Search Frictions in International Good Markets*

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Abstract

We develop and estimate a model of search frictions in international good markets and study its implications for individual and aggregate trade flows. We introduce random meeting of buyers in an otherwise standard Eaton and Kortum (2002) (EK) framework. We show that search frictions impede aggregate exports but have a non-trivial impact on individual firms' trade. A reduction in these frictions increases sellers' exposure to foreign buyers but also reduces their chance to be the lowest cost supplier because of more competition among sellers. We build on this model to structurally estimate search frictions faced by French exporters using a generalized method of moments and firm-to-firm French export data. We document the magnitude of these frictions across sectors and destinations and show that their presence help; i) reconcile the EK framework with heterogeneity in firm-level export behaviours; and ii) quantify the relative role of search frictions and productivity heterogeneity in the selection of firms into export.

JEL Classification: F10, F11, F14, L15

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1 Introduction

Search frictions constitute part of the difficulty encountered by firms in international markets. Meeting with foreign buyers induces extra costs to learn about potential clients, their specific needs, etc. Such information frictions contribute to explaining the sensitivity of bilateral trade flows to elements that do not directly induce a substantial physical trade cost. Rauch (2001) thus explains the role of migrant networks in international markets by way of such frictions. This paper introduces search frictions into a Ricardian model of international trade and recovers a structural estimation of these costs. Estimated search frictions are shown to affect the geography of international trade and the heterogeneity in firms' participation to export markets. By inducing some randomness in the self-selection of firms into export, they make the relationship between firms' productivity and their ability to serve foreign markets more fuzzy.

Our argument is based on the structural estimation of a Ricardian model of trade augmented with search frictions. The modeling strategy is motivated by a set of original stylized facts obtained from French firm-to-firm export data.[1] First, using the stock of migrants as a proxy (Rauch and Trindade, 2002), we document a significant impact of information frictions on the magnitude of bilateral French exports. A larger stock of migrants increases the probability that any French firm exports to the destination and, conditional on exporting there, the number of clients that they serve. Second, we confirm the Eaton et al. (2011) evidence regarding the large amount of randomness in the geography of individual firms' exports. In particular, small exporters tend to "over-export" in difficult markets, in comparison with what is predicted in a standard trade model with heterogeneous firms. Third, and consistent with Bernard 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 from France. The heterogeneity in the number of buyers within a firm contributes to explaining aggregate trade flows. On the other hand, we show that, once conditioning on a particular product, the vast majority of importing firms interact with at most one French exporter.[2]

[1] Bernard et al. (2014) and Carballo et al. (2013) use comparable data for other exporting countries and document similar patterns regarding the heterogeneity in the number of clients served by exporters within each destination country.

[2] Instead, Bernard et al. (2014) emphasize the two-sided heterogeneity of firms involved in international markets. In their data, both exporters *and* importers greatly vary regarding the number of partners they interact with. This two-sided heterogeneity, they argue, is best captured in a model of many-to-many matching in international markets. At least in the French data, this result holds true when the product dimension is

These stylized facts can be rationalized by the combined effect of search frictions between exporters and importers and Ricardian advantages across exporters. Our model extends Eaton and Kortum (2002) to include search frictions. In a partial equilibrium framework, a continuum of heterogeneous producers endowed with different technologies compete in price to sell a perfectly substitutable variety. On the demand side, a large number of buyers in each destination meet with a random sample of those producers and choose the lowest cost supplier, within their random choice set.[3] The random component of the matching process comes down to relaxing two implicit assumptions used in most trade models namely that; i) foreign consumers perfectly observe 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.[4] In particular, Eaton and Kortum (2002) rely on the second assumption. In their framework, perfect competition among heterogeneous suppliers implies that, in equilibrium, a maximum of one technology per country and per good serves a given destination market. In frictional markets however, ex-ante homogeneous buyers end up heterogeneous ex-post, in terms of the suppliers they meet and ultimately contract with. As a consequence, several heterogeneous suppliers can simultaneously serve the same destination market with the same good, to different buyers.

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. The probability for a particular seller to be selected by any buyer in any destination country depends on; i) its productivity, through its probability to be the lowest-cost supplier that the buyer has met; and ii) the magnitude of frictions as measured by the bilateral meeting probability. On average, more productive sellers are more likely to serve a given destination. But the random nature of the meeting process implies that any outcome is possible; a low-productive firm may be lucky enough to reach any difficult destination. Such randomness is useful inasmuch as it allows reproducing any form of unobserved heterogeneity across firms and destinations, which is notoriously important in disaggregated trade data (Eaton et al., 2011).

We discuss how frictions affect aggregate and firm-level trade flows. At the aggregate level,

neglected. But when we condition on the product being traded, we see many exporters interacting with several foreign firms but the vast majority of foreign firms purchasing a particular product from a maximum of one French firm. Since we are interested in estimating product-level frictions, we argue that this feature of the data is consistent with a one-to-many matching model.

[3]The modeling of search frictions is inspired from Eaton et al. (2014).

[4]Exceptions include Drozd and Nosal (2012) and Arkolakis (2010) who relax the second assumption. In these models, individual exporters can pay an increasing marketing cost to serve an increasing share of the destination market.

reducing frictions always increases trade. From that point of view, information frictions do not differ from other sources of trade frictions such as iceberg trade costs. At the firm level, the effect is ambiguous however; it improves the seller's exposure to foreign buyers but also reduces its chance to be the lowest cost supplier because of more competition among sellers. For low-productivity firms, the competition channel dominates and their chance to serve a particular destination is increasing in search frictions. On the contrary, highly productive firms benefit from less frictions as their lack of exposure to foreign buyers is what prevents them from serving more buyers and destinations. A corollary of this result is that bilateral frictions not only affect the level of bilateral trade but also the composition of aggregate trade flows. More information frictions induce a less stringent self-selection of firms into exports, thus lower gains from trade.

The magnitude of search frictions can be estimated structurally for each sector and destination using a generalized method of moments approach and the firm-to-firm French export data. The empirical moments used to feed the estimation are obtained from the dispersion across exporters in the number of buyers served in a given country and sector. We discuss how this particular moment helps identify search frictions, independently from other barriers to international trade. Intuitively, the strategy exploits the fact that physical trade costs affect the competitiveness of all French exporters in the same way while search frictions affect differently small and large firms. This is the reason why the *dispersion* in the number of buyers per seller is an insightful statistics to estimate search frictions.

Estimated frictions confirm ex-post our theoretical predictions. Within a sector they are weakly correlated with GDP and distance and negatively correlated with the number of French migrants living in the destination. Within a country, we show using Rauch (1999) classification that search frictions are higher in more differentiated sectors. This is consistent with an interpretation of the model in terms of information frictions, provided that information is more difficult to gather in non organized markets and/or for less homogeneous goods. Results also confirm the predictions of the model regarding aggregate trade flows. Namely, aggregate trade is positively correlated with estimated meeting probabilities. Finally, increasing the meeting probability has a non-monotonic impact on individual sales; the elasticity is estimated slightly negative on the lower side of the size distribution while significantly positive on the sub-sample of the largest firms. In terms of policy implications, our results reveal that nation-wide programs which aim at increasing the visibility of domestic sellers abroad can be an efficient tool for promoting trade.[5]

[5] The French export promoting agency offers several programs, either firm-level or nation-wide, which are meant to help firms meet with foreign clients. The agency notably helps financing firms' participation to

Our work relates to the recent 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. The same holds true in Eaton et al. (2013), where sellers learn about their product appeal, for foreign buyers. We instead introduce information frictions on the demand 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.[6] In comparison with theirs, our model is based on simpler assumptions since the search process is purely random. The tractability of this framework allows us to derive closed-form solutions for the expected number of clients that a given exporter serves in a market and recover from there a structural estimation of the search frictions. On the empirical side, Lendle et al. (2012) and Steinwender (2014) also highlight the importance of information frictions for trade.[7]

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 a destination country (resp. origin country) in the origin country (resp. destination country) have a positive impact on trade as it allegedly reduces search 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 search frictions into an otherwise standard Eaton and Kortum (2002) model. This is what makes it possible to derive predictions regarding the correlation between firms' size and their expected stock of foreign buyers.

As in the above-mentioned literature, our modeling strategy assumes some randomness in the matching process between exporters and importers. An alternative way to reproduce

international trade fairs or organizing bilateral meetings with representatives of the sector in the destination country. See details on the agency's website, www.businessfrance.fr

[6] Dragusanu (2013) also develops a model of costly search for suppliers. She focuses on the benefit of a good match at different stages of global supply chains.

[7] 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.

observed patterns in firm-to-firm relationships consists in assuming some form of sorting between heterogeneous exporters and heterogeneous importers. This is the strategy in Carballo et al. (2013) and Bernard et al. (2014). Namely, Bernard et al. (2014) assume that buyers differ in their size or capacity while Carballo et al. (2013) introduce heterogeneous tastes. Such a strategy implies that the matching process between sellers and 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 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 describes our theoretical model and derives analytical predictions regarding the expected number of clients that an exporter will serve in its typical destination. Section 4 explains how we estimate the magnitude of search frictions using a GMM approach. Section 5 presents the results and discusses how search frictions affect the geography of trade for firms and in the aggregate. Finally, Section 6 concludes.

2 Data and stylized facts

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. Our analysis focuses on data for 2007 but we checked that statistics are not sensitive to the choice of the reference year.

For each transaction, the data set records the identity of the exporting firm (its SIREN identifier), the identification number of the importer (an anonymized version of its 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. It is also possible to link each exporter to its sector of activity using the "INSEE-Siren" database. 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 its foreign partner. The product dimension will allow conditioning our results on the good being traded, as in the model. A "seller" will thus be an exporter of a specific product. This hypothesis comes down to redefining a French exporter as a single-product firm and neglecting any potential complementarity between products sold by the same firm.

Since we are interested in the extent of search frictions that an exporter faces in foreign markets, we restrict each exporter's product portfolio to products that represent at least 5% of export sales for at least one French seller in the firm's sector of activity. The rational for such restriction is that we see in the data firms selling many different products, some of which being relatively "close" to the firm's activity (say exports of wine in agricultural sectors) and others being hardly related to their main activity (e.g. export of glasses for wine producers). In this example, glasses are most probably side products which the firm sells to its customers while they buy some of its wine. While information frictions might be important to identify potential wine consumers, we shall not expect frictions in the market of glasses to affect the wine producer's ability to sell this product; such tied selling only depends on the firm's ability to meet with wine consumers. In practice, it is almost impossible to decide which products are tied and which are not. The statistical criterion that we use thus considers that a product which no firm in the sector sells in large enough quantities is probably tied and is thus removed from the sample. De facto, such restriction limits the number of potential suppliers of a product to firms belonging to sectors in which the product is indeed an important part of export activities. This restriction substantially reduces the number of exporter $\times$ product pairs covered (by around X%) without having much of an impact on the aggregate value of exports (X%).

In the rest of the analysis, French exporters will be indexed by s_j and individual importers by b_i where j and i respectively denote the country of origin of the seller (France in our data) and the location of the buyer (one of the 26 EU destinations the dataset covers). Table 1 provides summary statistics on the number of sellers, buyers and products, by destination. As shown by the comparison of Columns (1) and (4), there are 19,511 exporters in the overall database, but 149,739 exporter$\times$product pairs. This means that the average exporter sells 7.7 different products, with important variations across firms and markets.[8]

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 consumption. This explains that the data are exhaustive. One caveat is that 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

[8]Among the 19,511 exporters, 12,697 are multi-product firms. The median number of products per firm is equal to 2 and 10% of exporters export more than 17 products. **say something about the likelihood that a seller provide the same buyer with several products?**

the product category of exported goods. As we adopt the definition of a seller at the siren-hs6 level we have no choice but to drop these transactions. We did however check that the most important stylized facts regarding the number of buyers per firm are robust to including these firms (assuming that they sell a single product abroad). 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 in 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 2% representing 3% of the total value of exports.

In 2007, we have information on 19,511 French firms exporting to 357,571 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' worldwide exports. 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, 79,616 German firms import from France against 922 in Estonia. Likewise, the number of French exporters serving the German market is an order of magnitude larger than those serving 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 number of active exporters times the number of 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 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.[9] The distance between a French firm and her buyers is proxied by the weighted distance between France and the destination. As an alternative, we have also constructed a measure of distance

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

which takes into account the firm's location in France and its distance to the destination country, in kilometers and in terms of the time to drive there.[10] 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 the stock of migrants per origin and destination countries, taken from the UN database on Trends in International Migrant Stock. Following Rauch and Trindade (2002), the degree of information frictions between France and destination i is assumed to be inversely related to the share of French citizens in the destination's population and the share of migrants from i in France.

2.2 Descriptive Statistics

As explained in Section 2.1, the most important novelty in our data is the identification of both sides of international trade flows, not only individual exporters but also their foreign clients in each destination. We now present new facts exploiting this dimension to characterize the nature of interactions between sellers and buyers engaged in international trade. The facts are later used to motivate the model's assumptions and back out a number of theoretical 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.[11] The left panel documents the share of sellers interacting with a given number of buyers while the right panel illustrates their relative weight in overall exports. To illustrate the amount of heterogeneity across destination countries, Figure 1 displays the distribution obtained in the average European destination (circle points) as well as those computed for two specific destinations, which represent extreme cases around this average, namely Romania and Germany (triangle and diamond points, respectively).

In France's typical export market, 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 in Figure 1 describes the weight of these different categories of sellers in overall French exports. Sellers interacting with a single buyer in their typical destination account for about a third of French exports

[10] See Laboureau (2017) for a full description of the database.

[11] Remember that here and in the rest of the paper, a seller is identified by its siren number *and* the product category. The statistics underlying this graph is thus somewhat difference than in Bernard et al. (2014), although the conclusion regarding the strong heterogeneity in exporters' number of clients holds in both cases.

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. From this, we conclude that French exports are dominated by sellers interacting with a small number of buyers.

Figure 1, circle points, hides a substantial amount of heterogeneity in the number of buyers per seller, across both sectors and destinations. The other two distributions depicted in Figure 1 illustrate the cross-country heterogeneity, based on two extreme cases, namely Romania and Germany.[12] While the median degree of sellers is equal to just one buyer in all destination countries, the mean varies quite substantially, due to varying shares of sellers who manage to serve more clients. In the extreme, 45% of exporters to Germany serve more than one buyer there, to be compared with only 19% for exports to Romania. Here as well, the heterogeneity across firms serving the same destination markets is correlated with their size (see the comparison of the left and right panels in Figure 1).

Figure 2 shows that such dispersion also exists across sectors, although perhaps less marked. The average degree of sellers varies between 1.3 in the Mineral products industry and 3.6 in the Footwear industry. The share of sellers with a single partner lies in between 68% in the textile industry and 84% for oil and waxes. Actually, most of the variance across HS2 chapters is found when one compares the mean degree of sellers in the destination where it is the highest (blue triangles in the left panel). This number varies between 3 buyers on average for products of animal origin, not elsewhere specified and more than 10 for oil seeds and oleaginous fruits.

We examine the dispersion in the number of buyers per seller more systematically using a variance decomposition. 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 2-digit level of the product classification. Finally, country $\times$ sector fixed effects explain 10% of the overall variance, a number which stays stable when sectors are defined at a finer 6-digit level. This suggests that most of the heterogeneity in the data (more than 80%) comes from the heterogeneity across firms serving the same country with the same type of goods. This is the dimension that the model will explain.

Figure 3 presents a non-linear polynomial fit of the (log of the) number of EU buyers served against the seller's size, as measured by the total value of individual exports. 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 sellers' size to reach a plateau around 40 European buyers. The positive correlation between a seller's size and the number of importers it is able to serve within a destination is consistent with evidence in Bernard

[12]Table A1 in Appendix provides more systematic evidence based on the whole set of destination countries.

et al. (2014) and Carballo et al. (2013) based on similar data for other countries.

This set of stylized facts is summarized in Fact 1:

Fact 1. There is a substantial heterogeneity in the number of buyers served by sellers in their 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.

2.2.2 Number of sellers per buyer

Table 2 documents the number of sellers per buyer in the data. More than 90% of buyers (times HS6 product) import from a single French seller.[13] 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 2:

Fact 2. More than 90% of the buyers interact with a single French seller.

2.2.3 Number of sellers per destination

Statistics on the number of buyers per seller were not documented in the literature until recently. More well-known is the tendency of exporters to self-select into export markets. On average, "difficult" markets, which are either small or isolated, tend to be served by a smaller number of more productive firms. While this is true on average, the literature, notably Eaton et al. (2011), has documented a large degree of randomness around the average. In firm-level data, one systematically observes a number of small, unproductive firms that unexpectedly manage to serve difficult destination countries. We now provide some further evidence on this.

Figure 4 shows the correlation between the stock of French exporters active in a destination and the country's market potential, as measured by its GDP over the distance from France. As expected, the correlation is positive meaning that more French exporters are active in "easier destinations" such as Germany or the UK. The exercise is replicated for two sub-samples of firms representing exporters at the top and the bottom of the distribution of firms' size. The positive correlation is significantly more pronounced for large exporters while the relationship is more noisy when the analysis is restricted to small exporters. This means that, in relative

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

terms, small exporters tend to "over-perform" in difficult markets which they manage to serve almost as frequently as easier destinations. The randomness observed in Eaton et al. (2011) is actually more systematic than suggested. This new piece of evidence is summarized in Fact 3:

Fact 3. On average, French exporters self-select into export markets with larger and closer destinations being served by more firms. Small exporters however tend to over-succeed in serving less accessible countries.

Such evidence is difficult to reconcile with Melitz type models of heterogeneous firms. In this class of deterministic models, the ranking of countries in terms of their market potential fully determines the probability for firms to enter and large firms are always more likely to enter a less accessible country. Explaining this deviation from the model requires another degree of heterogeneity. In our framework, this comes from the randomness of the matching process which lets small/low-productive firms eventually be lucky enough to end up serving difficult markets.

2.2.4 Gravity regressions

Having documented new dimensions of heterogeneity in firm-to-firm trade data, we now use the gravity framework to show how the buyer margin affects the geography of French exports.

Standard gravity equations: Table 3 reports estimates of a standard gravity equation, at the product- and exporter- levels (Columns (1)-(4) and (5)-(7), respectively). Bilateral trade is explained by distance to France and proxies for market size, namely the country's (product-specific) import demand and GDP per capita.[14]

Column (1) confirms the results found in the rest of the literature, namely that product-level bilateral trade is larger towards closer, bigger and wealthier destination markets. This is also true within a firm, as confirmed in Column (5). As largely documented in the previous literature, see e.g. Bernard et al. (2007), gravity effects in international trade are attributable to the cross-country heterogeneity of bilateral trade flows at the intensive margin, i.e. in terms of the mean shipment per firm and product, *and* at the extensive margin, in terms

[14] It has to be noted that our data, which cover a single exporting country, do not allow to control for exporter and importer fixed effects as is recommended in the related literature, see Head and Mayer (2014). As a consequence, the estimated impact of distance might not be unbiased. Estimates in Columns (1) and (5) of Table 3 however serve as a benchmark for the subsequent decomposition of gravity effects in terms of intensive and extensive margins. For the bias to be a problem, it must be the case that it more strongly affects coefficients obtained on one or the other margins which is not clear.

of the number of firms and products being sold. We confirm this result in Columns (2)-(4) and Columns (6)-(7) of Table 3, where bilateral trade flows are further decomposed into intensive and extensive components. Importantly, the buyer dimension of the data allows us to control for an additional source of extensive adjustments, namely the net entry of new buyers in existing exporters' portfolio of clients (see also Bernard et al. (2014) for a similar decomposition based on Norwegian data).[15]

Consistent with the rest of the literature, results confirm that all margins of bilateral trade significantly contribute to the sensitivity of trade to gravity variables. In particular, the "buyer" extensive margin is responsible for 25% of the overall distance elasticity at the product-level, a number that jumps to 65% once gravity coefficients are identified within a firm.[16]

These results are summarized into Fact 4:

Fact 4. The buyer extensive margin is positively correlated with market size and negatively correlated with distance. These correlations hold true at the product- and the firm-level.

[15]More specifically, the product-level decomposition used in Table 3, Columns (1)-(4), is based on the following decomposition:

$$\ln x_{pd} = \underbrace{\ln \#^S_{pd}}_{\#\ Sellers} + \underbrace{\ln \frac{1}{\#^S_{pd}} \sum_{s\in S_{pd}} \#^B_{spd}}_{\#\ Buyers\ per\ Seller} + \underbrace{\ln \frac{1}{\#^{SB}_{pd}} \sum_{s\in S_{pd}} \sum_{b\in B_{spd}} x_{sbpd}}_{Mean\ exports\ per\ Buyer-seller}$$

where x_{pd} denotes the value of French exports of product p in destination d which is the sum of all firm-to-firm transactions x_{sbpd}. S_{pd} is the set of the $\#^S_{pd}$ sellers serving this market and B_{spd} the set of the $\#^B_{spd}$ importers purchasing product p from seller s.

Likewise, the decomposition of firm-level exports in Columns (5)-(7) of Table 3 is based on the following decomposition of trade into an extensive and an intensive terms:

$$\begin{aligned} \ln x_{spd} &\equiv \ln \sum_{b\in B_{spd}} x_{sbpd} \\ &= \underbrace{\ln \#^B_{spd}}_{\#\ Buyers} + \underbrace{\ln \frac{1}{\#^B_{spd}} \sum_{b\in B_{spd}} x_{sbpd}}_{Exports\ per\ Buyer} \end{aligned}$$

[16]Note that the contribution of the buyer margin is artificially low in the decomposition of product-level trade in Columns (1)-(4) because of some multicolinearity between the "seller" and "buyer" extensive margins. If we instead work with this decomposition:

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

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

Gravity and information frictions: In order to illustrate the importance of information frictions in international trade, we augment the above gravity framework with additional proxies for the extent of such frictions. Following Rauch and Trindade (2002), we use as proxies the number of migrants from the 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 4.

Consistent with expectations, the impact of migrants is almost always positive and significant. Both the share of French migrants in the foreign population and the share of migrants from abroad in the French population are positively correlated with the value of product- and firm-level exports to that destination. Importantly, controlling for these variables reduces the distance elasticity (see the comparison of Tables 3 and 4). This is consistent with the view that the impact of distance is in part attributable to information frictions being more pronounced between distant countries. The effect of migrants 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.

These results are summarized in Fact 5.

Fact 5. Information frictions, as proxied by the stock of migrants in the population, have a positive and significant effect on trade, especially at the (seller and buyer) extensive margin.

Facts 1 to 5 both confirm previous results in the literature and 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 5, the model relies on search frictions to explain the heterogeneity observed across firms and destinations.

3 The model

In this section, we present our model which is a partial equilibrium version of Eaton and Kortum (2002), extended to search frictions. After having summarized the main assumptions, we derive a number of analytical predictions which are later 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 specific 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). To alleviate notations, we do not keep track of 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 $[\underline{z}, +\infty[$.[17] The measure of firms in country j that can produce with efficiency above z is thus:

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

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. Heterogeneity across firms regarding the number of buyers they serve in a destination (Fact 1) will later 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 transportation. The cost of serving market i for a firm s_j is thus:

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

As in Eaton and Kortum (2002), iceberg trade costs reduce the competitiveness of domestic firms serving foreign markets. The larger trade costs, the less competitive a firm abroad, conditional on her productivity. Contrary to Eaton and Kortum (2002), a firm which is

[17] 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 search frictions will be introduced.

efficient enough to serve a foreign market will not however be able to serve the whole market, because of search frictions. Likewise, search 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 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) homogeneous consumers, each one being willing to spend one unit of the numeraire into the good. Because of search frictions, each buyer $b_i \in [1, B_i]$ meets with a discrete number of suppliers, drawn into the distribution $\mu_i(p)$. Conditional on the subset of producers met, she decides on which one to purchase from, by comparing the prices they offer. The assumption that buyers interact with a maximum of one seller is consistent with Fact 2 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 4, 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 the good from the lowest-cost supplier who she met and pays the price:[18]

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

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

The number of potential suppliers in the set Ω_{b_i} reflects the extent of search 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. Due to the assumption of independent draws, the number of suppliers from j that buyer b_i meets follows a binomial law of parameter $(T_j \underline{z}^{-\theta}, \lambda_{ij})$, that can be approximated by a Poisson law of parameter $\lambda_{ij} T_j \underline{z}^{-\theta}$.[19] 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 an inverse measure of frictions, which we assume is specific to each country pair (and each sector). A coefficient closer to one implies

[18] 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 which would equal the marginal cost of the second lowest-cost supplier. Under the assumption of inelastic demands, this does not change the results. If demand was elastic, we would need to keep track of both the first and second lowest cost supplier while computing the ex-post value of trade. Since most of our results exploit predictions regarding who each buyer is matched with, while neglecting the price at which the good is purchased, we think of the problem as being irrelevant. For this reason, we will stick to the simpler assumption of marginal cost pricing.

[19] 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. We assume that this is indeed the case.

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 is consistent with the interpretation of results in Table 4, is that λ_{ij} is systematically correlated with past migration flows between countries.

Heterogeneity in the magnitude of search frictions across countries means that the subset of firms which a buyer meets is biased towards firms located in countries with which search frictions are lower, on average. Within an origin country, all producers however 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 homogeneous 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. This property is what will help rationalize Fact 3 in our theoretical framework.

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):

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

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 and $\kappa_i = \frac{\sum_{j=1}^{N} \frac{\lambda_{ij} T_j}{\sum_{j=1}^{N} \lambda_{ij} T_j} (d_{ij} c_j)^{-\theta}}{\sum_{j=1}^{N} \frac{T_j}{\sum_{j=1}^{N} T_j} (d_{ij} c_j)^{-\theta}}$ is a measure of how search frictions distort the distribution of the nationality of sellers that the buyer meets, in comparison with a frictionless world in which this dispersion only depends on the geography of costs. 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 $\kappa_i \Upsilon_i$) and the lower search 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 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 search 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 search 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 search 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, denoted π_{ij}, 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.[20] It is the probability that the lowest cost supplier encountered by any buyer from i is located in country j.

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 (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:

[20] 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 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.

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

See the proof in Appendix A.2.

The share of products from country j in destination 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 search frictions its firms encounter while serving market i, $\frac{\lambda_{ij}}{\widetilde{\lambda}_i}$.[21] 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 the combined impact of technology and geography determines international trade flows in a Ricardian world. The key insight from our model is that search frictions can distort trade flows, in comparison with this benchmark. Taking the derivative of equation (1) with respect to λ_{ij} yields Proposition 1 regarding the sensitivity of aggregate trade to search frictions:

Proposition 1. The market share of a country always increases following a reduction in bilateral frictions:

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

See the Proof in Appendix A.3.

To recover the intuition surrounding this result, first note that

$$\frac{d\ln\pi_{ij}}{d\lambda_{ij}} = \underbrace{\frac{d\ln\lambda_{ij}}{d\lambda_{ij}}}_{\text{Visibility channel}} - \underbrace{\left[\frac{d\ln\kappa_i}{d\lambda_{ij}} + \frac{d\ln\widetilde{\lambda}_i}{d\lambda_{ij}}\right]}_{\text{Competition channel}}$$

[21] In this formula, κ_i can be interpreted as the distortion that frictions induce on the destination's multilateral resistance index. 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 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. $\Upsilon_i\kappa_i \rightarrow \Upsilon_i$ when $\lambda_{ij} \rightarrow 1, \ \forall i$). κ_i can be below or above 1 depending on whether frictions correlate with countries' competitiveness.

The impact of a reduction in bilateral search frictions on aggregate trade flows can be decomposed into two channels. First a "Visibility" channel that captures the direct impact of search frictions on the likelihood that any exporter from j meets with a buyer from i. Second, a "Competition" channel which affects the likelihood that any seller is chosen for serving a buyer, conditional on meeting with her. The first effect is positive since lower search frictions increase the probability that any supplier from j will be drawn by any buyer from i. As shown in Appendix A.3, an increase in the bilateral matching probability has a negative impact on average frictions (i.e. increases $\widetilde{\lambda}_i$) such that the level of competition in this destination increases with a negative end-effect on bilateral trade. Finally, a change in bilateral search frictions has an ambiguous effect on the frictional multilateral resistance term (i.e. on κ_i). Reducing search frictions for a country which is a large contributor to multilateral resistance will increase the distorting effect of these frictions. If it happens to a relatively remote country then the distorting effect will be reduced. As a result, the sign of $d \ln \kappa_i / d\lambda_{ij}$ is ambiguous.

As shown in Appendix A.3, the "Visibility" effect always dominates the "Competition" channel and a reduction in search frictions positively affects bilateral trade flows. This is in line with the argument in Rauch (1999) that search frictions can contribute to reducing the magnitude of bilateral trade between more distant countries, if correlated with (physical and cultural) distance between countries. Fact 5 is consistent with this view.

Finally, note that the model is compatible with structural gravity. Namely, log-linearizing equation (1) implies:

$$\ln \pi_{ij} = FE_i + FE_j - \theta \ln d_{ij} + \ln \lambda_{ij} \tag{2}$$

The cross-sectional variation in bilateral trade flows can be explained by a full set of origin- and destination-country fixed effects and a number of bilateral variables correlated with the magnitude of trade frictions. In comparison with standard gravity-compatible models, the difference is that our model predicts physical trade barriers as well as information frictions to enter the gravity equation.

3.2.2 Firm-to-firm matching

Having derived predictions regarding the magnitude of aggregate trade flows, we now study the matching process between any two firms. Such predictions are new to our model and can be confronted to firm-to-firm trade data. 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 meets with b_i times the probability that it is the lowest cost supplier, within b_i's random set:[22]

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

where $\mathbb{1}\{s(b_i) = s_j\}$ is a dummy equal to one if buyer b_i chooses seller s_j as provider of the good. Because of the Poisson assumption, the probability of being drawn by a buyer is constant and only depends on the size of search frictions. Consistent with Fact 1, 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 productivity, a seller has a better chance to serve a buyer located in an "easy" market which can be served 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). This last set of predictions is compatible with firm-level gravity estimates leading to Facts 4 and 5.

One can verify that an increase in the meeting probability has an ambiguous impact on the probability of a seller to be chosen by a particular buyer. This leads us to Proposition 2:

Proposition 2. There is an "optimal" level of bilateral search frictions for each seller, defined as the level of search frictions which maximizes its chance to be chosen by a buyer from i:

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

The "optimal" level of search frictions is decreasing in the seller's productivity: $\frac{\partial \lambda_{ij}^{\text{Opt}}(z_{s_j})}{\partial z_{s_j}} > 0$.

See the Proof in Appendix A.3.

A corollary of Proposition 2 is that more bilateral search frictions (a lower meeting probability λ_{ij}) have an ambiguous effect on the probability to serve a particular buyer conditional on the level of productivity. This ambiguous effect comes from two opposite forces:

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

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

On the one hand, a decrease in search frictions through the "visibility" channel increases the chances that seller s_j will serve any buyer in country i as it enhances its probability to meet with the buyer. On the other hand, conditional on being drawn, less bilateral search frictions means than s_j faces fiercer competition from other domestic suppliers. This reduces the probability that it is the lowest-cost supplier met by any particular buyer, especially if the seller's productivity is low. For low productivity sellers the competition channel dominates and their "optimal" value of meeting probability is low. On the contrary, the visibility channel dominates for high productivity sellers and their "optimal" value of meeting probability is high. The main issue they face while exporting is their visibility as they have a high probability of being the lowest-cost supplier, conditional on meeting with a buyer.

We argue that such non-linearity can help rationalize Fact 3. In difficult countries featuring high search frictions, low productivity exporters do relatively 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 exporters' productivity no longer determines their ability to export. Exporters need to be lucky enough to meet with a buyer to have a chance of serving the destination. Less frictional markets instead work in a way which is closer to the assumptions in the Ricardian benchmark. Namely, high productivity exporters have a substantially larger probability of serving any particular buyer because of their cost advantages.

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 it serves in a destination, though with quite different arguments.[23]

[23] In Carballo et al. (2013), more productive exporters serve more consumers in each destination because they can produce and sell products further 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.

While the above formula provides insights on the *expected* number of buyers in each destination, the randomness of the matching process generates dispersion around this mean. We also derive the probability that seller s_j has *exactly* M buyers in country i, conditional on its 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:

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

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:[24]

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

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.

The shape of $h_{ij}(M)$ is also a function of λ_{ij}. 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 provides details on the estimation strategy.

[24] See the proof in Appendix A.5.

4 Estimation

Equation (5) relates the number of buyers per exporter in a given country to observable variables and the parameter scaling search frictions. We will use it together with its empirical counterpart to recover an estimate of search frictions, by sector and destination country.[25] In this section, we first justify the moments used to estimate search frictions, independently from other barriers to international trade. We then describe the GMM estimator. Finally, we briefly describe the actual implementation, with further details postponed to Appendix B.

4.1 Moment choice

Equation (5) gives a closed form solution to the exact measure of firms having M buyers in destination i. Once normalized by the total measure of firms in the market ($T_j \underline{z}^{-\theta}$) to recover a convergent moment, this can be used to estimate search frictions. The formula indeed relates a variable which empirical counterpart is directly observed in the data and a function of the parameter scaling frictions in the model, plus other observables.

We decided not to use this exact moment, though, because of its empirical sensitivity to distance, that potentially reflects the impact of other physical trade barriers on the firm-level stock of partners within a destination. This sensitivity is illustrated in Table 5 which shows the correlation between various transformation of the empirical moment, and distance from France, used as a proxy for iceberg trade costs.[26] The correlation between the mass $h_{ij}(M)$ of firms with exactly M buyers in a destination and the distance to this destination is negative and strongly significant. This is consistent with Fact 4 which shows that French sellers tend to serve less partners, if any at all, in more distant countries. This result should be expected from the model, since the π_{ij} component in equation (5) is negatively correlated with iceberg trade costs d_{ij} which can reasonably be assumed to be increasing in distance. In principle, this can be controlled for using readily available data for those trade shares.

What is not directly explained by the model is that the negative correlation with distance survives when these shares are further normalized by the destination-specific proportion of sellers with one buyer, i.e. when the empirical counterpart of $\frac{h_{ij}(M)}{h_{ij}(1)}$ is correlated with distance, as in the second panel of Table 5. In principle, the normalization shall neutralize the impact of trade shares, thus of iceberg trade costs. In practice, these ratios continue to be negatively correlated with distance. The negative correlation might explain by search frictions being

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

[26]For practical reasons further detailed below, we restrict our attention to four values for $h_{ij}(M)$, namely $M = 1$, $M = 2$, $M \in [3, 4]$ and $M \in [5, B_i]$.

stronger in destinations further away from France. However, it might also be that such negative correlation reveals other channels through which iceberg trade costs affect the ratios, which the model does not encompass but the data reveal. To avoid that this pollutes our estimates of search frictions, we decided to use an alternative moment which is not affected by distance to France and is thus more likely to help us extract from the data information on pure search frictions.

The moment chosen exploits information on the *dispersion* of degrees across sellers serving the same destination. Namely, the theoretical moment is defined as the variance in the $\frac{h_{ij}(M)}{h_{ij}(1)}$ ratios:

$$Var_{ij}\left(\lambda_{ij}\right) = \frac{1}{B_i - 1} \sum_{M=1}^{B_i - 1} \left(\frac{h_{ij}(M)}{h_{ij}(1)} - \frac{1}{B_i - 1} \sum_{M=1}^{B_i - 1} \frac{h_{ij}(M)}{h_{ij}(1)} \right)^2 \tag{6}$$

It measures the variance in the number of firms with a given number of buyers, normalized by the mass of firms with one buyer, where the dispersion is calculated across different values for the number of buyers. In theory, the dispersion can be calculated across $B_i - 1$ ratios. However, these ratios do not convey a lot of relevant information since they are almost all equal to zero above a certain level of M. As shown in Figure 1 (left panel), most of the variance in the number of buyers served by French exporters is indeed 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, this would artificially reduce the dispersion in the data, in a way that is not independent from B_i. We decided to restrict our attention to a limited number of $\frac{h_{ij}(M)}{h_{ij}(1)}$ ratios. Namely, we chose three empirically relevant ratios measuring the relative shares of sellers with two buyers in the destination ($M = 2$), with three or four buyers ($M \in [3, 4]$) and with five or more buyers ($M \in [5, B_i]$). This combination is found to maximize the subset of countries and sectors that we can exploit.

As documented in the last panel of Table 5, the empirical counterpart of the moment in equation (6) is not correlated with distance from France. As such, it is a good candidate for estimating search frictions independently from other physical trade barriers. The intuition behind this empirical finding can directly be drawn from the model. Physical trade barriers affect French exporters in a homogeneous way along the whole distribution. They reduce their relative competitiveness with respect to foreign competitors. However, search frictions do not impact small and large exporters in the same way, as discussed in Proposition 2. Small exporters "benefit" from high search frictions because they reduce competition exerted by other French firms on these low-competitive sellers. Instead, large exporters suffer from the lack of visibility induced by large enough frictions. This non-monotonous relationship is the key reason why the dispersion in sellers' degrees is informative on the size of search frictions in our framework.

4.2 Estimation strategy

We estimate search frictions with a Generalized Method of Moments. As just explained, we focus on the theoretical moment defined in equation (6) which conditional on B_i solely depends on λ_{ij}. The empirical counterpart of this theoretical moment is observed in our data :

$$\widehat{Var_{ij}} = Var\left(\frac{\sum_{s_j=1}^{S_j} \mathbb{1}\{B_{s_j i} = 2\}}{\sum_{s_j=1}^{S_j} \mathbb{1}\{B_{s_j i} = 1\}}, \frac{\sum_{s_j=1}^{S_j}\sum_{M=3}^{6} \mathbb{1}\{B_{s_j i} = M\}}{\sum_{s_j=1}^{S_j} \mathbb{1}\{B_{s_j i} = 1\}}, \frac{\sum_{s_j=1}^{S_j}\sum_{M=3}^{B_i} \mathbb{1}\{B_{s_j i} = M\}}{\sum_{s_j=1}^{S_j} \mathbb{1}\{B_{s_j i} = 1\}}\right) \quad (7)$$

where $\mathbb{1}\{B_{s_j i} = M\}$ is an observed dummy equal to one when any firm s_j has exactly M buyers in destination i.

As explained in Appendix B.2, the following convergence result applies:

$$\sqrt{S_j}\left(\widehat{Var_{ij}} - Var_{ij}(\lambda_{ij})\right) \xrightarrow[S_j \to +\infty]{\mathcal{D}} \mathcal{N}(0, \Omega_{ij}(\lambda_{ij})) \quad (8)$$

where $\Omega_{ij}(\lambda_{ij})$ is the variance of $\widehat{Var_{ij}}$.[27]

Using the convergence result, it is possible to identify λ_{ij} uniquely. Indeed, $Var_{ij}(\lambda_{ij}, M) - \widehat{Var_{ij}} = 0$ has a unique solution on $[0, 1]$. The minimization program writes as follows:

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

Note that $\Omega_{ij}(\lambda_{ij})$ is the optimal matrix of weights as defined in Appendix B.2. Moreover, with an Asymptotic Least Squares estimation methodology, the estimated variance of estimated frictions writes:

$$\widehat{\Sigma}_{\lambda_{ij}} = \left[\frac{\partial Var_{ij}(\widehat{\lambda_{ij}})}{\partial \lambda_{ij}}' \Omega_{ij}^{-1}(\hat{\lambda_{ij}}) \frac{\partial Var_{ij}(\widehat{\lambda_{ij}})}{\partial \lambda_{ij}}\right]^{-1}$$

In the rest of the analysis, we will focus on sellers from one single country, $j = France$ and buyers from 23 European countries (all EU member states less France where Baltic countries are pooled together to maximize the number of strictly positive empirical ratios used in the computation of $\widehat{Var_{ij}}$). One search parameter will be estimated for each $hs2$ sector and destination. While the data are defined at the 6-digit level of the HS nomenclature, we constrain the meeting probability to be the same across $hs6$ products within a $hs2$ chapter

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

and weight each $hs6$ sector in the objective function by its precision. The pooling of products within an $hs2$ sector is meant to gain identification power.

With a targeted moment which has an analytical formula, the implementation is straightforward. The only practical difficulty concerns the measurement of S_j and B_i in the data. Indeed, the theoretical moment in (6) is a function of λ_{ij} and B_i such that we need to measure the population of buyers in each destination country and sector. Moreover, the total number S_j of potential suppliers of a $hs6$ reference is needed to compute both the optimal weights entering the objective function and the asymptotic variance of the estimator (see details in Appendix B.2).

We recover measures of the 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 from 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.[28] B_{ij} is directly observed into our data, for $j = France$ and i being one of the 23 EU destinations. Based on this, one can recover a value of B_i for each destination and sector.[29] Ex-post, we show that 60% of the heterogeneity in the recovered B_is is explained by the combination of a country and a sector fixed effects. Consistent with expectations, it is positively correlated with the country's GDP while being orthogonal to distance and GDP per capita.

Information on the number of *potential* suppliers by $hs6$ product is not available in any administrative dataset. We develop an algorithm for recovering a proxy for this variable. Namely, we exploit information on the universe of French firms and the sector of activity they belong to. For each product, we first identify a set of industries in which there is a substantial number of exporters. Since a significant number of firms in these sectors export the product under consideration, we posit that all firms sharing the same activity could as well. S_j is thus defined as the total number of firms belonging to those sectors. Details are available in Appendix B.3. Note that Atalay et al. (2014) use a comparable strategy to proxy the number of firms susceptible of purchasing a firm's output.

Using information on the number of potential sellers and buyers in each country and destination plus the information on the number of buyers in each seller's portfolio, one can

[28] We use bilateral trade flows from the CEPII-BACI database (Gaulier and Zignago, 2010) and production data from Prodcom. π_{ij} is defined as the ratio of trade from j to i over absorption in country i.

[29] In sectors and countries in which the market share of French firms is very low, our empirical strategy implies very high values for B_i, above a million firms. Such high values might artificially bias our estimation of λ_{ij} down. To avoid this, we constrained the number of potential buyers to be below 20,000, i.e. $B_i = max\left\{20,000; \frac{B_{iF}}{\pi_{iF}}\right\}$.

directly solve the program in (9) and recover estimated values for the meeting probabilities. Appendix B.4 gives further details on the practical implementation.

5 Results

5.1 Matching Frictions estimates

Matching frictions are estimated at the (sector×country) level for a total of 1,059 λ_{ij} parameters, among which 706 are significant at the 10% level. Note that non-significant parameters are on average higher than significant ones meaning that statistical non-significance reveals poorly estimated coefficients rather than very high levels of matching frictions. For this reason, the rest of the analysis focuses on statistically significant estimates.[30]

Table 6, first column, provides summary statistics on the estimated parameters. Remember that, in the model, the λ_{ij} coefficient is defined as the share of the (continuum of) sellers from country i a given buyer in country j would meet, on average. For this reason, the interpretation of the very low average coefficient (.63%) is not straightforward. More easy to interpret is the implication of these estimates in terms of the probability that a given French exporter meets with zero buyer in each destination, which is positively linked with the extent of matching frictions. Since the matching process is a binomial, these probabilities are easy to compute, as $(1-\lambda_{ij})^{B_j}$. The distribution of probabilities over all country and hs6 product pairs is summarized in the second column of Table 6. On average, the probability of meeting with zero buyer in a destination is high, around one third. This number however hides a lot of heterogeneity. In 25% of country and sector pairs, the probability is below one percent, meaning that the extent of matching frictions is quite limited. At the other side of the distribution, 10% of country×sector pairs display very high frictions, with French exporters having less than 20% of chances of meeting with at least one buyer there.

– Table 6 about here –

We investigate further the origin of such heterogeneity using a variance decomposition. The λ_{ij} coefficients being estimated at the level of a country and a hs2 sector, we first compute the share of the variance in no-match probabilities that is attributable to factors that are either country or hs2-sector specific. Country-specific factors explain 3.5% of the overall variance in

[30] On top of the 706 statistically significant coefficients, we add the 42 coefficients that are not statistically different from zero but are estimated lower than 10^{-6}. At this low level, a well-identified coefficient can be found statistically non-significant.

the data, while another 13% is due to hs2-specific determinants. This contribution increases to almost 34% when the variance decomposition has hs6-specific components. This partly reflects the fact that the no-match probability is jointly determined by the unconditional probability λ_{ij} of being drawn by any buyer in country j *and* the number of such buyers B_j, which varies by hs6 product. Indeed, when the no-match probabilities are regressed on the (log of) the number of buyers in country j plus a full set of country and hs6-product fixed effects, the coefficient on B_j is found significant and negative. This correlation is to be expected since a larger population of buyers in a given country mechanically reduces the probability of meeting zero buyer there. Alone, this variable explains a third of the variance in the data.

– Figures 5 and 6 about here –

Figures 5 and 6 illustrate the heterogeneity in meeting probabilities, across countries and sectors. Namely, we use the predictions of a model regressing the estimated λ_{ij} coefficients on a full set of country and sector fixed effects. The resulting country fixed effects are informative on the heterogeneity in the mean coefficient across countries while estimated sector fixed effects capture average differences across hs2 categories. In the raw data, the lowest mean coefficients which correspond to the most frictional markets, are estimated for Italy, Germany, the UK and Spain, as well as a few Eastern European countries including Slovenia and Poland (Figure 5, top panel). At first view, the presence of Western European countries in this list is surprising, given the strength and long history of their trade relationships with France. This comes from the empirical correlation between estimated coefficients and the number of buyers in the destination (B_j). Once we control for this, the ranking of countries is closer to expectations with new members of the European Union ranked among the most frictional countries while core European countries are found relatively little affected by information frictions (Figure 5, bottom panel).[31] As shown by the comparison of the top and bottom panels in Figure 6, the ranking of sectors in terms of their mean degree of frictions is less sensitive to the numbers of buyers. Among the most frictional sectors, one can cite the industries producing Sugars, Musical Instruments or Fish & crustaceans. At the other side of the spectrum, industries featuring a low degree of frictions include Aircraft and spacecraft and Dairy products.

[31]While the correlation between the probability of meeting with zero buyer ($(1-\lambda_{ij})^{B_j}$) and the number of such buyers is mechanical, there is nothing in the model that explains that meeting probabilities (λ_{ij}) should be lower in markets where there are more buyers. The rest of the analysis further shows that the correlation remains when controlling for country-specific variables that are also found correlated with matching frictions. Since the correlation might be related to the way the number of buyers is estimated in the data, we are currently running a version of the estimator in which the number of buyers is capped. This shall avoid that the heterogeneity in the estimated number of buyers has a strong impact on estimated meeting probabilities.

Correlates of matching frictions

– Table 7 about here –

Table 7 summarizes the correlation between the estimated λ_{ij} parameters and a set of country-specific determinants, controlling for sectoral fixed effects. Column (1) shows the correlation of estimated frictions with distance from France. As expected, the correlation is negative which means that the unconditional probability of meeting with a foreign buyer is lower in more distant countries.[32] The correlation is however not significant which in a sense is reinsuring given previously explained concerns that the estimation might capture the impact that physical trade barriers could have on the equilibrium number of buyers per seller. Column (2) augments the specification with two measures of the country's density, namely its area and the number of metropolitan regions. One might indeed expect information frictions to be more pronounced in countries where the population is less concentrated, since such dispersion increases the cost of meeting with more buyers. Estimated coefficients are indeed consistent with the intuition. Matching frictions are found stronger in larger countries in which the population is spread across a higher number of metroplitan areas.

Column (3) adds measures of the stock of migrants in France and the destination country. As explained in Section 2.2, we expect these variables to be correlated with the amount of information conveyed by migrants on their country of origin, which might reduce information frictions. As expected, matching frictions are found lower in countries where French migrants are more numerous. The impact of foreign migrants in France is instead found negative, contrary to expectation, albeit non-significant. Moreover, controlling for the stock of French migrants in the destination makes the impact of the number of metropolitan areas non-significant. Finally, Column (4) further controls for the (mean) number of buyers in the destination country. As shown before, there is a negative empirical correlation between estimated coefficients and this variable, that survives when controling for other country-specific correlates of matching frictions. Controlling for the number of buyers does not however affect the size and significance of the correlation with the number of French migrants in the destination. This suggests that estimates of meeting probabilities are indeed correlated with proxies for information frictions and that the correlation does not come from the size of the destination market (in terms of buyers) being affecting the number of migrants there.

– Table 8 about here –

[32] Remember that λ_{ij} is a measure of the probability of being drawn by a foreign buyer and is thus inversely related to the extent of matching frictions.

Table 8 presents the regression of (the log of) meeting probabilities on the degree of product differenciation, measured using the Rauch classification.[33] Consistent with expectations, we find more differentiated sectors to be more strongly affected by matching frictions.

5.2 Model Fit

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5.3 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 an "Augmented gravity analysis" in which estimated matching frictions are introduced into an otherwise standard gravity model.

Table 10 shows that estimated matching frictions are significantly correlated with aggregated trade flows, a result in line with proposition 1 of our theoretical framework. Increasing the meeting probability by 10% would increase by 1.03% the total value of exports towards a destination. This significant positive impact is robust to the introduction of proxies for information frictions (namely migrants and language proximity) and for the quality of institutions.[34] As expected, the coefficient on meeting probabilities is reduced when the model separately controls for the stock of migrants in the destination, which is consistent with the result in Section 5.1 that this variable is a significant determinant of matching frictions.

Table 11 presents results of gravity regression at the firm- and product level. As discussed in Proposition 2, the model predicts non-linearities regarding the impact that matching frictions have on firms, along the distribution of probabilities. Namely, highly productive firms suffer from being unable to meet with foreign buyers because, conditional on a meeting, their chances to be the lowest-cost producer are relatively high. On the contrary, low-productive firms would not necessarily export more in less frictional markets, because matching frictions are what help them survive their competitive disadvantage. Such firms are able to serve foreign markets because they are lucky enough to meet with buyers that did not meet with more productive exporters. To test this prediction, we estimate the same gravity model on various sub-samples of firms, namely the top and bottom 15% of the distribution of exporters' size in Table 11. Interestingly, we find the value of firm-level exports to be significantly higher in less frictional markets, for firms at the top of the distribution (Column (2)). Instead, the impact

[33] A complementary analysis using Nunn classification in Appendix in table 9 presents robust results.

[34] The quality of institutions is measured by... Coefficients are not reported as none of them turned out statistically significant.

of matching frictions is found positive, albeit non-significant, for low-productive firms. This result is in line with the predictions of the model.

– Tables 10 and 11 about here –

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6 Conclusion

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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
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
Finland	3,273	3,778	7,554	12,914	19,691	22,175
Germany	12,705	79,616	141,019	62,501	281,747	314,309
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
Latvia	1,188	977	1,783	5,216	5,530	6,198
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
Malta	974	634	1,391	4,144	4,340	4,909
Netherlands	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
Slovakia	2,250	1,702	3,737	7,420	8,236	9,307
Slovenia	1,946	1,593	3,206	7,959	8,991	10,051
Spain	11,635	45,283	86,021	56,719	215,266	240,913
Sweden	4,641	6,621	12,328	18,063	32,686	36,213
United Kingdom	9,990	34,030	63,425	47,403	161,057	185,496

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: ***Number of sellers per buyer***

	Mean	Median	p75	Sh. with 1 seller
	(1)	(2)	(3)	(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 3: ***Product- and Firm-level gravity equations***

	Dependent Variable (all in log)						
	Product-level				Firm-level		
	Value of Exports	# Sellers	# Buyers per Seller	Mean export per Buyer-seller	Value of Exports	# Buyers	Exports per Buyer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log Distance	-1.219***	-0.550***	-0.305***	-0.363***	-0.517***	-0.340***	-0.178***
	(0.027)	(0.008)	(0.007)	(0.022)	(0.009)	(0.004)	(0.009)
log Import Demand	0.791***	0.228***	0.106***	0.456***	0.445***	0.133***	0.312***
	(0.007)	(0.002)	(0.002)	(0.006)	(0.003)	(0.001)	(0.003)
log GDP per Capita	0.124***	0.0481***	0.109***	-0.0334***	0.035***	0.023***	0.012**
	(0.015)	(0.004)	(0.004)	(0.012)	(0.006)	(0.003)	(0.006)
Observations	64,179	64,179	64,179	64,179	471,753	471,753	471,753
R-squared	0.624	0.752	0.414	0.571	0.699	0.433	0.712
Fixed effects	Product	Product	Product	Product	Firm	Firm	Firm

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 product-level French exports 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)). Column (5) uses as LHS variable the log of firm-level bilateral exports (column (5)), while columns (6) and (7) decompose it in terms of the number of buyers served and the value of exports per buyer, respectively. 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: ***Product- and Firm-level augmented gravity equations: The role of information frictions***

	Dependent Variable (all in log)						
	Product-level				Firm-level		
	Value of Exports	# Sellers	# Buyers per Seller	Mean export per Buyer-seller	Value of Exports	# Buyers	Exports per Buyer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log Distance	-1.055***	-0.400***	-0.258***	-0.397***	-0.404***	-0.239***	-0.164***
	(0.029)	(0.008)	(0.007)	(0.024)	(0.011)	(0.005)	(0.010)
log Import Demand	0.733***	0.214***	0.093***	0.426***	0.424***	0.135***	0.289***
	(0.007)	(0.002)	(0.002)	(0.006)	(0.003)	(0.001)	(0.003)
log GDP per Capita	0.178***	0.066***	0.122***	-0.011	0.107***	0.052***	0.055**
	(0.014)	(0.004)	(0.004)	(0.012)	(0.006)	(0.003)	(0.006)
French Migrants	0.020***	0.031***	0.007***	-0.017***	0.018***	0.016***	0.001
	(0.004)	(0.001)	(0.001)	(0.003)	(0.001)	(0.000)	(0.000)
Migrants in France	0.119***	0.042***	0.029***	0.048***	0.059***	0.021***	0.039***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
Observations	64,179	64,179	64,179	64,179	471,753	471,753	471,753
R-squared	0.643	0.784	0.444	0.575	0.705	0.446	0.715
Fixed effects	Product	Product	Product	Product	Firm	Firm	Firm

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. "French migrants" is the number of French citizens in the destination country, per 1000 inhabitants. "Migrants in France" is the number of migrants from the destination in France, expressed as a stock per 1000 inhabitants in France. The dependent variable is either the log of product-level French exports 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)). Column (5) uses as left-hand side variable the log of firm-level bilateral exports (column (5)) while columns (6) and (7) use one of its components, the number of buyers served (column (6)) or the value of exports per buyer (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 5: ***Correlation between various empirical moments and distance from France***

Dependent Variable	log Distance	Std Dev.	Adjusted R-squared
# sellers with:			
1 buyer	-9.84***	(1.22)	.696
2 buyers	-4.07***	(.409)	.572
3-6 buyers	-5.63***	(.681)	.454
7+ buyers	-5.25***	(.831)	.323
# sellers (in relative terms with respect to the # of non-exporters) with:			
1 buyer	-.067***	(.019)	.260
2 buyers	-.024***	(.007)	.179
3-6 buyers	-.028***	(.007)	.244
7+ buyers	-.030***	(.008)	.145
# sellers (in relative terms with respect to the sellers with 1 buyer) with:			
2 buyers	-.084***	(.021)	.161
3-6 buyers	-.028***	(.007)	.243
7+ buyers	-.099***	(.032)	.295
Variance of the relative shares of sellers with:			
2, 3-6 and 7+ sellers	.022	(.034)	.032

Notes: Robust standard errors, clustered at the country$\times$hs2 level, in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels.

Table 6: ***Summary statistics on estimated coefficients***

	Meeting Probability λ_{ij} (en %)	Probability of Meeting 0 buyer $(1-\lambda_{ij})^{B_j}$ (en %)
Mean	.60	32
Percentile 10	.01	.00
Percentile 25	.04	.16
Percentile 50	.16	17
Percentile 75	.52	62
Percentile 90	1.5	87
# Observations	748	9,747

Notes: The first column in this table presents summary statistics on the λ_{ij} coefficients, estimated by country $\times$ hs2 sector. The second column summarizes the subsequent probabilities that a French exporter meets with no buyer in the destination computed as $(1-\lambda_{ij})^{B_j}$ for each country and hs6 product. Probabilities computed on the distribution of estimates that are significant at the 10% level.

Table 7: ***Search frictions correlates at the country level***

	Meeting probability λ_{ij} (log)			
	(1)	(2)	(3)	(4)
Distance (log)	-.641	-.728	.097	-.296
	(.600)	(.491)	(.570)	(.550)
Area (log)		-.063	-.038	.117
		(.178)	(.168)	(.152)
# metropolitan regions (log)		-.475**	-.157	.097
		(.183)	(.203)	(.160)
French migrants per 1000 hab			.068**	.058**
			(.025)	(.024)
Migrants in France per 1000 hab			-.022	.012
			(.023)	(.018)
# Buyers (log)				-.555***
				(.114)
Observations	748	741	741	741
R-squared	.11	.17	.19	.25
Sector (hs2) FE	yes	yes	yes	yes
# Sectors	79	79	79	79
Within R-squared	.02	.08	.10	.18

Notes: Standard errors (clustered at the country level) in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels. "Distance (log)" is the log of the weighted distance between France and the destination. "Area (log)" is the log of the country's area. "# metropolitan regions (log)" measures the number of metropolitan regions used as proxy for how dispersed buyers. "French migrants per 1000 hab" is the number of French migrants in the destination country per 1000 inhabitants. "Migrants in France per 1000 hab" is the number of destination country migrants living in France per 1000 French inhabitants. "# Buyers (log)" is the log of the (mean) number of buyers. All regressions control for sector-specific fixed effects. Meeting probabilities are estimated at the hs2×country level.

Table 8: ***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. Search frictions are estimated at the hs2*country level.

Table 9: ***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. Search frictions are estimated at the hs2*country level.

Table 10: ***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%

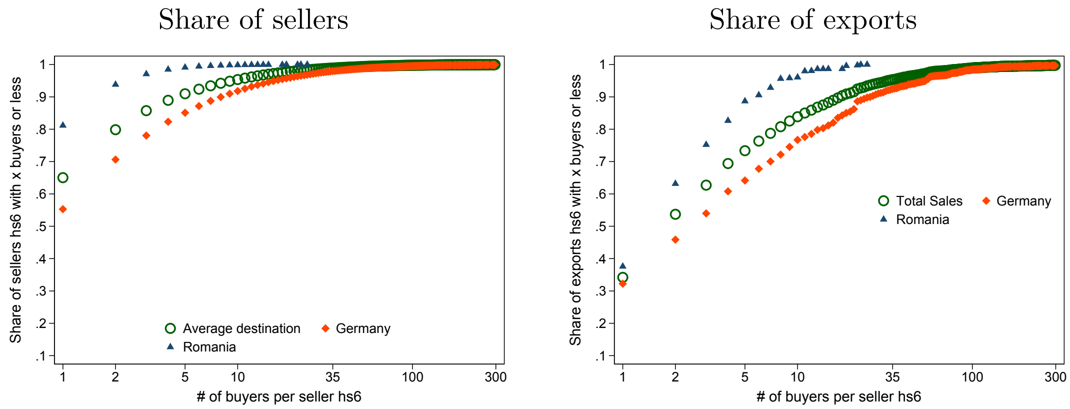
Notes: Dependent variable is log of exports per product (hs6)×destination. Standard errors are robust and clustered at the country level, they are in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels. "log Distance" is the log of the weighted distance between 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 search frictions are estimated.

Table 11: ***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: ***Distribution of the number of buyers per seller, across exporters***



Notes: The figure displays the proportion of sellers (left panel) and the 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. The green circles correspond to the average across EU destinations. The blue triangles and red diamonds are respectively obtained from exports to Romania and Germany.

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:

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

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 drawn 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. This implies:

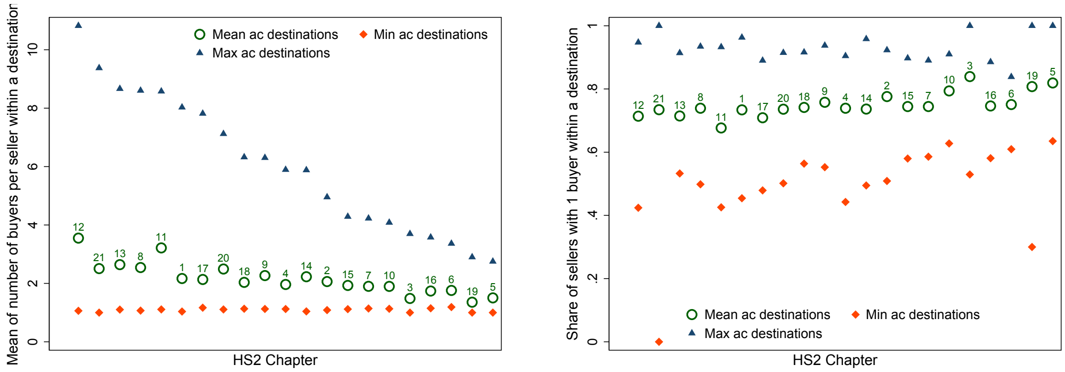
$$\mathbb{P}\left[\underset{s_j \in \Omega_{b_i}}{\text{Min}}\left(\frac{c_j d_{ij}}{z_{s_j}}\right) > p \mid D_{b_i} = d\right] = \left[1 - \frac{p^\theta \sum_{j=1}^N \lambda_{ij} T_j (d_{ij} c_j)^{-\theta}}{\sum\limits_{j=1}^N \lambda_{ij} T_j \underline{z}^{-\theta}}\right]^d$$

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

Figure 2: ***Heterogeneity in the number of buyers per seller across HS2 Chapter***

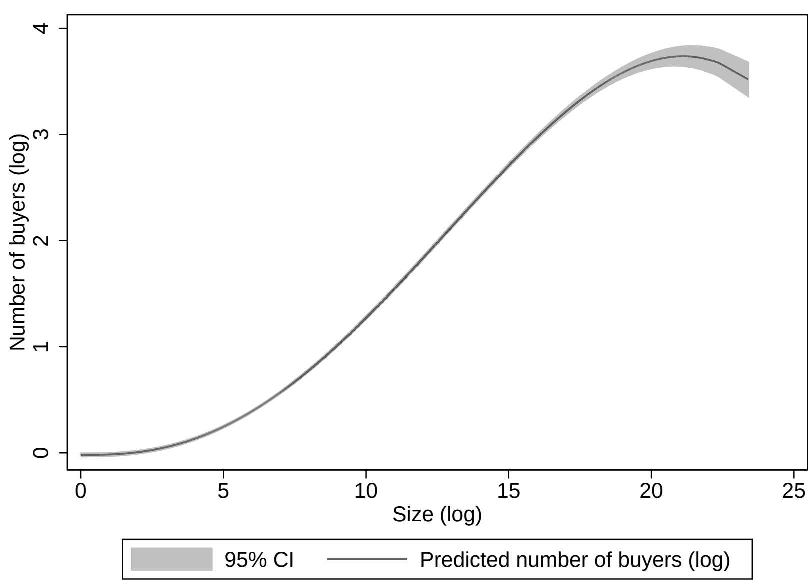
Statistics on the average number of buyers per firm

Share of sellers interacting with a single buyer



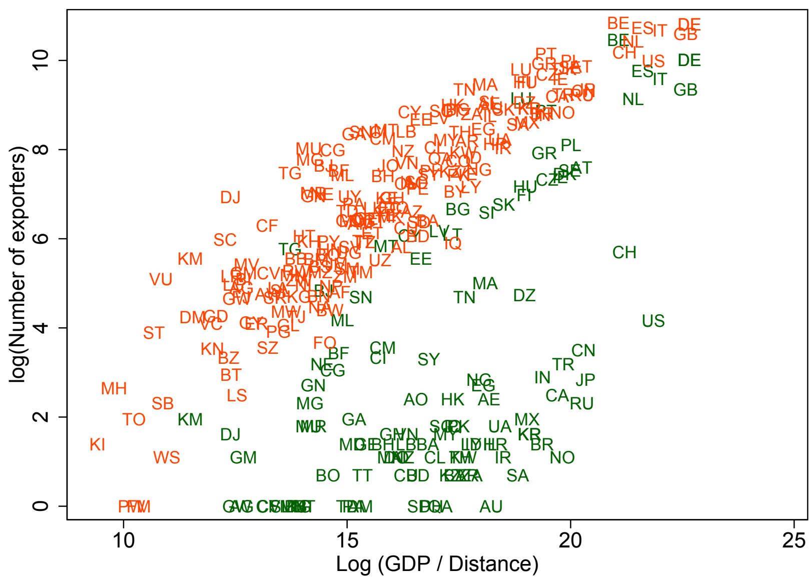
Notes: The left panel shows statistics computed across destinations within an HS2 chapter regarding the mean number of buyers per seller there. The right panel is the share of sellers interacting with a single buyer, computed for each destination within each HS2 chapter and then averaged across destinations. Data are for 2007. A seller is defined as an exporter-HS6 product pair.

Figure 3: ***Number of buyers and the size of sellers***



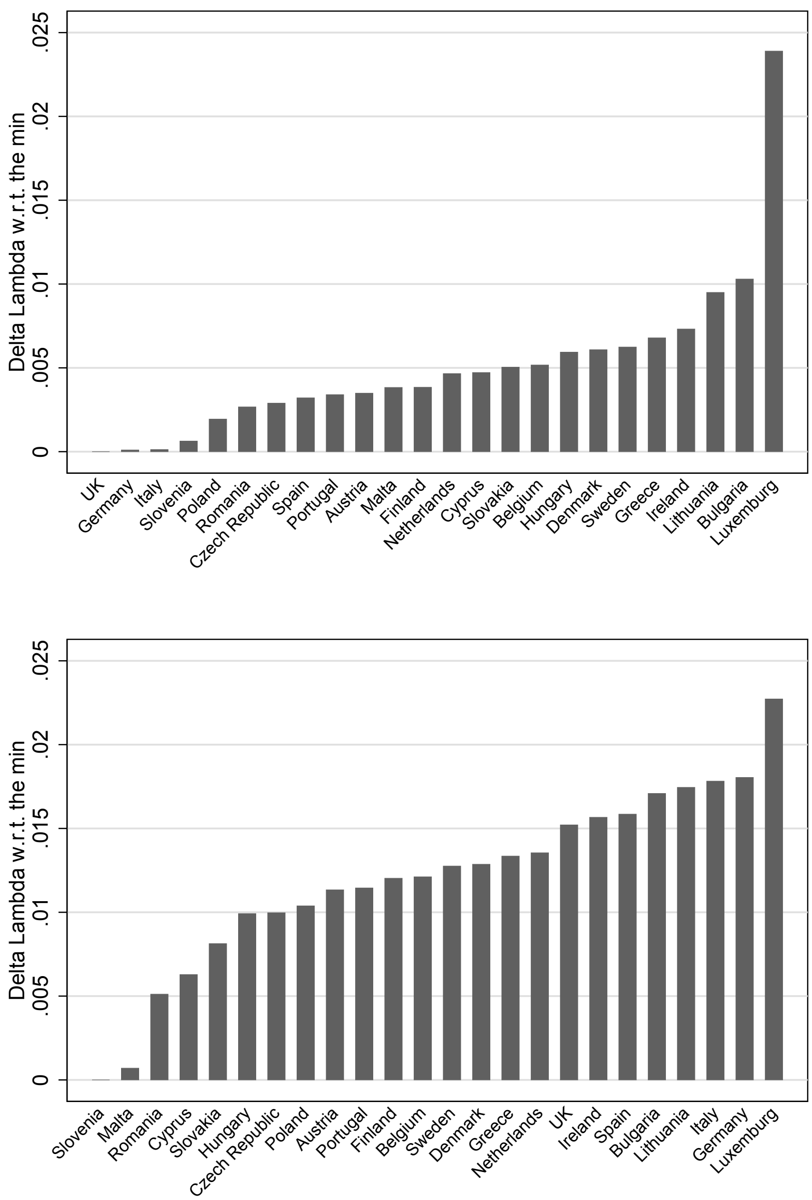
Notes: Non-linear polynomial fit of the log of the total number of EU buyers served against the log size of the seller. Size is measured by the seller's total exports. A seller is defined as an exporter-HS6 product pair. The data are for 2007 and are restricted to transactions with recorded CN8-products.

Figure 4: ***Self-selection of firms into export markets: Comparison between small and large exporters***



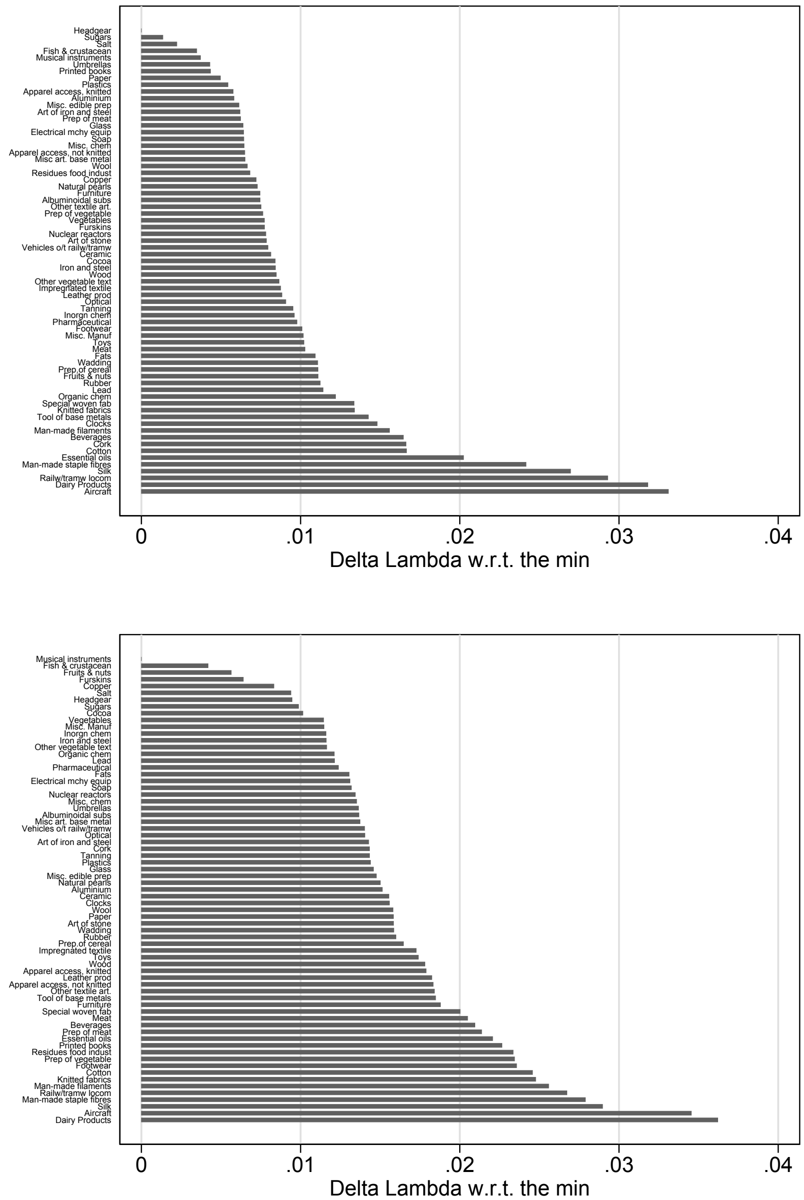
Notes: This figure correlates the stock of French exporters active in a given destination with a measure of the destination's market potential, namely the (log of the) GDP over distance from France. The correlation is plotted for two sub-samples of firms respectively belonging to the top 15% and the bottom 15% of the distribution of firms' size, where the size of a firm is defined as the value of her worldwide exports. Data are for 2007 and cover the universe of French exporters and worldwide destination countries (Source: French customs).

Figure 5: ***Comparison of the mean meeting probabilities across countries***



Notes: The figure shows the deviation in the mean λ_{ij} parameters across countries, in deviation from the most frictional country. The top panel is obtained by regressing estimated λ_{ij} parameters on a full set of country and (hs2) sector fixed effects and taking the predicted country fixed effects, in deviation from the lowest value. The bottom panel further controls for the (log of the mean) number of buyers in the destination. The reference (most frictional) country is Italy in the top panel and Slovenia in the bottom panel.

Figure 6: ***Comparison of the mean meeting probabilities across hs2 sectors***



Notes: The figure shows the deviation in the mean λ_{ij} parameters across countries, in deviation from the most frictional country. The top panel is obtained by regressing estimated λ_{ij} parameters on a full set of country and (hs2) sector fixed effects and taking the predicted sector fixed effects, in deviation from the lowest value. The bottom panel further controls for the (log of the mean) number of buyers in the destination. The reference (most frictional) sector is "Sugars" in the top panel and "Musical instruments" in the bottom panel.

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

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 "mean" level of frictions in country i, $\Upsilon_i=\sum_{j=1}^N T_j\left(d_{ij}c_j\right)^{-\theta}$ is the multilateral resistance index and $\kappa_i=\frac{\sum_{j=1}^N\frac{\lambda_{ij}T_j}{\sum_{j=1}^N\lambda_{ij}T_j}(d_{ij}c_j)^{-\theta}}{\sum_{j=1}^N\frac{T_j}{\sum_{j=1}^N T_j}(d_{ij}c_j)^{-\theta}}$ is a measure of how matching frictions distort the distribution of the nationality of sellers that the buyer meets, in comparison with a frictionless world in which this dispersion only depends on the geography of costs. 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 j in i's consumption is equal to the probability that a buyer from i chooses a seller from j to purchase the good:

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

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

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

which, after some calculations becomes:

$$\begin{aligned}
&\mathbb{E}_{b_i}[\mathbb{1}\{s(b_i)=j\}|p]\\
&=\sum_{n=1}^{+\infty}\sum_{n_j=0}^{n}\mathbb{P}[s(b_i)=j|D_{b_{ij}}(p)=n_j,\ D_{b_{i\setminus\{j\}}}(p)=n-n_j]\ \mathbb{P}[D_{b_{ij}}(p)=n_j]\ \mathbb{P}[D_{b_{i\setminus\{j\}}}(p)=n-n_j]\\
&=\sum_{n=1}^{+\infty}\sum_{n_j=0}^{n}\frac{n_j}{n}\frac{[\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p)]^{n-n_j}}{(n-n_j)!}e^{-\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p)}\frac{[\lambda_{ij}\mu_{ij}(p)]^{n_j}}{n_j!}e^{-\lambda_{ij}\mu_{ij}(p)}\\
&=e^{-\sum_{k=1}^{N}\lambda_{ik}\mu_{ik}(p)}\sum_{n=1}^{+\infty}\frac{[\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p)]^{n}}{n}\sum_{n_j=1}^{n}\frac{1}{(n-n_j)!(n_j-1)!}\left(\frac{\lambda_{ij}\mu_{ij}(p)}{\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p)}\right)^{n_j}\\
&=\frac{\lambda_{ij}\mu_{ij}(p)}{\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p)}e^{-\sum_{k=1}^{N}\lambda_{ik}\mu_{ik}(p)}\sum_{n=1}^{+\infty}\frac{(\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p))^{n}}{n}\frac{1}{(n-1)!}\sum_{n_j=0}^{n-1}\frac{(n-1)!}{(n-1-n_j)!(n_j)!}\left(\frac{\lambda_{ij}\mu_{ij}(p)}{\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p)}\right)^{n_j}\\
&=\frac{\lambda_{ij}\mu_{ij}(p)}{\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p)}e^{-\sum_{k=1}^{N}\lambda_{ik}\mu_{ik}(p)}\sum_{n=1}^{+\infty}\frac{(\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p))^{n}}{n!}\left(\frac{\lambda_{ij}\mu_{ij}(p)}{\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p)}+1\right)^{n-1}\\
&=\frac{\lambda_{ij}\mu_{ij}(p)}{\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p)}e^{-\sum_{k=1}^{N}\lambda_{ik}\mu_{ik}(p)}\sum_{n=1}^{+\infty}\frac{(\lambda_{ij}\mu_{ij}(p)+\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p))^{n-1}}{n!}(\sum_{k\neq j}^{N}\lambda_{ik}\mu_{ik}(p))\\
&=\frac{\lambda_{ij}\mu_{ij}(p)}{\sum_{k=1}^{N}\lambda_{ik}\mu_{ik}(p)}e^{-\sum_{k=1}^{N}\lambda_{ik}\mu_{ik}(p)}[e^{\sum_{k=1}^{N}\lambda_{ik}\mu_{ik}(p)}-1]\\
&=\frac{\lambda_{ij}\mu_{ij}(p)}{\sum_{k=1}^{N}\lambda_{ik}\mu_{ik}(p)}[1-e^{-\sum_{k=1}^{N}\lambda_{ik}\mu_{ik}(p)}]
\end{aligned}$$

Moreover,

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

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

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

A.3 Proof of proposition 1

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

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

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

$$\frac{\partial ln(\kappa_i)}{\partial \lambda_{ij}} = \frac{\frac{\partial \kappa_i}{\partial \lambda_{ij}}}{\kappa_i} = \frac{T_j}{\sum_j \lambda_{ij} T_j} [\frac{\sum_j \lambda_{ij} T_j}{\sum_k \lambda_{ik} T_k (\frac{d_{ij} c_j}{d_{ik} c_k})^{\theta}} - 1] \tag{10}$$

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

$$\frac{\partial ln \widetilde{\lambda}_i}{\partial \lambda_{ij}} = \frac{T_j}{\sum_j T_j} \frac{\sum_j T_j}{\sum_j \lambda_{ij} T_j} = \frac{T_j}{\sum_j \lambda_{ij} T_j} \tag{11}$$

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 10 and 11 in equation **??**.

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

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.4 Proof of proposition 2

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

$$\begin{aligned}
\frac{\partial\rho_{s_j}}{\partial d_{ij}} &= -\left[(\frac{c_j}{z_{s_j}})^\theta d_{ij}^{\theta-1}(\sum_{k=1}^{N}\lambda_{ik}T_k(c_kd_{ik})^{-\theta}) - \theta(\frac{c_jd_{ij}}{z_{s_j}})^\theta\lambda_{ij}T_jd_{ij}^{-\theta-1}c_j^{-\theta}\right]\rho_{s_j} \\
&= -\theta(\frac{c_j}{z_{s_j}})^\theta d_{ij}^{\theta-1}\left[\sum_{k=1}^{N}\lambda_{ik}T_k(c_kd_{ik})^{-\theta} - \lambda_{ij}T_j(c_jd_{ij})^{-\theta}\right] \\
\epsilon_d = \frac{\partial\rho_{s_j}}{\partial d_{ij}}\frac{d_{ij}}{\rho_{s_j}} &= -\theta p_{s_j}^\theta[\sum_{k\neq j}\lambda_{ik}T_k(c_kd_{ik})^{-\theta}]
\end{aligned}$$

A.5 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:

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

B Details on the empirical strategy

B.1 Data and nomenclature

B.2 Distribution of the Auxiliary Parameter

We will work with the following convergent moments as auxiliary parameters:

$$\theta_{ij}(\lambda_{ij}, M) = \frac{h_{ij}(M)}{\sum\limits_{M=0}^{B_i} h_{ij}(M)} = \frac{1}{M} \frac{I_{\lambda_{ij}}(M, B_i - M + 1)}{\int_0^{\lambda_{ij}} \frac{(1 - \rho_{s_j i})^{B_i}}{\rho_{s_j i}} d\rho_{s_j i} + \sum\limits_{M=1}^{B_i} \frac{1}{M} I_{\lambda_{ij}}(1, B_i - M + 1)} \tag{12}$$

i.e. the proportion of firms from j having exactly M buyers in destination i.[35] We first show that the empirical counterparts of these auxiliary parameters are normally distributed. Then we apply the delta-method to work with the moment we chose to identify λ_{ij}. Finally, we discuss the asymptotic distribution of our estimator of λ_{ij}.

In line with our theoretical framework we note $\left[\mathbb{1}\{B_{s_j i} = M\}\right]_{s_j \in S_j}$ the vector of dummy variables which equal one whenever a firm in the sample has exactly M buyers in country i. The vector is of size S_j, the number of observations in the sample under consideration. The dummies are independent and identically distributed random variables of mean $\frac{h_{ij}(M)}{\sum_{M=0}^{B_j} h_{ij}(M)}$ and of variance $\sigma_{ij}^2(M)$. This is true for all $M \in [0, B_i]$.[36] The Central Limit Theorem implies:

$$\sqrt{S_j}\left(\hat{\theta}_{ij} - \theta_{ij}(\lambda_{ij})\right) \underset{S_j \to +\infty}{\xrightarrow{\mathcal{D}}} \mathcal{N}_B(0, \Sigma_{ij}) \tag{13}$$

where

$$\hat{\theta}_{ij} = \begin{pmatrix} \frac{\sum_{s_j=1}^{S_j} \mathbb{1}\{B_{s_j i}=1\}}{S_j} \\ \frac{\sum_{s_j=1}^{S_j} \mathbb{1}\{B_{s_j i}=2\}}{S_j} \\ \dots \\ \frac{\sum_{s_j=1}^{S_j} \mathbb{1}\{B_{s_j i}=B_i\}}{S_j} \end{pmatrix} \quad \text{and} \quad \theta_{ij}(\lambda_{ij}) = \begin{pmatrix} \frac{h_{ij}(1)}{\sum_{M=0}^{B_j} h_{ij}(M)} \\ \frac{h_{ij}(2)}{\sum_{M=0}^{B_i} h_{ij}(M)} \\ \dots \\ \frac{h_{ij}(B_i)}{\sum_{M=0}^{B_i} h_{ij}(M)} \end{pmatrix}$$

respectively denote the vector of empirical and auxiliary parameters and Σ_{ij} is the variance-covariance matrix of the B_i random variables $\mathbb{1}\{B_{s_j i} = M\}$, for $M \in \{0, 1..., B_i\}$.

We then consider the function

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

[36] Independence comes from the fact that sellers are independent from each other. Note that this assumption could be relaxed since we could eventually use a version of the central limit theoreim based on weak dependence conditions. They are identically distributed ex-ante as sellers draw there productivity in the same distribution and face the same degree of search frictions.

$$
\begin{array}{cccc}
g & : & \mathbb{R}^{B_i} & \mapsto & \mathbb{R} \\
 & & \begin{pmatrix} \theta_{ij}(\lambda_{ij},1) \\ \theta_{ij}(\lambda_{ij},2) \\ \ldots \\ \theta_{ij}(\lambda_{ij},B_i) \end{pmatrix} & \rightarrow & Var\left(m_1 = \frac{\theta_{ij}(\lambda_{ij},2)}{\theta_{ij}(\lambda_{ij},1)}, m_2 = \frac{\sum\limits_{M=3}^{6} \theta_{ij}(\lambda_{ij},M)}{\theta_{ij}(\lambda_{ij},1)}, m_3 = \frac{\sum\limits_{M=7}^{B_i} \theta_{ij}(\lambda_{ij},M)}{\theta_{ij}(\lambda_{ij},1)} \right)
\end{array}
$$

where $Var(.)$ is the variance operator. g is derivable and verifies the property $\nabla g(\theta_{ij}(\lambda_{ij})) \neq 0$. Using the Delta-Method, one can show that an estimate of λ_{ij} based on $g(.)$ is asymptotically normal:

$$
\sqrt{S_j}[g(\hat{\theta}_{ij}) - g(\theta_{ij}(\lambda_{ij}))] \underset{S_j \to +\infty}{\xrightarrow{\mathcal{D}}} \mathcal{N}\Big((\ 0\ ), \Omega(\theta_{ij}(\lambda_{ij})) = \nabla' g(\theta_{ij}(\lambda_{ij}))\Sigma_{ij} \nabla g(\theta_{ij}(\lambda_{ij})) \Big) \quad (14)
$$

where $\nabla g(\theta_{ij}(\lambda_{ij}))$ is of dimension $[B_i, 1]$ and is defined as

$$
\begin{pmatrix}
\frac{\partial g}{\partial \theta_{ij}(\lambda_{ij},1)} = -\frac{2}{3} \sum_{p=1}^{3} \frac{(m_p - \bar{m})m_p}{\theta_{ij}(\lambda_{ij},1)} \\
\frac{\partial g}{\partial \theta_{ij}(\lambda_{ij},2)} = \frac{2}{3} \frac{m_1 - \bar{m}}{\theta_{ij}(\lambda_{ij},1)} \\
\frac{\partial g}{\partial \theta_{ij}(\lambda_{ij},3)} = \frac{2}{3} \frac{m_2 - \bar{m}}{\theta_{ij}(\lambda_{ij},1)} \\
\ldots \\
\frac{\partial g}{\partial \theta_{ij}(\lambda_{ij},6)} = \frac{2}{3} \frac{m_2 - \bar{m}}{\theta_{ij}(\lambda_{ij},1)} \\
\frac{\partial g}{\partial \theta_{ij}(\lambda_{ij},7)} = \frac{2}{3} \frac{m_3 - \bar{m}}{\theta_{ij}(\lambda_{ij},1)} \\
\ldots \\
\frac{\partial g}{\partial \theta_{ij}(\lambda_{ij},B_i)} = \frac{2}{3} \frac{m_3 - \bar{m}}{\theta_{ij}(\lambda_{ij},1)}
\end{pmatrix}
$$

with $\bar{m} = \frac{1}{3} \sum_{p=1}^{3} m_p$.

In practice, our estimation is implemented in two steps. First we use an estimation of the $\Omega(\widehat{\theta}_{ij})$ weight matrix using our observations $\nabla g(\hat{\theta}_{ij})$ and $\widehat{\Sigma_{ij}}$. Second, with the $\hat{\lambda}_{ij}$ estimated in the first step we re-run our estimation with $\Omega(\theta(\hat{\lambda}_{ij}))$.

As proved in Gouriéroux et al. (1985), the variance of the GMM estimator of λ_{ij} is:

$$
\Sigma_{\lambda_{ij}} = \left[\frac{\partial g(\theta_{ij}(\lambda_{ij}))}{\partial \lambda_{ij}} \Omega(\theta_{ij}(\lambda_{ij}))^{-1} \frac{\partial g(\theta_{ij}(\lambda_{ij}))}{\partial \lambda_{ij}} \right]^{-1}
$$

with

$$
\begin{aligned}
\frac{\partial g(\theta_{ij}(\lambda_{ij}))}{\partial \lambda_{ij}} &= \tfrac{2}{3}(m_1-\bar{m})\frac{\partial \theta_{ij}(\lambda_{ij},2)/\theta_{ij}(\lambda_{ij},1)}{\partial \lambda_{ij}} \\
&+\tfrac{2}{3}(m_2-\bar{m})\textstyle\sum_{M=3}^{6}\displaystyle\frac{\partial \theta_{ij}(\lambda_{ij},M)/\theta_{ij}(\lambda_{ij},1)}{\partial \lambda_{ij}} \\
&+\tfrac{2}{3}(m_3-\bar{m})\textstyle\sum_{M=7}^{B_i}\displaystyle\frac{\partial \theta_{ij}(\lambda_{ij},M)/\theta_{ij}(\lambda_{ij},1)}{\partial \lambda_{ij}}
\end{aligned}
$$

NB: We can also try we the following alternative transformation of the auxiliary parameters:

$$
\begin{array}{rccc}
g \quad : & \mathbb{R}^{B_i} & \mapsto & \mathbb{R} \\
& \begin{pmatrix} \theta_{ij}(\lambda_{ij},1) \\ \theta_{ij}(\lambda_{ij},2) \\ \ldots \\ \theta_{ij}(\lambda_{ij},B_i) \end{pmatrix} & \rightarrow & Var\left(m_1,m_2,m_3\right)
\end{array}
$$

where

$$
\begin{aligned}
m_1 &= \textstyle\sum_{M=2}^{B_i}\displaystyle\frac{\theta_{ij}(\lambda_{ij},M)}{\theta_{ij}(\lambda_{ij},1)} \\
m_2 &= \textstyle\sum_{M=3}^{B_i}\displaystyle\frac{\theta_{ij}(\lambda_{ij},M)}{\theta_{ij}(\lambda_{ij},1)} \\
m_3 &= \textstyle\sum_{M=4}^{B_i}\displaystyle\frac{\theta_{ij}(\lambda_{ij},M)}{\theta_{ij}(\lambda_{ij},1)}
\end{aligned}
$$

Under this alternative definition:

$$
\begin{pmatrix}
\frac{\partial g}{\partial \theta_{ij}(\lambda_{ij},1)} & = & -\tfrac{2}{3}\sum_{p=1}^{3}\tfrac{(m_p-\bar{m})m_p}{\theta_{ij}(\lambda_{ij},1)} \\
\frac{\partial g}{\partial \theta_{ij}(\lambda_{ij},2)} & = & \frac{2}{3}\tfrac{m_1-\bar{m}}{\theta_{ij}(\lambda_{ij},1)} \\
\frac{\partial g}{\partial \theta_{ij}(\lambda_{ij},3)} & = & \frac{2}{3}\tfrac{m_1-\bar{m}}{\theta_{ij}(\lambda_{ij},1)}+\frac{2}{3}\tfrac{m_2-\bar{m}}{\theta_{ij}(\lambda_{ij},1)} \\
\frac{\partial g}{\partial \theta_{ij}(\lambda_{ij},4)} & = & \frac{2}{3}\tfrac{m_1-\bar{m}}{\theta_{ij}(\lambda_{ij},1)}+\frac{2}{3}\tfrac{m_2-\bar{m}}{\theta_{ij}(\lambda_{ij},1)}+\frac{2}{3}\tfrac{m_3-\bar{m}}{\theta_{ij}(\lambda_{ij},1)} \\
\ldots & & \\
\frac{\partial g}{\partial \theta_{ij}(\lambda_{ij},B_i)} & = & \frac{2}{3}\tfrac{m_1-\bar{m}}{\theta_{ij}(\lambda_{ij},1)}+\frac{2}{3}\tfrac{m_2-\bar{m}}{\theta_{ij}(\lambda_{ij},1)}+\frac{2}{3}\tfrac{m_3-\bar{m}}{\theta_{ij}(\lambda_{ij},1)}
\end{pmatrix}
$$

with $\bar{m} = \frac{1}{3}\sum_{p=1}^{3} m_p$.

$$
\begin{aligned}
\frac{\partial g(\theta_{ij}(\lambda_{ij}))}{\partial \lambda_{ij}} &= \tfrac{2}{3}(m_1-\bar{m})\textstyle\sum_{M=2}^{B_i}\displaystyle\frac{\partial \theta_{ij}(\lambda_{ij},M)/\theta_{ij}(\lambda_{ij},1)}{\partial \lambda_{ij}} \\
&+\tfrac{2}{3}(m_2-\bar{m})\textstyle\sum_{M=3}^{B_i}\displaystyle\frac{\partial \theta_{ij}(\lambda_{ij},M)/\theta_{ij}(\lambda_{ij},1)}{\partial \lambda_{ij}} \\
&+\tfrac{2}{3}(m_3-\bar{m})\textstyle\sum_{M=4}^{B_i}\displaystyle\frac{\partial \theta_{ij}(\lambda_{ij},M)/\theta_{ij}(\lambda_{ij},1)}{\partial \lambda_{ij}}
\end{aligned}
$$

B.3 Observed and inferred variables

B.4 Grid Search Procedure

1. Calculate the objective function for 1000 different values of λ_{ij} and store the 5 best λ_{ij}s that minimize it

2. Check that these values all belong to an interval centered around the best λ_{ij}

3. Conduct a second grid search with 100 potential values of λ_{ij} in the interval mentioned above and select the best value of λ_{ij}, which minimizes the objective function

4. Run the estimation procedure using this value as initial point and verify that we obtain an estimate which is not too far from this initial point

5. Run the estimation again, using this $\hat{\lambda}_{ij}$ as starting point

6. Verify that the algorithm converges quickly and gives a result close to $\hat{\lambda}_{ij}$.

Table 12: ***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

Table A1: ***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%
Denmark	2.2	1	2	68%
Estonia	1.2	1	1	87%
Finland	1.7	1	2	74%
Germany	5.0	1	3	55%
Greece	2.2	1	2	68%
Hungary	1.3	1	1	82%
Ireland	2.6	1	2	67%
Italy	5.0	1	3	59%
Latvia	1.2	1	1	87%
Lithuania	1.3	1	1	83%
Luxembourg	1.8	1	2	70%
Malta	1.2	1	1	87%
Netherlands	3.3	1	2	61%
Poland	1.7	1	2	74%
Portugal	2.8	1	2	67%
Romania	1.3	1	1	81%
Slovenia	1.3	1	1	82%
Slovakia	1.3	1	1	85%
Spain	4.2	1	3	59%
Sweden	2.0	1	2	67%
United Kingdom	3.9	1	3	59%
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.