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Abstract

This paper develops a multi-country model of international trade that provides a simple micro-foundation for buyer-seller relationships in trade. We explore a rich dataset that identifies buyers and sellers in trade and establish a set of basic facts that guide the development of the theoretical model. We use predictions of the model to examine the role of buyer heterogeneity in a market for firm-level adjustments to trade shocks, as well as to quantitatively evaluate how firms' marginal costs depend on access to suppliers in foreign markets.

Keywords: Heterogeneous firms, Exporters, Importers, Sourcing costs, Trade elasticity
JEL Classification: F10, F12, F14

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1 Introduction

Global trade is the sum of millions of transactions between individual buyers (importers) and sellers (exporters). Micro-level data has traditionally revealed exports of individual firms, summed across all buyers; or conversely, imports of individual firms, summed across all sellers. Naturally, theories of international trade have also focused on firms on either side of the market, exporters in Melitz (2003) or importers in Antràs et al. (2014). In this paper, we explore the individual matches between exporters and importers and examine the consequences of this micro-structure on firm-level and aggregate outcomes. In doing so, we build a model of international trade where exporters and importers are put on an equal footing.

We have access to a rich data set for Norwegian firms where the identities of both the exporter and the importer are known, and where a firm's annual export transactions can be linked to specific buyers in every destination country, and each firm's annual import transactions can be linked to specific suppliers in every source country. This allows us to establish a set of basic facts about sellers and buyers across markets which guide the development of a parsimonious multi-country theoretical model with two-sided heterogeneity.

In the model, 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 exporters reach many customers and their marginal customer is small; highly productive importers purchase from many sellers and their marginal supplier is small. This setup delivers parsimonious expressions for both upstream firms' exports and downstream firms' imports, which in equilibrium may differ because a seller can match to multiple buyers and a buyer can match to multiple suppliers. Buyer-seller matches are therefore entirely explained by selection based on heterogeneity and fixed costs. These represent the simplest possible ingredients of a model that are needed in order to explain broad features of the buyer-seller data.

Our theoretical modeling of the two-sided nature of trade brings several new insights. At the firm-level, trade integration lowers marginal costs among downstream firms by reducing the cost of inputs and by facilitating more matches between input suppliers and final goods producers. The importance of intermediate inputs for productivity growth has strong empirical support; Gopinath and Neiman (2014) find that a collapse in imports leads to a fall in productivity among Argentinian firms during the 2001-2002 crisis, while Amiti and Konings (2007), Goldberg et al. (2010) and Khandelwal and Topalova (2011) all find that declines in input tariffs are associated with sizable measured productivity gains. The model can generate firm-level responses to trade cost shocks that are consistent with the empirical evidence. Our work highlights that measured firm-level productivity gains not only arise from falling costs or access to higher quality inputs, but also from gaining access to new suppliers.

At the macro level, global trade will depend on the magnitude of relation-specific costs: lower relation-specific costs facilitate more matches between buyers and sellers, therefore generating more trade between nations as well as improving consumer welfare. In the aggregate, the model also retains the properties of one-sided models, as it gives us a simple gravity equation of bilateral trade flows as well as the same welfare results as in Arkolakis et al. (2012). In that sense, our model nests previous work while featuring a richer micro foundation.

We explore various empirical applications of the model starting with predictions for firm-level exports. For an exporter, lower variable trade costs in a destination country will lead to higher export growth when buyers in that market are less dispersed in terms of their productivity. When buyers are more similar, an exporter will find many new profitable matches, whereas if buyers are dispersed, only a few more matches will become profitable. In other words, the customer extensive margin response will be strong when buyer heterogeneity is low. We develop a theory-consistent sufficient statistic for unobservable trade costs and test this prediction by exploiting variation in import shares across industries and countries over time. We find strong empirical support for the prediction from the model. An implication of our work is therefore that characteristics on the importer side (such as buyer heterogeneity) matter for firm-level adjustment dynamics. The firm-level export response after a change to trade policy, exchange rate movements or other kinds of shocks, will vary across countries depending on characteristics of the importers.

Second, based on the predictions of the model we develop an empirical methodology to evaluate downstream firms' marginal cost response when foreign market access is changing due to a fall in trade barriers or a reduction in the pool of potential suppliers. We show that a sufficient statistic for a firm's change in marginal costs is the level of, and the change in, intermediate import shares and the trade elasticity. Evaluating the impact of the 2008-2009 trade collapse on firms' production costs, we find that worsened market access during the trade collapse had a substantial negative impact on production costs, especially for downstream firms with high ex-ante exposure to international markets. The empirical exercise also allows us to assess the fit of the model and to evaluate the relative importance of the supplier margin. Overall, the model does well in matching the fall in the number of buyer-seller connections during the trade collapse.

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. (2015) relate the importing activity of manufacturing firms to increases in productivity. In recent work, Blaum et al. (2015) develop a model of firm-level imports and show, as we do, that a firm's marginal costs depend on the share of intermediates sourced domestically as well as the trade elasticity. They generalize this result and show that this holds for a wide class of models, while our framework emphasizes the two-sided nature of trade, i.e. that one firm's exports is another firm's imports.

Papers by Rauch (1999), Rauch and Watson (2004), Antràs and Costinot (2011) and Petropoulou (2011) consider exporter-importer linkages. Chaney (2014) 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 (2010, 2011). 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; 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; 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. Monarch (2013) estimates switching costs using a panel of U.S importers and Chinese exporters and Dragusanu (2014) explores how the matching process varies across the supply chain using U.S.-Indian data. Sugita et al. (2014) study matching patterns in U.S.-Mexico trade while Benguria (2014) estimates a trade model with search costs using matched French-Colombian data. 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 the distribution of export sales across buyers within a product-country, while we study the implications of importer heterogeneity on exporting firms' responses to exogenous shocks to trade barriers and the role of buyer-seller matches in the marginal cost of importers.

The rest of the paper is structured as follows. In Section 2 we document the main dataset, and present a set of facts on the role of buyers in trade, the heterogeneity of buyers and sellers, and their bilateral relationships. In Section 3 we develop a multi-country trade model with heterogeneous sellers and buyers which is guided by the basic facts in Section 2. Section 4 tests the predictions of the model with respect to the impact of trade cost shocks and the role of importer heterogeneity on firm level performance and adjustment. Section 5 develops an empirical methodology to quantify the impact of supply shocks on downstream firms' marginal cost, while Section 6 concludes.

2 Exporters and Importers

2.1 Data

The main data set employed in this paper is based on Norwegian transaction-level customs data from 2004-2012. 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. 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.[1] Our data include the universe of Norwegian non-oil merchandise exports, and we observe export value and quantity. In 2005 total Norwegian non-oil merchandise exports amounted to US$41 Billion, equal to approximately 18 percent of Mainland Norway GDP (GDP excluding the oil and gas sector). The firm-level evidence from Norwegian non-oil exports looks remarkably similar to that of other developed countries, see Cebeci et al. (2012), Irarrazabal et al. (2013) and Mayer and Ottaviano (2008). Table 1 report the top 5 exported products from Mainland Norway.

2.2 Basic Facts

This section explores the matched buyer-seller data for Norwegian exporters. We establish the relevance of the buyer dimension as a margin of trade, and document a set of facts on the heterogeneity of buyers and sellers and their relationships. We let these facts guide our model of international trade and subsequent empirical specifications.

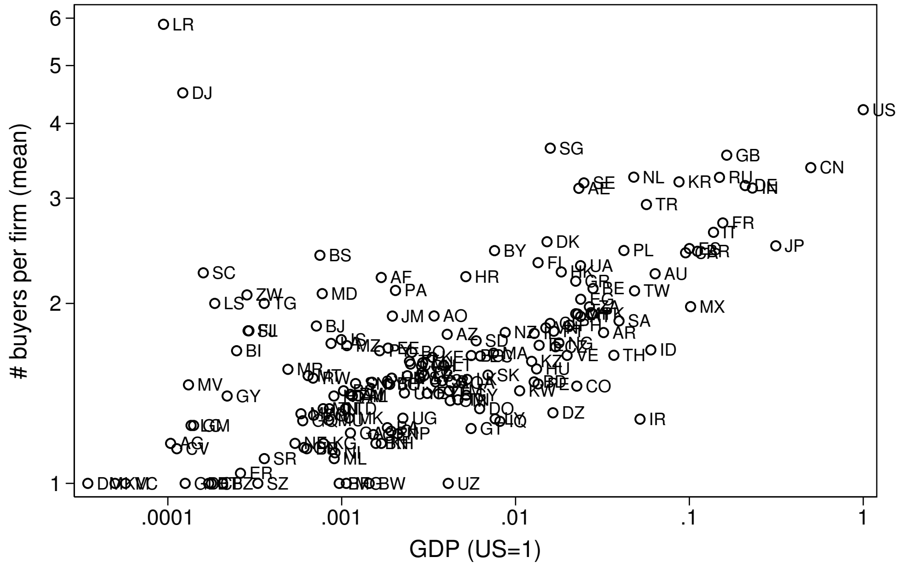
Fact 1: The buyer margin explains a large fraction of the variation in aggregate trade. To examine the role of buyers in the variation of exports across countries, we decompose total exports to country j, x_j, into the product of the number of exporting firms, f, the number of exported products, p, the number of buyers (importers), b, the density of trade, d, i.e. the fraction of all possible exporter-product-buyer combinations for country j for which trade is positive, and the average value of exports, $\bar{x}$. 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 exporter-product-buyer observations for which trade with country j is positive and $\bar{x_j} = x_j/o_j$ is average value per exporter-product-buyer. We regress

[1] Statistics Norway identifies buyers using the raw transaction-level records; however they aggregate the data to the annual level before allowing external access to the data.

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



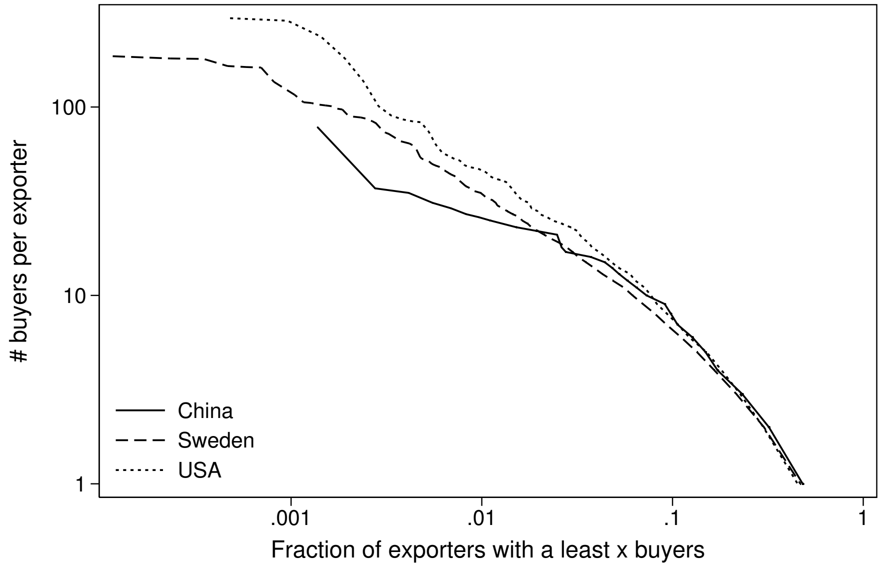
Note: 2006 Norwegian data, log scales. GDP from Penn World Table 7.1 (cgdp×pop), US normalized to 1.

the logarithm of each component 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. While it has been shown in a variety of contexts that the number of exporting firms and products increases as total exports to a destination increase, our results show the comparable 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 destination market characteristics such as GDP and distance. Looking within the firm across markets, we show how the buyer margin responds to these standard gravity variables by regressing a firm's number of customers on a firm fixed effect, distance and GDP in the destination market (all in logs). The results in Table 3 column 2 show that a firm's number of customers is significantly higher in larger markets and smaller in remote markets, i.e. importers per exporter vary systematically with GDP and distance.[2] The importance of market size is also illustrated in Figure 1. Here, the vertical axis denotes the average

[2]We also use total firm-level exports and average firm-level exports per buyer as dependent variables in columns 1 and 3.

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



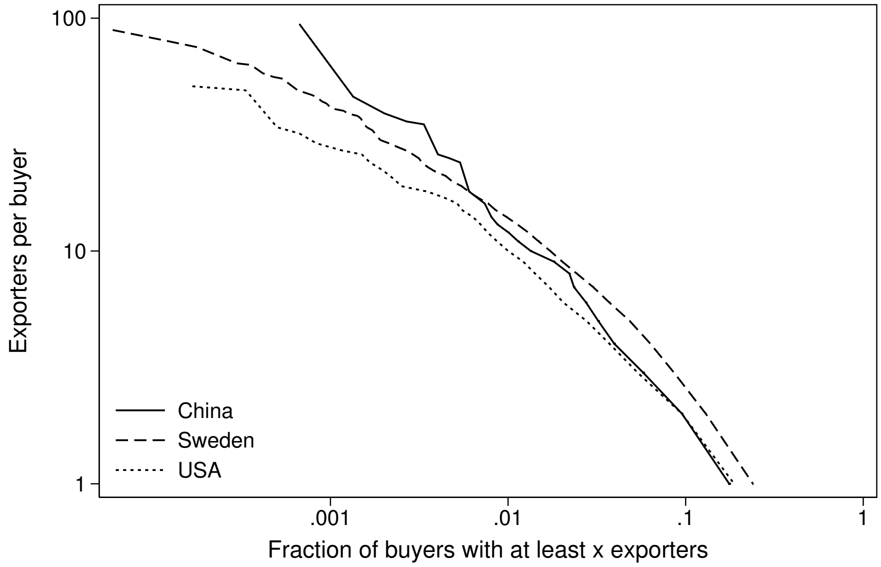
Note: 2006 Norwegian data, log scale. The estimated slope coefficients are -1.02 (s.e. 0.010) for China, -1.02 (s.e. 0.002) for Sweden and -1.13 (s.e. 0.005) for the U.S. The distribution is Pareto if the slope is constant. The slope coefficient equals the negative of the inverse of the Pareto shape parameter ($-1/a$, see footnote 3).

number of customers per Norwegian exporter while the horizontal axis denotes destination market GDP. The larger the market size, the greater the number of buyers for a given Norwegian exporter.

Fact 2: 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 (Table 4). Although a handful of exporters and importers account for a large share of aggregate trade, these large firms are matching with many partners; one-to-one matches are typically not important in the aggregate. Table 5 shows that one-to-one matches represent 9.5 percent of all exporter-importer connections but account for only 4.6 percent of aggregate trade. Many-to-many matches, i.e. where both exporter and importer have multiple connections, make up almost two thirds of aggregate trade. These facts motivate us to develop a model allowing for suppliers to match with several customers and buyers to match with multiple sellers.

Fact 3: The distributions of buyers per exporter and exporters per buyer are characterized by many firms with few connections and a few firms with many connections. 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

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



Note: 2006 data, log scale. The estimated slope coefficients are -0.92 (s.e. 0.002) for China, -0.88 (s.e. 0.001) for Sweden and -0.80 (s.e. 0.001) 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 3).

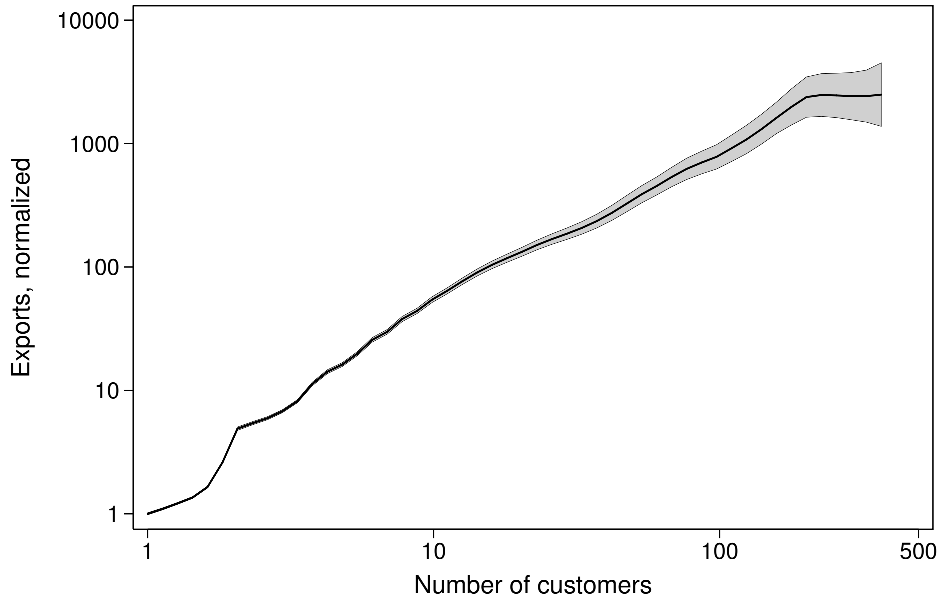
across markets, Figure 2 plots the results for China, the US and Sweden.[3] The average number of buyers per seller is 4.5 in the U.S. and 3.6 in China and Sweden (see Table 4). The distributions appear to be largely consistent with a Pareto distribution as the cdfs are close to linear except in the tails. The Pareto fails to capture the discreteness of the actual empirical distribution (the number of customers per exporter is discrete) but we view the Pareto as a continuous approximation of the discrete case.

We also plot the number of exporters per buyer in a particular market against the fraction of buyers in this market who buy from at least that many exporters (see Figure 3). Again the distributions are approximately Pareto, except in the tails, with many buyers having a few suppliers, and a few buyers with many suppliers. The average number of exporters per buyer in China, Sweden and the US is 1.7, 1.9 and 1.6, respectively.

Fact 4: Within a market, exporters with more customers have higher total sales, but the distribution of exports across customers does not vary systematically with the number of customers. Figure 4 plots the relationship between a firm's number of customers on the horizontal axis and its

[3]To interpret Figure 2 as the empirical CDF, let x_j^ρ be the ρth percentile of the number of buyers per exporter 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 $-1/a$.

Figure 4: Number of buyers & firm-level exports.



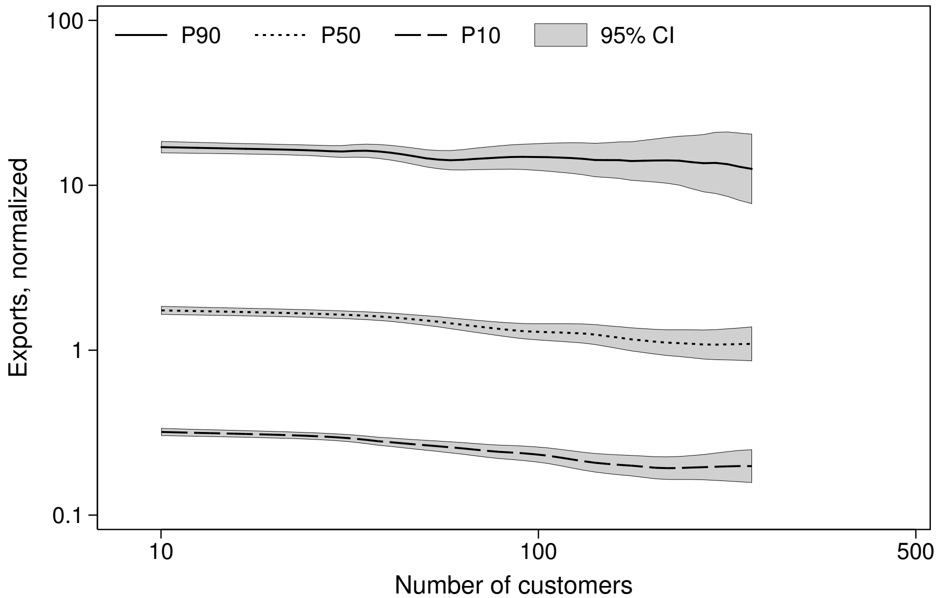
Note: 2006 data. The Figure shows the fitted line from a kernel-weighted local polynomial regression of log firm-destination exports on log firm-destination number of customers. Axes scales are in logs. Exports are normalized, see footnote 4.

total exports on the vertical axis using log scales. The solid line is the fit from a kernel-weighted local polynomial regression, and the gray area is the 95 percent confidence interval. We pool all destination countries and normalize exports such that average exports for one-customer firms in each destination equal 1.[4] Not surprisingly, firms with more buyers typically export more. The average firm with 10 customers in a destination exports more than 10 times as much as a firm with only one customer.

In Figure 5, we examine how the distribution of exports across buyers varies with the number of buyers. The plot shows the fitted lines from polynomial regressions of the 10th, median and 90th percentile of firm-level log exports (across buyers) and the log number of customers using log scales. We focus on firms with 10 or more customers because the 10th and 90th percentiles are not well defined for firms with fewer than 10 buyers. Again, we pool all destinations and normalize exports such that average exports for one-customer firms are 1. Firm-level exports to the median buyer are roughly constant, so that better-connected sellers are not selling more to their median buyer in a destination compared to less well-connected sellers. The 10th and 90th percentiles are also relatively

[4]The unit of observation is a firm-destination. Log exports are expressed relative to average log exports for one-customer firms, $\ln Exports_{mj} - \ln \overline{ExportsOCF_j}$, where $\ln Exports_{mj}$ is log exports from seller m to market j and $\ln \overline{ExportsOCF_j}$ is average log exports for one-customer firms in market j. This normalization is similar to removing country fixed effects from export flows. Furthermore it ensures that the values on the vertical axis are expressed relative to one-customer firms.

Figure 5: Number of buyers & within-firm dispersion in exports.



Note: 2006 data. The Figure shows the fitted lines from kernel-weighted local polynomial regressions of the x'th percentile of within-firm-destination log exports on firm-destination log number of customers. Axes scales in logs. Exports are normalized, see footnote 4.

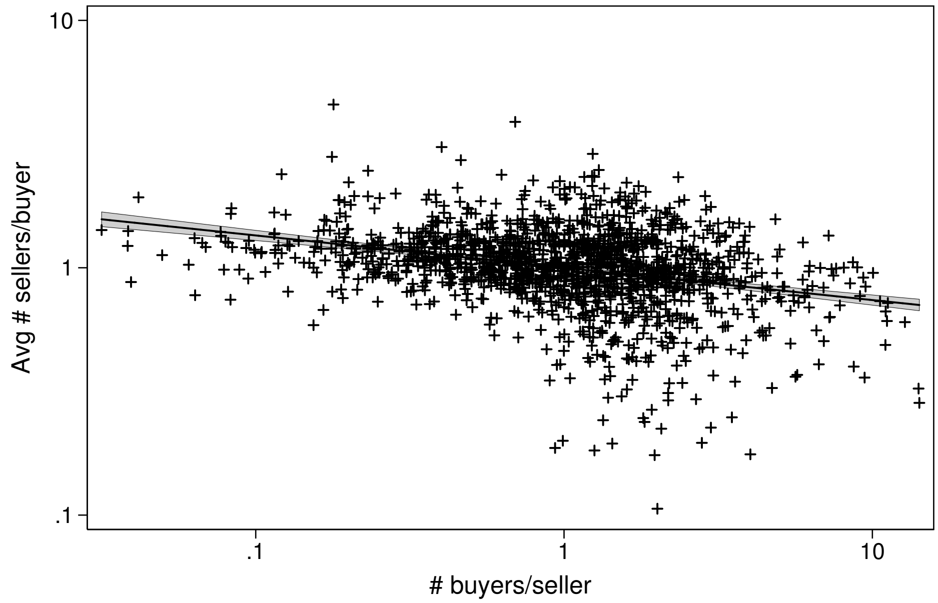
flat. Dispersion in firm-level exports (across buyers), measured as the difference between the 90th and 10th percentiles, is constant for firms with more than 10 buyers. In our theoretical model, the variation in firm sales in a market is driven by the extensive margin of the number of customers.

Fact 5: There is negative degree assortivity among sellers and buyers. We characterize sellers according to their number of buyers, and buyers according to their number of sellers. 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 demeaned and axes are in logs.[5] The interpretation of a point with the coordinates (10,0.1) is that the customers of Norwegian exporters in a market with 10 times more customers than average have 1/10th the average number of Norwegian suppliers. The slope of 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] In recent work by Bernard et al. (2014), negative degree assortivity is also found for

[5]This Figure shows $b_j(a_j)/\bar{b}_j(a_j)$, where $\bar{b}_j(a_j)$ 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. Estimating the relationship separately for each country,

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 j, a_j, on the x-axis, and the average number of Norwegian connections among these buyers, $b_j(a_j)$, on the y-axis. Axes scales are in logs. Both variables are demeaned, i.e. we show $b_j(a_j)/\bar{b_j}(a_j)$, 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. 0.01).

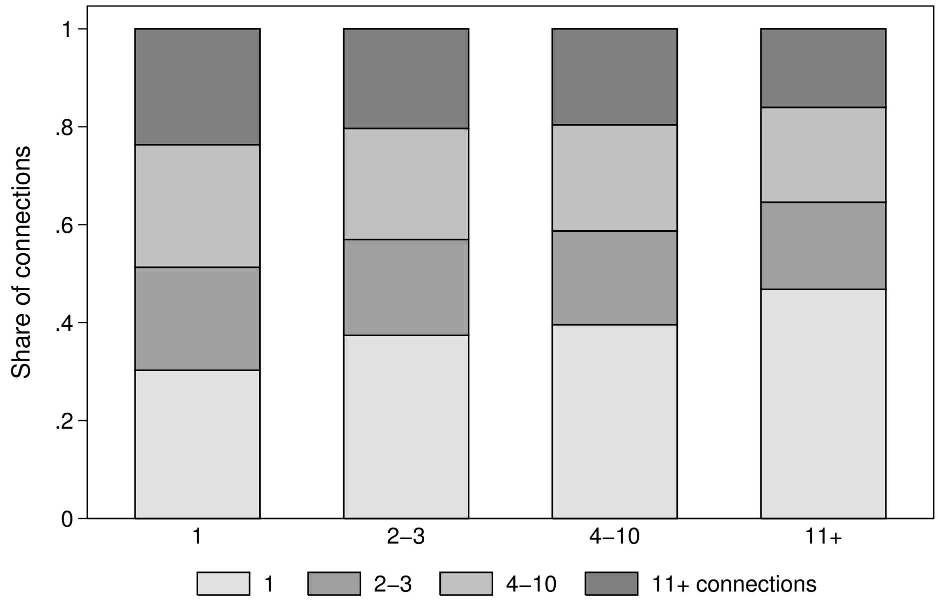
buyer-seller links among Japanese firms. Their Japanese dataset covers close to the universe of domestic buyer-seller links and therefore contains information about the full set of buyer linkages (not only the linkages going back to the source market,).

Negative degree assortivity does not mean that well-connected exporters only sell to less-connected buyers; instead it suggests that well-connected exporters typically sell to *both* well-connected buyers and less-connected buyers, whereas less-connected exporters typically *only* sell to well-connected buyers. This is illustrated in Figure 7. We divide firms into groups with 1 connection, 2-3, 4-10 and 11+ connections in Sweden, the largest market for Norwegian exporters.[7] For each group, we then calculate the share of customers that have 1 Norwegian connection, 2-3, 4-10 and 11+ Norwegian connections. The far left bar shows that among exporters with 1 Swedish connection, around 30 percent of the total number of matches are made with buyers with 1 Norwegian connection. The far right bar shows that among exporters with 11+ Swedish connections, almost

instead of pooling all countries, produces a negative assortivity coefficient for 89 percent of the countries we have sufficient data for (defined as countries with 10 or more observations in the regression). In appendix G, we show that the elasticity is informative of a structural parameter of the model.

[7]The median, 75th percentile and 90th percentile number of number of customers per exporter is 1, 3 and 7 respectively. Patterns for other markets are broadly similar.

Figure 7: Matching buyers and sellers.



Note: 2006 data. Destination market is Sweden. Each bar represents a group of exporters. The groups are (i) Firms with 1 connection, (ii) 2-3, (iii) 4-10 and (iv) 11+ connections. For each group, we plot the share of buyers that have 1, 2-3, 4-10, 11+ connections. For example, the left bar shows that among exporters with 1 connection, roughly 30 percent of these connections are made with buyers that also have 1 connection.

half of the number of matches made are with buyers with 1 Norwegian connection. Hence, better connected exporters are much more exposed to single-connection buyers.

Degree assortivity is only a meaningful measure in economic environments with many-to-many matching. Moreover, negative degree assortivity can coexist with positive assortative matching on the intensive (export value) margin. For example, Sugita et al. (2014) study one-to-one matches in Mexico-U.S. trade and find evidence that more capable sellers typically match with more capable buyers.[8] In fact, this would also be the outcome of a one-to-one matching version of our model because the profits of a match are supermodular in seller and buyer efficiency, see Appendix C.[9]

[8]Dragusanu (2014) and Benguria (2014) also find evidence of positive assortivity on the intensive margin.

[9]Social networks typically feature positive degree assortivity, that is, highly connected nodes 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). In the friendship network among prison inmates considered by Jackson and Rogers (2007), the correlation between a node's in-degree (incoming connections) 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.

2.3 Robustness

The basic facts presented here show empirical regularities between buyers and sellers irrespective of the product dimension. However, firms with many customers are typically firms selling many products. To control for the product dimension, we recalculate the facts using the firm-product as the unit of analysis.[10] The qualitative evidence from the facts reported above remains robust to this change. These findings suggest that the basic facts cannot be explained by variation in the product dimension alone.

Products in the data are a mix of homogeneous and differentiated goods. We therefore recalculate the facts above for differentiated products only. Specifically, we drop all products that are classified as "reference priced" or "goods traded on an organized exchange" according the the Rauch classification.[11] The qualitative evidence from the facts section remains robust to this change. A different concern is that the data includes both arm's length trade and intra-firm trade. We drop all Norwegian multinationals from the dataset and recalculate the facts.[12] Again, the evidence is robust to this change.

The data used in this paper is the universe of non-oil merchandise exports and a subset of the exporters are outside manufacturing. We match the customs data to the manufacturing census, which allows us to remove exporters outside manufacturing. The qualitative evidence from the facts reported above remains robust to this change.[13]

An additional concern is that Norway may somehow be unusual and the facts are not found elsewhere. In Appendix J, we test the external validity of our results using import data from Colombia that has similar buyer-seller information to that in the Norwegian data. We find that the basic facts also hold in the Colombian data.

Finally, one may question if the basic facts presented above can be generated from a simple stochastic process where buyers and sellers meet randomly. If so, a theory for the relationship between exporters and importers may seem superfluous. We investigate this in Appendix Section I, where we simulate a balls and bins model of trade similar to Armenter and Koren (2013). The main finding is that a random model fails to explain key empirical characteristics of exporter-importer connections.

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

[11] The Rauch classification is concorded from SITC rev. 2 to 6 digit HS 1996 using conversion tables from the UN (http://unstats.un.org/unsd/trade).

[12] The trade transactions themselves are not identified as intra-firm or arm's length. Norwegian multinationals account for 38 percent of the total value of Norwegian exports.

[13] The export value for non-manufacturing firms is 9 percent relative to total exports in 2006. Detailed results available upon request.

3 A Trade Model with Two-Sided Heterogeneity

In this section, we develop a multi-country trade model that provides a micro-foundation for buyer-seller relationships and allows us to examine the role of buyer heterogeneity and buyer-seller links for firm-level adjustments. As in Melitz (2003), firms (sellers) within narrowly defined industries produce with different efficiencies. 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.

3.1 Setup

Each country i is endowed with L_i workers, and the labor market is characterized by perfect competition, so that wages are identical across sectors and workers. In each country there are three sectors of production: a homogeneous good sector characterized by perfect competition, a traded intermediates sector and a non-traded final goods sector; the two last sectors are characterized by monopolistic competition. Workers are employed in the production of the homogeneous good as well as the production of the intermediates.[14] 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 an aggregate 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 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,

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

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

where productivity for firm υ is denoted by $Z(\upsilon)$, which is drawn from the Pareto distribution $G(Z) = 1 - Z^{-\Gamma}$ with support $[1, \infty)$. $c(\omega)$ 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 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, the act of meeting a buyer and setting up a supplier contract is 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.[15] 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, buyer-seller links are the result of intermediate firms that endogenously choose their set of customers.

The total mass of buyers and sellers, N_i and n_i', in each country i is proportional to total income Y_i, so there are more firms in larger economies. As there is no free entry, the production of intermediates and final goods leaves rents. We follow Chaney (2008) and assume that consumers in each country derive income not only from labor but also from the dividends of a global mutual fund. Each consumer owns 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. Appendix H develops an extension of the model where the number of buyers N_i is determined by a free entry condition; in that case the number of buyers N_i is indeed proportional to country income Y_i.[16]

Variable trade barriers. Intermediates are traded internationally, and firms face 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.[17]

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 generates a profitable match for a seller in i with productivity z. We solve

[15] Kang et al. (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.

[16] Introducing free entry on the seller side is more complex, as there is no closed-form solution for the number of sellers in a market n_i.

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

for $\underline{Z}_{ij}(z)$ in Section 3.3. 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.[18] 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. 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. The specific form of $E_j(Z)$ depends on the equilibrium sorting pattern in the economy, see Section 3.3 and Appendices A-B.

3.2 A Limiting Case

Because the lower support of the seller productivity distribution is z_L, a buyer (final goods producer) can potentially meet every seller (intermediate goods producer) in the economy. An implication is that we have two types of buyers: (i) buyers that match with a subset 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 $\underline{z}_{ij}(Z) \leq z_L$.

The discontinuity of the Pareto distribution at z_L is inconvenient, as the sorting function $\underline{z}_{ij}(Z)$ will be non-smooth (not continuously differentiable) and important relationships will not have closed-form solutions. 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. In addition, we assume that the measure of sellers is an inverse function of the

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

productivity lower bound, $n_i = z_L^{-\gamma} n_i'$, where n_i' is the normalized measure of sellers. Therefore, a lower productivity threshold is associated with more potential firms.[19] 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.

The support of the buyer distribution is $[1, \infty)$, which means that a highly productive seller can potentially meet every buyer in the market. This discontinuity is analytically tractable, so we allow for this to occur in equilibrium. We denote the productivity of the marginal seller that meets every buyer $z_H \equiv \underline{z}_{ij}(1)$. Hence, sellers with $z \geq z_H$ meet every buyer in the market.

3.3 Equilibrium Sorting

Based on the setup presented in Section 3.1, 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 $\pi_{ij}(z, Z) = r_{ij}(z, Z)/\sigma - w_i f_{ij}$. Given the optimal price from Section 3.1, 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

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

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 Appendices 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:

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

where

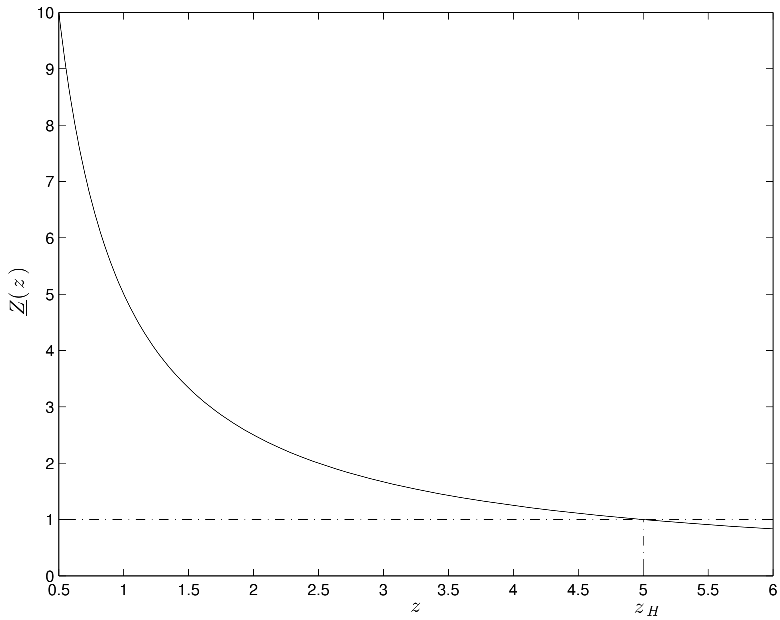
$$\Omega_j = \left(\frac{\sigma}{\kappa_3} \frac{\gamma}{\gamma_2} \sum_k Y_k (\tau_{kj} w_k)^{-\gamma} (w_k f_{kj})^{-\gamma_2/(\sigma-1)} \right)^{1/\gamma}, \quad (5)$$

and κ_3 is a constant.[20] These expressions are valid under any distribution for buyer productivity, i.e. it is not necessary to assume Pareto distributed buyer productivity to derive this particular result.

[19] n_i' is constant as $z_L \to 0$. The normalization is similar to Oberfeld (2013).

[20] $\kappa_3 = \mu (\Gamma - \gamma)/\Gamma$.

Figure 8: Matching function.



We plot the matching function $\underline{Z}_{ij}(z)$ in Figure 8.[21] $\underline{Z}_{ij}(z)$ is downward sloping in z, so more efficient sellers match with less efficient buyers on the margin. The point z_H on the horizontal axis denotes the cutoff productivity where a seller matches with every buyer. 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 8 shifts towards the origin). Higher wages in country i mean that exporters (from i) cannot profitably match with lower efficiency buyers. Conversely higher GDP in the destination market, Y_j, increases the range of profitable matches.

The model is multi-country in that matching costs, variable trade costs, and wages in third countries affect the buyer cutoff between i and j. A firm from i matches with a greater range of (lower efficiency) buyers in j when trade costs from third countries to j are higher (market access to j, Ω_j, is lower). This occurs because the downstream firms' price index on inputs, $q_j(Z)$ is decreasing in market access Ω_j, see equation (19) in Appendix A. Ω_j in equation (5) therefore has a similar interpretation as the multilateral resistance variable in Anderson and van Wincoop (2004). Highly productive downstream firms also will have a lower input price index, i.e. $q_j(Z)$ is decreasing in Z. Hence, all else equal, a given seller will face tougher competition when selling to a high productivity buyer (which will in equilibrium have many suppliers).

3.4 Firm-level Exports and Imports

Having determined the equilibrium sorting function between intermediate and final goods producers, we can now derive equilibrium expressions for firm-level exports and imports and decompose trade

[21] The Figure is based on parameter values $\tau_{ij} w_i \Omega_j (w_i f_{ij})^{1/(\sigma-1)} (Y_j/N_j)^{-1/\gamma} = 5$.

into the extensive margin in terms of number of buyers (suppliers) and the intensive margin in terms of sales per buyer (supplier).

Firm-level Exports Using (2), for a given firm with productivity $z < z_H$, 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 C, we show that firm-level intermediate exports to market j are

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

where κ_1 is a constant.[22] The corresponding expression for firms with $z \geq z_H$ is shown in Appendix C. The $z > z_H$ case is in our context less interesting because the seller will match with every buyer and the expression for firm-level trade therefore resembles the case with no buyer heterogeneity. The sorting function also allows us to determine marginal exports, i.e. exports to the least productive buyer. We insert equation (4) into (22) which yields

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

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 an upstream firm with productivity $z < z_H$ in country i (see Appendix C), which yields

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

We emphasize two properties of these results. First, a firms will sell more in larger markets (higher Y_j), but the marginal export flow, i.e. a firm's transaction to the smallest buyer, is unaffected by market size because the marginal transaction is pinned down by the magnitude of the relation-specific fixed cost.[23] Second, the elasticity of exports and of the 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 Krugman (1980)). 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 e.g. a decline in trade barriers. Consequently, trade liberalization in a destination market with low heterogeneity among importers translates into higher export growth than in a market with high heterogeneity among importers. We summarize these findings in the following proposition.

[22] $\kappa_1 \equiv \sigma\Gamma / [\Gamma - (\sigma - 1)]$.

[23] Also a higher match cost f_{ij} dampens both firm exports and the number of buyers because $1 - \Gamma/(\sigma - 1) < 0$, given the previous restrictions that $\gamma - (\sigma - 1) > 0$ and $\Gamma > \gamma$.

Proposition 1. *For $z < z_H$, the elasticity of firm-level exports with respect to variable trade costs equals Γ, the Pareto shape coefficient for buyer productivity.*

A potential concern is that this result are not robust to other distributional assumptions. Section D in the Appendix derives general expressions for the firm-level trade elasticity given *any* distribution for buyer productivity. We show that the qualitative result that the elasticity is higher in markets with less buyer dispersion continues to hold for many commonly used distributions (lognormal, exponential and Frechet).

Firm-level Imports The model also delivers parsimonious expressions for a downstream firm's intermediate imports as well as a firm's measure of suppliers. Appendix C shows that intermediate imports from country i to a downstream firm in j are

$$R_{ij}^{TOT}(Z) = \kappa_4 Y_i (w_i f_{ij})^{1-\gamma/(\sigma-1)} \left(\frac{Z}{\tau_{ij} w_i \Omega_j} \right)^{\gamma}, \tag{9}$$

while the measure of suppliers is

$$L_{ij}(Z) \quad = \quad Y_i (w_i f_{ij})^{-\gamma/(\sigma-1)} \left(\frac{Z}{\tau_{ij} w_i \Omega_j} \right)^{\gamma}. \tag{10}$$

At the firm level, an upstream firm's exports to country j, r_{ij}^{TOT}, are not identical to a downstream firm's imports from i, R_{ij}^{TOT}. At the aggregate level, of course, total export revenue must equal total import costs between i and j.

In the model, falling trade barriers or a greater number of potential suppliers lower marginal costs among downstream firms by reducing the cost of inputs and by facilitating more matches between input and final goods producers. Specifically, as shown in Appendix A equation (19), the marginal cost of a final goods producer in country j is inversely proportional to the market access term Ω_j. We summarize this in the following proposition:

Proposition 2. *A downstream firm's marginal costs are inversely proportional to the market access term Ω_j.*

This result follows directly from the sorting function described in equations (4) and (5). Hence, Proposition 2 holds for any distribution of buyer productivity, not just Pareto.

The importance of intermediate inputs for productivity growth has strong empirical support. Gopinath and Neiman (2014) find a large productivity decline due to an input cost shock during the 2001-2002 Argentinian crisis, while Amiti and Konings (2007), Goldberg et al. (2010) and Khandelwal and Topalova (2011) all find that declines in input tariffs are associated with sizable measured productivity gains. Hence, the model generates firm-level responses to trade cost shocks that are consistent with the empirical evidence. Moreover, our theoretical results show that measured productivity gains can arise not only from falling costs or access to higher quality inputs, but also from gaining access to new suppliers. We will apply this insight later in Section 5.

3.5 Aggregate Trade

We now proceed to derive expressions for total trade and welfare. Aggregate trade from i to j is

$$X_{ij} \quad = n_i N_j \int_1 \int_{\underline{z}_{ij}(Z)} r_{ij}(z, Z)\, dF(z)\, dG(Z).$$

Solving the integrals, the trade share $X_{ij}/\sum_k X_{kj}$ is[24]

$$\pi_{ij} \equiv \frac{X_{ij}}{\sum_k X_{kj}} = \frac{Y_i (w_i f_{ij})^{1-\gamma/(\sigma-1)} (\tau_{ij} w_i)^{-\gamma}}{\sum_k Y_i (w_k f_{kj})^{1-\gamma/(\sigma-1)} (\tau_{kj} w_k)^{-\gamma}}. \tag{11}$$

We emphasize two implications for aggregate trade. First, higher relation-specific cost f_{ij} reduces the number of matches between exporters and importers and therefore dampens aggregate trade with a partial elasticity $1-\gamma/(\sigma-1) < 0$. Second, the partial aggregate trade elasticity with respect to variable trade barriers, $\partial \ln X_{ij}/\partial \ln \tau_{ij}$, is $-\gamma$, the Pareto coefficient for seller productivity. This result mirrors the finding in models with one-sided heterogeneity, e.g. Eaton et al. (2011). Our model produces similar macro trade elasticities compared to models with one-sided heterogeneity while being able to explain a range of new facts at the micro level.

It may seem surprising that the aggregate trade elasticity is γ, given that the firm-level elasticity is Γ. This occurs because the aggregate elasticity is the weighted average of firm-level elasticities for $z < z_H$ firms and $z \geq z_H$ firms. These elasticities are Γ and $\sigma - 1$ respectively (see Appendix C). In equilibrium, the weighted average of the two becomes γ.[25]

Real wages in our model are

$$\frac{w_j}{Q_j} \quad = \quad \kappa_6 Y_j^{2/\gamma} \left(\frac{f_{jj}}{L_j}\right)^{-\gamma_2/[\gamma(\sigma-1)]} \frac{\pi_{jj}^{-1/\gamma}}{\tau_{jj}}, \tag{12}$$

where Q_j is the price index on final goods in j and κ_6 is a constant (see Appendix E).[26] Higher spending on home goods (higher π_{jj}) lowers real wages with an elasticity $1/\gamma$, mirroring the finding in Arkolakis et al. (2012).

3.6 Linking Facts and Theory

In presenting the model we pointed out that our theory was guided by the basic facts on buyer-seller relationships presented in Section 2.2. This section revisits the basic facts and examines the extent to which the model fits them.

[24] We can alternatively write $X_{ij} = \kappa_5 n_i' Y_j (w_i f_{ij})^{1-\gamma/(\sigma-1)} (\tau_{ij} w_i \Omega_j)^{-\gamma}$ where $\kappa_5 = \Gamma\sigma\gamma/[\gamma_2(\Gamma-\gamma)]$.

[25] Aggregate trade can alternatively be written $X_{ij} = n_i \int_{z_L}^{z_H} r_{ij}^{TOT}(z)\, dF(z) + n_i \int_{z_H}^{\infty} \tilde{r}_{ij}^{TOT}(z)\, dF(z)$, where $\tilde{r}_{ij}^{TOT}(z)$ is exports for $z > z_H$ firms (see Appendix C). Solving the two integrals yields the same expression for X_{ij} as the equation above.

[26] $\kappa_6 = \left(\frac{\sigma}{\kappa_3}\frac{\gamma}{\gamma_2}\right)^{1/\gamma} \left(\bar{m}^{2(1-\sigma)}\frac{\mu}{\sigma}\right)^{1/(\sigma-1)} (1+\psi)^{-1/\gamma+1/(\sigma-1)}$.

According to Fact 1 and Table 3 a firm's number of customers is increasing in GDP and decreasing in distance. As displayed in equation (8), according to the model, the number of buyers per firm increases with market size and falls with trade costs, with elasticities 1 and $-\Gamma$ respectively.

The distribution of firm-level exports $r_{ij}^{TOT}(z)$, imports $R_{ij}^{TOT}(Z)$, the number of customers per exporter $b_{ij}(z)$ and the number of exporters per customer $L_{ij}(Z)$, are all Pareto, consistent with Facts 2 and 3.[27]

Fact 4 states that while total firm-level exports are increasing in the number of customers, the distribution of exports across buyers is roughly invariant to the firm's number of customers. In our model, the within-firm sales distribution is (see Appendix F)

$$\Pr\left[r_{ij} < r_0 \mid z\right] = 1 - \left(\frac{\sigma w_i f_{ij}}{r_0}\right)^{\Gamma/(\sigma-1)},$$

so that all exporters to a market j have the same Pareto distribution of sales across buyers.

Fact 5 shows that highly connected exporters to market j have, on average, customers that have few connections to Norwegian exporters. In the model, among exporters from i with b_{ij} customers in j, the average number of connections in i among these customers is (see Appendix G):

$$\hat{L}_{ij}(b_{ij}) = \frac{\Gamma}{\Gamma-\gamma}\left(\frac{b_{ij}}{b_{ij}(1)}\right)^{-\gamma/\Gamma}.$$

Hence, the elasticity is negative with a slope coefficient $-\gamma/\Gamma$.

4 Firm-level adjustment to trade shocks

Proposition 1 states that the firm-level trade elasticity with respect to variable trade barriers is higher when importer productivity is less dispersed. In this section, we aim to test this main prediction of the model.

A sufficient statistic. An empirical challenge is that we do not directly observe either variable trade barriers τ_{ij} or the market access term Ω_j. We solve this by obtaining a sufficient statistic based on the predictions of the model. We proceed as follows. From equation (11), we know that the aggregate trade share is

$$\pi_{ij} = Y_i \left(w_i f_{ij}\right)^{1-\gamma/(\sigma-1)} \left(\Omega_j \tau_{ij} w_i\right)^{-\gamma}.$$

Solving this for $\Omega_j \tau_{ij} w_i$ and inserting it back into the expression for firm-level exports in equation (6) gives us

$$r_{ij}^{TOT}(z) = \kappa_1 Y_j Y_i^{-\Gamma/\gamma} \left(w_i f_{ij}\right)^{1-\Gamma/\gamma} \pi_{ij}^{\Gamma/\gamma} z^{\Gamma}. \tag{13}$$

[27] The distributions of buyers per seller and sellers per buyer in the model are exactly Pareto while those in the data approximate a Pareto except in the tails. Adding random matching to the model would allow the theoretical cdfs to more closely align with the empirical cdfs.

Hence, the unobserved variable trade cost and market access terms are replaced by the observable trade share π_{ij}.

Empirical specification. We take the logs of equation (13), add subscripts m, k and t to denote firm, industry and year, respectively, and remove subscript i as Norway is always the source country in our data. Furthermore, we add a subscript j to the importer heterogeneity term Γ, as we want to use differences in importer heterogeneity as a source of identification. This gives us

$$\ln x_{mjkt} = \alpha_{mj} + \delta_{jt} + \ln Y_{jkt} + \frac{\Gamma_j}{\gamma} \ln \pi_{jkt},$$

where $\ln x_{mjkt}$ denotes a firm-level export variable, α_{mj} is a firm-country fixed effect, which captures time-invariant firm-country-specific factors such as idiosyncratic demand across destinations, and δ_{jt} is a destination-year fixed effect which captures time-varying country-wide shocks such as the real exchange rate or changes in relation-specific costs. We choose to work with empirical specifications exploiting industry-level variation (subscript k) because this allows us to include country-year fixed effects. This is potentially important because those fixed effects will absorb various factors that may be correlated with the trade shares π_{jkt}. In the robustness section below, we also experiment with other combinations of fixed effects.

We do not have sufficient variation in the Norwegian data to estimate every single measure of buyer dispersion Γ_j across markets. Instead we choose to calculate Γ_j using an international cross-country database (see next Section) on the firm size distribution. Specifically, we estimate

$$\ln x_{mjkt} = \alpha_{mj} + \delta_{jt} + \beta_1 \ln Y_{jkt} + \beta_2 \ln \pi_{jkt} + \beta_3 \ln \pi_{jkt} \times \Gamma_j + \epsilon_{mjkt}, \tag{14}$$

where we have added an error term ϵ_{mjkt}. Because $\partial \ln x_{mjkt}/\partial \ln \pi_{jkt} = \beta_2 + \Gamma_j \beta_3$, the prediction of our model is that $\beta_3 > 0$, so that the elasticity is higher in markets with less importer dispersion.

Instrumental variable approach. A concern is that changes in the trade shares π_{jkt} are endogenous. For example, high productivity growth among one or several Norwegian firms could increase Norway's total market share, creating a causal relationship from firm-level export growth to the aggregate trade share. We deal with this by using the remaining Nordic countries' trade share, $\pi_{Nordic,jkt}$, as an instrument for Norway's trade share, π_{jkt}.[28] Because of geographical and cultural proximity, as well as substantial economic integration among the Nordic countries, their trade shares are highly positively correlated (see Section 2.1). The exclusion restriction is that changes in the Nordic market share do not directly impact Norwegian firm-level exports. Although we cannot completely rule this out, we find it unlikely because the Nordic market shares are typically very small in other countries (see Section 4.1). Moreover, if the exclusion restriction is not fully satisfied, then our estimator would be negatively biased, suggesting that the 2SLS estimates can be interpreted as a lower bound. We estimate the model by 2SLS using $\ln \pi_{Nordic,jkt}$ and $\ln \pi_{Nordic,jkt} \times \Gamma_j$ as instruments for $\ln \pi_{jkt}$ and $\ln \pi_{jkt} \times \Gamma_j$, respectively.

[28]The remaining Nordic countries are Denmark, Finland, Iceland and Sweden.

Identification. Identification comes from comparing within firm-destination export growth across industries and firms, while controlling for country-specific trends. Our approach resembles a triple differences model as we compare growth in exports both across industries and across firms. Specifically, for two firms A and B and two industries 1 and 2, the β's are identified by firm A's exports growth in country-industry jk relative to (i) its own export growth in industry 2 and (ii) other firms' export growth in industry 2.[29]

4.1 Measures of Dispersion

To test our hypothesis, we require data on the degree of firm heterogeneity among importers located in different countries. 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.[30] We therefore use data on the firm size distribution in different countries to calculate two measures of dispersion; a Pareto slope coefficient (Γ_j^1) and the standard deviation of log employment (Γ_j^2).[31]

Our preferred data source is Bureau van Dijk's Orbis database. Orbis has information on over 100 million private companies across the world.[32] 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.[33] We calculate our two measures of dispersion for all countries with 1000 or more Orbis firms. In total, this gives us information on buyer dispersion in 48 countries, covering 89 percent of Norwegian exports (based on 2006 values). Figure 9 shows the resulting Pareto coefficients. There is substantial variation across countries, e.g. dispersion in Russia (label "RU") is much lower than dispersion in Germany and Sweden (labels "DE" and "SE"). Also, the standard errors associated with the Pareto coefficient estimates are typically very small, suggesting that the Pareto distribution fits the empirical firm-size distribution quite well.[34]

4.2 Construction of variables

Our sufficient statistic approach requires data on Norway's trade share, π_{jkt}, and the Nordic countries' trade share, $\pi_{Nordic,jkt}$. Moreover, we need data on country income Y_{jkt}. Within the context

[29]The fixed effects α_{mn} and δ_{jt} are differenced out for $\Delta \ln y_{mjkt} - \Delta \ln y_{mjk't}$ and $\Delta \ln y_{mjkt} - \Delta \ln y_{m'jk't}$ where $k' \neq k$ and $m' \neq m$.

[30]The relationship between productivity and size has also been documented in a set of studies for many of countries (see Bartelsman et al. (2013) for recent evidence). Helpman et al. (2004) also use the firm size distribution as a proxy for firm-level heterogeneity.

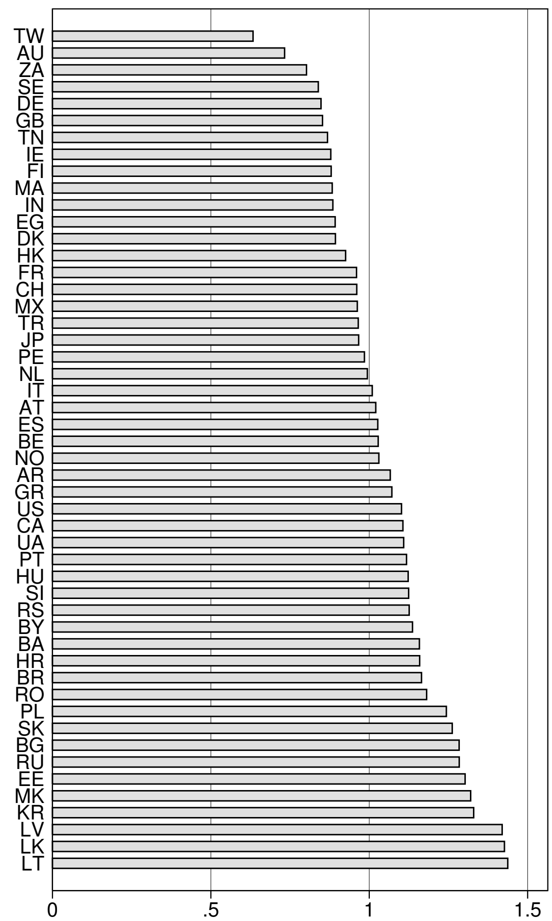
[31]We calculate the Pareto slope coefficient by regressing the empirical $1 - CDF$ on firm employment, both in logs, for each destination market; the resulting slope coefficient is (the negative of) the Pareto slope coefficient.

[32]See 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.

[33]Varying this size threshold has a negligible effect on our estimates of dispersion.

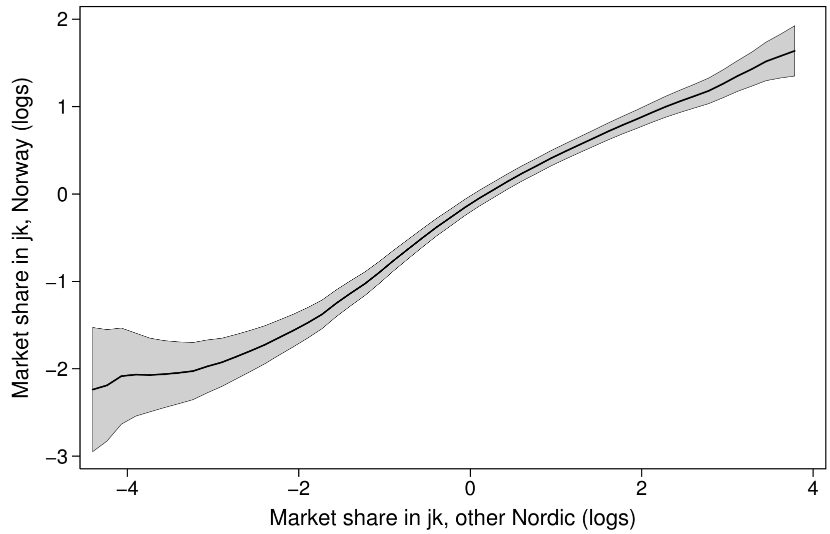
[34]Results not shown but available upon request.

Figure 9: Firm-level heterogeneity across countries.



Note: The figure shows estimated Pareto coefficients for each country using firm-level data from Bureau van Dijk's Orbis database. Only countries with more than 1000 Orbis firms are included in the sample.

Figure 10: Market shares π_{jkt} and $\pi_{Nordic,jkt}$.



Note: 2004 data. The figure shows the kernel-weighted local polynomial regression of normalized log Norwegian market share π_{jkt} (vertical axis) on normalized log other Nordic market share $\pi_{Nordic,jkt}$ (horizontal axis). Gray area denotes the 95 percent confidence bands. The data is normalized by taking the deviation from country means, i.e. we show $\ln \pi_{jk2004} - \ln \bar{\pi}_{j2004}$. Sample is first trimmed by excluding the 1 percent lowest and highest observations.

of the theoretical model, the correct proxy for Y_{jkt} is absorption. Hence, we construct Y_{jkt} as output minus exports plus imports from UNIDO's Industrial Demand-Supply Balance Database (IDSB) which provides nominal output, total imports and exports at the 4-digit level of ISIC revision 3, for in total 127 manufacturing sectors and 121 countries over the sample period 2004 to 2012. In addition, our approach requires bilateral trade data by ISIC sector. We convert 6-digit Harmonized System bilateral trade data to ISIC revision 3 by utilizing a concordance from The World Bank.[35] The trade shares are then calculated as $\pi_{jkt} = X_{NOjkt}/Y_{jkt}$ and $\pi_{Nordic,jkt} = X_{Nordic,jkt}/Y_{jkt}$ where X_{NOjkt} and $X_{Nordic,jkt}$ are trade from Norway and the remaining Nordic countries, respectively. The mean (median) trade share of Norway in 2004 was 0.21 (0.004) percent. There is a strong positive correlation between π_{jkt} and $\pi_{Nordic,jkt}$ in the data. Figure 10 shows a local polynomial regression of π_{jkt} on $\pi_{Nordic,jkt}$ (in logs) in 2004, where the market shares are measured relative to the mean log market share in country j.[36] Hence, even after controlling for the overall market share of Norway in country j, there is a positive and significant relationship.

[35] Specifically, we use the COMTRADE/BACI trade database from CEPII and the WITS concordance from http://wits.worldbank.org/product_concordance.html.

[36] This is identical to including country fixed effects in a regression. The correlation is similar in other years. See also the first stage results in Section 4.3.

4.3 Results

The 2SLS results from estimating the specification in Equation 14 are shown in Table 6. Columns (1) and (3) use total firm-level exports as the dependent variable, while columns (2) and (4) use the firm-level number of buyers (both in logs). The first two columns use the Pareto coefficient as the measure of firm-level heterogeneity while columns (3) and (4) use the standard deviation of log employment. The last column show the first stage results, i.e. the regression of π_{jkt} on the exogenous variables Y_{jkt}, $\pi_{Nordic,jkt}$ and $\pi_{Nordic,jkt} \times \Gamma_j$.[37]

We find that the export elasticity is significantly dampened in markets with more heterogeneity, consistent with the predictions of our model. The elasticity for the number of buyers is also consistent with the model, although the magnitude of the estimate is smaller than for the export elasticity. The coefficients for the interaction term are positive rather than negative in columns (1) and (2) since the Pareto coefficient is inversely related to dispersion. The magnitudes are also economically significant: Increasing the Pareto coefficient by one standard deviation raises the elasticity, $\beta_2 + \beta_3\Gamma_j$, by 33 percent, suggesting that firm heterogeneity is quantitatively important for our understanding of firm-level trade adjustment.[38]

We report OLS and first stage results in Table 7. The OLS estimates in columns (1) and (2) are overall close to the IV estimates. The first stage results in columns (3) and (4) confirm the evidence presented in Figure 10 - the market shares among other Nordic countries are strongly associated with Norway's market share in country j.

The model predicts that the trade elasticity of exports to variable trade barriers is identical to the elasticity of the number of customers to variable trade barriers, see equations (6) and (8), while the empirical results show that the export elasticity is stronger than the customer elasticity. One possible explanation for these discrepancies is that we are testing the predictions of the model using within-firm changes in a market over time while the model is about cross-firm variation in a market at a point in time. Actual matching costs may have both sunk and fixed components.

Robustness

A potential concern is that buyer dispersion may be correlated with other factors that also affect the trade elasticity; for example both buyer dispersion and trade elasticities may be different in low-income countries. We address this issue by purging GDP per capita from our Pareto shape coefficient Γ_j^1. Specifically we regress Γ_j^1 on GDP per capita and replace Γ_j^1 with the fitted residual. The 2SLS results are reported in columns (1) and (2) in Table 8. Overall the results are very similar to the baseline case in Table 6.

[37]To save space, the table does not show OLS results as well as the second first stage regression of $\pi_{jkt} \times \Gamma_j$ on Y_{jkt}, $\pi_{Nordic,jkt}$ and $\pi_{Nordic,jkt} \times \Gamma_j$.

[38]Γ_j is normalized with mean zero and standard deviation one, hence an increase of one standard deviation increases the elasticity from β_2 to $\beta_2 + \beta_3$. Inserting the numbers from the table, we get $(\beta_2 + \beta_3)/\beta_2 \approx 4/3$.

We also experiment with a different set of fixed effects. Columns (3) and (4) in Table 8 replace the firm-country and destination-year fixed effects with firm-destination-year and 2-digit ISIC industry fixed effects, essentially only exploiting variation within a single firm-destination pair, across various sectors. This reduces the magnitude of the interaction term somewhat, but it is still significant and positive. In sum, we confirm one of the main predictions of the model: Improvement in market access results in higher export growth to countries where firms are less heterogeneous.

Market Access and the Marginal Buyer

We conclude this section by testing a second prediction from the model. Recall from equation (7) that a firm's exports to her marginal (smallest) buyer are unaffected by both market size and trade costs - exports to the marginal buyer are pinned down by magnitude of the relation-specific cost.

To test this prediction, we estimate equation 14 by 2SLS using the firm's marginal export ($\min_b y_{mbjt}$), and exports to the firm's median buyer ($median_b\,(y_{mbjt})$) as dependent variables. According to our theory, the coefficients for absorption Y_{jkt} and market access π_{jkt} should be zero when the dependent variable is exports to the marginal or median buyer. The results largely confirm the predictions from the model. Table 8 shows that the marginal export flow is unrelated to market size and access (column 5). However, exports to the median buyer (column 4) are increasing in market size and market access.[39]

5 The Role of Supply Shocks

In this section, we develop a simple methodology to estimate the impact of foreign market access on firms' marginal costs when buyers are heterogeneous. In doing so, we show that a sufficient statistic for a firm's change in marginal costs is (i) the level of, and the change in, intermediate import shares and (ii) the trade elasticity γ.[40] Second, we apply the methodology to evaluate the impact of the 2008-2009 trade collapse on firms' production costs. This also allows us to assess the fit of the model and to evaluate the quantitative importance of the buyer margin.

5.1 Methodology

Firms' marginal costs are inversely proportional to their market access Ω_j, see Proposition 2. Following Dekle et al. (2007), we solve the model in changes. Using equation (5), the change in the market access term Ω_j is

$$\hat{\Omega}_{mj} \equiv \left(\sum_i \pi_{mij} \hat{\rho}_{ij} \right)^{1/\gamma}, \tag{15}$$

[39] In the min and *median* exports regressions, we only use firms with more than 5 customers.

[40] Blaum et al. (2015) show that an importing firm's marginal costs depend on the share of intermediates sourced domestically in a wide class of models.

where $\hat{x}$ denotes the the annual change x_t/x_{t-1} and ρ_{ij} is a composite index of costs associated with sourcing from location i, $\hat{\rho}_{ij} \equiv \hat{Y}_i \left(\hat{\tau}_{ij}\hat{w}_i\right)^{-\gamma} \left(\hat{w}_i\hat{f}_{ij}\right)^{1-\gamma/(\sigma-1)}$. Henceforth, we use the terminology sourcing costs for ρ_{ij}. Finally, π_{mij} is firm m's trade share in $t-1$, $\pi_{mij} \equiv X_{mijt-1}/\sum_k X_{mkjt-1}$. We have added a firm subscript m to the market access term Ω_{jm} because, at the firm level, ex-ante trade shares π_{ijm} vary across firms.[41]

Using equations (9) and (21), the change in a downstream firm's import share from i is

$$\hat{\pi}_{mij} \equiv \frac{\hat{R}_{ij}^{TOT}(Z)}{\hat{E}_j(Z)} = \hat{\rho}_{ij}\hat{\Omega}_{mj}^{-\gamma}. \tag{16}$$

Using the import share π_{mij} instead of the value of imports R_{ij}^{TOT} is useful because it allows us to eliminate a firm's productivity Z (which appear in R_{ij}^{TOT}, see equation 9), thus isolating sourcing costs ρ_{ij}. Intuitively, equations (15) and (16) make it clear that one can use data on the change in the import share to obtain information about the change in sourcing costs. This allows us to calculate the change in market access, $\hat{\Omega}_{mj}$, which is a weighted average of sourcing costs, using ex-ante trade shares π_{mij} as weights.

Fixed point procedure. There is no closed form solution for $\hat{\Omega}_{mj}$ because $\hat{\Omega}_{mj}$ and $\hat{\rho}_{ij}$ are non-linear functions of each other. Hence, we solve numerically for $\hat{\Omega}_{mj}$ using the following fixed point procedure. Step 1: choose initial values for $\hat{\rho}_{ij}$. Step 2: solve for $\hat{\Omega}_{mj}^{\gamma}$ for firm m, using equation (15) and ex-ante trade shares π_{mij} for firm m. Step 3: from equation (16), calculate $\hat{\rho}_{ij} = \hat{\Omega}_{mj}^{\gamma}\hat{\pi}_{mij}$. In practice, the resulting sourcing cost $\hat{\rho}_{ij}$ will vary across firms because of measurement error and firm-country specific shocks. We eliminate this noise by taking the median of $\hat{\rho}_{ij}$ across firms. We return to step 2 if the difference between the current and previous $\hat{\rho}_{ij}$ is large, and we stop if the difference is sufficiently small. The fixed point procedure converges quickly. In our experience, the choice of starting values $\hat{\rho}_{ij}$ has no impact on the solution.

Normalization. We can only identify $\hat{\rho}_{ij}$ up to a constant because, for given m and j, one of the i elements in the vector $\hat{\pi}_{mij}$ is linearly dependent on the other elements. We normalize the change in domestic sourcing cost to one, $\hat{\rho}_{1j} = 1$ there $i = 1$ is the domestic market.

After obtaining the solution to the change in sourcing costs $\hat{\rho}_{ij}$, one only needs one model parameter, the trade elasticity γ, in order to calculate the firm level change in marginal costs from equation (15). The change in marginal costs will vary across firms because their ex-ante trade shares π_{ijm} differ, i.e. some firms are using imported inputs intensively while other firms are not.

5.2 Data

This quantitative exercise requires data on firms' imports across suppliers and source countries, as well as data on firms' total purchases of intermediate goods. In this part of the paper, we therefore

[41] In the model, import shares do not vary across downstream firms. One could add firm-country specific shocks to the relation-specific fixed cost that would bring the model closer to the data.

use customs data on imports that have an identical structure to the export data described above. In addition, we match the import data to balance sheet data for manufacturing firms, which includes a variable for total intermediate purchases. The balance sheet data is from Statistics Norway's Capital database, which is an annual unbalanced panel of all non-oil manufacturing joint-stock firms. It includes approximately $8,000$ firms per year, which is roughly 90 percent of all manufacturing firms.[42]

5.3 Application : The Trade Collapse

As is well known, global trade fell much faster than world GDP during the global recession of 2008-2009. The global downturn hit Norwegian trade hard as well. In our data, total exports and intermediate imports both fell by 15 percent from 2008 to 2009. The forces driving the trade collapse are complex, see Eaton et al. (2013). Here we ask how much one particular channel, the rise in sourcing costs due to increased trade costs and a reduced pool of potential of suppliers, reduced buyer-seller links and and increased downstream firms' marginal production costs. While there is little doubt that the crisis caused the exit of many firms worldwide, there is also evidence of increased trade barriers in the aftermath of the collapse in 2008 (see Evenett (2009)).

Estimation exploits firm-level import data as described in Section 2.1. Recall that the trade data is matched with balance sheet data from the manufacturing sector to obtain firm-level total intermediate purchases. Hence, in this section we are limiting the analysis to manufacturing firms. From this, we calculate π_{mij} and the 2008 to 2009 change $\hat{\pi}_{mij}$ for all sources i, including Norway itself.[43] We also restrict the data in two other ways. First, firms with no foreign sourcing are dropped as their $\hat{\Omega}_{mj}$ is normalized to one (see previous section). Second, we focus on the set of firm-sources with positive imports in both 2008 and 2009. This is necessary because $\hat{\pi}_{mij}$ is not defined if a firm adds or drops a sourcing market.

Results. Table 9 provides an overview of the results. The mean market access (log Ω^{γ}_{mj}), across all importers, fell by 2.7 percent, while the weighted mean, using firm revenue as weights, fell by 3.5 percent. This translates into substantial cost increases among the importing firms. For example, with a trade elasticity of $\gamma = 4$, the weighted mean increase in marginal costs is roughly 1 percent $((1 - 0.035)^{1/\gamma})$.[44]

There is also great dispersion across firms. Figure 11 shows the density of $\ln \hat{\Omega}^{\gamma}$. The mode of the density is around 1 because many firms import relatively small amounts. For big importers, however, the decline in Ω_{mj} is much larger; the decline for the first decile of $\ln \hat{\Omega}^{\gamma}_{mj}$ is -0.08, or a 2

[42] Statistics Norway's capital database is described in Raknerud et al. (2004).

[43] Firm-level domestic sourcing is calculated as total intermediate purchases minus total imports. A small number firms have imports $>$ intermediate purchases. We set the domestic sourcing share to zero for these firms. We also drop firm-country pairs with import growth $>$ 100 percent or import decline $>$ 99 percent.

[44] Recall that the change in domestic sourcing costs is normalized to zero. Hence, we only identify changes in marginal costs coming from changes in foreign market access.

percent increase in marginal costs given $\gamma = 4$. Overall, our results suggest that the trade collapse had a relatively large negative impact on production costs among importers, and that this was driven by changes in sourcing costs. Recall that, these marginal cost estimates are not contaminated by the demand side of the economy, because the demand side was effectively differenced out in the quantitative procedure.

Model fit. Table 9 shows the median, mean and weighted mean change in firms' import shares ($\ln \hat{\pi}_{mij}$) across all firm-country pairs, in the data and in the model. Import shares fell both in the data and in the model and the model's median change is very close to the data. This is as expected because we used data on the changes in the trade shares to calculate $\hat{\rho}_{ij}$ and $\hat{\Omega}_{mj}$. We evaluate the out-of-sample fit in terms of changes in buyer-seller linkages in the economy. In the model, the change in the firm-level measure of suppliers is

$$\hat{L}_{mij} = \frac{\hat{\rho}_{ij}}{\hat{w}_i \hat{f}_{ij}} \hat{\Omega}_{mj}^{-\gamma} \hat{Z}^{\gamma}.$$

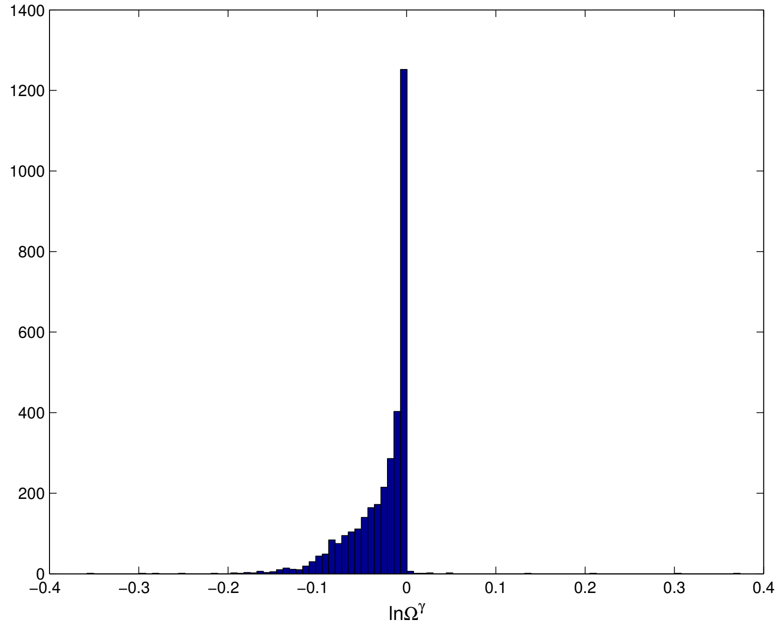
We calculate $\hat{L}_{mij}$ for each firm using our estimates of $\hat{\rho}_{ij}$ and $\hat{\Omega}_{mj}^{\gamma}$, while keeping other factors fixed (productivity Z and relation-specific costs $w_i f_{ij}$). We then compare the model response to data. Overall, the model captures the decline in supplier connections well; the model generates an average 11 percent fall in the number of supplier connections (median across firms), while the actual average decline was 8 percent. The fit for the median $\ln \hat{L}_{mij}$ is poor as the median log change in the data is 0. This occurs because L in the data is an integer and cannot take a value lower than one. If we take the median of $\ln \hat{L}_{mij}$ across firm-country pairs with two or more suppliers, we find a median decline in suppliers of 15 percent - slightly more than the model prediction (rows 4 and 7 in Table 9). In sum, the model is able to quantitatively replicate the buyer margin adjustment during the 2008-2009 trade collapse.

6 Conclusion

We use highly disaggregated trade transaction data from Norway to explore the role of buyers and buyer-seller relationships in international trade. We find that the extensive margin of the number of buyers plays an important role in explaining variation in exports in the aggregate and at the firm level. The buyer margin is comparable in magnitude to previously documented extensive margins of trade of exporters, destinations and products.

We introduce a series of basic facts about buyer-seller relationships 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 but exports to the median customer are not increasing with the number of customers within a

Figure 11: Change in $\ln \Omega^{\gamma}$ across importers.



Note: The figure shows the density of $\ln \hat{\Omega}^{\gamma}_{mj}$ from 2008 to 2009.

destination, and that there is negative degree assortivity in the exporter-importer matches. In other words, large exporters on average reach importers who buy from a relatively smaller number of Norwegian firms.

Guided by these facts, we develop a parsimonious multi-country model of heterogeneous exporters and importers where matches are subject to a relation-specific fixed cost. We explore various applications of the model. First, we empirically test predictions of the model. An interesting feature of the model is that, for an exporter, a lower variable trade costs in a destination country will lead to higher export growth when buyers in that market are less dispersed in terms of their productivity. When buyers are more similar, an exporter will find many new profitable matches, whereas if buyers are dispersed, only a few more matches will become profitable. In other words, the customer extensive margin response will be strong when buyer heterogeneity is small. We test this prediction by exploiting variation in import shares across industries and countries over time and find strong empirical support for this prediction.

Second, we develop an empirical methodology to back out downstream firms' marginal cost response when market access is changing due to a fall in variable or fixed trade costs. We show that a sufficient statistic for a firm's change in marginal costs depends on the level of, and the change in, intermediate import shares and the trade elasticity. The methodology is subsequently applied to evaluate the impact of the 2008-2009 trade collapse on firms' production costs. Our results indicate that worsened market access during the trade collapse had a significantly negative impact on production costs, and especially so for downstream firms that were ex-ante highly exposed to international markets. The quantitative exercise also shows that the model matches well the fall in the number of buyer-seller matches observed during the trade collapse.

Our results suggest that buyer-seller links are important in understanding firm-level and aggregate trade, as well as fluctuations in marginal costs and measured productivity. Future research might fruitfully focus on the growth and stability of exporter-importer relationships as well as the sources of heterogeneity across sellers and buyers.

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Table 1: Top Exported Products by Number of Exporters and Value.

Top HS8 Products - Number of Exporters		
HS code	Description	Share of exporters, %
84799090	Subgroup of: 847990 Parts of machines and mechanical appliances n.e.s.	9.1
84733000	Parts and accessories for automatic data-processing machines or for other machines of heading 8471, n.e.s.	7.6
73269000	Articles of iron or steel, n.e.s. (excl. cast articles or articles of iron or steel wire)	5.8
39269098	Subgroup of: 392690 Articles of plastics or other materials of headings 3901 to 3914, for civil aircraft, n.e.s	4.9
84099909	Subgroup of: 840999 Parts suitable for use solely or principally with compression-ignition internal combustion piston engine "diesel or semi-diesel engine", n.e.s	4.4

Top HS8 Products - Value		
HS code	Description	Share of value, %
76012001	Subgroup of: 760120 Unwrought aluminium alloys	9.9
03021201	Subgroup of: 030212 Fresh or chilled Pacific salmon	5.1
75021000	Nickel, not alloyed, unwrought	4.8
89069009	Subgroup of: 890690 Vessels, incl. lifeboats (excl. warships, rowing boats and other vessels of heading 8901 to 8905 and vessels for breaking up)	1.3
31052000	Mineral or chemical fertilisers containing the three fertilising elements nitrogen,	1.2

Note: 2006 data. HS8 codes refer to 2006 edition eight digit HS codes. Oil and gas exports excluded (HS 27x products).

Table 2: The Margins of 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: 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 exports, $\bar{x}$. 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 $\bar{x_j} = x_j/o_j$ is average exports per firm-product-buyer. We regress the logarithm of each component on the logarithm of total exports to a given market in 2006, $\ln f_j$ against $\ln x_j$. Robust standard errors in parentheses. ^{a} p< 0.01, ^{b} p< 0.05, ^{c} p< 0.1.

Table 3: Within-Firm Gravity.

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 4: Descriptive Statistics.

	Overall	Sweden	Germany	US	China	OECD	non-OECD
Number of exporters	18,219	8,614	4,067	2,088	725	1,588.2	98.2
Number of buyers	81,362	16,822	9,627	5,992	1,489	3,055.6	144.5
Buyers/exporter, mean	9.0	3.6	3.6	4.5	3.6	2.7	1.6
Buyers/exporter, median	2	1	1	1	1	1	1
Exporters/buyer, mean	2.0	1.9	1.5	1.6	1.7	1.5	1.2
Exporters/buyer, median	1	1	1	1	1	1	1
Share trade, top 10% sellers	.98	.94	.97	.96	.86	.90	.75
Share trade, top 10% buyers	.96	.95	.95	.97	.89	.89	.73
Log max/median exports	13.0	10.7	11.4	11.2	7.9	8.7	4.6
Log max/median imports	12.2	10.8	10.8	11.7	8.4	8.4	4.6
Share in total NO exports, %	100	11.3	9.6	8.8	2.1	81.6	18.4

Note: 2006 data. The overall column refers to outcomes unconditional on destination country. 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 5: Types of Matches, %.

	(1) One-to-one	(2) Many-to-one	(3) One-to-many	(4) Many-to-many
Share of value, %	4.6	26.9	4.9	63.6
Share of counts, %	9.5	40.1	11.0	39.4

Note: 2006 data. Column (1) refers to matches between exporters (E) and importers (I) where both have one connection in a market, column (2) refers to matches where the E has many connections and the I has one, columns (3) refers to matches where the E has one connection and the I has many, column (4) refers to matches where both E and I have many connections. The unit of observation is firm-destination, e.g. an exporter with one customer in two destinations is counted as a single-customer exporter. The first row shows the trade value for each group relative to total trade. The second row shows the number of matches in the group relative to the total number of matches.

Table 6: Market Access and Heterogeneity. 2SLS Estimates.

	(1) Exports	(2) # Buyers	(3) Exports	(4) # Buyers
Y_{jkt}	.18[a]	.05[a]	.18[a]	.05[a]
	(.01)	(.00)	(.01)	(.00)
π_{jkt}	.30[a]	.07[a]	.33[a]	.08[a]
	(.01)	(.00)	(.01)	(.00)
$\pi_{jkt} \times \Gamma_j^1$ (Pareto)	.07[a]	.01[b]		
	(.01)	(.00)		
$\pi_{jkt} \times \Gamma_j^2$ (Std. Dev.)			-.10[a]	-.01[a]
			(.01)	(.00)
$\pi_{Nordic,jkt}$				
$\pi_{Nordic,jkt} \times \Gamma_j^1$				
Firm-country FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes
N	264,544	264,544	264,544	264,544

Note: Robust standard errors in parentheses, clustered by firm. [a] p< 0.01, [b] p< 0.05, [c] p< 0.1. All variables in logs. Y_{jkt} and π_{jkt} are absorption and Norwegian market share in country-industry jk, respectively, Γ_j^1 is the Pareto shape parameter and Γ_j^2 is the standard deviation of log employment. π_{jkt} and $\pi_{jkt} \times \Gamma_j^1$ are instrumented with $\pi_{Nordic,jkt}$ and $\pi_{Nordic,jkt} \times \Gamma_j^1$ respectively, where $\pi_{Nordic,jkt}$ is the Nordic (excluding Norway) market share in country-industry jk.

Table 7: Market Access and Heterogeneity. OLS and First Stage Estimates.

	(1) OLS Exports	(2) OLS # Buyers	(3) $1st$ stage π_{jkt}	(4) $1st$ stage $\pi_{jkt} \times \Gamma_j^1$
Y_{jkt}	$.17^a$	$.04^a$	.01	$-.05^a$
	(.02)	(.01)	(.01)	(.00)
π_{jkt}	$.27^a$	$.06^a$		
	(.02)	(.01)		
$\pi_{jkt} \times \Gamma_j^1$ (Pareto)	$.05^a$	.00		
	(.01)	(.00)		
$\pi_{Nordic,jkt}$			$.76^a$	$.46^a$
			(.01)	(.01)
$\pi_{Nordic,jkt} \times \Gamma_j^1$			$.02^a$	$.83^a$
			(.01)	(.01)
Firm-country FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes
F-stat			4280.6	4260.8
N	264,544	264,544	264,544	264,544

Note: Robust standard errors in parentheses, clustered by firm. ^{a} p< 0.01, ^{b} p< 0.05, ^{c} p< 0.1. All variables in logs. Columns (1) and (2) show OLS results while colums (3) and (4) show the two first stage regressions corresponding to the IV estimates reported in columns (1) and (2) in Table 6. The F-statistics reported in the table refer to the F-statistics for the joint significance of the instruments in the first stage regressions.

Table 8: 2SLS estimates. Various specifications.

	(1) Exports	(2) # Buyers	(3) Exports	(4) # Buyers	(5) Marginal buyer	(6) Median buyer
Y_{jt}	.18[a]	.05[a]	.24[a]	.08[a]	.02	.08[a]
	(.01)	(.00)	(.01)	(.00)	(.02)	(.02)
π_{jt}	.31[a]	.08[a]	.33[a]	.11[a]	.00	.12[a]
	(.01)	(.00)	(.02)	(.00)	(.04)	(.04)
$\pi_{jkt} \times \Gamma_j^1$ (Pareto)			.03[a]	.00	.05	.10[a]
			(.01)	(.00)	(.03)	(.03)
$\pi_{jkt} \times \Gamma_j^3$ (Pareto resid)	.09[a]	.01[a]				
	(.01)	(.00)				
Firm-country FE	Yes	Yes	No	No	Yes	Yes
Country-year FE	Yes	Yes	No	No	Yes	Yes
Firm-country-year FE	No	No	Yes	Yes	No	No
2-digit industry FE	No	No	Yes	Yes	No	No
N	264,544	264,544	264,544	264,544	14,551	14,551

Note: Robust standard errors in parentheses, clustered by firm. [a] p< 0.01, [b] p< 0.05, [c] p< 0.1. All variables in logs. Y_{jkt} and π_{jkt} are absorption and Norwegian market share in country-industry jk, respectively, Γ_j^1 is the Pareto shape parameter and Γ_j^3 is the Pareto shape parameter purged of the correlation with GDP per capita. In all specifications, π_{jkt} and $\pi_{jkt} \times \Gamma_j^1$ are instrumented with $\pi_{Nordic,jkt}$ and $\pi_{Nordic,jkt} \times \Gamma_j^1$ respectively, where $\pi_{Nordic,jkt}$ is the Nordic (excluding Norway) market share in country-industry jk. The dep. variables in columns (3) and (4) are the minimum (median) export value for a firm, across its buyers; $\min_b y_{mbjt}$ and $median_b y_{mbjt}$. Only exporters with $>$ 5 buyers in columns (3) and (4).

Table 9: A Supply Shock: The Trade Collapse.

	Median	Mean	Weighted mean	Stdev
Data:				
$\ln \hat{\pi}_{mij}$	-.099	-.208	-.212	1.099
$\ln \hat{L}_{mij}$	0	-.079	-.080	.546
$\ln \hat{L}_{mij}$, $\geq$ 2 suppliers	-.154	-.216	-.164	.524
Model:				
$\ln \hat{\Omega}_{mj}^{\gamma}$	-.014	-.027	-0.035	.036
$\ln \hat{\pi}_{mij}$	-.112	-.106	-.106	.109
$\ln \hat{L}_{mij}$	-.112	-.106	-.106	.109
$\ln \hat{L}_{mij}$, $\geq$ 2 suppliers	-.105	-.105	-.117	.086
Firms	3,331			
Countries	110			

Notes: 2008 to 2009 changes. Firm revenue is used as weights in weighted mean calculations. $\hat{\Omega}_{mj}^{\gamma}$ is change in market access for firm m, $\hat{\pi}_{mij}$ is change in the import share from i for firm m, and $\hat{L}_{mij}$ is change in the measure of suppliers from i for firm m .

Appendix

A Equilibrium Sorting

The solution to the sorting function is:

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

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 $E_j(Z) = \kappa_3 Z^{\gamma}$, where κ_3 is a constant term, and show in Section B that this is consistent with the equilibrium. Inserting these expressions, as well as the price index (equation (1)), into equation (3) yields

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

Hence,

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

and

$$\begin{aligned}
\left(\frac{1}{S_{ij}}\right)^{1/s} &= \left[\frac{\sigma w_i f_{ij}}{\kappa_3} \frac{\gamma z_L^{\gamma}}{\gamma_2} (\bar{m}\tau_{ij} w_i)^{\sigma-1} \sum_k n_k (\bar{m}\tau_{kj} w_k)^{1-\sigma} S_{kj}^{-\gamma_2}\right]^{1/(s\gamma_2+\gamma)} \iff \\
S_{ij} &= \left[\frac{\sigma w_i f_{ij}}{\kappa_3} \frac{\gamma z_L^{\gamma}}{\gamma_2} (\tau_{ij} w_i)^{\sigma-1} \sum_k n_k (\tau_{kj} w_k)^{1-\sigma} S_{kj}^{-\gamma_2}\right]^{1/(\sigma-1)}. \qquad (17)
\end{aligned}$$

In sum, the cutoff is

$$\underline{z}_{ij}(Z) = \frac{S_{ij}}{Z}. \qquad (18)$$

We proceed by solving for S_{ij} and q_j. Inserting the expression for the cutoff (equation (18)) 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 (17) then yields

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

This must hold for all i, so

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

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

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

We define

$$\Omega_j \equiv \kappa_2 \left(\sum_k n_k' (\tau_{kj} w_k)^{-\gamma} (w_k f_{kj})^{-\gamma_2/(\sigma-1)} \right)^{1/\gamma},$$

where $\kappa_2 = \left(\frac{\sigma}{\kappa_3} \frac{\gamma}{\gamma_2} \right)^{1/\gamma}$ and given the normalization $n_i = z_L^{-\gamma} n_i'$, we get the closed form solution for the sorting function,

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

□

We can now write the price index as

$$\begin{aligned}
q_j(Z)^{1-\sigma} &= Z^{\gamma_2} \bar{m}^{1-\sigma} \frac{\kappa_3}{\sigma w_i f_{ij}} \left(\frac{S_{ij}}{\tau_{ij} w_i} \right)^{\sigma-1} \\
&= Z^{\gamma_2} \bar{m}^{1-\sigma} \frac{\kappa_3}{\sigma w_i f_{ij}} \left(\frac{\tau_{ij} w_i (w_i f_{ij})^{1/(\sigma-1)} \Omega_j}{\tau_{ij} w_i} \right)^{\sigma-1} \\
&= Z^{\gamma_2} \frac{\bar{m}^{1-\sigma} \kappa_3}{\sigma} \Omega_j^{\sigma-1}. \qquad (19)
\end{aligned}$$

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

$$\begin{aligned} Q_i^{1-\sigma} &= N_i \int_1^\infty P_i(Z)^{1-\sigma}\, dG(Z) \\ &= N_i \int_1^\infty (\bar{m} q_i(Z)/Z)^{1-\sigma}\, dG(Z) \\ &= Y_i \frac{\bar{m}^{2(1-\sigma)}\kappa_3}{\sigma} \frac{\Gamma}{\Gamma-\gamma} \Omega_i^{\sigma-1}. \end{aligned} \tag{20}$$

Rewriting revenue as a function of E and inserting the equilibrium expressions for $q_i(Z)$ and Q_i yields

$$\begin{aligned} \bar{m}E_i &= \left(\frac{\bar{m} q_i(Z)}{Z Q_i}\right)^{1-\sigma} \mu Y_i \\ &= \bar{m}^{1-\sigma} Z^{\sigma-1} \frac{Z^{\gamma_2} \frac{\bar{m}^{1-\sigma}\kappa_3}{\sigma} \Omega_i^{\sigma-1}}{\frac{\bar{m}^{2(1-\sigma)}\kappa_3}{\sigma} \frac{\Gamma}{\Gamma-\gamma} Y_i \Omega_i^{\sigma-1}} \mu Y_i \quad \Longleftrightarrow \\ E_i(Z) &= \kappa_3 Z^{\gamma}, \end{aligned} \tag{21}$$

where $\kappa_3 = \mu(\Gamma-\gamma)/\Gamma$. Hence, total spending on intermediates is increasing in productivity with an elasticity γ. he expression for $E_i(Z)$ is the same as the one we started with in Section G.

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

$$r_{ij}(z, Z) = \left(\frac{p_{ij}(z)}{q_j(Z)}\right)^{1-\sigma} E_j(Z) = \sigma \left(\frac{zZ}{\tau_{ij} w_i \Omega_j}\right)^{\sigma-1}. \tag{22}$$

Note that revenue is supermodular in (z, Z): $\partial^2 r/\partial z \partial Z > 0$. Buyer productivity is distributed Pareto, $G(Z) = 1 - Z^{-\Gamma}$. For firms with $z < \underline{z}_{ij}(Z_L) \equiv z_H$, total firm-level exports to country j are

$$\begin{aligned} r_{ij}^{TOT}(z) &= N_j \int_{\underline{Z}_{ij}(z)} r_{ij}(z, Z)\, dG(Z) \\ &= \kappa_1 Y_j (w_i f_{ij})^{1-\Gamma/(\sigma-1)} \left(\frac{z}{\tau_{ij} w_i \Omega_j}\right)^{\Gamma}, \end{aligned} \tag{23}$$

where we defined $\kappa_1 \equiv \sigma\Gamma/[\Gamma-(\sigma-1)]$. We can alternatively express revenue as a function of the hurdle $\underline{Z}_{ij}(z)$, which yields

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

For firms with $z \geq z_H$, total firm-level exports are

$$\begin{aligned}\tilde{r}_{ij}^{TOT}(z) &= N_j \int_{Z_L} r_{ij}(z, Z)\, dG(Z) \\ &= \kappa_1 Y_j \left(\frac{z}{\tau_{ij} w_i \Omega_j}\right)^{\sigma-1}.\end{aligned}$$

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

$$\begin{aligned}b_{ij}(z) &= N_j \int_{\underline{Z}_{ij}(z)} dG(Z) \\ &= Y_j (w_i f_{ij})^{-\Gamma/(\sigma-1)} \left(\frac{z}{\tau_{ij} w_i \Omega_j}\right)^{\Gamma}. \qquad (24)\end{aligned}$$

Given that z is distributed Pareto, the distribution of customers per firm (out-degree distribution) is also Pareto. For firms with $z \geq z_H$, the measure of buyers per seller is by definition N_j.

Knowing firm-level exports from equation (23) as well as the number of buyers from equation (24), the firm's average exports is given by

$$\frac{r_{ij}^{TOT}(z)}{b_{ij}(z)} = \kappa_1 w_i f_{ij}. \qquad (25)$$

Inversely, we calculate purchases from i of a final goods firm Z located in j. This is

$$\begin{aligned}R_{ij}^{TOT}(Z) &= n_i \int_{\underline{z}_{ij}(Z)} r_{ij}(z, Z)\, dF(z) \\ &= \kappa_4 Y_i (w_i f_{ij})^{1-\gamma/(\sigma-1)} \left(\frac{Z}{\tau_{ij} w_i \Omega_j}\right)^{\gamma},\end{aligned}$$

where $\kappa_4 = \sigma\gamma / [\gamma - (\sigma - 1)]$. The firm-level measure of sellers for a buyer located in j with productivity Z is

$$L_{ij}(Z) = n_i \int_{\underline{z}_{ij}(Z)} dF(z) = Y_i (w_i f_{ij})^{-\gamma/(\sigma-1)} \left(\frac{Z}{\tau_{ij} w_i \Omega_j}\right)^{\gamma}. \qquad (26)$$

Hence, given that Z is distributed Pareto, both the distribution of purchases R_{ij}^{TOT} and the distribution of number of sellers per buyer $L_{ij}(Z)$ (in-degree distribution) are Pareto. These results are symmetric to the findings on the seller side.

Finally, equilibrium firm-level profits for intermediate producers with productivity $z < z_H$ is given by

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

For firms with $z \geq z_H$, firm-level profits are

$$\begin{aligned}\tilde{\pi}_{ij}(z) &= \frac{\tilde{r}_{ij}^{TOT}(z)}{\sigma} - w_i f_{ij} N_j \\ &= \frac{\kappa_1}{\sigma} Y_j \left(\frac{z}{\tau_{ij} w_i \Omega_j}\right)^{\sigma-1} - w_i f_{ij} Y_j.\end{aligned}$$

D Other distributional assumptions

Proposition 1 was derived under the assumption that both buyer and seller productivities are distributed Pareto. In this section, we investigate the robustness of Proposition 1 under other distributional assumptions for buyer productivity.

Consider the elasticity of firm-level exports with respect to variable trade barriers. From the expression $r_{ij}^{TOT}(z) = N_j \int_{\underline{Z}_{ij}(z)} r_{ij}(z, Z)\, dG(Z)$, and by using Leibnitz' rule, we get

$$\frac{\partial \ln r_{ij}^{TOT}(z)}{\partial \ln \tau_{ij}} = \frac{\tau_{ij}}{r_{ij}^{TOT}} N_j \int_{\underline{Z}_{ij}(z)} \frac{\partial r_{ij}(z, Z)}{\partial \tau_{ij}} dG(Z) - \frac{\tau_{ij}}{r_{ij}^{TOT}} N_j \frac{\partial \underline{Z}_{ij}(z)}{\partial \tau_{ij}} r_{ij}\left(z, \underline{Z}_{ij}\right) G'\left(\underline{Z}_{ij}\right).$$

The first and second parts of this expression are the intensive and extensive margin elasticities, respectively. From equation (22) we get that $\partial r_{ij}(z, Z)/\partial \tau_{ij} = -(\sigma - 1) r_{ij}(z, Z)/\tau_{ij}$. Hence the intensive margin is

$$\begin{aligned}\epsilon_{intensive} &= \frac{\tau_{ij}}{r_{ij}^{TOT}} N_j \int_{\underline{Z}_{ij}(z)} \frac{\partial r_{ij}(z, Z)}{\partial \tau_{ij}} dG(Z) \\ &= -\frac{\tau_{ij}}{r_{ij}^{TOT}} N_j \int_{\underline{Z}_{ij}(z)} (\sigma - 1) \frac{r_{ij}(z, Z)}{\tau_{ij}} dG(Z) \\ &= -(\sigma - 1).\end{aligned}$$

From equation (4) we get that $\partial \underline{Z}_{ij}(z)/\partial \tau_{ij} = \underline{Z}_{ij}(z)/\tau_{ij}$. Hence the extensive margin is

$$\begin{aligned}\epsilon_{extensive} &= -\frac{\tau_{ij}}{r_{ij}^{TOT}} N_j \frac{\partial \underline{Z}_{ij}(z)}{\partial \tau_{ij}} r_{ij}\left(z, \underline{Z}_{ij}\right) G'\left(\underline{Z}_{ij}\right) \\ &= -N_j \frac{r_{ij}\left(z, \underline{Z}_{ij}\right)}{r_{ij}^{TOT}(z)} \underline{Z}_{ij} G'\left(\underline{Z}_{ij}\right).\end{aligned}$$

Inserting the expression for r_{ij}^{TOT} above, and using equations (7) and (22), we get

$$\epsilon_{extensive} = -\frac{\underline{Z}_{ij}^{\sigma} G'\left(\underline{Z}_{ij}\right)}{\int_{\underline{Z}_{ij}} Z^{\sigma-1} dG(Z)}.$$

First, consider the case of a Pareto distribution for $G(Z)$. Then $\epsilon_{extensive} = -(\Gamma - (\sigma - 1))$, so that the overall elasticity is simply Γ, as in the main text. Second, consider the case of a lognormal

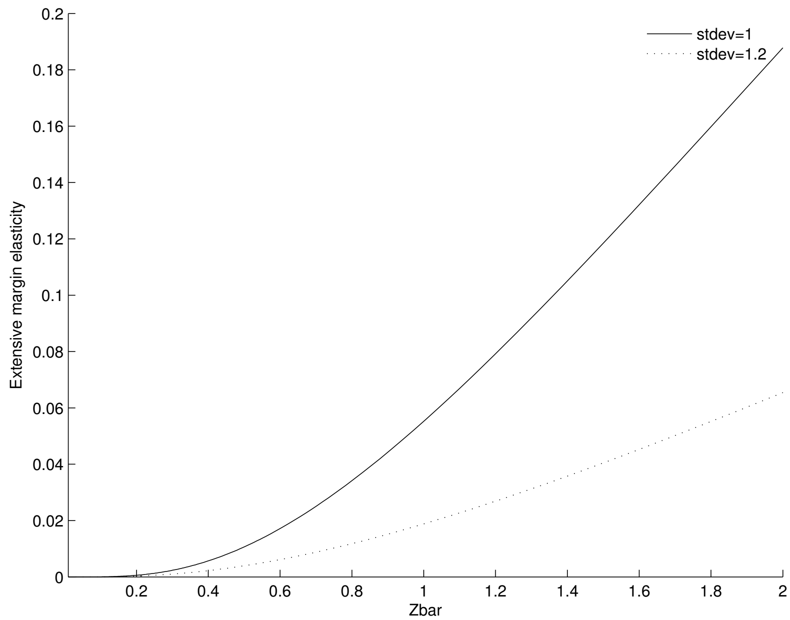


Figure 12: Extensive margin elasticity under the lognormal distribution.

distribution with $E\left[\ln Z\right]=0$ and with either $\sigma_Z = stdev\left[\ln Z\right]=1$ or $stdev\left[\ln Z\right]=1.2$. Figure 12 plots $\epsilon_{extensive}$ for different values of $\underline{Z}_{ij}^{\sigma}$, and for the two values of dispersion. As is clear from the figure, $\epsilon_{extensive}$ is greater (in absolute value) when σ_Z is low compared to when σ_Z is high, for all values of $\underline{Z}_{ij}$.

We also test two other distributions. Consider the case of an exponential distribution for $G\left(Z\right)$ with rate parameters $\lambda=1$ and $\lambda=1.2$ and corresponding variance λ^2. This also generates a greater $\epsilon_{extensive}$ when dispersion is low compared to when dispersion is high.[45] Finally, consider the case of a Frechet distribution with shape parameters $\theta=1$ and $\theta=1.2$. Again, $\epsilon_{extensive}$ is higher when dispersion is low (θ high).

In sum, the finding that the trade elasticity is higher when dispersion is low holds under various other commonly used distributions.

E Welfare

As shown in equation (20), the price index on final goods is

$$Q_i^{1-\sigma} \quad = \bar{m}^{2(1-\sigma)}\tfrac{\mu}{\sigma}N_i\Omega_i^{\sigma-1}.$$

Using the expression for the trade share in equation (11), we can rewrite Ω_i as

$$\Omega_j = \left(\frac{\sigma}{\kappa_3}\frac{\gamma}{\gamma_2}n_j'\left(w_j f_{jj}\right)^{1-\gamma/(\sigma-1)}\right)^{1/\gamma}\pi_{jj}^{-1/\gamma}\frac{1}{\tau_{jj}w_j}.$$

[45]The numerical results are available upon request.

Inserting this back into the price index Q_i and rearranging yields the real wage

$$\frac{w_j}{Q_j} = \kappa_6 \left(n_j^{'} N_j\right)^{1/\gamma} \left(\frac{f_{jj}}{L_j}\right)^{1/\gamma - 1/(\sigma-1)} \frac{\pi_{jj}^{-1/\gamma}}{\tau_{jj}},$$

where κ_6 is a constant.[46]

F The Within-Firm Export Distribution

Using the expression for sales for a given (z, Z) match in equation (22) as well as the sorting function $\underline{Z}_{ij}(z)$, the distribution of exports across buyers for a seller with productivity z is

$$\Pr\left[r_{ij} < r_0 \mid z\right] = 1 - \left(\frac{\sigma w_i f_{ij}}{r_0}\right)^{\Gamma/(\sigma-1)}.$$

Hence, within-firm sales is distributed Pareto with shape coefficient $\Gamma/(\sigma-1)$. Note that the distribution is identical for every exporter in i selling to j.

G Sorting

Using the Norwegian trade data, Figure 6 shows the empirical relationship between a firm's number of customers in destination j and average number of connections to Norwegian exporters 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 (26) and (4), the number of connections for the marginal customer of a firm with productivity z is $L_{ij}\left(\underline{Z}_{ij}(z)\right) = Y_i z^{-\gamma}$. Using equation (24), we can rewrite this as

$$\underline{L}_{ij}(b_{ij}) = Y_i Y_j (w_i f_{ij})^{-\gamma/(\sigma-1)} (\tau_{ij} w_i \Omega_j)^{-\gamma} b_{ij}^{-\gamma/\Gamma},$$

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

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

[46] $\kappa_6 = \left(\frac{\sigma}{\kappa_3}\frac{\gamma}{\gamma_2}\right)^{1/\gamma} \left(\bar{m}^{2(1-\sigma)}\frac{\mu}{\sigma}\right)^{1/(\sigma-1)} (1+\psi)^{-1/\gamma+1/(\sigma-1)}$.

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

$$\hat{L}_{ij}(b_{ij}) = \frac{\Gamma}{\Gamma-\gamma} Y_i \left(\frac{b_{ij}}{b_{ij}(1)}\right)^{-\gamma/\Gamma}.$$

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

H Free entry

This section develops a simple extension of the model where the number of buyers in a market, N_j, is endogenous and determined by free entry. Assume that downstream firms incur a fixed cost f_e, paid in terms of labor, in order to observe a productivity draw Z. Prior to entry, expected firm profits are therefore $\int_1 \Pi_j(Z)\, dG(Z) - w_j f_e$, where $\Pi_j(Z)$ is profits of a downstream firm with productivity Z. From equation (21), we know that a downstream firm's revenue is

$$R_j(Z) = \bar{m}\mu \frac{\Gamma-\gamma}{\Gamma} \frac{Y_j}{N_j} Z^{\gamma}.$$

Because gross profits are proportional to revenue, $\Pi_j(Z) = R_j(Z)/\sigma$, we can rewrite the free entry condition as

$$\begin{aligned}
\int_1 \Pi_j(Z)\, dG(Z) &= w_j f_e \\
\bar{m}\frac{\mu}{\sigma}\frac{\Gamma-\gamma}{\Gamma}\frac{Y_j}{N_j}\int_1 Z^{\gamma} dG(Z) &= w_j f_e \\
\bar{m}\frac{\mu}{\sigma}\frac{Y_j}{N_j} &= w_j f_e \\
N_j &= \bar{m}\frac{\mu}{\sigma}\frac{Y_j}{w_j f_e}.
\end{aligned}$$

Hence, the number of buyers in a market is proportional to income Y_j.

I A Random Matching Model

In this section, we ask to what extent a random matching model can replicate the basic facts presented in the main text. The main finding is that a random model fails to explain key empirical facts.

We model the matching process as a balls-and-bins model, similar to Armenter and Koren (2013). There are B buyers, S sellers and n balls. The number of bins is SB, the total number of possible buyer-seller combinations, and we index each bin by sb. The probability that a given ball lands in bin sb is given by the bin size s_{sb}, with $0 < s_{sb} \leq 1$ and $\sum_s^S \sum_b^B s_{sb} = 1$. We assume that $s_{sb} = s_s s_b$, so that the buyer match probability (s_b) and seller match probability (s_s) are independent. Trade from seller s to buyer b is the total number of balls landing in bin sb, which we denote by r_{sb}. A buyer-seller match is denoted by $m_{sb} = 1[r_{sb} > 0]$.

Parameters and simulation. We simulate the random model as follows. Focusing on Norway's largest export destination, Sweden, we set B and S equal to the number of buyers in Sweden and exporters to Sweden (see Table 4). The number of balls, n, equals the total number of connections made (24,400). The match probabilities s_s correspond to each seller's number of customers relative to the total number of connections made; s_b correspond to each buyer's number of suppliers relative to the total number of connections made.

Results. We focus on the key relationships described in the main text; (i) degree distributions,[47] (ii) number of connections versus total sales and within-firm sales dispersion and (iii) assortivity in in-degree and average out-degree of the nodes in:

(i) We plot the simulated degree distributions in Figure 13, in the same way as in the main text. Given that the match probabilities s_b and s_s are taken from the actual data, it is not surprising that the simulated degree distributions resemble the actual distributions in Figures 2 and 3.

(ii) The relationship between the number of customers and total exports per seller is plotted in the left panel of Figure 14. The relationship is positive and log linear. The right panel plots the number of customers on the horizontal axis and the value of 10th, 50th and 90th percentile of buyer-seller transactions (within firm) on the vertical axis. In contrast to the actual data and our main model (see Figure 5), the large majority of firms sell the same amount to each buyer; hence both the 10th and the 90th percentile cluster at $r_{sb} = 1$. For the firms with dispersion in sales, the magnitude of dispersion is small, with the 90th percentile not exceeding $r_{sb} = 2$.

(iii) Figure 15 plots the relationship between out-degree and mean in-degree (and the opposite), as illustrated in the main text in Figure 6. The relationship is essentially flat, so that the contacts of more popular sellers are on average similar to the contacts of less popular sellers. This is also at odds with the data and our main model.

In sum, the random matching model is not able to reproduce all the basic facts from the data.

[47] The degree of a node in a network is the number of connections it has to other nodes, while the degree distribution is the probability distribution of these degrees over the whole network.

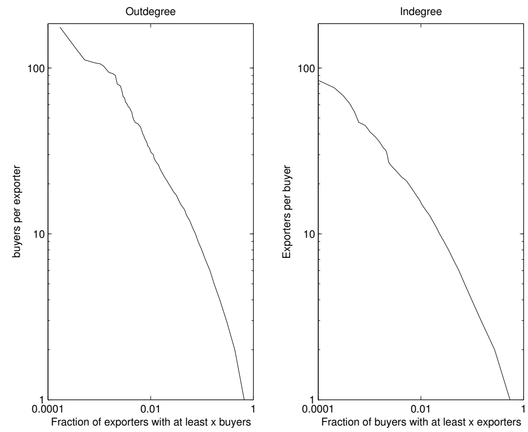


Figure 13: Distribution of out-degree and in-degree.

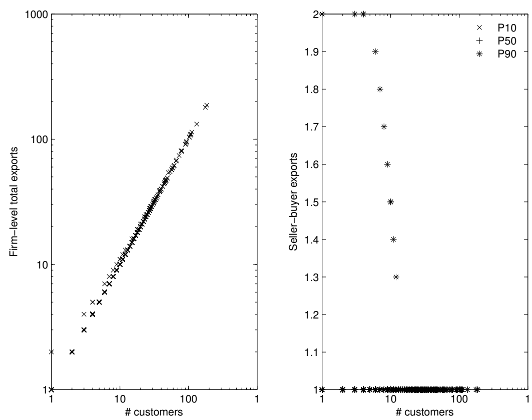


Figure 14: Firm-level total exports and within-firm dispersion in exports.

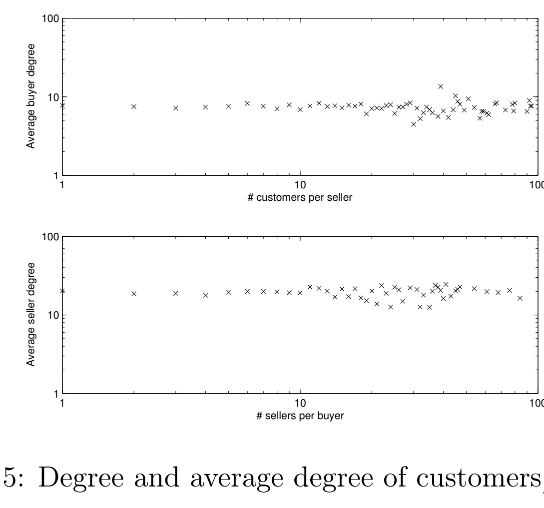


Figure 15: Degree and average degree of customers/suppliers.

J Basic Facts Revisited

This section presents descriptive evidence on buyer-seller relationships using trade data from a different country, Colombia. We show that the basic facts from Section 2 also hold in the Colombian data.

The data set includes all Colombian import transactions in 2011 as assembled by ImportGenius.[48]As in the Norwegian data, we can identify every domestic buyer (importer) and foreign sellers (exporters) in all source countries. However unlike the Norwegian data, transactions must be matched to firms (either exporters or importers) using raw names and thus are potentially subject to more error than the comparable Norwegian data. However, there is no reason to believe the noise in the data is systematic and thus we are comfortable using the data as a robustness check. Since we only have import data from Colombia, the roles of buyers and sellers are reversed compared to the Norwegian data, i.e. in the descriptive evidence that follows, an exporter represents a foreign firm exporting to Colombia, and an importer denotes a Colombian firm purchasing from abroad.

We reproduce the same facts as in the Norwegian data. Table 10 reports exporter and importer concentration for all imports and imports from Colombia's largest sourcing markets in 2011, U.S., China and Mexico. Both sellers and buyers of Colombian imports are characterized by extreme concentration, mirroring the finding in Table 4 (basic fact 2). Figure 16 confirms that the degree distributions in Colombia are close to Pareto, mirroring the finding in Figures 2 and 3 in the main text. Moreover, Table 11 shows that one-to-one matches are relatively unimportant in total imports (basic fact 3). Figures 17 and 18 show that while more connected exporters typically sell more, the within-firm distribution of sales is relatively constant, mirroring the finding in Figures 4 and 5 (basic fact 4). Figure 19 illustrates that more popular exporters on average match to less connected importers, mirroring the finding in Figure 6 (basic fact 5).

Table 10: Descriptive statistics: Colombian Imports.

	Overall	U.S.	China	Mexico
Number of exporters	95,185	28,926	32,677	5,349
Number of buyers	34,166	15,047	15,445	5,050
Share trade, top 10% sellers	.90	.93	.84	.96
Share trade, top 10% buyers	.93	.93	.87	.93
Share in total CO imports, %	100	26.2	15.5	11.4

Note: 2011 data. The overall column refers to outcomes unconditional on importer country.

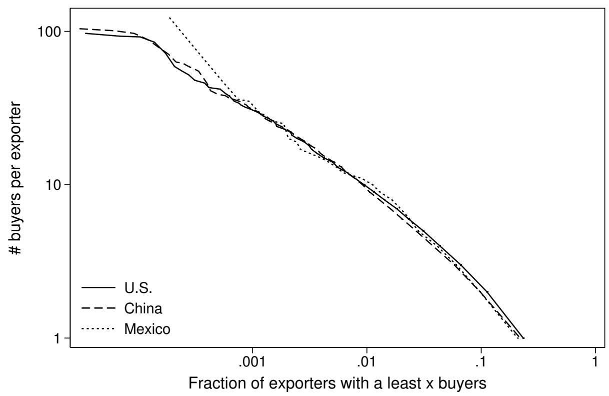
[48]The data are available at http://importgenius.com. See Bernard and Dhingra (2014) for details on the data construction.

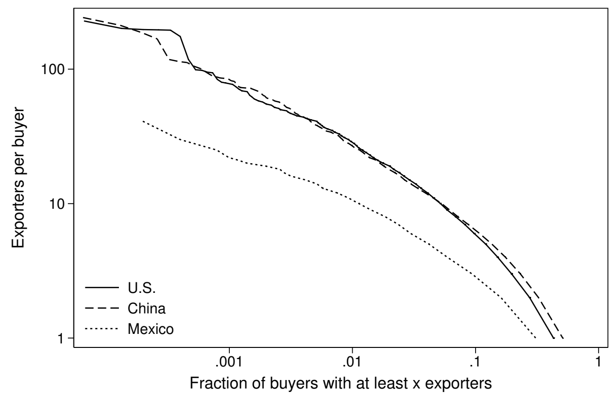
Table 11: Types of matches, % : Colombia.

	(1) One-to-one	(2) Many-to-one	(3) One-to-many	(4) Many-to-many
Share of value, %	4.9	36.4	7.6	51.1
Share of counts, %	15.8	36.5	12.8	34.9

Note: 2011 data. See Table 5 footnote.

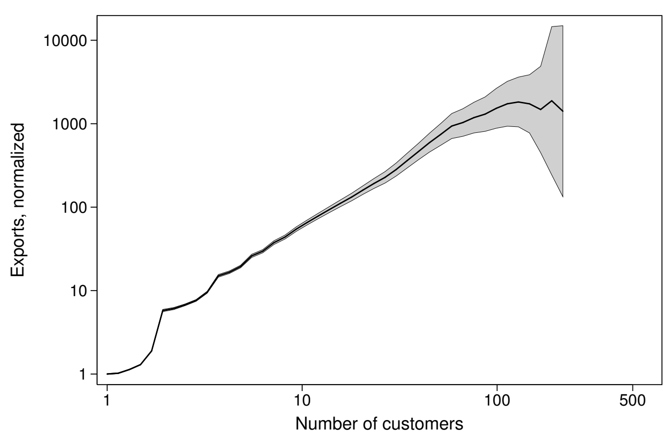
Figure 16: Distribution of # buyers per exporter (left) and exporters per buyer (right): Colombia.





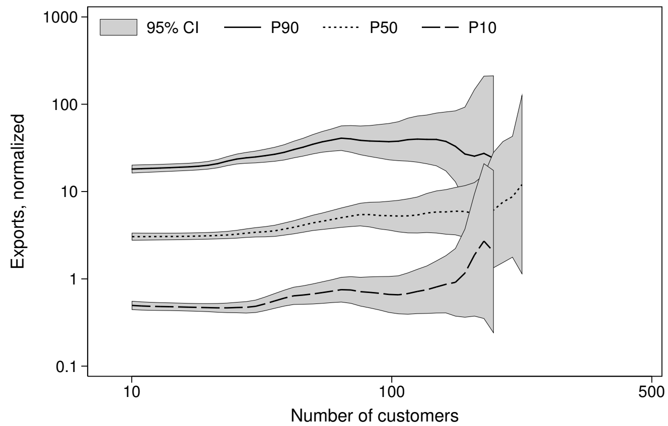
Note: 2011 data. Buyers per exporter: The estimated slope coefficients are -0.74 (s.e. 0.0004) for U.S., -0.78 (s.e. 0.001) for China and -0.78 (s.e. 0.001) for Mexico. Exporters per buyer: The estimated slope coefficients are -0.99 (s.e. 0.002) for U.S., -0.74 (s.e. 0.002) for China and -0.74 (s.e. 0.002) for Mexico.

Figure 17: Number of buyers & firm-level exports: Colombia.



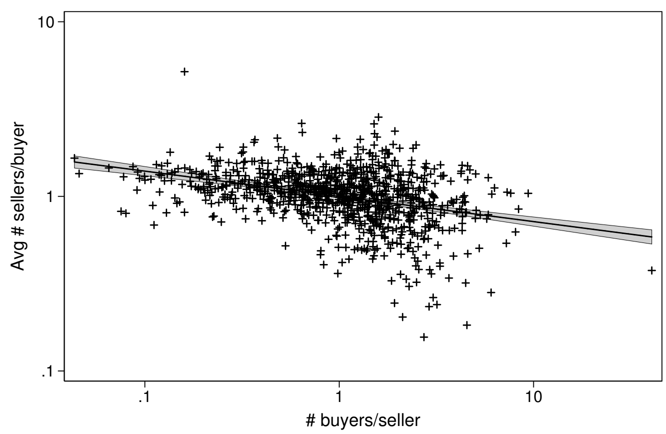
Note: 2011 data. See Figure 4 footnote.

Figure 18: Number of buyers & within-firm dispersion in exports: Colombia.



Note: 2011 data. See Figure 5 footnote.

Figure 19: Matching buyers and sellers across markets: Colombia.



Note: 2011 data. The linear regression slope is -0.14 (s.e. 0.01). See Figure 6 footnote.