sellers, who sold 5,154 products to 68,052 buyers across 205 destinations.

3 Exports, Exporters and Importers

In this section we begin to explore the matched exporter-importer data. We first decompose exports to a country into intensive and extensive margins where we extend the usual extensive margins of firms, i.e. sellers, and products to include the number of buyers. We then consider the customer margin response to the standard gravity variables of distance to and GDP of the destination market. Next we examine the margins of trade within the firm.

3.1 Market level

To examine the role of buyers in the variation of exports across countries, we decompose total exports to country j into the product of the number of trading firms, f, the number of traded products, p, the number of buyers, b, the density of trade, d, and the average value of trade,

$$x_j = f_j p_j b_j d_j x_j$$

where $d_j = o_j/(f_j p_j b_j)$, o_j is the number of firm-product-buyer observations for which trade with country j is positive and $x_j = x_j/o_j$, the intensive margin, is average value per observation with positive trade. In order to decompose the impact of the different margins of trade on total exports, we regress each component of country-level exports on total exports to a given market in 2006, e.g. lnf_j, against lnx_j.

The results, shown in Table 2, confirm and extend previous findings on the importance of the extensive and intensive margins of trade. The sum of the four extensive margins, firms, products, buyers and density, accounts for two thirds of the variation in Norwegian exports across countries. While it has been shown in a variety of contexts that the number of firms and products increases as total exports to a destination increase, these results that shows the equal importance of the number of importing buyers in total exports. In fact, the buyer margin is as large or larger than the firm or product margins.

It is well documented that the total value of exports, the number of exporting firms and the number of exported products are all systematically related to market characteristics. Figure 1 plots the the average number of customers per firm against destination market GDP. The larger is the market size, the greater is the number of buyers for each Norwegian exporter. We examine how this new extensive margin of trade responds to distance to markets and market size (measured by GDP), by estimating the following gravity model,

$$y_j = \beta_0 + \beta_1 \ln GDP_j + \beta_2 \ln Dist_j + \epsilon_j$$

Figure 1: Average numbers of buyers per seller versus market size.

Note: 2006 data, log scales. GDP in \$1000 from Penn World Table 7.1 (cgdp×pop).

where y_j is either total exports, number of firms exporting to a market (sellers), number of buyers of Norwegian exports in the market, average number of buyers per seller, and average exports to each buyer (all in logs).

Total exports, number of firms exporting to a market (sellers) as well as number of buyers in a market (buyers) are all significantly negatively related to distance and positively associated with market size, as shown in Table 3. Moreover, the number of buyers per seller and average exports per buyer are significantly negatively associated with distance and positively associated with GDP.

3.2 Firm level

Having considered the role of buyers in aggregate exports, we now turn to the firm level. Exports of firm m to country j can be decomposed

$$x_{mj} = p_{mj} b_{mj} d_{mj} x_{mj}$$

where $d_{mj} = o_{mj}/(p_{mj} b_{mj})$, o_{mj} is the number of product-buyer observations for which trade with country j is positive and $x_{mj} = x_{mj}/o_{mj}$. In order to decompose the impact of the various margins of trade on firms' total exports to a market, we regress the log of each of the components of firm level exports on the log of total firm exports and include firm and country fixed effects in Table 4. We do this for a given year, here chosen to be 2006. The findings are in line with previous results on the importance of the extensive and intensive margins of trade within firms. Decomposing firm-level

exports, the number of buyers is positively and significantly associated with firm-country exports even after including country and firm fixed effects. The buyer margin is equal in magnitude to the product margin of firm-level trade that has been the subject of a large new round of both theoretical and empirical research. The extensive margins of products and buyers together account for one third of the variation in Norwegian exports across countries within the firm.

We next consider a simple gravity model at the firm-country level to examine how the number of customers and average exports per customer for the firm respond to distance and GDP,

$$y_{mj} = \alpha_m + \beta_1 \ln Dist_j + \beta_2 \ln GDP_j + \epsilon_{mj}$$

where y_{mj} is either export value for firm m to destination j, or the number of buyers per firm, or average export value per firm-buyer, all in logs.

The results in Table 5 show that both the number of customers and average exports per customer are significantly related to all the gravity variables in the expected direction. The number of buyers responds more to distance than average exports per buyer. The magnitude on the other gravity variables is comparable for the extensive and intensive margins.

4 Exporters and Importers

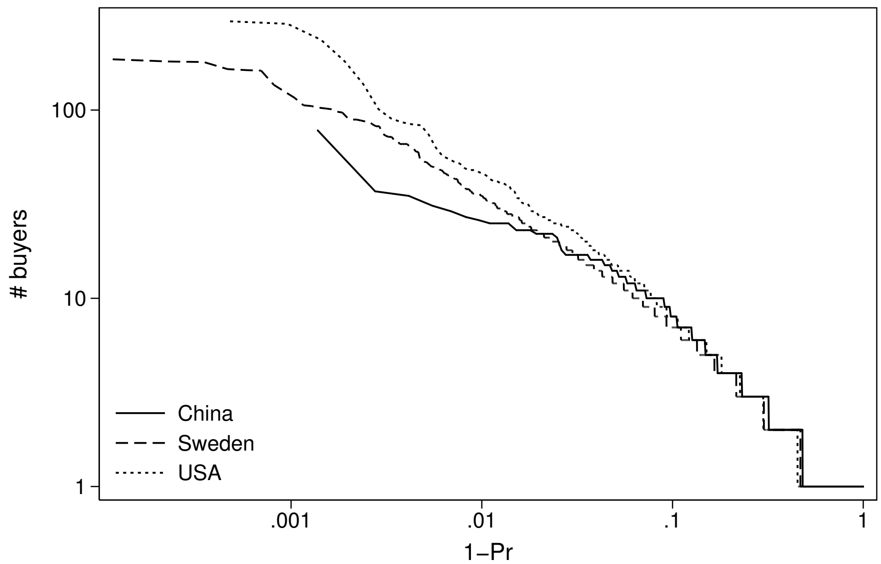
While the prior results establish the relevance of the buyer dimension as a margin of trade, we develop a model of international trade to more formally examine the role of buyer-seller relationships in trade flows. Before presenting the model, we document a set of facts on the heterogeneity of buyers and sellers and their relationships, which will guide our theory and subsequent empirical specification.

Fact 1: The populations of sellers and buyers of Norwegian exports are both characterized by extreme concentration. The top 10 percent sellers account for 98 percent of Norwegian aggregate exports. At the same time, the top 10 percent buyers are almost as dominant, and account for 96 percent of the purchase of Norwegian exports.

Fact 2: The distributions of buyers per firm and exporters per buyer are approximately Pareto. Figure 2 shows that the inverse cdfs of buyers per firm for exporters serving the Chinese, Swedish and the US market are approximately Pareto. The average number of buyers per seller is higher in the US, 4.5, than in China and Sweden, 3.6 and 3.6 respectively (Table 1). We have chosen Sweden and the US as they are among the main destinations of Norwegian exports. Figure 3 shows the distribution of sellers per buyer for the same export markets. Again the distributions are approximately Pareto. The average number of sellers per buyer in China, Sweden and the US is 1.7, 1.9 and 1.6, respectively.

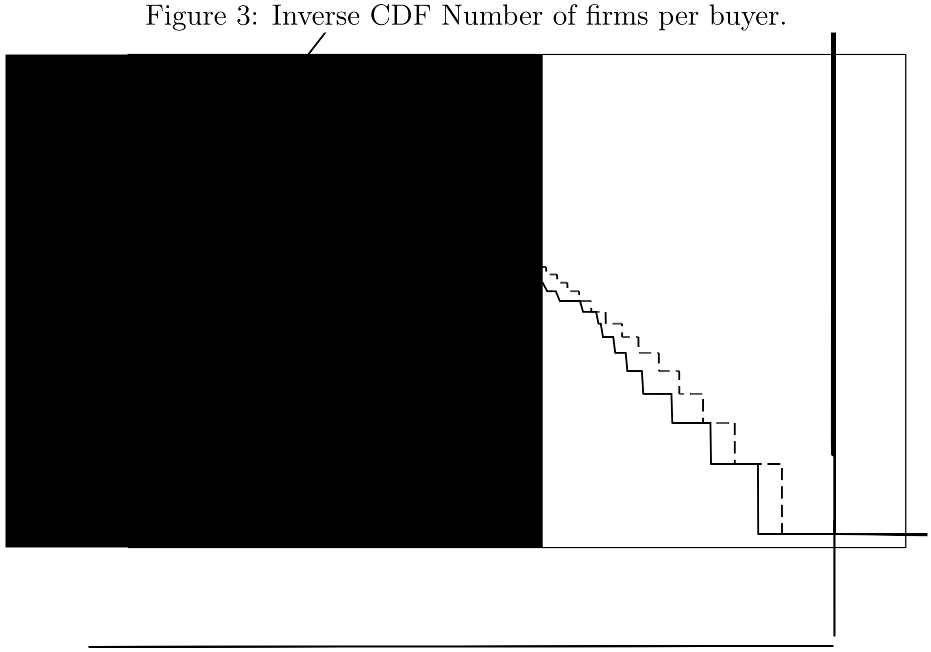
Fact 3: Dispersion of importer expenditure varies across countries. While the distributions of importer expenditure is approximately Pareto in every country, there is substantial heterogeneity

Figure 2: Inverse CDF Number of buyers per firm.



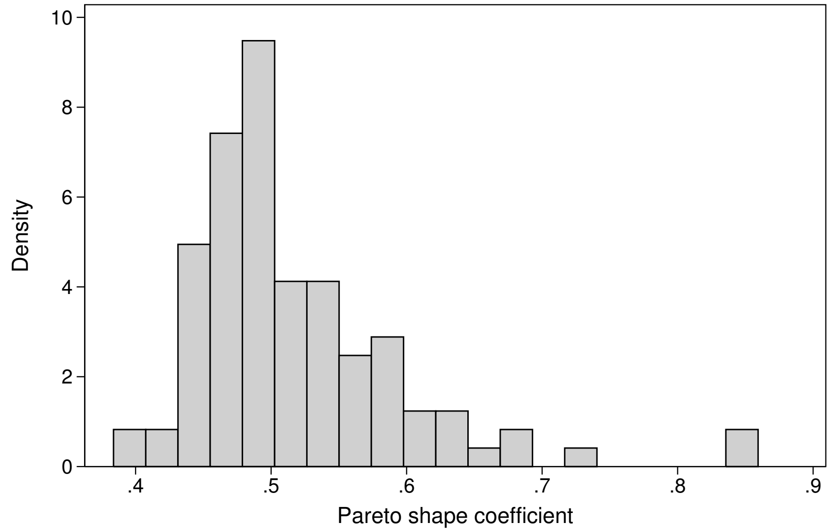
Note: 2006 data, log scales. Horizontal axis is Pr(# buyers > x). The estimated regression slopes for China, Sweden and the U.S. are -0.88 (s.e. 0.008), -0.87 (s.e. 0.002) and -0.95 (s.e. 0.004) respectively.

Figure 3: Inverse CDF Number of firms per buyer.



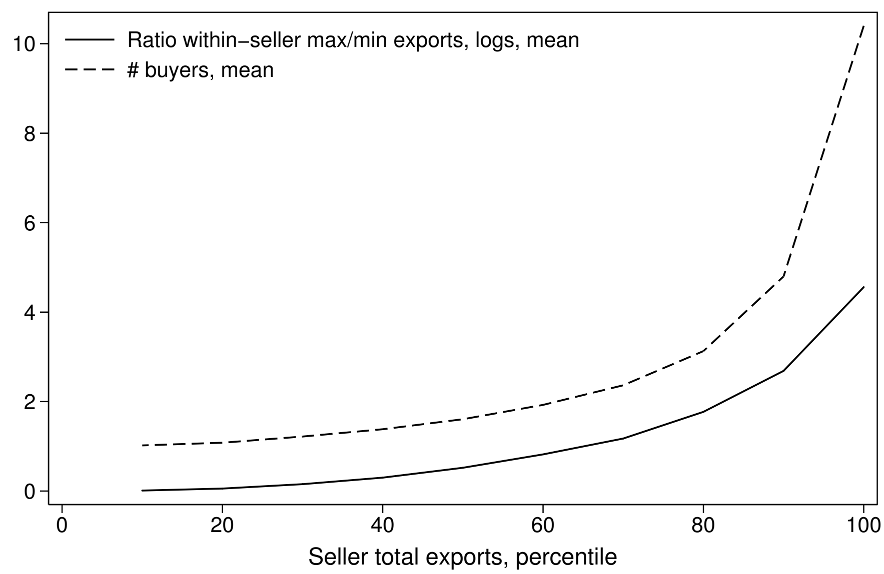
Note: 2006 data, log scales. Horizontal axis is Pr(# firms > x). The estimated regression slopes for China, Sweden and the U.S. are -0.49 (s.e. 0.006), -0.57 (s.e. 0.002) and -0.46 (s.e. 0.003) respectively.

Figure 4: Heterogeneity of importer expenditure across markets.



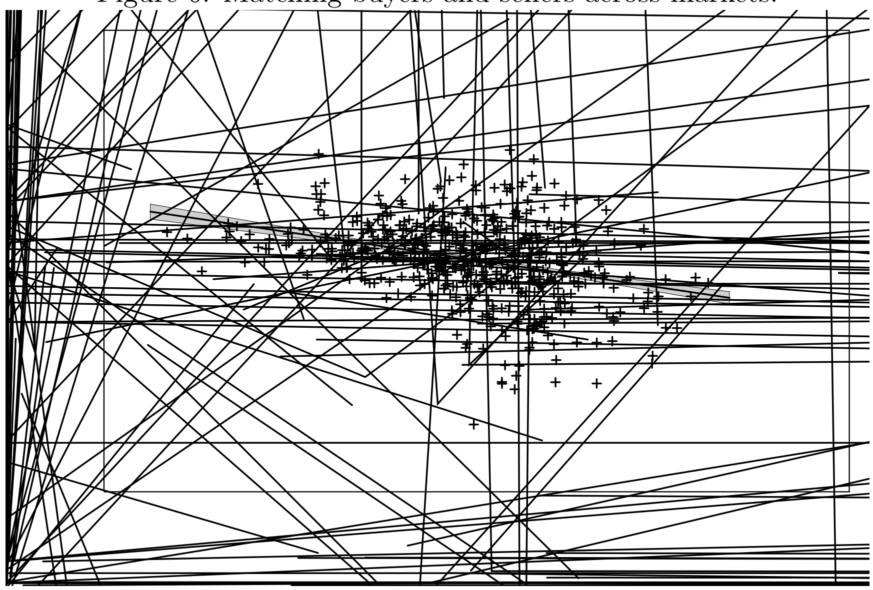
Note: 2006 data. The figure shows the density of Pareto shape coefficient, calculated based on buyer expenditure of Norwegian exports in different markets. The shape coefficients are computed by regressing the empirical inverse cdf on buyer expenditure, both in logs, for each country; the resulting slope coefficient is (the negative of) the Pareto slope coefficient. Only markets with more than 50 buyers are included.

Figure 5: Number of buyers & buyer dispersion per exporter.



Note: 2006 data. The figure shows the # buyers and log(max/min) ratio for a given firm-destination combination, and then averaged across all firm-destinations within a percentile range (0-10, 11-20, etc). The percentiles are referring to firm-destination level exports. The max/min ratio is the maximum relative to the minimum export value, for a given firm-destination.

Figure 6: Matching buyers and sellers across markets.



Note: 2006 data. The figure shows all possible values of the number of buyers per Norwegian firm in a given market, a_j, on the x-axis, and the average number of Norwegian connections among these buyers, $b_j(a_j)$, on the y-axis. Both variables are in logs and demeaned, i.e. we show $\ln b_j(a_j) - \ln \bar{b_j}(a_j)$, where $\bar{b_j}(a_j)$ is the average number of Norwegian connections among all buyers in market j. The fitted regression line and 95% confidence intervals are denoted by the solid line and gray area. The slope coefficient is -0.13 (s.e. 0.009).

across countries. Figure 4 shows the density of Pareto shape coefficients across countries, where the shape coefficients are calculated based on the buyer expenditure (of Norwegian exports) distribution in each country. The median shape parameter is 0.44, and the standard deviation is 0.06.[6]

Fact 4: Larger sellers reach more customers and have more dispersion in across-buyer exports. Figure 5 shows that the more a firm exports, the more buyers it reaches. The difference in exports to the smallest and the largest buyers is much greater for larger exporters.

Fact 5: There is negative assortative matching among sellers and buyers. We characterize sellers according to their number of buyers, and buyers according to the number of sellers they purchase from. We find that the larger a seller, the smaller its average buyer in terms of seller contacts. Figure 6 provides an overview of seller-buyer relationships. The figure shows all possible values of the number of buyers per Norwegian firm in a given market, a_j, on the x-axis, and the average number of Norwegian connections among these buyers, $b_j(a_j)$, on the y-axis. Both variables are in logs and demeaned.[7] A point with the coordinates, (0.2,-0.2), means that among the customers of exporters with 20% more customers than average, their average number of Norwegian connections is 20% smaller than average. The fitted regression line is -0.13, so a 10 percent increase

[6] Only markets with more than 50 buyers are included. This amounts to 102 export destinations.

[7] I.e. we show $\ln b_j(a_j) - \ln \bar{b_j}(a_j)$, where $\ln \bar{b_j}(a_j)$ is the average number of Norwegian connections among all buyers in j.

in number of customers is associated with a 1.3 percent decline in average connections among the customers.[8] Interestingly, social networks typically feature positive assortative matching, that is, highly connected notes tend to attach to other highly connected nodes, while negative correlations are usually found in technical networks such as servers on the Internet (Jackson and Rogers, 2007).[9]

5 The Model

5.1 Basic Setup

In this section, we develop a trade model with networks of heterogeneous sellers and buyers. As in Melitz (2003), firms ("sellers") within narrowly defined industries produce with different efficiencies.[10] Departing from Melitz (2003), consumers ("buyers") in a market have different incomes, leading to a sorting pattern between sellers and buyers in equilibrium. We let the model be guided by the descriptive evidence and stylized facts on sellers and buyers and their relationship as presented above. In particular, both firm productivity and buyer expenditure are Pareto distributed, which will give rise to high levels of concentration in trade, both on the supply and demand side, as well as Pareto distributed degree distributions (number of customers per firm and number of firms per customer), consistent with Facts 1 and 2. Due to the presence of a buyer-seller specific fixed cost, buyers are more likely to connect to larger exporters, as larger exporters are more efficient and/or produce higher quality goods, consistent with Fact 4. This in turn leads to negative sorting, so that well-connected exporters on average connect to customers that are less connected, consistent with Fact 5.

Firms produce goods using only labor. Country i has total hours worked L_i, and each buyer is endowed with l labor hours. Importantly, l is heterogeneous across buyers, which gives rise to heterogeneity in labor income $w_i l$, where w_i is the hourly wage rate.[11] We assume that labor endowment is drawn from a Pareto distribution with support $[1, \infty]$ and shape parameter γ_b, so that $G(l) = 1 - l^{-\gamma_b}$.[12] Workers are otherwise identical and the labor market is characterized by perfect competition, so that hourly wages w_n are identical across workers.

Buyers derive utility from consumption of a homogeneous good and a continuum of differentiated goods. Specifically, utility is

[8] Using the median number of connections instead of the average number of connections as the dependent variable also generates a significant and negative slope coefficient. In appendix E, we show that the elasticity is informative of a structural parameter of the model.

[9] In the friendship network among prison inmates considered by Jackson and Rogers (2007), the correlation between a node's in-degree and the average in-degree of its neighbors is 0.58. The correlation in our data is -0.31. Serrano and Boguna (2003) find evidence of negative sorting in the network of trading *countries*; i.e. highly connected countries, in terms of trading partners, tend to attach to less connected countries.

[10] Or, unit costs are homogeneous but quality is heterogeneous. The two interpretations of the model are isomorphic.

[11] In our data, we recognize that buyers are most likely other firms, with heterogeneity across firm expenditure. This distinction makes little difference in terms of the substantive predictions of the model.

[12] We assume that $\gamma_b > (\sigma - 1)/\gamma_s$, where γ_s is the shape parameter of the firm productivity distribution and σ is the elasticity of substitution. This ensures that firm revenue is finite.

$$U = q_0^{1-\mu} \left(\int_{\Omega_j} q(\omega)^{(\sigma-1)/\sigma} \, d\omega \right)^{\mu\sigma/(\sigma-1)},$$

where q_0 is consumption of the homogeneous good and $q(\omega)$ is purchases of the variety ω. μ is the constant Cobb Douglas expenditure share on the homogeneous good and $\sigma > 1$ is the elasticity of substitution.

As is common in the literature, we assume that the homogeneous good is freely traded, produced under constant returns to scale with one hour of labor producing w_i units of the homogeneous good. Normalizing the price to 1, the wage rate in country i is w_i.

Relationship specific investments. The act of meeting buyers and setting up supplier contracts is associated with transaction costs that are fixed, and thus not proportional to the value of the buyer-seller transaction. These costs are to be regarded as sunk, and thus as investments that will be lost if the transactional relationship were terminated. These costs may typically be related to the search for suppliers, bureaucratic procedures, contract agreements and need for sellers to customize their output to the requirements of particular buyers which would make it difficult to find alternative buyers.[13] Formally, we model this is a match specific fixed cost f_{ij}, which may vary according to seller country i and buyer country j.

Trade barriers. Firms also face a standard iceberg trade costs $\tau_{ij} \geq 1$, so that τ_{ij} must be shipped from country i in order for one unit to arrive in country j.[14]

Technology. Firms in the differentiated sector are heterogeneous in productivity z, which we model as a random draw from a distribution $G(z)$. As in Chaney (2008) and others, we assume that efficiency is drawn from a Pareto distribution with support $[1, \infty]$ and shape parameter $\gamma_s > \sigma - 1$, so that $F(z) = 1 - z^{-\gamma_s}$.[15] Technology is characterized by increasing returns-to-scale due the the presence of the fixed cost f_{ij}, which is incurred by the seller. The market structure is monopolistic competition, so that the price charged is a constant mark-up over marginal costs, $p_{ij} = \overline{m}\tau_{ij}w_i/z$, where $\overline{m} = \sigma/(\sigma - 1)$.

Sorting functions. In the presence of a fixed cost, a given seller will find it optimal to export to buyers with expenditure higher than a lower bound $\underline{E}_{ij}$. We introduce the equilibrium sorting function $\underline{E}_{ij}(z)$, which is the lowest possible expenditure level a firm with productivity z is willing to sell to. Formally, $\underline{E}_{ij}(z)$ is the solution to $\pi_{ij}(z, E) = 0$, where $\pi_{ij}(z, E)$ is the net profit produced from a (z, E) match; we find the explicit solution for $\underline{E}_{ij}(z)$ later in the paper. Symmetrically,

[13] Kang, Mahoney and Tan (2009) provide examples of such relationship-specific investments and analyze under what circumstances firms are more likely to make these types of investments. For example, a newly adopted just-in-time (JIT) business model by Dell required that its suppliers prepare at least three months buffering in stock. However, Dell did not offer any guarantee on purchasing volumes due to high uncertainty in final product markets.

[14] We normalize $\tau_{ii} = 1$ and impose the common triangular inequality, $\tau_{ik} \leq \tau_{ij}\tau_{jk} \; \forall \; i, j, k$.

[15] As is well known, the Pareto distribution is a good approximation of the U.S. firm size distribution (Luttmer (2007)Axtell (2001)) although the results here raise the question of whether this is due to underlying the productivity distribution or the expenditure distribution of buyers.

we define $\underline{z}_{ij}(E)$ as the lowest efficiency seller a buyer with expenditure E can buy from. By construction, $\underline{z}_{ij}(E)$ is the inverse of $\underline{E}_{ij}(z)$, i.e. $E = \underline{E}_{ij}\left(\underline{z}_{ij}(E)\right)$.

Demand. Given the utility function specified above, and conditional on a match (z, E), exports from country i to j are

$$r_{ij}(z,E) \quad = \quad \left(\frac{p_{ij}(z)}{P_j(E)}\right)^{1-\sigma} \mu E, \tag{1}$$

where $P_j(E)$ is the ideal price index facing a buyer with expenditure E in market j. Following Chaney (2010), expenditure E is the sum of labor income $w_i l$ and dividends from their portfolio $w_i l \pi$, where π is the dividend per share of the global mutual fund, i.e. the budget constraint is $E = \varpi_i l$, where $\varpi_i \equiv w_i(1+\pi)$.

The price index for a buyer in j with expenditure E is

$$P_j^{1-\sigma}(E) \quad = \quad \frac{\gamma_s}{\gamma_2} \sum_k N_{sk} \left(m \tau_{kj} w_k\right)^{1-\sigma} \underline{z}_{kj}(E)^{-\gamma_2}, \tag{2}$$

where N_{sk} is the measure of sellers in market k and $\gamma_2 \equiv \gamma_s - (\sigma - 1)$. Since there is no free entry, the measure of sellers is exogenous.

5.2 Equilibrium Sorting

The firm's net profits from a (z, E) match is $\pi_{ij}(z,E) = r_{ij}(z,E)/\sigma - f_{ij}$. Inserting the demand equation (1) and the optimal price, we can express $\underline{E}$ implicitly as

$$P_j(\underline{E})^{\sigma-1} \underline{E} = \frac{\sigma f_{ij}}{\mu} \left(m \tau_{ij} w_i\right)^{\sigma-1} z^{1-\sigma}. \tag{3}$$

As the price index is also a function of $\underline{z}_{ij}(E)$, it is not straightforward to calculate equilibrium sorting. In the appendix, we show that the solution is:

$$\underline{z}_{ij}(E) \quad = \quad f_{ij}^{1/(\sigma-1)} \tau_{ij} w_i \quad {}_j E^{-1/\gamma_s} \tag{4}$$

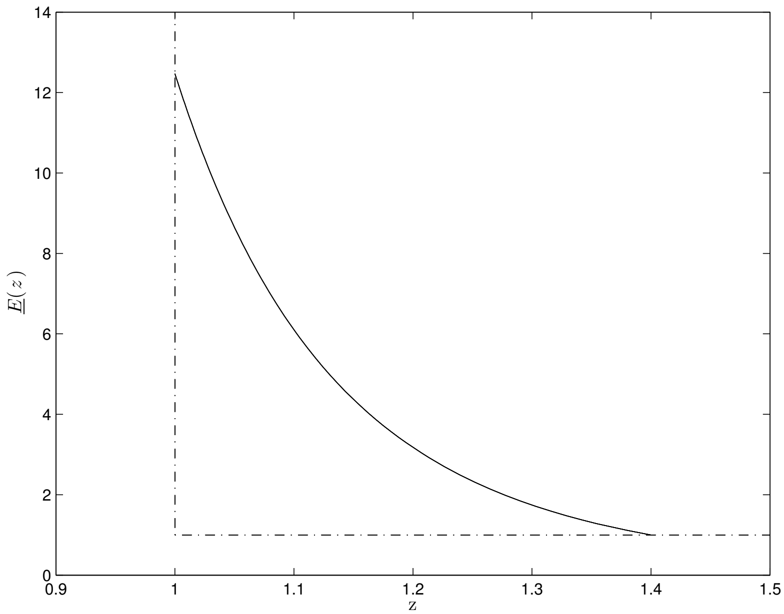
$$\underline{E}_{ij}(z) \quad = \quad f_{ij}^{\gamma_s/(\sigma-1)} \left(\tau_{ij} w_i \quad {}_j\right)^{\gamma_s} z^{-\gamma_s}, \tag{5}$$

where

$$_j = \left(\frac{\sigma}{\mu} \frac{\gamma_s}{\gamma_2} \sum_k N_{sk} \left(\tau_{kj} w_k\right)^{-\gamma_s} f_{kj}^{-\gamma_2/(\sigma-1)}\right)^{1/\gamma_s}. \tag{6}$$

We plot the matching function $\underline{E}_{ij}(z)$ in Figure 7. $\underline{E}_{ij}(z)$ is, not surprisingly, downward sloping in z, so that more efficient firms match with lower expenditure buyers, on the margin. A firm with efficiency z matches with lower expenditure buyers whenever variable or fixed trade costs (τ_{ij} and f_{ij}) are lower. Moreover, a firm also matches with lower expenditure buyers when trade costs from 3rd countries to j are higher (via $\ {}_j$). Hence, $\ {}_j$ has a similar interpretation as the multilateral resistance variable in Anderson and van Wincoop (2004).

Figure 7: Matching function.



The slope of the matching function is determined by the degree of seller heterogeneity, γ_s, so a one percent increase in expenditure E leads to a weaker percent decline in the hurdle $\underline{z}_{ij}(E)$ when heterogeneity is low, i.e. γ_s is high. This occurs as higher E enables buyers to meet more firms, and the number of new connections is increasing in γ_s (the heterogeneity effect).[16] More suppliers lead to a lower price index, and therefore the decline in the price index is also stronger when γ_s is high (the price index effect). This in turn means that $\underline{z}_{ij}(E)$ declines by less when γ_s is high, as the price index effect deters matches from taking place.[17]

Because the lower support of our productivity and expenditure distributions is 1 and ϖ_j respectively, no firm can ever reach buyers with expenditure lower than ϖ_j, and no buyer can ever match with firms with productivity less than 1. This is indicated by the dotted lines in Figure 7. An implication is that we have two types of buyers and sellers in our economy: (i) Sellers (buyers) that match with a subset of the buyers (sellers), and (ii) sellers (buyers) that match with every buyer (seller). Case (i) is characterized by $\underline{z}_{ij}(E) > 1$ and $\underline{E}_{ij}(z) > \varpi_j$, or, equivalently, $E < f_{ij}^{\gamma_s/(\sigma-1)}(\tau_{ij}w_i \;\, _j)^{\gamma_s} \equiv E_{ij}$ and $z < \varpi_j^{-1/\gamma_s} f_{ij}^{1/(\sigma-1)}\tau_{ij}w_i \;\, _j \equiv \overline{z}_{ij}$, while case (ii) is characterized by $E \geq E_{ij}$ and $z \geq \overline{z}_{ij}$. In words, very productive firms (with $z \geq z_{ij}$) will meet even the smallest buyers in the market, so that changes in trade costs will not affect the set of buyers they are matched to. In our dataset, no exporter is selling to every buyer, and no customer is buying from every exporter. We therefore choose to focus on the more interesting case of type (i) buyers

[16] The measure of suppliers for a buyer with expenditure E is $L_{ij}(E) = N_{si}\int_{\underline{z}_{ij}(E)} dF(z) = N_{si}\underline{z}_{ij}(E)^{-\gamma_s}$, so the absolute value of the elasticity of L with respect to $\underline{z}_{ij}$ is increasing in γ_s.

[17] The price index effect cancels out with the heterogeneity effect, so that in sum, the elasticity of the measure of suppliers per buyer with respect to expenditure E is invariant to γ_s, see appendix.

and sellers in the remaining part of this section.[18] In appendix Section D, we also argue that, for plausible parameter values, $\overline{z}_{ij}$ and $\overline{E}_{ij}$ are far in the right tail in the productivity and expenditure distributions, so that they have a negligible impact on firm-level and aggregate outcomes.

Firm-level trade. Firm-level exports from country i to j, for a firm with productivity z, is $R_{ij}(z) = N_{bj} \int_{\underline{E}_{ij}(z)} r_{ij}(z, E)\, d\tilde{G}_j(E)$, where N_{bj} is the measure of buyers in country j and $d\tilde{G}_j(E)$ is the distribution of expenditure in country j.[19] In the appendix, we show that exports for a type (i) firm ($z < z_{ij}$) are approximated by

$$R_{ij}(z) \quad = \quad \kappa_1 N_{bj} f_{ij}^{1-\gamma_b\gamma_s/(\sigma-1)} w_j^{\gamma_b} \left(\frac{z}{\tau_{ij} w_i \quad {}_j} \right)^{\gamma_s\gamma_b}, \tag{7}$$

where κ_1 is a constant.[20] We can derive the optimal number of buyers in a similar fashion, which yields[21]

$$B_{ij}(z) = \kappa_2 N_{bj} f_{ij}^{-\gamma_b\gamma_s/(\sigma-1)} w_j^{\gamma_b} \left(\frac{z}{\tau_{ij} w_i \quad {}_j} \right)^{\gamma_s\gamma_b}. \tag{8}$$

We emphasize two properties of these expressions. First, the elasticity of exports (and the number of buyers) with respect to variable trade barriers is $\gamma_s\gamma_b$, so that the degree of both buyer and seller heterogeneity matters for the elasticity. In a standard model with no buyer heterogeneity, this elasticity is only related to the elasticity of substitution $(\sigma - 1)$. Second, the elasticity of exports (and the number of buyers) with respect to income in the destination market, w_j, is γ_b, whereas in a model with no buyer heterogeneity the elasticity is 1. The intuition is that in markets with low heterogeneity (high γ_b), a positive shift in income gives many new buyers, as more buyers are initially below $\underline{E}_{ij}(z)$ threshold, leading to a large increase in exports (and the number of buyers). We summarize this in the following proposition.

Proposition 1. *The firm-level elasticity of exports with respect to variable trade costs is $\gamma_s\gamma_b$, and the firm-level elasticity of exports with respect to destination country income is γ_b.*

In Section 6, we empirically test this prediction of the model, by exploiting cross-country differences in the degree of firm size heterogeneity. Also note that higher match cost f_{ij} dampens both firm exports and the number of buyers, as expected.[22]

Finally, we can express the price index as a function of exogenous variables. Using equation (2) and the sorting function, given $E < E_{ij}$, yields

$$P_j(E)^{1-\sigma} \quad = \quad E^{\gamma_2/\gamma_s} m^{1-\sigma} \frac{\mu}{\sigma} \quad {}_j^{\sigma-1}. \tag{9}$$

[18] We derive expressions for type (ii) firms in the appendix.

[19] $\tilde{G}_j(E) = 1 - \tilde{w}_j^{\gamma_b} E^{-\gamma_b}$.

[20] $\kappa_1 = \frac{\gamma_b \sigma (1+\pi)^{\gamma_b}}{\gamma_2/\gamma_s + \gamma_b - 1}$. Alternatively, we can express exports as a function of the hurdle $\underline{E}$, which yields $R_{ij}(z) = \kappa_1 N_{bj} f_{ij} w_j^{\gamma_b} \underline{E}_{ij}(z)^{-\gamma_b}$. We show the details of both calculations in the appendix.

[21] $\kappa_2 = (1+\pi)^{\gamma_b}$.

[22] The elasticity of exports with respect to f_{ij} is $1 - \gamma_b\gamma_s/(\sigma - 1)$, which is negative given the restriction that $\gamma_b > (\sigma - 1)/\gamma_s$, see Section 5.1.

The price index is decreasing in expenditure with an elasticity of $\gamma_2 / [\gamma_s (\sigma - 1)] > 0$, reflecting that larger buyers get access to a wider range of goods.

The Export Distribution. In a model without buyer heterogeneity, the export distribution inherits the properties of the productivity distribution, and with Pareto distributed productivities, the shape coefficient for the export distribution is simply $\gamma_s / (\sigma - 1)$. In our model with buyer heterogeneity, dispersion in the export distribution is determined by the inverse of *buyer* heterogeneity exclusively. To see this, we calculate

$$\Pr[R_{ij}(z) < R_0] = 1 - \kappa_{3ij} R_0^{-1/\gamma_b},$$

where κ_{3ij} is a constant.[23] We summarize this in the following proposition.

Proposition 2. *The distribution of firm-level exports from country i to country j is Pareto with shape parameter $1/\gamma_b$. Hence, more heterogeneity among buyers in j leads to less heterogeneity in the export distribution among sellers in i.*

The intuition for this result is the following. If buyer expenditure is highly dispersed, then there are many large buyers in the market and most exporters will sell to them. This tends to dampen the dispersion in the number of buyers reached by different exporters. On the other hand, if buyer expenditure is less dispersed, then we have fewer large buyers in the market. higher dispersion in the number of buyers reached by different exporters.

The assumption of Pareto distributions on both the supply and demand side of the market helps us generate simple analytical results. With other distributional assumptions, dispersion in seller productivity would play a role in the export distribution. However, the main insight that buyer heterogeneity matters for the export distribution would most likely still survive under alternative distributional assumptions.

6 Empirical Implications

In this section, we test two main predictions of the model that emphasize the importance of buyer heterogeneity in explaining firm-level and aggregate trade patterns. The first prediction (Section 6.2) is that a demand shock facing firm m should increase firm-level exports, but the marginal export flow, i.e. the transaction to the smallest buyer, should remain unchanged as the marginal transaction is pinned down by the magnitude of buyer-seller fixed costs. The second prediction (Section 6.3) is that a similar-sized demand shock facing firm m in different destinations should translate into more sales in markets with less heterogeneity, as shown in Proposition 1. The empirical evidence is consistent with both predictions of the model.

[23] $\kappa_{3ij} = \frac{\tilde{w}_j (\kappa N_{bj})^{1/\gamma_b}}{(\tau_{ij} w_i \Omega_j)^{\gamma_s}} f_{ij}^{1/\gamma_b + \gamma_s/[\gamma_b(\sigma-1)]}$.

6.1 A Measure of Demand

We start by calculating a measure of firm-destination specific demand. The objective is to create a variable that proxies for income among buyers in the destination country (w_j in the model, see e.g. equation (7)). In addition, we would like the variable to be firm-specific, so that we can control for market-wide factors that may also impact sales by fixed effects that vary at the destination over time. We create the demand shock variable by exploiting the buyer-seller structure of the data. Specifically, we proxy the demand facing firm i in market j by the purchases of i's connections from other Norwegian suppliers. Formally, we take the weighted average of log buyer expenditure,

$$d_{mjt} = \sum_{b \in \Omega_{mj}} \omega_{mb} \ln y_{-m,bjt}$$

where $y_{-m,bjt}$ is the purchases of buyer b in market j from all Norwegian suppliers except firm m, ω_{mb} is the weight assigned to buyer b, and $\ _{mj}$ is the set of firm m's buyers in market j. We calculate the weights based on total exports from m to b over the sample period. The sample is restricted to buyers that are present in every period and that purchase from more than one seller, so that $y_{-m,bjt}$ is always positive. This reduces the sample size by roughly a half.[24] We investigate the robustness of our results to other specifications of demand in Section 6.3.1.

6.2 Demand Shocks and the Marginal Buyer

In the model, a demand shock in market j has no impact on sales to the marginal buyer. This occurs because the gross profits associated with the marginal buyer exactly equals the buyer-seller fixed cost.[25] We estimate

$$\ln y_{mjt} = \alpha_{mt} + \beta_{jt} + \eta \ln d_{mjt} + \epsilon_{mjt}, \tag{10}$$

where y_{mjt} is the log marginal export flow for firm m in market j at time t (i.e. $\min_b y_{mbjt}$, where b is buyer), and d_{mjt} is the demand shock facing firm m in market j. We include both firm-year (α_{mt}) and country-year (β_{jt}) fixed effects, allowing for changes in time-varying firm-specific factors such as productivity, and time-varying market-wide shocks, e.g. the real exchange rate. Identification then comes from comparing growth in exports within the same firm across markets, while controlling for country-specific trends. Our approach resembles a triple differences model as we compare growth in exports both across markets and across firms. Specifically, for two firms A and B and two markets 1 and 2, η is identified by the difference in firm A's exports growth to markets 1 and 2, relative to the difference in firm B's exports growth in markets 1 and 2.[26] In addition to using marginal exports as the dependent variable, we also estimate equation (10) using total firm-level exports ($\sum_b y_{mbjt}$), number of buyers, and maximum exports across buyers ($\max_b y_{mbjt}$) as dependent variables.

[24] The number of firm-years falls from 43,872 to 22,334, see Table 6.

[25] Inserting equation (5) into (14) yields $r_{ij} \ \ z, \underline{E}_{ij}(z) \ \ = \sigma f$.

[26] The fixed effects α_{mt} and β_{jt} are differenced out for $\Delta \ln y_{mjt} - \Delta \ln y_{mj-1,t} - (\Delta \ln y_{jt} - \Delta \ln y_{j-1,t})$.

The results confirm the predictions from the model. Table 6 shows that positive demand shocks have no impact on the marginal export flow (column 3), while both total exports, maximum exports, and the number of buyers per firm (columns 1, 2, and 4) are positively and significantly related to positive demand shocks in the destination country.[27] The model, however, would predict that the elasticity of exports to a demand shock is identical to the elasticity of the number of customers to a demand shock, see equations (7) and (8), while the results show that the exports elasticity is stronger than the customers elasticity. One possible reason for this discrepancy is that the empirical productivity and expenditure distributions may deviate from the assumed Pareto shape.[28]

6.3 Demand Shocks and Importer Heterogeneity

One of the main features of the theoretical framework is the role of buyer-side heterogeneity in determining the response of exports to demand shocks, i.e. that the demand shock elasticity is greater in markets with less buyer heterogeneity. We test this prediction by calculating various measures of buyer dispersion, and then checking whether the demand elasticities estimated in Section 6.2 are higher in markets with less heterogeneity. Specifically, we estimate

$$\ln y_{mjt} = \alpha_{mt} + \beta_{jt} + \eta_1 \ln d_{mjt} + \eta_2 \ln d_{mjt} \times \ _j + \epsilon_{mjt}, \tag{11}$$

where $\ _j$ is a measure of buyer dispersion in destination market j.

Ideally, we would want a measure of dispersion in expenditure, E, in different markets. A close proxy for this is a measure of dispersion in firm size. We gather data on the firm size distribution from World Bank's Enterprise Surveys, and calculate a Pareto slope coefficient ($\ ^1$), the 90/10 percentile ratio ($\ ^2$), and the standard deviation of log employment for each country ($\ ^3$).[29] The Enterprise Surveys are firm-level surveys of a representative sample of an economy's private sector (manufacturing and services). The survey aims to achieve cross-country comparisons, so that our dispersion measures should not be contaminated by differences in sampling design. Formal companies with 5 or more employees are included.[30]

The results are shown in Table 7. We find that the elasticity (for both export value and the number of buyers) is significantly dampened in markets with more heterogeneity, consistent with our model. Note that the coefficient is positive in columns 1 and 2 since the Pareto coefficient is the inverse of dispersion. The magnitudes are also economically significant: Moving from the

[27] In the min and max regressions, we only use firms with more than 5 customers. We also restrict the sample size to be identical to the sample size in the regressions in Section 6.3. Results based on the entire sample are not significantly different.

[28] Pareto implies that average exports per customer $R_{ij}(z)/B_{ij}(z) = \kappa f$, i.e. only a function of the buyer-seller fixed cost.

[29] We calculate the Pareto slope coefficient by regressing the empirical inverse CDF on firm employment, both in logs, for each destination market; the resulting slope coefficient is (the negative of) the Pareto slope coefficient.

[30] The survey covers 87 countries, mostly developing countries. We drop countries where the survey has less than 100 observations per country. These countries are: BR, ER, GY, JM, LB, LS, ME, OM, TR.

25th to the 75th percentile of the Pareto coefficient increases the demand elasticity by 21 percent, suggesting that demand-side factors are quantitatively important for our understanding of trade elasticities.[31]

6.3.1 Robustness

In this section, we perform a number of robustness checks. First, a concern is that the data for dispersion from the Enterprise Surveys are limited to a non-representative sample of countries. We therefore check the robustness of our results by using an alternative measure of dispersion from the World Bank's Exporter Dynamics database. This dataset has information about export dispersion for 39 countries.[32] We use the coefficient of variation (^{4}) and estimate the model again. Columns (1) and (2) in Table 8 show that the same pattern holds in this case.[33] A second concern is that buyer dispersion may be correlated with other factors that also affect the demand elasticity; for example both buyer dispersion and demand elasticities may be different in low-income countries. We address this issue by purging GDP per capita from our Pareto shape coefficient ^{1}. Specifically we regress ^{1} on GDP per capita and use the fitted residual instead of ^{1}. This is what is shown in columns (3) and (4); overall the results are very similar to the baseline case in Table 7. A third concern is that our baseline regression is based on a smaller sample due to the construction of the demand shock variable d_{mjt}; see Section 6.1. We therefore replace d_{mjt} with GDP_{jt} as our proxy for demand. In this case, we cannot include country-year fixed effects (only country fixed effects and a real exchange rate control variable). The results in columns (5) and (6) show the same pattern as in the baseline case, although the standard errors are somewhat higher. Also note that the number of observations increases, since we now utilize more information in the dataset.

In sum, we find confirmation of the main prediction of the model. Markets with more homogenous firm/buyer distributions have greater elasticities for both the log level of exports and the number of buyers than do markets with more heterogeneous firm distributions.

7 Conclusion

We use highly disaggregated trade transaction data from Norway to explore the role of buyers (importers) in aggregate and firm-level exports. We find that the extensive margin of the number of buyers plays an important role in cross-country exports at the aggregate level and within firms. This new extensive margin is comparable in magnitude to previously documented extensive trade margins, e.g. firms, destinations and products.

[31] The 25th and 75th percentiles are 0.58 and 0.79, so that the demand elasticities are 0.34 and 0.41 respectively.

[32] Unfortunately, only aggregate measures of dispersion are available and the Pareto shape coefficient is not one of them.

[33] The magnitudes are not directly comparable due to the different measures of dispersion.

We introduce a series of stylized facts about buyers in international trade including extreme concentration of exports across both sellers and buyers, heterogeneity of the dispersion in cross-buyer expenditures across destinations, and the Pareto nature of the distributions of buyers per exporter and sellers per importer. We find that large exporters reach more customers and have more dispersion in exports across buyers within a destination and there is negative assortativity in the exporter-import matches, large exporters on average reach importers who buy from a smaller number of foreign firms.

We extend a basic model of heterogeneous exporters to include heterogeneity in expenditures across buyers within a destination. Exporter must pay a fixed cost to match with any given buyer. In our stylized model with the strong assumption of both Pareto-distributed productivity across exporters and Pareto-distributed expenditures across buyers, variation in buyer dispersion determines the dispersion of firm-level exports. This framework matches the stylized facts and yields interesting new testable implications that are confirmed in the Norwegian data. An increase in foreign demand increases firm-level exports but the marginal export flow does not change as it is pinned down by the magnitude of the buyer-seller fixed costs. In addition, the heterogeneity of buyer expenditures matters for the response to demand and trade cost shocks. We find that the response of firm-level exports to comparable demand shocks across destinations varies systematically with the dispersion of expenditures. Exports respond more to destinations with low dispersion across buyer firms.

These results suggest that demand-side characteristics may play an important role in determining the aggregate export response to shocks. Future research might fruitfully focus on the growth and stability of these exporter-importer networks as well as the sources of heterogeneity in buyer expenditure itself.

References

Amiti, M., and J. Konings (2007): "Trade Liberalization, Intermediate Inputs and Productivity: Evidence from Indonesia," *American Economic Review*, 97(5), 1611–1638. 1

Anderson, J. E., and E. van Wincoop (2004): "Trade Costs," *Journal of Economic Literature*, 42(3), 691–751. 5.2

Antràs, P., and A. Costinot (2011): "Intermediated Trade," *The Quarterly Journal of Economics*, 126(3), 1319–1374. 1

Arkolakis, K. (2009): "A Unified Theory of Firm Selection and Growth," Working paper, Yale University, Department of Economics. 1

——— (2010): "Market Access Costs and the New Consumers Margin in International Trade," *Journal of Political Economy*, 118(6), 1151–1199. 1

Axtell, R. L. (2001): "Zipf Distribution of US Firm Sizes," *Science*, 293, 1818–1820. 15

Bernard, A. B., J. B. Jensen, and P. K. Schott (2009): "Importers, Exporters, and Multinationals: A Portrait of Firms in the U.S. that Trade Goods," in *Producer dynamics: New Evidence from Micro Data*, ed. by T. Dunne, J. Jensen, and M. Roberts. University of Chicago Press. 1, 1

Blum, B., S. Claro, and Horstmann (2011): "Intermediation and the nature of trade costs: theory and evidence," Unpublished, Rotman School of Management. 2, 1

Castellani, D., F. Serti, and C. Tomasi (2010): "Firms in international trade: Importers' and exporters' heterogeneity in Italian manufacturing industry," *The World Economy*, 33(3), 424–457. 1

Chaney, T. (2008): "Distorted gravity: the Intensive and Extensive Margins of International Trade," *American Economic Review*, 98(4), 1707–1721. 5.1

——— (forthcoming): "The Network Structure of International Trade," *American Economic Review*. 1

Eaton, J., M. Eslava, D. Jinkins, C. J. Krizan, and J. Tybout (2012): "A Search and Learning Model of Export Dynamics," working paper. 2, 1

Halpern, L., M. Koren, and A. Szeidl (2011): "Imported Inputs and Productivity," Cefig working paper, Central European University. 1

Jackson, M. O., and B. W. Rogers (2007): "Meeting Strangers and Friends of Friends: How Random Are Social Networks?," *American Economic Review*, 97(3), 890–915. 4, 9

Luttmer, E. G. J. (2007): "Selection, growth and the size distribution of firms," *The Quarterly Journal of Economics*, 122(3), 1103–1144. 15

Melitz, M. J. (2003): "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71(6), 1695–1725. 5.1

Muuls, M., and M. Pisu (2009): "Imports and Exports at the Level of the Firm: Evidence from Belgium," *The World Economy*, 32(5), 692–734. 1

Petropoulou, D. (2011): "Information costs, networks and intermediation in international trade," Globalization and Monetary Policy Institute Working Paper 76, Federal Reserve Bank of Dallas. 1

Rauch, J. E. (1999): "Networks versus markets in international trade," *Journal of International Economics*, 48(1), 7–35. 1

Rauch, J. E., and J. Watson (2004): "Network Intermediaries in International Trade," *Journal of Economics & Management Strategy*, 13(1), 69–93. 1

Serrano, M. A., and M. Boguna (2003): "Topology of the World Trade Web," *The Accounting Review*, 68(1). 9

Appendix

A Equilibrium Sorting

Proof. Equation (3) implicitly defines the $\underline{z}_{ij}(E)$ function. We start with the guess $\underline{z}_{ij}(E) = S_{ij}E^{s}$ and the inverse $\underline{E}_{ij}(z) = (z/S_{ij})^{1/s}$, where S_{ij} and s are unknowns. Insert this, as well as the price index (equation (2)), into equation (3) ,

$$\begin{aligned}\frac{\gamma_2/\gamma_s}{\sum_k N_{sk}(m\tau_{kj}w_k)^{1-\sigma}(S_{kj}\underline{E}^{s})^{-\gamma_2}} &= \frac{\sigma f_{ij}}{\mu\underline{E}}z^{1-\sigma}(m\tau_{ij}w_i)^{\sigma-1}\\ \frac{\underline{E}^{s\gamma_2+1}}{\sum_k N_{sk}(m\tau_{kj}w_k)^{1-\sigma}S_{kj}^{-\gamma_2}} &= \frac{\sigma f_{ij}}{\mu}\frac{\gamma_s}{\gamma_2}(m\tau_{ij}w_i)^{\sigma-1}z^{1-\sigma}.\end{aligned}$$

Hence,

$$\frac{1}{s} = \frac{1}{s}\frac{1-\sigma}{s(\gamma_2+1/s)} \quad\Longleftrightarrow\quad \frac{1}{s} = -\gamma_s,$$

and

$$\begin{aligned}\left(\frac{1}{S_{ij}}\right)^{1/s} &= \left[\frac{\sigma f_{ij}}{\mu}\frac{\gamma_s}{\gamma_2}(m\tau_{ij}w_i)^{\sigma-1}\sum_k N_{sk}(m\tau_{kj}w_k)^{1-\sigma}S_{kj}^{-\gamma_2}\right]^{1/(s\gamma_2+1)}\\ \left(\frac{1}{S_{ij}}\right)^{-\gamma_s} &= \left[\frac{\sigma f_{ij}}{\mu}\frac{\gamma_s}{\gamma_2}(m\tau_{ij}w_i)^{\sigma-1}\sum_k N_{sk}(m\tau_{kj}w_k)^{1-\sigma}S_{kj}^{-\gamma_2}\right]^{1/(-\gamma_2/\gamma_s+1)}\\ S_{ij} &= \left[\frac{\sigma f_{ij}}{\mu}\frac{\gamma_s}{\gamma_2}(\tau_{ij}w_i)^{\sigma-1}\sum_k N_{sk}(\tau_{kj}w_k)^{1-\sigma}S_{kj}^{-\gamma_2}\right]^{1/(\sigma-1)}. \qquad (12)\end{aligned}$$

In sum, the cutoffs are

$$\begin{aligned}\underline{z}_{ij}(E) &= S_{ij}E^{-1/\gamma_s} \qquad (13)\\ \underline{E}_{ij}(z) &= S_{ij}^{\gamma_s}z^{-\gamma_s}\end{aligned}$$

□

B Solving S_{ij} and P_j

Proof. Given $E < E_{ij}$, inserting the expression for the cutoff (equation (13)) into the price index in equation (2) yields

$$P_j(E)^{1-\sigma} = E^{\gamma_2/\gamma_s}m^{1-\sigma}\frac{\gamma_s}{\gamma_2}\sum_k N_{sk}(\tau_{kj}w_k)^{1-\sigma}S_{kj}^{-\gamma_2}.$$

Inserting the expression for S_{kj} from equation (12) then yields

$$P_j(E)^{1-\sigma} = E^{\gamma_2/\gamma_s}m^{1-\sigma}\frac{\mu}{\sigma f_{ij}}\left(\frac{S_{ij}}{\tau_{ij}w_i}\right)^{\sigma-1}.$$

This must hold for all i, so

$$f_{ij}^{-1/(\sigma-1)} \frac{S_{ij}}{\tau_{ij} w_i} = f_{kj}^{-1/(\sigma-1)} \frac{S_{kj}}{\tau_{kj} w_k}.$$

By exploiting this fact, we can transform the expression for S_{ij},

$$S_{ij}^{\sigma-1} = \frac{\sigma f_{ij}}{\mu} \frac{\gamma_s}{\gamma_2} \left(\tau_{ij} w_i\right)^{\sigma-1} \sum_k N_{sk} \left(\tau_{kj} w_k\right)^{1-\sigma} S_{kj}^{-\gamma_2}.$$

$$\begin{aligned}
S_{ij}^{\sigma-1} &= \left(\tau_{ij} w_i\right)^{\sigma-1} \frac{\sigma f_{ij}}{\mu} \frac{\gamma_s}{\gamma_2} \sum_k N_{sk} \left(\tau_{kj} w_k\right)^{1-\sigma} \left(\tau_{kj} w_k\right)^{-\gamma_2} f_{kj}^{-\gamma_2/(\sigma-1)} \left(f_{kj}^{-1/(\sigma-1)} \frac{S_{kj}}{\tau_{kj} w_k} \right)^{-\gamma_2} \\
&= \left(\tau_{ij} w_i\right)^{\sigma-1} \frac{\sigma f_{ij}}{\mu} \frac{\gamma_s}{\gamma_2} \left(f_{ij}^{-1/(\sigma-1)} \frac{S_{ij}}{\tau_{ij} w_i} \right)^{-\gamma_2} \sum_k N_{sk} \left(\tau_{kj} w_k\right)^{-\gamma_s} f_{kj}^{-\gamma_2/(\sigma-1)} \quad \Longleftrightarrow \\
S_{ij}^{\gamma_s} &= \left(\tau_{ij} w_i\right)^{\gamma_s} \frac{\sigma}{\mu} f_{ij}^{\gamma_s/(\sigma-1)} \frac{\gamma_s}{\gamma_2} \sum_k N_{sk} \left(\tau_{kj} w_k\right)^{-\gamma_s} f_{kj}^{-\gamma_2/(\sigma-1)} \quad \Longleftrightarrow \\
S_{ij} &= \tau_{ij} w_i f_{ij}^{1/(\sigma-1)} \left(\frac{\sigma}{\mu} \frac{\gamma_s}{\gamma_2} \sum_k N_{sk} \left(\tau_{kj} w_k\right)^{-\gamma_s} f_{kj}^{-\gamma_2/(\sigma-1)} \right)^{1/\gamma_s}.
\end{aligned}$$

We define

$$_j \equiv \left(\frac{\sigma}{\mu} \frac{\gamma_s}{\gamma_2} \sum_k N_{sk} \left(\tau_{kj} w_k\right)^{-\gamma_s} f_{kj}^{-\gamma_2/(\sigma-1)} \right)^{1/\gamma_s},$$

which yields the closed form solutions for the sorting functions, $\underline{z}_{ij}(E) = f_{ij}^{1/(\sigma-1)} \tau_{ij} w_i \,{}_j E^{-1/\gamma_s}$ and $\underline{E}_{ij}(z) = f_{ij}^{\gamma_s/(\sigma-1)} \left(\tau_{ij} w_i \,{}_j\right)^{\gamma_s} z^{-\gamma_s}$. □

Note that we can now write the price index as

$$P_j(E)^{1-\sigma} = E^{\gamma_2/\gamma_s} m^{1-\sigma} \frac{\mu}{\sigma} \,{}_j^{\sigma-1}.$$

C Firm-level Trade

Using equations (1) and (2), as well as the sorting function $\underline{E}_{ij}(z)$, and given $z < \bar{z}_{ij}$ and $E < E_{ij}$, firm-level exports are

$$\begin{aligned}
R_{ij}(z) &= N_{bj} \int_{\underline{E}_{ij}(z)}^{\bar{E}_{ij}} r_{ij}(z, E)\, dG_j(E) \\
&= N_{bj} \int_{\underline{E}_{ij}(z)}^{\bar{E}_{ij}} \left(P_j(E) \right.
\end{aligned}$$

As argued in appendix Section D, E_{ij} will take a high value, so that $E_{ij}^{-\gamma_2/\gamma_s-\gamma_b+1} \approx 0$. Exports are then

$$
\begin{aligned}
R_{ij}(z) &\approx N_{bj}\left(\tau_{ij}w_i \ \ {}_j/z\right)^{1-\sigma}\sigma\varpi_j^{\gamma_b}\frac{\gamma_b\left(f_{ij}^{\gamma_s/(\sigma-1)}\left(\tau_{ij}w_i \ \ {}_j/z\right)^{\gamma_s}\right)^{-\gamma_2/\gamma_s-\gamma_b+1}}{\gamma_2/\gamma_s+\gamma_b-1}\\
&= \kappa_1 N_{bj} f_{ij}^{1-\gamma_b\gamma_s/(\sigma-1)} w_j^{\gamma_b}\left(\frac{z}{\tau_{ij}w_i \ \ {}_j}\right)^{\gamma_s\gamma_b},
\end{aligned}
$$

where $\kappa = \frac{\gamma_b\sigma(1+\pi)^{\gamma_b}}{\gamma_2/\gamma_s+\gamma_b-1}$. Note that, given our assumption that $\gamma_b > (\sigma-1)/\gamma_s$, $\partial \ln R_{ij}/\partial \ln f_{ij} < 0$, so higher buyer-seller fixed costs lower firm sales.

We can alternatively express revenue as a function of the hurdle $\underline{E}_{ij}(z)$, which yields

$$
R_{ij}(z) = \kappa_1 N_{bj} f_{ij} w_j^{\gamma_b}\underline{E}_{ij}(z)^{-\gamma_b}.
$$

We can also express revenue for a given buyer seller match as

$$
r_{ij}(z,E) = \sigma\left(\frac{z}{\tau_{ij}w_i \ \ {}_j}\right)^{\sigma-1}E^{1-\gamma_2/\gamma_s}. \tag{14}
$$

The distribution of within-firm sales is, using equation (14), is

$$
\begin{aligned}
H(r_0) &= \Pr\left[r_{ij}(z,E) < r_0 \mid E > \underline{E}_{ij}(z),\ z\right]\\
&= \Pr\left[\sigma\left(\frac{z}{\tau_{ij}w_i \ \ {}_j}\right)^{\sigma-1}E^{1-\gamma_2/\gamma_s} < r_0 \mid E > \underline{E}_{ij}(z),\ z\right]\\
&= \Pr\left[E < \left(\frac{z}{\tau_{ij}w_i \ \ {}_j}\right)^{-\gamma_s}\left(\frac{r_0}{\sigma}\right)^{\gamma_s/(\sigma-1)} \mid E > \underline{E}_{ij}(z),\ z\right]\\
&= 1-\underline{E}_{ij}(z)^{\gamma_b}\left(\frac{z}{\tau_{ij}w_i \ \ {}_j}\right)^{\gamma_b\gamma_s}\left(\frac{r_0}{\sigma}\right)^{-\gamma_b\gamma_s/(\sigma-1)}\\
&= 1-(\sigma f_{ij})^{\gamma_b\gamma_s/(\sigma-1)} r_0^{-\gamma_b\gamma_s/(\sigma-1)}.
\end{aligned}
$$

The firm-level measure of buyers for a firm with productivity z is

$$
\begin{aligned}
B_{ij}(z) &= N_{bj}\int_{\underline{E}_{ij}(z)} dG_j(E)\\
&= N_{bj}\varpi_j^{\gamma_b}\underline{E}_{ij}(z)^{-\gamma_b}\\
&= \kappa_2 N_{bj} w_j^{\gamma_b} f_{ij}^{-\gamma_s\gamma_b/(\sigma-1)}\left(\frac{z}{\tau_{ij}w_i \ \ {}_j}\right)^{\gamma_s\gamma_b},
\end{aligned} \tag{15}
$$

where $\kappa_2 = (1+\pi)^{\gamma_b}$.

The firm-level measure of sellers for a buyer with expenditure E is

$$
L_{ij}(E) = N_{si}\int_{\underline{z}_{ij}(E)} dF(z) = N_{si} f_{ij}^{-\gamma_s/(\sigma-1)}\left(\tau_{ij}w_i \ \ {}_j\right)^{-\gamma_s} E, \tag{16}
$$

so buyer expenditure and the number of sellers are proportional.

Finally, equilibrium firm-level profits are

$$
\begin{aligned}
{}_{ij}(z) &= \frac{R_{ij}(z)}{\sigma} - f_{ij} B_{ij}(z) \\
&= \frac{\kappa}{\sigma} N_{bj} f_{ij}^{1-\gamma_b\gamma_s/(\sigma-1)} \varpi_j^{\gamma_b} \left(\frac{z}{\tau_{ij} w_i \quad j}\right)^{\gamma_s\gamma_b} - f_{ij} N_{bj} \varpi_j^{\gamma_b} f_{ij}^{-\gamma_s\gamma_b/(\sigma-1)} \left(\frac{z}{\tau_{ij} w_i \quad j}\right)^{\gamma_s\gamma_b} \\
&= \left(\frac{\kappa}{\sigma} - 1\right) N_{bj} f_{ij}^{1-\gamma_b\gamma_s/(\sigma-1)} \varpi_j^{\gamma_b} \left(\frac{z}{\tau_{ij} w_i \quad j}\right)^{\gamma_s\gamma_b}.
\end{aligned}
$$

For $z \geq \bar{z}_{ij}$ firms, the buyer threshold is ϖ_j, $\underline{E}_{ij} = \varpi_j$, so that firm-level exports are

$$
R_{ij}(z) = \kappa_1 N_{bj} w_j^{-\gamma_2/\gamma_s+1} \left(\frac{z}{\tau_{ij} w_i \quad j}\right)^{\sigma-1},
$$

and the number of buyers is simply $B_{ij}(z) = N_{bj}$.

D Approximations

In this section, we show that for plausible parameter values, we can safely ignore the impact of type (ii) buyer and sellers. Given autarky, the expressions for z and E are

$$
\begin{aligned}
z &= \left(\frac{\sigma}{\mu}\frac{\gamma_s}{\gamma_2}\frac{f}{\varpi} N_s\right)^{1/\gamma_s} \\
E &= \frac{\sigma}{\mu}\frac{\gamma_s}{\gamma_2} f N_s.
\end{aligned}
$$

We normalize hourly wages to 1, $\varpi = 1$, set match-specific costs f to 100 hours of work, use $\sigma = 4$ from Broda and Weinstein (2006)[34], set γ_s to 4.12 from Simonovska and Waugh (2012)[35], and $\mu = 0.52$ from Norwegian national accounts.[36] We do not observe the measure of firms, N_s, directly, but we can get a lower bound by looking at the number of exporters in the most popular destination, Sweden, which gives us $N_s = 8379$.[37] In sum, this yields $z = 0.6 \times 10^2$ and $E = 2.4 \times 10^7$, both in the far right tail of productivity and expenditure distributions. Introducing more countries and positive trade costs, $\tau_{ij} > 1$, would increase the thresholds further.

With these parameter values, we can evaluate the error in the expression for firm-level exports $R_{ij}(z)$ in Section C. Given a value of $\gamma_b = \gamma_s = 4.12$, we get $E_{ij}^{-\gamma_2/\gamma_s-\gamma_b+1} = 3.9 \times 10^{-29}$.

[34] The 1990-2001 mean at the SITC-3 level.

[35] They estimate the aggregate trade elasticity to 4.12, which is equivalent to γ_s in a broad range of models. This gives us $\gamma_2 = \gamma_s - (\sigma - 1) = 1.12$.

[36] Table 26, the share of goods in total consumption, 2005, http://www.ssb.no/english/subjects/09/01/nr_en/tabe-26.html.

[37] Total sales in a market is $N_s \int_{\underline{z}} R(z)\, dF(z)$, where $R(z)$ is sales for a firm with productivity z and $\underline{z}$ is the entry hurdle. Assuming that the entry hurdle in Sweden is close to the lower support of the distribution, N_s is simply total sales divided by average sales.

E Sorting in Model and Data

Figure 6 shows the empirical relationship between a firm's number of customers and average number of connections among its customers, i.e. the correlation between the degree of a node and the average degree of its' neighbors. In this section, we derive the corresponding relationship in the model.

Using equations (16) and (5), the number of connections for the marginal customer of a firm with productivity z is $L_{ij}\left(\underline{E}_{ij}(z)\right) = N_{si} z^{-\gamma_s}$. Using equation (15), we can rewrite this as

$$\underline{L}_{ij} = N_{si} \frac{\varpi_j N_{bj}^{1/\gamma_b} f_{ij}^{\gamma_s/(\sigma-1)}}{(\tau_{ij} w_i \quad {}_j)^{\gamma_s}} B_{ij}{}^{-1/\gamma_b},$$

which relates a firm's number of of customers B_{ij} to the number of connections for the firm's marginal customer $\underline{L}_{ij}$.

In the data, we explore the average number of connections among all the firm's customers, not just the marginal one. The average number of connections among the customers of a firm with productivity z is

$$\begin{aligned}
\hat{L}_{ij}(z) &= \frac{1}{1 - G_j\left(\underline{E}_{ij}(z)\right)} \int_{\underline{E}_{ij}(z)} L_{ij}(E)\, dG_j(E) \\
&= \frac{1}{\varpi_j^{\gamma_b} \underline{E}_{ij}(z)^{-\gamma_b}} N_{si} f_{ij}^{-\gamma_s/(\sigma-1)} (\tau_{ij} w_i \quad {}_j)^{-\gamma_s} \varpi_j^{\gamma_b} \gamma_b \int_{\underline{E}_{ij}(z)} E^{-\gamma_b} dE \\
&= N_{si} f_{ij}^{-\gamma_s/(\sigma-1)} (\tau_{ij} w_i \quad {}_j)^{-\gamma_s} \frac{\gamma_b}{\gamma_b - 1} \underline{E}_{ij}(z) \\
&= \frac{\gamma_b}{\gamma_b - 1} N_{si} z^{-\gamma_s}.
\end{aligned}$$

The average number of connections among the customers of a firm with B_{ij} customers is then

$$\hat{L}_{ij}(B_{ij}) = \frac{\gamma_b}{\gamma_b - 1} \frac{N_{si} N_{bj}^{1/\gamma_b} f_{ij}^{\gamma_s/(\sigma-1)} \varpi_j}{(\tau_{ij} w_i \quad {}_j)^{\gamma_s}} B_{ij}{}^{-1/\gamma_b}.$$

Hence, the elasticity of $\hat{L}_{ij}$ with respect to B_{ij} is simply $-1/\gamma_b$.

Table 1: Descriptive statistics.

	CN	DE	SE	US	OECD	non-OECD
Number of exporters	725	4,067	8,614	2,088	1,588.2	98.2
Number of buyers	1,489	9,627	16,822	5,992	3,055.6	144.5
Buyers/exporter, mean	3.6	3.6	3.6	4.5	2.7	1.6
Buyers/exporter, median	1	1	1	1	1	1
Exporters/buyer, mean	1.7	1.5	1.9	1.6	1.5	1.2
Exporters/buyer, median	1	1	1	1	1	1
Share trade, top 10% sellers	.86	.97	.94	.96	.90	.75
Share trade, top 10% buyers	.89	.95	.95	.97	.89	.73
Log max/median exports	7.9	11.4	10.7	11.2	8.7	4.6
Log max/median imports	8.4	10.8	10.8	11.7	8.4	4.6

Note: 2006 data. Country codes are CN: China, DE: Germany, JP: Japan, SE: Sweden, US: U.S.A. OECD and non-OECD are the unweighted means of outcomes for all countries in the two groups. Log max/median exports (imports) is the log ratio of the largest exporter (importer), in terms of trade value, relative to the median exporter (importer).

Table 2: The margins of aggregate trade.

VARIABLES	(1) Sellers	(2) Products	(3) Buyers	(4) Density	(5) Intensive
Exports (log)	0.57^{a}	0.53^{a}	0.61^{a}	-1.05^{a}	0.32^{a}
	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)
N	205	205	205	205	205
R^2	0.86	0.85	0.81	0.81	0.50

Note: 2006 data. Robust standard errors in parentheses. ^{a} $p< 0.01$, ^{b} $p< 0.05$, ^{c} $p< 0.1$.

Table 3: Gravity equation coefficients, aggregated level.

VARIABLES	(1) Exports	(2) # sellers	(3) # buyers	(4) Avg. buyers/seller	(3) Avg. exports/buyer
Distance	-1.15[a]	-0.83[a]	-0.81[a]	-0.05[b]	-0.13[a]
GDP	1.06[a]	0.64[a]	0.71[a]	0.11[a]	0.28[a]
N	167	167	167	167	167
R^2	0.75	0.75	0.75	0.44	0.26

Note: 2006 data. Robust standard errors in parentheses. [a] $p< 0.01$, [b] $p< 0.05$, [c] $p< 0.1$. All variables in logs. The dep. variable in column (4) is the number of buyers per firm, averaged across all exporters. The dep. variable in column (5) is firm-level average exports per buyer (x_{mj}/b_{mj}), averaged across all exporters.

Table 4: The margins of firm level trade.

VARIABLES	(1) Products	(2) Buyers	(3) Density	(4) Intensive
Exports (log)	0.22^a	0.22^a	-0.12^a	0.69^a
	(0.003)	(0.003)	(0.002)	(0.003)
Firm & country FE	Yes	Yes	Yes	Yes
N	61,853	61,853	61,853	61,853
R^2	0.48	0.49	0.40	0.81

Note: 2006 data. Robust standard errors in parentheses, clustered by firm. ^{a} $p< 0.01$, ^{b} $p< 0.05$, ^{c} $p< 0.1$.

Table 5: Gravity equation coefficients, firm level.

VARIABLES	(1) Exports	(2) # buyers	(3) Exports/buyer
Distance	-0.48^a	-0.31^a	-0.17^a
GDP	0.23^a	0.13^a	0.10^a
Firm FE	Yes	Yes	Yes
N	53,269	53,269	53,269
R^2	0.06	0.15	0.01

Note: 2006 data. Robust standard errors in parentheses, clustered by firm. ^{a} p< 0.01, ^{b} p< 0.05, ^{c} p< 0.1. All variables in logs.

Table 6: Firm responses to demand shocks.

	(1) Revenue	(2) # buyers	(3) min	(4) max
d_{mjt}	.34[a]	.08[a]	-.01	.31[a]
	(.01)	(.00)	(.01)	(.01)
Country-year FE	Y	Y	Y	Y
Firm-year FE	Y	Y	Y	Y
N	44,185	44,185	7,194	7,194
Firms-years	22,334	22,334	3,811	3,811
Destinations	42	42	37	37

Note: Robust standard errors in parentheses, clustered by firm-year. [a] $p< 0.01$, [b] $p< 0.05$, [c] $p< 0.1$. All variables in logs. The dep. variables in columns (3) and (4) are the minimum (maximum) export value for a firm, across its buyers; $\min_j y_{ijnt}$ and $\max_j y_{ijnt}$. Only exporters with > 5 buyers in columns (3) and (4).

Table 7: Demand shocks and heterogeneity.

	Revenue	# buyers	Revenue	# buyers	Revenue	# buyers
d_{mjt}	.14^a	.03^c	.62^a	.17^a	.63^a	.15^a
	(.04)	(.02)	(.06)	(.02)	(.06)	(.03)
$d_{int} \times \ ^1$ (Pareto)	.34^a	.09^a				
	(.07)	(.02)				
$d_{int} \times \ ^2$ (P90/10)			-.07^a	-.02^a		
			(.01)	(.01)		
$d_{int} \times \ ^3$ (Stddev)					-.18^a	-.04^b
					(.04)	(.02)
Country-year FE	Y	Y	Y	Y	Y	Y
Firm-year FE	Y	Y	Y	Y	Y	Y
N	44,185	44,185	44,185	44,185	44,185	44,185
Firms-years	22,334	22,334	22,334	22,334	22,334	22,334
Destinations	42	42	42	42	42	42

Note: Robust standard errors in parentheses, clustered by firm-year. ^{a} p< 0.01, ^{b} p< 0.05, ^{c} p< 0.1. All variables in logs. Ξ^1, Ξ^2 and Ξ^3 denote the interaction between the demand shock d_{int} and the Pareto shape parameter, the log firm size 90/10 percentile ratio, and the standard deviation of log employment, respectively.

Table 8: Robustness : Demand shocks and heterogeneity.

	(1) Revenue	(2) # buyers	(3) Revenue	(4) # buyers	(5) Revenue	(6) # buyers
d_{mjt}	$.50^a$	$.15^a$	0.39^a	$.09^a$	0.06	-0.07
	(.03)	(.01)	(.01)	(.00)	(.26)	(.08)
$d_{int} \times {}^{1}$ (Pareto)					$.50^c$	$.17^c$
					(.29)	(.09)
$d_{int} \times {}^{4}$ (CV)	$-.01^a$	$-.01^a$				
	(.00)	(.00)				
$d_{int} \times {}^{5}$ (Alt pareto)			$.41^a$	$.10^a$		
			(.07)	(.03)		
Country FE	N	N	N	N	Y	Y
Country-year FE	Y	Y	Y	Y	N	N
Firm-year FE	Y	Y	Y	Y	Y	Y
N	48,235	48,235	43,340	43,340	102,856	102,856
Firms-years	38,055	38,055	22,201	22,201	43,732	43,732
Destinations	20	20	42	42	75	75

Note: Robust standard errors in parentheses, clustered by firm-year. ^{a} p< 0.01, ^{b} p< 0.05, ^{c} p< 0.1. All variables in logs. Ξ^4 denotes the coefficient of variation from the World Bank's Exporter Dynamics Database, while Ξ^5 is the Pareto shape coefficient purged of correlation with GDP/capita. Columns (1) and (2) use Ξ^4; columns (3) and (4) use Ξ^5; columns (5) and (6) use GDP as a proxy for d_{int}.