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TWO-SIDED HETEROGENEITY AND TRADE

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ABSTRACT

Two-sided Heterogeneity and Trade*

Empirical studies of firms within industries consistently report substantial heterogeneity in measures of performance such as size and productivity. This paper explores the consequences of joint heterogeneity on the supply side (sellers) and the demand side (buyers) in international trade using a novel transaction-level dataset from Norway. Domestic exporters as well as foreign importers are explicitly identified in each transaction to every destination. The buyer-seller linked data reveal a number of new stylized facts on the distributions of buyers per exporter and exporters per buyer, the matching among sellers and buyers and the variation of buyer dispersion across destinations. The paper develops a model of trade with heterogeneous importers as well as heterogeneous exporters where matches are subject to a relation-specific fixed cost. The model matches the stylized facts and generates new testable predictions emphasizing the importance of importer heterogeneity in explaining trade patterns.

JEL Classification: F10, F12 and F14
Keywords: exporters, heterogeneous firms, importers and trade elasticity

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1 Introduction

The importance of exporter heterogeneity for aggregate and firm-level outcomes is well established. More recently, researchers have found comparable variation in size and performance across importers (Bernard et al., 2009). However, there has been far less work on the interaction of supply side (exporter) and demand size (importer) heterogeneity and the consequences for international trade.[1]

This paper makes use of a novel dataset that links all Norwegian export transactions with every importer in every country. We establish a set of stylized facts about sellers and buyers across markets and develop a parsimonious theoretical model with two-sided heterogeneity. The model is able to match many of the stylized facts and generates additional testable implications about the role of buyer heterogeneity in international trade. A key theoretical and empirical finding is that buyer-side heterogeneity plays an important role in generating the variation of exports across sellers and in explaining the response of exports to aggregate shocks.

In our data, the identities of both the exporter and the importer are available. For the first time, we can link a firm's export transactions to specific buyers in every destination country and, at the same time, examine all of an importer's transactions with Norwegian firms. It is well known that the large majority of a country's international transactions, both exports and imports, are handled by a relatively small number of trading firms. The largest decile of exporters accounts for the lion's share of a country's total exports, and imports are comparably concentrated in the top ten percent of importers (see Bernard et al., 2009). We confirm that Norwegian exports and imports show the same degree of concentration with the top 10 percent of importers in a country typically accounting for more than 90 percent of total exports from Norway to that country (Table 1). However, while importer heterogeneity exists in every destination, there is substantial variation across markets; Norwegian exports to the U.S. are more concentrated in the largest buyers of Norwegian products while China has less dispersion (Table 1). We also examine the importer-exporter relationship across exporters of different sizes. Larger sellers reach more customers and have more dispersion in sales across buyers. In addition, there is negative assortativity among seller-buyer pairs. The larger is an exporter, the smaller is its average buyer in terms of seller contacts.

We develop a framework to match these stylized facts about buyers and sellers by building a model of international trade with joint heterogeneity among exporters and importers. Exporters vary in their efficiency in producing differentiated intermediate goods and pay a relation-specific fixed cost to match with each buyer. These fixed costs can be related to bureaucratic procedures, contract agreements and the customization of output to the requirements of particular buyers. Importers bundle inputs into a final product with heterogeneity in efficiency. Due to the presence of the relation-specific cost, not every exporter sells to every buyer in a market. Highly productive

[1] Exceptions are Blum et al. (2010) and Blum et al. (2012), Carballo et al. (2013) and Eaton et al. (2012) who examine exporter-importer pairs for individual pairs of countries.

exporters reach many customers and their marginal customer is small; highly productive importers purchase from many sellers and their marginal supplier is small.

Beyond matching the stylized facts, the model generates three main testable implications. First, a demand shock in a destination market has no impact on a firm's exports to its marginal customer in that market. The marginal transaction is determined only by the relation-specific cost. Second, the change in a firm's exports following a demand shock in the destination country depends on the extent of buyer heterogeneity in that market. Specifically, the trade elasticity is higher in markets with less dispersion of buyer efficiency. Third, dispersion in exports across firms in a destination market is inversely related to dispersion in buyer productivity in that market. Exports are therefore more dispersed in markets with less buyer dispersion. The intuition is that if dispersion among buyers is high, then there are many large buyers, and even small and low productivity exporters will sell to them, thus compressing the exports distribution.

We find empirical support for all three predictions from the model. As predicted by the model, a positive demand shock has no impact on exports to the marginal buyer, whereas total firm-level exports increase. The firm-level elasticity of exports with respect to a demand shock is higher in countries with less dispersion in buyer productivity. Finally, using a differences-in-differences estimator, we find that exports to country-product pairs are less dispersed in markets with more buyer dispersion.

An implication of our work is that the variance of demand matters for how responsive trade flows is to changes in trade policy, exchange rate movements, or other types of shocks. Previous research has shown that dispersion in firm size and productivity differs both across regions and over time (Bartelsman et al., 2013, Braguinsky et al., 2011, Garicano et al., 2013 and Hsieh and Klenow, 2009), due to policy-induced distortions. Our work may thus improve our understanding of the impact of both previous and future policy changes on international trade.

Relation to the Literature

This paper is related to several new streams of research on firms in international trade. Importing firms have been the subject of work documenting their performance and characteristics. Bernard et al. (2009), Castellani et al. (2010) and Muuls and Pisu (2009) show that the heterogeneity of importing firms rivals that of exporters for the US, Italy and Belgium respectively. Amiti and Konings (2007), Halpern et al. (2011) and Boler et al. (2012) relate the importing activity of manufacturing firms to increases in productivity. We show that Norwegian exports to a market are concentrated in a small number of sellers and buyers but that there is substantial variation across different markets.

Papers by Rauch (1999), Rauch and Watson (2004), Antràs and Costinot (2011) and Petropoulou (2011) consider exporter-importer linkages. Chaney (ming) also has a search-based model of trade

where firms must match with a contact in order to export to a destination. These papers adopt a search and matching approach to linking importers and exporters, while in this paper we abstract from these mechanisms and instead focus on the implications of buyer heterogeneity for international trade.

Our work is also related to the literature on exports and heterogeneous trade costs initiated by Arkolakis (2009, 2010). In these papers, the exporter faces a rising marginal cost of reaching additional (homogeneous) customers. In our framework, buyers themselves are heterogeneous in their expenditures, but in equilibrium, exporting firms face rising costs per unit of exports as they reach smaller importers.

Our paper is most closely related to the nascent literature using matched importer-exporter data. Blum et al. (2010) and Blum et al. (2012)examine characteristics of trade transactions for the exporter-importer pairs of Chile-Colombia and Argentina-Chile while Eaton et al. (2012) consider exports of Colombian firms to specific importing firms in the United States. Blum et al. (2010) and Blum et al. (2012) find, as we do, that small exporters typically sell to large importers and small importers buy from large exporters. Their focus is on the role of import intermediaries in linking small exporters and small customers. Eaton et al. (2012) develop a model of search and learning to explain the dynamic pattern of entry and survival by Colombian exporters and to differentiate between the costs of finding new buyers and to maintaining relationships with existing ones. In contrast to those papers but similar to Carballo et al. (2013), we focus on the role of importer heterogeneity across destinations. Carballo et al. (2013) focus on export margins across goods, countries and buyer, while we study the implications of importer heterogeneity on exporting firms' responses to exogenous shocks to trade barriers and demand.

2 Data

The data employed in this paper are Norwegian transaction-level customs data from 2005-2010. The data have the usual features of transaction-level trade data in that it is possible to create annual flows of exports by product, destination and year for all Norwegian exporters. However, in addition, this data has information on the identity of the buyer for every transaction in every destination market. As a result we are able to see exports of each seller at the level of the buyer-product-destination-year. Our data include the universe of Norwegian merchandise exports, and we observe export value and quantity. In 2005 total Norwegian merchandise exports amounted to USD 41 billions, equal to around 18 percent of Mainland Norway GDP.[2] Exports were undertaken by 18,023 sellers, who sold 5,154 products to 68,052 buyers across 205 destinations.

[2]Mainland Norway GDP refers to national GDP excluding the oil and gas sector.

3 The Buyer Margin of Trade

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, x_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, i.e. the fraction of all possible firm-product-buyer combinations for country j for which trade is positive, and the average value of trade, $\bar{x}$. Hence,

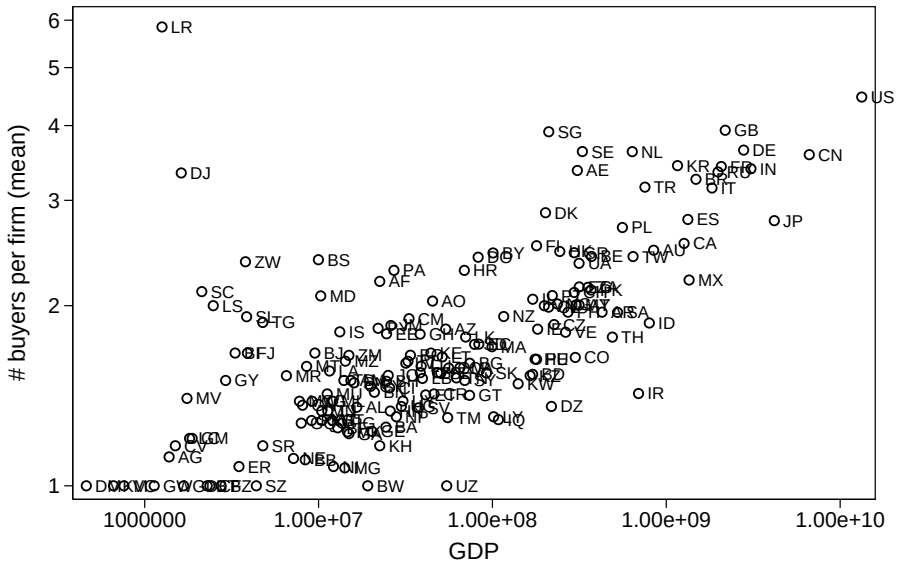
$$x_j = f_j p_j b_j d_j \bar{x_j}$$

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 $\bar{x_j} = x_j/o_j$, 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 the logarithm of each component of country-level exports on the logarithm of total exports to a given market in 2006, e.g. $\ln f_j$, against $\ln x_j$. Given that OLS is a linear estimator and its residuals have an expected value of zero, the coefficients for each set of regressions sum to unity, with each coefficient representing the share of overall variation in trade explained by the respective margin.

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 show 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,

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).

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

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

$$x_{mj} = p_{mj} b_{mj} d_{mj} \bar{x}_{mj}$$

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 $\bar{x}_{mj} = x_{mj}/o_{mj}$. In order to decompose the impact of the various margins of trade on firms' total exports to a market, we proceed as we did with the aggregate exports, and regress the log of each of the components of firm level exports on the log of total firm exports,

while also including firm and country fixed effects. We do this for a given year, here chosen to be 2006, and the results are reported in Table 4. 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

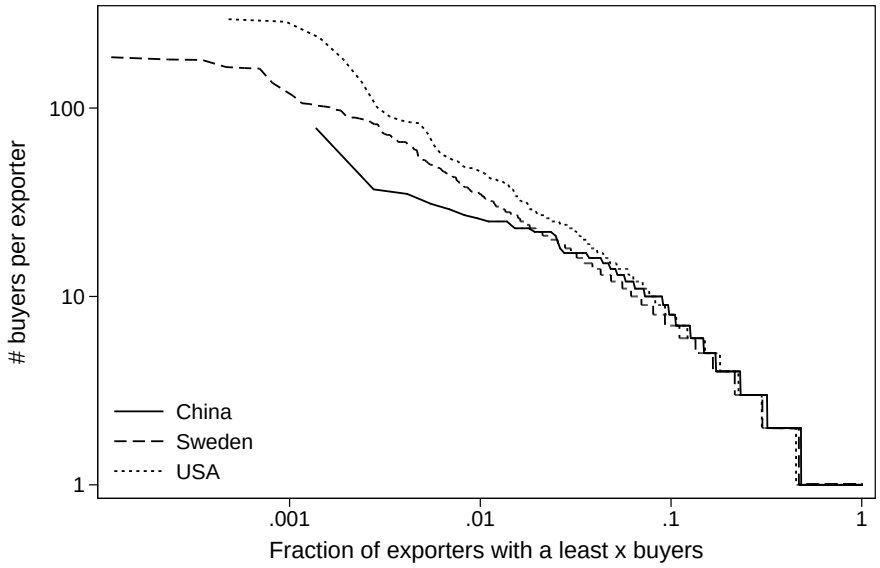
While the prior results establish the relevance of the buyer dimension as a margin of trade, we develop a model of international trade to more formally examine the role of buyer-seller relationships in trade flows. Before presenting the model, we document a set of facts on the heterogeneity of buyers 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 of sellers account for 98 percent of Norwegian aggregate exports. At the same time, the top 10 percent of buyers are almost as dominant and account for 96 percent of the purchases of Norwegian exports.

Fact 2: The distributions of buyers per exporter and exporters per buyer are approximately Pareto. We plot the number of buyers of each exporting firm in a particular market against the fraction of exporters selling in the market who sell to at least that many buyers. We find that the distributions are remarkably similar and approximately Pareto. Figure 2 plots the results for China, the US and Sweden.[3] The average number of buyers per seller is 4.5 in the U.S. and 3.6 in China and Sweden (Table 1). We also plot the number of exporters per buyer in a particular

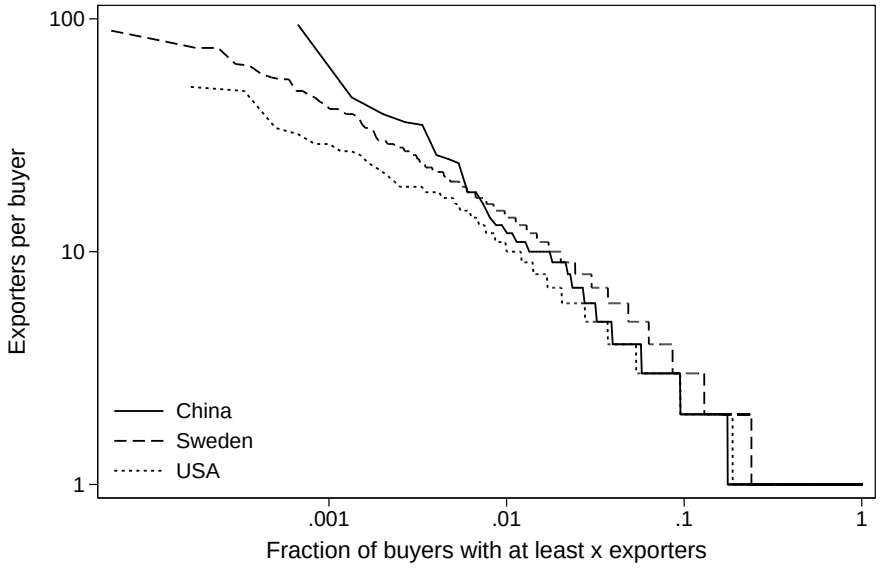
[3]To interpret Figure 2 as the empirical CDF, let x_j^ρ be the ρth percentile of the number of buyers per exporter

Figure 2: Distribution of the number of buyers per exporter.



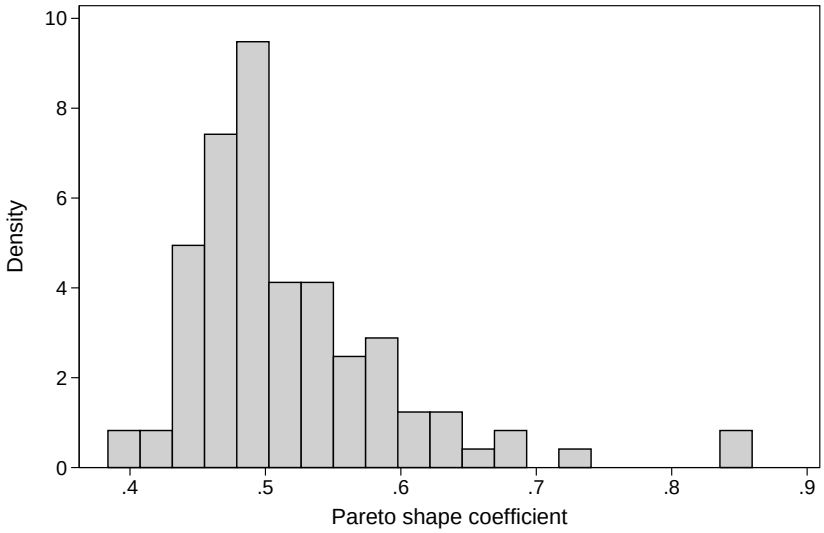
Note: 2006 data, log scale. The estimated slope coefficients are -0.88 (s.e. 0.008) for China, -0.87 (s.e. 0.002) for Sweden and -0.95 (s.e. 0.004) for the U.S. The distribution is Pareto if the slope is constant. The slope coefficient equals the negative of the inverse of the Pareto shape parameter ($-1/a$, see footnote 7).

Figure 3: Distribution of the number of exporters per buyer.



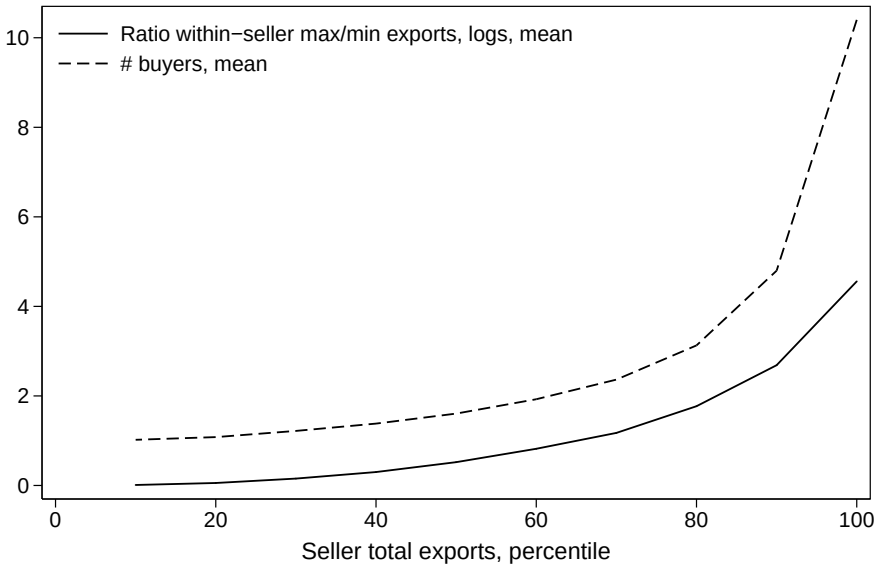
Note: 2006 data, log scale. The estimated slope coefficients are -0.49 (s.e. 0.006) for China, -0.57 (s.e. 0.002) for Sweden and -0.46 (s.e. 0.003) for the U.S. The distribution is Pareto if the slope is constant. The slope coefficient equals the negative of the inverse of the Pareto shape parameter ($-1/a$, see footnote 7).

Figure 4: Heterogeneity of importer expenditure across markets.



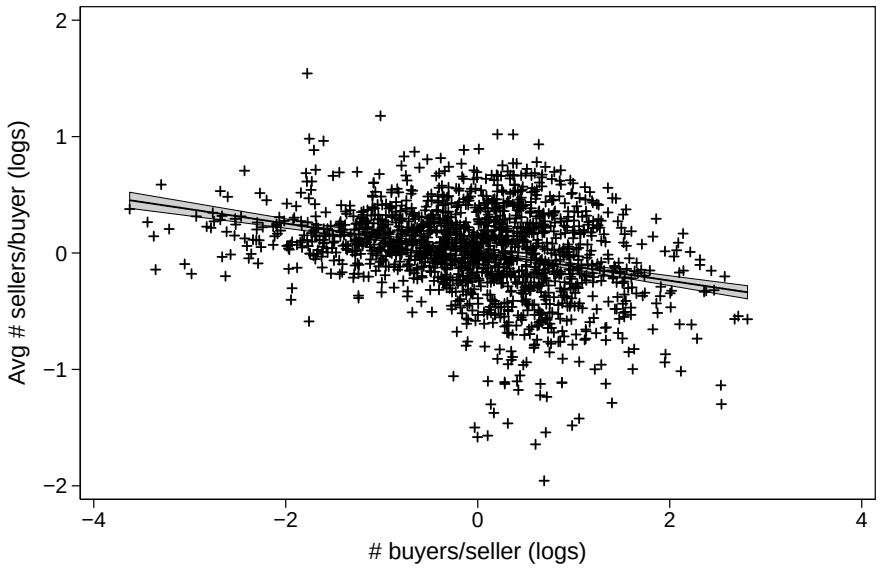
Note: 2006 data. The figure shows the density of the Pareto shape coefficient, based on the distribution of buyer expenditure of Norwegian exports in different markets. The shape coefficients are computed by regressing $1-CDF$ on buyer expenditure, both in logs, for each country. Following the same logic as described in footnote 7, 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 $b_j(\bar{a}_j)$ 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).

market against the fraction of buyers in this market who buys from at least that many exporters (Figure 3). Again the distributions are approximately Pareto, and the average number of exporters per buyer in China, Sweden and the US is 1.7, 1.9 and 1.6, respectively.

Fact 3: The dispersion of importer expenditure varies across countries. While the distribution of importer expenditures is approximately Pareto in every country, there is substantial heterogeneity 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.[4]

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

in market j. We can then write $\Pr\left[X \leq x_j^\rho\right] = \rho$. If the distribution is Pareto with shape parameter a and location parameter x_0, we have $1 - \left(x_0/x_j^\rho\right)^a = \rho$, and taking logs this gives us $\ln x_j^\rho = \ln x_0 - \frac{1}{a}\ln(1-\rho)$. Hence, the slope in Figure 2 is $-1/a$.

[4]Only markets with more than 50 buyers are included. This amounts to 102 export destinations and 97 percent of Norwegian exports.

sellers according to their number of buyers, and buyers according to the number of sellers they purchase from. We find that the better connected a seller, the less well-connected is its average buyer. 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.[5] The interpretation of a point with the coordinates (0.2,-0.2) is that customers of Norwegian exporters with 20 percent more customers than average buy from 20 percent fewer exporters than average. The fitted regression line is -0.13, so a 10 percent increase in number of customers is associated with a 1.3 percent decline in average connections among the customers.[6] 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).[7] In a recent paper, Lu et al. (2013) also find negative assortivity using Colombian buyer-seller trade data.

The stylized facts presented here showed empirical regularities between buyers and sellers irrespective of which product is traded. A potential concern is that firms with many customers are typically firms selling many products. This suggests a model where firms meet new buyers by expanding product scope, rather than overcoming fixed costs, which is the mechanism we focus on in our model. A simple way control for the product dimension is to re-calculate Facts 1, 2, 4 and 5 with the firm-product instead of the firm as the unit of analysis.[8] The qualitative evidence from Facts 1, 2, 4 and 5 remain robust to this change. For example, the distribution of the number of buyers per firm-product combination is approximately Pareto (Fact 1) and firm-products selling to many customers match on average with less connected buyers (Fact 5). This shows that our results cannot be explained by variation in the product dimension alone.

5 A Trade Model with Two-Sided Heterogeneity

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.

[5] This Figuree shows $\ln b_j(a_j) - \ln \bar{b}_j(a_j)$, where $\ln \bar{b}_j(a_j)$ is the average number of Norwegian connections among all buyers in j.

[6] 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 D, we show that the elasticity is informative of a structural parameter of the model.

[7] 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.

[8] A product is defined as a HS1996 6 digit code. Results available upon request.

We think of these firms as producers of intermediates as in Ethier (1979). Departing from Melitz (2003), we assume that intermediates are purchased by final goods producers (buyers or customers) who bundle inputs into final goods that in turn are sold to consumers. Final goods producers also produce with different efficiencies, giving rise to heterogeneity in their firm size as well as a sorting pattern between sellers and buyers in equilibrium. The key ingredient in our model is heterogeneity in efficiency that in turn gives rise to heterogeneity in size both among sellers and buyers. However, two-sided heterogeneity in size could potentially also arise from other sources, e.g. differences in endowments among buyers and differences in quality among sellers. The significant testable implications from such alternative models would not depart much from the current setup.

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, buyer and seller productivities are Pareto distributed, which gives 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 match 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.

Each country i is endowed with L_i workers, and the labor market is characterized by perfect competition, so that wages are identical across workers. In each country there are three sectors of production: a homogeneous good sector characterized by perfect competition, a traded intermediate good sector and a non-traded final goods sector, the two last sectors characterized by monopolistic competition. Workers are employed in the production of the homogeneous good as well as the production of the intermediates.[9] The homogeneous good is freely traded and is produced under constant returns to scale with one hour of labor producing w_i units of the homogeneous good. Normalizing the price of this good to 1 sets the wage rate in country i to w_i.

Consumers. Consumers derive utility from consumption of the homogeneous good and a continuum of differentiated final goods. Specifically, upper level utility is Cobb-Douglas between the homogeneous good and differentiated good with a differentiated good expenditure share μ, and lower level utility is CES across differentiated final goods with an elasticity of substitution $\sigma > 1$.

Intermediates. Intermediates are produced using only labor, by a continuum of firms, each producing one variety of the differentiated input. Firms are heterogeneous in productivity z, and firms' productivity is a random draw from a Pareto distribution with support $[z_L, \infty)$ and shape parameter $\gamma > \sigma - 1$, so that $F(z) = 1 - (z_L/z)^{\gamma}$. As a notational convention, lower case symbols

[9] Adding workers to the final goods sector would only add more complexity to the model, without generating new insights.

refer to intermediate producers whereas upper case symbols refer to final goods producers.

Final goods producers. Final goods are produced by a continuum of firms, each producing one variety of the final good. Their production technology is CES over all intermediate inputs available to them,

$$Z(\upsilon)\left(\int_{\Omega_j(\upsilon)} c(\omega)^{(\sigma-1)/\sigma}\, d\omega\right)^{\sigma/(\sigma-1)},$$

where productivity for firm υ is denoted by $Z(\upsilon)$, which is drawn from the Pareto distribution $G(Z) = 1 - (Z_L/Z)^{\Gamma}$ with support $[Z_L, \infty)$. $c(\omega)$ represents purchases of intermediate variety ω and $\Omega_j(\upsilon)$ is the set of varieties available for firm υ in country j. To simplify the notation, the elasticity of substitution among intermediates is identical to the elasticity of substitution among final goods, both denoted by σ. This restriction does not significantly affect the qualitative results of the paper. We also impose $\Gamma > \gamma$, which ensures that the price index for final goods is finite (see Appendix Section B).

Relationship specific investments. Intermediate producers sell to an endogenous measure of final goods producers, and they incur a match-specific fixed cost for each buyer they choose to sell to. Hence, meeting buyers and setting up supplier contracts are associated with a cost that is not proportional to the value of the buyer-seller transaction. These costs may typically be related to the search for suppliers, bureaucratic procedures, contract agreements and costs associated with sellers customizing their output to the requirements of particular buyers.[10] Formally, we model this as a match specific fixed cost, f_{ij}, paid by the seller in terms of labor, and it may vary according to seller country i and buyer country j. Consequently, production networks are the result of intermediate firms that endogenously choose their set of customers, while final good producers do not engage in strategic sourcing.

We follow Chaney (2008) and assume that there are exogenous measures of buyers and sellers, N_i and n_i, in each country i. In order to simplify the analysis, we assume that the total mass of buyers N_i is proportional to L_i so that larger economies have more entrants. As there is no free entry, the production of intermediates and final goods leaves rents, and consumers in each country derive income not only from labor but also from the dividends of a global mutual fund. Each consumer own w_i shares of the fund and profits are redistributed to them in units of the numeraire good. Total worker income in country i, Y_i, is then $w_i(1+\psi)L_i$, where ψ is the dividend per share of the global mutual fund.

Variable trade barriers. Intermediates are traded internationally, and firms 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

[10] Kang 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.

in country j.[11]

Sorting functions. Due to the presence of the match-specific fixed cost, a given seller in i will find it optimal to sell only to buyers in j with productivity higher than a lower bound $\underline{Z}_{ij}$. Hence, we introduce the equilibrium sorting function $\underline{Z}_{ij}(z)$, which is the lowest possible productivity level Z of a buyer in j that generate a profitable match for a seller in i with productivity z. We solve for $\underline{Z}_{ij}(z)$ in Section 5.3. Symmetrically, we define $\underline{z}_{ij}(Z)$ as the lowest efficiency for a seller that generates a profitable match for a buyer in country j with productivity Z. By construction, $\underline{z}_{ij}(Z)$ is the inverse of $\underline{Z}_{ij}(z)$, i.e. $Z = \underline{Z}_{ij}\left(\underline{z}_{ij}(Z)\right)$.

Pricing. As intermediates and final goods markets are characterized by monopolistic competition, prices are a constant mark-up over marginal costs. For intermediate producers, this yields a pricing rule $p_{ij} = \overline{m}\tau_{ij}w_i/z$, where $\overline{m} \equiv \sigma/(\sigma-1)$ is the mark-up.[12] For final goods, the pricing rule becomes $P_j = \overline{m}q_j(Z)/Z$, where $q_j(Z)$ is the ideal price index for intermediate inputs facing a final goods producer with productivity Z in market j. Note that the restriction of identical elasticities of substitution across final and intermediate goods also implies that the mark-up $\bar{m}$ is the same in both sectors. Using the Pareto assumption for seller productivity z, the price index on inputs facing a final goods producer with productivity Z can be written as

$$q_j(Z)^{1-\sigma} = \frac{\gamma z_L^{\gamma}}{\gamma_2}\sum_k n_k\left(\bar{m}\tau_{kj}w_k\right)^{1-\sigma}\underline{z}_{kj}(Z)^{-\gamma_2}, \tag{1}$$

where $\gamma_2 \equiv \gamma - (\sigma-1)$.

Exports of intermediates. Given the production function of final goods producers specified above, and conditional on a match (z, Z), firm-level intermediate exports from country i to j are

$$r_{ij}(z,Z) = \left(\frac{p_{ij}(z)}{q_j(Z)}\right)^{1-\sigma}E_j(Z), \tag{2}$$

where $E_j(Z)$ is total spending on intermediates by a final goods producer with productivity Z in market j. As final goods are non-traded, $E_j(Z)$ will be a function of country income Y_j. However, the specific form of $E_j(Z)$ depends on the equilibrium sorting pattern in the economy, see Appendix Section B.

5.2 A Limiting Case

Because the lower support of our seller productivity distribution is z_L, no buyer (final goods producer) can ever reach a seller (intermediate goods producer) with productivity lower than z_L. An implication is that we have two types of buyers in our economy: (i) Buyers that match with a subset

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

[12] Because marginal costs are constant, the optimization problem of the firm of finding the optimal price and the measure of buyers to match to, simplifies to standard constant mark-up pricing, and a separate problem of finding the optimal measure of buyers.

of the sellers, and (ii) buyers that match with every seller. Case (i) is characterized by $\underline{z}_{ij}(Z) > z_L$, while case (ii) is characterized by $\underline{z}_{ij}(Z) \leq z_L$. Similarly, due to the lower support of the buyer productivity distribution, there are two groups of sellers: those who match with a subset of buyers and those who reach all buyers.

The discontinuity of the Pareto distributions at z_L and Z_L is inconvenient, as we would rather focus exclusively on the economically interesting case where no buyer matches with every seller and no seller with every buyer. Henceforth, we choose to work with a particular limiting economy. Specifically, we let $z_L \to 0$, so that even the most productive buyer is not large enough to match with the smallest seller. Similarly, we let $Z_L \to 0$, so that even the most productive seller does not match with the smallest buyer. In addition, we assume that the measure of sellers and buyers is an inverse function of the productivity lower bound, i.e. $n_i = z_L^{-\gamma}\tilde{n}_i$ and $N_i = Z_L^{-\Gamma}\tilde{N}_i$, where $\tilde{n}_i$ and $\tilde{N}_i$ are constants. Therefore, a lower productivity threshold is associated with more potential firms. When z_L declines, a given seller is more likely to have lower productivity, but there are also more sellers, so that the number of sellers in a given country with productivity z or higher remains constant. In equilibrium, the two forces exactly cancel out, so that the sorting patterns and as well as expressions for trade flows and other equilibrium objects are well defined.

5.3 Equilibrium Sorting

Based on the setup presented in Section 5.1, we now pose the question: for a given seller of intermediates in country i, what is the optimal number of buyers to match with in market j? An intermediate firm's net profits from a (z, Z) match is $\pi_{ij}(z, Z) = r_{ij}(z, Z)/\sigma - f_{ij}$. Given the optimal price from Section 5.1, the matching problem of the firm is equivalent to determining $\underline{Z}_{ij}(z)$, the lowest productivity buyer that generates a profitable match for a seller with productivity z is willing to sell to. Hence, we find $\underline{Z}_{ij}(z)$ by solving for $\pi_{ij}(z, Z) = 0$. Inserting the demand equation (2) and a firm's optimal price, we can express $\underline{Z}_{ij}(z)$ implicitly as

$$q_j(\underline{Z})^{\sigma-1} E_j(\underline{Z}) = \sigma f_{ij} (\bar{m}\tau_{ij} w_i)^{\sigma-1} z^{1-\sigma}. \tag{3}$$

A complication is that the price index is also a function of the unknown $\underline{z}_{ij}(Z)$, and furthermore that total spending on intermediates, $E_j(Z)$, is unknown and depends on the equilibrium sorting pattern. In appendix Sections A-B, we show that we can start with a guess of the functional forms for $\underline{z}_{ij}(Z)$ and $E_j(Z)$, derive the equilibrium, and then confirm that the functional forms are indeed valid. The solution to the sorting function is:

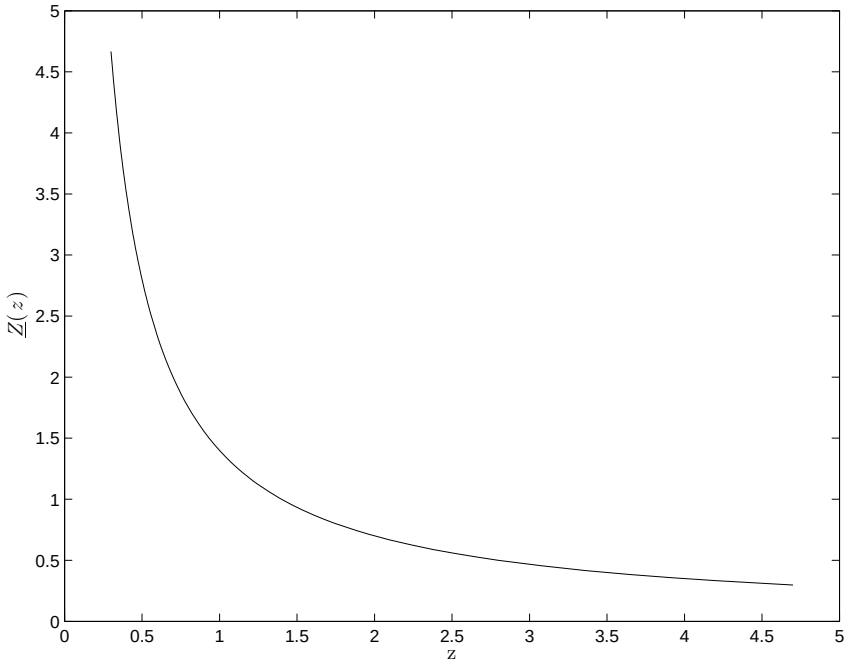
$$\underline{z}_{ij}(Z) = \frac{\tau_{ij} w_i \Omega_j}{Z} f_{ij}^{1/(\sigma-1)} w_j^{-1/\gamma}, \tag{4}$$

where

$$\Omega_j = \left(\frac{\sigma}{\kappa_3} \frac{\gamma}{\gamma_2} \sum_k \tilde{n}_k (\tau_{kj} w_k)^{-\gamma} f_{kj}^{-\gamma_2/(\sigma-1)} \right)^{1/\gamma}. \tag{5}$$

We plot the matching function $\underline{Z}_{ij}(z)$ in Figure 7. $\underline{Z}_{ij}(z)$ is downward sloping in z, so more

Figure 7: Matching function.



efficient sellers match with less efficient buyers on the margin. A firm with efficiency z matches with lower efficiency buyers whenever variable or fixed trade costs (τ_{ij} and f_{ij}) are lower (the curve in Figure 7 shifts towards the origin). Moreover, a firm also matches with lower efficiency buyers when trade costs from 3rd countries to j are higher where Ω_j in equation (5) has a similar interpretation as the multilateral resistance variable in Anderson and van Wincoop (2004).[13]

5.4 Export Margins and Buyer Dispersion

Having determined the equilibrium sorting function between intermediate and final goods producers, we can now derive equilibrium expressions for firm-level trade and decompose trade into the extensive margin in terms of number of buyers and the intensive margin in terms of sales per buyer leading to additional testable implications of the model.

Firm-level exports. Using (2), for a given firm with productivity z, we can express total firm-level intermediate exports, from country i to j across all the buyers with which the firm has matched as $r_{ij}^{TOT}(z) = N_j \int_{\underline{Z}_{ij}(z)} r_{ij}(z, Z)\, dG(Z)$. In Appendix Section C, we show that firm-level exports to market j are

$$r_{ij}^{TOT}(z) = \kappa_1 \tilde{N}_j f_{ij}^{1-\Gamma/(\sigma-1)} \left(\frac{z}{\tau_{ij} w_i \Omega_j}\right)^{\Gamma} w_j^{\Gamma/\gamma}, \tag{6}$$

[13]Note that the sorting function in equation (4) is valid under any distribution for buyer productivity, i.e. it is not necessary to assume Pareto buyer productivity to derive this particular result.

where κ_1 is a constant.[14] The sorting function also allows us to determine marginal exports, i.e. exports to the least productive buyer. We insert equation (4) into (14) which yields

$$r_{ij}\left(z, \underline{Z}_{ij}(z)\right) = \sigma f. \tag{7}$$

Hence, marginal exports are entirely pinned down by the relation-specific fixed cost. We can also derive the optimal measure of buyers in an export market j for a firm with productivity z in country i (see Appendix Section C), which yields

$$b_{ij}(z) = \tilde{N}_j f_{ij}^{-\Gamma/(\sigma-1)} \left(\frac{z}{\tau_{ij} w_i \Omega_j}\right)^{\Gamma} w_j^{\Gamma/\gamma}. \tag{8}$$

We emphasize two properties of these results. First, the elasticity of exports and number of buyers with respect to variable trade barriers equals Γ, the shape parameter of the buyer productivity distribution. Hence, a lower degree of buyer heterogeneity (higher Γ) amplifies the negative impact of higher variable trade costs for both exports and the number of customers. This is in contrast to models with no buyer heterogeneity, where the trade elasticity is determined by the elasticity of substitution, σ (see e.g. Krugman (1980)). Also note that, as expected, a higher match cost f_{ij} dampens both firm exports and the number of buyers.[15]

The second key property of these results is that the elasticity of exports and the number of buyers with respect to income in the destination market, w_j, is determined by the ratio of buyer to seller heterogeneity, Γ/γ. The intuition is that in markets with low heterogeneity (high Γ), there are many potential buyers that a seller can form profitable matches with after a positive shift in buyer expenditure. Consequently, a positive demand shock in a market with low heterogeneity among buyers translates into more exports than in a market with high heterogeneity among buyers. We summarize these findings in the following proposition.

Proposition 1. *The elasticity of firm-level exports with respect to variable trade costs equals Γ, the Pareto shape coefficient for buyer productivity. The elasticity of firm-level exports with respect to destination country income, w_j, equals Γ/γ, the ratio of the buyer to seller productivity Pareto shape coefficient.*

In Section 6, we empirically test this prediction of the model, by exploiting cross-country differences in the degree of firm size heterogeneity.

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 $\gamma/(\sigma-1)$. In our model with buyer heterogeneity, dispersion in the export distribution is determined by seller heterogeneity *relative to* buyer

[14] $\kappa_1 \equiv \sigma \bar{m}^{\sigma-1}\Gamma/[\Gamma-(\sigma-1)]$.

[15] The elasticity of exports with respect to f_{ij} is $1-\Gamma/(\sigma-1)$, which is negative given the previous restrictions that (i) $\gamma-(\sigma-1)>0$ and $\Gamma>\gamma$.

heterogeneity. To see this, we calculate

$$\Pr\left[r_{ij}^{TOT}(z) < r_0^{TOT}\right] = 1 - \left(\kappa_{3ij}/r_0^{TOT}\right)^{\gamma/\Gamma},$$

where κ_{3ij} is a constant.[16] 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 γ/Γ. Hence, while more heterogeneity in seller productivity translates into more heterogeneity in export sales, more heterogeneity in buyer productivity leads to less heterogeneity in export sales.*

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, and consequently higher dispersion in the number of buyers reached by different exporters.

An implication of our work is therefore that buyer dispersion plays a role in shaping the sales distribution, and consequently the firm size distribution, in a market. As documented by Luttmer, 2007 and Axtell, 2001, the Pareto distribution is a good approximation of the U.S. firm size distribution, although the results here raise the question of whether this is due to underlying the productivity distribution of sellers or buyers. Our results also add to the debate on firm-level heterogeneity and misallocation of resources (see e.g. Hsieh and Klenow (2009)). Hence, the variation in the strength of the link between productivity and size across countries, industries and over time reported by Bartelsman et al. (2013) may not only be the result of policy-induced distortions, but also due to differences in buyer distributions across markets.

6 Empirical Implications

In this section, we test three main predictions of the model developed above that emphasize the importance of buyer heterogeneity in explaining trade patterns. The first prediction is that a demand shock facing firm m should change 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 the relation specific fixed cost. The second prediction is that a similar-sized positive demand shock facing firm m across different destinations should translate into relatively higher sales in markets with less heterogeneity, as stated in Proposition 1. The third prediction is that heterogeneity in sales across exporters is not only driven by heterogeneity in exporter productivity, but inversely related to importer heterogeneity, as stated in Proposition 2. The empirical evidence presented below is consistent with these main predictions of the model.

[16] $\kappa_{3ij} = \kappa_1 \left(\frac{z_L}{\tau_{ij} w_i \Omega_j}\right)^{\Gamma} \tilde{N}_j f_{ij}^{1-\Gamma/(\sigma-1)} w_j^{\Gamma/\gamma}$.

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 size among buyers in the destination country (w_j in the model, see equation (6)). 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 level over time.

We therefore choose to proxy for the demand facing Norwegian firm m in destination country j for all its exported products by calculating total imports in j of those products from other sources than Norway. Given the small market share of Norwegian firms in most markets, this measure should be exogenous with respect to firm m's exports. We proceed by using product-level (HS6 digit) trade data from COMTRADE and denote total imports of product p to country j at time t from all sources except Norway as I_{pjt}.[17] The firm-level demand shock d_{mjt} in market j at time t is then defined as the unweighted average of imports for the products that firm m is exporting

$$d_{mjt} = \frac{1}{N_m} \sum_{p \in \Omega_m} \ln I_{pjt},$$

where Ω_m is the set of products firm m is exporting (to any country in any year), and N_m is the number of products firm m is exporting.[18] We also investigate the robustness of our results to other specifications of demand. These are discussed in Section 6.3.

6.2 Demand Shocks and the Marginal Buyer

According to the model (see Section 5.4), a positive demand shock in market j will increase total firm-level exports and the number of buyers, but will have no impact on sales to the marginal buyer. This occurs because the gross profits associated with the marginal buyer exactly equals the buyer-seller match fixed cost. To test this prediction we let equations (6)-(8) guide us, and estimate

$$\ln y_{mjt} = \alpha_{mt} + \beta_{jt} + \eta \ln d_{mjt} + \epsilon_{mjt}, \tag{9}$$

where y_{mjt} is an outcome variable for firm m in market j at time t 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. We estimate the model for the firm's marginal export ($\min_b y_{mbjt}$ where b denotes buyer), total firm-level exports ($\sum_b y_{mbjt}$), number of buyers, and maximum exports across buyers ($\max_b y_{mbjt}$).

[17] We use CEPII's BACI database using the HS 1996 revision.

[18] Ω_m is the same in all destinations and in all years, so that firm behavior across time and countries does not change the set. A few importer-product pairs are missing in one or more years, these pairs are dropped.

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.[19]

The results confirm the predictions from the model. Table 6 shows that positive demand shocks have no impact on the marginal export flow (column 1), while both maximum exports, total exports and the number of buyers per firm (columns 2, 3, and 4) are positively and significantly related to positive demand shocks in the destination country.[20]

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 (6) and (8), while the empirical results show that the export elasticity is stronger than the customer elasticity.[21] One possible reason for this discrepancy is that the empirical productivity distributions of buyers and sellers may deviate from the assumed Pareto shape.

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. Hence, we would expect a similar-sized demand shock facing firm m across different destinations to translate into relatively greater changes in sales for markets with less heterogeneity, as stated in Proposition 1. We test this prediction by amending the model in equation (9) by including an interaction term which accounts for buyer dispersion, allowing us to check whether the demand elasticities are higher in markets with less heterogeneity. Specifically, we estimate

$$\ln y_{mjt} = \alpha_{mt} + \beta_{jt} + \eta_1 \ln d_{mjt} + \eta_2 \ln d_{mjt} \times \Theta_j + \epsilon_{mjt}, \tag{10}$$

where Θ_j is a measure of buyer dispersion in destination market j.

Ideally, in line with our theoretical model, we would want a measure of buyer productivity dispersion in different markets. A close proxy for this is a measure of dispersion in firm size.[22] We therefore use data on the firm size distribution from the World Bank's Enterprise Surveys, and

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

[20] In the min and max exports regressions (columns (1) and (2)), we only use firms with more than 5 customers. The sample is also restricted to countries with information about firm size dispersion from the World Bank Enterprise Surveys, so that the sample size is identical to the sample size in the regressions in Section 6.3. Results based on the entire sample are not significantly different.

[21] Note that the empirical estimates for elasticities are average elasticities across destination countries.

[22] The relationship between productivity and size has also been documented in a set of studies for many of countries (see e.g. Bartelsman et al. (2013) for recent evidence).

calculate a Pareto slope coefficient (Θ^1), the 90/10 percentile ratio (Θ^2), and the standard deviation of log employment for each country (Θ^3).[23] 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.[24]

The results from estimating the specification in (10) 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 the predictions of our model. Note that the coefficients for the interaction term are positive rather than negative in columns (1) and (2) since the Pareto coefficient is the inverse of dispersion. The magnitudes are also economically significant: Moving from the 25th to the 75th percentile of the Pareto coefficient Θ^1 increases the demand elasticity, $\eta_1 + \eta_2\Theta^1$, by 11 percent, suggesting that demand-side factors are quantitatively important for our understanding of trade elasticities.[25]

Robustness In this section, we perform a number of robustness checks. First, a concern is that Norwegian exports to countries included in the Enterprise Surveys only amount to roughly 1/3 of total exports. We therefore check the robustness of our results by using alternative data sources, allowing us to include other destination countries in the sample.

The World Bank's Exporter Dynamics database provide data on exports for 39 countries.[26] Unfortunately, the Exporter Dynamics database does not include firm-level information on firm size or on exports, but it does provide the mean and standard deviation of exports. This allows us to calculate the coefficient of variation for exports for all 39 countries, which we use as our measure buyer dispersion. A potential concern is that this measure of buyer dispersion is inferred from the exports distribution. However, as our buyers are importers, and as importers themselves tend to be exporters (Bernard et al., 2007), there should be a strong positive correlation between imports and exports dispersion. In fact, we can estimate this correlation using the Norwegian data, and we do indeed find a strong positive correlation. We refer the reader to Appendix Section E for more information. We estimate equation (10) using the the calculated coefficient of variation (Θ^4).

[23] We calculate the Pareto slope coefficient by regressing the empirical $1 - CDF$ on firm employment, both in logs, for each destination market; the resulting slope coefficient is (the negative of) the Pareto slope coefficient.

[24] The survey covers 87 countries, mostly developing countries. In 2006 these countries received 29 percent of Norwegian exports. We drop countries where the survey has fewer than 100 observations per country. These countries are: Brazil, Eritrea, Guyana, Jamaica, Lebanon, Lesotho, Montenegro, Oman andTurkey.

[25] The 25th and 75th percentiles of Θ^1 are 0.58 and 0.80, so that the demand elasticities are 0.41 and 0.46 respectively.

[26] See Cebeci et al. (2012) for details on the data set. In 2006, the countries for which the database provide information received 20 percent of Norwegian exports. The countries included are Albania, Bangladesh, Belgium, Burkina Faso, Bulgaria, Brazil, Botswana, Chile, Cameroon, Costa Rica, Dominican Republic, Ecuador, Estonia, Egypt, Spain, Guatemala, Iran, Jordan, Kenya, Cambodia, Laos, Morocco, Macedonia, Mali, Mauritius, Malawi, Mexico, Nicaragua, New Zealand, Peru, Pakistan, Sweden, Senegal, El Salvador, Turkey, Tanzania, Yemen and South Africa.

Columns (1) and (2) in Table 8 show that the same significant pattern holds in this case, although the magnitudes are not directly comparable due to the different measures of dispersion.

A second alternative data source providing information on dispersion is the Bureau van Dijk's Orbis database, which has information on over 100 million private companies across the world.[27] Unfortunately, Orbis does not cover all firms and, especially among smaller firms, sampling may vary across countries. We therefore calculate dispersion based on the population of firms with more than 50 employees. We calculate Pareto coefficients for firm employment, as in in the baseline case, for all countries with 1000 or more Orbis firms. In total, this gives us information on buyer dispersion for 48 countries, covering 89 percent of Norwegian exports (based on 2006 values).[28] The estimates in columns (3) and (4) of Table 8 show that using Orbis produces remarkably similar results to those reported for the baseline case in Table 7, even though the the sample of countries (and firms) is quite different compared to the baseline.

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 Θ^1. Specifically we regress Θ^1 on GDP per capita and use the fitted residual instead of Θ^1. The results are reported in columns (5) and (6) in Table 8. Overall the results are very similar to the baseline case in Table 7. A third concern is that the demand shock variable d_{mjt} may suffer from measurement error, as imports may not fully capture demand facing Norwegian firms. As a simple test, we instead replace d_{mjt} with GDP_{jt} as our proxy for demand. In this case, we cannot include country-year fixed effects , but we do include country fixed effects and a real exchange rate control variable. The results in columns (7) and (8) in Table 8 show the same pattern as in the baseline case, although the standard errors are somewhat higher.

In sum, we confirm one of the main predictions of the model: Export markets with more homogeneous buyer distributions have greater elasticities for both exports and the number of buyers than do markets with more heterogeneous firm distributions.

6.4 Sorting among Importers and Exporters

According to proposition 2, more importer heterogeneity is associated with less exporter heterogeneity. We test this prediction exploiting variation in dispersion across countries and products in our data. Specifically, we ask whether increased buyer dispersion in a market is correlated with less

[27] http://www.bvdinfo.com/Products/Company-Information/International/ORBIS.aspx and Alfaro and Chen (2013) for a thorough discussion of the coverage of the database.

[28] The 48 countries are Argentina, Austria, Australia, Bosnia and Herzegovina, Belgium, Bulgaria, Brazil, Belarus, Canada, Switzerland, Germany, Denmark, Estonia, Egypt, Spain, Finland, France, United Kingdom, Greece, Hong Kong, Croatia, Hungary, Ireland, India, Italy, Japan, Korea, Sri Lanka, Lithuania, Latvia, Morocco, Macedonia, Mexico, Netherlands, Peru, Poland, Portugal, Romania, Serbia, Russia, Sweden, Slovenia, Slovakia, Tunisia, Turkey, Ukraine, United States and South Africa.

dispersion among Norwegian exporters serving that market.

We proceed by defining a market as a country-product combination, where a product is defined as a unique 2 digit HS code. To measure buyer dispersion in a given market we again use the World Bank's Exporter Dynamics Database. The database contains information about dispersion in exports for different countries and HS 2 digit products. We proceed as in the previous section, and calculate the coefficient of variation Θ^4_{jp}, for each country j and each 2-digit HS product p. Moreover, we calculate corresponding measures of dispersion for Norwegian exporters, y_{jp}, serving market j for product p. The model we estimate is then

$$y_{jp} = \alpha_j + \delta_p + \mu\Theta^4_{jp} + \epsilon_{jp},$$

where α_j and δ_p are country and product fixed effects, and all variables are measured in logs.

This is a differences-in-differences model, where identification comes from comparing differences in dispersion across products within a country (first difference) across different countries (second difference). Country-specific variation in dispersion will be differenced out by α_j, while product-specific variation in dispersion will be differenced out by δ_p.

There are two potential concerns with the chosen approach. First, buyer dispersion is inferred from the value of exports, but as discussed above (see Section 6.3 and Appendix Section E), import dispersion is highly correlated with export dispersion. Second, as dispersion is measured per product, we implicitly make the assumption that the buyers of a product(e.g., beverages) are themselves exporting the same product. Although this certainly does not hold perfectly, we know from input-output tables that the sourcing matrix is dominated by the diagonal, i.e. that industries tend to source a significant share of their intermediates from themselves.[29]

Table 9 presents the results. As our dispersion measures can be calculated for each year, each column show the results for each 2005 to 2010 cross-section. For a product-destination pair to be included in the sample, we must choose a threshold for how many Norwegian firms are exporting to jp and how many foreign firms are exporting from jp. We choose a threshold of 30 or more firms in the first rows and 50 or more firms in the last rows.

Focusing on the first rows, in all years except 2006, the empirical estimates show that more buyer dispersion is significantly associated with less seller dispersion. The magnitudes are also quantitatively large; a one percent increase in buyer dispersion leads to a 0.3-0.7 decrease in seller dispersion. The last rows show results in the 50 firm threshold case. This decreases the number of country-product pairs included in the sample and increases the standard errors, but the magnitudes are largely unchanged. We conclude that the empirical evidence supports the prediction of our model.

[29]See the discussion of input-output linkages in Caliendo and Parro (2012).

7 Conclusion

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

We introduce a series of stylized facts about buyers in international trade which point to extreme concentration of exports across both sellers and buyers, distinct differences in the degree of dispersion of buyer expenditures across destinations, and Pareto shaped 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 that there is negative assortativity in the exporter-import matches. In other words, large exporters on average reach importers who buy from a relatively smaller number of foreign firms.

We develop a parsimonious model of heterogeneous exporters and importers where matches are subject to a relation-specific fixed cost. 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 relation-specific fixed cost. The response of firm-level exports to comparable demand shocks across destinations varies systematically with the dispersion of expenditures. Specifically, the export response is amplified in destinations with less buyer dispersion. Finally, we provide evidence supporting the theoretical prediction that more buyer dispersion in a market is associated with less dispersion in exports to that market.

These results suggest that demand-side characteristics plays 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.

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Appendix

A Equilibrium Sorting

The solution to the sorting function is:

$$\underline{z}_{ij}(Z) = \frac{\tau_{ij} w_i \Omega_j}{Z} f_{ij}^{1/(\sigma-1)} w_j^{-1/\gamma}$$

Proof. Equation (3) implicitly defines the $\underline{z}_{ij}(Z)$ function. We start with the guess $\underline{z}_{ij}(Z) = S_{ij} Z^s$ and the inverse $\underline{Z}_{ij}(z) = (z/S_{ij})^{1/s}$, where S_{ij} and s are unknowns. Furthermore, the relationship between E and Z is not yet determined, but we start with a guess $E_j(Z) = \kappa_3 w_j Z^\gamma$, where κ_3 is a constant term, and show in SectionB that this is consistent with the equilibrium. Inserting these expressions, as well as the price index (equation (1)), into equation (3) yields

$$\begin{aligned}
\frac{1}{\sum_k n_k (\bar{m}\tau_{kj} w_k)^{1-\sigma} (S_{kj} \underline{Z}^s)^{-\gamma_2}} &= \frac{\sigma f_{ij}}{E_j(\underline{Z})} \frac{\gamma z_L^\gamma}{\gamma_2} (\bar{m}\tau_{ij} w_i)^{\sigma-1} z^{1-\sigma} \\
\frac{\underline{Z}^{s\gamma_2+\gamma}}{\sum_k n_k (\bar{m}\tau_{kj} w_k)^{1-\sigma} S_{kj}^{-\gamma_2}} &= \frac{\sigma f_{ij}}{\kappa_3 w_j} \frac{\gamma}{\gamma_2} z_L^\gamma (\bar{m}\tau_{ij} w_i)^{\sigma-1} z^{1-\sigma}.
\end{aligned}$$

Hence,

$$\frac{1}{s} = \frac{1-\sigma}{s(\gamma_2 + \gamma/s)} \iff \frac{1}{s} = -1,$$

and

$$\begin{aligned}
\left(\frac{1}{S_{ij}}\right)^{1/s} &= \left[\frac{\sigma f_{ij}}{\kappa_3 w_j} \frac{\gamma z_L^\gamma}{\gamma_2} (\bar{m}\tau_{ij} w_i)^{\sigma-1} \sum_k n_k (\bar{m}\tau_{kj} w_k)^{1-\sigma} S_{kj}^{-\gamma_2}\right]^{1/(s\gamma_2+\gamma)} \iff \\
S_{ij} &= \left[\frac{\sigma f_{ij}}{\kappa_3 w_j} \frac{\gamma z_L^\gamma}{\gamma_2} (\tau_{ij} w_i)^{\sigma-1} \sum_k n_k (\tau_{kj} w_k)^{1-\sigma} S_{kj}^{-\gamma_2}\right]^{1/(\sigma-1)}. \qquad (11)
\end{aligned}$$

In sum, the cutoff is

$$\underline{z}_{ij}(Z) = \frac{S_{ij}}{Z}. \qquad (12)$$

□

We proceed by solving for $S_{ij}$and q_j. Inserting the expression for the cutoff (equation (12)) into the price index in equation (1) yields

$$q_j(Z)^{1-\sigma} = Z^{\gamma_2} \bar{m}^{1-\sigma} \frac{\gamma z_L^\gamma}{\gamma_2} \sum_k n_k (\tau_{kj} w_k)^{1-\sigma} S_{kj}^{-\gamma_2}.$$

Inserting the expression for S_{kj} from equation (11) then yields

$$q_j(Z)^{1-\sigma} = Z^{\gamma_2} \bar{m}^{1-\sigma} \frac{\kappa_3 w_j}{\sigma f_{ij}} \left(\frac{S_{ij}}{\tau_{ij} w_i}\right)^{\sigma-1}.$$

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},

$$\begin{aligned}
S_{ij}^{\sigma-1} &= (\tau_{ij} w_i)^{\sigma-1} \frac{\sigma f_{ij}}{\kappa_3 w_j} \frac{\gamma z_L^{\gamma}}{\gamma_2} \sum_k n_k (\tau_{kj} w_k)^{1-\sigma} (\tau_{kj} w_k)^{-\gamma_2} f_{kj}^{-\gamma_2/(\sigma-1)} \left(f_{kj}^{-1/(\sigma-1)} \frac{S_{kj}}{\tau_{kj} w_k} \right)^{-\gamma_2} \\
&= (\tau_{ij} w_i)^{\sigma-1} \frac{\sigma f_{ij}}{\kappa_3 w_j} \frac{\gamma z_L^{\gamma}}{\gamma_2} \left(f_{ij}^{-1/(\sigma-1)} \frac{S_{ij}}{\tau_{ij} w_i} \right)^{-\gamma_2} \sum_k n_k (\tau_{kj} w_k)^{-\gamma} f_{kj}^{-\gamma_2/(\sigma-1)} \quad \Longleftrightarrow \\
S_{ij}^{\gamma} &= (\tau_{ij} w_i)^{\gamma} \frac{\sigma}{\kappa_3 w_j} f_{ij}^{\gamma/(\sigma-1)} \frac{\gamma z_L^{\gamma}}{\gamma_2} \sum_k n_k (\tau_{kj} w_k)^{-\gamma} f_{kj}^{-\gamma_2/(\sigma-1)} \quad \Longleftrightarrow \\
S_{ij} &= \tau_{ij} w_i f_{ij}^{1/(\sigma-1)} w_j^{-1/\gamma} z_L \left(\frac{\sigma}{\kappa_3} \frac{\gamma}{\gamma_2} \sum_k n_k (\tau_{kj} w_k)^{-\gamma} f_{kj}^{-\gamma_2/(\sigma-1)} \right)^{1/\gamma}.
\end{aligned}$$

We define

$$\Omega_j \equiv \left(\frac{\sigma}{\kappa_3} \frac{\gamma}{\gamma_2} \sum_k \tilde{n}_k (\tau_{kj} w_k)^{-\gamma} f_{kj}^{-\gamma_2/(\sigma-1)} \right)^{1/\gamma},$$

and given the normalization $n_i = z_L^{-\gamma} \tilde{n}_i$, we get the closed form solution for the sorting function,

$$\underline{z}_{ij}(Z) = \frac{\tau_{ij} w_i \Omega_j}{Z} f_{ij}^{1/(\sigma-1)} w_j^{-1/\gamma}.$$

Note that we can now write the price index as

$$\begin{aligned}
q_j(Z)^{1-\sigma} &= Z^{\gamma_2} \bar{m}^{1-\sigma} \frac{\kappa_3 w_j}{\sigma f_{ij}} \left(\frac{S_{ij}}{\tau_{ij} w_i} \right)^{\sigma-1} \\
&= Z^{\gamma_2} \bar{m}^{1-\sigma} \frac{\kappa_3 w_j}{\sigma f_{ij}} \left(\frac{\tau_{ij} w_i f_{ij}^{1/(\sigma-1)} w_j^{-1/\gamma} \Omega_j}{\tau_{ij} w_i} \right)^{\sigma-1} \\
&= Z^{\gamma_2} \frac{\bar{m}^{1-\sigma} \kappa_3}{\sigma} w_j^{\gamma_2/\gamma} \Omega_j^{\sigma-1}.
\end{aligned}$$

B Final Goods Producers Expenditure on Intermediates and Productivity

In this section, we derive the equilibrium relationship between final goods expenditure E and productivity Z. Revenue for a final goods producer is

$$R_i = \left(\frac{P_i}{Q_i} \right)^{1-\sigma} \mu Y_i = \left(\frac{\bar{m} q_i(Z)}{Z Q_i} \right)^{1-\sigma} \mu Y_i,$$

where $P_i = \bar{m}q_i(Z)/Z$ is the price charged and Q_i is the CES price index for final goods. The price index for final goods is

$$\begin{aligned} Q_i^{1-\sigma} &= N_i \int_0^\infty P_i(Z)^{1-\sigma} dG(Z) \\ &= N_i \int_0^\infty (\bar{m}q_i(Z)/Z)^{1-\sigma} dG(Z) \\ &= N_i \frac{\bar{m}^{2(1-\sigma)}\kappa_3}{\sigma} w_i^{\gamma_2/\gamma} \Omega_i^{\sigma-1} \int_0^\infty Z^\gamma dG(Z) \\ &= \kappa_2 N_i w_i^{\gamma_2/\gamma} \Omega_i^{\sigma-1}, \end{aligned}$$

where $\kappa_2 = \frac{\bar{m}^{2(1-\sigma)}\kappa_3}{\sigma} \int_0^\infty Z^\gamma dG(Z)$. Rewriting revenue as a function of E, and inserting the equilibrium expression for $q_i(E)$, yields

$$\begin{aligned} \bar{m}E_i &= \left(\frac{\bar{m}q_i(Z)}{ZQ_i}\right)^{1-\sigma} \mu Y_i \\ &= \bar{m}^{1-\sigma} Z^{\sigma-1} \frac{Z^{\gamma_2} \frac{\bar{m}^{1-\sigma}\kappa_3}{\sigma} w_j^{\gamma_2/\gamma} \Omega_j^{\sigma-1}}{N_i \frac{\bar{m}^{2(1-\sigma)}\kappa_3}{\sigma} w_j^{\gamma_2/\gamma} \Omega_i^{\sigma-1} \int_0^\infty Z^\gamma dG(Z)} \mu Y_i \\ &= \frac{\mu}{\int_0^\infty Z^\gamma dG(Z)} Z^\gamma \frac{Y_i}{N_i} \quad \Longleftrightarrow \\ E_i(Z) &= \kappa_3 w_i Z^\gamma, \end{aligned} \tag{13}$$

where we collected the terms $\kappa_3 \equiv \mu(1+\pi)/\left[\bar{m}\int_0^\infty Z^\gamma dG(Z)\right]$. Hence, total spending on intermediates is increasing in productivity with an elasticity γ. Note that the expression for $E_i(Z)$ is the same as the one we started with in Section D.

C Firm-level Trade

Using equations (2) and (1), as well as the sorting function $\underline{Z}_{ij}(z)$, sales for a (z, Z) match are

$$r_{ij}(z,Z) = \left(\frac{p_{ij}(z)}{q_j(Z)}\right)^{1-\sigma} E_j(Z) = \sigma \left(\frac{zZ}{\tau_{ij} w_i \Omega_j}\right)^{\sigma-1} w_j^{(\sigma_s-1)/\gamma}. \tag{14}$$

Buyer productivity is distributed Pareto, $G(Z) = 1 - (Z_L/Z)^\Gamma$. We focus on the limiting case with $Z_L \to 0$ and $N_j = Z_L^{-\Gamma}\tilde{N}_j$, so that total firm-level exports to country j are

$$\begin{aligned} r_{ij}^{TOT}(z) &= N_j \int_{\underline{Z}_{ij}(z)} r_{ij}(z,Z)\, dG(Z) \\ &= \kappa_1 \tilde{N}_j f_{ij}^{1-\Gamma/(\sigma-1)} \left(\frac{z}{\tau_{ij} w_i \Omega_j}\right)^\Gamma w_j^{\Gamma/\gamma}, \end{aligned} \tag{15}$$

where $\kappa_1 \equiv \sigma\Gamma/[\Gamma - (\sigma-1)]$. Note that the integral in the price index for final goods (see section above and the definition of κ_3) is only finite when $\Gamma > \gamma$, hence we impose this restriction when $G(Z)$ is Pareto.

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

$$\underline{z}_{ij}(Z) = \left(\frac{\tau_{ij} w_i \Omega_j}{Z}\right) f_{ij}^{1/(\sigma-1)} w_j^{-1/\gamma}$$

$$r_{ij}^{TOT}(z) = \kappa_1 \tilde{N}_j f_{ij} \underline{Z}_{ij}(z)^{-\Gamma}.$$

Using the sorting function, we can also derive the measure of buyers in country j for a firm in country i with productivity z,

$$\begin{aligned} b_{ij}(z) &= N_j \int_{\underline{Z}_{ij}(z)} dG(Z) \\ &= \tilde{N}_j f_{ij}^{-\Gamma/(\sigma-1)} \left(\frac{z}{\tau_{ij} w_i \Omega_j}\right)^{\Gamma} w_j^{\Gamma/\gamma}. \end{aligned} \tag{16}$$

Knowing firm-level exports from equation (15) as well as the number of buyers from equation (16), the firm's average exports is given by

$$\frac{r_{ij}^{TOT}(z)}{b_{ij}(z)} = \kappa_1 f_{ij}. \tag{17}$$

The firm-level measure of sellers for a buyer with productivity Z is

$$L_{ij}(Z) = n_i \int_{\underline{z}_{ij}(Z)} dF(z) = \tilde{n}_i f_{ij}^{-\gamma/(\sigma-1)} \left(\frac{Z}{\tau_{ij} w_i \Omega_j}\right)^{\gamma} w_j. \tag{18}$$

Finally, equilibrium firm-level profits for intermediate producers is given by

$$\begin{aligned} \pi_{ij}(z) &= \frac{r_{ij}^{TOT}(z)}{\sigma} - f_{ij} b_{ij}(z) \\ &= \left(\frac{\kappa_1}{\sigma} - 1\right) \tilde{N}_j f_{ij}^{1-\Gamma/(\sigma-1)} \left(\frac{z}{\tau_{ij} w_i \Omega_j}\right)^{\Gamma} w_j^{\Gamma/\gamma}. \end{aligned}$$

D Sorting

Using the Norwegian trade 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 (18) and (4), the number of connections for the marginal customer of a firm with productivity z is $L_{ij}\left(\underline{Z}_{ij}(z)\right) = \tilde{n}_i z^{-\gamma}$. Using equation (16), we can rewrite this as

$$\underline{L}_{ij}(b_{ij}) = \tilde{n}_i \tilde{N}_j f_{ij}^{-\gamma/(\sigma-1)} (\tau_{ij} w_i \Omega_j)^{-\gamma} w_j b_{ij}^{-\gamma/\Gamma},$$

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

$$\begin{aligned}\hat{L}_{ij}(z) &= \frac{1}{1-G\left(\underline{Z}_{ij}(z)\right)}\int_{\underline{Z}_{ij}(z)} L_{ij}(Z)\,dG(Z) \\ &= \frac{\Gamma}{\Gamma-\gamma}\tilde{n}_i z^{-\gamma}.\end{aligned}$$

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

$$\hat{L}_{ij}(b_{ij}) = \frac{\Gamma}{\Gamma-\gamma}\tilde{n}_i \tilde{N}_j f_{ij}^{-\gamma/(\sigma-1)} \left(\tau_{ij} w_i \Omega_j\right)^{-\gamma} w_j b_{ij}^{-\gamma/\Gamma}.$$

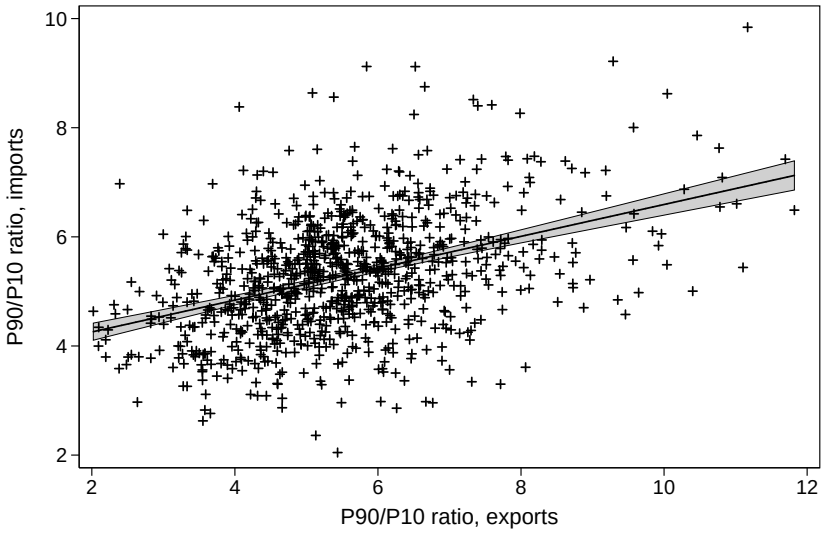
Hence, the elasticity of $\hat{L}_{ij}$ with respect to b_{ij} is $-\gamma/\Gamma$.

E Dispersion in exports and imports

In Section 6.4, we test the hypothesis that imports dispersion is negatively correlated with exports dispersion. As imports dispersion is not directly observed, we instead use exports dispersion from the World Banks Exporter Dynamics database (WBED) as a proxy for imports dispersion. The robustness check in Section 6.3 also uses the WBED data in the same way.

In this Section, we estimate the correlation between exports and imports dispersion using the Norwegian data. For the 2004 cross-section, we observe both export and import values by firm, product and year. We proceed as follows. First, the data is aggregated to the HS 2 digit level, as in Section 6.4. Second, the exports and imports log 90/10 percentile ratios are calculated for each product-destination combination. In Figure 8, we plot the resulting scatter for every product-destination pair with more than 10 firms present. Choosing a different threshold has a negligible impact on the results. The correlation is positive and significant, and the estimated slope coefficient is 0.29 (s.e. 0.02). This suggests that the WBED data should proxy imports dispersion reasonably well.

Figure 8: Heterogeneity of importer expenditure across markets.



Note: 2004 data. The figure shows log 90/10 percentile ratios for imports and exports for product-destination pairs with more than 10 firms present. The fitted regression line and 95% confidence intervals are denoted by the solid line and gray area. The slope coefficient is 0.29 (s.e. 0.02).

Table 1: Descriptive statistics.

	Sweden	Germany	US	China	OECD	non-OECD
Number of exporters	8,614	4,067	2,088	725	1,588.2	98.2
Number of buyers	16,822	9,627	5,992	1,489	3,055.6	144.5
Buyers/exporter, mean	3.6	3.6	4.5	3.6	2.7	1.6
Buyers/exporter, median	1	1	1	1	1	1
Exporters/buyer, mean	1.9	1.5	1.6	1.7	1.5	1.2
Exporters/buyer, median	1	1	1	1	1	1
Share trade, top 10% sellers	.94	.97	.96	.86	.90	.75
Share trade, top 10% buyers	.95	.95	.97	.89	.89	.73
Log max/median exports	10.7	11.4	11.2	7.9	8.7	4.6
Log max/median imports	10.8	10.8	11.7	8.4	8.4	4.6
Share in Norwegian total exports (in %)	11.3	9.6	8.8	2.1	81.6	18.4

Note: 2006 data. 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 dependent 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) Marginal buyer	(2) Largest buyer	(3) Exports	(4) # Buyers
d_{mjt}	.00	$.96^a$	$.43^a$	$.14^a$
	(.07)	(.08)	(.02)	(.01)
Country-year FE	Yes	Yes	Yes	Yes
Firm-year FE	Yes	Yes	Yes	Yes
N	8,106	8,106	105,756	105,756
Firms-years	4,055	4,055	44,068	44,068
Destinations	57	57	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. The dep. variables in columns (3) and (4) are the minimum (maximum) export value for a firm, across its buyers; $\min_b y_{mbjt}$ and $\max_b y_{mbjt}$. Sample is restricted to countries with information about dispersion from the World Bank Enterprise Surveys. Only exporters with $>$ 5 buyers in columns (3) and (4).

Table 7: Demand shocks and heterogeneity.

	(1) Exports	(2) # Buyers	(3) Exports	(4) # Buyers	(4) Exports	(4) # Buyers
d_{mjt}	.30^a	.04^b	.60^a	.27^a	.70^a	.30^a
	(.05)	(.02)	(.07)	(.03)	(.08)	(.03)
$d_{int} \times \Theta^1$ (Pareto)	.20^a	.15^a				
	(.08)	(.03)				
$d_{int} \times \Theta^2$ (P90/10)			-.04^b	-.03^a		
			(.02)	(.01)		
$d_{int} \times \Theta^3$ (Stddev)					-.18^a	-.11^a
					(.05)	(.02)
Country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	105,756	105,756	105,756	105,756	105,756	105,756
Firms-years	44,068	44,068	44,068	44,068	44,068	44,068
Destinations	75	75	75	75	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. Θ^1, Θ^2 and Θ^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) Exports	(2) # Buyers	(3) Exports	(4) # Buyers	(5) Exports	(6) # Buyers	(7) Exports	(8) # Buyers
d_{mjt}	.61^a	.27^a	.22^a	.03^c	.39^a	.17^a	.06	-.07
	(.11)	(.05)	(.04)	(.02)	(.01)	(.01)	(.26)	(.08)
$d_{mjt} \times \Theta^4$ (CV WBED)	-.11^a	-.06^a						
	(.04)	(.02)						
$d_{mjt} \times \Theta^5$ (Pareto Orbis)			.23^a	.16^a				
			(.04)	(.02)				
$d_{mjt} \times \Theta^6$ (Alt Pareto WBES)					.27^a	.21^a		
					(.08)	(.03)		
$d^{GDP}_{mjt} \times \Theta^1$ (Pareto WBES)							.50^c	.17^c
							(.29)	(.09)
Country FE	No	No	No	No	No	No	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Firm-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	90,951	90,951	296,045	296,045	103,716	103,716	102,856	102,856
Firms-years	58,939	58,939	100,895	100,895	43,757	43,757	43,732	43,732
Destinations	37	37	50	50	74	74	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. Θ^4 denotes the log coefficient of variation obtained from the World Bank's Exporter Dynamics Database (WBED); Θ^5 is the Pareto coefficient from Orbis data, see main text. Θ^6 is the residual purged from regressing the Pareto shape coefficient from the World Bank Enterprise Survey (WBES) on GDP/capita. d^{GDP}_{mjt} denotes the alternative demand measure based on country GDP.

Table 9: Buyer versus seller heterogeneity.

	Threshold	2005	2006	2007	2008	2009	2010
	30 firms	-.37^a	-.15	-.63^b	-.40^c	-.68^a	-.36^a
		(.11)	(.14)	(.22)	(.22)	(.15)	(.09)
N		101	107	52	56	47	23
Destinations		11	14	12	13	12	8
	50 firms	-.16	-.13	-.77^c	-.55^c	-.89^b	-.49^a
		(.21)	(.29)	(.39)	(.28)	(.37)	(.04)
N		72	73	28	29	27	12
Destinations		9	9	8	8	8	3
Country FE		Yes	Yes	Yes	Yes	Yes	Yes
Product FE (HS2)		Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the log coefficient of variation for Norwegian exports to a product-destination pair. The independent variable is the log coefficient of variation for foreign exports from a product-destination pair (WBED data). Robust standard errors in parentheses, clustered by country. ^{a} p$<$ 0.01, ^{b} p$<$ 0.05, ^{c} p$<$ 0.1. Each column represents a regression for a particular year. Threshold=30 firms uses a threshold of 30 or more buyers and sellers per country-product, while threshold=50 uses a threshold of 50 or more buyers and sellers per country-product.