148***	.158***	.17***	.112***	.069***
	(.006)	(.0066)	(.0063)	(.0061)	(.0077)	(.0074)	(.0067)	(.0074)	(.0123)	(.0063)	(.0049)
R.P.	.096***	.126***	.069***	.06***	.043**	.082***	.122***	.114***	.175***	.086***	.053***
	(.0128)	(.016)	(.0127)	(.0117)	(.0166)	(.0161)	(.0149)	(.0143)	(.0259)	(.0117)	(.0086)
Obs	11465750	675950	205550	14288150	6614750	1381550	1499150	3145550	29150	20373950	2175350
R2	.425	.518	.397	.417	.446	.48	.471	.475	.476	.477	.494
Share Exp.	0.147	0.236	0.116	0.127	0.159	0.206	0.210	0.205	0.257	0.150	0.123
Sector (NACE rev.2)	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
$\ln dist$	1.9e-03	.012	2.0e-03	7.4e-03	4.4e-04	1.6e-03	3.4e-03	7.9e-04	9.4e-03*	.023	4.0e-03
	(.0113)	(.0082)	(.0072)	(.0096)	(.0049)	(.0085)	(.0075)	(.0094)	(.005)	(.015)	(.0059)
C.L.	2.2e-03	2.8e-03	-5.6e-03	-.012	.014	1.8e-03	-4.6e-03	-8.7e-03	-3.6e-03	-.032	6.2e-03
	(.0353)	(.0275)	(.0249)	(.0286)	(.0163)	(.0265)	(.0249)	(.0301)	(.0145)	(.0549)	(.0155)
C.T.	.052	.029	.053*	.049	.027	.087**	.04	.039	.057	.099	.053
	(.0425)	(.0411)	(.0289)	(.0344)	(.0314)	(.0433)	(.0371)	(.0343)	(.0488)	(.0849)	(.0367)
C.B.	6.2e-03	.027	-.016	.028	-7.4e-03	.016	.066*	.024	.023	.074	8.0e-03
	(.0475)	(.0311)	(.03)	(.0301)	(.0174)	(.0309)	(.0387)	(.0388)	(.0233)	(.0521)	(.0278)
RTA	.188***	.138***	.135***	.139***	.07***	.145***	.122***	.183***	.081***	.231***	.086***
	(.008)	(.007)	(.0072)	(.0072)	(.0047)	(.0072)	(.0069)	(.008)	(.0048)	(.0104)	(.0053)
R.P.	.131***	.114***	.1***	.118***	.062***	.111***	.104***	.126***	.074***	.14***	.078***
	(.016)	(.0149)	(.0135)	(.0146)	(.0092)	(.014)	(.0131)	(.0155)	(.0097)	(.0204)	(.0114)
Obs	3292550	4527350	9613550	6938150	6996950	5203550	13288550	1822550	2351750	528950	4762550
R2	.524	.472	.436	.49	.506	.511	.508	.534	.451	.53	.496
Share Exp.	0.294	0.203	0.163	0.213	0.132	0.252	0.221	0.293	0.127	0.424	0.147

[a] OLS estimation. Each column represents a different estimation by sector. Dependent variable is a dummy equal one if it exists a positive trade flows from i to n, for product j, at time t; otherwise zero. Product j is defined at HS 6-digit level. Importer-Year-Product and Exporter-Year-Product fixed effects included. *Dist*: distance; *C.L.*: common language; *C.B.*: common border; *C.T.*: colonial ties; *RTA*: regional trade agreement; *R.P.*: religious proximity. Share Exp: share of positive trade flows. Standard errors are clustered at exporter-importer level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 24: Elasticity estimation (2001-2012) - Tariff and selection [a]

Sector (NACE rev.2)	$1/\theta$	S.E.	Tariff	S.E.	ξ	S.E.	Obs	R2	θ	ε
10	.856***	(.0015)	-.018***	(.0017)	.373***	(.0115)	1682545	.803	1.17	6.94
11	.795***	(.0037)	-.027***	(.0036)	.425***	(.0308)	159691	.74	1.26	4.88
12	.884***	(.0061)	7.5e-03	(.0066)	.448***	(.0737)	23921	.803	1.13	8.62
13	.821***	(.0028)	-.027***	(.002)	.312***	(.0187)	1815950	.722	1.22	5.59
14	.734***	(.0064)	-.043***	(.0047)	.686***	(.0304)	1054493	.6	1.36	3.76
15	.761***	(.0057)	-.036***	(.004)	.542***	(.0299)	284415	.607	1.31	4.18
16	.795***	(.0031)	-.02***	(.0038)	.194***	(.0251)	314660	.724	1.26	4.88
17	.815***	(.0022)	-.025***	(.0033)	.277***	(.018)	645814	.776	1.23	5.41
18	.634***	(.0136)	-.114***	(.031)	.215	(.1552)	7559	.547	1.58	2.73
20	.795***	(.002)	-.026***	(.0021)	.372***	(.0141)	3064543	.744	1.26	4.88
21	.691***	(.0042)	-.015***	(.0054)	.535***	(.0351)	268048	.49	1.45	3.24
22	.785***	(.0029)	-.023***	(.0024)	.354***	(.0163)	967394	.702	1.27	4.65
23	.738***	(.0025)	-.024***	(.0029)	.303***	(.0247)	920454	.678	1.36	3.82
24	.849***	(.0019)	-.041***	(.003)	.299***	(.0163)	1563562	.807	1.18	6.62
25	.742***	(.0032)	-.034***	(.0032)	.373***	(.0206)	1481124	.626	1.35	3.88
26	.644***	(.0051)	-.03***	(.004)	.903***	(.0355)	924278	.488	1.55	2.81
27	.748***	(.0036)	-.033***	(.0031)	.409***	(.0233)	1313518	.623	1.34	3.97
28	.778***	(.0022)	-.031***	(.0025)	.461***	(.0202)	2937118	.613	1.29	4.50
29	.88***	(.0026)	-.012***	(.0031)	.378***	(.0197)	534490	.748	1.14	8.33
30	.772***	(.0039)	-.04***	(.0041)	.41***	(.0328)	299075	.567	1.30	4.39
31	.814***	(.0032)	-.038***	(.0042)	.307***	(.0241)	224341	.729	1.23	5.38
32	.688***	(.0047)	-.037***	(.0034)	.574***	(.0292)	702295	.53	1.45	3.21

[a] OLS estimation of equation 20. Estimation sample includes only observations with positive trade flows $x_{jnit} > 0$. Each row refers to an estimation. Robust standard errors are clustered at exporter-destination level and are reported in parenthesis. Column ε reports the estimated elasticity Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 25: Price equation (2001-2012) - Double differnce [a]

Sector (NACE rev.2)	10	11	12	13	14	15	16	17	18	20	21
$\ln T$	2.3e-03	-7.5e-03	.048	-3.2e-03	-.018	-.019	-1.3e-03	3.8e-03	.236**	.049***	.067***
	(.0059)	(.015)	(.0303)	(.0072)	(.0206)	(.016)	(.0182)	(.0124)	(.1126)	(.0079)	(.0225)
$\ln q$	-.188***	-.192***	-.181***	-.197***	-.207***	-.167***	-.271***	-.294***	-.428***	-.28***	-.298***
	(.0026)	(.0082)	(.0148)	(.0037)	(.006)	(.0074)	(.0057)	(.0035)	(.0301)	(.0027)	(.0071)
$(\ln T)^2$	-4.3e-03***	-7.2e-03**	-6.8e-03	-8.0e-03***	-.011	-7.3e-03	-3.3e-03	-3.1e-03	-.101**	-.026***	-.03***
	(.0014)	(.0033)	(.0064)	(.0022)	(.0068)	(.0048)	(.0053)	(.0034)	(.0447)	(.0023)	(.0076)
$(\ln q)^2$	5.7e-03***	-1.7e-03	8.6e-03***	3.0e-03***	-.012***	-.014***	8.2e-03***	.014***	.012***	9.7e-03***	-2.0e-03*
	(3.3e-04)	(.0011)	(.0017)	(6.8e-04)	(.0014)	(.0016)	(8.1e-04)	(4.2e-04)	(.0046)	(3.4e-04)	(.0011)
$\ln T \cdot \ln q$	-4.4e-03***	-1.1e-03	-7.0e-03	-2.6e-03	-6.1e-03**	-3.6e-03	-3.1e-03	-6.3e-03***	-.078***	-4.3e-03***	-.012**
	(9.4e-04)	(.0025)	(.0061)	(.0017)	(.0028)	(.003)	(.0039)	(.0024)	(.025)	(.0015)	(.0049)
$(\ln T \cdot \ln q)^2$	1.6e-04***	1.5e-04**	1.6e-04	8.2e-05	4.0e-04***	2.8e-04*	2.9e-06	7.4e-05	4.3e-03**	6.9e-05	7.0e-04**
	(2.7e-05)	(7.4e-05)	(1.9e-04)	(9.6e-05)	(1.5e-04)	(1.5e-04)	(2.0e-04)	(1.3e-04)	(.0021)	(6.7e-05)	(2.9e-04)
ξ	.353***	.44***	.281***	.221***	.655***	.531***	.122***	.207***	.422**	.314***	.454***
	(.0108)	(.0309)	(.0783)	(.0128)	(.0249)	(.0285)	(.0246)	(.0147)	(.1946)	(.0108)	(.0328)
Obs	1682525	159657	23888	1815935	1054479	284399	314644	645787	7418	3064511	268019
R^2	.11	.174	.106	.114	.165	.142	.159	.166	.37	.168	.163
Sector (NACE rev.2)	22	23	24	25	26	27	28	29	30	31	32
$\ln T$	.025***	.015	.034***	.017*	-7.1e-04	-3.7e-03	-.031***	-.015	-.039**	-.037**	.03***
	(.0094)	(.0106)	(.0092)	(.0096)	(.0125)	(.0093)	(.0078)	(.011)	(.0172)	(.0175)	(.0117)
$\ln q$	-.213***	-.345***	-.249***	-.269***	-.311***	-.225***	-.231***	-.147***	-.196***	-.162***	-.254***
	(.0042)	(.0037)	(.0031)	(.0037)	(.0057)	(.0054)	(.0035)	(.0045)	(.0071)	(.0056)	(.0062)
$(\ln T)^2$	-.012***	-8.6e-03***	-.015***	-9.5e-03***	-.013***	-.011***	-3.1e-03	6.0e-04	-8.9e-03*	-1.9e-03	-.022***
	(.0028)	(.0031)	(.0028)	(.0029)	(.0045)	(.0029)	(.0027)	(.0032)	(.0053)	(.0052)	(.004)
$(\ln q)^2$	-2.1e-04	.011***	.012***	2.3e-03***	-8.1e-03***	-4.7e-03***	9.7e-04	3.0e-03***	-5.4e-03***	-4.6e-03***	-.011***
	(7.7e-04)	(4.9e-04)	(3.0e-04)	(7.3e-04)	(.0012)	(.0011)	(6.7e-04)	(5.6e-04)	(.0011)	(7.5e-04)	(.0014)
$\ln T \cdot \ln q$	-5.6e-03**	-6.6e-03***	-.012***	-9.4e-03***	-4.4e-04	8.6e-04	6.1e-03***	-2.7e-03	4.5e-03	4.1e-03	-1.8e-03
	(.0024)	(.0018)	(.0013)	(.0028)	(.0033)	(.0027)	(.0018)	(.0018)	(.0035)	(.0033)	(.0034)
$(\ln T \cdot \ln q)^2$	-3.6e-05	1.6e-04***	1.7e-04***	-1.6e-05	-1.9e-05	-1.8e-04	-3.4e-04***	2.0e-04***	2.4e-04	-2.0e-04	-2.1e-04
	(1.6e-04)	(6.1e-05)	(4.9e-05)	(2.1e-04)	(2.8e-04)	(2.0e-04)	(1.3e-04)	(7.0e-05)	(1.8e-04)	(1.7e-04)	(2.7e-04)
ξ	.249***	.199***	.232***	.271***	.833***	.296***	.372***	.325***	.359***	.257***	.496***
	(.0131)	(.0189)	(.0121)	(.0152)	(.029)	(.0182)	(.0128)	(.018)	(.0307)	(.0228)	(.0229)
Obs	967342	920431	1563542	1481086	924256	1313470	2937071	534447	299059	224291	702273
R^2	.156	.217	.136	.174	.209	.161	.117	.059	.108	.137	.187

[a] OLS estimation of price equation C-5 with double difference. Estimantion sample inlcudes only observations with positive trade flows $x_{jnit} > 0$. The estimation includes origin-year fixed effects. T: bilateral tariff for product j at time t. q: exported quantity j, from i to n at time t. ξ is the linear selection term (Eq.C-5). Robust standard errors are clustered at origin-destination level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 26: Trade Liberalization - Counterfactual Analysis by sector [a]

	$\ln \widehat{x'} - \ln \widehat{x}$		$\frac{\lvert \ln \widehat{x'} - \ln \widehat{x} \rvert}{\lvert \ln dist' - \ln dist \rvert}$		Obs.
Sector	Baseline	Augmented	Baseline	Augmented	
10	0.138071	0.129322	1.310462	1.227425	27969
11	0.118637	0.115849	1.126009	1.099544	22671
12	0.151449	0.140102	1.437432	1.329734	14000
13	0.140172	0.131102	1.3304	1.244319	27914
14	0.139463	0.136693	1.323671	1.297384	27609
15	0.126272	0.119752	1.198478	1.136597	25830
16	0.16438	0.15977	1.560164	1.516411	24745
17	0.175351	0.169168	1.664296	1.605611	18919
18	0.131204	0.129841	1.245286	1.232346	11955
20	0.151336	0.141653	1.436367	1.344463	28072
21	0.09431	0.089001	0.895113	0.844728	17802
22	0.15746	0.153053	1.494491	1.45266	27441
23	0.161844	0.153816	1.536101	1.459906	26795
24	0.165777	0.154606	1.573426	1.467403	25517
25	0.151815	0.148376	1.440913	1.408273	27646
26	0.110015	0.107459	1.044174	1.019918	28226
27	0.127836	0.123672	1.213321	1.173799	27878
28	0.125515	0.119205	1.191288	1.131396	28126
29	0.160387	0.153264	1.522271	1.454666	25295
30	0.130028	0.120425	1.234126	1.14298	25125
31	0.150017	0.148969	1.423841	1.413901	24579
32	0.10842	0.105658	1.029042	1.002823	27669

[a] Average trade growth and trade elasticity responses to a reduction of 10% in distance.

Table 27: Descriptive Statistics - Pairwise correlation LogNormal[a]

	μ	σ	y_H	y_L	μ	σ	P99	P1
μ_b	1							
σ_b	-0.867***	1						
y_H	-0.331***	0.430***	1					
y_L	0.169***	-0.053**	0.332***	1				
μ_u	0.205***	-0.03	0.340***	0.647***	1			
σ_u	-0.02	0.111***	0.176***	-0.001	0.097***	1		
P99	0.117***	0.027	0.488***	0.810***	0.378***	-0.024	1	
P1	0.142***	-0.034*	0.323***	0.836***	0.322***	-0.093***	0.974***	1

[a] Source: our calculation from CompNet database. Bounded parameters are the the solutions of Eq. 28 and 28 (subscritpt b). Unbounded parameters are the solutions of Eq. C-8 and C-9 (subscritpt u). P1 and P99 are the average value of the 1st and 99th percentile of TFP distribution reported in CompNet.

Table 28: Descriptive Statistics - Pairwise correlation Pareto[a]

Variables	k_b	y_H	y_L	k_u	y_{uL}	P1	P99
k_b	1						
y_H	-0.013	1					
y_L	0.008	0.889***	1				
k_u	0.242***	-0.019	0.203***	1			
y_{uL}	-0.048**	0.910***	0.990***	0.146***	1		
P1	-0.02	0.839***	0.969***	0.158***	0.992***	1	
P99	-0.084***	0.978***	0.909***	0.098***	0.987***	0.974***	1

[a] Source: our calculation from CompNet database. Bounded parameters are the the solutions of Eq. 28 and 28 (subscritpt b). Unbounded parameters are the solutions of Eq. C-8 and C-9 (subscritpt u). y_{uL}: scale parameter from unbounded distribution. P1 and P99 are the average value of the 1st and 99th percentile of TFP distribution reported in CompNet.

Table 29: Gravity data - Aggregated Level (Origin) [a]

Exporter (ISO code)	Percentage positive trade flows	Log (Export)
ARG	0.736	6.867
AUS	0.859	7.574
AUT	0.937	9.393
BEL	0.974	9.696
BGD	0.446	6.069
BRA	0.899	8.365
CAN	0.920	8.363
CHE	0.977	8.969
CHL	0.591	6.897
CHN	0.966	10.969
CZE	0.903	8.771
DEU	0.997	11.388
DNK	0.951	8.744
ESP	0.967	9.730
EST	0.667	6.849
FIN	0.886	8.559
FRA	0.980	10.532
GBR	0.990	10.112
GRC	0.842	7.168
HRV	0.699	6.622
HUN	0.863	8.322
IDN	0.889	8.411
IND	0.932	8.831
IRL	0.869	7.992
ISR	0.828	7.692
ITA	0.979	10.717
JPN	0.921	9.354
KOR	0.905	9.065
LKA	0.625	6.128
LTU	0.697	7.051
LVA	0.626	6.542
MAR	0.580	6.402
MEX	0.831	7.651
MLT	0.499	5.612
NLD	0.982	9.789
NOR	0.857	7.797
NZL	0.736	6.704
PHL	0.773	7.176
POL	0.906	9.027
PRT	0.893	8.069
ROM	0.815	7.727
RUS	0.828	7.853
SVK	0.805	7.862
SVN	0.810	7.575
SWE	0.933	9.255
THA	0.910	8.725
TUN	0.561	6.455
TUR	0.900	8.527
URY	0.425	5.914
USA	0.992	10.486
Total	0.827	8.432

[a] Source: BACI-CEPII. Percentage positive trade flows: average share of positive trade flows by origin. Log (Export): average log of exports (in th euros, fob), by orign

Table 30: Omitted bias - correlation omitted heterogeneity vs distance [a]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln \widehat{\widetilde{y}}(s)^*_{nist}$	$\ln \widehat{\widetilde{y}}(s)^*_{nist}$	$\ln \widehat{\widetilde{y}}(s)^*_{nist}$	$\ln \widehat{\widetilde{y}}(s)^*_{nist}$	$\ln \widehat{y}_{nist}$	$\ln \widehat{y}_{nist}$	$\ln \widehat{y}_{nist}$	$\ln \widehat{y}_{nist}$
$\ln dist_{ni}$	-1.109***	-1.112***	-1.156***	-1.112***	.0174***	.0169***	.0089	.0169***
	(.0352)	(.0353)	(.0358)	(.0353)	(.0056)	(.0056)	(.0056)	(.0056)
Cons	17.22***	17.25***	17.61***	17.25***	1.284***	1.288***	1.354***	1.288***
	(.2973)	(.2985)	(.3025)	(.2984)	(.047)	(.0471)	(.047)	(.0471)
Obs.	562356	562356	562356	562356	516892	516892	516892	516892
R^2	.525	.5331	.6138	.5393	.2161	.2305	.3021	.2369
Fixed Effects								
Origin	✓				✓			
Destination	✓				✓			
Year	✓		✓		✓		✓	
Sector	✓	✓			✓	✓		
Origin x Year		✓		✓		✓		✓
Destination x Year		✓		✓		✓		✓
Origin x Sector			✓				✓	
Destination x Sector			✓				✓	
Sector x Year				✓				✓

[a] Source: OLS estimation from BACI. Each column represents a regression with a different combination of fixed effects. Dependent variable in Col. (1) to (4) is exporters' heterogeneity normalized by exporter efficiency (Eq.22). Dependent variable in Col (5) to (8) is the average exporters' productivity: $\widehat{y}_{nist} = \frac{1}{J(s)} \sum_j^J exp(\widehat{y}_{jnist})$ is the average value across products of normalized residuals (numerator of Eq.22). Standard errors are clustered at exporter-importer level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

Table 31: Omitted bias - correlation producers productivity vs distance [a]

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln \widehat{I}_{ist}$	$\ln \widehat{I}_{ist}$	$\ln \widehat{I}_{ist}$	$\ln \widehat{I}_{ist}$	$\ln \widehat{I}_{ist}$	$\ln \widehat{I}_{ist}$
$\ln Weighted\ Distance_{ist}$	.0183***	.0066	.0181***	.0159**	.0075	.0157**
	(.0061)	(.0053)	(.0062)	(.0065)	(.0052)	(.0066)
Share Exporter$_{ist}$				.0539	-.1441**	.0537
				(.039)	(.0586)	(.0395)
Cons.	.36***	.45***	.3621***	.3676***	.4717***	.3699***
	(.0467)	(.0403)	(.0474)	(.0492)	(.0424)	(.0499)
Obs	13200	13200	13200	13200	13200	13200
R^2	.6241	.8489	.6365	.6253	.8496	.6377
Fixed effects						
Origin	✓		✓	✓		✓
Sector	✓			✓		
Year	✓	✓		✓	✓	
Origin x Sector		✓			✓	
Sector x Year			✓			✓

[a] Source: OLS estimation from BACI. Each column represents a regression with a different combination of fixed effects. Dependent variable is $\widehat{I}_{ist}$, fixed effects from the estimation of Eq.21. Weighted Distance is the average distance of market reached by country i, where weight the share of trade that country i as with country n in sector s. Share Exporter$_{ist}$ is the average share of exported products across destinations. Standard errors are clustered at exporter level and are reported in parenthesis. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.