Seller-buyer matching in international good markets

Clémence Lenoir* Isabelle Mejean† Julien Martin‡

March 6, 2017

Very preliminary - Do not circulate

Abstract

We develop and estimate a model of matching frictions in international good markets in order to study the implications of matching frictions on aggregates trade flows and individual exporters. The model is a simple extension of the Eaton and Kortum (2002) framework to matching frictions. In each market, a finite number of buyers meet with a random number of sellers located domestically or abroad. Conditional on their random choice-set, buyers choose the lowest cost supplier they have met. At the aggregate level, our model predicts that bilateral matching frictions have a monotonic and negative impact on bilateral trade flows like other well known bilateral frictions such as ice-berg costs. Nevertheless, matching frictions present an ambiguous impact on sellers' extensive margins. Specifically, we show that small exporters do not benefit from a reduction of bilateral matching frictions so that our random matching framework rationalize the randomness of small exporters serving obscure destinations observed in the data without adding idiosyncratic demand shocks. We use firm-to-firm trade data in the European Union to estimate the matching frictions parameter separately from ice-berg costs using statistics on the number of buyers served by a given seller in each European destination.

JEL Classification: F10, F11, F14, L15

Keywords: International trade, matching frictions, firm-to-firm trade networks, Structural estimation

*CREST and Université Paris-Saclay, Email address: clemence.lenoir@ensae-paristech.fr.

†Ecole Polytechnique, CREST and CEPR, Email address: isabelle.mejean@polytechnique.edu.

‡UQAM, Email address: martin.julien@uqam.ca.

1 Introduction

It has long been argued that search and matching frictions participate to the various difficulties encountered by firms in international markets. Meeting with foreign buyers induces extra costs to gather information on potential clients, their specific needs, etc. This is one potential reason why the magnitude of bilateral trade flows is so sensitive to cultural elements such as sharing the same language, even though such elements do not directly induce a substantial physical trade cost.[1] In this paper, we introduce such frictions into a Ricardian model of international trade and analyse how they affect the structure of aggregate trade.

We exploit a detailed database which identifies the exact number of buyers of each French exporter in each EU destination. Consistent with Rauch and Trindade (2002) we find that the number of French migrants living abroad and the number of migrants from the destination country have a positive and significant correlation with aggregate trade flows between France and his foreign partners, more particularly at the extensive margin. This finding reflects the importance of networks effect in trade and can be explained either by the presence of common taste or by the presence of search frictions. Using worldwide French customs we then show that small firms tend to relatively well access some obscure countries compare to large firms. Indeed, ranking destinations in terms of the number of entrants of large and small exporters we find that destinations which have a better rank i.e which are relatively more accessible for small firms are both of a small market size and remote. This finding is at odd with what model of sunk cost of export would predict and with the classic EK framework and reflects the high level of randomness of export activities observed in the data. Finally, as inBernard et al. (2014) and Carballo et al. (2013), we show that individual exporters greatly vary in terms of the number of buyers they interact with in their typical foreign market. In particular, large firms tend to serve more buyers. Within a firm, the number of clients served is increasing in the size of the destination and decreasing in its distance to France. The heterogeneity in the number of buyers within a firm contributes to explaining aggregate trade flows.

We argue that such heterogeneity and randomness can be rationalized by the combined effect of matching frictions between exporters and importers and Ricardian advantages across exporters. Our model is an extension of Eaton and Kortum (2002) to matching frictions. Our model focuses only on one good and the supply-side is the same as in their model with a continuum of potential producers of a perfectly substitutable variety endowed with some marginal cost of producing. On the demand side, a large discrete number of buyers in each destination meet with a random sample of producers and choose the lowest cost supplier,

[1] Rauch (2001) thus explains the role of networks in international markets by such information frictions.

within this random choiceset.[2] The random component of the matching process comes down to relaxing the implicit assumptions used in most trade models that i) foreign consumers observe perfectly the whole set of potential suppliers for the product they are looking for, and ii) individual exporters serve the whole market, conditional on entering a destination.[3] It notably implies that ex-ante homogeneous buyers end up heterogeneous ex-post, in terms of the price they pay for the same good. Lucky buyers thus draw a larger and/or more heterogeneous choiceset which allows them to purchase from a lower cost supplier.

We discuss how this simple extension to the Eaton and Kortum (2002) model generates interesting predictions regarding the selection of firms into export and the number of clients they serve, conditional on entering a destination. In the benchmark, the frictionless Eaton and Kortum (2002) model, perfect competition among heterogeneous suppliers implies that, in equilibrium, a maximum of one firm per country and per good serves a given destination market. Our model does not display such degenerated distribution. Instead, several heterogeneously productive suppliers can simultaneously serve the same market with the same good, though to different buyers. On average, more productive sellers are however more likely to serve a given destination because, conditional on meeting with a buyer, they are more likely to be picked for serving her. This reasoning also explains why, on average, more productive firms serve a larger number of buyers, within a destination.

Moreover, in our framework the probability for a particular buyer to be selected by any buyer in a destination depends both on its level of productivity through its probability to be the lowest-cost supplier met and on the level of the bilateral meeting probability. Reducing matching frictions via an increase in the meeting probability has then an ambiguous effect : it has a positive effect on the seller's visibility but a negative effect on the seller's probability to be the lowest cost supplier met through an increase in the level of competition coming from other domestic firms. For small potential exporters the competition channel dominates and they have a higher probability to export if matching frictions are high. On the opposite, as large and productive firms are very likely to be lowest-cost supplier met by any potential buyer and the visibility channel dominates for them and a reduction in matching frictions increases their probability to export. As a result the level of bilateral frictions also affect the composition and the nature of exporters which reach different destinations. Countries with low bilateral frictions have a more concentrated import market.

Heterogeneity in the cross-country dimension of the number of buyers by a firm served and the nature of exporters are explained by i) international trade costs, which reduce the firm's

[2]Our modeling of the matching process is inspired from Eaton et al. (2014).

[3]Arkolakis (2010) is an exception since his model relaxes the second assumption. He instead assumes that individual exporters can pay an increasing marketing cost to serve an increasing share of the destination market.

relative price competitiveness, as in Eaton and Kortum (2002), and ii) matching frictions, which magnitude varies across destinations. Note that such predictions regarding the number of buyers served by a given firm in a given destination hold true on average. But the random nature of the process also implies that any outcome is possible ex-post. Namely, a highly productive firm can end up being unlucky enough to be picked by no firm, even in a quite easy destination. Such randomness is useful inasmuch as it allows reproducing any form of unobserved heterogeneity across firms and destinations, which has been shown important in disaggregated trade data (see Eaton et al, 2011).

Having discussed the main analytical properties of the model, we then use a structural approach to estimate its main parameters. The magnitude of matching frictions can be estimated for each sector and destination using a method of asymptotic least squares. The empirical moments used to feed the estimation measure the shares of French firms serving a given number of clients, within a given (country×sector) market. Within a (product×destination) couple the dispersion between these moments is driven by matching frictions due to the non-monotonic effect of matching frictions on sellers' extensive margin. This allows us to estimate the matching frictions separately from ice-berg costs.

We show that estimated matching frictions within a sector are weakly correlated with GDP and distance[4] and are highly negatively correlated with the number of French migrants living in the destination considered. Moreover, within a country matching frictions are higher in sectors with the higher share of differentiated products[5] reflecting the fact that search frictions are higher in non organized market place or for less homogeneous products. In line with the predictions of our model we first show that there is a positive correlation between aggregate trade flows and bilateral meeting probabilities. Then, we show that at the firm level an increase in the meeting probability has a negative though not significant impact the firms' sales, while it has a strong positive impact for large firms.

Our results provide empirical support for trade policies targeting firms and destinations displaying important search and matching frictions. Our findings call for more firm-specific programs rather than nation-wide programs which can have a counter-intuitive effect. Indeed while promotion agencies try to reinforce French sellers' visibility as a whole they can have detrimental effect for small exporters.[6]

---

[4]This finding is also a validation ex-post of our estimation strategy.

[5]Differentiated products using the Rauch classification meaning that these products are neither traded in an organized market place neither have a reference price.

[6]An example of such policies can be found in the programs organized by Business France, a French institution providing public support for exporting activities. Business France has several offers which are meant to help firms meet with foreign clients through international trade fairs, or bilateral meetings organized with

Our work relates to the emerging literature on information frictions and trade. Allen (2014) provides empirical evidence of the importance of such information frictions in the agricultural market in developing countries. In his model, information frictions hit the seller side of the economy: Exporters ignore the potential price of their crops abroad, thus enter into a sequential search process. We instead introduce information frictions on the buyer side of the economy, with buyers having an imperfect knowledge of the supply curve. From this point of view, our model is closer to Dasgupta and Mondria (2014). Their model of inattentive importers assumes that buyers optimally choose how much to invest into information processing to discover potential suppliers. They show how such information frictions magnify the impact of physical trade costs in a gravity context. We instead assume that the matching process is purely random and derive predictions regarding the expected number of clients that a given exporter serves in a given market. On the empirical side, Lendle et al. (2012) and Steinwender (2014) also highlight the importance of information frictions for trade. In this literature, the empirical challenge is to find convincing proxies for information frictions. Lendle et al. (2012) compare goods traded on eBay and in physical markets using the argument that information frictions are reduced online. Steinwender (2014) uses the establishment of the transatlantic telegraph cable as a natural experience of a reduction in the cost of gathering information.

Our paper also contributes to the literature on trade networks. Rauch (1999) shows that proximity, common language and colonial ties are relevant explanatory variables for trade in differentiated products, which is more prone to information frictions. In a social network perspective, Rauch and Trindade (2002) show that shares of migrants from destination country (resp. origin country) in the origin country (resp. destination country) have a positive impact on trade as it allegedly reduces matching frictions between buyers and sellers. More recently, Chaney (2014) develops a dynamic model of random matching in international trade markets. In his model, exporter-importer relationships are purely random ex-post and are only history dependent. Instead, we embed random matching into an otherwise standard Eaton and Kortum (2002) model but we assume a static framework.

Finally, the use of firm-to-firm trade data naturally draws a link with recent papers which also use such highly disaggregated data, notably Carballo et al. (2013), Eaton et al. (2013), Sugita et al. (2014) and Bernard et al. (2014). To explain the dispersion in the number of buyers served by different exporters, they introduce an additional source of heterogeneity on the buyers' side.[7] Such strategy implies that the matching process between sellers and

representatives of the sector in the destination country. Such programs are especially targeted to small and medium firms, which are more likely to be severely hurt by information frictions.

[7]Namely, Bernard et al. (2014) and Sugita et al. (2014) assume that buyers differ in their size or capacity while Carballo et al. (2013) and Eaton et al. (2013) introduce heterogeneous tastes.

buyers is deterministic: conditional on their size or taste, buyers will sort out to interacting with a specific class of exporters. In our framework, buyers are homogeneous ex-ante but heterogeneous ex-post, due to the randomness in the matching process.

The rest of the paper is organized as follows. We first present the data and stylized facts on firm-to-firm intra-EU trade. We most specifically focus on the number of buyers served by a given firm, and study how it varies across firms and destinations. Section 3 presents our theoretical model and derives analytical predictions regarding the expected number of clients that an exporter will serve in her typical destination. Section 4 explains how we estimate the magnitude of matching frictions using a structural approach based on asymptotic least squares. Section 5 presents the results and discusses how matching frictions vary across sectors and destinations. Finally, Section 6 concludes.

2 Data and stylized facts

We first describe the firm-to-firm data used in the empirical analysis (Section 2.1). Section 2.2 then presents new stylized facts motivating our model, and the moments used to estimate it.

2.1 Data

The empirical analysis is conducted using detailed export data covering the universe of French firms. The data are provided by the French Customs. The full data set covers all transactions that involve a French exporter and an importing firm located in the European Union, over 1995-2010. Most of our analysis will focus on data for 2007 but we checked that statistics are not sensitive to the choice of the reference year. In order to avoid including French wholesalers whose behaviours are hardly explained by the model, we focus the analysis to firms in the manufacturing sector. Another reason why we focus on these firms is that they are more likely to produce "differentiated goods", which are more prone to information frictions (Rauch, 1999).

For each transaction, the data set records the identity of the exporting firm (her SIREN identifier), the identification number of the importer (an anonymized version of her VAT code), the date of the transaction (month and year), the product category (at the 8-digit level of the combined nomenclature) and the value of the shipment. In the analysis, data will be aggregated across transactions within a year, for each exporter-importer-hs6 product triplet. Such aggregation helps focus on the most important novelty in the data, which is the explicit identification of both sides of the markets, the exporter and her foreign partner. The product dimension will permit us to condition our results on the good being traded, as in the model. In the rest of the analysis, French exporters will be indexed by s and individual importers by b_i where i denotes the country of location, one of the 26 EU destinations. This hypothesis comes down to redifining a French exporter as a single-product firm. Comparing columns (1) and (4) of Table 1 which displays the number of French exporter in each destinations then the number of firm-products couples in each destination an idea about the average the number of product exported by each firm and in how many part this firm is divided to consider only single-product firm. On aggregate in our sample, the typical firm is divided in 7,67 entities as also shown in Table 2.

While goods are perfectly free to move across countries within the European Union, firms selling goods outside France are still compelled to fill a Customs form. These forms are used to repay VAT for transactions on intermediate consumptions. This explains that the data are exhaustive. One caveat, though: small exporters, with total exports in the European Union in a given year below 150,000 euros, are allowed to fill a "simplified" form that does not require the product category of exported goods. As we adopt the definition of a seller at the siren-hs6 level we had no choice but to drop these transactions.

Given the quality of the data, little cleaning is necessary to construct the final data set. The only issue which is worth mentioning is related to situations in which the physical trade flow is not geographically confounded with the financial trade flow. For instance, a French firm can export a good which is sent from a third country, say because the commodity is stored into another plant of the firm. Or a good can be sold to a firm located in a given country, but the firm requests the good to be delivered in a third country. In the first example, the trade flow is not recorded in our data. In the second one, it is but we decided to drop it in order to avoid confounding several sources of frictions. The number of observations thus neglected is however small, less than **X%**.

In 2007, we have information on 19,263 French firms exporting to 355,240 individual importers located in the 26 countries of the European Union. Total exports by these firms amount to 241 billions euros. This represents 59% of France total exports.

– Table 1 about here –

Table 1 displays the number of individuals involved in each bilateral trade flow. Most of the time, the number of importers is larger than the number of exporters selling to this destination (Columns (1) and (2)). This suggests that the degree of exporters (number of importers they are connected to) is on average larger than the degree of importers (number of French exporters they interact with). This is even more true once we focus on product-specific trade flows as in Columns (4) and (5). Both the number of exporters and the number of importers vary across destinations. For instance, 78,896 German firms import from France against 915 in Estonia. Likewise, the number of French exporters serving the German market is an order of magnitude larger than in Estonia.

Column (3) in Table 1 reports the number of exporter-importer pairs which are active in 2007. These numbers are small in comparison with the number of *potential* relationships, equal to the product of the numbers of exporters and importers. This suggests that the density of trade networks is small on average. This is even more true once we focus on the number of pairs active in a particular product category (column (6)). The comparison of Columns (1)-(3) and Columns (4)-(6) further shows that most firms involved in international trade, either on the exporter or on the importer side, trade several products. In the rest of the paper, we will consider the pair composed by an exporting firm and the product she sells as the unit of observation. For simplicity, we will call a “seller” the pair they form.

The firm-to-firm dataset is complemented with several aggregate variables used to run gravity regressions in Section 2.2. Distance data are taken from the CEPII’s website.[8] The distance between a French firm and her buyers is proxied by the weighted distance between France and the destination. We control for the market’s overall demand using HS2-specific imports in the destination, less the demand for French goods. Multilateral import data are from WITS. Finally, information frictions are controlled for using information on the stock of migrants per origin and destination countries, taken from the UN database on Trends in International Migrant Stock. The degree of information frictions between France and a destination j is assumed to be inversely related to the share of French citizens in the destination’s population and the share of migrants from j in France.

2.2 Descriptive Statistics

This section presents new facts on the interaction between sellers and buyers engaged in international trade. The facts are later used to motivate the model’s assumptions and to back some predictions.

2.2.1 Number of buyers per seller

Figure 1 shows the strong heterogeneity in the number of buyers per seller within a destination. The left panel documents the share of sellers interacting with a given number of buyers, within a definition. 65% of the sellers interact with a single buyer, and 90% with at most 5 buyers. At the other side of the spectrum, one percent of sellers interact with more than 100 buyers in the same destination. The right panel describes the weight of these different categories of

[8]Detailed on the database can be found in Mayer and Zignago (2011).

sellers in French exports. Sellers interacting with a single buyer account for about a third of French exports and are thus smaller than the average firm in the distribution. Still, 80% of trade is made up by sellers interacting with at most 10 buyers. This means that French exports are not dominated by sellers interacting with more than 100 buyers.

– Figure 1 about here –

Heterogeneity across sectors and countries: There is a substantial amount of heterogeneity in the number of buyers per seller across firms both within destinations and within sectors. Tables 3 and 4 report this dispersion. The average number of buyers per seller varies widely across countries ranging from 1.2 in Bulgaria to 5.1 in Germany (Table 3). The number of buyers per seller in each HS section exhibits a similar level of dispersion, the average degree of sellers varying between 1.6 for Arms and 5.5 in the Footwear industry.

– Tables 3 and 4 about here –

We examine the extent of dispersion in the number of buyers per seller more systematically using variance decompositions. Alone, country fixed effects explain 5% of the dispersion in the number of buyers served by firms. Sector fixed effects explain another 3% when sectors are defined at the HS2 level. Finally, country $\times$ sector fixed effects explain 10% of the overall variance, a number which stays stable when sectors are defined at the HS6 level[9]. This suggests that most of the heterogeneity across firms (more than 80%) comes from the heterogeneity across firms serving the same country with the same type of goods.

– Figures 3 about here –

To conduct further analysis of the dispersion of the number of buyers per seller across country we split sellers in four categories : sellers which have one buyer, two buyers, 3 to 6 buyers and more than 7 buyers per destination[10]. Figures 3 show that there is a humped shaped relationship between the number of French migrants in destination country and the number of French exporters in these for categories. This stylized fact is new and reflects that the number of migrants have an ambiguous effect on the seller extensive margin and the buyer extensive margin. Our theoretical model rationalizes this fact through a non linear effect of matching frictions on the extensive margins through two channels : a visibility effect and a competition effect. When the number of French migrants living in the destination country is

[9]in terms of adjusted R-squared

[10]We use this decomposition because most sellers have less that 7 buyers, and this decomposition maximises the number of product-country pairs for which we have a positive number of observations in all categories.

low, increasing its level increases the meeting probability of French sellers and then increases both seller and buyers margins. On the other hand, when the number of French migrants living in the destination country is already high, an increase mostly enhances competition coming from other French sellers and eventually has a negative effect on the number of entrants.

Figures 4 show that there is a log-linear decreasing relationship between these extensive margins and distance. In conclusion, Figures 3 and 4 show that proxies of ice-berg costs and matching frictions do not seem to have the same impacts on these extensive margins : distance has a monotonous impact while a non-monotonous relationship between extensive margins and matching frictions appear.

– Figures 4 about here –

Sellers' size and the number of buyers: Figure 2 presents a non-linear polynomial fit of the (log of the) number of EU buyers served against the seller's size. The number of buyers is almost flat for small sellers, with most of these sellers interacting with a single buyer. Then, the number of buyers increases rapidly with the seller's size to reach a plateau around 40 buyers. Table 5 presents the mean number of buyers per seller, in each destination and at different points of the distribution of firms' size. For instance, French sellers in the first decile of the size distribution interact on average with 1.3 German importers against 15.8 on average in the 10th decile. The last column further reports the correlation between sellers size and the number of buyers they interact with. The spearman correlation is around 10% and significant for all but two countries. However, the correlation between seller's size and its number of partners is less pronounced in small markets. For instance, the correlation between firm size and the number of buyers is almost nil in Cyprus and Estonia. This less pronounced correlation between size and the number of buyers in obscure places reveal that it seems that more randomness[11] is needed to describe the various margins of exports in these destinations, Eaton et al. (2011) proposes an explanation with a firm specific idiosyncratic demand shock in each destination, we propose an explanation through matching frictions.

– Table 5 and Figure 2 about here –

This set of stylized facts is summarized in Fact 1:

[11] In models with fixed cost to export this less significant correlation between size and the number of buyers in obscure places is not rational : in obscure places with a high fixed cost to export (and even a high costs to reach new buyers as in Arkolakis (2011) we should observe a higher correlation between size and the number of buyer served.

Fact 1. There is a substantial amount of dispersion in the number of buyers served by a given seller in her typical destination. More than 80% of the variance is across firms serving the same destination with the same type of goods. On average, large sellers tend to serve more buyers, the correlation between size and the number of buyer served is less intense in obscure destinations.

Fact 2. There is a hump-shaped relationship between the log number of French sellers serving 1, 2, 3-6 and than 7 buyers and the number of French migrants living in the destination country, whereas this relationship is linearly decreasing with log distance.

2.2.2 Number of sellers per buyer

Table 6 documents the number of sellers per buyer in the data. More than 90% of buyers (times HS6 product) import from a single French seller.[12] In unreported results, we have explored the heterogeneity across sectors and countries. Across countries, the average number of sellers per buyer is very stable - around 1.12. It is slightly larger in Bulgaria, at 1.2. The distribution is equally stable across HS sections. This leads us to Fact 3:

Fact 3. More than 90% of the buyers interact with a single French seller.

– Table 6 about here –

2.3 Randomness of the number of entrants

– Figure 5 about here –

Figure 5 shows the rank of worldwide destinations of French sellers in terms of number of entrants for two groups of firms : small exporters and large exporters[13]. Countries which are situated on the bisector are ranked the same for small and large firms which is the case for the top 20 destinations[14]. Countries which are above the bisector are countries which have a lower rank (meaning that they are relatively more accessible) for small firms than for large firms. These countries present a very low accessibility measured by the ratio of GDP by distance. It means that these obscure countries seem to be relatively more accessible by small firms. This fact can not be rationalize by models of fixed costs like in Melitz (2003). Indeed

[12]Because we define a seller as a exporter-HS6 product pair, we can interpret this table as the number of sellers per product for a given buyer. Note that if one looks at 8-digit product level data, the average number of sellers per buyer slightly declines to 1.11. The median and third quartile are left unchanged.

[13]Size in defined at this stage by aggregate level of exports

[14]A low rank between 1 and 20 means a high number of entrants.

in these frameworks, the ranking of countries should be the same for both small and large exporters. Moreover, due to cut-off effects small firms should not even be able to export in obscure destinations with high fixed costs of exports while we observe that not only they do but even relatively succeed better there. Moreover, this fact cannot be explained by a bilateral demand shifter for French products, such as more pronounced taste for French products in a particular destination. Indeed in a context of a bilateral demand shifter, it should affect small and large firms the same way such that rankings of countries in terms of the number of entrants should be the same. Our framework with bilateral matching frictions can rationalize this stylized fact.

Fact 4. Sorting destinations in terms of number of entrants, small firms succeed better than large firms in some obscure destinations

2.4 Gravity regressions

Having documented new dimensions of heterogeneity in firm-to-firm trade data, in terms of the number of partners exporters and importers interact with, we now use the gravity framework to show how this "new" margin affects the geographic composition of French exports. Gravity equations are first run at the product-level, then using firm-level exports.

Product-level gravity: Table 7 describes the contribution of the different margins of trade to the gravity equation. Namely, the value and margins of product-level exports to each destination are regressed on the distance between France and the destination, and proxies for the destination's market potential, its import demand and GDP per capita.[15] The left-hand side variable is either the total value of product-level exports or one of its components, where the decomposition is defined as follows:

$$\begin{aligned}
\ln x_{pd} &\equiv \ln \sum_{s \in S_{pd}} \sum_{b \in B_{spd}} x_{sbpd} \\
&= \ln \#^S_{pd} + \ln \frac{1}{\#^S_{pd}} \sum_{s \in S_{pd}} \#^B_{spd} + \ln \frac{1}{\#^{SB}_{pd}} \sum_{s \in S_{pd}} \sum_{b \in B_{spd}} x_{sbpd}
\end{aligned}$$

Here, x_{pd} denotes the value of French exports of product p in destination d, S_{pd} is the set of sellers serving this market and B_{spd} the set of importers purchasing product p from seller s. Product-level bilateral exports (x_{pd}) are decomposed into the number of French exporters to the destination ($\#^S_{pd}$) times the mean number of buyers each of these sellers serve

[15] Note that the very structure of the data, which only cover a single origin country makes it impossible to control for the destination's market potential using fixed effects. We instead rely on the above-mentioned proxies.

($\frac{1}{\#^S_{pd}} \sum_{s \in S_{pd}} \#^B_{spd}$ where $\#^B_{spd}$ denotes the number of buyers served by seller s) times the mean value of a transaction ($\frac{1}{\#^{SB}_{pd}} \sum_s \sum_b x_{sbpd}$).[16]

Column (1) in Table 7 reproduces a well-known result of the trade literature, namely that the value of bilateral trade is decreasing in the distance to the destination and increasing in its market potential. These effects hold true at the extensive margin (in terms of the number of firms serving the destination, Column (2)) *and* at the intensive margin (in terms of the mean value per seller). What our analysis further reveals is that the "intensive" effect is explained by firms serving more buyers in closer, larger and richer markets (Column (3)) as much as by the value of exports to each of these partners being large in those destinations (Column (4)). Said otherwise, the "intensive margin" which the previous literature has discussed further decomposes into a buyer margin and an intensive margin in terms of the export value per exporter-importer transaction. Both participate to explaining why exporter-specific sales tend to decrease with distance, such that the new "buyer-extensive" margin behaves as classic margins of trade.[17] In Appendix in Table 8 we show that these results hols at the firm-level.

– Table 7 about here –

These gravity results lead us to Fact 5:

Fact 5. The buyer extensive margin reacts as other margins of trade with classic gravity controls : it is positively correlated with market size and negatively correlated with distance. These correlations hold both at the aggregate and at the firm level.

Gravity and information frictions: In order to illustrate the importance of matching frictions in international trade, we augment the above gravity framework with additional proxies for the extent of matching and network frictions between France and the destination. Following Rauch and Trindade (2002), we use as proxies the number of migrants from the

[16] The proposed decomposition is not the only way one can decompose product-level trade flows into different margins. The above analysis has shown that most of the heterogeneity in the data comes from the number of buyers which a given seller serves, rather than the number of sellers a buyer interacts with. Based on this, we have chosen to work on the decomposition which best underlines this particular dimension.

[17] The larger effect of distance attributed to the seller margin rather than the buyer margin is entirely explained by the definition we arbitrarily adopted. Namely, when we treat sellers and buyers symmetrically as in:

$$\ln x_{pd} \quad = \quad \ln \#^S_{pd} + \ln \#^B_{pd} + \ln \frac{\#^{SB}_{pd}}{\#^S_{pd} \times \#^B_{pd}} + \ln \frac{1}{\#^{SB}_{pd}} \sum_{s \in S_{pd}} \sum_{b \in B_{spd}} x_{sbpd}$$

the distance elasticity is larger on the buyer than on the seller margin (i.e. $\left|\frac{d \ln \#^B_{pd}}{d \ln Dist_d}\right| > \left|\frac{d \ln \#^S_{pd}}{d \ln Dist_d}\right|$).

destination country living in France and the number of French citizens living in the destination country, both expressed in proportion of the country's total population. The underlying assumption is that migrants convey information on their origin country, which helps create new trade relationships. Results are summarized in Table 9, where the gravity regression in Table 7 is augmented with the above-mentioned variables.

– Table 9 about here –

Consistent with expectations, the impact of migrants is positive and significant. Namely, both the share of French migrants in the foreign population (Columns (1) and (3)) and the share of migrants from abroad in the French population (Columns (2) and (3)) are positively correlated with the value of product-level exports to that destination. Importantly, controlling for these variables reduces the distance elasticity. This is consistent with the view that the impact of distance is in part attributable to information frictions being more pronounced between distant countries. Columns (4)-(6) further dig into the effect of information frictions. We estimate the impact of migrants on the number of sellers, the mean number of buyers they serve, and the value of the average seller-buyer transaction. The effect of having a large migrant community is the strongest at the extensive margin, on the number of sellers and buyers involved in a given trade flow, and less pronounced, if not negative, on the intensive margin, the mean value of exports per transaction.

– Table 10 about here –

These results are further confirmed in Table 10, when the augmented gravity equation is estimated within a firm, across destinations. Both the stock of foreign migrants in France and the stock of French migrants in the destination continue to be positively correlated with the value of a firm's exports, especially through the number of buyers that she serves there. These results are summarized in Fact 6.

Fact 6. Proxies of French networks have a positive a significant effect on trade and both seller and buyer extensive margins. The elasticity of trade to distance is in part attributable to these network frictions, which are more pronounced between distant countries.

Facts 1 to 6 thus document a new dimension of heterogeneity across exporting firms, in terms of the number of buyers they serve in a destination. This number is systematically correlated with the size of the exporter. It also varies within a firm, across destinations, with on average less buyers served in distant destinations displaying more information frictions. In the next section, we build a model which is consistent with the main features of the data.

Consistent with evidence in Fact 6, the model relies on matching frictions to explain the heterogeneity in the degree of sellers, across firms and destinations.

3 The model

In this section, we present our model which is an extension of Eaton and Kortum (2002) to matching frictions. After having summarized the main assumptions, we derive a number of analytical predictions which will later be used in the structural estimation.

The purpose of the analytical framework is to study the matching process between sellers and buyers of a homogeneous good. To better emphasize the properties of this process, the rest of the analysis is kept as simple as possible. We focus on trade patterns *within* a sector and do not aggregate across sectors as in Eaton and Kortum (2002).[18] To alleviate notations, we do not keep track on the sector dimension but all country-specific variables must be understood as potentially varying across sectors. Production costs are considered exogenously given in a partial equilibrium framework. Finally, the nominal demand, conditional on a match, is supposed to be inelastic and normalized to one. Those assumptions are arguably unrealistic. They help simplify the analysis while not interacting with the matching process which the model is more particularly interested in.

3.1 Assumptions

The economy is composed of N countries indexed by $i = 1, ..., N$. In this economy, a single good is consumed and produced into perfectly substitutable varieties by a continuum of firms, some of which being inactive ex-post.

The supply side of the model is almost the same as in Eaton and Kortum (2002). Namely, there is a continuum of producers of the good in each country j, of measure $T_j \underline{z}^{-\theta}$. Those firms produce with a constant-returns-to-scale technology using an input bundle which unit price c_j is taken as exogenous. The productivity of a firm s_j located in country j is independently drawn from a Pareto distribution of parameter θ and support $[\underline{z}, +\infty[$.[19] The measure of firms in country j that can produce with efficiency above z is thus:

$$\mu_j^Z(z) = T_j z^{-\theta}$$

[18]Based on the cross-sector heterogeneity in the mean number of buyers per seller uncovered in Section 2, we chose to estimate the model sector-by-sector. This explains why we do not seek to aggregate across sectors.

[19]While Eaton and Kortum (2002) assume the distribution of productivities to be Fréchet, we instead parametrize it to be Pareto, which will later reveal useful once matching frictions will be introduced.

In the rest of the analysis, firms will be designated by their productivity, with z_{s_j} being the realized productivity of firm s_j. The exporter-hs6 product pairs studied in Section 2 are the empirical counterpart of these firms. As explained later, the heterogeneity across firms regarding the number of buyers they serve in a destination (Fact 1) will in part be explained by the underlying productivity heterogeneity.

There are iceberg trade costs between countries. To serve market i with one unit of the good, firms from country j need to produce $d_{ij} > 1$ units, a fraction $d_{ij} - 1$ being lost during the transportation. By convention, the cost of serving the domestic market is normalized to zero and thus $d_{ii} = 1$. As a consequence of iceberg trade costs, the cost of serving market i for a firm s_j is:

$$\frac{c_j d_{ij}}{z_{s_j}}$$

As in Eaton and Kortum (2002), iceberg trade costs reduce the competitiveness of domestic firms serving foreign markets. The larger the trade cost, the less competitive a firm abroad, conditional on her productivity. Contrary to Eaton and Kortum (2002), a firm which is efficient enough to serve a foreign market will not however be able to serve the whole market, because of matching frictions. Likewise, matching frictions will imply that a firm serving a given market is not necessarily active in all other markets which are “easier” in the sense of being less costly to serve or less competitive. A key consequence is that the equilibrium distribution of firms within a market is non-degenerated. As we will explain now, several firms which are unequally productive can simultaneously produce the same perfectly substitutable good and sell it to different buyers within a given market.

Given input prices and international trade costs, the measure of firms from j that can serve market i at a cost below p is:

$$\mu_{ij}(p) = \mu_j^Z \left(\frac{d_{ij} c_j}{p} \right) = T_j \left(\frac{d_{ij} c_j}{p} \right)^{-\theta}$$

Summing up over all producing countries gives the measure of firms which can serve country i at a cost below p:

$$\mu_i(p) = p^\theta \sum_{j=1}^{N} T_j (d_{ij} c_j)^{-\theta} = p^\theta \Upsilon_i$$

As in Eaton and Kortum (2002), $\Upsilon_i = \sum_{j=1}^{N} T_j (d_{ij} c_j)^{-\theta}$ reflects “multilateral resistance” in country i and governs the country’s price distribution: the higher Υ_i, the more competitors with low costs in this country.

In Eaton and Kortum (2002), the demand side of the model is summarized by the CES demand of a representative consumer in each country i. We depart from their framework and instead assume that each country is populated by a large number B_i of (ex-ante) homogenous consumers, each one being willing to spend one unit of the numeraire into the homogenous good. Because of matching frictions, each buyer $b_i \in [1, B_i]$ only meets with a discrete number of suppliers, drawn into the distribution $\mu_i(p)$. Conditional on the subset of producers she met, she decides on which one she will purchase from, by comparing the prices they offer. The assumption that buyers interact with a maximum of one seller is consistent with Fact 3 which shows that, conditional on importing from France, foreign buyers concentrate their purchase on a single partner. The inelastic demand assumption further neutralizes any adjustment occurring at the intensive margin, through variations in the demand expressed by a buyer to a seller. The focus on extensive margin adjustments is motivated by Fact 5, which emphasizes the role of the seller and buyer margins in a gravity context.

In the rest of the analysis, we will assume that producers price at their marginal cost, as in a perfect competition framework. As a consequence, buyer b_i chooses to purchase her good from the lowest-cost supplier who she met and pays the price:[20]

$$p_{b_i} = \min_{s_j \in \Omega_{b_i}} \left\{ \frac{c_j d_{ij}}{z_{s_j}} \right\}$$

where Ω_{b_i} is the set of producers drawn by buyer b_i in the distribution $\mu_i(p)$, which can be located in any country $j = 1...N$.

The number of potential suppliers in the set Ω_{b_i} reflects the extent of matching frictions in the economy. In a frictionless world, each buyer b_i would meet with all the firms in $\mu_i(p)$. Within a destination, all buyers would thus end up paying the same price for the homogenous good and the assumption of a representative consumer would be suitable. This is the assumption in Eaton and Kortum (2002), which generates an ex-post degenerated distribution of firms since only the lowest-cost suppliers are active ex-post in market i. We instead assume that the number of price quotes in Ω_{b_i} is a random variable. Namely, every producer located in j has a probability λ_{ij} to be drawn by buyer b_i. Because of the independence of draws, the number of suppliers from j that buyer b_i meets follows a binomial law of parameter

[20] One might question the assumption of marginal cost pricing in a context of frictional good markets. We think of marginal cost pricing as the result of some "price-posting" process, a situation in which producers need to define their price ex-ante, before the matching process. Under such pricing rule, and because the extent of competition within the mass $\mu_i(p)$ is important, marginal cost pricing is an equilibrium outcome. Ex-post, the producer might however be willing to deviate from this pricing rule. An alternative would be to assume that firms drawn by a buyer b_i compete à la Bertrand. Under such assumption, buyer b_i would optimally match with the lowest cost supplier, as in the case of marginal cost pricing, but would be charged a price slightly below the marginal cost of the second lowest-cost supplier. In the rest of the analysis, we will solely exploit predictions regarding the identity of the firms which are matched. For this reason, we will stick to the simpler assumption of marginal cost pricing.

$(T_j \underline{z}^{-\theta}, \lambda_{ij})$, that can be approximated by a Poisson law of parameter $\lambda_{ij} T_j \underline{z}^{-\theta}$.[21] Likewise, the number of suppliers from j offering a price below p can be represented by a Poisson of parameter $\lambda_{ij}\mu_{ij}(p)$. Summing over countries implies that the total number of price quotes drawn by buyer b_i follows a Poisson of parameter:

$$\sum_{j=1}^{N} \lambda_{ij} T_j \underline{z}^{-\theta}$$

In the rest of the analysis, λ_{ij} is interpreted as a measure of frictions, which we assume is specific to each country pair (and each sector). A coefficient closer to one implies that buyers from i gather more information on potential suppliers in country j and are thus more likely to identify the most competitive ones. A testable assumption, which would be consistent with the interpretation we make of results in Tables 9 and 10, is that λ_{ij} is systematically correlated with past migration flows between countries.

Heterogeneity in the magnitude of matching frictions across countries means that the subset of firms which a buyer meets is biased towards firms located in countries with which matching frictions are lower, on average. Within an origin country, however, all producers have the same probability of being drawn, no matter their productivity. This is the key assumption which will generate ex-post heterogeneity across buyers regarding the price they pay. Namely, lucky buyers will end up with a random choiceset Ω_{b_i} which contains low cost producers. As a consequence, they will pay the homogenous good at a low price. At the other side of the border, even poorly productive sellers can end up serving a distant country, which happens if they are lucky enough to be drawn by an unlucky buyer which has no better choice than buying the good from this high cost producer.[22]

As shown in Eaton et al. (2014), the assumption of Poisson draws into a Pareto distribution is analytically convenient because it delivers a Weibull distribution for the minimum price at which a buyer b_i can purchase the good (see the proof in Appendix A.1):

$$G_i(p) = 1 - e^{-p^{\theta} \Upsilon_i \widetilde{\lambda}_i}$$

[21] The approximation rests on the convergence in law of the binomial distribution towards the Poisson law, when the number of trials goes to infinity while the product $T_j \underline{z}^{-\theta} \lambda_{ij}$ remains constant, which we assume is the case.

[22] Such analytical property is consistent with evidence obtained from firm-level data, that export behaviors display a lot of heterogeneity around the predictions of perfect sorting between firms induced by Melitz (2003) type models. In Eaton et al. (2011), the heterogeneity is explained by additional sources of heterogeneity across firms, regarding the fixed cost of exporting and the level of demand in different markets. In our framework, the heterogeneity is the consequence of the randomness introduced through the matching process.

where $\widetilde{\lambda_i} = \frac{\sum\limits_{j=1}^{N} \lambda_{ij} T_j \underline{z}^{-\theta}}{\sum\limits_{j=1}^{N} T_j \underline{z}^{-\theta}}$ is the share of the overall mass of suppliers which buyers from i have access to, on average. One can also interpret this variable as the mean level of frictions encountered in country i. From this, it comes that the price paid by a consumer in country i is on average smaller the more intense competition in this country (the larger Υ_i) and the lower matching frictions (the higher $\widetilde{\lambda_i}$). Finally, the probability of being matched with a low cost supplier is also increasing in θ, conditional on Υ_i: A less heterogeneous distribution of prices indeed implies that even unlucky buyers will end up paying a price which is not very far from the lowest cost supplier they would have been able to reach in the absence of matching frictions.

3.2 Analytical predictions

In this section, we first derive predictions regarding the magnitude of bilateral trade flows between any two countries. Such predictions help understand how matching frictions modify the benchmark frictionless model in Eaton and Kortum (2002). We then derive predictions regarding the number of buyers served by individual suppliers, in expectation. These theoretical results will later be confronted with the data, to estimate the magnitude of matching frictions.

3.2.1 Aggregate trade

Consider first the determinants of bilateral trade flows. Under the assumption of inelastic demand, the share of country j's consumption which is imported from country i, π_{ij} in what follows, is the sum of unitary demands aggregated across all buyers which interact with a seller from j divided by aggregate consumption:

$$\pi_{ij} = \frac{\sum_{b_i=1}^{B_i} \mathbb{1}\{s(b_i) = j\}}{\sum_{b_i=1}^{B_i} 1} = \mathbb{E}_{b_i}[\mathbb{1}\{s(b_i) = j\}]$$

where $\mathbb{1}\{s(b_i) = j\}$ is a dummy variable which is equal to one if buyer b_i ultimately chooses to purchase the good from a supplier from j and $\mathbb{E}_{b_i}[.]$ is the expectation operator, defined across buyers from i. Under the assumptions of the model, $\{\mathbb{1}\{s(b_i) = j\}\}_1^{B_i}$ are random variables which are independent and identically distributed. Using the law of large numbers, π_{ij} is thus equal to the expected value of $\mathbb{1}\{s(b_i) = j\}$, across buyers in i.[23] It is the probability that the lowest cost supplier encountered by any buyer from i is located in country j.

[23] Eaton and Kortum (2002) also use the same kind of reasoning to define the magnitude of bilateral trade flows. In their model, π_{ij} is defined at the aggregate level and the law of large numbers is used across varieties

In order to derive analytical predictions regarding π_{ij}, two assumptions are important. First, the assumption that firms' productivity is drawn in a Pareto distribution which shape parameter is homogeneous across source countries implies that, at any price p, the share of firms from j in the distribution $\mu_i(p)$ is constant. Second, the assumption that draws in this distribution follow a Poisson process means that this property subsists in the frictional world (see Eaton et al., 2012). Namely, conditional on the minimum price drawn, buyers from i have a constant probability to draw a supplier from j. Using these two assumptions, one can show that:

$$\begin{aligned} \pi_{ij} &= \frac{\lambda_{ij}\mu_{ij}(p)}{\sum_{j=1}^{N}\lambda_{ij}\mu_{ij}(p)} \\ &= \frac{T_j(d_{ij}c_j)^{-\theta}}{\Upsilon_i\kappa_i}\frac{\lambda_{ij}}{\widetilde{\lambda}_i} \end{aligned} \tag{1}$$

where $\kappa_i \equiv \frac{\sum_{j=1}^{N}\frac{\lambda_{ij}T_j}{\sum_{j=1}^{N}\lambda_{ij}T_j}(d_{ij}c_j)^{-\theta}}{\sum_{j=1}^{N}\frac{T_j}{\sum_{j=1}^{N}T_j}(d_{ij}c_j)^{-\theta}}$. See the proof in Appendix A.2.

The share of products from j in country i's final consumption depends on i) the relative competitiveness of its firms in comparison with the rest of the world, $\frac{T_j(d_{ij}c_j)^{-\theta}}{\Upsilon_i\kappa_i}$, and ii) the relative size of matching frictions its firms encounter while serving market i, $\frac{\lambda_{ij}}{\widetilde{\lambda}_i}$.[24] The first determinant is almost identical to the formula derived in Eaton and Kortum (2002), though they derive it for the aggregate economy exploiting the law of large numbers across imperfectly substitutable varieties rather than across buyers within a sector. It shows how

of the differentiated aggregate consumption good, rather than across buyers of the same homogeneous variety. Note that this definition heavily relies on the assumption that individual demands are homogeneous across buyers, and thus inelastic to prices. With elastic demand functions, we would need to correct the above formula by the expected demand, conditional on buying from country j.

[24] In this formula, κ_i can be interpreted as the distortion that frictions induce on the the destination's multilateral resistance index. κ_i can be larger or below 1 : if lower frictions affect countries that are larger and which face lower marginal costs and trade barriers then the level of competition in market i, the 'ex-post" multilateral resistance will be higher than in a friction-less world. To see why, notice that:

$$\Upsilon_i\kappa_i = \frac{\sum_{j=1}^{N}T_j}{\sum_{j=1}^{N}\lambda_{ij}T_j}\sum_{j=1}^{N}\lambda_{ij}T_j\left(d_{ij}c_j\right)^{-\theta}$$

This term can thus be interpreted as an "ex-post" multilateral resistance index measuring how input costs, geographic barriers *and* frictions distort country i's effective state of technology towards technologies emanating from closer, cheaper and less frictional countries. This "ex-post" multilateral index is equal to the "ex-ante" multilateral index described in Eaton and Kortum (2002) when frictions disappear (i.e. $\Upsilon_i\kappa_i \to \Upsilon_i$ when $\lambda_{ij} \to 1,\ \forall i$).

the combined impact of technology and geography determines international trade flows in a Ricardian world. Namely, the closer a country and the cheaper its inputs, the larger its share in the destination country's consumption. The key insight of our model is that matching frictions can distort trade flows, in comparison with this benchmark[25].

Proposition 1. The market share of a country is always increasing with a reduction of bilateral frictions.

$$\frac{\frac{\partial \pi_{ij}}{\lambda_{ij}}}{\pi_{ij}} > 0 \ \forall \ \lambda_{ij} \ \in \ [0,1]$$

See the Proof in Annexe A.5.

To get an intuition behind this result, first note that

$$\frac{\frac{\partial \pi_{ij}}{\lambda_{ij}}}{\pi_{ij}} = \frac{\partial ln \pi_{ij}}{\partial \lambda_{ij}} = \underbrace{\frac{\partial ln \lambda_{ij}}{\lambda_{ij}}}_{\text{Visibility channel}} - \underbrace{[\frac{ln \kappa_i}{\partial \lambda_{ij}} + \frac{\partial ln \widetilde{\lambda_i}}{\partial \lambda_{ij}}]}_{\text{Competition channel}} \tag{2}$$

Equation (2) shows that the impact of a reduction in bilateral matching frictions on aggregate trade flows goes through two channels. First a direct channel related to the visibility of exporters through their meeting probability λ_{ij}. Then through two indirect channels related to the level of competition in destination market through the average level of frictions $\widetilde{\lambda_i}$ and the distortion of multilateral resistance effect κ_i. First, the direct effect of the bilateral meeting probability on market share is positive. This comes from the fact that lower matching frictions increase the probability that any supplier from j will be drawn by any buyer from i, which is a pre-requisite for being chosen to serve the destination. Then as shown in Appendix A.5 with equation 13, an increase in the bilateral matching probability frictions has a positive impact on the average meeting frictions $\widetilde{\lambda_i}$ such that the level of competition in this destination increases and bilateral trade flows are reduced. On the other hand, as shown in Appendix A.5 with Equation 12 a change in bilateral matching frictions has an ambiguous effect on the distorting effect of matching frictions on multilateral resistance. The final effect depend on the relative level of distance and marginal cost of the origin country compared the rest of the world. Reducing matching frictions for a country which is a large contributor to multilateral resistance will increase the distorting effect of matching frictions, whereas if it happens to a relatively remote country then the distorting effect will be reduced. As a result, the effect is also ambiguous on aggregated trade flows.

[25] One could also remark that consequences of matching frictions at the aggregate level are very similar to the introduction of bilateral fixed costs to export, we show in the next implications of the model that predictions at the firm level are not similar to the ones of model with fixed costs.

At the end of the day, the "visibility" effect is always larger and a reduction of bilateral matching frictions always increases bilateral trade flows : at a given level of technological advantage, a country which faces less matching frictions for serving a given country will end up selling more there as stated in 1. This is in line with argument advanced by Rauch (1999) that matching frictions might contribute to reducing the magnitude of bilateral trade between more distant countries, if they are somewhat correlated with the physical and cultural distance between countries. Fact 6 is consistent with this view[26].

3.2.2 Firm-to-firm matching

Having derived predictions regarding the magnitude of aggregate trade flows, we then study the matching process between any two firms. Such predictions are new to our model and can be confronted to the data on firm-to-firm trade. Because we observe the universe of French exporters, and their clients abroad, we will take the point-of-view of individual sellers and derive predictions regarding the expected number of clients they can reach, in each destination.

Consider first the probability that a given supplier from j, France in our data, serves a buyer in i. In our framework, this probability decomposes into the probability that s_j is drawn by b_i times the probability that she is the lowest cost supplier, within b_i's random set:[27]

$$\begin{aligned}
\rho_{s_j i} &= \mathbb{P}\left(\mathbb{1}\{s(b_i) = s_j\} = 1 \; | z_{s_j} > \underline{z}\right) \\
&= \mathbb{P}\left(s_j \in \Omega_{b_i}\right) \mathbb{P}\left(\min_{s'_k \in \Omega_{b_i}} \left\{\frac{c_k d_{ik}}{z_{s'_k}}\right\} = s_j\right) \\
&= \lambda_{ij} e^{-(c_j d_{ij})^\theta z_{s_j}^{-\theta} \Upsilon_i \kappa_i \widetilde{\lambda}_i} \qquad (3)
\end{aligned}$$

where $\mathbb{1}\{s(b_i) = s_j\}$ is a dummy equal to one if buyer b_i chooses seller s_j as her provider of the good. Because of the Poisson assumption, the probability of being drawn by a buyer is

[26]Namely, suppose that both matching frictions and international trade costs only depend on the distance between countries: $\lambda_{ij} = Dist_{ij}^{-\alpha}$ and $d_{ij} = Dist_{ij}^{\beta}$ where $Dist_{ij}$ is the distance between i and j and α and β are positive parameters. Then a log-linearized version of Equation (1) implies:

$$\ln \pi_{ij} = -(\alpha + \theta\beta) \ln Dist_{ij} + \ln T_j c_j^{-\theta} - \ln \Upsilon_i \kappa_i \tilde{\lambda}_i$$

which is a standard gravity equation. The elasticity of trade to distance is then affected by the response of trade to changes in international trade costs *and* matching frictions. Both elements affect international trade at the extensive margin. A decrease in λ_{ij} reduces the probability that a seller from j meets with buyers from i while an increase in d_{ij} reduces her chances to be chosen to supply the good, conditional on meeting with a buyer.

[27]Since buyers are ex-ante homogeneous, the probability is the same for all buyers b_i located in country i.

constant and only depends on the size of matching frictions. More productive sellers have a higher probability to be matched with any buyer from i because, conditional on being drawn, they have a better chance to be the lowest cost supplier. And conditional on her productivity, a seller has a better chance to serve a buyer located in an "easy" market which she can serve at a low cost (d_{ij} close to one), where competition is limited (Υ_i low) and which displays important frictions, on average ($\tilde{\lambda}_i$ small).

Contrary to aggregate trade flows 1, an increase in the meeting probability has an ambiguous impact on the probability of a seller to be chosen by a particular buyer.

Proposition 2. There is an "optimal" level of bilateral matching frictions for each seller. This "optimal" level of meeting probability is increasing with the seller's productivity:

$$\lambda_{ij}^{\mathrm{Opt}_{s_j}}(z_{s_j}) = \frac{z_{s_j}^{\theta} \sum_j Tj}{T_j (d_{ij} c_j)^{\theta} \Upsilon_i} \tag{4}$$

See the Proof in Appendix A.5.

Proposition 2 states that more bilateral matching frictions (a lower meeting probability λ_{ij} parameter) have an ambiguous effect on the probability to export to a particular buyer conditional on the level of productivity. This ambiguous effect comes from two opposite effect of two channels:

$$\underbrace{\frac{\partial ln\rho_{s_j}}{\partial \lambda_{ij}}}_{\partial\text{Proba to be chosen}} = \underbrace{\frac{\partial ln\lambda_{ij}}{\partial \lambda_{ij}}}_{\text{Visibility channel}} - \underbrace{\frac{\partial \left(c_j d_{ij}\right)^{\theta} z_{s_j}^{-\theta} \kappa_i \Upsilon_i \widetilde{\lambda}_i}{\partial \lambda_{ij}}}_{\text{Competition channel}}$$

On one hand, an increase in the meeting probability through the "visibility" channel increases the probability that seller s_j will serve any buyer in country i as it enhances its probability to meet with potential buyers. On the other hand, conditional on being drawn, as meeting probabilities are defined at the bilateral level the seller s_j will face more competition from other domestic supplier and thus have a lower probability to be the lowest-cost supplier met by any particular buyer. Indeed, with less matching frictions buyers will meet with more potential sellers on average such that, drawn sellers will face more competition and have a lower probability to the lowest-cost supplier. As a consequence, conditional on seller's s_j productivity level, its probability to export to any particular buyer in country i is increasing then decreasing in the meeting probability due to the contradictory effect of matching frictions on visibility and competition. For low productivity sellers the competition channel dominates and their "optimal" value of meeting probability is low : with a high level of matching frictions, low productivity suppliers are more likely to face small competition and to be the lowest-cost supplier. This predictions is in line with stylized facts 4 and 1. In obscure countries with high matching frictions low productivity exporters relatively do well compared to high productivity exporters. These countries can be qualified as "Get-Lucky" countries in which the level of frictions is so high that the level of productivity of exporters is not the main determinants of their exports but the mere fact that they succeed meeting with a buyer there. On the opposite, for high productivity sellers the visibility channel dominates and their "optimal" value of matching frictions is very low because the main issue they face in exporting is their visibility as they have a very high probability to be the lowest-cost supplier.

Since all buyers play independently from each other, equation (3) immediately delivers an analytical expression for the expected number of buyers served in country i, conditional on the location and productivity of the seller. Namely, the expected number of clients in i of a seller s_j is:

$$\mathbb{E}[B_{s_j i}|z_{s_j} > \underline{z}] = \lambda_{ij} e^{-(c_j d_{ij})^\theta z_{s_j}^{-\theta} \Upsilon_i \kappa_i \widetilde{\lambda}_i} B_i$$

where $B_{s_j i}$ denotes the number of buyers from i in s_j's portfolio of clients. Again, more productive sellers are expected to serve more buyers in each destination, a prediction which is consistent with Fact 1. In our framework, this relationship comes from more productive sellers being more likely to be chosen by any buyer. This differentiates us from Carballo et al. (2013) and Bernard et al. (2014) who also rationalize the relationship between a firm's productivity and the number of buyers she serves in a destination, though with very different arguments.[28]

While the above formula provides insights on the *expected* number of buyers in each destination, the randomness of the matching process generates some variance around this mean. We thus also derive the probability that seller s_j has *exactly* M buyers in country i, conditional on her productivity. Given the independence of draws, one can show that it follows a binomial law of parameters B_i and $\rho_{s_j i}$:

$$\mathbb{P}(B_{s_j i} = M|z_{s_j} > \underline{z}) = C_{B_i}^M \rho_{s_j i}^M (1 - \rho_{s_j i})^{B_i - M}$$

Finally, integrate over the distribution of productivities to derive the expected measure of firms from j with exactly M buyers in i:

$$h_{ij}(M) = -\int_{\underline{z}}^{+\infty} C_{B_i}^M \rho_{s_j i}^M (1 - \rho_{s_j i})^{B_i - M} d\mu_j^Z(z)$$

[28] In Carballo et al. (2013), more productive exporters serve more consumers in each destination because they can produce and sell products far away from their "core segment", thus reaching a wider set of heterogeneous buyers. In Bernard et al. (2014), the heterogeneity comes from more productive exporters being able to serve a larger range of less productive buyers in presence of match-specific fixed costs. Both papers need to introduce another source of ex-ante heterogeneity, between buyers. We instead assume buyers to be ex-ante homogeneous and attribute all the ex-post heterogeneity to random matching.

Using the following change of variable:

$$\rho_{s_j i} = \lambda_{ij} e^{-\frac{\lambda_{ij}}{\pi_{ij}} T_j z_{s_j}^{-\theta}}$$

one can finally show that:[29]

$$\begin{aligned} h_{ij}(M) &= \frac{\pi_{ij}}{\lambda_{ij}} C_{B_i}^M \int_{\underline{\rho_{ij}}}^{\lambda_{ij}} \rho_{s_j i}^{M-1} (1-\rho_{s_j i})^{B_i - M} d\rho_{s_j i} \\ &= \frac{\pi_{ij}}{\lambda_{ij}} \frac{1}{M} \Big(I_{\lambda_{ij}}(M, B_i - M + 1) - I_{\underline{\rho_{ij}}}(M, B_i - M + 1) \Big) \end{aligned}$$

where the second line is restricted to values of M which are strictly positive. $I_a(b,c) = \frac{B(a;b,c)}{B(b,c)}$ denotes the regularized incomplete beta function and $\underline{\rho_{ij}} \equiv \lambda_{ij} e^{-\frac{\lambda_{ij}}{\pi_{ij}\kappa_i} T_j \underline{z}^{-\theta}}$ is the probability for the less efficient firm of j to be picked by a buyer from i. If we further assume this probability to be sufficiently close to zero, the last term of the above equation cancels out and we obtain a simple analytical formula for the expected number of firms with M buyers:

$$h_{ij}(M) \underset{\underline{\rho_{ij}} \to 0}{\approx} \frac{\pi_{ij}}{\lambda_{ij}} \frac{1}{M} I_{\lambda_{ij}}(M, B_i - M + 1) \tag{5}$$

Equation (5) shows that the mass of firms serving a given number of clients is decreasing in M, which is consistent with Fact 1. In our model, this comes from the independence of matches: The probability that a given seller is drawn by a large number of buyers shrinks rapidly when the number of buyers increases.

Proposition 3. The measure of firms exporting to exactly M buyers in destination market i is humped shape in the inverse of matching frictions.

The "optimal" level of matching frictions[30] increases with the level of competition coming from domestic sellers compared to foreign sellers.

$$\lambda_{ij}^{\text{Opt}} = g^{-1}\Big(\frac{T_j}{\sum_{k \neq j}^{N} \lambda_{ik}}\Big) \tag{6}$$

Where g is a strictly decreasing function, See proof in Appendix **??**.

6 restates at the aggregate level the ambiguous effect of a reduction of matching frictions on the measure of sellers which have M buyers in a foreign country : reducing matching

[29] See the proof in Appendix A.3.

[30] the level of bilateral matching frictions which maximizes the measure of firms from j which have exactly M buyers in i

frictions at the same time increases visibility of domestic sellers and also foster competition from other domestic sellers.

The level of frictions that maximizes the measure of firms from j that have M buyers in i depends on the relative level of competition in the destination country coming from origin country versus the rest of the world. If competitors in destination market mostly come from the domestic market then the "optimal" level of meeting probability λ_{ij} will be low (high bilateral matching frictions) as a reduction in matching frictions will increase competition a lot from other domestic sellers. On the reverse if competition in destination market is mostly driven by foreign competitors then lower matching frictions would be "optimal" in terms of the number of domestic sellers having M buyers abroad. This prediction of 6 is in line with Stylized fact 2. Indeed, Equation (5) hides[31] a negative log-linearity with ice-berg costs that we observe in the data and a hump-shape relationship with matching frictions which we observed with proxies of frictions.

In the rest of the analysis, we will use equation (5) to estimate the magnitude of matching frictions. Figure 6 on the left panel shows the theoretical prediction[32] for the cumulative distribution function of the number of buyers per French exporters in the typical destination, Romania and Germany and on the right panel its empirical counterpart. Theoretical CDF is les fat tail than what we observe in the data, this fact is mostly driven by the fact that we did not assume a seller specific meeting probability related to is level of productivity. Conditional on κ_i, π_{ij} and B_i, one can use the predicted value for $h_{ij}(M)$ and its counterpart in the data to recover an estimate for λ_{ij}. Section 4 details the estimation strategy.

– Figure 6 about here –

4 Estimation

Equation (5) relates the number of buyers per exporter in a given country to observable variables and the parameter scaling matching frictions. In this section, we use it and the corresponding empirical moments in the data to recover an estimate of matching frictions, by sector and destination country.[33] We first describe the estimator, which uses asymptotic least

[31] ice-berg costs are hidden in π_{ij}

[32] The theoretical CDF precisely is $\frac{H_{ij}(M)}{\sum_{M=1}^{B_i} H_{ij}(M)}$ and we present it calibrating values for B_i from observations in the data following the procedure described in 4.2.

[33] Since our dataset only covers exporters located in France, the j country will always be France in our analysis and we use the heterogeneity across destinations and countries to recover a distribution of estimated parameters.

squares, before describing the actual implementation in our data.

4.1 Asymptotic Least Squares

In order to estimate matching frictions we use the method of Asymptotic Least Squares (Gourieroux et al., 1985, among others). To satisfy with the method's applicability criteria, we will work with the following convergent moment:

$$P_{ij}(\lambda_{ij}, M) = \frac{h_{ij}(M)}{h_{ij}(0)} = \frac{1}{M} \frac{I_{\lambda_{ij}}(M, B_i - M + 1)}{\int_0^{\lambda_{ij}} \frac{(1-\rho_{s_j i})^{B_i}}{\rho_{s_j i}} d\rho_{s_{ji}}} \tag{7}$$

i.e. the expected mass $h_{ij}(M)$ of exporters with exactly M buyers normalized by the expected mass of producers from j which do not export to country i ($h_{ij}(0)$).[34]

The parameter to be estimated is $\lambda_{ij} \in [0, 1]$ and the corresponding auxiliary parameter

$$\widehat{P_{ij}(M)} = \frac{\sum_{s_j=1}^{S_j} \mathbb{1}\{B_{s_j i} = M\}}{\sum_{s_j=1}^{S_j} \mathbb{1}\{B_{s_j i} = 0\}}$$

is the ratio of the observed number of sellers from j with M clients in i divided by the observed number of sellers from j who do not export to country i. S_j denotes the total number of sellers in j which we assume observable.

As explained in Appendix A.4, the following convergence result applies:

$$\sqrt{S_j}\left(\widehat{P_{ij}} - P_{ij}(\lambda_{ij})\right) \underset{S_j \to +\infty}{\xrightarrow{\mathcal{D}}} \mathcal{N}(0, \Omega_{ij}) \tag{8}$$

where P_{ij} is the vector of the B_i ratio of $\frac{h_{ij}(M)}{h_{ij}(0)}$ for $M = \{1, ..., B_i\}$ and where Ω_{ij} is the covariance matrix of the random vector[35] $\hat{P_{ij}}$ as detailed in Appendix A.4.

Using the convergence result, it is possible to identify λ_{ij} uniquely. Indeed,

$$P_{ij}(\lambda_{ij}, M) - \widehat{P_{ij}(M)} = 0$$

has a unique solution on $[0, 1]$. As there are B_i buyers in the destination country and because we observe in our data all B_i auxiliary parameters, we have a total of B_i equations to estimate the λ_{ij} parameter. The minimization program writes as follows:

[34] Here and in the rest of the section, the number B_i of buyers in country i is treated as known. Section 4.2 explains how we measure it in the data. As a consequence, the only parameter in equation (7) is λ_{ij} which the method proposes to estimate.

[35] $\Omega_{ij} = \nabla g(\theta_0)\Sigma_{ij}\nabla' g(\theta_0)$ where Σ_{ij} is the variance-covariance matrix of the B_i random variables $\mathbb{1}\{B_{s_j i} = M\}$, for $M = 1...B_i$.

$$\min_{\lambda_{ij}}[P_{ij}(\lambda_{ij}) - \widehat{P_{ij}}]'\Omega_{ij}^{-1}[P_{ij}(\lambda_{ij}) - \widehat{P_{ij}}] \tag{9}$$

where $P_{ij}(\lambda_{ij})$ (resp. $\widehat{P_{ij}}$) is the $(B_i, 1)$ vector of theoretical (resp. empirical) moments and Ω_{ij} is the optimal matrix of weights as defined in the appendix A.4.

With Asymptotic Least Squares, the estimated variance of estimated frictions writes:

$$\hat{\sigma}^2_{\lambda_{ij}} = \frac{\partial P_{ij}(\widehat{\lambda_{ij}})}{\partial \lambda_{ij}}' \hat{\Omega}_{ij}^{-1} \frac{\partial P_{ij}(\widehat{\lambda_{ij}})}{\partial \lambda_{ij}}$$

4.2 Implementation

The above estimation procedure can be implemented using the moments $\widehat{P_{ij}(M)}$ which we observe in the French data. In the rest of the analysis, we will thus focus on sellers from one single country, $j = France$ and buyers from 23 European countries (all EU member states but pooling Baltic states together less France). One matching parameter will be estimated for each $HS2$ sector of each of these countries. As the estimator has an analytical formula, the implementation is straightforward. The only practical difficulties concern the measure of the total size of the population in the data, namely S_j and B_i, and the choice of the optimal number of moments to exploit from the data.

While the above estimator can potentially exploit B_i empirical moments for each country and sector, using all of them is not efficient because many identification equations are redundant. As shown in Figure 1 (left panel), most of the variance in the number of buyers served by French exporters is found at values for $B_{s_j i}$ below 10 and thus using all the individual moments regarding the number of firms with $B_{s_j i} > 10$ clients would be inefficient. Moreover, Σ_{ij} is not well-behaved when $\widehat{P_{ij}(M)} = 0$, which can happen for some values of M, at the country and sector level. As a consequence, we ultimately drop from the estimated sample all sector×country pairs for which at least one empirical moment is null. To reach the best balance between sample coverage and the amount of variance kept from the raw data, we arbitrarily decided to restrict the moment conditions to the following four moments:

$$\begin{aligned}
\tilde{P}_{ij}(\lambda_{ij}, 1) &= P_{ij}(\lambda_{ij}, 1) \\
\tilde{P}_{ij}(\lambda_{ij}, 2) &= P_{ij}(\lambda_{ij}, 2) \\
\tilde{P}_{ij}(\lambda_{ij}, 3) &= \sum_{M=3}^{6} P_{ij}(\lambda_{ij}, M) \\
\tilde{P}_{ij}(\lambda_{ij}, 4) &= \sum_{M=7}^{B_i} P_{ij}(\lambda_{ij}, M)
\end{aligned}$$

It is straightforward to show that the convergence result (8) continues to hold with this new definition of the theoretical moments and thus the ASL method still applies. The elements of the new variance-covariance matrix $\tilde{\Sigma}_{ij}$ are redefined accordingly, as the variances and covariances of the following four random variables: $\mathbb{1}\{B_{s_ji} = 1\}$, $\mathbb{1}\{B_{s_ji} = 2\}$, $\mathbb{1}\{B_{s_ji} \in [3, 6]\}$ and $\mathbb{1}\{B_{s_ji} \in [7, B_i]\}$.

The second practical issue concerns the definition of the size of the population, in the data. We first recover measures of the total population of buyers, in each destination country and sector, using predictions of the model regarding trade shares. Under the assumption of the model, π_{ij} is both the share of goods produced in country j in country i's total consumption and the ratio of the number of buyers from i buying their consumption from a seller in j divided by the total number of buyers in i ($\pi_{ij} = B_{ij}/B_i$). π_{ij} can easily be recovered from sectoral bilateral trade and absorption data. B_{ij} is directly observed into our data, for $j = France$ and i one of the 26 EU destinations which the dataset covers. Based on this, one can recover an estimate of B_i for each destination and sector. In practice, we measure π_{iF} at the $HS6$ level using bilateral trade flows from the CEPII-BACI database (Gaulier and Zignago, 2010) and production data from Prodcom as the ratio of (fob) export from France to country i over country i's absorption:

$$\pi_{iF} = \frac{X_{iF}}{\sum_j X_{ij} + Y_i - \sum_j X_{ji}}$$

Based on that, we define:

$$B_i = \frac{B_{iF}}{\pi_{iF}}$$

where B_{iF} is the number of exporter×importer pairs in our data. B_i is rounded to the closest integer[36]. Ex-post the variation observed between the different B_i is explained at 60% by a country fixed effect and a sector fixed effect, and B_i are strongly positively correlated with GDP, whereas variable that should not be correlated with it are not (distance or GDP per Capita).

In our estimation procedure, the matching frictions i.e the λ parameter, is completely over-identified. In order to estimate the λ which minimizes the objective function without

[36]This definition is in line with our theoretical framework. Our estimation of λ are robust to medium variation of B. Namely, when the French share in a foreign market is high, B_i is probably well estimated and the true number of potential buyers should not be too far from $\hat{B}_i$. These close variations of B_i do not affect the estimation of lambda too badly. On the opposite when the French market share is very low, some B_i are very high (more than several decades of potential buyer up to several millions). In order to investigate whether this potential overestimation of the total number of buyer lead to different estimation of λ we conduct other estimation with a maximum number of buyers arbitrarily set at 20000. This cap does not affect qualitative results.

estimated a λ around a minimum local, we adopt the following grid search procedure

1. We calculate for 1000 different values of λ the objective function and we store the 5 best λ which minimize most this function. We then verify that these 5 λ minimizing the objective function belongs to the an interval of length λ centered around the best λ found for that grid search. We conduct a second round of grid search with 100 potential values of λ in the interval mentioned above. We select from this second grid search the best value of λ i.e the value minimizing the objective function.

2. We run our estimation procedure with all this robust grid search λ as initial point and verify we obtain a estimated $\hat{\lambda}$ not too far from this initial point.

3. We run the estimation procedure with the $\hat{\lambda}$ estimated in step 2 as initial point. We verify that the algorithm converges very quickly and gives a result very close to $\hat{\lambda}$.

5 Results

5.1 Matching Frictions estimates

Matching frictions are estimated at the (sector$\times$country) level, which means that we have 1003 matching frictions estimates. Nevertheless as described in 4.2, our estimates of meeting probabilities are conditional on B_i the total number of buyers in the destinations. This could lead to a downward bias of the estimates of meeting probabilities for countries with a large number of buyers. Indeed, for these countries the conditional meeting probability is mechanically low due to relative small number of potential French sellers with respect to the number of buyers. In order to recover an estimator unconditional of the total number of buyer B_i and only related to frictions we specify a Cobb-Douglas relationship[37] between the inverse of the market-tightness (the ratio between the total number of buyer B_i and the number of French competitors S_F) in the destination country and the level of meeting probability. We use the inverse of the market-tightness as it represents the queue length i.e the average number of potential French sellers per buyer in the destination country. Namely, we estimate this equation $\lambda_{iF} = (F_{iF})^{\alpha}\ (\frac{S_F}{B_i})^{1-\alpha}$ where $F_{iF} = exp(\frac{log(\lambda)-\alpha log(\frac{S_F}{B_i})}{1-\alpha})$ is our final parameter of interest. Table 11 presents results of our estimates aggregated at the country level for conditional and unconditional meeting probabilities.

[37] Assuming a non-loglinear relationship does not change the qualitative results so we keep with this simple formulation.

In column (1) Table 11 presents the average value of conditional meeting probabilities at the country level, the average value estimated is very small around $10^{-}4$. This reflects the difficulties French firms face when they want to meet a potential foreign buyer. Estimates are made jointly for the three Baltic countries. Column (2) presents the ranking of the countries in terms of unconditional meeting probability : Portugal and Belgium are the first two countries where meeting probabilities are the highest, while Malta is the Last one. Considering the conditional meeting probability Germany is the twentieth destination. This is due to the fact that these estimates are conditional on market tightness which is very high in Germany due to the presence of many potential buyers. Columns (3) and (4) present ranking and estimates of unconditional meeting probabilities. Top and bottom countries remain the same while Germany recovers a central rank at the eleventh place.

– Table 11 about here –

Correlates of matching frictions

– Table 12 about here –

We investigate the relationship between distance, GDP, migrants and matching frictions. In Table 12 we regress the unconditional meeting probabilities on classic gravity controls : log weighted distance and log GDP [38]. First column (1) and (2) show that distance and the square of GDP are negatively correlated with unconditional meeting probability, while GDP present a positive correlation. Nevertheless these significant correlations do not appear to be robust to the introduction of variables correlated with French presence in destination country, meaning that distance and GDP are not significantly correlated with unconditional meeting probabilities. This result confirms that our estimation strategy with the choice of our moment enabled us to estimate separately meeting probability from more common frictions related to distance such as ice-berg costs. The number of French migrants per 1000 inhabitants in destination country capture 9% of the dispersion between country within sector of unconditional meeting probability. Sector fixed effects control for particularities at the sector level such as the level of competition or a more formalized market place (Rauch's "differentiated goods" vs "referenced good").

Table 13 presents the regression of log unconditional meeting probabilities on sector specific characteristics such as the share of differentiated products measured as in the Rauch

[38] We take logs for two reasons. First, the relationship in log seem rather linear whereas it is not the case without logs. Second, as matching frictions are very small, taking log is a way to increase very small differences that can be observed between matching frictions.

classification[39]. The bigger the share of differentiated product is within a sector the more matching frictions there are (lower λ). The results is in line with our interpretation of λ : it represents frictions in the meeting process with potential supplier and these frictions are larger in markets without common and organized market place.

5.2 Augmented gravity

In order to test our analytical predictions about the positive impact of λ on aggregate trade flows and its ambiguous impact on the extensive margins we conduct some "Augmented gravity regressions" by including matching frictions in gravity regressions.

Table 15 shows that estimated matching frictions are significantly correlated with aggregated trade flows, a result in line with proposition 1 of our theoretical framework. Reducing matching frictions by 10% (increasing λ by 10%) would increase by 0.3% the total value of exports towards a destination. This significant positive impact is robust to the introduction of lots of proxies of information frictions (migrants and language proximity) and proxies of the quality of institutions, which make us believe that our model made us able to identify a new gravity parameter. Moreover, when proxies of information frictions are introduced in column (3) and (4), we observe a drop in the matching frictions correlation with the volume of exports. This fact confirms our statement that part of the impact of our measured matching frictions is explained by Rauch information and network frictions mechanisms.

We showed that unconditional matching frictions are weakly correlated with GDP and in a less significant way with distance. Then introducing matching frictions in the gravity framework reduces in absolute value the distance elasticity and increases the GDP elasticity. Even if the variations in the various estimated points in Table 15 are not significant, they indicate that part of the distance elasticity captures matching frictions effects as in column (2) which introduces unconditional meeting probability and where the distance elasticity is reduced.

Table 16 presents results of gravity regression at the firm-product couple level. Defining size as the aggregate exports of a firm-product couple, column (1) presents results for the bottom 10% of sellers and column (2) for top 10% of exporters. In line with proposition 2 an increase in the unconditional meeting probability has a negative though not significant correlation with the seller's exports while the correlation is positive and strongly significant for large exporters.

– Tables 15 and 16 about here –

[39] A complementary analysis using Nunn classification in Appendix in table 14 presents robust results.

5.3 Counterfactual analysis

TO BE COMPLETED

6 Conclusion

TO BE COMPLETED

References

Allen, T. (2014). Information Frictions in Trade. *Econometrica*, 82:2041–2083.

Arkolakis, C. (2010). Market Penetration Costs and the New Consumers Margin in International Trade. *Journal of Political Economy*, 118(6):1151 – 1199.

Arkolakis, C. (2011). A Unified Theory of Firm Selection and Growth. NBER Working Papers 17553, National Bureau of Economic Research, Inc.

Bernard, A., Moxnes, A., and Ulltveit-Moe, K. H. (2014). Two-sided Heterogeneity and Trade.

Carballo, J., Ottaviano, G., and Volpe Martincus, C. (2013). The Buyer Margins of Firms' Exports. CEPR Discussion Papers 9584, C.E.P.R. Discussion Papers.

Chaney, T. (2014). The Network Structure of International Trade. *American Economic Review*, 104(11):3600–34.

Dasgupta, K. and Mondria, J. (2014). Inattentive Importers. Working Papers tecipa-512, University of Toronto, Department of Economics.

Eaton, J., Eslava, M., Krizan, C. J., Kugler, M., and Tybout, J. (2013). A Search and Learning Model of Export Dynamics.

Eaton, J. and Kortum, S. (2002). Technology, Geography, and Trade. *Econometrica*, 70(5):1741–1779.

Eaton, J., Kortum, S., and Kramarz, F. (2011). An Anatomy of International Trade: Evidence From French Firms. *Econometrica*, 79(5):1453–1498.

Eaton, J., Kortum, S., and Kramarz, F. (2014). Firm-to-Firm Trade: Imports, Exports, and the Labor Market.

Eaton, J., Kortum, S. S., and Sotelo, S. (2012). International trade: Linking micro and macro. Technical report, National bureau of economic research.

Gaulier, G. and Zignago, S. (2010). BACI: International Trade Database at the Product-Level. The 1994-2007 Version. CEPII Working Papers 2010-23, CEPII.

Gourieroux, C., Monfort, A., and Trognon, A. (1985). Moindres carrés asymptotiques. In *Annales de l'INSEE*, pages 91–122. JSTOR.

Lendle, A., Olarreaga, M., Schropp, S., and Vézina, P.-L. (2012). There goes gravity: how ebay reduces trade costs.

Mayer, T. and Zignago, S. (2011). Notes on CEPII's distances measures : the GeoDist Database. CEPII Working Papers 2011-25, CEPII Working Paper.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725.

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

Rauch, J. E. (2001). Business and Social Networks in International Trade. *Journal of Economic Literature*, 39(4):1177–1203.

Rauch, J. E. and Trindade, V. (2002). Ethnic chinese networks in international trade. *Review of Economics and Statistics*, 84(1):116–130.

Steinwender, C. (2014). Information frictions and the law of one price:" when the states and the kingdom became united". Technical report, WTO Staff Working Paper.

Sugita, Y., Teshima, K., and Seira, E. (2014). Assortative matching of exporters and importers. *T able*.

Table 1: ***French sellers and EU buyers, 2007***

	Number of			*Number of*		
	Exporters	Importers	Pairs	Exporter-HS6	Importer-HS6	Triplets
	(1)	(2)	(3)	(4)	(5)	(6)
All	19,511	357,571	693,522	149,739	1,673,638	1,893,085
Austria	5,004	8,806	16,039	18,703	39,813	43,759
Belgium	14,219	41,027	106,024	66,122	246,209	286,923
Bulgaria	1,547	1,594	2,611	8,740	8,339	10,512
Cyprus	1,330	1,093	2,066	6,391	7,377	8,175
Czech Republic	4,292	4,466	9,254	16,234	20,578	23,109
Germany	12,705	79,616	141,019	62,501	281,747	314,309
Denmark	4,345	6,207	11,736	16,801	32,761	37,197
Estonia	1,104	922	1,654	4,895	5,091	5,762
Spain	11,635	45,283	86,021	56,719	215,266	240,913
Finland	3,273	3,778	7,554	12,914	19,691	22,175
Great-Britain	9,990	34,030	63,425	47,403	161,057	185,496
Greece	4,610	7,076	14,437	22,318	42,445	49,121
Hungary	3,500	3,117	6,576	13,508	16,140	18,234
Ireland	3,420	4,657	9,193	13,691	30,410	35,847
Italy	10,896	56,468	96,907	52,192	235,424	259,859
Lithuania	1,439	1,179	2,187	5,237	5,679	6,601
Luxembourg	5,288	4,002	12,830	17,548	26,208	31,708
Latvia	1,188	977	1,783	5,216	5,530	6,198
Malta	974	634	1,391	4,144	4,340	4,909
Netherland	8,312	20,590	36,595	32,995	96,627	107,469
Poland	5,467	7,508	15,341	23,631	35,818	41,037
Portugal	6,660	11,503	23,312	27,846	69,759	77,565
Romania	3,211	3,122	6,296	15,552	17,416	20,636
Sweden	4,641	6,621	12,328	18,063	32,686	36,213
Slovenia	1,946	1,593	3,206	7,959	8,991	10,051
Slovakia	2,250	1,702	3,737	7,420	8,236	9,307

Notes: This table gives the number of exporters, importers, exporter-importer pairs, exporter-HS6 product pairs, importer-HS6 product pairs, and importer-exporter-HS6 products triplets involved in a given bilateral trade flow. The data are for 2007 and are restricted to transactions with recorded CN8-products.

Table 2: ***French firms and their number of products, 2007***

Sample	# of Firms	# of Multiproduct firms	Products per firm		
			Mean	Median	p90
Manufacturers	19,527	12,697	7.7	2	17

Notes: This table gives the number of uniquely identified firms (siren) in our final dataset, and their number of products they export.

Table 3: ***Number of buyers per seller across destination countries***

	Mean	Median	p75	Sh. with 1 buyer
	(1)	(2)	(3)	(4)
Austria	2.3	1	2	67%
Belgium	4.3	1	3	54%
Bulgaria	1.2	1	1	87%
Cyprus	1.3	1	1	82%
Czech Republic	1.4	1	1	79%
Germany	5.0	1	3	55%
Denmark	2.2	1	2	68%
Estonia	1.2	1	1	87%
Spain	4.2	1	3	59%
Finland	1.7	1	2	74%
Great-Britain	3.9	1	3	59%
Greece	2.2	1	2	68%
Hungary	1.3	1	1	82%
Ireland	2.6	1	2	67%
Italy	5.0	1	3	59%
Lithuania	1.3	1	1	83%
Luxembourg	1.8	1	2	70%
Latvia	1.2	1	1	87%
Malta	1.2	1	1	87%
Netherland	3.3	1	2	61%
Poland	1.7	1	2	74%
Portugal	2.8	1	2	67%
Romania	1.3	1	1	81%
Sweden	2.0	1	2	67%
Slovenia	1.3	1	1	82%
Slovakia	1.3	1	1	85%
Across countries	12.6	2	8	39%

Notes: Columns (1)-(3) respectively report the mean, median, and third quartile number of buyers per seller in each destination. Column (4) gives the share of sellers having a unique buyer. A seller is defined as an exporter-HS6 product pair. The data are for 2007 and are restricted to transactions with recorded CN8-products.

Table 4: ***Number of buyers per seller across sectors***

	Mean	Median	p75	Sh. with 1 buyer
	(1)	(2)	(3)	(4)
Animal products	3.39	1	3	84%
Vegetables	3.26	1	2	87%
Fats and oils	2.22	1	2	93%
Beverages & Tobacco	2.92	1	2	90%
Mineral products	1.93	1	2	93%
Chemicals	2.25	1	2	95%
Plastic products	2.58	1	2	94%
Leather products	3.87	1	2	94%
Wood products	3.61	1	2	86%
Paper products	2.68	1	2	95%
Textiles	4.89	1	3	94%
Footwear	5.48	1	3	95%
Glass products	4.05	1	2	93%
Precious metals	3.39	1	2	96%
Base metals	2.70	1	2	93%
Machineries	2.24	1	2	95%
Vehicles	3.10	1	2	94%
Optical products	2.89	1	2	95%
Arms	1.55	1	2	96%
Misc. Manufacturing	3.72	1	2	93%
Works of art	3.68	1	1	94%

Notes: Columns (1)-(3) respectively report the mean, median, and third quartile number of buyers per seller in each HS2 section. Column (4) gives the share of sellers having a unique buyer. A seller is defined as an exporter-HS6 product-destination triplet. The data are for 2007 and are restricted to transactions with recorded CN8-products.

Table 5: ***Number of buyers per seller and sellers' size***

	Size deciles					Correlation
Country	1	2	3	4	5	(size, # buyers)
Austria	1.3	1.8	2.4	2.9	3.3	0.014
Belgium	1.6	2.6	4.0	5.5	7.3	0.014
Bulgaria	1.0	1.1	1.1	1.3	1.6	0.029
Cyprus	1.1	1.2	1.3	1.3	1.4	0.034
Czech Republic	1.1	1.2	1.3	1.5	2.1	0.041
Germany	1.5	2.4	3.8	6.0	11.3	0.015
Denmark	1.2	1.8	2.3	2.6	2.6	0.004
Estonia	1.0	1.1	1.2	1.2	1.4	0.187
Spain	1.4	2.6	4.3	6.0	7.4	0.011
Finland	1.2	1.5	1.7	1.9	2.2	0.011
Great-Britain	1.4	2.5	3.8	4.8	6.0	0.009
Greece	1.3	1.8	2.3	2.6	3.0	0.010
Hungary	1.0	1.2	1.3	1.5	1.8	0.037
Ireland	1.4	2.2	2.9	3.2	2.5	-0.005
Italy	1.5	2.6	4.9	6.9	9.5	0.015
Lithuania	1.1	1.2	1.2	1.3	1.5	0.164
Luxembourg	1.2	1.5	1.8	2.0	2.3	0.008
Latvia	1.0	1.1	1.1	1.3	1.4	0.170
Malta	1.1	1.1	1.2	1.2	1.3	0.050
Netherland	1.3	2.1	3.3	3.9	5.0	0.009
Poland	1.1	1.4	1.7	2.0	2.6	0.059
Portugal	1.3	2.0	2.8	3.9	3.9	0.002
Romania	1.0	1.1	1.2	1.4	1.9	0.119
Sweden	1.2	1.6	2.0	2.4	2.8	0.030
Slovenia	1.1	1.1	1.2	1.3	1.6	0.099
Slovakia	1.0	1.1	1.2	1.3	1.7	0.101
Across countries	1.7	3.5	6.9	15.2	35.9	0.032

Notes: This table reports the average number of buyers per seller within a destination, across size deciles. The last column reports the correlation between seller size and its number of buyers computed using the overall distribution of firms. Correlations under parenthesis are not significantly different from zero. Size is measured as the value of the seller's total exports. A seller is defined as an exporter-HS6 product pair. The data are for 2007 and are restricted to transactions with recorded CN8-products.

Table 6: ***Number of sellers per buyer***

	Mean (1)	Median (2)	p75 (3)	Sh. with 1 seller (4)
Austria	1.10	1	1	93%
Belgium	1.17	1	1	90%
Bulgaria	1.27	1	1	90%
Cyprus	1.11	1	1	94%
Czech Republic	1.12	1	1	92%
Germany	1.11	1	1	93%
Denmark	1.14	1	1	90%
Estonia	1.13	1	1	91%
Spain	1.12	1	1	92%
Finland	1.13	1	1	91%
Great-Britain	1.15	1	1	91%
Greece	1.16	1	1	90%
Hungary	1.13	1	1	92%
Ireland	1.18	1	1	88%
Italy	1.10	1	1	93%
Lithuania	1.16	1	1	91%
Luxembourg	1.21	1	1	88%
Latvia	1.13	1	1	92%
Malta	1.12	1	1	93%
Netherland	1.11	1	1	92%
Poland	1.15	1	1	91%
Portugal	1.11	1	1	93%
Romania	1.19	1	1	92%
Sweden	1.11	1	1	93%
Slovenia	1.12	1	1	92%
Slovakia	1.13	1	1	92%
Across country	1.13	1	1	92%

Notes: Columns (1)-(3) respectively report the mean, median, and third quartile number of sellers per buyer in each destination. Column (4) gives the share of buyers interacting with a single French seller. A buyer is defined as an importer-HS6 product pair. The data are for 2007 and are restricted to transactions with recorded CN8-products.

Table 7: ***Product-level gravity at the intensive and extensive margins***

	Dependent Variable (all in log)			
	Value of Exports	# Sellers	# Buyers per Seller	Mean export per Buyer-seller
log Distance	-1.219***	-0.550***	-0.305***	-0.363***
	(0.027)	(0.008)	(0.007)	(0.022)
log Import Demand	0.791***	0.228***	0.106***	0.456***
	(0.007)	(0.002)	(0.002)	(0.006)
log GDP per Capita	0.124***	0.0481***	0.109***	-0.0334***
	(0.015)	(0.004)	(0.004)	(0.012)
Observations	64,179	64,179	64,179	64,179
R-squared	0.624	0.752	0.414	0.571
HS6 FE	YES	YES	YES	YES

Notes: Robust standard errors in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels. "log Distance" is the log of the weighted distance between France and the destination. "log Import demand" is the log of the value of the destination's demand of imports for the hs6-product, less the demand addressed to France. "log GDP per capita" is the log-GDP per capita in the destination. The dependent variable is either the log of French exports of the hs6-product in the destination (column (1)) or one of its components, namely the number of sellers involved in the trade flow (column (2)), the mean number of buyers they serve (column (3)) and the mean value of a seller-buyer transaction (column (4)). A seller is defined as an exporter-HS6 product pair. The data are for 2007 and are restricted to transactions with recorded CN8-products.

Table 8: ***Exporter-level gravity at the intensive and extensive margins***

	Dependent variable (all in log)					
	Value of Exports	# of Buyers	Exports per Buyer	Value of Exports	# of Buyers	Exports per Buyer
	(1)	(2)	(3)	(4)	(5)	(6)
log Distance	-0.303***	-0.245***	-0.0583***	-0.517***	-0.340***	-0.178***
	(0.012)	(0.004)	(0.012)	(0.009)	(0.004)	(0.009)
log Import Demand	0.290***	0.0236***	0.266***	0.445***	0.133***	0.312***
	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)
log GDP per Capita	-0.0829***	0.118***	-0.201***	0.0350***	0.0232***	0.0118**
	(0.009)	(0.003)	(0.008)	(0.006)	(0.003)	(0.006)
Constant	8.284***	0.705***	7.579***			
	(0.154)	(0.044)	(0.145)			
Observations	535,077	535,077	535,077	471,753	471,753	471,753
R-squared	0.044	0.037	0.036	0.699	0.433	0.712
Seller FE				YES	YES	YES

Notes: Robust standard errors in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels. "log Distance" is the log of the weighted distance between France and the destination. "log Import demand" is the log of the value of the destination's demand of imports for the hs6-product, less the demand addressed to France. "log GDP per capita" is the log-GDP per capita in the destination. The dependent variable is either the log of firm-level exports in the destination (Columns (1) and (4)) or one of its components, namely the number of buyers she serves (Columns (2) and (5)) or the mean value of exports per buyer (Columns (3) and (6)). Columns (3)-(6) control for seller-specific fixed effects. A seller is defined as an exporter-HS6 product pair. The data are for 2007 and are restricted to transactions with recorded CN8-products.

Table 9: ***Product-level gravity: The role of information frictions***

	Dependent variable (all in log)						
	Value of product-level exports				# of Sellers	Mean of # Buyer	Exports per buyer-seller
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log Distance	-1.219***	-1.126***	-0.801***	-1.055***	-0.400***	-0.258***	-0.397***
	(0.027)	(0.026)	(0.029)	(0.029)	(0.008)	(0.007)	(0.024)
log Import Demand	0.791***	0.724***	0.819***	0.733***	0.214***	0.0929***	0.426***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.002)	(0.002)	(0.006)
log GDP per Capita	0.124***	0.182***	0.119***	0.178***	0.0661***	0.122***	-0.0107
	(0.015)	(0.014)	(0.015)	(0.014)	(0.004)	(0.004)	(0.012)
Migrants in France		0.127***		0.119***	0.0424***	0.0290***	0.0479***
		(0.002)		(0.003)	(0.001)	(0.001)	(0.002)
French Migrants			0.107***	0.0198***	0.0306***	0.00670***	-0.0174***
			(0.003)	(0.004)	(0.001)	(0.001)	(0.003)
Observations	64,179	64,179	64,179	64,179	64,179	64,179	64,179
R-squared	0.624	0.643	0.631	0.643	0.784	0.444	0.575
HS6 FE	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels. "log Distance" is the log of the weighted distance between France and the destination. "log Import demand" is the log of the value of the destination's demand of imports for the hs6-product, less the demand addressed to France. "log GDP per capita" is the log-GDP per capita in the destination. "Migrants in France" is the number of migrants from the destination in France, expressed as a stock per 1000 inhabitants in France. "French Migrants" is the number of French citizens in the destination country, per 1000 inhabitants. The dependent variable is either the log of French exports of the hs6-product in the destination (column (1)-(4)) or one of its components, namely the number of sellers involved in the trade flow (column (5)), the mean number of buyers they serve (column (6)) and the mean value of a seller-buyer transaction (column (7)). A seller is defined as an exporter-HS6 product pair. The data are for 2007 and are restricted to transactions with recorded CN8-products.

Table 10: ***Exporter-level gravity: The role of information frictions***

	Dependent variable (all in log)					
	Value of Exports	Mean # Buyer	Exports per Buyer	Value of Exports	Mean # Buyer	Exports per Buyer
	(1)	(2)	(3)	(4)	(5)	(6)
log Distance	-0.361***	-0.214***	-0.147***	-0.404***	-0.239***	-0.164***
	(0.014)	(0.004)	(0.014)	(0.011)	(0.005)	(0.0104)
log Import Demand	0.281***	0.0221***	0.259***	0.424***	0.135***	0.289***
	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)
log GDP per Capita	-0.0738***	0.130***	-0.204***	0.107***	0.0523***	0.0551***
	(0.009)	(0.003)	(0.008)	(0.006)	(0.003)	(0.006)
French Migrants	-0.0160***	0.00249***	-0.0185***	0.0176***	0.0162***	0.00142
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Migrants in France	0.0306***	0.0166***	0.0141***	0.0594***	0.0208***	0.0386***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Constant	8.625***	0.322***	8.303***			
	(0.168)	(0.048)	(0.158)			
Observations	535,077	535,077	535,077	471,753	471,753	471,753
R-squared	0.045	0.043	0.036	0.705	0.446	0.715
Seller FE				YES	YES	YES

Notes: Robust standard errors in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels. "log Distance" is the log of the weighted distance between France and the destination. "log Import demand" is the log of the value of the destination's demand of imports for the hs6-product, less the demand addressed to France. "log GDP per capita" is the log-GDP per capita in the destination. "Migrants in France" is the number of migrants from the destination in France, expressed as a stock per 1000 inhabitants in France. "French Migrants" is the number of French citizens in the destination country, per 1000 inhabitants. The dependent variable is either the log of firm-level exports in the destination (Columns (1) and (4)) or one of its components, namely the number of buyers she serves (Columns (2) and (5)) or the mean value of exports per buyer (Columns (3) and (6)). Columns (3)-(6) control for seller-specific fixed effects. A seller is defined as an exporter-HS6 product pair. The data are for 2007 and are restricted to transactions with recorded CN8-products.

Table 11: ***Estimated meeting probabilities, 2007***

	Meeting Probabilities			
	Conditional		Unconditional	
	Mean	Rank	Rank	Mean
Country	($\times 10^{-3}$)			($\times 10^{-3}$)
Portugal	2.65	1	1	7.80
Belgium	1.92	2	2	6.16
Netherland	1.10	6	3	4.98
Spain	0.67	9	4	4.45
Poland	0.74	8	5	4.14
Austria	1.69	3	6	3.94
Greece	0.67	10	7	3.43
Czech Republic	0.62	11	8	3.08
Italy	0.29	19	9	2.81
Hungary	1.22	5	10	2.81
Germany	0.22	20	11	2.74
Ireland	1.23	4	12	2.61
Baltic States	0.79	7	13	2.38
Finland	0.50	12	14	2.17
United Kingdom	0.18	21	15	2.09
Denmark	0.40	15	16	1.93
Sweden	0.40	14	17	1.86
Cyprus	0.41	13	18	1.46
Romania	0.31	17	19	1.41
Slovenia	0.32	16	20	1.17
Bulgaria	0.17	22	21	1.14
Slovakia	0.30	18	22	1.01
Malta	0.06	23	23	0.45

Notes: This table presents estimated values of lambda at the country level. Estimates are made jointly for the three Baltic countries. As Matching frictions are estimated at the $country * hs2$. Columns (1) and (2) present the average of meeting probability within a country between sector and its ranking.Columns (3) and (4) are for unconditional meeting probability $:= exp(\frac{log(\lambda)-\alpha log(\mu)}{1-\alpha})$ where μ is the market tightness and α the Cobb-Douglas coefficient of market tightness in Meeting probability

Table 12: ***Matching frictions correlates at the country level -(1)***

	Unconditional meeting probability (log)		
	(1)	(2)	(3)
Distance (log)	-0.472*	-0.278	0.078
	(0.236)	(0.197)	(0.145)
GDP (log)	3.974**	2.476**	1.080
	(1.512)	(1.010)	(0.838)
GDP2̂ (log)	-0.076**	-0.051**	-0.023
	(0.028)	(0.019)	(0.016)
French migrants per 1000 hab			0.071***
			(0.017)
Migrants in France per 1000 hab			-0.010
			(0.010)
Constant	-55.69**		
	(20.08)		
Observations	951	948	948
R-squared	2%	49%	50%
Sector (hs2) FE	NO	YES	YES
# Sectors		78	78
R-squared Within		6%	9%

Notes: Clustered at the country level standard errors in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels. "log Distance" is the log of the weighted distance between France and the destination. "French migrants" is the number of French migrants in the destination country per 1000 inhabitants in the destination country. "Migrants in France" is the number of destination country migrants living in France per 1000 French inhabitants. Regressions control for sector-specific fixed effects. Matching frictions are estimated at the hs2*country level.

Table 13: ***Correlates of unconditional meeting probability within country, Rauch's share of differentiated products***

	Residual Matching Frictions (log)	
Frac. Rauch differenciated products	(1)	(2)
Liberal	-0.206	
	(0.152)	
Conservativ		-0.297*
		(0.154)
Observations	909	909
R-squared	0.060	0.062
Country FE	YES	YES
# Countries	22	22
R-squared Within	0.2%	0.5%

Notes: Regressions control for country fixed effects. Matching frictions are estimated at the hs2*country level.

Table 14: ***Correlates of unconditional meeting probability, Nunn share of differentiated products***

	Residual Matching frictions (Log)			
Nunn Measure of diff product	(1)	(2)	(3)	(4)
Not Homogeneous, conservativ	-1.309***			
	(0.479)			
Diff. , conservativ		-0.471*		
		(0.286)		
Not Homogeneous, lib			-1.219***	
			(0.347)	
Diff. , lib				-0.509*
				(0.291)
Observations	949	949	949	949
R-squared	0.065	0.060	0.070	0.061
Country FE	YES	YES	YES	YES
# Countries	22	22	22	22
R-squared Within	0.8%	0.3%	1.4%	0.4%

Notes: Regressions control for country-specific fixed effects. Matching frictions are estimated at the hs2*country level.

Table 15: ***Augmented product-level gravity***

	Product level Exports (log)			
	(1)	(2)	(3)	(4)
Distance (log)	-1.039*	-1.018**	-0.274	-0.349*
	(0.511)	(0.487)	(0.211)	(0.169)
Unconditional meeting probability (log)		0.103***	0.061**	0.054**
		(0.027)	(0.025)	(0.024)
Demand (log)	0.354***	0.354***	0.463***	0.488***
	(0.109)	(0.106)	(0.084)	(0.091)
GDP (log)	0.774***	0.783***	0.824***	0.774***
	(0.167)	(0.162)	(0.113)	(0.121)
GDP per Capita (log)	-0.456**	-0.390**	-0.386***	-0.249
	(0.167)	(0.156)	(0.114)	(0.170)
French migrants per 1000 hab			0.130***	0.094***
			(0.029)	(0.015)
Migrants in France per 1000 hab			0.009	-0.012
			(0.029)	(0.015)
Institution quality Controls				Yes
Observations	51,433	48,578	48,578	48,578
R-squared	68.0%	68.5%	69.9%	70.3%
Produt (hs6) FE	YES	YES	YES	YES
# Products	4,338	4,296	4,296	4,296
R-squared Within	36.9%	37.4%	40.1%	40.9%

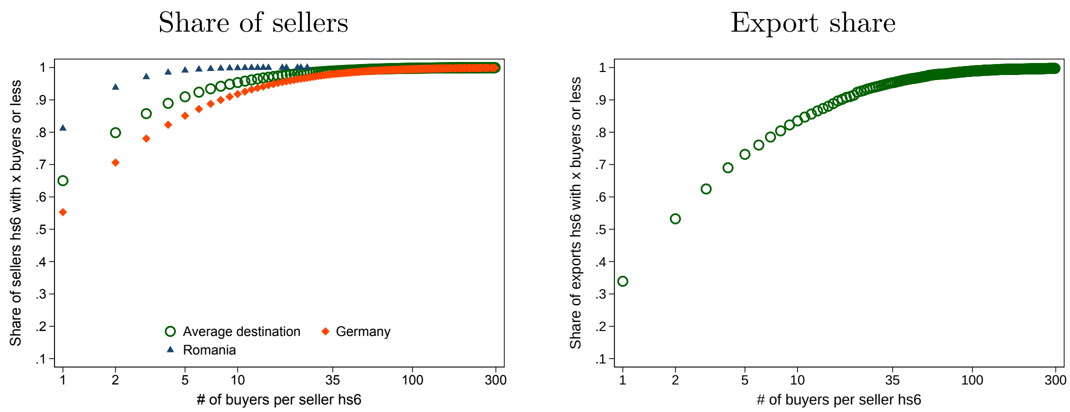
Notes: Dependent variable is log of exports per product (hs6)×destination. Standard errors are robust and clustered at the country level, they are in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels. "log Distance" is the log of the weighted distance between France and the destination. "log Import demand" is the log of the value of the destination's demand of imports for the hs6-product, less the demand addressed to France. "log GDP per capita" and "log GDP" are the log-GDP per capita and the log GDP in the destination. "Migrants in France" is the number of migrants from the destination in France, expressed as a stock per 1000 inhabitants in France. "French Migrants" is the number of French citizens in the destination country, per 1000 inhabitants. The dependent variable is either the log of exports in the sector*destination. Sector fixed effects are at the HS6 level. The data are for 2007 and are restricted to transactions with recorded CN8-products and sectors for which matching frictions are estimated.

Table 16: ***Augmented firm-level gravity***

	Firm-product exports (log)	
	Bottom 15% Sellers	Top 15% Sellers
	(1)	(2)
Distance (log)	-0.331***	-0.643*
	(0.115)	(0.314)
Unconditional meeting probability (log)	-0.007	0.131***
	(0.016)	(0.037)
Demand (log)	-0.147**	0.277***
	(0.061)	(0.081)
GDP (log)	0.154**	0.683***
	(0.065)	(0.126)
GDP per Capita (log)	0.004	-0.258*
	(0.107)	(0.126)
Observations	2,238	49,893
R-squared	66%	50%
Seller*Product FE	YES	YES
\# FE	876	5,264
R-squared Within	1%	24%

Notes: Dependent variable is log of exports of a firm-product (hs2) couple destination. A firm-product fixed effect is added, and sectors are defined at the HS2 level. Firm-product size is defined as the level of aggregate exports, small are bottom 15% and large are top 15%. Standard errors are robust and clustered at the country level in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels. "log Distance" is the log of the weighted distance between France and the destination. "lDemand" is the log of the value of the destination's demand of imports for the hs6-product, less the demand addressed to France. "log GDP per capita" and "log GDP" are the log-GDP per capita and the log GDP in the destination.

Figure 1: ***Number of buyers per seller***



Notes: Proportion of sellers (left panel) and share of trade accounted for by sellers (right panel) that serve x buyers or less in a given destination, in 2007. A seller is defined as an exporter-HS6 product pair.

A Appendix: Proof of analytical results

A.1 Weibull distribution of minimum price

To derive the distribution of the minimum price drawn by a buyer in country i, start with the probability of paying a price above p, conditional on the number of price quotes in the buyer's random choiceset:

$$\begin{aligned}\mathbb{P}\left[\underset{s_j \in \Omega_{b_i}}{\text{Min}}\left(\frac{c_j d_{ij}}{z_{s_j}}\right) > p \,|\, D_{b_i} = d\right] &= \prod_{s_j \in \Omega_{b_i}} \mathbb{P}\left[\left(\frac{c_j d_{ij}}{z_{s_j}}\right) > p \,|\, s_j \in \Omega_{b_i}\right] \\ &= \left[1 - \mathbb{P}\left(\left(\frac{c_j d_{ij}}{z_{s_j}}\right) < p\right)\right]^d\end{aligned}$$

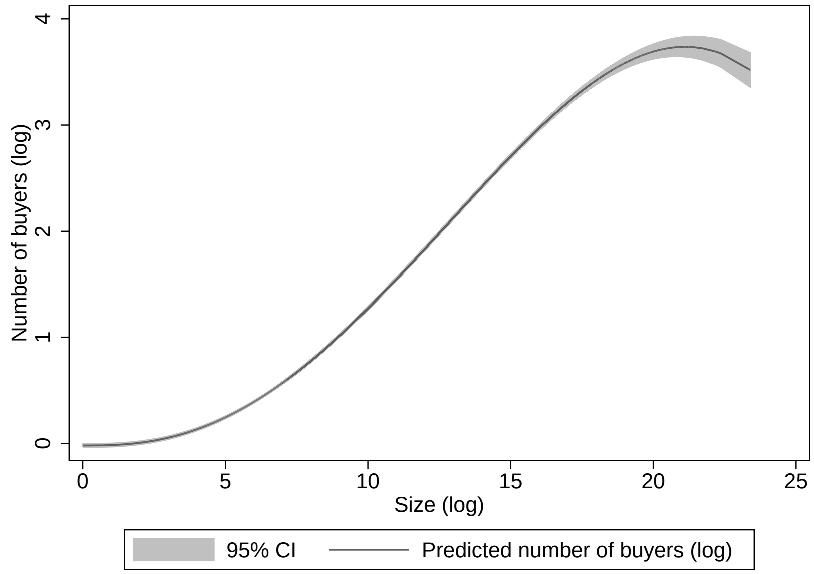
where D_{b_i} is the number of prices in buyer b_i's random choiceset Ω_{b_i}. Here, we use the fact that all price quotes are drawned independently by buyer b_i and are independent from each other under the assumption of marginal cost pricing.

$\mathbb{P}\left(\left(\frac{c_j d_{ij}}{z_{s_j}}\right) < p\right)$ represents the probability that a randomly drawn price is cheaper than price p in country i. Using properties of the overall distribution of prices, we finally obtain:

$$\mathbb{P}\left[\underset{s_j \in \Omega_{b_i}}{\text{Min}}\left(\frac{c_j d_{ij}}{z_{s_j}}\right) > p \,|\, D_{b_i} = d\right] = \left[1 - \frac{p^\theta \sum_{j=1}^N \lambda_{ij} T_j (d_{ij} c_j)^{-\theta}}{\sum\limits_{j=1}^N \lambda_{ij} T_j \underline{z}^{-\theta}}\right]^d$$

Integrating over all possible random numbers of price quotes gives the unconditional probability of paying a price above p:

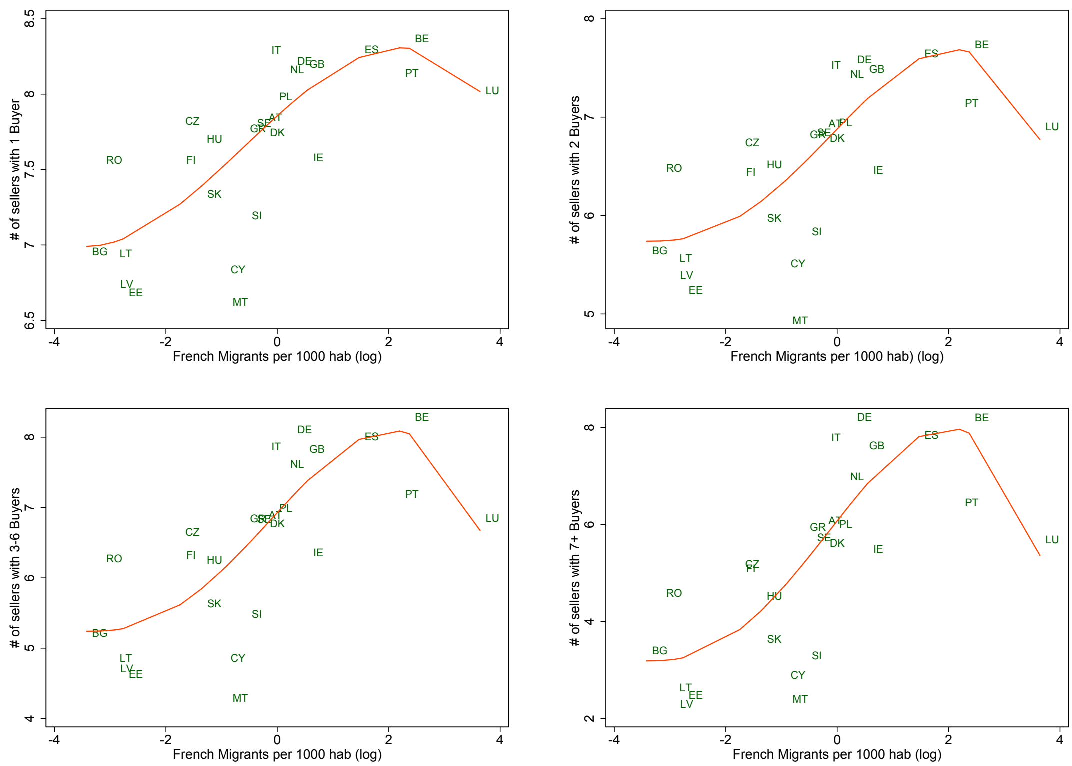
Figure 2: ***Number of buyers and the size of sellers***



Notes: Non-linear polynomial fit of the log of the total number of EU buyers served against the log size of the seller. Size is measured by the seller's total exports. A seller is defined as an exporter-HS6 product pair. The data are for 2007 and are restricted to transactions with recorded CN8-products.

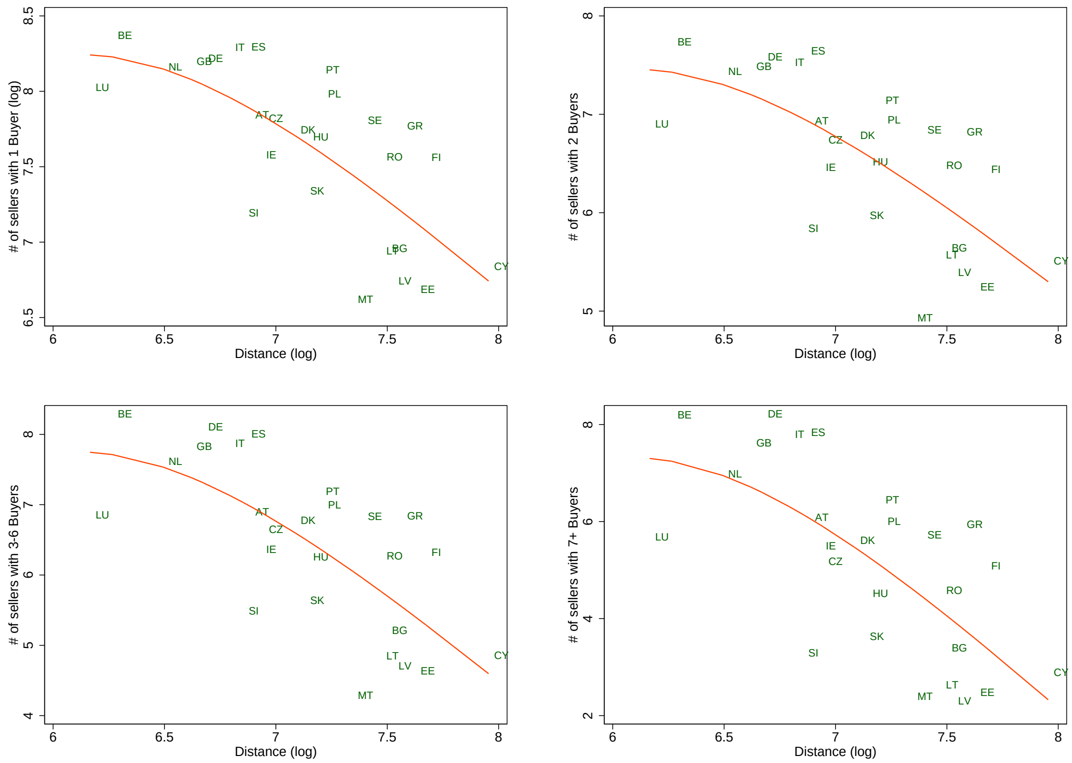
$$
\begin{aligned}
\mathbb{P}\left[\underset{s_j\in\Omega_{b_i}}{\mathrm{Min}}\left(\frac{c_j d_{ij}}{z_{s_j}}\right)>p\right] &= \sum_{d=0}^{+\infty}\mathbb{P}\left(\underset{s_j\in\Omega_{b_i}}{\mathrm{Min}}\left(\frac{c_j d_{ij}}{z_{s_j}}\right)>p|D_{b_i}=d\right)\mathbb{P}(D_{b_i}=d)\\
&= \sum_{d=0}^{+\infty}\left[1-\frac{p^\theta\sum_{j=1}^N\lambda_{ij}T_j(d_{ij}c_j)^{-\theta}}{\sum\limits_{j=1}^N\lambda_{ij}T_j\underline{z}^{-\theta}}\right]^d\left[\frac{\left(\sum\limits_{j=1}^N\lambda_{ij}T_j\underline{z}^{-\theta}\right)^d e^{-\sum\limits_{j=1}^N\lambda_{ij}T_j\underline{z}^{-\theta}}}{d!}\right]\\
&= e^{-\sum\limits_{j=1}^N\lambda_{ij}T_j\underline{z}^{-\theta}}\sum_{d=0}^{+\infty}\frac{1}{d!}\left(\sum_{j=1}^N\lambda_{ij}T_j\underline{z}^{-\theta}-p^\theta\sum_{j=1}^N\lambda_{ij}T_j(d_{ij}c_j)^{-\theta}\right)^d\\
&= e\left(-p^\theta\sum_{j=1}^N\lambda_{ij}T_j(d_{ij}c_j)^{-\theta}\right)\\
&= e^{-p^\theta\Upsilon_i\kappa_i\widetilde{\lambda}_i}
\end{aligned}
$$

Figure 3: ***Number of sellers with 1, 2, 3-6 , 7+ buyers and GDP***



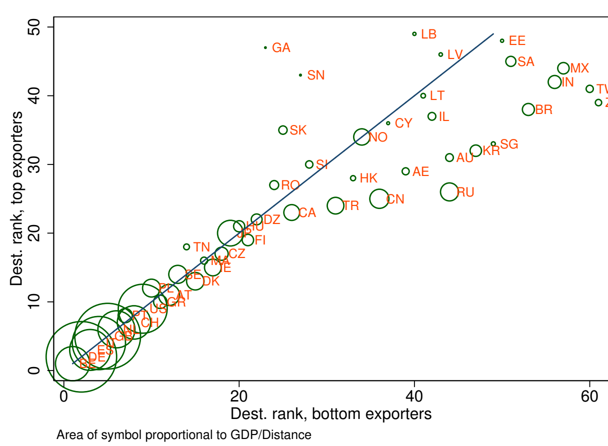
Notes: Number of sellers with 1, 2, 3-6 and 7+ buyers per destination. A seller is defined as an exporter (siren).

Figure 4: ***Number of sellers with 1, 2, 3-6 , 7+ buyers and Distance (log)***



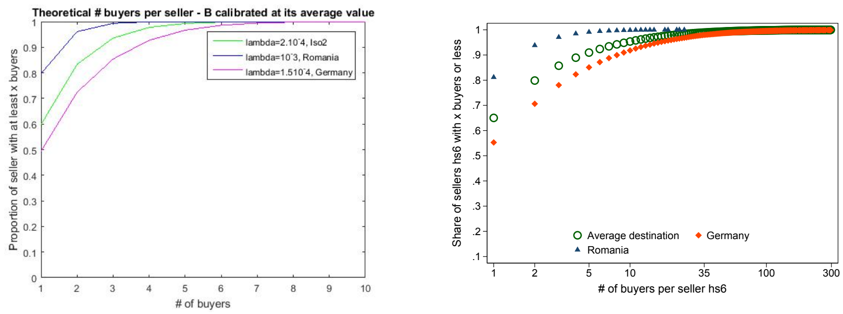
Notes: Sales per seller with 1, 2, 3-6 and 7+ buyers per destination. A seller is defined as an exporter (siren).

Figure 5: ***Ranking of destinations for large and small exporters - World***



Notes: Belgium and Germany are the first destinations in terms of number of entrants for both small and large sellers. Slovakia is the 25th destination for small exporters while it ranks 33 for large exporters. An entrant is a firm*product couple. Size is measured by aggregate sales, bottom exporters belong to bottom 15% and top exporters to top 15%.

Figure 6: ***Seller's Degree : Theory vs Data***



Notes: Predicted (left panel) and observed (right panel) proportion of sellers that serve x buyers or less in a given destination, in 2007. A seller is defined as an exporter-HS6 product pair.

where $\widetilde{\lambda}_i = \dfrac{\sum\limits_{j=1}^{N} \lambda_{ij} T_j \underline{z}^{-\theta}}{\sum\limits_{j=1}^{N} T_j \underline{z}^{-\theta}}$ is the "mean" level of frictions in country i and $\Upsilon_i = \sum_{j=1}^{N} T_j \left(d_{ij} c_j\right)^{-\theta}$ is the multilateral resistance index. The probability for the minimum price encountered to be below p is thus the exponential of the total measure of firms whose price is below p in country i times the proportion of those which will be encountered on average.

Based on this, the distribution of the lower price encountered by a particular buyer b_i in country i has the following Weibull cumulated distribution function:

$$G_i(p) = 1 - e^{-p^{\theta} \Upsilon_i \kappa_i \widetilde{\lambda}_i}$$

A.2 Aggregate trade

Under the law of large numbers, the share of products from F in i's consumption is equal to the probability that a buyer from i chooses a seller from F to purchase the good:

$$\pi_{iF} = \mathbb{E}_{b_i}[\mathbb{1}\{s(b_i) = F\}]$$

Under the assumption of binomial draws in the country-specific distribution, the distribution of the random variable $D_{b_i F}(p)$ which describes the number of firms from F met by seller b_i with a price below p can be approximated by a Poisson of parameter $\lambda_{iF}\mu_{iF}(p)$. Given the independence of draws, the random variable $D_{b_i \setminus \{F\}}(p)$ designating the number of firms from *any* country but F met by seller b_i at a price below p is also Poisson of parameter $\sum_{j \neq F}^{N} \lambda_{ij}\mu_{ij}(p)$. Conditional on a price p, the probability that buyer b_i has met with a firm from j can then be computed.

First, one should remark that conditioning the probability on the best price, comes down to conditioning the probability with meeting at least one potential seller.

$$\mathbb{E}_{b_i}[\mathbb{1}\{s(b_i) = F\}|p] = \mathbb{P}[s(b_i) = F|p, D_{b_i}(p) > 0]$$

Then,

$$\begin{aligned}
&= \mathbb{P}[(s(b_i) = F) \cap (D_{b_i}(p) > 0)] \\
&= \sum_{n=1}^{+\infty} \sum_{n_F=0}^{n} \mathbb{P}[s(b_i) = F|D_{b_{iF}}(p) = n_F,\ D_{b_{i\setminus\{F\}}}(p) = n - n_F]\ \mathbb{P}[D_{b_{iF}}(p) = n_F]\ \mathbb{P}[D_{b_{i\setminus\{F\}}}(p) = n - n_F] \\
&= \sum_{n=1}^{+\infty} \sum_{n_F=0}^{n} \frac{n_F}{n} \frac{[\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p)]^{n-n_F}}{(n-n_F)!} e^{-\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p)} \frac{[\lambda_{iF}\mu_{iF}(p)]^{n_F}}{(n-n_F)!} e^{-\lambda iF\mu_{iF}(p)} \\
&= e^{-\sum_{j=1}^{N} \lambda_{ij}\mu_{ij}(p)} \sum_{n=1}^{+\infty} \frac{[\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p)]^{n}}{n} \sum_{n_F=1}^{n} \frac{1}{(n-n_F)!(n_F-1)!} \left(\frac{\lambda_{iF}\mu_{iF}(p)}{\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p)}\right)^{n_F} \\
&= \frac{\lambda_{iF}\mu_{iF}(p)}{\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p)} e^{-\sum_{j=1}^{N} \lambda_{ij}\mu_{ij}(p)} \sum_{n=1}^{+\infty} \frac{(\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p))^{n}}{n} \frac{1}{(n-1)!} \sum_{n_F=0}^{n-1} \frac{(n-1)!}{(n-1-n_F)!(n_F)!} \left(\frac{\lambda_{iF}\mu_{iF}(p)}{\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p)}\right)^{n_F} \\
&= \frac{\lambda_{iF}\mu_{iF}(p)}{\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p)} e^{-\sum_{j=1}^{N} \lambda_{ij}\mu_{ij}(p)} \sum_{n=1}^{+\infty} \frac{(\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p))^{n}}{n!} \left(\frac{\lambda_{iF}\mu_{iF}(p)}{\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p)} + 1\right)^{n-1} \\
&= \frac{\lambda_{iF}\mu_{iF}(p)}{\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p)} e^{-\sum_{j=1}^{N} \lambda_{ij}\mu_{ij}(p)} \sum_{n=1}^{+\infty} \frac{(\lambda_{iF}\mu_{iF}(p) + \sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p))^{n-1}}{n!} (\sum_{j\neq F}^{N} \lambda_{ij}\mu_{ij}(p)) \\
&= \frac{\lambda_{iF}\mu_{iF}(p)}{\sum_{j=1}^{N} \lambda_{ij}\mu_{ij}(p)} e^{-\sum_{j=1}^{N} \lambda_{ij}\mu_{ij}(p)} [e^{\sum_{j=1}^{N} \lambda_{ij}\mu_{ij}(p)} - 1] \\
&= \frac{\lambda_{iF}\mu_{iF}(p)}{\sum_{j=1}^{N} \lambda_{ij}\mu_{ij}(p)} [1 - e^{-\sum_{j=1}^{N} \lambda_{ij}\mu_{ij}(p)}]
\end{aligned}$$

Moreover,

$$\begin{aligned}
\mathbb{P}[s(b_i) = F] &= \mathbb{P}[(s(b_i) = F) \cap (D_{b_i}(p) > 0)] \\
&= \mathbb{P}[s(b_i) = F|D_{b_i}(p) > 0]\mathbb{P}[D_{b_i}(p) > 0]
\end{aligned}$$

Such that, the probability that buyer b_i has chosen a seller from F conditionally on having met some sellers, corresponds to the share of products from F in i's consumption π_{iF} is :

$$\pi_{iF} = \mathbb{P}[s(b_i) = F|D_{b_i}(p) > 0] = \frac{\mathbb{P}[s(b_i) = F]}{\mathbb{P}[D_{b_i}(p) > 0]} = \frac{\lambda_{iF}\mu_{iF}(p)}{\sum_{j=1}^{N} \lambda_{ij}\mu_{ij}(p)}$$

A.3 Expected mass of firms serving M buyers

Start from the expected mass of firms serving M buyers derived in the text:

$$h_{ij}(M) = \frac{\kappa_i\pi_{ij}}{\lambda_{ij}} C_{B_i}^{M} \int_{\underline{\rho_{ij}}}^{\lambda_{ij}} \rho_{s_j,i}^{M-1}(1-\rho_{s_j,i})^{B_i-M} d\rho_{s_j,i}$$

If we assume that $M > 0$ we can recognize a function of the family of the Beta function:

$$h_{ij}(M) = \frac{\kappa_i \pi_{ij}}{\lambda_{ij}} C_{B_i}^M \Big(B(\lambda_{ij}, M, B_i - M + 1) - B(\underline{\rho_{s_j,i}}, M, B_i - M + 1) \Big)$$

with $B(\lambda_{ij}, M, B_i - M + 1) = \int_0^{\lambda_{ij}} \rho_{s_j,i}^{M-1}(1-\rho_{s_j,i})^{B_i - M} d\rho_{s_j,i}$ being the incomplete beta function.

Using properties of the Beta function, notice that :

$$\begin{aligned} B(M, B_i - M + 1) &= \frac{\Gamma(M)\Gamma(B_i - M + 1)}{\Gamma(M + B_i - M + 1)} = \frac{\Gamma(M)\Gamma(B_i - M + 1)}{\Gamma(B_i + 1)} \\ &= \frac{(M-1)!(B_i - M)!}{B_i!} = \frac{1}{M} \frac{(M)!(B_i - M)!}{B_i!} \\ &= \frac{1}{M} \frac{1}{C_{B_i}^M} \end{aligned}$$

Then, the regularized incomplete beta function is :

$$I_{\lambda_{ij}}(M, B_i - M + 1) = \frac{B(\lambda_{ij}, M, B_i - M + 1)}{B(M, B_i - M + 1)} = B(\lambda_{ij}, M, B_i - M + 1) C_{B_i}^M M$$

Now, we can rewrite the expression for the mass of suppliers from j with M buyers in i with the help of the regularized incomplete beta function:

$$h_{ij}(M) = \frac{\kappa_i \pi_{ij}}{\lambda_{ij}} \frac{1}{M} \Big(I_{\lambda_{ij}}(M, B_i - M + 1) - I_{\underline{\rho_{ij}}}(M, B_i - M + 1) \Big)$$

Finally, note that if $\underline{\rho_{ij}}$ goes to 0, $I_{\underline{\rho_{ij}}}(M, B_i - M + 1)$ goes to 0 as well:

$$\lim_{\underline{\rho_{ij}} \to 0} I_{\underline{\rho_{ij}}}(M, B_i - M + 1) = \lim_{\underline{\rho_{ij}} \to 0} \int_0^{\underline{\rho_{ij}}} \rho_{s_j,i}^{M-1}(1 - \rho_{s_j,i})^{B_i - M} d\rho_{s_j,i} = 0$$

Using this, one recovers equation (5) in the main text:

$$h_{ij}(M) = \frac{\kappa_i \pi_{ij}}{\lambda_{ij}} \frac{1}{M} I_{\lambda_{ij}}(M, B_i - M + 1)$$

A.4 Distribution of the Auxiliary Parameter

In line with our theoretical framework we note $\Big[\mathbb{1}\{B_{s_j i} = M\} \Big]_{sj \in \mathbb{S}}$ the dummies of any supplier from j to have exactly M buyers in country i. These dummies are independent[40] and

[40] Independence comes from the fact that sellers are independent from each other, this assumption could be relaxed as version of CLT exists with weak dependence conditions

identically distributed [41] random variables of mean $\frac{h_{ij}(M)}{\sum\limits_{M=0}^{B_j} h_{ij}(M)}$.[42] and of variance $\sigma_{ij}^2(M)$. This is true for all $M \in [0, B_i]$.

With this structure, we can apply the Central Limit Theorem :

$$\sqrt{S_j}\begin{pmatrix} \frac{\sum\limits_{s_j=1}^{S_j}\mathbb{1}\{B_{s_j i}=1\}}{S_j} & - & \frac{h_{ij}(1)}{\sum\limits_{M=0}^{B_j} h_{ij}(M)} \\ \frac{\sum\limits_{s_j=1}^{S_j}\mathbb{1}\{B_{s_j i}=2\}}{S_j} & - & \frac{h_{ij}(2)}{\sum\limits_{M=0}^{B_j} h_{ij}(M)} \\ ... & - & ... \\ \frac{\sum\limits_{s_j=1}^{S_j}\mathbb{1}\{B_{s_j i}=0\}}{S_j} & - & \frac{h_{ij}(0)}{\sum\limits_{M=0}^{B_j} h_{ij}(M)} \end{pmatrix} \xrightarrow[S_j \to +\infty]{\mathcal{D}} \mathcal{N}_N(0, \Sigma_{ij}) \tag{10}$$

We note Σ_{ij} the variance-covariance matrix of the N random variables $\mathbb{1}\{B_{s_j i} = M\}$, for $M \in \{0, 1...N-1\}$

For simplicity of notations we note $\theta_0 = \begin{pmatrix} \frac{h_{ij}(1)}{\sum\limits_{M=0}^{B_j} h_{ij}(M)} \\ \frac{h_{ij}(2)}{\sum\limits_{M=0}^{B_i} h_{ij}(M)} \\ ... \\ \frac{h_{ij}(0)}{\sum\limits_{M=0}^{B_i} h_{ij}(M)} \end{pmatrix}$ and $\hat{\theta} = \begin{pmatrix} \frac{\sum\limits_{s_j=1}^{S_j}\mathbb{1}\{B_{s_j i}=1\}}{S_j} \\ \frac{\sum\limits_{s_j=1}^{S_j}\mathbb{1}\{B_{s_j i}=2\}}{S_j} \\ ... \\ \frac{\sum\limits_{s_j=1}^{S_j}\mathbb{1}\{B_{s_j i}=0\}}{S_j} \end{pmatrix}$

[41] They are identically distributed ex-ante as sellers draw there productivity in the same distribution and face the same matching friction.

[42] First remark that $\mathbb{E}\left[\mathbb{1}\{B_{s_{ji}} = M\}\right] = \mathbb{P}(B_{s_j i} = M) = \int_{\underline{z}}^{+\infty} \mathbb{P}(B_{s_j i} = M|z)\mathbb{P}(z_{s_j} \leq z)dz = \frac{1}{T_j \underline{z}^{-\theta}} \int_{\underline{z}}^{+\infty} \mathbb{P}(B_{s_j i} = M|z)d\mu(z)$. Then note that $\sum\limits_{M=0}^{B_j} h_{ij}(M)$ is not a random component as it is equal to $T_j \underline{z}^{-\theta}$ the measure of seller from j. On the other hand $h_{ij}(M)$ is the expected measure of firms with exactly M buyers, the expectation is taken with respect to both the productivity draws and matching frictions. Consequently, $\frac{h_{ij}(M)}{\sum\limits_{M=0}^{B_j} h_{ij}(M)} = \mathbb{E}\left[\mathbb{1}\{B_{s_j i} = M\}\right]$ as the expectation is taken with respect to the two level of randomness.

such that we can rewrtie (10) :

$$\sqrt{S_j}(\hat{\theta} - \theta_0) \xrightarrow[S_j \to +\infty]{\mathcal{D}} \mathcal{N}_N(0, \Sigma_{ij})$$

We then consider the function
$$\begin{array}{cccc} g & : & \mathbb{R}^N & \mapsto & \mathbb{R}^{N-1} \\ & & \begin{pmatrix} \theta_1 \\ \theta_2 \\ ... \\ \theta_{N-1} \\ \theta_N \end{pmatrix} & \to & \begin{pmatrix} \frac{\theta_1}{\theta_N} \\ \frac{\theta_2}{\theta_3} \\ ... \\ \frac{\theta_{N-1}}{\theta_N} \end{pmatrix} \end{array}$$

This function g is derivable and verifies the property $\nabla g(\theta_0) \neq 0$.

Applying the Delta-Method we obtain :

$$\sqrt{S_j}[g(\hat{\theta}_N) - g(\theta_{0,N})] \underset{S_j \to +\infty}{\xrightarrow{\mathcal{D}}} \mathcal{N}_{N-1}\left(\begin{pmatrix} 0 \end{pmatrix}, \nabla g(\theta_0)\Sigma_{ij}\nabla' g(\theta_0)\right) \tag{11}$$

Where $\nabla g(\theta_0)\Sigma_{ij}\nabla' g(\theta_0)$ is notes Ω_0 in the $\text{Dim}[\nabla g(\theta_0)] = [N-1, N]$ and $\nabla g(\theta_0)$ is defined as

$$\begin{pmatrix} \frac{\sum_{M=0}^{B_i} h_{ij}(M)}{h_{ij}(0)} & 0 & ... & ... & -\frac{(\sum_{M=0}^{B_i} h_{ij}(M))h_{ij}(1)}{h_{ij}(0)^2} \\ 0 & \frac{\sum_{M=0}^{B_i} h_{ij}(M)}{h_{ij}(0)} & ... & ... & -\frac{(\sum_{M=0}^{B_i} h_{ij}(M))h_{ij}(2)}{h_{ij}(0)^2} \\ ... & ... & ... & ... & -\frac{(\sum_{M=0}^{B_i} h_{ij}(M))h_{ij}(k)}{h_{ij}(0)^2} \\ 0 & 0 & ... & \frac{\sum_{M=0}^{B_i} h_{ij}(M)}{h_{ij}(0)} & -\frac{(\sum_{M=0}^{B_i} h_{ij}(M))h_{ij}(N-1)}{h_{ij}(0)^2} \end{pmatrix}.$$

When conducting our estimation, we will use an estimation of this variance-covariance matrix using our observations $\nabla g(\hat{\theta})$ and $\widehat{\Sigma_{ij}}$.

A.5 Proof of proposition 1

First compute the deravitive of κ_i wrt to λ_{ij}.

$$\begin{aligned} \frac{\partial \kappa_i}{\partial \lambda_{ij}} &= \frac{-T_j}{(\sum_j^N \lambda_{ij} T_j)^2} * \sum_j^N \lambda_{ij} T_j (d_{ij} c_j)^{-\theta} + \frac{T_j (d_{ij} c_j)^{-\theta}}{\sum_j \lambda_{ij} T_j} \\ &= \frac{T_j}{\sum_j \lambda_{ij} T_j}[\frac{(d_{ij} c_j)^{-\theta}}{\frac{\sum_j T_j (d_{ij} c_j)^{-\theta}}{\sum_j T_j}} - \kappa_i] \end{aligned}$$

This allows us to compute the growth rate of κ_i wrt to a marginal change in λ_{ij}

$$\frac{\partial ln(\kappa_i)}{\partial \lambda_{ij}} = \frac{\frac{\partial \kappa_i}{\partial \lambda_{ij}}}{\kappa_i} = \frac{T_j}{\sum_j \lambda_{ij} T_j} \; [\frac{\sum_j \lambda_{ij} T_j}{\sum_k \lambda_{ik} T_k (\frac{d_{ij} c_j}{d_{ik} c_k})^\theta} - 1] \tag{12}$$

As a result if $\frac{\sum_j \lambda_{ij} T_j}{\sum_k \lambda_{ik} T_k (\frac{d_{ij} c_j}{d_{ik} c_k})^\theta} < 1$ then $\frac{\frac{\partial \kappa_i}{\partial \lambda_{ij}}}{\kappa_i} < 0$. This happens when $d_{ij} c_j$ is larger than $d_{ik} c_k$ for lots of countries k or for countries k which are large and face low frictions (high $\lambda_{ik} T_k$).

Reducing matching frictions for countries which face relatively high marginal cost and trade barriers with country i will reduce the distortions implied by matching frictions on the multilateral resistance. On the opposite, reducing matching frictions for countries which face relatively low trade barriers and marginal costs will increase the level of competition in destination market i such that distortion of multilateral resistance, κ_i will be higher. Intuitively, if countries that contribute the more to the multilateral resistance face a reduction in their bilateral matching frictions, then "ex-post" multilateral resistance, namely $\kappa_i \Upsilon_i$ will be higher.

Effect of a change in bilateral matching frictions on $\widetilde{\lambda}_i$

$$\frac{\partial \widetilde{\lambda}_i}{\partial \lambda_{ij}} = \frac{\partial \frac{\sum_j \lambda_{ij} T_j}{\sum_j T_j}}{\partial \lambda_{ij}} = \frac{T_j}{\sum_j T_j}$$

Such that

$$\frac{\partial ln \widetilde{\lambda}_i}{\partial \lambda_{ij}} = \frac{T_j}{\sum_j T_j} \frac{\sum_j T_j}{\sum_j \lambda_{ij} T_j} = \frac{T_j}{\sum_j \lambda_{ij} T_j} \tag{13}$$

The average level of matching frictions in destination market i is reduced whenever a bilateral matching friction is reduced.

Effect of a change in bilateral matching frictions on bilateral trede flows $\widetilde{\pi_{ij}}$

To conclude on the effect of a change in bilateral matching frictions on bilateral trade flows, just use equations 12 and 13 in equation 2.

$$\frac{\partial ln \pi_{ij}}{\partial \lambda_{ij}} = \frac{-T_j}{\sum_k \lambda_{ik} T_k (\frac{d_{ij} c_j}{d_{ik} c_k})^{\theta}} + \frac{1}{\lambda_{ij}}$$

From where we can states that

$$\begin{aligned}
&\frac{\partial ln \pi_{ij}}{\partial \lambda_{ij}} > 0 \\
&\Rightarrow \lambda_{ij} < \frac{\sum_k \lambda_{ik} T_k (\frac{d_{ij} c_j}{d_{ik} c_k})^{\theta}}{T_j} = \lambda_{ij} + \frac{\sum\limits_{k \neq j} \lambda_{ik} T_k (d_{ik} c_k)^{-\theta}}{T_j (d_{ij} c_j)^{-\theta}} \\
&\Rightarrow 0 < \frac{\sum\limits_{k \neq j} \lambda_{ik} T_k (d_{ik} c_k)^{-\theta}}{T_j (d_{ij} c_j)^{-\theta}}
\end{aligned}$$

The last statement is always true whatever λ_{ij}.

A.6 Proof of proposition 2

$$
\begin{aligned}
\frac{\partial ln\rho_{s_j}}{\partial \lambda_{ij}} = & \underbrace{\frac{\partial ln\lambda_{ij}}{\partial \lambda_{ij}}}_{\text{Visibility channel}} + \underbrace{\frac{\partial ln e^{-(c_j d_{ij})^{\theta} z_{s_j}^{-\theta} \kappa_i \Upsilon_i \widetilde{\lambda}_i}}{\partial \lambda_{ij}}}_{\text{Competition channel}} \\
= & \frac{1}{\lambda_{ij}} - \frac{T_j (d_{ij} c_j)^{\theta}}{z_{s_j}^{\theta}}
\end{aligned}
$$

B Annexe A

B.1 Data and nomenclature

Table 17: ***Nomenclature of traded products***

Main CPA	Detailed name
10	Food products
11	Beverages
12	Tobacco products
13	Textiles
14	Wearing apparel
15	Leather and related products
16	Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials
17	Paper and paper products
18	Printing and recording services
19	Coke and refined petroleum products
20	Chemicals and chemical products
21	Basic pharmaceutical products and pharmaceutical preparations
22	Rubber and plastic products
23	Other non-metallic mineral products
24	Basic metals
25	Fabricated metal products, except machinery and equipment
26	Computer, electronic and optical products
27	Electrical equipment
28	Machinery and equipment n.e.c.
29	Motor vehicles, trailers and semi-trailers
30	Other transport equipment
31	Furniture
32	Other manufactured goods
33	Repair and installation services of machinery and equipment

Source: Eurostat