The Intensive Margin in Trade: Moving Beyond Pareto

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Abstract

The Melitz model with Pareto-distributed firm productivity has become a tractable benchmark in international trade. It predicts that, conditional on the fixed costs of exporting, all variation in exports across trading partners will occur on the extensive margin (the number of firms exporting). In the World Bank's *Exporter Dynamics Database* on firm-level exports from 45 countries, however, we find that half of export variation occurs on the intensive margin (exports per exporting firm). We explore several ways to explain this discrepancy. Most importantly, firm productivity does not follow a Pareto distribution.

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1. Introduction

The Melitz (2003) model with Pareto-distributed firm productivity has become a useful and tractable benchmark in international trade. It is consistent with many firm-level facts – see, for example, Eaton et al. (2011). It generates a gravity equation (Chaney, 2008). And it yields a simple summary statistic for the welfare gains from trade (Arkolakis et al., 2012).

The Melitz-Pareto model makes a sharp prediction: conditional on the fixed costs of exporting, all variation in exports across trade partners should occur through the number of exporters – the extensive margin. Lower variable trade costs should stimulate sales of a given exporter, but draw in marginal exporters to the point that average exports per exporter – the intensive margin – is unchanged. This exact offset is a special property of the Pareto distribution. But it is not so dependent on other aspects of the Melitz model. The dominance of the extensive margin extends to some environments with firm-market idiosyncratic shocks to demand and fixed costs (e.g., Eaton et al. (2011)), non-CES preferences (e.g., Arkolakis et al. (2015)), non-monopolistic competition (e.g., Jensen et al. (2003)), multi-national production (e.g., Arkolakis et al. (2014)), and convex marketing costs (e.g., Arkolakis (2010)).

It has been difficult to test the sharp prediction of the Melitz-Pareto model because most firm-level empirical studies have only a few exporting origins or importing destinations. Eaton et al. (2008) analyze firm-level exports for Colombia, Eaton et al. (2011) France, Eaton et al. (2012a) (henceforth EKS) Denmark and France, Manova and Zhang (2012) China, and Arkolakis and Muendler (2013) Brazil, Chile, Denmark and Norway. With just one destination or origin, it is possible that exports vary on the intensive margin because of differences in fixed costs of exporting to a given market, rather than because of any deviation from Pareto-distributed firm productivity.[1]

[1] One could look at whether firm exports from a given origin follow a Pareto distribution. But this begs the question of whether the deviation is widespread across origins and, more to our point, generates a lot of variation on the intensive margin.

We use the World Bank's *Exporter Dynamics Database* (hereafter EDD) to examine the importance of the extensive and intensive margins empirically. The EDD currently covers firm-level exports from 50 developing countries to all destination countries in most years from 2004–2013.[2] Because the EDD contains so many different origin-destination pairs, we can control for both origin-specific and destination-specific fixed trade costs. Controlling for such fixed trade costs, the elasticity of the intensive margin with respect to overall exports is around 50 percent in the EDD. Considering mean exports in each percentile of a country's exporter size distribution, the intensive margin elasticity with respect to overall exports rises steadily from around 20 percent for the smallest exporters to over 50 percent for the largest exporters.

We next explore potential explanations for the positive intensive margin elasticity (i.e., the tendency of big exports per exporter to go along with big overall exports). First, we consider the possibility that fixed trade costs vary by origin-destination pairs. The problem with this story is that higher fixed trade costs raise average exports per exporter, but also *lower* overall exports. To explain why the intensive margin is increasing in overall exports, one would need variable trade costs to be very negatively correlated with fixed trade costs. A corollary is that, whereas variable trade costs rise decisively with distance between trade partners, one would need the fixed trade costs to fall with distance between trade partners. Moreover, this explanation would require that the intensive margin elasticity be equally important for the smallest and the largest exporters, rather than rising steadily with exporter size percentile.

Second, we explore the role of multi-product firms. If the typical firm exports more products where overall export flows are larger, this could account for the importance of the intensive margin for exports. We show that the number of HS 6-digit products per exporting firm do indeed account for about 12 percent of the variation in overall exports, or about one-fourth of the 50 percent contri-

[2]Within exporting firms, the exports can be broken into products at least down to the HS 6-digit level. Cebeci et al. (2012) describe the dataset in detail.

bution of the intensive margin to overall exports. However, in the context of the multi-product Melitz-Pareto model developed by Bernard, Redding and Schott (2011), this explanation still requires a negative correlation between *firm-level* fixed costs of exporting and variable trade costs, and for firm-level fixed costs to fall with the distance between trading partners. Moreover, the significant intensive margin elasticity per firm-product implies that fixed costs of exporting *per product* also fall with distance.

A third hypothesis we investigate is granularity – a finite number of firms. The stark result that, conditional on fixed trade costs, the extensive margin should explain all variation in overall exports applies to the Melitz-Pareto model with a continuum of firms. With a finite number of firms, the intensive margin (and overall exports) can be high because of good productivity draws from the Pareto distribution within a country. We develop a general method of moments (GMM) estimator for the elasticity of fixed trade costs to distance that is valid under granularity as in Eaton et al. (2012a). This estimator yields a negative elasticity, implying that even under granularity fixed trade costs are required to fall with distance to explain a positive intensive margin elasticity. Using simulations of finite draws from a Pareto distribution, we find that granularity generates only a modest intensive margin elasticity, and – in contrast to what we observe in the data – almost entirely in the right tail of the exporter size distribution.

Lastly, we depart from the Pareto distribution to consider a lognormal distribution of firm productivity. Head et al. (2014) analyze how the welfare gains from trade in the Melitz model differ with a lognormal instead of a Pareto distribution. Bas et al. (2015) show how the trade elasticity varies with a lognormal distribution. Both papers marshal evidence from firms in France and China pointing to the empirical relevance of the lognormal distribution. With this motivation, we show that lognormally-distributed firm productivity (with realistic dispersion) can indeed generate a sizable intensive margin elasticity. When variable trade costs fall and fixed costs are constant, the ratio of mean to mini-

mum exports increases with the productivity cutoff under the lognormal distribution (while being constant under Pareto). Shifting to lognormal productivity also changes our inference about fixed trade costs, rendering them positively correlated with variable trade costs and *rising* with distance. It also implies that the intensive margin elasticity rises steadily with the size percentile of exporters, though too sharply relative to the data.

The rest of the paper is organized as follows. In Section 2 we formalize the predictions of the Melitz-Pareto model. In Section 3 we describe the EDD data. In Section 4 we document the empirical importance of the intensive margin in explaining the cross-country variation in exports, as well as other implications of the EDD data in the context of the Melitz-Pareto model. In Sections 5 and 6 explore how allowing for multi-product firms and granularity, respectively, affects the implications of the Melitz-Pareto model for the intensive margin and contrast those implications against the data in various ways. Finally, in Section 7 we study how the implications of the Melitz model change when we drop the Pareto assumption and assume instead that the productivity distribution is lognormal.

2. Properties of the Melitz-Pareto Model

We start with the Melitz model with a continuum of single-product firms with a Pareto distribution for productivity as in Chaney (2008) and Arkolakis et al. (2008). As this is a well-known model, we will be brief in the presentation of the main assumptions. There are many countries indexed by i, j. Labor is the only factor of production available in fixed supply L_i in country i and the wage is w_i. Preferences are constant elasticity of substitution (CES) with elasticity of substitution across varieties denoted by σ and common across countries. Each firm produces one variety under monopolistic competition. Firm-level productivity φ is distributed Pareto with shape parameter $\theta > \sigma - 1$, $\Pr(\varphi \leq \varphi_0) = G_i(\varphi_0) = 1 - (\varphi_0/b_i)^{-\theta}$. Firms from country i also incur fixed trade costs F_{ij} as well as ice-

berg trade costs τ_{ij} to sell in country j. In each country country i there is a large pool of prospective entrants and firms pay an entry cost of F_i^e.[3]

The value of overall exports from i to j is

$$X_{ij} = N_i \int_{\varphi \geq \varphi_{ij}^*} A_j \left(\tilde{\sigma} \frac{w_i \tau_{ij}}{\varphi} \right)^{1-\sigma} dG_i(\varphi), \tag{1}$$

where $A_j \equiv P_j^{1-\sigma} w_j L_j$, $P_j^{1-\sigma} = \sum_i N_i \int_{\varphi \geq \varphi_{ij}^*} \left(\tilde{\sigma} \frac{w_i \tau_{ij}}{\varphi} \right)^{1-\sigma} dG_i(\varphi)$, N_i is the total number of firms in country i, $\tilde{\sigma} \equiv \sigma/(\sigma-1)$ is the markup, and φ_{ij}^* is the productivity cutoff for exports from i to j, which is defined implicitly by

$$A_j \left(\tilde{\sigma} \frac{w_i \tau_{ij}}{\varphi_{ij}^*} \right)^{1-\sigma} = \sigma F_{ij}. \tag{2}$$

The free-entry condition entails

$$F_i^e = \sum_j \left[(X_{ij}/\sigma) - F_{ij} \left(1 - G_i(\varphi_{ij}^*) \right) \right].$$

Combined with Equations (1) and (2) and using the fact that $G_i(\varphi)$ is Pareto, this implies

$$N_i = \frac{\sigma - 1}{\sigma \theta} \frac{L_i}{F_i^e}.$$

The equilibrium is a set of wages w_i such that $w_i L_i = \sum_j X_{ij}$.

The number of firms from i that export to j is $N_{ij} = N_i \int_{\varphi \geq \varphi_j^*} dG_i(\varphi)$. Using again that $G_i(\varphi)$ is Pareto we get from (1) that

$$X_{ij} = A_j \left(w_i \tau_{ij} \right)^{1-\sigma} N_i \frac{\theta b_i^\theta \left(\varphi_{ij}^* \right)^{\sigma-\theta-1}}{\theta - (\sigma - 1)} \tag{3}$$

and

$$N_{ij} = N_i \left(\varphi_{ij}^* / b_i \right)^{-\theta}. \tag{4}$$

[3]Both F_{ij} and F_i^e are in units of the numeraire. Since we focus on cross-section properties of the equilibrium, we do not need to specify whether the fixed trade cost entails hiring labor in the origin or the destination country.

Combining (2) , (3) and (4), the extensive margin is

$$N_{ij} = N_i \left(\frac{w_i}{b_i}\right)^{-\theta} \left(\frac{\sigma}{A_j}\right)^{-\theta/(\sigma-1)} \tau_{ij}^{-\theta} F_{ij}^{-\theta/(\sigma-1)}, \tag{5}$$

while the intensive margin is

$$x_{ij} \equiv \frac{X_{ij}}{N_{ij}} = \frac{\theta\sigma}{\theta - (\sigma-1)} F_{ij}. \tag{6}$$

We can always decompose variable and fixed trade costs as follows: $\tau_{ij} = \tau_i^o \tau_j^d \widetilde{\tau}_{ij}$ and $F_{ij} = F_i^o F_j^d \widetilde{F}_{ij}$. Taking logs in (5) and (6), and defining variables appropriately, we have

$$\ln N_{ij} = \mu_i^{N,o} + \mu_j^{N,d} - \theta \ln \widetilde{\tau}_{ij} - \widetilde{\theta} \ln \widetilde{F}_{ij} \tag{7}$$

and

$$\ln x_{ij} = \mu_i^{x,o} + \mu_j^{x,d} + \ln \widetilde{F}_{ij}, \tag{8}$$

where $\widetilde{\theta} \equiv \frac{\theta}{\sigma-1}$. These are the two key equations that we use to derive the results in the rest of this section.

Consider the OLS regression of $\ln x_{ij}$ on $\ln X_{ij}$ with origin and destination fixed effects,

$$\ln \bar{x}_{ij} = FE_i^o + FE_j^d + \alpha \ln X_{ij} + \varepsilon_{ij}. \tag{9}$$

The estimated regression coefficient is given by (ignoring origin and destination fixed effects)[4]

$$\hat{\alpha} = \frac{cov(\ln x_{ij}, \ln X_{ij})}{var\left(\ln X_{ij}\right)}. \tag{10}$$

We refer to $\hat{\alpha}$ as the Intensive Margin Elasticity (IME), $IME \equiv \hat{\alpha}$. The extensive margin elasticity is $EME = \frac{cov(\ln N_{ij}, \ln X_{ij})}{var(\ln X_{ij})} = 1 - IME$.

According to the model (i.e., using equations 7 and 8), the coefficient $\hat{\alpha}$ is

[4]The true coefficient is given by $\hat{\alpha} = \frac{cov(\ln \mathring{x}_{ij}, \ln \mathring{X}_{ij})}{var\left(\ln \mathring{X}_{ij}\right)}$ where $\mathring{x_{ij}}$ denotes variable x_{ij} demeaned by origin and destination fixed effects.

given by

$$IME = -\frac{\left(\widetilde{\theta}-1\right) var(\ln \widetilde{F}_{ij}) + \theta cov(\ln \widetilde{\tau}_{ij}, \ln \widetilde{F}_{ij})}{var\left(-\theta \ln \widetilde{\tau}_{ij} - \left(\widetilde{\theta}-1\right) \ln \widetilde{F}_{ij}\right)}. \tag{11}$$

This result can be used to extract several implications of the model, which we present in the form of four observations in the rest of this section.

Our first observation says that if all variation in fixed trade costs comes from origin and destination fixed effects, for example because $F_{ij} \propto w_i^{\gamma} w_j^{1-\gamma}$ (as in Arkolakis (2010)), then the model implies that the intensive margin elasticity is zero.

Observation 1: If $var\left(\ln \widetilde{F}_{ij}\right) = 0$ then $IME = 0$.

Combined with the assumption that $\widetilde{\theta} > 1$, the result in (11) also implies that if the intensive margin elasticity is positive then there must be a negative correlation between the variable and fixed trade costs (ignoring origin and destination fixed costs).

Observation 2: If $IME > 0$ then $corr(\ln \widetilde{F}_{ij}, \ln \widetilde{\tau}_{ij}) < 0$.

Ignoring origin and destination fixed effects, equation 8 implies that

$$cov(\ln \widetilde{F}_{ij}, \ln dist_{ij}) = cov(\ln x_{ij}, \ln dist_{ij}).$$

Thus, if average exports per firm fall with distance then fixed trade costs must also be falling with distance. This is captured formally by our third observation which is related to the fixed trade costs elasticity with respect to distance.

Observation 3: If $\frac{cov(\ln x_{ij}, \ln dist_{ij})}{var(\ln dist_{ij})} < 0$ then $\frac{cov(\ln \widetilde{F}_{ij}, \ln dist_{ij})}{var(\ln dist_{ij})} < 0$.[5]

Exports of a firm in the p^{th} percentile of the exporter size distribution are $\tilde{\sigma} F_{ij} \left(\varphi^p / \varphi^*_{ij}\right)^{\sigma-1}$, where φ^p is such that $\Pr\left[\varphi < \varphi^p | \varphi > \varphi^*_{ij}\right] = p$. Since productivities are distributed Pareto, the ratio $\varphi^p / \varphi^*_{ij}$ and thus average exports per firm in each percentile should be the same for all ij pairs. Denote average exports per firm in percentile pct as $\bar{x}_{ij}^{pct}$ and consider the following regression:

[5]The term $\frac{cov(\ln \bar{x}_{ij}, \ln dist_{ij})}{var(\ln dist_{ij})}$ should be seen as $\frac{cov(\ln \mathring{\bar{x}}_{ij}, \ln dist_{ij})}{var(\ln dist_{ij})}$, where $\mathring{x}_{ij}$ denotes variable x_{ij} demeaned by origin and destination fixed effects.

$$\ln \bar{x}_{ij}^{pct} = FE_i^o + FE_j^d + \alpha^{pct} \ln X_{ij} + \epsilon_{ij}$$

and define the IME for each percentile as $IME^{pct} \equiv \alpha^{pct}$. The previous argument implies that the intensive magin elasticity calculated separately for each percentile is the same as the overall intensive margin elasticity.

Observation 4: $IME^{pct} = IME, \ \forall p$

In the Appendix we show that Observation 4 is robust to the assumption of firm-specific fixed costs of exporting as long as the marginal distribution of productivities is Pareto and the distribution of fixed costs is the same across country pairs up to a multiplicative factor.

We can go beyond the previous qualitative observations and derive the fixed and variable trade costs implied by the model so as to compute actual values for $corr(\ln \widetilde{F}_{ij}, \ln \widetilde{\tau}_{ij}) < 0$ and $\frac{cov(\ln \widetilde{F}_{ij}, \ln dist_{ij})}{var(\ln dist_{ij})}$. Combining equations 7 and 8 to solve for $\ln \widetilde{F}_{ij}$ and $\ln \widetilde{\tau}_{ij}$ in terms of $\ln \bar{x}_{ij}$ and $\ln N_{ij}$ yields

$$\ln \widetilde{F}_{ij} = \delta_i^{F,o} + \delta_j^{F,d} + \ln \bar{x}_{ij} \tag{12}$$

and

$$\theta \ln \widetilde{\tau}_{ij} = \delta_i^{\tau,o} + \delta_j^{\tau,d} - \widetilde{\theta} \ln \bar{x}_{ij} - \ln N_{ij}. \tag{13}$$

Model-implied values for $\ln \widetilde{F}_{ij}$ are (ignoring origin and destination fixed effects) directly given by $\ln x_{ij}$, but for $\ln \widetilde{\tau}_{ij}$ we need a value for $\widetilde{\theta}$ to go from $\ln x_{ij}$ and $\ln N_{ij}$ in the data to model-implied values for $\theta \ln \tilde{\tau}_{ij}$ (again, ignoring origin and destination fixed effects).[6]

[6]To show results for τ_{ij}, we need to estimate $\widetilde{\theta}$. The Appendix outlines the procedure that we use which follows that in Eaton et al. (2011).

3. World Bank *Exporter Dynamics Database*

We use the Exporter Dynamics Database (EDD) described in Cebeci et al. (2012) to study the intensive and extensive margins of trade using firm-level data. The EDD is based on customs data covering the universe of export transactions provided by customs agencies from 70 countries (56 developing and 14 developed countries). For each country, the raw customs data contains annual export flows disaggregated by firm, destination and Harmonized System (HS) 6-digit product, based on a time-consistent product classification. Oil exports (HS chapter 27) are excluded from the customs data due to lack of accurate firm-level data for many of the oil-exporting countries. For most countries total non-oil exports in the EDD are close to total non-oil exports reported in COMTRADE/WITS. The set of more than 100 statistics included in the EDD are publicly available at the exporting country-year, exporting country-product-year, exporting country-destination country-year, or exporting country-product-destination country-year levels for download, and include in particular, measures of average exports per firm as well as the number of exporters, which are comparable across countries.

In this paper we exploit the underlying exporter-level customs data for 49 countries included in the second release of the EDD as well as China.[7] Hence we use an unbalanced panel of 50 developing countries whose sample periods cover some or all of the years between 2004 and 2013, as shown in Table 1.

Using these data we calculate variants of average exports per firm, number of exporters, and total exports at the exporting country-destination country-year level or at the exporting country-product or industry-destination country-year level. We focus on products or industries belonging to the broad manufacturing sector. Specifically, using a concordance across the ISIC rev. 3 classification and the HS 6-digit classification we consider only HS 6-digit codes that correspond to ISIC manufacturing sub-sectors 15-37. The product disaggrega-

[7] China is not included in the EDD due to confidentiality concerns, but we do include the statistics based on exporter-level customs data for China in this paper.

tions that we use are HS 2-digit, HS 4-digit, or HS 6-digit. The industries that we use are groups of HS 2-digit codes as defined in the Table 2. For exporter size percentiles, we calculate average exports per firm based on firms within each size percentile at the exporting country-destination country-year level.

4. The Melitz-Pareto Model vs. the Data

We start by plotting the intensive margin ($\bar{x}_{ij}$), the extensive margin (N_{ij}), and total exports (X_{ij}) from all countries in the EDD to four large destinations: the United States (US), Japan, Germany and France for each year – see Figure 1.[8] Each dot corresponds to (x_{ij},X_{ij}) (panel a) or (N_{ij},X_{ij}) (panel b). The plotted line represents the prediction of the Melitz-Pareto model with a continuum of firms and fixed trade costs that vary by origin and destination but not across country pairs, i.e., $var(\tilde{F}_{ij}) = 0$. Observation 1 in Section 2 indicates this is a horizontal line for the intensive margin (panel a) and has a unit slope for the extensive margin (panel b). The IME is the slope of the regression line running through the data in panel a – it corresponds to $\hat{\alpha}$ from regression 9. The intensive margin elasticity is clearly positive while the extensive margin elasticity is clearly less than one.

We supplement Figure 1 with Table 3, which shows results for the IME from the benchmark regression 9 with several alternative specifications. In the benchmark specification it ranges between 0.49 and 0.52, with the latter being our preferred estimate due to the inclusion of origin and destination fixed effects. The results are robust in wider samples. When all destinations are included, the IME estimate only falls to 0.47 in the third column of Table 4. In a sample with country pairs with less than 100 exporters, IME estimates remain higher than 0.5, as reported in Table 5, and reach 0.7 when origin and destination fixed

[8]We restrict destination countries to be the US, Japan, Germany and France to reduce noise associated with country pairs with few exporters. We further restrict the sample to the 676 country pairs with more than 100 exporters (i.e., ij pairs for which $N_{ij} > 100$ when j is US, Japan, Germany or France).

effects are included.

As a further robustness check, we estimated the IME based on data with an industry disaggregation for each country pair each year. It could be the case that average exports per firm are constant across different countries within the same industry, but differ across industries. Positive IME estimates could thus arise from a different sectoral composition of exports across country pairs, but be consistent with the basic Melitz-Pareto model at the sector level. We show, however, that this is not the case. Consider Figure 2 where we plot the intensive and extensive margins against total exports at the exporting country-industry-destination country-year level. The slope of the regression line going through the data is still positive for the intensive margin. Table 6 shows that the IME actually increases when moving from aggregate to disaggregated data, implying that the sectoral composition of trade is not an explanation for the puzzle. At the lowest level of aggregation available, which is HS 6-digit products, the IME is as high as 0.75.

Finally, we check whether the results are driven by the prevalence of small firms in the data. To do this, we calculate average exports per firm, number of firms and total exports using only data on exporters whose annual exports were at least $1,000. The results reported in Table 7 change only slightly, with the IME never falling below 0.47.

We further explore the implications of a positive IME for fixed and variable trade costs. Using Equations (12) and (13) we uncover model-implied fixed and variable trade costs components that vary by origin-destination pairs. As per Observation 2, the Melitz-Pareto model can have a positive IME, but this would imply a negative correlation between fixed and variable trade costs. Indeed, Table 8 reports that this correlation -0.891 is negative and strong.

Moreover, Observation 3 implies that fixed trade costs must decline with distance if $cov(\ln x_{ij}, \ln dist_{ij}) < 0$. We plot fixed trade costs against distance in Figure 4. As expected from the positive sign of the IME and the fact that total exports fall with distance, the figure shows that fixed trade costs are decreasing

with distance, while variable trade costs are increasing with distance. This finding is puzzling, since one would expect trade barriers to increase rather than fall with distance. Table 9 confirms that the fixed trade cost elasticity with respect to distance, reported in column 1, is negative and statistically significant.

We also check the implications of Observation 4 by plotting the IME^{pct} for each exporter size percentile in Figure 3. The horizontal line corresponds to the theoretical prediction of a common elasticity across percentiles while the dots represent the estimated elasticities for each percentile. Contrary to Observation 4, the IME is not constant across percentiles, it is significantly lower than the overall IME of 0.52 for the first 90 percentiles, and is increasing gradually. The largest IME is observed in the top percentile, possibly reflecting the granular nature of the exporting firms (see Section 6).

To conclude, in the data we find the intensive margin elasticity to be positive and significant, both statistically and economically. This finding is robust to inclusion of a variety of fixed effects, various samples, disaggregation and exclusion of small firms, and is at odds with the simple version of the Melitz-Pareto model with fixed trade costs varying only because of origin and destination effects. One can of course allow a richer pattern of variation in fixed trade costs across country pairs to make the model perfectly consistent with the data, but then the positive IME has further puzzling implications for fixed trade costs, which should fall with distance and be very negatively correlated with variable trade costs. To the best of our knowledge, there are no models that would microfound such a strong and negative correlation between the two types of trade costs and a negative fixed trade costs elasticity with respect to distance. The data is also at odds with the implication from the Melitz-Pareto model of a constant IME across percentiles.

5. Multi-Product Extension of Melitz-Pareto

In Section 4 we show that around half of the variation in bilateral exports is explained by the firm-level intensive margin. This contradicts the basic Melitz-Pareto model with a continuum of single-product firms and no variation in bilateral fixed trade costs, $var(\tilde{F}_{ij}) = 0$. One can always assume that bilateral fixed trade costs are such that the model matches the data, but this leads to the awkward implications that the covariance between fixed trade costs and either variable trade costs or distance is negative. In this section we explore whether the contradictions between the model and the data are maintained for a popular extension of the Melitz-Pareto model to multi-product firms. The idea is that what the basic Melitz-Pareto model considers as the intensive margin is really an extensive margin operating at the level of the firm. Thus, perhaps the reason why average exports per firm fall with distance in the data is that firms export fewer products (because of higher product-level fixed trade costs) even though they export more per product to more distant destinations.

5.1. Theory

We consider an extension of the Melitz-Pareto model due to Bernard, Redding and Schott (2011). Each firm can produce a differentiated variety of each of a continuum of products in the interval [0,1] with productivity $\varphi\lambda$, where φ is common across products and λ is product-specific. The firm component φ is drawn from a Pareto distribution $G^f(\varphi)$ with shape parameter θ^f, while the firm-product component λ is drawn from a Pareto distribution $G^p(\lambda)$ with shape parameter θ^p. To have well-defined terms given a continuum of firms, we impose $\theta^f > \theta^p > \sigma - 1$. To sell any products in market j, firms from country i have to pay a fixed cost F_{ij}, and to sell each individual product requires an additional fixed cost of f_{ij}. Variable trade costs are still τ_{ij}.

The cutoff λ for a firm from i with productivity φ that wants to export to j,

$\lambda^*_{ij}(\varphi)$, is given implicitly by

$$A_j \left(\frac{w_i \tau_{ij}}{\varphi \lambda^*_{ij}(\varphi)} \right)^{1-\sigma} = \sigma f_{ij}. \tag{14}$$

We can then write the profits in market j for a firm from country i with productivity φ as

$$\pi_{ij}(\varphi) \equiv \int_{\lambda^*_{ij}(\varphi)}^{\infty} \left[\left(\frac{\lambda}{\lambda^*_{ij}(\varphi)} \right)^{\sigma-1} - 1 \right] f_{ij} dG^p(\lambda). \tag{15}$$

The cutoff productivity for firms from i to sell in j is given implicitly by $\pi_{ij}(\varphi^*_{ij}) = F_{ij}$. As in the canonical model, the number of firms from country i that export to market j is $N_{ij} = \left[1 - G^f(\varphi^*_{ij})\right] N_i$, while the number of products sold by firms from i in j is $M_{ij} = N_i \int_{\varphi^*_{ij}}^{\infty} \left[1 - G^p\left(\lambda^*_{ij}(\varphi)\right)\right] dG^f(\varphi)$. Combining the previous expressions, using the fact that $G^p(\lambda)$ and $G^f(\varphi)$ are Pareto, writing $f_{ij} = f_i^o f_j^d \tilde{f}_{ij}$, $F_{ij} = F_i^o F_j^d \tilde{F}_{ij}$, and $\tau_{ij} = \tau_i^o \tau_j^d \tilde{\tau}_{ij}$, and defining variables appropriately we get

$$\ln X_{ij} = \mu_i^{X,o} + \mu_j^{X,d} - \theta^f \ln \widetilde{\tau}_{ij} - \left(\frac{\theta^f}{\sigma - 1} - \frac{\theta^f}{\theta^p} \right) \ln \widetilde{f}_{ij} - \left(\frac{\theta^f}{\theta^p} - 1 \right) \ln \widetilde{F}_{ij}, \tag{16}$$

$$\ln x^p_{ij} \equiv \ln X_{ij} - \ln M_{ij} = \mu_i^{x^p,o} + \mu_j^{x^p,d} + \ln \widetilde{f}_{ij}, \tag{17}$$

and

$$\ln x^f_{ij} \equiv \ln X_{ij} - \ln N_{ij} = \mu_i^{x^f,d} + \mu_j^{x^f,d} + \ln \widetilde{F}_{ij}. \tag{18}$$

It is easy to verify that if $f_{ij} = 0$ for all i, j then this model collapses to the canonical model with single-product firms.

From regressions similar to regression 9 (ignoring origin and destination fixed effects) we now have two intensive margin elasticities, one for the intensive margin defined over products and one for the intensive margin defined over firms:

$$IME^s \equiv \frac{cov(\ln x^s_{ij}, \ln X_{ij})}{var(\ln X_{ij})}, \tag{19}$$

with $s = f, p$. Letting $\tilde{\theta} \equiv \theta^f / (\sigma - 1)$ and $\chi \equiv \theta^f / \theta^p$, then from Equations (16) to

(18) we have

$$IME^p = -\frac{\left(\tilde{\theta}-\chi\right) var\left(\ln \widetilde{f}_{ij}\right) + (\chi-1)\, cov(\ln \widetilde{f}_{ij}, \ln \widetilde{F}_{ij}) + \theta cov(\ln \widetilde{f}_{ij}, \ln \widetilde{\tau}_{ij})}{var(\ln X_{ij})} \tag{20}$$

and

$$IME^f = -\frac{(\chi-1)\, var\left(\ln \widetilde{F}_{ij}\right) + \left(\tilde{\theta}-\chi\right) cov(\ln \widetilde{f}_{ij}, \ln \widetilde{F}_{ij}) + \theta cov(\ln \widetilde{F}_{ij}, \ln \widetilde{\tau}_{ij})}{var(\ln X_{ij})} \tag{21}$$

Letting $m_{ij} \equiv M_{ij}/N_{ij}$ be the average number of products sold by firms from i in j, we have that $x^f_{ij} = x^p_{ij} m_{ij}$ and $X_{ij} = x^p_{ij} m_{ij} N_{ij}$. This implies that IME^f is equal to IME^p plus the extensive product margin elasticity, $cov(\ln m_{ij}, \ln X_{ij})/var(\ln X_{ij})$.

Observation 1 in the single-product firm model remains valid in the multi-product firm model, while we now have an analogous observation for the product-level intensive margin elasticity:

Observation 5: $IME^p = 0$ if $var\left(\ln \widetilde{f}_{ij}\right) = 0$.

The assumption $\theta^f > \theta^p > \sigma - 1$ implies that $\chi > 1$ and $\tilde{\theta} > \chi > 1$ and in turn this leads to the following extensions of observation 2:

Observation 6: If $IME^f > 0$ then either $cov(\ln \widetilde{f}_{ij}, \ln \widetilde{F}_{ij}) < 0$ or $cov(\ln \widetilde{F}_{ij}, \ln \widetilde{\tau}_{ij}) < 0$ (or both).

Observation 7: If $IME^p > 0$ then either $cov(\ln \widetilde{f}_{ij}, \ln \widetilde{F}_{ij}) < 0$ or $cov(\ln \widetilde{f}_{ij}, \ln \widetilde{\tau}_{ij}) < 0$ (or both).

Observation 3 remains valid in the multi-product firm model, and we now also have an analogous observation for product-level fixed trade costs:

Observation 8: If $cov(\ln x^p_{ij}, \ln dist_{ij}) < 0$ then $cov(\ln \widetilde{f}_{ij}, \ln dist_{ij}) < 0$.

As in the single-product model, we can use the model to back out the implied trade costs. Equation (18) can be used to obtain a model-implied $\tilde{F}_{ij}$ (ignoring origin and destination fixed effects) while Equation (17) can be used to obtain a model-implied $\tilde{f}_{ij}$ (ignoring origin and destination fixed effects).

5.2. Data

Table 10 reports the estimated product-level IME, IME^p. In our basic sample with the 4 large destinations the IME^p never falls below 0.384 (see panel a). When all destinations are included, the IME^p remains virtually unchanged (see panel b). Of course, the IME^f is the same as that reported in Section 4. While we could have the model match the data by allowing both firm-level and product-level fixed trade costs to vary appropriately across country pairs, from observations 6 and 7 this would imply that those fixed trade costs would be negatively correlated, or that the covariances between those fixed trade costs and variable trade costs would be negative.

Observation 8 indicates that if product-level fixed trade costs increase with distance, then a positive covariance between average exports per product-firm and distance should be observed. In fact, the opposite is verified in the data: $\bar{x}^p_{ij}$, demeaned by origin and destination (which from Equation (17) equals product-level fixed trade costs), decline with distance in Figure 5, as was the case for firm-level fixed trade costs in Section 4. The estimated elasticity of product-level fixed trade costs with respect to distance shown in Table 9 is negative and statistically significant.

6. Granularity

The previous sections have considered a model with a continuum of firms. With a discrete and finite number of firms it may be possible to generate a positive covariance between the intensive margin and total exports that could in principle explain our empirical findings. We explore this possibility in this section.

6.1. Theory

Eaton et al. (2012b) extend the Melitz-Pareto model above to allow for granularity. As we show in the Appendix, in that setup equations 7 and 8 become

$$\ln N_{ij} = \mu_i^{N,o} + \mu_j^{N,d} - \theta \ln \widetilde{\tau}_{ij} - \widetilde{\theta} \ln \widetilde{F}_{ij} + \xi_{ij} \tag{22}$$

and

$$\ln x_{ij} = \mu_i^{x,o} + \mu_j^{x,d} + \ln \widetilde{F}_{ij} + \varepsilon_{ij}, \tag{23}$$

where ξ_{ij} and ε_{ij} are error terms arising from the fact that now the number of firms is discrete and random. Using the same definition for the intensive margin elasticity as in Section 3, the previous equations imply that

$$IME = -\frac{\left(\widetilde{\theta}-1\right) var(\ln \widetilde{F}_{ij}) + \theta cov\left(\ln \widetilde{\tau}_{ij}, \ln \widetilde{F}_{ij}\right) + var(\varepsilon_{ij}) + cov(\varepsilon_{ij}, \xi_{ij})}{var\left(-\theta \ln \widetilde{\tau}_{ij} - \left(\widetilde{\theta}-1\right) \ln \widetilde{F}_{ij} + \varepsilon_{ij} + \xi_{ij}\right)}. \tag{24}$$

Even if $cov(\varepsilon_{ij}, \xi_{ij}) = 0$, since $var(\varepsilon_{ij}) > 0$, this could explain $IME > 0$ even with $cov\left(\ln \widetilde{F}_{ij}, \ln \widetilde{\tau}_{ij}\right) > 0$. Thus, in theory, granularity could explain the positive intensive margin elasticity that we find in the data without relying on implausible patterns for fixed trade costs.

To check whether granularity is a plausible explanation for the positive IME in the data we will conduct two tests. First, we will estimate the fixed trade cost elasticity with respect to distance taking into account granularity and the possible biases it may induce. Second, we will simulate firm-level exports under the assumption of fixed trade costs that vary by origin and destination only and estimate the implied IME. We describe each of these tests in turn.

Fixed Trade Costs and Distance with Granularity

In the Melitz-Pareto model with a continuum of firms average exports per firm can be expressed as $x_{ij} = \upsilon F_{ij}$, where $\upsilon \equiv \frac{\sigma\theta}{\theta-(\sigma-1)}$. We assume here that $F_{ij} =$

$F_i^o F_j^d e^{\zeta \ln dist_{ij}} + v_{ij}$, where v_{ij} is iid and has zero mean. If we relax the continuum assumption to allow for granularity, then average exports per firm can be expressed as

$$x_{ij} = \upsilon F_{ij} + \varepsilon_{ij}, \tag{25}$$

where ε_{ij} is an error term that arises from random realizations of productivity draws with the property that

$$\mathbb{E}\left[\varepsilon_{ij} | \ln dist_{ij}\right] = 0. \tag{26}$$

We can then write

$$x_{ij} = \upsilon F_i^o F_j^d e^{\zeta \ln dist_{ij}} + u_{ij}, \tag{27}$$

where $u_{ij} \equiv v_{ij} + \varepsilon_{ij}$ is a mean-zero error term (i.e., $\mathbb{E}\left[u_{ij} | \ln dist_{ij}\right] = 0$) that captures both the deviation of F_{ij} from its mean as well as the granularity error term ε_{ij}. The challenge in estimating the fixed trade costs elasticity with respect to distance, ζ, from this equation is that we cannot simply take logs to obtain a log-linear equation to be estimated by OLS, because the error term that comes from granularity is not log-additive.

To proceed, we follow Charbonneau (2012) to derive a GMM estimate of ζ. To take advantage of the time dimension of our data, we extend 27 to allow for a time-specific component in the expression of fixed trade costs,

$$x_{ijt} = e^{F_i^o + F_j^d + F_t + \zeta \ln dist_{ij}} + u_{ijt},$$

where again $\mathbb{E}\left[u_{ijt}|\ln dist_{ij}\right] = 0$. As is shown in the Appendix, manipulating equation 27 yields the moment condition

$$\mathbb{E}\Big[\Big(x_{ikt}x_{ljt} - x_{lkt}x_{ijt}e^{\zeta\left(-\ln dist_{ij}+\ln dist_{ik}+\ln dist_{lj}-\ln dist_{lk}\right)}\Big) \times (-\ln dist_{ij} + \ln dist_{ik} + \ln dist_{lj} - \ln dist_{lk})\Big] = 0 \tag{28}$$

In the next subsection we will use this moment condition to estimate ζ.

The IME under Granularity: Simulation

To assess how well granularity can explain a positive IME, we simulate exports of N_{ij} firms for each of the country pairs in the sample. We add demand shocks to allow for a less than perfect correlation between exports of different firms across different destinations. In the standard Melitz model with demand shocks, exports from i to j of a firm with productivity φ and destination-specific demand shock α_j can be calculated as

$$x_{ij}\left(\varphi,\alpha_j\right) = \sigma F_{ij}\left(\frac{\alpha_j\varphi}{\alpha^*_{ij}\varphi^*_{ij}}\right)^{\sigma-1}, \tag{29}$$

where $\alpha^*_{ij}\varphi^*_{ij}$ is a combination of productivity and demand shocks of the smallest exporter from i selling to j . To estimate the IME in simulations we perform the following steps:

1. Draw φ and α_j from some distribution. The number of draws is equal to N_{ij}, the number of exporters in the EDD dataset for each origin-destination pair in 2009. To be more precise, we draw the product $\alpha_j\varphi$ for each firm-destination pair assuming either that, as in the standard Melitz model, there are no demand shocks and hence the product is perfectly correlated across destinations or that, at the other extreme, there is no correlation in the product across destinations (pure demand shocks case). In both cases, we draw $\alpha_j\varphi$ from a Pareto distribution with a shape parameter to

be specified below.

2. Assume that $Var\left(\widetilde{F}_{ij}\right) = 1$, so that $F_{ij} = F_i^o F_j^d$. This will allow us to study the IME generated by granularity by itself.

3. Use Equation (29) to simulate the exports for each firm and to calculate average exports per firm (in total and in each percentile) for each origin-destination pair.

4. Run the IME regression 9 on the simulated export data, with $\ln x_{ij}$ being either the intensive margin for all firms exporting from i to j, or for each percentile in the size distribution of exporters from i to j .

6.2. Data

We now discuss the evidence obtained first for the fixed trade costs elasticity with respect to distance and second for the IME with simulated data.

We use 28 to estimate firm-level as well as product-level fixed trade cost elasticities with respect to distance (ζ). Table 11 shows that both of these elasticities and negative and statistically significant, so that both firm-level and product-level model-implied fixed trade costs are decreasing with distance even when granularity is taken into account. So granularity does not help to eliminate one of the puzzles emerging from the comparison between the Melitz-Pareto model and the data.

Table 12 reports estimated IME using simulated data for alternative values of $\widetilde{\theta}$ and for either zero or perfect correlation between the product of demand and productivity shocks across destinations. We consider 4 values of $\widetilde{\theta}$: our estimate $\widetilde{\theta} = 2.3$, the value that can be inferred from standard estimates of θ and σ in the literature (i.e., $\theta = 5$, the central estimate of the trade elasticity in Head and Mayer, 2014, and $\sigma = 5$ from Bas et al. (2015), so $\tilde{\theta} = 1.25$), as well as $\widetilde{\theta} = 1.75$ from Eaton et al. (2011) (which they estimate using the procedure outlined in the Appendix) and $\tilde{\theta} = 1$ (as in Zipf's Law).

Two broad patterns emerge from the table. First, the simulated IME decreases with $\widetilde{\theta}$. This is because the effect of granularity on the IME is stronger when there is more dispersion in productivity levels. Second, the simulated IME is highest when productivity is less correlated across destinations, again because this gives granularity more room to generate a covariance between average exports per firm and total exports.

For our estimate of $\widetilde{\theta}$ ($\widetilde{\theta} = 2.3$) and with no demand shocks (so there is perfect correlation in firm-level productivity across destinations), the simulated IME of 0.002 is quite low. The highest simulated IME occurs for the case in which $\widetilde{\theta} = 1$ and there is no correlation between the product of demand shocks and productivity across destinations. In this case the simulated IME is around 0.4, not too far from our preferred estimate based on the data of 0.522. But we think of this as an extreme case because $\widetilde{\theta} = 1$ is far from the estimates that come out of trade data, and because of the implausible assumption that firm-level exports are completely uncorrelated across destinations.

To explore this further, we examine the implications for the IME across percentiles. We calculate average simulated exports per firm in each percentile and use those to estimate an IME per percentile. We plot the resulting 100 IME estimates in Figure 6 along with the corresponding IME estimates based on the actual data. The IME based on the actual data is increasing with a spike at the top percentile. Granularity and the Pareto distribution fail to reproduce this pattern in the simulated data, since the corresponding IME is much smaller than in the data for most percentiles. The IME in the simulated data is almost zero for small percentiles and is relatively high for a small number of top percentiles. We conclude that granularity does not offer a plausible explanation for the positive estimated IME in the data.

7. Lognormal

In this section we depart from the assumption of common Pareto distribution of firm-level productivities and instead assume a lognormal distribution.

7.1. Theory

Following Bas et al. (2015) (henceforth BMT), let

$$H\left(\varphi_{ij}^{*}\right) \equiv \frac{1}{\left(\varphi_{ij}^{*}\right)^{\sigma-1}} \int_{\varphi_{ij}^{*}}^{\infty} \varphi^{\sigma-1} \frac{g(\varphi)}{1-G(\varphi_{ij}^{*})} d\varphi.$$

Since $x_{ij}(\varphi) \propto \varphi^{\sigma-1}$ then the ratio of average to minimum exports for each country pair satisfies

$$x_{ij}/x_{ij}(\varphi_{ij}^{*}) = H(\varphi_{ij}^{*}). \tag{30}$$

If productivity is distributed Pareto with parameter $\theta > \sigma - 1$ (as in Section 2) then it is easy to show that $H(\varphi) = \frac{\theta}{\theta-(\sigma-1)}$ (see Equation 6), so that the average to minimum ratio does not depend on selection. This property only holds with Pareto.

Assume that in each origin country i firm-level productivities are drawn from lognormal distribution with location parameter $\bar{\varphi}_i$ and scale parameter σ_φ. Letting $\Phi()$ be the CDF of the standard normal distribution, this implies that

$$G\left(\varphi\right) = \Phi\left(\frac{\ln\varphi - \bar{\varphi}_i}{\sigma_\varphi}\right). \tag{31}$$

Letting $h(x) \equiv \phi(x)/\Phi(x)$ be the ratio of the PDF to the CDF of the standard normal, BMT show that

$$H\left(\varphi_{ij}^{*}\right) = \frac{h\left[\left(\ln\varphi_{ij}^{*} - \bar{\varphi}_i\right)/\sigma_\varphi\right]}{h\left[\left(\ln\varphi_{ij}^{*} - \bar{\varphi}_i\right)/\sigma_\varphi + \left(\sigma-1\right)/\sigma_\varphi\right]}. \tag{32}$$

Combined with $1 - G(\varphi_{ij}^*) = N_{ij}/N_i$, we have

$$\frac{x_{ij}}{x_{ij}(\varphi_{ij}^*)} = \Omega\left(\frac{N_{ij}}{N_i}\right) \equiv H\left(\exp\left[\sigma_\varphi \Phi^{-1}\left(1 - \frac{N_{ij}}{N_i}\right) + \bar{\varphi}_i\right]\right). \tag{33}$$

Thus, the average to minimum ratio of exports for country pair ij only depends on the share of total firms in i that export to j, with the relationship given by the function $\Omega()$.

As argued by BMT, $\Omega()$ is decreasing function. To understand the implication of this property, imagine that the variable trade cost falls, so that φ_{ij}^*decreases with no effect on minimum sales (which remain at σF_{ij}). The decline in τ_{ij} leads to an increase in exports of incumbent firms (which increases average exports) and entry of low productivity firms (which lower average exports). Under Pareto these two effects exactly offset each other so that there is no change in the average. If productivity is distributed lognormal the second effect does not fully offset the first, and hence average exports increase with a decline in τ_{ij}. Since this also increases the number of firms that export, this will naturally generate a positive IME.

To calculate the IME we need to estimate the shape of the lognormal distribution (σ_φ) and the total number of firms in the country (N_i). We use Bento et al. (2015) (henceforth BR) data to impute the former, and the methodology developed by Head et al. (2014) (henceforth HMT) along with imputed number of firms to estimate the latter. Using census data as well as numerous surveys and registry data, BR compiled a dataset with a number of firms for a set of countries. Unfortunately, the sample in BR has missing observations for a number of countries in EDD. We impute missing values projecting log number of firms on log population.[9]

Exports from country i to country j of a firm with productivity φ in the model with CES preferences and monopolistic competition is given by $x_{ij}(\varphi) = \sigma F_{ij}\left(\varphi/\varphi_{ij}^*\right)^{\sigma-1}$. Since $\ln\varphi \sim N(\bar{\varphi}_i, \sigma_\varphi)$ then $\ln x_{ij}(\varphi) \sim N_{trunc}(\bar{\varphi}_{ij}, \widetilde{\sigma}_\varphi; \ln(\sigma F_{ij}))$, where $\widetilde{\sigma}_\varphi =$

[9]There exists a positive and tight relationship between log number of firms in the BR dataset and log population with elasticity of 0.945, as reported in Table 13 and on Figure 7.

$\sigma_\varphi(\sigma-1)$, $\bar{\varphi}_{ij}=\bar{\varphi}_i(\sigma-1)+\ln(\sigma F_{ij})$, and the truncation point is $\ln(\sigma F_{ij})$.

As in HMT, we estimate $\widetilde{\sigma}_\varphi$ using quantile-quantile regression, which minimizes the distance between the theoretical and empirical quantiles of log exports. Empirical quantiles are given by

$$Q^E_{ij,n}=\ln x_{ij,n} \tag{34}$$

where n is the rank of the firm among exporters from i to j. We calculate theoretical quantiles of exports from i to j as

$$Q^T_{ij,n}=\bar{\varphi}_{ij}+\widetilde{\sigma}_\varphi\Phi^{-1}\left(\hat{\Phi}_{ij,n}\right), \tag{35}$$

where $\hat{\Phi}_{ij,n}=\frac{N_i-(n-1)}{N_i}$ is the empirical CDF and N_i is the imputed number of firms from the BR data. Following HMT we adjust empirical CDF so that $\hat{\Phi}_{ij,n}=\frac{N_i-(n-1)-0.3}{N_i+0.4}$ since otherwise we would get $\Phi^{-1}\left(\hat{\Phi}_{ij,1}\right)=\infty$. The QQ-estimator of $\widetilde{\sigma}_\varphi$ is the coefficient β obtained from the regression

$$\ln x_{ij,n}=\alpha_{ij}+\beta\Phi^{-1}\left(\hat{\Phi}_{ij,n}\right)+\varepsilon_{ij,n}. \tag{36}$$

Using the estimated value of $\widetilde{\sigma}_\varphi$ we can calculate $\Omega(N_{ij}/N_i)$ for all country-pairs and, assuming that fixed costs have only origin and destination specific components, calculate IME. We will also use this estimated shape parameter in our simulations of firm-level productivities to gauge the role of granularity under the assumption of lognormal distribution.

Finally, we can use the estimated value of $\widetilde{\sigma}_\varphi$ to imputed fixed and variable trade costs similarly to what we did under the assumption of Pareto-distributed productivities. Note that we can express average exports as

$$x_{ij} = \sigma F_{ij} \Omega \left(\frac{N_{ij}}{N_i} \right). \tag{37}$$

From the definition of the cutoff productivity φ^*_{ij} and Equations (31) we can get that

$$\frac{\ln \varphi^*_{ij} - \bar{\varphi}_i}{\widetilde{\sigma}_\varphi} = \Phi^{-1} \left(1 - \frac{N_{ij}}{N_i} \right).$$

Recalling our notation $F_{ij} = F^o_i F^d_j \widetilde{F}_{ij}$ and $\tau_{ij} = \tau^o_i \tau^d_j \widetilde{\tau}_{ij}$, we can uncover $\widetilde{F}_{ij}$ and $\widetilde{\tau}_{ij}$ as follows:

1. $\tilde{F}_{ij}$ is estimated as a residual from the regression

$$\ln x_{ij} - \ln \Omega \left(\frac{N_{ij}}{N_i} \right) = \delta^o_i + \delta^d_j + \ln \widetilde{F}_{ij} \tag{38}$$

2. $\widetilde{\tau}_{ij}$ is estimated as a residual from the regression

$$-\frac{1}{\sigma - 1} \ln x_{ij} + \frac{1}{\sigma - 1} \ln \Omega \left(\frac{N_{ij}}{N_i} \right) + \widetilde{\sigma}_\varphi \Phi^{-1} \left(1 - \frac{N_{ij}}{N_i} \right) = \delta^o_i + \delta^d_j + \ln \widetilde{\tau}_{ij} \tag{39}$$

Armed with estimates of $\widetilde{F}_{ij}$ and $\widetilde{\tau}_{ij}$, we can compute their correlation and also check whether $\widetilde{F}_{ij}$ increases or decreases with distance. We can also compute the elasticity of $\widetilde{F}_{ij}$ with respect to distance for the case of granularity following a similar procedure as to what we used for the case of Pareto in the previous section (see the Appendix). In the Appendix we also explain how we simulate exports to estimate IME in case of lognormal with granularity.

The previous exercises assume that there are no demand shocks and that fixed costs are homogenous across firms. We are now working on using MLE to estimate a model with firm-level productivity, (destination specific) demand

shocks and fixed costs that are all lognormally distributed.

7.2. Data

Table 14 reports QQ-estimates of the slope in equation (36). Unlike HMT, who assume that export sales are distributed lognormally (without truncation), we follow the theory which implies that exports are distributed according to a truncated lognormal distribution. In microdata, however, we see that the left tail doesn't behave like truncated lognormal because of some exporters with very small sales (this is why in current work we are allowing for heterogeneous fixed costs). In theory, the estimates of the slope should not change when we truncate the data. We report three sets of estimates: for the full sample, largest 50% of firms and largest 25% of firms for each origin-destination pair. Dropping the smallest exporters allows us to focus on the right tail, which is more robust to allowing for convex marketing costs, as in Arkolakis (2010).

Our estimate for the shape parameter for the top 25% is around 4.9, which is larger than the HMT estimate of 2.4. The difference comes from the fact that HMT effectively assume $N_i^{HMT} = N_{ij}$, which is much smaller than the N_i's that we use (based on the BR data). In our case exporters make up only a tiny fraction of all firms, and the small $\widetilde{\sigma}_\varphi$ estimated by HMT would not be able to match the dispersion of sales of exporters. In general, the higher the N_i one takes as an input in the QQ regression, the higher the estimate of the shape parameter that one obtains.

We compute the IME for the case of a continuum firms as well as for the case with granularity. Results for $\widetilde{\sigma}_\varphi = \{2.4; 4.9\}$ are reported in Table 15. First, a lognormal distribution allows the intensive margin elasticity to be positive even under the assumption of a continuum of firms. Second, for our estimates of the shape parameter $\widetilde{\sigma}_\varphi = 4.9$, the size of IME is very close to that from the data. The intensive margin elasticity is even higher under granularity. Third, even in the case of a continuum of firms, most action comes from the right tail of the

distribution, as can be seen on Figure 8.

Using equations (38) and (39) we estimated fixed and variable trade costs. Results are reported in Table 16 and plotted on Figures 9 and 10. In contrast to our results under Pareto, now both the model-implied variable and fixed trade costs are increasing with distance. Table 17 reports results for the fixed trade cost elasticity with respect to distance in the presence of granularity for the two different values of $\widetilde{\sigma}_{\varphi}$. We find a positive elasticity for our estimate of the shape parameter ($\widetilde{\sigma}_{\varphi} = 4.9$), and a negative elasticity when we use the HMT shape parameter of 2.4.

Overall, the model does much better in fitting the data when we assume that productivity is distributed lognormal than when we assume that it is distributed Pareto. However, the IME for each percentile is not a perfect match to the data.

8. Conclusion

To be added

Appendix - INCOMPLETE

IME for each percentile and firm-specific fixed trade costs

Consider the standard Melitz-Pareto model with the assumption that firm-level fixed costs F_{ij} are random. Assume that conditional on fixed trade costs, firm-level productivities are distributed Pareto:

$$G\left(\varphi|f_{ij}\right)=1-\left(\frac{\varphi}{\varphi_{min}\left(F_{ij}\right)}\right)^{-\theta} \tag{40}$$

For each level of fixed trade costs F_{ij} there exists a cutoff productivity $\varphi_{ij}^{*}\left(F_{ij}\right)$ such that only firms with higher productivity export from i to j. Assume that $\varphi_{ij}^{*}\left(F_{ij}\right)\geq\varphi_{min}\left(F_{ij}\right)$ for all i,j. As in the standard model, given the fixed costs F_{ij}, exports from i to j of a firm with productivity φ are given by:

$$x_{ij}\left(\varphi|F_{ij}\right)=\tilde{\sigma}F_{ij}\left(\frac{\varphi}{\varphi_{ij}^{*}\left(F_{ij}\right)}\right)^{\sigma-1} \tag{41}$$

Note that exports are distributed Pareto with scale parameter $\tilde{\sigma}F_{ij}$ and shape parameter $\widetilde{\theta}$. If the distribution of F_{ij} is similar across ij country pairs, so will the distribution of exports (not conditional on fixed trade costs) be, and so average exports per firm in each percentile shall be the same. Thus, $IME^{p}=0$.

Next, imagine that $F_{ij}=F_{i}^{o}F_{j}^{d}\widetilde{F}_{ij}F$ were F is a firm-level random variable with unit mean, whose distribution is common across all origin-destination country pairs, and F_{i}^{o}, F_{j}^{d}, and $\widetilde{F}_{ij}$ change by origin, destination and origin-destination pair, respectively, but are constant across firms. Now percentiles will be similar up to the factor of $F_{i}^{o}F_{j}^{d}\widetilde{F}_{ij}$, i.e.:

$$x_{ij}\left(p\right)=F_{i}^{o}F_{j}^{d}\widetilde{F}_{ij}f\left(p\right)$$

where $f(p)$ is a function that only depends on the percentile p. Thus, $IME^p = IME$.

Estimation of $\widetilde{\theta}$

An estimate of $\widetilde{\theta}$is required to compute model-implied $\ln \widetilde{F}_{ij}$ and $\ln \widetilde{\tau}_{ij}$ as functions of $\ln \bar{x}_{ij}$, $\ln N_{ij}$, and estimated fixed effects. To obtain it we follow the Melitz-Pareto model in Eaton et al. (2011) to derive the following expression

$$\frac{\bar{x}_{il|j}}{\bar{x}_{il|l}} = \left(\frac{N_{ij}}{N_{il}}\right)^{-1/\widetilde{\theta}} \tag{42}$$

where $\bar{x}_{il|j}$ are average exports per firm for firms from i that sell in market l but restricted to those firms that sell in markets l and j. EKK have information on domestic sales for each firm, so they use $l = i$. We do not have such information, so we use $l^*(i) \equiv \arg\max_k N_{ik}$, that is the largest destination market for each exporting country (e.g., the United States for Mexico). Letting

$$z_{ij} \equiv \frac{\bar{x}_{il^*(i)|j}}{\bar{x}_{il^*(i)|l^*(i)}} \tag{43}$$

and

$$m_{ij} \equiv \frac{N_{ij}}{N_{il^*(i)}} \tag{44}$$

then we have

$$\ln z_{ij} = -\frac{1}{\widetilde{\theta}} \ln N_{ij}. \tag{45}$$

This suggests an OLS regression to recover an estimate for $\widetilde{\theta}$.

Eaton et al. (2011) estimate this regression for French firm-level data (including information on sales in France) and obtain a coefficient of -0.57, which implies $\widetilde{\theta} = 1.75$. In their case, they keep in their estimating sample only firms with positive sales in France, so the variables $\bar{x}_{FF|j}$ and N_{Fj} are calculated based on the same set of firms. To implement an approach comparable to theirs, we drop all firms from country i that do not sell to $l^*(i)$, so the sample includes only

$N_{il^*(i)}$ firms for country i. This implies that all firms that make up N_{ij} are selling to $l^*(i)$. Figure 11 reproduces Figure 3 from Eaton et al. (2011) by plotting the variables in Equation (45). The slope in the graph is equal to $\frac{1}{\widetilde{\theta}}$, and the corresponding estimated values are reported in Table 18. Based on the full sample and using no weighting, the estimated $\widetilde{\theta}$ is over 28. But in Figure 11 for small values of m_{ij}, which correspond to small values of N_{ij}, there is a lot of dispersion in z_{ij}. To minimize the effect of that noise we weight observations by $\sqrt{N}_{ij}$and this lowers the estimate of $\widetilde{\theta}$ to 5.65. Finally, when we drop all observations with $N_{ij} < 100$ we obtain $\widetilde{\theta} = 2.3$, which is still higher than in Eaton et al. (2011). We will use this estimate in our simulations of the intensive margin elasticity.

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Table 1: EDD sample countries and years

ISO3	Country name	1st year	Last year	ISO3	Country name	1st year	Last year
ALB	Albania	2004	2012	KHM	Cambodia	2003	2009
BFA	Burkina Faso	2005	2012	LAO	Laos	2006	2010
BGD	Bangladesh	2005	2013	LBN	Lebanon	2008	2012
BGR	Bulgaria	2003	2006	MAR	Morocco	2003	2013
BOL	Bolivia	2006	2012	MDG	Madagascar	2007	2012
BWA	Botswana	2003	2013	MEX	Mexico	2003	2012
CHL	Chile	2003	2012	MKD	Macedonia	2003	2010
CHN	China	2003	2005	MMR	Myanmar	2011	2013
CIV	Cote d'Ivoire	2009	2012	MUS	Mauritius	2003	2012
CMR	Cameroon	2003	2013	MWI	Malawi	2009	2012
COL	Colombia	2007	2013	NIC	Nicaragua	2003	2013
CRI	Costa Rica	2003	2012	NPL	Nepal	2011	2013
DOM	Dominican Rep.	2003	2013	PAK	Pakistan	2003	2010
ECU	Ecuador	2003	2013	PRY	Paraguay	2007	2012
EGY	Egypt	2006	2012	PER	Peru	2003	2013
ETH	Ethiopia	2008	2012	QOS	Kosovo	2011	2013
GAB	Gabon	2003	2008	ROU	Romania	2005	2011
GEO	Georgia	2003	2012	RWA	Rwanda	2003	2012
GIN	Guinea	2009	2012	THA	Thailand	2012	2013
GTM	Guatemala	2005	2013	TZA	Tanzania	2003	2012
HRV	Croatia	2007	2012	UGA	Uganda*	2003	2010
IRN	Iran	2006	2010	URY	Uruguay	2003	2012
JOR	Jordan	2003	2012	YEM	Yemen	2008	2012
KEN	Kenya	2006	2013	ZAF	South Africa	2003	2012
KGZ	Krygyztan	2006	2012	ZMB	Zambia	2003	2011

* indicates that Uganda does not have data for 2006

Table 2: Industry groupings

	HS 2-digit codes that are included in each industry
Food and beverages	02-05; 07-12; 14-24
Mineral	25-26
Chemicals	28-38
Plastic and rubber	39-40
Apparel	41-43; 60-67
Wood	44-46
Paper	47-49
Textiles	50-59
Glass	68-70
Precious metals	71
Metals	72-83
Machinery	84
Electrical machinery	85
Transport equipment	86-89
Miscellaneous	90-96

Table 3: Benchmark IME regression

	Coefficient from $\ln \bar{x}_{ij}$ on $\ln X_{ij}$		
IM elasticity	0.491***	0.487***	0.522***
Standard error	[0.0135]	[0.0141]	[0.0137]
Year FE	Yes	Yes	Yes
Destination FE		Yes	Yes
Origin FE			Yes

Note: 4 main destinations, $N_{ij} > 100$, 524 obs.

Robust standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: IME regression, all destinations

	Coefficient from $\ln \bar{x}_{ij}$ on $\ln X_{ij}$		
IM elasticity	0.562***	0.508***	0.526***
Standard error	[0.00599]	[0.00629]	[0.00590]
Year FE	Yes	Yes	Yes
Destination FE		Yes	Yes
Origin FE			Yes

Note: all destinations, $N_{ij} > 100$, 5289 obs.

Robust standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: IME regression, countries with low N_{ij} included

	Coefficient from $\ln \bar{x}_{ij}$ on $\ln X_{ij}$		
IM elasticity	0.502***	0.514***	0.718***
Standard error	[0.00867]	[0.00906]	[0.0146]
Year FE	Yes	Yes	Yes
Destination FE		Yes	Yes
Origin FE			Yes

Note: 4 main destinations, 1203 obs.

Robust standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: IME regression, disaggregated

	Coefficient from $\ln \bar{x}_{ij}$ on $\ln X_{ij}$		
Panel a: manufacturing industries			
IM elasticity	0.685***	0.695***	0.713***
Standard error	[0.0111]	[0.0108]	[0.00894]
Observations	1856	1856	1856
Panel b: HS2 (within manufacturing)			
IM elasticity	0.710***	0.721***	0.787***
Standard error	[0.00906]	[0.00869]	[0.00913]
Observations	2120	2120	2120
Panel c: HS4 (within manufacturing)			
IM elasticity	0.714***	0.731***	0.751***
Standard error	[0.00836]	[0.00800]	[0.00908]
Observations	2821	2821	2821
Panel d: HS6 (within manufacturing)			
IM elasticity	0.740***	0.755***	0.755***
Standard error	[0.0111]	[0.0104]	[0.0118]
Observations	3190	3190	3190
Year FE	Yes	Yes	Yes
Destination FE		Yes	Yes
Origin FE			Yes
Industry/HS FE	Yes	Yes	Yes

Note: 4 main destinations, $N_i j > 100$

Robust standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: IME regression, small firms excluded

	Coefficient from $\ln \bar{x}_{ij}$ on $\ln X_{ij}$		
Panel a: 4 main destinations, $N_{ij} > 100$			
IM elasticity	0.489***	0.483***	0.523***
Standard error	[0.0135]	[0.0142]	[0.0134]
Observations	517	517	517
Panel b: all destinations, $N_{ij} > 100$			
IM elasticity	0.564***	0.508***	0.472***
Standard error	[0.00604]	[0.00644]	[0.00595]
Observations	5204	5204	5204
Panel c: 4 main destinations			
IM elasticity	0.499***	0.509***	0.719***
Standard error	[0.00869]	[0.00911]	[0.0144]
Observations	1203	1203	1203
Year FE	Yes	Yes	Yes
Destination FE		Yes	Yes
Origin FE			Yes

Firms with sales less than $1000 excluded

Robust standard errors in brackets

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Table 8: Fixed and variable trade costs

	$corr(\ln N_{ij}, \ln \bar{x}_{ij})$	$corr(\ln \widetilde{\tau}_{ij}, \ln \widetilde{F}_{ij})$
Raw data	**0.341**	
	[0.041]	
Purged of:		
Origin FE	**0.480**	
	[0.038]	
Destination FE	**0.333**	
	[0.041]	
Origin and Destination FE	**0.428**	**-0.891**
	[0.039]	[0.019]

Note: $\theta = 5$, $\sigma = 5$, $N_{ij} > 100$, 524 obs.

Robust standard errors in parentheses

Table 9: Trade costs and distance

	$\ln \widetilde{F}_{ij}$	$\ln \widetilde{\tau}_{ij}$	$\ln \widetilde{f}_{ij}$
$\ln dist$	-0.171***	0.112***	-0.0912**
Standard error	[0.0377]	[0.0133]	[0.0343]

Note: 4 main destinations, $N_{ij} > 100$, 524 obs.

Robust standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Product-level IME

	Coefficient from $\ln \bar{x}_{ij}^{p}$ on $\ln X_{ij}$		
Panel a: 4 main destinations			
IM elasticity	0.401***	0.407***	0.384***
Standard error	[0.0180]	[0.0182]	[0.0171]
Observations	524	524	524
Panel b: all destinations			
IM elasticity	0.513***	0.432***	0.386***
Standard error	[0.00934]	[0.00884]	[0.00773]
Observations	5289	5289	5289
Year FE	Yes	Yes	Yes
Destination FE		Yes	Yes
Origin FE			Yes

Note: $N_{ij} > 100$

Robust standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Fixed trade costs distance elasticity and granularity

	Fixed costs elasticity	
	Firm-level	Product-level
ζ	-0.582***	-0.128**
Standard error	[0.0360]	[0.0401]

Note: $N_{ij} > 100$, 524 obs.

Robust standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: IME under granularity

	$corr(\alpha_j\varphi, \alpha_k\varphi)$	
	0	1
$\widetilde{\theta} = 2.3$	**0.006**	**0.002**
$\widetilde{\theta} = 1.75$	**0.025**	**0.007**
$\widetilde{\theta} = 1.25$	**0.169**	**0.038**
$\widetilde{\theta} = 1$	**0.390**	**0.106**

Note: $N_{ij} > 100$

Table 13: Number of firms and population

	(1)	(2)
	Log number of firms	Log number of firms
Log population	0.945***	0.944***
	[0.0136]	[0.0139]
Observations	468	468
R^2	0.911	0.914
Year FE	No	Yes

Standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: QQ estimates of $\tilde{\sigma}_\varphi$

	All firms	Top 50%	Top 25%
$\widetilde{\sigma}_\varphi$			4.913***
			[0.00399]
Observations			139755
R^2			0.942
Bilateral FE	Yes	Yes	Yes

Robust standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: IME under lognormal distribution

		$corr(\zeta_j\phi, \zeta_k\phi)$	
	Continuum	0	1
$\widetilde{\nu} = 4.9$	**0.470**	**0.591**	**0.407**
$\widetilde{\nu} = 2.4$	**0.164**	**0.179**	**0.125**

Bold entries are IM elasticities

Table 16: Trade costs and distance, lognormal

	(1)	(2)
	log Fixed costs	log Variable costs
log Distance	0.165***	0.642***
	[0.0391]	[0.0580]
Observations	524	524
R^2	0.033	0.190

Standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Trade costs and distance, lognormal and granularity

	Fixed costs elasticity	
	$\widetilde{\nu} = 4.9$	$\widetilde{\nu} = 2.4$
ζ	0.398***	-0.326***
Standard error	[0.0325]	[0.0323]

Note: $N_{ij} > 100$

Robust standard errors in brackets

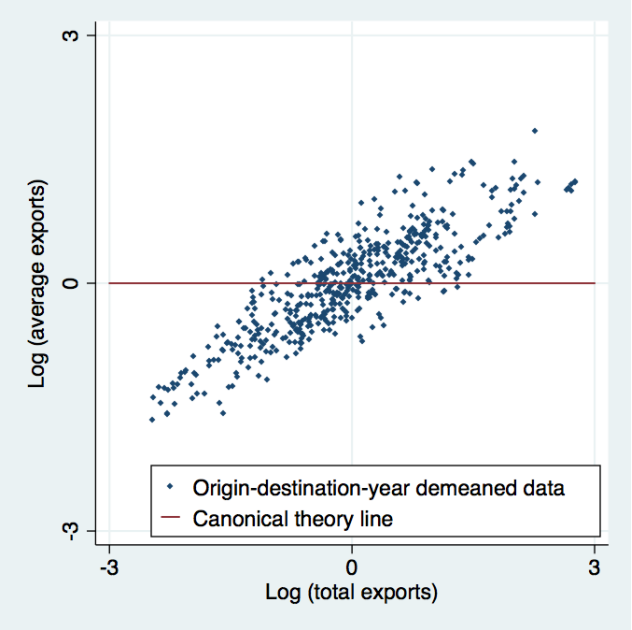
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Estimates of $\widetilde{\theta}$

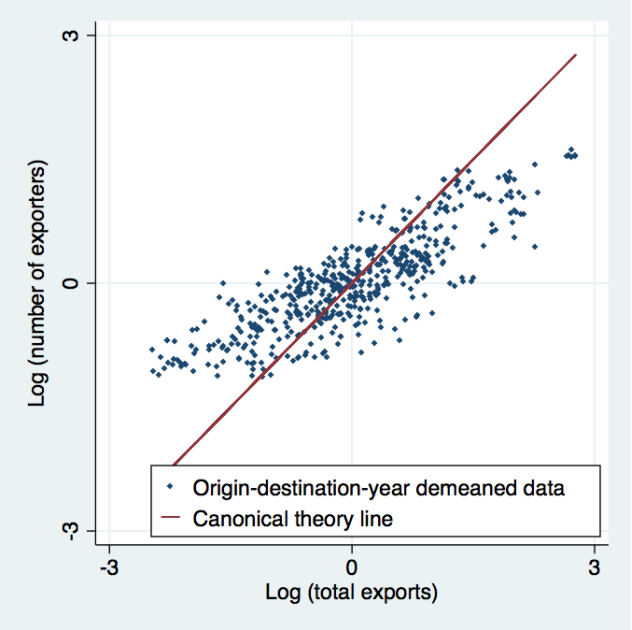
	$\widetilde{\theta}$	s.e.
Full sample	**28.42**	[2.08]
Weights = $\sqrt{(N_{ij})}$	**5.65**	[0.07]
Dropping $N_{ij} < 100$	**2.30**	[0.02]

Figure 1: Intensive and Extensive Margins of Exporting

Panel a: Average size of exporters (intensive margin) and total exports



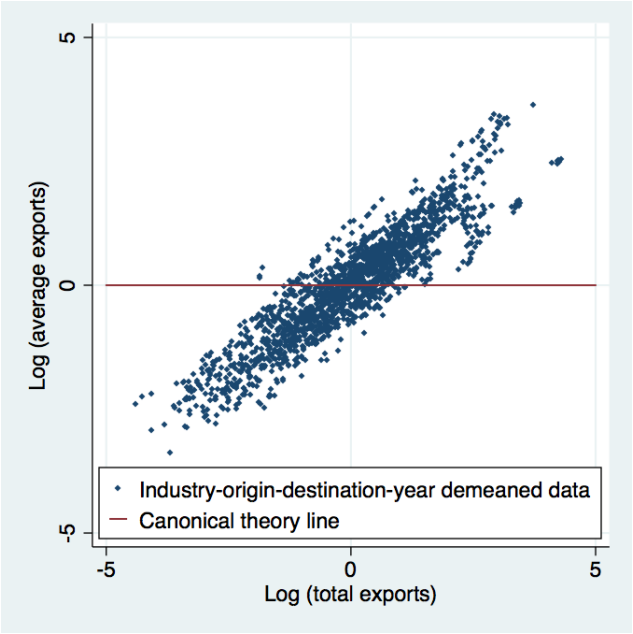
Panel b: Number of exporters (extensive margin) and total exports



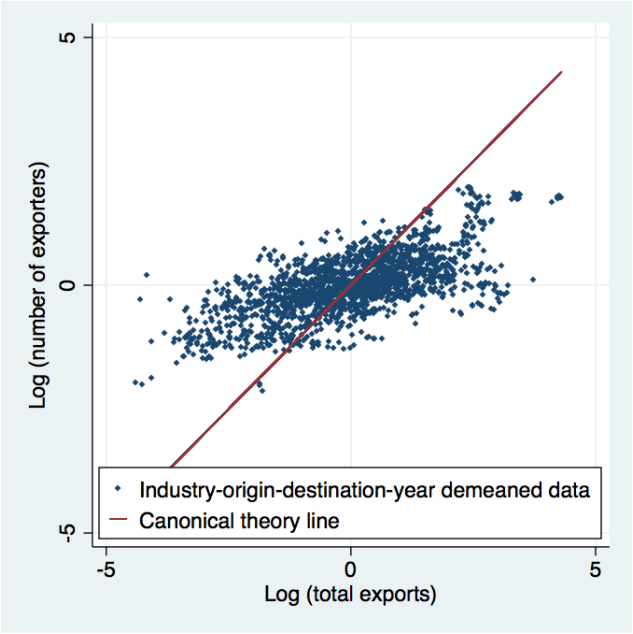
Note: the source is the exporter-level data used for the Exporter Dynamics Database. The x-axis represents log total exports at the exporting country-destination country-year level demeaned by country, destination, and year fixed effects. Only four destination countries are considered: France, Germany, Japan, and the US. The dots represent the raw measures. The line is the slope predicted by the Melitz-Pareto model.

Figure 2: Intensive and Extensive Margins of Exporting

Panel a: Average size of exporters (intensive margin) and total exports



Panel b: Number of exporters (extensive margin) and total exports



Note: source is the exporter-level data used for the Exporter Dynamics Database. The x-axis represents log total exports at the exporting country-industry-destination country-year level demeaned by country, destination, industry, and year fixed effects. Only four destination countries are considered: France, Germany, Japan, and the US. The dots represent the raw measures. The line is the slope predicted by the Melitz-Pareto model.

Figure 3: IME for each percentile, data

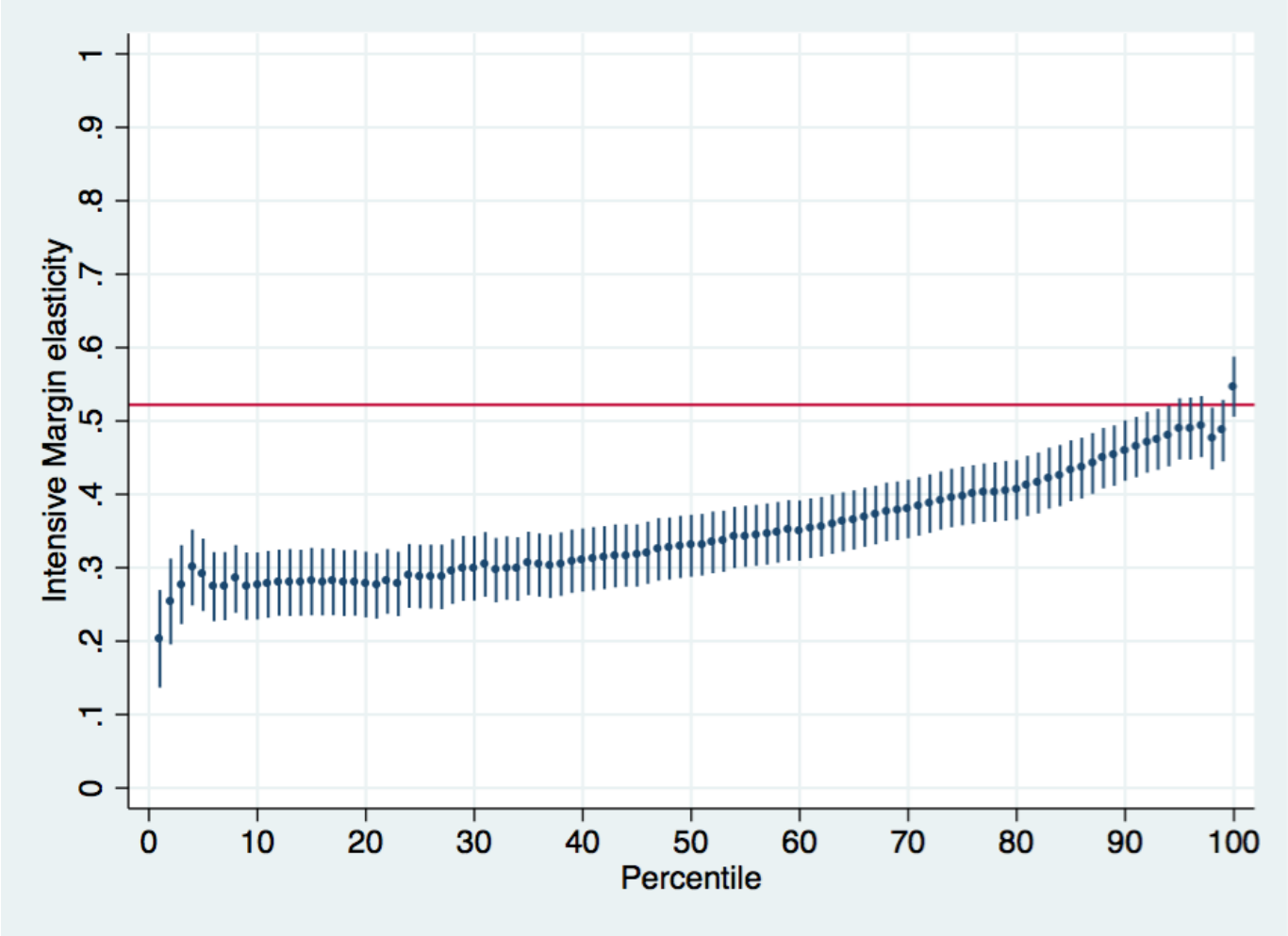
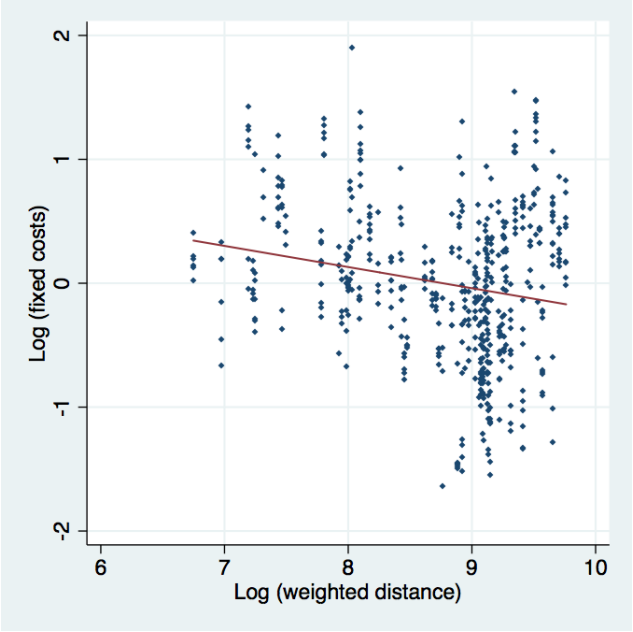
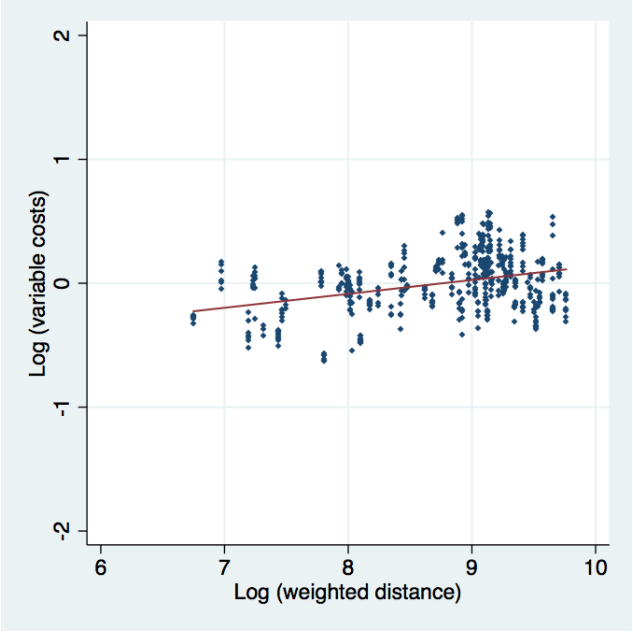


Figure 4: Fixed and Variable Trade Costs and Distance

Panel a: fixed trade costs and distance



Panel b: variable trade costs and distance



Note: source is the exporter-level data used for the Exporter Dynamics Database. The x-axis represents log distance taken from Mayer and Zignago (2011). Only four destination countries are considered: France, Germany, Japan, and the US. To calculate the model-implied fixed and variable trade costs we use $\theta = 5$ from Eaton et al. (2011) and $\sigma = 5$ from Bas et al. (2015)

Figure 5: Fixed product-level trade costs and distance

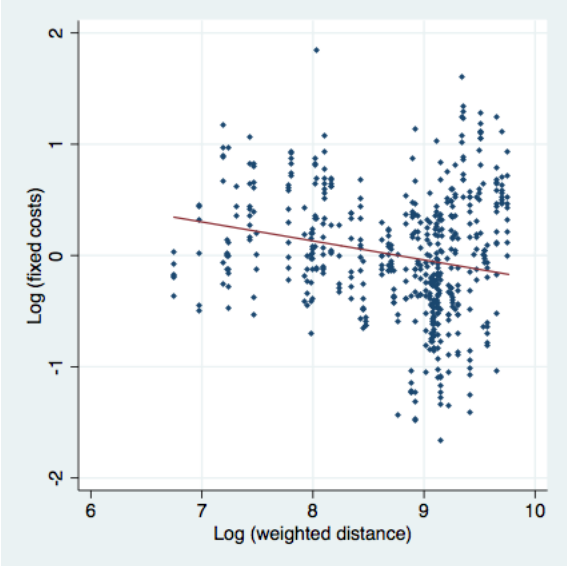


Figure 6: IME for each percentile, Pareto

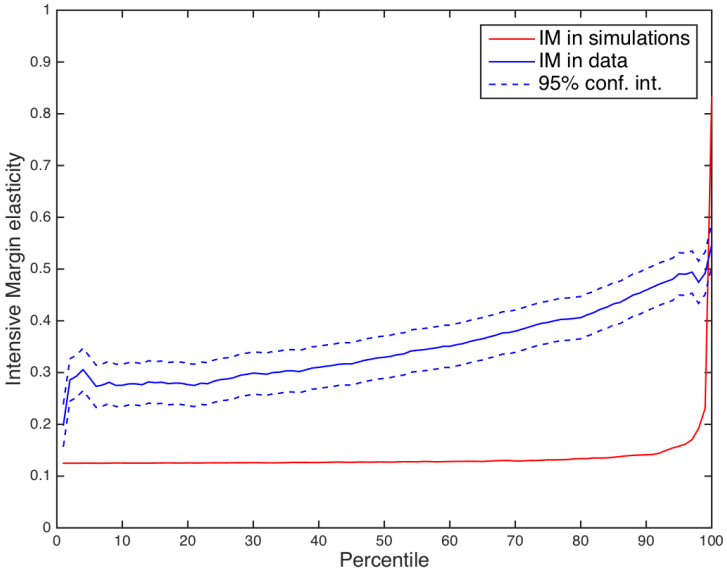


Figure 7: Number of firms and population

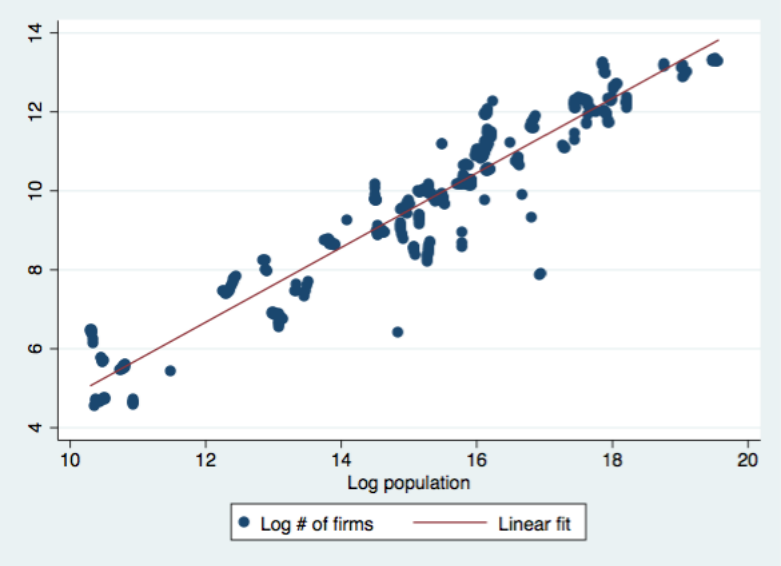


Figure 8: IME for each percentile, lognormal

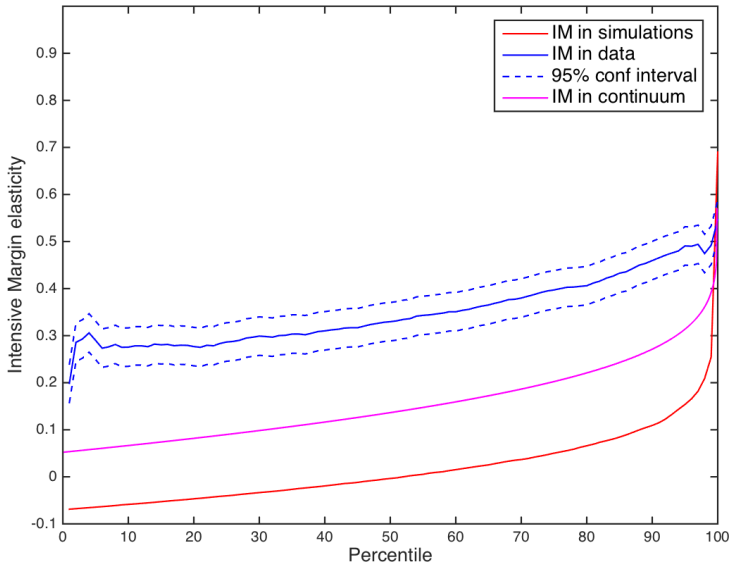


Figure 9: Variable trade costs and distance, lognormal

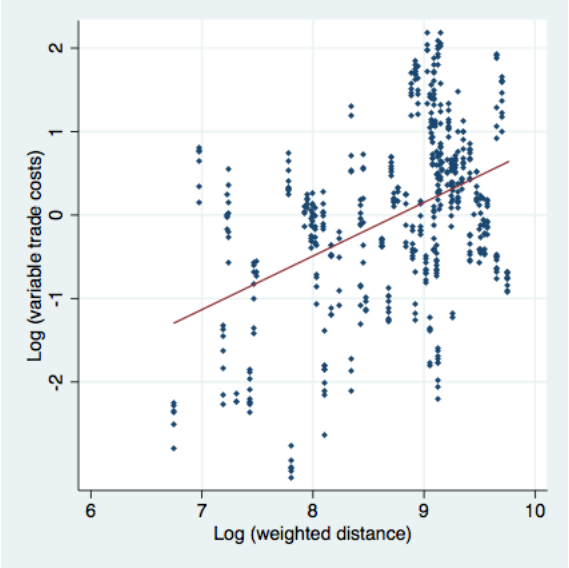


Figure 10: Fixed trade costs and distance, lognormal

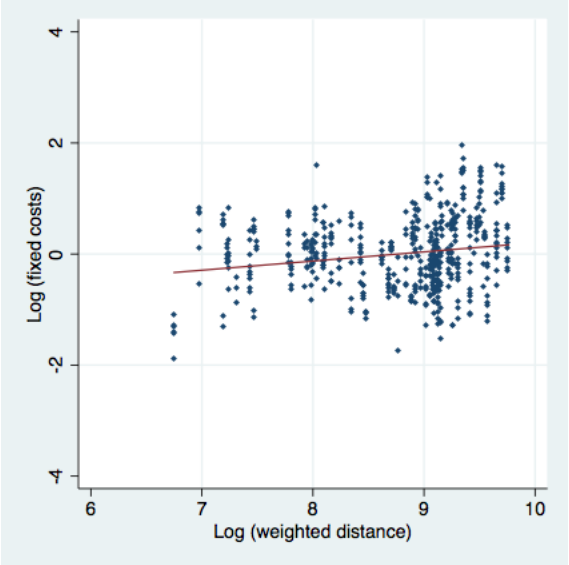


Figure 11: Exports to largest destination and market entry

