It takes (more than) a moment: Revisiting the link between firm productivity and aggregate exports*

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PRELIMINARY VERSION

Abstract

This paper exploits a unique data set covering a panel of 16 European countries and 21 manufacturing industries to examine within sectors which features of a country's firm productivity distribution are related to its aggregate export performance. It provides robust evidence that not only the first but also also higher moments of the firm productivity distribution matter. This is at odd with the predictions of the 'standard' trade model with firm heterogeneity à la Melitz (2003), in which the joint assumptions of CES demand, 'iceberg' export cost and Pareto productivity distribution imply that only the first moment should matter. It also offers a word of caution on the quantification of the welfare effects of trade policies based on that model in the wake of Arkolakis et al. (2012).

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1 Introduction

We exploit a unique data set covering a large sample of European countries to examine which features of their firm productivity distributions are related to their aggregate export performance. We provide robust evidence that not only the first but also also higher moments of the firm productivity distribution matter. We argue that these findings are at odd with the predictions of the 'standard' trade model of monopolistic competition with firm heterogeneity *à la* Melitz (2003) under the joint assumptions of CES demand, 'iceberg' trade costs and Pareto-distributed firm productivity as these imply that only the first moment should matter. [1] Our findings offer a word of caution on using the 'standard' trade model under those assumptions to quantify the welfare effects of trade policies as is increasingly done in the wake of Arkolakis et al. (2012).

Specifically, the 'standard' trade model with firm heterogeneity generates a structural gravity equation in which aggregate exports are determined by the number of firms in the exporting country and their average productivity (Head and Mayer, 2014). As a result, the exporter fixed effect (a.k.a. 'multilateral resistance'), which broadly speaking cane be taken as a measure of the exporting country's 'competitiveness' as an exporter, depends only on the first moment of the underlying firm productivity distribution. Other moments are irrelevant.

This prediction does not square well with existing evidence that the dominant share of a country's aggregate exports is mostly due to a small set of very large firms, the so called 'happy few' (Ottaviano and Mayer, 2011), and with further evidence of 'granularity' showing that aggregate economic outcomes frequently relate to the behavior of few large firms (Gabaix, 2011). Given that within countries the 'happy few' are typically concentrated in the top percentiles of the firm productivity distribution, it would be reasonable not to expect average firm productivity to be a sufficient statistics for aggregate outcomes and additional statistics of the distribution to be also relevant. In particular, productivity distributions with identical means but different higher moments related to the features of the right tail could well entail very different aggregate export performance.

To test the symmetric first-moment-only prediction of the 'standard' model against the alternative asymmetric higher-moment-too hypothesis associated with the 'happy few' phenomenon, we proceed in two steps. First, we estimate exporter fixed effects for our sample of countries through state-of-the-

[1]The original version of the model by Melitz (2003) does not make the Pareto assumption, which has subsequently become 'standard' in the wake of Chaney (2008).

art gravity regressions within sectors. We then regress, again within sectors, the estimated exporter fixed effects on countries' average firm productivities as well as on measures of the dispersion and the asymmetry of their firm productivity distributions.

As our identification exploits within-sector variations across countries, it is vital to be able to access harmonized cross-country data at the right level of disaggregation. This type of data is generally not available, with one exception on which we rely: the CompNet data set developed by the Competitiveness Research Network involving the European Central Bank and all EU National Central Banks (CompNet Task Force, 2014). This dataset provides a panel of cross-country, cross-sector data for 16 European countries and 21 manufacturing industries. CompNet data have been generated by running identical codes on firm-level harmonized data bases made available by National Central Banks or Statistical Institutes. Among its rich set of variables, CompNet provides detailed information on firm productivity distributions at the industry-country-year level. Hence, once matched with Eurostat's ComExt trade data (by origin country, destination market, sector and year), CompNet represents an ideal and unique data source allowing for the empirical investigation of within-sector connections between firm productivity distribution and aggregate exports on a cross-country basis.

For the sample of CompNet countries, we find strong and robust evidence rejecting the null hypothesis that only the average productivity of its firm matters for a country's aggregate export performance. In particular, after controlling for bilateral distance and importing country characteristics, within sectors and across countries exporter fixed effects are not only positively correlated with average firm productivity but also with measures of dispersion and asymmetry of firm productivity distributions. Especially asymmetry, measured by both parametric and non-parametric indexes, explains a considerable share of the cross-industry and cross-country variance of export competitiveness, in line with the happy few hypothesis.

Our findings suggest that different functional forms than those used in the 'standard' trade model are needed to explain aggregate bilateral exports. This has important implications. Other works rethinking the theoretical foundations of gravity models with the inclusion of heterogeneous firms have recently highlighted that it is not possible to give a structural interpretation of gravity estimates of multilateral resistance terms without assuming CES demand, 'iceberg' export cost and Pareto productivity distribution (Chaney, 2008; Head and Mayer, 2014; Helpman et al., 2008). Moreover, following initial work by Arkolakis et al. (2012), a growing number of contributions have recently relied on those assumptions to quantify the welfare effects of trade policies using a parsimonious set of aggregate statistics (see Costinot and Rodriguez-Clare, 2014, for a survey) . To fruitfully push this research agenda ahead, some of the key assumptions of the 'standard' trade model with firm heterogeneity should be reconsidered. For example, a key statistics needed to compute the welfare effects of trade policies is the elasticity of trade flows to trade costs. Recent studies argue that, to correctly measure that elasticity, it is necessary to deviate from the Pareto distribution assumption (Bas et al., 2015; Melitz and Redding, 2015). We show that, under this assumption, it is also quite hard to understand the link between firm productivity and aggregate exports.

The rest if the paper is organized as follows. Section 2 uses a streamlined version of Melitz (2003), based on the three key assumptions of CES demand, iceberg export cost and Pareto firm productivity distribution to generate a structural gravity equation connecting the exporter fixed effect with average firm productivity. Section 3 describes the CompNet data set. Section 4 outlines our empirical strategy. Section 5 discusses the corresponding results. The last section concludes.

2 Theoretical Framework

Our aim is to investigate which features of the productivity distribution of a country's producers explain its aggregate exports. Specifically, we want to check whether the implications of a standard model with heterogeneous firms à la Melitz (2003) are supported by the data. As the model is well known, here we only provide a streamlined presentation. Further details can be found in the original paper and in recent surveys such as those by Costinot and Rodriguez-Clare (2014) and Head and Mayer (2014).

Consider an economy consisting of M countries indexed $m = 1, ..., M$. Focus on bilateral exports from an 'origin' country o to a 'destination' country d. In each country m there are a large number of monopolistically competitive producers N_m, each supplying a unique variety of a horizontally differentiated good with marginal cost c distributed according to a continuous cumulative density function $G_m(c)$ with support $[0, c_{mm}]$.

The associated productivity is $1/c$ and, therefore, the upper bound of the support c_{mm} identifies the marginal cost level of the lowest efficiency producers in m. With costly trade exporters from m to d are producers in m that are at least as efficient as the lowest efficiency producers in d after taking trade costs into account. The lowest efficiency exporters from m to d have thus marginal cost $c_{md} < c_{dd}$, where the gap is due to the presence of trade costs. Accordingly the fraction of producers in m exporting to d is $G_m(c_{md})$, and their number is

$$N_{md}^{x} = N_m G_m(c_{md}). \tag{1}$$

This is the 'extensive margin' of trade from m to d. Using $x_{md}(c)$ to denote the value of exports from m to d for a producer with marginal cost c, the average value of exports per exporter from m to d can be written as

$$\overline{x}_{md} = \left[\int_0^{c_{md}} x_{md}(c)dG_m(c)\right] / G_m(c_{md}). \tag{2}$$

This is the 'intensive margin' of trade from m to d. Then, by definition, aggregate exports X_{md} are such that

$$X_{md} = N_{md}^{x}\overline{x}_{md} = N_m \left[\int_0^{c_{md}} x_{md}(c)dG_m(c)\right]. \tag{3}$$

While expressions (1), (2) and (3) have broad validity, Melitz (2003) makes two additional restrictive assumptions with a bearing on the functional form of $x_{md}(c)$ and the gap between c_{dd} and c_{md}. Most subsequent applications of Melitz's model also make the third restrictive assumption that productivity $1/c$ follows a specific distribution. When all three assumptions hold, we have what we call the 'standard' model of international trade with heterogeneous firms.

To understand what the three additional assumptions imply, it is useful to consider the general additive separable demand system studied by Zhelobodko et al. (2012). Specifically, let a mass L_d of identical consumers in country d share the following utility function

$$U_d = \int_0^{N_d^s} u(q_d(n))dn \tag{4}$$

which they maximize subject to the budget constraint

$$\int_0^{N_d^s} p_d(n)q_d(n)dn = y_d$$

where y_d is individual income, N_d^s is the number of sellers in d (including both local producers N_d and exporters from elsewhere N_{md}^{x}), $q_d(n)$ is consumption of the variety supplied by seller n, and $p_d(n)$ is its price. Utility maximization generates individual inverse demand

$$p_d(n) = \frac{u'(q_d(n))}{\int_0^{N_d^s} u'(q_d(n))q_d(n)dn} y_d$$

with associated individual expenditure

$$r_d(n) = p_d(n)q_d(n) = \frac{u'(q_d(n))q_d(n)}{\int_0^{N_d^s} u'(q_d(n))q_d(n)dn} y_d.$$

The value of exports from origin country o to destination country d for an exporter with marginal cost c can thus be stated as

$$x_{od}(c) = p_{od}(c)q_{od}(c)L_d = \frac{u'(q_{od}(c))q_{od}(c)}{\sum_{m=1}^{M} N_m \left[\int_0^{c_{md}} u'(q_{md}(c))q_{md}(c)dG_m(c)\right]} y_d L_d \tag{5}$$

with a corresponding value of aggregate exports equal to

$$X_{od} = \frac{N_o \int_0^{c_{od}} u'(q_{od}(c))q_{od}(c)dG_o(c)}{\sum_{m=1}^{M} N_m \left[\int_0^{c_{md}} u'(q_{md}(c))q_{md}(c)dG_m(c)\right]} y_d L_d \tag{6}$$

In line with Melitz (2003), the 'standard' model assumes $u(q_d(n)) = (q_d(n))^{1-1/\sigma}$ so that (4) implies a CES demand system. It also assumes that there are two types of trade costs: an iceberg variable export cost $\tau_{md} > 1$ and a fixed export cost $f_{md} > 0$. Local sales incur a fixed production cost $f_{mm} > 0$ instead of the fixed export cost but no variable trade cost ($\tau_{dd} = 1$).[2] The value of aggregate exports (6) then becomes

$$X'_{od} = \frac{[N_o G_o(c_{od})] (\bar{c}_{od})^{1-\sigma} (\tau_{od})^{1-\sigma}}{\left[\sum_{m=1}^{M} N_m G_m(c_{md})\right] (\bar{c}_d^s)^{1-\sigma}} y_d L_d \tag{7}$$

where $\bar{c}_{md}$ is the average (delivered) marginal cost of exporters from m to country d defined as

$$\bar{c}_{md} = \left[\int_0^{c_{md}} c^{1-\sigma} dG_m(c)/G_m(c_{md})\right]^{\frac{1}{1-\sigma}},$$

[2] In order to obtain 'selection into export status', the fixed export cost is assumed to be larger than the fixed production cost ($f_{md} > f_{mm}$). This ensures that in equilibrium a country m's marginal exporters are more productive than its marginal producers.

$\overline{c}_d^s$ is the average (delivered) marginal cost of all sellers to d defined as

$$\overline{c}_d^s = \left[\sum_{m=1}^{M} \frac{N_m}{N_d^s} \left(\overline{c}_{md}\right)^{1-\sigma} \left(\tau_{md}\right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}},$$

and $\sum_{m=1}^{M} N_m G_m(c_{md})$ is the total number of sellers N_d^s.[3] Collecting country indices, (7) can be rewritten as

$$X'_{od} = N_o\ G_o \left(\frac{c_{dd}}{\tau_{od}} \left(\frac{f_{dd}}{f_{od}} \right)^{\frac{1}{\sigma-1}} \right) \left(\overline{c}_{od}\right)^{1-\sigma} \left(\tau_{od}\right)^{1-\sigma}\ \frac{y_d L_d}{N_d^s \left(\overline{c}_d^s\right)^{1-\sigma}} \tag{8}$$

given that we have

$$c_{od} = \frac{c_{dd}}{\tau_{od}} \left(\frac{f_{dd}}{f_{od}} \right)^{\frac{1}{\sigma-1}}.$$

Lastly, the 'standard' model assumes that productivity follows a Pareto distribution implying the cumulative density function of marginal cost $G_m(c) = (c/c_{mm})^k$ with $c \in [0, c_{mm}]$ and $k > 1$. Larger k shifts density towards the upper bound of the support c_{mm}.

Under this third assumption, the term $G_o\left(c_{od}\right)\left(\overline{c}_{od}\right)^{1-\sigma}\left(\tau_{od}\right)^{1-\sigma}$ can be unbundled into monadic and dyadic components so that (8) can be further specified as

$$X''_{od} = N_o \left(\overline{c}_{oo}\right)^{-k}\ \ \left(f_{od}\right)^{1-\frac{k}{\sigma-1}} \left(\tau_{od}\right)^{-k}\ \frac{y_d L_d \left(\overline{c}_{dd}\right)^{1-\sigma+k} \left(f_{dd}\right)^{\frac{k}{\sigma-1}-1}}{N_d^s \left(\overline{c}_d^s\right)^{1-\sigma}} \tag{9}$$

This is a gravity equation that explains aggregate bilateral exports from origin country o to destination country d in terms of the 'capabilities' of country o as a supplier to all destinations $N_o\left(\overline{c}_{oo}\right)^{-k}$, the characteristics of destination country d that promote imports from all origins

$$y_d L_d \left(\overline{c}_{dd}\right)^{1-\sigma+k} \left(f_{dd}\right)^{\frac{k}{\sigma-1}-1} / N_d^s \left(\overline{c}_d^s\right)^{1-\sigma},$$

and bilateral trade costs due to crossing the border f_{od} and covering distance τ_{od} (Head and Mayer, 2014). [4] For conciseness, we introduce the term '(export) competitiveness' of origin country o to refer to its 'capabilities' as a supplier to all destinations. Then (9) has the strong implication that the country's competitiveness $N_o\left(\overline{c}_{oo}\right)^{-k}$ and thereby its aggregate exports to d depend only on the

[3] These are output weighted marginal costs such that the average (delivered) price equals the (delivered) price of the firm with average marginal cost.

[4] In (Head and Mayer, 2014) the 'capabilities' of country o are expressed in terms of the marginal cost c_{oo} of its lowest efficiency producers instead of the average marginal cost of all its producers $\overline{c}_{oo}$. Ours and theirs are, of course, equivalent expressions as under Pareto we have $\overline{c}_{oo} = \left[k/\left(k-\sigma+1\right)\right]^{1/(1-\sigma)} c_{oo}$. An analogous mapping between $\overline{c}_{dd}$ and c_{dd} holds for the characteristics of destination country d that promote imports from all origins.

first moment $\bar{c}_{oo}$ of the productivity distribution of its producers but not on higher order moments. In (8) the role of higher order moments is channeled through the export probability $G_o(c_{od})$. This role is obfuscated by the Pareto assumption for the unconditional distribution $G(c)$ as the conditional distribution $G_o(.)$ is also Pareto and for a Pareto distribution the different moments are all defined as functions of the upper bound of the support and the shape parameter k. This implies that, after controlling for the first moment, all other moments are irrelevant.

In the next section we will bring this implication of the 'standard model' to data in two steps. First, we will run gravity regressions based on (9) to estimate origin country fixed effects for a sample of Eurozone countries. These fixed effects will measure the 'competitiveness' of the sampled countries as suppliers, netting out importer-specific and country-pair-specific characteristics. Second, we will check to which extent the variation in the estimated origin country fixed effects across countries is related to the moments of their firm productivity distribution. Given (9), the null hypothesis of the 'standard' model is that only the first moment of the productivity distribution should matter. The alternative hypothesis based on (6) is that higher moments should matter too. Rejection of the null hypothesis in favor of the alternative should, therefore, be interpreted as confutation of the CES-iceberg-Pareto restrictions imposed by the 'standard' model.[5]

Two final comments are in order before proceeding with the empirical analysis. First, so far we have assumed that marginal cost is simply the inverse of productivity. We have done so to streamline the presentation of the model but this ignores the role of variations in factor prices for given productivity, which could bias the estimation. To deal with this omitted variable issue, we follow Head and Mayer (2004) in assuming that technology is Cobb-Douglas in labor and capital with respective shares α and $1-\alpha$ ($0<\alpha<1$). Using w_o and r_o to denote the wage and the rental rate of capital in country o, the marginal cost of a firm with productivity φ then equals $c_o(\varphi) = \alpha^{\alpha}(1-\alpha)^{1-\alpha} w_o^{\alpha} r_o^{1-\alpha} \varphi^{-1}$, where w_o and r_o are the same for all firms under the assumption of perfectly competitive factor markets.[6] Under these hypotheses, the exporter's 'capabilities' $N_o\left(\bar{c}_{oo}\right)^{-k}$ can be rewritten as

$$N_o\left(\bar{c}_{oo}\right)^{-k} = N_o\left(\alpha^{\alpha}(1-\alpha)^{1-\alpha}\right)^{-k}\left(w_o^{\alpha} r_o^{1-\alpha}\right)^{-k}\left(\overline{\varphi}_{oo}\right)^{k} \tag{10}$$

[5]These restrictions also underpin the finding by Arkolakis et al. (2012) that several trade models share the same aggregate welfare properties.

[6]Analogously, the fixed export cost would be $\alpha^{\alpha}(1-\alpha)^{1-\alpha} w_o^{\alpha} r_o^{1-\alpha} f_{od}$, with similar expressions for fixed and marginal costs in country d.

where $\overline{\varphi}_{oo} = [k/(k-\sigma+1)]^{\frac{1}{\sigma-1}} \varphi_{oo}$ is the average productivity of all producers in country o with φ_{oo} referring to the productivity level of the most efficient producers in that country. Second, as we will use firm level data across several sectors, apart from assuming that parameters are sector specific, we also need to generalize our results accounting for factor prices variations to a multi-sector set-up. We do so by assuming that capital is freely mobile between sectors within a country and also between countries whereas labor is freely mobile between firms within a sector in a country but not between sectors within the country (and a fortiori between countries). Under these assumptions, the rental rate of capital will be the same across countries and sectors while the wage will be sector-country specific.[7]

3 Data

For the empirical analysis, we use three main sources of data: European System of Central Banks' Competitiveness Network dataset (CompNet), Eurostat's ComExt trade database, and the CEPII database.

Under the coordination of the European Central Bank, 17 (Austria, Belgium, Croatia, Estonia, Finland, France, Germany, Hungary, Italy, Malta, Lithuania, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain) national central banks have produced a set of harmonized and comparable sector - and year-level production function indicators based on national firm-level samples (see CompNet Task Force, 2014).[8] The indicators available are the amount of inputs and output, labor productivity, total factor productivity (TFP) and measures of allocative efficiency such as the so-called OP covariance (Olley and Pakes, 1996). What is special in CompNet is that the firm-level data have been used to compute not only averages (by country, sector and year) but also other moments of each variable's distribution. Thus for a country-sector-year triple and for each indicator, the dataset reports information on the mean, the median, the standard deviation, the skewness, and the values of various percentiles.

CompNet comprises two different samples. The *"full sample"* is produced from countries' samples based on firms with at least one employee and covers the period 1995-2012, while the *"20E sample"* is restricted to firms with at least 20 employees and starts from 2001.[9] However, the *"20E sample"*

[7] In several respects, at the sectoral level the model we use is observationally equivalent to the Ricardian model of Costinot et al. (2012). From this viewpoint, our empirical analysis can be interpreted as looking into finer details at how higher moments of the firm productivity distribution within sector-country pairs may affect revealed comparative advantages across countries.

[8] The unit of analysis is the firm. Self-employed (physical persons with economic activity) are generally not included.

[9] Both samples are slightly unbalanced: for example, Portugal data begin in 2006, while Belgian ones end in 2011.

ensures a relatively higher degree of representativeness (CompNet Task Force, 2014) because the *"full sample"* in some cases do not cover smaller firms (those with less than 10 employees in Poland, less than 20 employees in Slovakia, less than 750,000 euros of turnover in France), and in the other cases tend to be biased towards medium and large firms (such a bias is severe for Austria and Germany). To improve representativeness and homogeneity across countries, the *"20E sample"* has been enriched by a weighting scheme based on the total number of firms by country-year-sector-size class taken from Eurostat Structural Business Statistics (SBS). Thus, *"20E sample"* is the most appropriate database for cross-country analysis.

The *"20E sample"* has some drawbacks, too. First, it obviously 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 going to be a minor issue in our case since we aim at explaining export performance and exporting is well-known to be an activity for more productive and relatively larger firms. Second, due to the ways some of the firm-level datasets are built there are potential sample biases towards more productive firms so that aggregate values (by country or sector) record sometimes non-negligible differences with respect to Eurostat official figures. We address these concerns by including in our econometric analysis country and sector fixed alone and in combination with year fixed effects. effects that may capture systematic differences across countries or sectors.

After excluding country-sector-year cells comprising less than 10 firms and all the observation for Malta [10] , we end up with an unbalanced panel of 3,529 observations for 16 European countries, two-digit manufacturing sectors (with the exclusion of Coke and Petroleum and Tobacco) over the period 2001-2012.

As already explained, the focus of this paper is on higher moments of the productivity distribution. At the country-sector-year level we therefore compute 2 indicators of dispersion and 2 indicators of asymmetry. As for dispersion, we consider: (i) the ratio of the 80th to the 20th percentile of the productivity distribution ($P80/P20$), and (ii) the ratio of the 90th to 10th percentile of the productivity distribution ($P90/P10$). These two ratios have the advantage of being independent of the type of the underlying distribution. A ratio $P90/P10$ equal to 2 means that the firm at the 90th percentile is twice more productive than a firm in the 10th percentile. Then, an increase of the ratio indicates that

[10] We have few observations for the average wage at sectoral level in Malta. The results are unaffected by the presence of Malta.

the tails of the distribution are more distant from each other in terms of productivity levels, or in other terms that the most productive firms (right part of the distribution) are relatively more productive than the least productive ones (left part of the distribution).

Asymmetry is captured by two indicators: i) the standard parametric skewness index (third central moment) (*Skew*); ii) the non-parametric Pearson's second skewness coefficient (*Pears*) computed as follows:

$$Pears = \frac{Mean - Median}{st.dev.} \tag{11}$$

This latter index is of easy interpretation. When *Pears* assumes positive (negative) values, i.e., when mean>median (mean<median), the productivity distribution is right-skewed (left-skewed). A higher index is therefore signaling a fatter and longer right tail of the distribution. The normalization of the Pearson coefficient by the standard deviation (*st.dev.*) allows a better comparability across countries and sectors. *Pears* is a distribution-free indicator while *Skew* works better in the case of normality.

Table 1 reports the descriptive statistics of the labor productivity distribution indicators by country, that is taking averages over sectors and years. At first glance, we see that average values range from the lowest figures of Romania, Hungary and Lithuania to the highest ones of Germany and Austria. With some exceptions somehow related to the sample biases previously described, there appears to be a positive correlation between country size and average productivity. The dispersion and asymmetry indicators display the opposite pattern, being larger in smaller and less advanced countries.

[Table 1 about here.]

Differences in labor productivity across countries can be better appreciated in Figure 1 which shows the box plot of the productivity distribution by country. With countries ranked by average labor productivity levels, it is quite evident that large countries are more productive than small ones and that there is a great dispersion in the data both within and between countries.

[Figure 1 about here.]

Since our goal is to relate the moments of the productivity distribution to countries' trade performance, we retrieve from Eurostat's ComExt database the values of exports (in euros) for each

European country participating to CompNet Network to 165 destination markets and for 21 manufacturing sectors (CPA 2008 2 digit) over the period 1996-2012.[11] Descriptive statistics (in log of millions of euros) of these data are reported in Table 2.

[Table 2 about here.]

Finally, we retrieve from the CEPII database (Mayer and Zignago, 2011) the standard dyadic variables to be used in the gravity model. In particular, for any exporting-importing country pair, we derive information on the geographical distance, on the existence of a common border and a common language, and on the former colony status of the importer with respect to the exporter. As geographical distance is concerned, we use the geodesic distances calculated with the great circle formula, which is based on latitudes and longitudes of the most important cities/agglomerations (in terms of population).

4 The empirical specification

In this section, we describe our empirical strategy to test the validity of the assumptions behind the standard trade model presented in Section 2. We follow a two-step approach.

In the first step, we estimate a general gravity equation with fixed effects for the importing and exporting country corresponding to Equation 9, that is:

$$Log(X)_{odst} = \alpha_{ost} + \beta_{dst} + \gamma_{od} + \epsilon_{odst}, \tag{12}$$

where aggregate bilateral exports (X_{odst}) from origin country o to destination market d in sector s and year t are regressed on: (i) exporting country-sector-year fixed effects (α_{ost}) which proxy for the the capabilities of country o to supply all destination markets in sector s and year t and correspond to the term $N_o(\bar{c}_{oo})^{-k}$ in Equation 9; (ii) importing country-sector-year fixed effects (β_{dst}) which absorbs all the characteristics (e.g., demand) of destination market d in sector s and year t; (iii) the standard bilateral (origin-destination) time- and sector-invariant trade cost (γ_{od}). Standard errors are always robust to heteroschedasticity and clustered at the exporting country-year level to control for asymmetric business cycles.

[11] Notice that the first two digits of CPA 2008 coincide with the first two digits of NACE rev.2.

As explained by (Head and Mayer, 2014), this specification has important advantages: it *"is now common practice and recommended by major empirical trade economists"*, and it *"does not involve strong structural assumptions on the underlying model"*. Moreover, in this setting we can retrieve the exporter-sector-year fixed effects that in the gravity literature language coincide with the exporter's multilateral resistance term once all possible destination markets' characteristics (again by sector and year) and the standard dyadic (geographical-cultural-historical) features are netted out.[12] From now on, we rename the exporter's multilateral resistance term as the competitiveness indicator $Comp.Ind._{ost}$.

We then take $Comp.Ind._{ost}$ to the second step, and with the aim of estimating the log-linear transformation of Eq. 10, we use it as the dependent variable in the following equation

$$\begin{aligned} Comp.Ind._{ost} = \quad & a_0 + a_1 Log(Mean)_{ost-1} + a_2 Log(firms)_{ost-1} + \\ & a_3 Log(wage)_{ost-1} + a_4 Asim_{ost-1} + a_5 Disp_{ost-1} + \\ & C_o + S_s + Y_t + e_{ost} \end{aligned} \tag{13}$$

where we directly test whether $N_o(\bar{c}_{oo})^{-k}$ in Eq. 9 depends only on the number of firms in the domestic market ($Log(firms)$), the average wage ($Log(wage)$) [13] and, more importantly, the exporting country-sector-year average productivity ($Log(Mean)$) as predicted by the standard Melitz model with heterogeneous firms (i.e., N, w, and $\overline{\varphi}$ in Eq. 10, respectively) or rather also on higher moments measuring the dispersion ($Disp$) or the asymmetry ($Asim$) of the productivity distribution.

All the regressors are one-period lagged to minimize endogeneity (due to simultaneity or reverse causality) concerns. Country fixed effects (C_o) are included to control for time-invariant characteristics, like country size, of the exporting economy that could affect its competitiveness. Sector fixed effects (S_s) capture different degrees of tradeability across products that could easily bias the estimates given that exporting countries have different sectoral specialization. Finally, year fixed effects (Y_t) control for common international cycles. We estimate Equation 13 by OLS with standard errors that are robust to heteroskedasticity and clustered at the sector X year level to account for autocorrelation

[12] Other estimation methods, such as tetrads transformation, even if less computationally intense in term of dummy variables, would not allow us to retrieve the estimates of the exporter's fixed effects.

[13] The number of firms at sector level is reported in CompNet database, while the average wage is computed from Eurostat as total labour compensation to total employment (at country sector year level).

due, for example, to sectoral shocks (such as as technology shocks or sectoral trade policies).

This two-step approach is commonly used to evaluate the effect of country-sector level characteristics (such as exchange rate or wages) on trade flows (Eaton and Kortum, 2002) and foreign direct investment (Head and Ries, 2008). Importantly, the mean and the higher moments of the productivity distribution would not be identified in a one-step estimation with the high dimensional dummies that are typically included in the gravity model (Head and Mayer, 2014).

5 Results

Table 3 reports the results from the fixed effects estimation of the gravity model. We estimate it over three different sample, so as to show that the exporter's multilateral resistance terms do not vary significantly when estimated over a different set of exporting countries or a different sample period.

The first sample considers export data from 1996 to 2012 participating to the CompNet network(column 1)[14]; the second sample focus on the same set of countries but restricts the period of analysis to 2001-12 (column 2); the third sample is based on the smaller set of 16 countries for which we have productivity indicators in the sample *20E*, again from 2001 to 2012. All the coefficients have the expected sign and do not vary in a relevant way across samples. Exports decrease with distance, while they are higher in case the exporting and importing countries share a common language and have colonial ties. Compared to the previous literature, the coefficient of distance is relatively large (above the average of 0.93 reported in Head and Mayer (2014) but still in the range of existing findings. However, it must be considered that typically trade elasticities with respect to distance tend to be higher when the estimates are mostly driven by trade flows within the same region, as is in our case (Disdier and Head (2008)).

[Table 3 about here.]

Since the $\hat{\alpha}_{ost}$ estimated with the three different samples are highly pairwise-correlated (the coefficients of correlation are always around 0.98), in Table 4 we show only the coefficients from column 3, i.e., from the restricted sample of CompNet countries for which we have productivity indicators. As expected, the highest values $\hat{\alpha}$ belong to the most advanced and larger European economies, namely

[14]These countries are: Austria, Belgium, Croatia, Czech Republic, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

Germany, Italy, France, and Spain, while the lowest ones to Estonia and the East European countries (Romania, Hungary, Slovakia, Slovenia).

[Table 4 about here.]

Even if the estimated $\hat{\alpha}_{ost}$ are positively affected by the size of the exporting country, we deem they are also good indicators of its competitiveness regardless of size. In Figure 2, we provide a scatter plot of $\hat{\alpha}_{ost}$ against the normalized trade balance (the ratio of exports minus imports to exports plus imports) and the correspondent linear fit line. These two variables are quite clearly positively related, to say that $\hat{\alpha}_{ost}$ are indeed capturing an exporting country's overall competitiveness on the international markets of manufacturing goods, even though they are just derived from an export equation.

[Figure 2 about here.]

As already mentioned, the exporter's fixed effects identify the multilateral resistance term[15] and take into account anything that can affect its propensity to export to all destinations. Therefore, *Comp.Ind.* can be used to analyze trade determinants that cannot be identified within a gravity equation (Head and Mayer, 2014). In this vein, we test if a country's competitiveness in the international markets is affected by its average firm productivity or also by more general features of its productivity distribution.

Our baseline estimates are based on the *"20E sample"* and on labor productivity (LProd) as a measure of sectoral efficiency. [16] Compared with the original *"20E sample"*, we loose some observations due to the lack of information on labour compensation and employment for some country-sector-year pairs.

Table 5 presents the baseline results. The coefficient of average labor productivity is, as expected, positive and statistically significant in all the specifications: in the spirit of Melitz-type models, higher average productivity is beneficial to a country's exporting capacity. But this is not the full story. When in columns 2-5 we add the higher moments of the productivity distribution one at a time, we find that the right-skewness and, though to a smaller extent, the dispersion of the productivity distribution are also positively related to competitiveness. In the case of asymmetry the coefficients of

[15] Anderson and Yotov (2012) show that structural multilateral terms explain almost all of the variation in the estimated fixed effects generated from gravity regressions.

[16] In an additional robustness, we consider a subsample of indicators based on TFP: see Table 9.

both $Pears.$ (column 4) and $Skew.$ (column 5) are positive and highly significant. As to dispersion, we find a positive and significant coefficient when using the $P80/P20$ ratio (column 3) and a positive but weaker one with the $P90/P10$ ratio. In the last four columns of Table 5, we run a horserace between mean, dispersion, and asymmetry indexes and confirm that average and asymmetry are both simultaneously and robustly relevant for a country's international competitiveness. Similarly, the link between the dispersion of productivity and competitiveness appears to be robust but not for extremely dispersed distribution (see column 6 and 7).

Quantitatively, the estimates of column 4 suggest that an increase of one standard deviation in the $Pears.$ index (corresponding to a 45% increase with respect to its mean) is associated to a competitiveness index 2.5 per cent higher; as a basis of comparison, the effect of an increase of one standard deviation in average labor productivity amounts to an increase of about 6.2 per cent in $Comp.Ind.$. [17] Besides, the coefficients of $Log(firms)$ and $Log(wage)$ are statistically significant and report the expected sign.

[Table 5 about here.]

5.1 Robustness

Our analysis has so far shown that average firm productivity is not a sufficient statistics of a country's competitiveness and that other moments of the productivity distributions convey novel and relevant information. Even if we are not aiming at providing any causal relationship between asymmetry or dispersion on one side and export performance on the other, we can strengthen our results by showing they are robust to different empirical specifications. To this aim, we perform four robustness exercises.

The first one addresses potential omitted variable biases. In particular, we enrich Equation 13 with country$X$year and sector$X$year fixed effects, thus controlling for developments in the exporting country's effective exchange rate or for sectoral or technology shocks. In this robustness, we replicate the specifications of columns 4, 5, 7, and 9 of Table 5.

For the case with country$X$year fixed effects, to which we add sector fixed effects, the results are reported in columns 1-4 of Table 6. Quite evidently, the strong results on average productivity,

[17] As noted in Section 2, the Ricardian model of Costinot et al. (2012) generates predictions that at the sectoral level are, in several respects, observationally equivalent to ours. While they do not consider higher moments of the productivity distribution, they do estimate the effect of average productivity on corrected exports across sectors (i.e., the value of bilateral exports divided by exporter's trade openess) in a regression that can be thought as someway combining our first and second stages (without, of course, the higher moments among the regressors). When we replicate their estimation on our data, we obtain very comparable results. These results are available from the authors upon request.

Pearson index, skewness, and $P80/P20$ ratio remain unchanged. The same occurs when we include sector$X$year fixed effects along with country fixed effects in columns 5-8. In all the specifications, the coefficients of $Log(firms)$ and $Log(wage)$ remain statistically significant and stable.

[Table 6 about here.]

Table 7 reports a second set of robustness checks, building on the richer specification of columns 1,2,5 and 6 of Table 6. In the first four columns of Table 7, we cluster the (robust) standard errors by country$X$year, instead of sector$X$year, to control for the serial correlation of the error term due to country-specific business cycle shocks. Again, $Log(LProd(Mean))$, $LProd(Pears.)$, and $LProd(Skew)$ are positive and statically significant.

Given that CompNet indicators are obtained by aggregating micro level data, in columns 5 to 8 of Table 7, we re-estimate the model using weighted least square (WLS). Similarly to Angrist (1998), we weight the observations with the number of firms within each country-sector-year cell that have been used to compute the CompNet indicators.[18] Given the definition of weights at country-sector-year level, the WLS estimator implies lower squared residuals (and consequently lower standard errors) for the observations generated with a large number of firms (i.e., large weights). Thus, the statistical significance relies more on those observations that are calculated on cells with a relatively larger number of firms. The WLS estimator conveys the same results: both the average, the asymmetry index, and, though to a minor extent, the skewness of the productivity distribution are related positively to a country's export capabilities

[Table 7 about here.]

We then test the robustness of our findings to sample composition. We re-estimate the specification of column 4 in Table 5 eliminating one country at a time from the *"20E sample"*. Table 8 shows the estimated coefficients for the various moments. Each row reports the result obtained when excluding the country indicated in the first column of the Table. The Pearson index is always positive and significant: it ranges from 0.31 (excluding Finland) to 0.57 (excluding Austria). Similarly, the estimated coefficient of $Log(LProd(Mean))$ is always positive and statistically significant. It suggests that our results are not driven by sample composition.

[18] Angrist (1998) shows that the weighted regression with grouped data (both dependent and main explanatory) produces coefficients equal to those generated when using the underlying micro-data sample.

[Table 8 about here.]

In a last robustness analysis, we replicate the estimates of columns 1 and 4 in Table 5 using TFP instead of labor productivity as indicator of sectoral efficiency. The available data allow us to compute only the mean and the Pearson index (see Eq. 11). [19] reported in Table 9, the estimated coefficients are consistent with the previous findings: both the mean and the Pearson index are positively correlated with the competitiveness index. These results are also robust to the inclusion of country$X$year (column 3 and 4) and sector$X$year (column 5 and 6). Quantitatively, an increase of one standard deviation in the $Pears.$ index of TFP (corresponding to a 31% increase with respect to its mean) is associated to a competitiveness index 2.2 per cent higher (2.5% with labor productivity).

[Table 9 about here.]

6 Concluding remarks

This paper provides a new contribution to the study of how the micro characteristics of firm productivity distributions affect aggregate trade. It shows that the 'standard' trade model with heterogeneous firms (based on the three key assumptions of CES demand functions, iceberg trade costs and Pareto productivity distributions) does not provide empirically valid predictions on the supply side factors that are relevant for aggregate exports.

In particular, we have shown that (country-sector-year) average productivity is not a sufficient statistics for a country's exporter fixed effect (which we have take as a proxy of its export competitiveness), once dyadic and importer's characteristics are controlled for. Instead, a country's export competitiveness is significantly and robustly correlated with the dispersion and the asymmetry of the productivity distribution. This suggests that, before relying on the 'standard' trade model to quantify the welfare effects of trade policies, one should rethink some of its key assumptions.

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[19] The TFP indicator (in both CompNet samples) has two main drawbacks. First, the cross country comparable statistics exist only for a limited number of moments: mean, median, and standard deviation. Second, TFP is not reported for Hungary and Austria (only 12 observations).

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A Average and dispersion of simulated distributions

In the micro-based trade model, the CES-Pareto-iceberg assumption implies that aggregate export are higher in country/sector showing higher average productivity. However, averages do not fully describe the characteristics of the underlying firms' population. For example, two countries with the same average productivity can not be identical: on the one side, a country may have both extremely productive and sluggish firms, and on the other side a country is characterized by homogenous firms. While averages are similar, the distributions of firms' productivity differ. To illustrate it, we report in Figure 3 kernel density for simulated data (10,000 observations). For each of the four plots, we draw the kernel density of two populations generated by different distributions but with the same mean.

Panel *(a)* reports two gamma distributions with the same mean but different shape and scale parameters. The continuous line depicts a skewed population with a thick tail (longer and fatter) , while the dotted lines is more symmetric (around the mean). Both populations show the same averages but different characteristics in term of standard deviation, skewness and non-parametric skewness (i.e., $Pears. = (mean - median)/st.dev.$).

Also populations with same mean and standard deviation can be different. Panel (b) reports a gamma (continuous line) and a normal distribution (dotted line) with the same mean and standard deviation. While gamma population is right skewed, the normal distribution is symmetric around the mean (by definition). The former has a longer right tail, while the latter a longer left tail. Finally, panel *(c)* and *(d)* depict Lognormal and Pareto distributions, respectively. Again, in both cases the mean is not informative of the characteristics of the underlying population. So any analysis, involving countries' comparison, risk to be not accurate whether it relies on the populations' mean. It is of particular interest in the international trade as long as the assumption of Pareto distribution (with CES preferences and iceberg trade cost) implies that aggregate export depends on the average productivity.

[Figure 3 about here.]

Tables

Table 1: Statistics on Productivity ‡

	Labour Productivity				
Country	LProd(Mean)	LProd(Asim.)	LProd(Skew.)	LProd(P90/P10)	LProd(P80/P20)
Austria	4.347	0.175	0.907	2.528	1.862
Belgium	4.004	0.220	1.287	2.725	1.908
Croatia	2.328	0.249	1.271	4.154	2.522
Estonia	2.321	0.208	0.976	3.726	2.402
Finland	4.018	0.218	1.234	2.469	1.753
France	4.121	0.217	1.207	2.714	1.910
Germany	4.516	0.200	1.193	3.175	2.108
Hungary	1.784	0.262	1.572	5.848	2.921
Italy	3.582	0.205	1.301	2.840	1.950
Lithuania	2.024	0.269	1.317	5.347	3.113
Poland	2.436	0.252	1.667	4.897	2.767
Portugal	2.978	0.202	1.125	3.278	2.163
Romania	1.497	0.300	1.813	5.814	3.178
Slovakia	2.263	0.273	1.921	5.555	2.954
Slovenia	2.392	0.182	1.045	2.967	1.960
Spain	3.496	0.204	1.127	3.021	2.039
Total	3.102	0.225	1.307	3.739	2.309

‡ Source: authors elaborations on CompNet data (sample 20E from 2001). Each cell reports country's averages (across sector-year) for the efficiency and the indicators of dispersion and asymmetry (see Section 3) Mean: micro-based average productivity (unweighted). Asim: second skewness coefficient. Skew: parametric skewness from CompNet. $P90/P10$: ratio of the 90th percentile of labor productivity to the 10th percentile. $P80/P20$: ratio of the 80th percentile of labor productivity to the 20th percentile.

Table 2: Exports by country (averaged by sector and year) - log values ‡

Country	Mean	St.Dev	IQR	Obs	Min	Max
Austria	2.719	2.434	4.158	34470	0	11.075
Belgium	3.143	2.500	3.940	37727	0	11.924
Croatia	1.541	1.788	2.519	15693	0	8.392
Estonia	1.511	1.802	2.495	16033	0	9.083
Finland	2.345	2.295	3.754	28154	0	9.937
France	3.786	2.625	4.267	39571	0	11.995
Germany	4.098	2.923	4.804	41009	0	12.417
Hungary	2.267	2.314	3.695	25388	0	11.001
Italy	3.801	2.648	4.461	39256	0	11.155
Lithuania	1.611	1.893	2.681	18882	0	8.873
Malta	0.914	1.362	1.234	11294	0	8.218
Poland	2.518	2.457	4.051	31281	0	11.015
Portugal	1.949	2.021	2.898	30134	0	9.852
Romania	2.016	2.111	3.255	22986	0	10.045
Slovakia	2.130	2.200	3.360	21887	0	10.711
Slovenia	2.004	2.013	3.172	22484	0	9.222
Spain	3.223	2.373	3.808	36072	0	11.758
Total	2.718	2.510	4.076	472321	0	12.417

‡ Source: authors elaborations on Eurostat ComExt data. IQR: inter quantile range.

Table 3: Gravity Model ‡

	(1) All	(2) From 2001	(3) From 2001 (Country in sample 20E)
Log(Distance)	-1.219***	-1.235***	-1.214***
	(.0601)	(.064)	(.0761)
Common Border	.5166***	.5775***	.4655***
	(.1476)	(.1527)	(.1546)
Common Language	.7079***	.7123***	.7222***
	(.1005)	(.1006)	(.1315)
Former Colony	.6125***	.5727***	.6496***
	(.1659)	(.1643)	(.1641)
Obs	775764	578965	472321
R^2	.8248	.8185	.8268
Fixed Effects 1	Origin*Sector*Year	Origin*Sector*Year	Origin*Sector*Year
Fixed Effects 2	Destination*Sector*Year	Destination*Sector*Year	Destination*Sector*Year

‡ Linear regression model with two high dimensional fixed effects (Guimarães and Portugal, 2010). Robust standard errors are clustered at origin X year level and reported in the parenthesis. Significance level: * 0.10>p-value, ** 0.05>p-value, *** 0.01>p-value Col.1: the estimation sample includes as origin all the countries in the CompNet network from 1995. Col.2: the estimation sample includes as origin all the countries in the CompNet network from 2001. Col.3: the estimation sample includes as origin all the countries in the CompNet *sample 20E* database (from 2001).

Table 4: Competitiveness Index ‡

Country	Mean	St.Dev	IQR	Obs	Min	Max
Austria	12.642	0.978	0.919	227	9.170	14.575
Belgium	13.132	1.278	1.836	242	9.217	15.327
Croatia	10.070	0.700	0.953	224	7.859	11.457
Estonia	10.285	0.795	0.879	239	7.065	11.775
Finland	12.002	1.247	1.518	250	8.606	14.519
France	13.959	1.298	1.554	252	9.735	15.798
Germany	14.535	1.276	1.698	252	11.088	17.048
Hungary	11.505	1.091	1.495	210	8.160	14.253
Italy	14.161	1.088	0.637	253	10.237	16.612
Lithuania	10.569	0.820	0.804	211	7.661	12.224
Malta	9.671	0.870	1.324	36	8.265	11.042
Poland	12.437	0.974	1.174	176	9.359	14.337
Portugal	12.087	0.691	0.714	147	9.512	13.016
Romania	11.251	0.896	1.119	210	8.519	12.853
Slovakia	11.012	0.934	0.937	229	8.338	13.615
Slovenia	10.976	0.860	1.063	237	8.128	12.601
Spain	13.388	1.023	1.148	252	9.603	14.997
Total	12.159	1.756	2.649	3647	7.065	17.048

‡ Source: authors elaborations on Eurostats Comext data. The competitiveness index coincides with the exporters multilateral resistance terms that has been estimated by the general gravity equation with fixed effects reported in Col.3 of Table 3. Here we report the countrys average across sectors (21 NACE rev.2 manufacturing) and year (2001-12).

Table 5: Baseline model - Productivity distribution and competitiveness index (sample20E)‡

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(LProd(Mean))$_{ost-1}$	.0841***	.0804***	.0748***	.0944***	.1056***	.0919***	.0835***	.1021***	.0947***
	(.0232)	(.0231)	(.0223)	(.022)	(.0222)	(.022)	(.0214)	(.0222)	(.0216)
Log(firms)$_{ost-1}$	.5957***	.595***	.5966***	.5964***	.5772***	.5961***	.597***	.5776***	.58***
	(.0314)	(.031)	(.0303)	(.0314)	(.0319)	(.0312)	(.0304)	(.0317)	(.0308)
Log(wage)$_{ost-1}$	-.0627***	-.0654***	-.0701***	-.0599***	-.0598***	-.0615***	-.067***	-.0618***	-.0671***
	(.0142)	(.0144)	(.0142)	(.0138)	(.014)	(.0141)	(.0139)	(.0142)	(.014)
LProd(P90/P10)$_{ost-1}$		.0136*				.0072		.0093	
		(.0079)				(.0082)		(.008)	
LProd(P80/P20)$_{ost-1}$			.1054***				.0886***		.0983***
			(.0251)				(.0251)		(.0249)
LProd(Pears.)$_{ost-1}$				.4133***		.3913***	.2887**		
				(.1177)		(.1244)	(.1192)		
LProd(Skew.)$_{ost-1}$					.0761***			.0728***	.0681***
					(.0191)			(.0195)	(.0185)
Cons.	9.784***	9.77***	9.628***	9.634***	9.661***	9.634***	9.548***	9.657***	9.529***
	(.2088)	(.2092)	(.2087)	(.202)	(.2052)	(.2023)	(.2048)	(.2055)	(.2078)
Obs.	2789	2789	2789	2789	2789	2789	2789	2789	2789
R2	.9293	.9294	.93	.9309	.9298	.9298	.9298	.9302	.9309
Country fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sector fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Clustering	Sector-year	Sector-year	Sector-year	Sector-year	Sector-year	Sector-year	Sector-year	Sector-year	Sector-year

‡ OLS model. Dependent variable: competitiveness index from Eq. 12 (see Col.3, Tab. 3). Time span: 2001-2012. Clustered robust standard errors are reported in parentheses. Significance level: * 0.10>p-value, ** 0.05>p-value, *** 0.01>p-value.

Table 6: Robustness I - Productivity distribution and competitiveness index (sample20E)‡

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(LProd(Mean))$_{ost-1}$	.0963***	.1068***	.0844***	.0949***	.0932***	.1021***	.0814***	.0903***
	(.0242)	(.0244)	(.0234)	(.0236)	(.0239)	(.0239)	(.0234)	(.0234)
Log(firms)$_{ost-1}$	.6208***	.5973***	.6215***	.601***	.5974***	.5799***	.5982***	.583***
	(.0336)	(.034)	(.0326)	(.0329)	(.0326)	(.0332)	(.0316)	(.032)
Log(wage)$_{ost-1}$	-.0542***	-.0543***	-.0611***	-.0613***	-.0596***	-.0597***	-.0664***	-.0666***
	(.0143)	(.0146)	(.0144)	(.0145)	(.0143)	(.0145)	(.0144)	(.0145)
LProd(P80/P20)$_{ost-1}$			.0902***	.1021***			.0875***	.0965***
			(.0256)	(.0254)			(.0271)	(.027)
LProd(Pears.)$_{ost-1}$	.473***		.345***		.3889***		.2624**	
	(.1193)		(.1206)		(.13)		(.1317)	
LProd(Skew.)$_{ost-1}$		.0858***		.0775***		.0678***		.0599***
		(.0199)		(.0193)		(.0211)		(.0205)
Cons.	8.097***	8.216***	8.283***	8.294***	11.3***	11.31***	11.2***	11.17***
	(.2748)	(.2776)	(.2166)	(.213)	(.155)	(.1564)	(.1617)	(.1646)
Obs.	2789	2789	2789	2789	2789	2789	2789	2789
R2	.9323	.9324	.9328	.933	.9322	.9322	.9327	.9328
Country X year fixed effects	yes	yes	yes	yes	no	no	no	no
Sector X year fixed effects	no	no	no	no	yes	yes	yes	yes
Sector fixed effects	yes	yes	yes	yes	no	no	no	no
Country fixed effects	no	no	no	no	yes	yes	yes	yes
Clustering	Sector-year	Sector-year	Sector-year	Sector-year	Sector-year	Sector-year	Sector-year	Sector-year

‡ OLS model. Dependent variable: competitiveness index from Eq. 12 (see Col.3, Tab. 3). Time span: 2001-2012. Clustered robust standard errors are reported in parentheses. Significance level: *0.10>p-value, ** 0.05>p-value, *** 0.01>p-value.

Table 7: Robustness II - Productivity distribution and competitiveness index (sample20E)‡

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Alternative clustering				**WLS**			
Log(LProd(Mean))$_{ost-1}$	.0963***	.1068***	.0932***	.1021***	.1185***	.1225***	.1385***	.1366***
	(.0223)	(.0214)	(.0198)	(.0195)	(.032)	(.0312)	(.0337)	(.0328)
Log(firms)$_{ost-1}$	.6208***	.5973***	.5974***	.5799***	.6285***	.6139***	.6212***	.6147***
	(.024)	(.0237)	(.0241)	(.0236)	(.0431)	(.044)	(.0425)	(.043)
Log(wage)$_{ost-1}$	-.0542***	-.0543***	-.0596***	-.0597***	-.0312**	-.0305**	-.0308**	-.0308**
	(.0144)	(.0141)	(.0129)	(.0126)	(.0148)	(.0148)	(.0142)	(.0143)
LProd(Asim.)$_{ost-1}$	.473***		.3889***		.606***		.4154**	
	(.1109)		(.1165)		(.137)		(.1652)	
LProd(Skew.)$_{ost-1}$		.0858***		.0678***		.066**		.0262
		(.0195)		(.0185)		(.0264)		(.0267)
Cons.	8.097***	8.216***	11.3***	11.31***	7.905***	8.017***	10.94***	11.01***
	(.1999)	(.182)	(.3341)	(.3275)	(.2941)	(.2946)	(.1999)	(.194)
Obs.	2789	2789	2789	2789	2770	2770	2770	2770
R2	.9323	.9324	.9322	.9322	.9496	.9495	.9513	.9512
Country X year fixed effects	yes	yes	no	no	yes	yes	no	no
Sector X year fixed effects	no	no	yes	yes	no	no	yes	yes
Sector fixed effects	yes	yes	no	no	yes	yes	no	no
Country fixed effects	no	no	yes	yes	no	no	yes	yes
Clustering	Country-year	Country-year	Country-year	Country-year	Sector-year	Sector-year	Sector-year	Sector-year

‡ OLS model. Dependent variable: competitiveness index from Eq. 12 (see Col.3, Tab. 3). WLS: weighted least square. Time span: 2001-2012. Clustered robust standard errors are reported in parentheses. Significance level: * 0.10>p-value, ** 0.05>p-value, *** 0.01>p-value.

Table 8: Robustness III - Productivity distribution and competitiveness index (sample20E)‡

Excluded Country	Log(LProd(Mean))$_{ost-1}$	Log(firms)$_{ost-1}$	Log(wage)$_{ost-1}$	LProd(Pears.)$_{ost-1}$	Obs.	R2
AUT	.0835***	.6282***	-.0514***	.5687***	2629	.9317
BEL	.1054***	.5857***	-.0665***	.3981***	2595	.9335
CRO	.0931***	.5815***	-.0658***	.392***	2709	.9282
EST	.0896***	.5842***	-.0512***	.4943***	2623	.9266
FIN	.1187***	.5756***	-.0562***	.3102**	2589	.9377
FRA	.1059***	.6004***	-.0641***	.3245***	2558	.9323
GER	.0842***	.6082***	-.0594***	.4337***	2558	.9171
HUN	.0843***	.5879***	-.0524***	.3009***	2601	.9308
ITA	.0854***	.572***	-.0751***	.3711***	2642	.9261
LIT	.0897***	.5768***	-.0817***	.4035***	2639	.9274
POL	.0951***	.5892***	-.0598***	.4335***	2697	.9305
PRT	.1206***	.6084***	-.0481***	.4678***	2663	.9317
ROM	.1071***	.6306***	-.0542***	.4242***	2602	.9351
SVK	.0761***	.6044***	-.0661***	.4027***	2586	.9299
SLO	.1051***	.6164***	-.0497***	.4624***	2586	.9291
SPA	.0805***	.5957***	-.0608***	.3866***	2558	.9288

‡ OLS model. Each row reports the estimates of Eq. 13 on a reduced sample (excluding one country). Dependent variable: competitiveness index from Eq. 12 (see Col.3, Tab. 3). Country, Sector, and Year dummies are included in all the specifications. Time span: 2001-2012. Robust standard error are clustered at sector*year level and are reported in parentheses. Significance level: * 0.10>p-value, ** 0.05>p-value, *** 0.01>p-value.

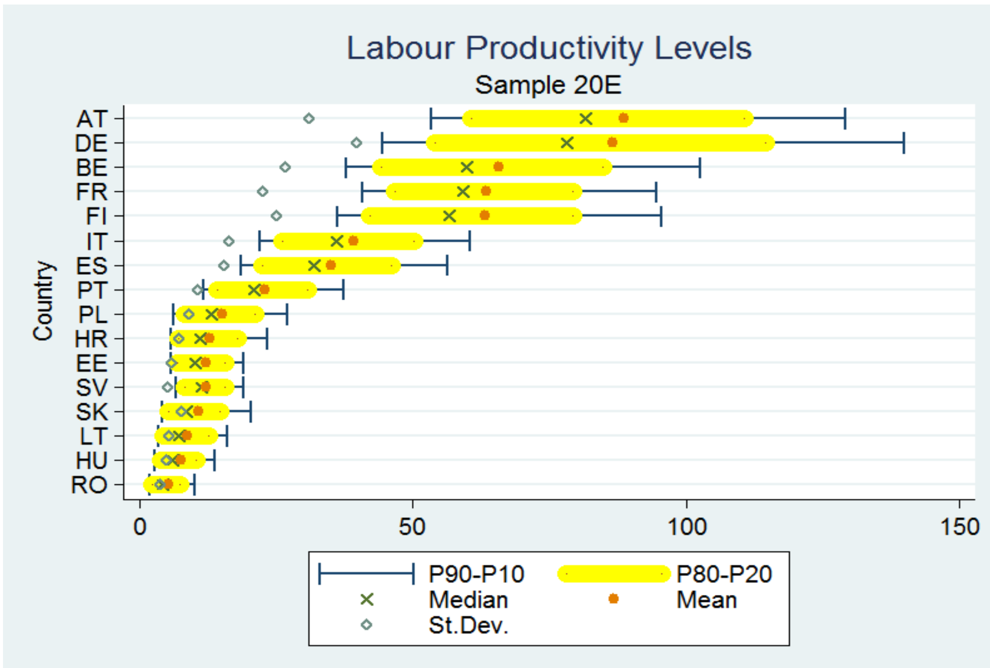
Table 9: Robustness III - TFP index‡

	(1)	(2)	(3)	(4)	(5)	(6)
Log(TFP(Mean))$_{ost-1}$	.0435**	.0527***	.0427**	.0519***	.0445**	.0535***
	(.0184)	(.0185)	(.0191)	(.0192)	(.0195)	(.0195)
Log(firms)$_{ost-1}$	.6162***	.6167***	.6202***	.6208***	.619***	.6199***
	(.0343)	(.0339)	(.0356)	(.0352)	(.0357)	(.0354)
Log(wage)$_{ost-1}$	-.0505***	-.0483***	-.0515***	-.0491***	-.0483***	-.0461***
	(.015)	(.015)	(.0159)	(.0157)	(.0158)	(.0156)
TFP(Pears.)$_{ost-1}$		.4085***		.3981***		.4124***
		(.111)		(.1178)		(.1253)
Cons.	10.02***	9.87***	10.32***	10.17***	11.66***	11.52***
	(.218)	(.2165)	(.1971)	(.2233)	(.1694)	(.1718)
Obs.	2464	2462	2464	2462	2464	2462
R2	.9327	.9332	.9341	.9346	.9351	.9355
Country fixed effects	yes	yes	no	no	yes	yes
Sector fixed effects	yes	yes	yes	yes	no	no
Country fixed effects	yes	yes	no	no	no	no
Country X year fixed effects	no	no	yes	yes	no	no
Sector X year fixed effects	no	no	no	no	yes	yes
Clustering	sector - year	sector - year	sector - year	sector - year	sector - year	sector - year

‡ OLS model. Dependent variable: competitiveness index from Eq. 12 (see Col.3, Tab. 3). WLS: weighted least square. Country, Sector, and Year dummies are included in all the specifications. Time span: 2001-2012. Clustered robust standard errors are reported in parentheses. Significance level: * 0.10>p-value, ** 0.05>p-value, *** 0.01>p-value.

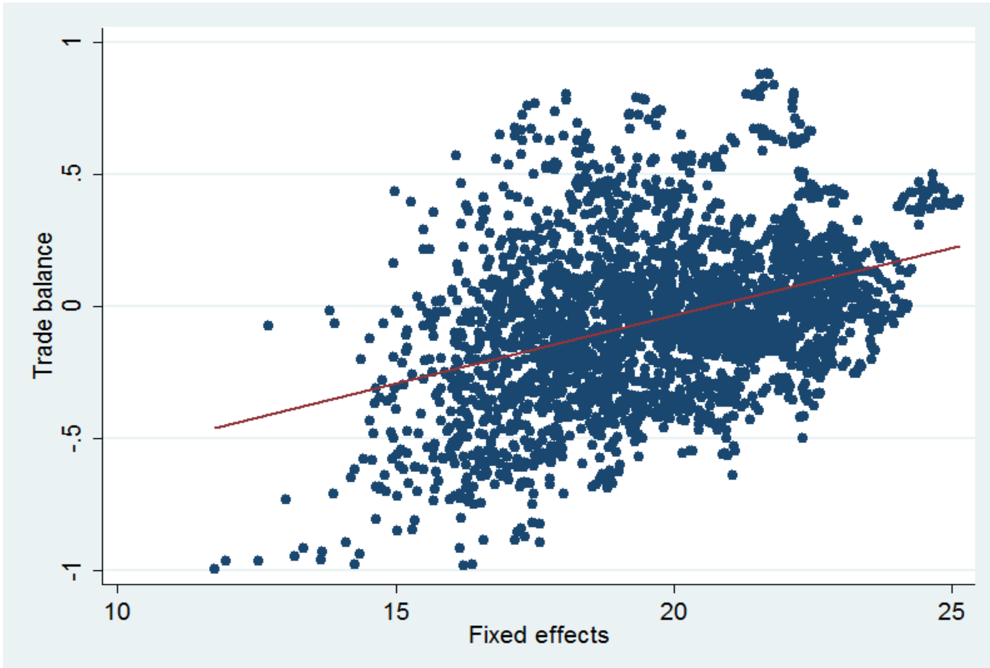
Figures

Figure 1: Labor productivity levels by country



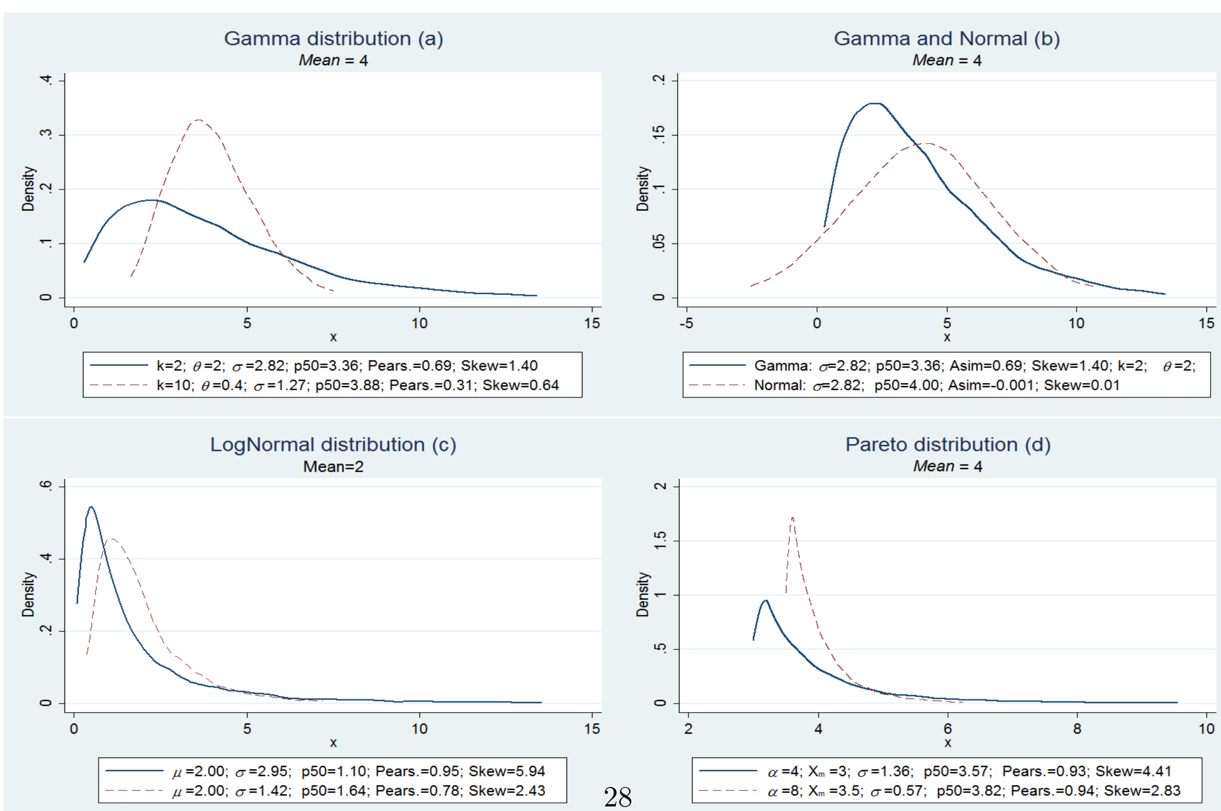
Source: authors elaborations on CompNet data (sample 20E from 2001). Countries are ranked by average productivity as computed in CompNet in decreasing order. Statistics are defined as country unweighted averages (across sector-years) of CompNet micro-based indicators. The red dot is the mean of average labor productivity. The cross represents the average median, while the diamond the average standard deviation. The blue line is the average difference between the 90th (right end) and the 10th percentile (left end) of labor productivity. The yellow bar measures the average difference between the 80th (right end) and the 20th percentile (left end) of labor productivity.

Figure 2: Trade balance and exporter's fixed effects



Source: authors elaborations on Eurostat ComExt data. Each dot is defined at country-sector-year level. The Y-axis reports the trade balance defined as $\frac{export-import}{export+import}$. The X-axis reports the fixed effect computed from Eq. 12 (see Table 3, Col.3.). The red line represents the linear interpolation.

Figure 3: Example of distributions



Source: simulated data on 10000 observations. Gamma distribution: k is the shape parameter and θ is the scale parameter. Asim. is the Pearson's Second Skewness Coefficient defined as $(mean - median)/(std.dev.)$