Diversification in the Small and in the Large: Evidence from Trade Networks*

Francis Kramarz† Julien Martin‡ Isabelle Mejean§

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Abstract

We study the extent to which the structure of an exporter's portfolio of buyers affects the volatility of its sales, the comovements in sales across exporters and, in the aggregate, the volatility of bilateral exports. Using firm-to-firm trade data, we show that exporters are little diversified in sales across foreign partners. The lack of diversification increases the volatility of their exports through their exposure to idiosyncratic buyer shocks. We also document some connectedness in trade networks, which arises from a few importers buying goods to many exporting firms. This connectedness generates comovements in sales across sellers. Both elements together with the extreme skewness of export sales contribute to generating "granular" fluctuations in aggregate exports. We develop a model in which those features arise endogenously. In our model, granularity explains by the heterogeneity of exporters in terms of their productivity. The lack of diversification is a consequence of matching frictions in international markets. We use the model to reproduce the heterogeneity across destinations and sectors in the volatility of trade flows.

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†CREST-ENSAE. francis.kramarz@ensae.fr.

‡Université du Québec à Montréal. julien.f.martin@gmail.com

§Ecole Polytechnique. isabelle.mejean@polytechnique.edu

1 Introduction

Does the magnitude of aggregate fluctuations depend on the microeconomic structure of an economy? In the recent period, there has been a renewed interest for this long standing question. Gabaix (2011) shows how aggregate fluctuations can be generated by idiosyncratic shocks to the largest firms in the economy, whenever the distribution of firms is fat-tailed. The aggregate impact of idiosyncratic shocks is further amplified in the presence of economic networks that help propagate shocks.[1] According to di Giovanni et al. (2014), a substantial share of the macroeconomic volatility is due to such "granular" fluctuations.

One limit of this literature is that the volatility of shocks that individual firms face and the structure of the economy in which firms operate are both considered as given.[2] Implicitly, each individual producer is hit by idiosyncratic supply shocks the volatility of which is exogenously given (and usually assumed homogenous across firms). And it is the (exogenous) structure of the economy that determines the extent to which these supply shocks wash out at the aggregate level. In this paper, we instead consider economic networks as endogenous outcomes of a random meeting process between firms. We discuss a set of new stylized facts concerning the degree of sales skewness at the individual level, the connectedness of sellers through common buyers, and the role of large players as a source of granular fluctuations. We then elaborate a stylized model of firm-to-firm trade in which these facts arise endogenously. Estimating the model structurally and simulating the dynamic of exports under the estimated parameters help identify the sources of volatility in this framework.

In doing so, we consider one specific type of economic networks, namely firm-to-firm trade linkages in international markets. We exploit newly available data that exhaustively describe the microeconomic structure of bilateral export flows, for different destinations and over time. The explicit identification of both sides of the market, namely individual exporters and the foreign firms they sell to, constitutes the originality of the data. They offer a unique opportunity to analyze in detail the direct and indirect linkages between firms involved in international markets. We then investigate the sources of granular fluctuations in bilateral trade.

To organize the data analysis, the paper starts with an analytical framework summarizing the potential sources of granular fluctuations in trade networks. As in Gabaix (2011), the main reason why we can expect the volatility of bilateral exports to be high is because the distribution of sales across firms is skewed. In such context, any source of idiosyncratic volatility shows up at the aggregate level because shocks to the largest firms are not compensated by shocks to

[1] Acemoglu et al. (2012) study such an amplification mechanism in an economy with input-output linkages across microeconomic units. In this economy, idiosyncratic shocks to upstream firms/sectors propagate downwards through the price of inputs. To the extent that firms in the right-tail of the distribution are more strongly connected to the rest of the economy, this propagation mechanism reinforces the magnitude of "granular" fluctuations.

[2] A notable exception is Carvalho and Grassi (2014) that develop a firm dynamics setup *à la* Hopenhayn (1992) in which granular fluctuations arise endogenously.

the smallest ones. Following Kelly et al. (2013), our framework also takes into account the possibility that the volatility faced by individual firms is heterogeneous, because their portfolio of clients is different. In presence of idiosyncratic demand risk, having a portfolio of clients that is more diversified exposes the firm to less risk. In our framework, this implies a negative correlation between the Herfindahl of sales, within sellers, and the volatility of their sales. Finally, we introduce a source of comovements in sales across exporters, as in Acemoglu et al. (2012). Here, comovements do not come from supply shocks propagating along production networks. Instead, we take into account the possibility that several exporters might serve the same buyers. In such "connected" trade networks, idiosyncratic demand shocks is a source of covariance in sales for indirectly connected sellers. And "key" players on the buyer's side, namely buyers connected to many sellers, become as important as large sellers as a source of granular fluctuations.

The analytical framework thus reproduces the main sources of granular fluctuations previously discussed in the literature, in the context of trade networks. We then analyze the data through this lens. Our data record all bilateral trade flows between any French exporter and the importing firms it interacts with, conditional on those importers being located in a EU country. Without any surprise, we first show that the distribution of sales among firms selling goods in a given destination is highly skewed. Less than 10% of large exporters account for 90% of the value of exports. As a consequence, the concentration of French exports to the Spanish market is 500 times larger than in a counterfactual world with symmetric firms.[3] As discussed in Gabaix (2011), such concentration of sales may generate granular fluctuations. If this is the case, any source of volatility that is specific to the largest French exporters will show up in the aggregate.

Less documented in the literature is the low degree of diversification of individual exporters' sales. The structure of a typical exporter's portfolio of clients is indeed highly concentrated. Among individual firms exporting to Spain, 40% have a single buyer there while only 15% serve at least ten clients. Moreover, even firms with a rich portfolio of clients concentrate their sales on one or two main partners. The lack of diversification implies a strong exposure to idiosyncratic demand shocks. Consistent with the analytical framework, we show that firms which sales are more diversified across buyers display significantly less volatility. In the aggregate, the effect is partially counteracted by the heterogeneity of firms in terms of the number of clients they serve. In our data, large firms indeed have a more diversified portfolio of clients, which also implies a lower exposure to idiosyncratic demand shocks.[4] Simulations however suggest that the aggregate volatility of exports could be reduced significantly if firms were better diversified.

While diversification allows exporters to reduce their individual exposure to

[3] Most of the data analysis is based on French exports to the Spanish market. The main results are however robust to the destination market we focus on.

[4] This result is consistent with di Giovanni et al. (2014) who also find a negative correlation between firms' size and the volatility of their sales.

demand risks, it also strengthens the “connectedness” of trade networks, a factor of positive comovements in our analytical framework. The structure of the data helps document this dimension. On average, the degree of connectedness is low with 70% of Spanish importers interacting with a single French exporter, thus generating zero comovements in sales. The degree of connectedness slightly increases once we focus on within-sector interactions. Namely, two exporters of the same 2-digit good are 10 times more likely to be indirectly connected through common buyers than a pair of exporters selling completely different goods. More importantly, the degree to which different importers “connect” individual exporters is highly skewed, as is the distribution of exporters. For instance, removing the largest buyer in terms of how strongly connected it is to the network of French exporters reduces the number of indirect links between sellers by almost 10%. This skewness suggests that, even if on average the connectedness of trade networks is small, a few “key” buyers are able to generate a lot of indirect connections. Such indirect connections are important inasmuch as they introduce a source of covariance in sales across exporters. This is the case in our data. Firms sharing a larger number of clients in their portfolio indeed display significantly larger covariance in sales. This matters for aggregate fluctuations: Reducing the degree of connectedness to zero would decrease the variance of aggregate exports by about 4%.

Having confirmed that the microeconomic structure of the data gives rise to granular fluctuations, we next build a theoretical model in which those features arise endogenously. In trade models, granularity comes up naturally once one takes into account the heterogeneity of exporting firms. Following Melitz (2003), this literature has developed a theoretical framework in which heterogeneous firms self-select into export markets. In equilibrium, this implies a strong degree of skewness in export sales, with a handle of highly productive firms accounting for the vast majority of aggregate trade. Reproducing the low degree of diversification in exporters' portfolios is less trivial, however. The standard trade model displays a single dimension of heterogeneity, namely heterogeneous exporters selling goods to a representative buyer in each country.[5] Implicitly, any firm that is productive enough to serve a market sells goods to all potential clients there. In our model, matching frictions between sellers and buyers is the key element explaining that even highly productive firms do not serve all potential clients in a market.

Our model is built on the Eaton and Kortum (2002) structure, that we augment with matching frictions in international markets. In each destination country, there is a large number of buyers that address a demand for goods to potential suppliers of perfectly substitutable varieties. On the supply side, producers are heterogeneous in terms of their productivity as well as their location. In a frictionless world, all buyers from the same destination would choose the same supplier, namely the one offering the good at the lowest price. In turn, this would imply extreme equilibria in terms of how well diversified a supplier

[5] Two recent exceptions are Bernard et al. (2014) and Carballo et al. (2013) which models both display two-sided heterogeneity, among exporters *and* importers.

is: Either does the firm serves zero client in a given destination, or does it serve all potential buyers, thus diversifying as much as possible.

Since such equilibria are inconsistent with evidence in the data, we augment the model with matching frictions. Namely, it is assumed that each potential buyer of a good randomly draws a finite number of price quotes in the distribution that is offered to it. Conditional on this set of prices, it then chooses the lowest cost supplier. The consequence of the matching frictions is that, ex-post, buyers are heterogeneous in terms of the supply of goods they are offered to. And any supplier, even the less productive one, has a strictly positive chance to be chosen by at least one buyer in a given destination. Since highly productive firms continue to be more likely to be chosen, conditional on their price being drawn, the ex-post distribution of exports is still skewed. However, even those very productive firms cannot serve all potential buyers in a destination, thus the low degree of diversification.[6]

Confronting the model to our data makes it possible to estimate the degree of heterogeneity and the magnitude of frictions, for different sectors and destination markets. Assuming a structure of idiosyncratic shocks, it is then possible to simulate the volatility of exports and compare it to actual data. The simulation is useful inasmuch as it gives insights about the sources of export volatility in the data. In our model, different degrees of volatility can explain by the heterogeneity in the magnitude of matching frictions and/or the fundamental volatility of demand that exporters face, given matching frictions. Our simulations of the model give insights about the relative importance of those different elements.

Our paper is related to several strands of the literature. The idea that the microeconomic structure of the economy matters for aggregate fluctuations dates back to, at least, Long and Plosser (1983). More recently, the role of the concentration of sales across firms has been discussed by Gabaix (2011) in a closed economy and di Giovanni and Levchenko (2012) in an international setting. Also closely related to our work is the literature that studies how economic networks can amplify aggregate fluctuations. Most of this literature emphasizes propagation mechanisms of supply shocks through input-output relationships (Acemoglu et al., 2012). We instead study the role of demand shocks and its interaction with the way individual firms allocate their sales across buyers. In that sense, our approach is similar to the one in Kelly et al. (2013) who also underlie the potential link between the number of clients that a firm serves and the risk it is exposed to. With respect to that paper, our contribution is to endogeneize the correlation, while they instead posit that large firms serve more buyers.

Our focus on international trade networks obviously draws a link with the trade literature. On the empirical side, we document new dimensions of het-

[6] In contrast with Eaton and Kortum (2002), the equilibrium of our model has a continuum of heterogeneously productive firms selling the same good in the same destination market. The distribution of these firms' sales is skewed, with the more productive firms selling larger volumes, in expectation. We thus reproduce the evidence in the data without having to rely on fixed exporting costs, as in Melitz (2003).

erogeneity across exporters, in terms of the number of clients they serve, the skewness of their sales across buyers and the degree of connectedness of their network with other exporters. Some of these elements have been discussed in the recent literature using similar transaction-level data. In particular, Bernard et al. (2014), Carballo et al. (2013) and Eaton et al. (2013) report qualitatively similar numbers concerning the repartition of an exporter's sales, across buyers within a destination. This dimension of heterogeneity is however interpreted in completely different contexts, to discuss the welfare gains from trade (Carballo et al., 2013) or the dynamics of trade patterns (Bernard et al., 2014; Eaton et al., 2013).

The theoretical part of the exercise borrows a lot from previous papers. The papers that are the most closely related to ours are those seeking to explain the way exporters and importers meet in international markets. Bernard et al. (2014) and Carballo et al. (2013) develop models in which the matching process is deterministic. Both the export and the import sides display some degree of heterogeneity and, in equilibrium, there is an assortative matching between exporters and importers. Chaney (2014) and Eaton et al. (2014) instead introduce some randomness in the matching process. In particular, Eaton et al. (2014) assume that buyers are not able to choose in the complete distribution of potential sellers because of some matching frictions. We follow their approach to generate endogenously the low degree of diversification in exporters' sales that we observe in our data.

The rest of the paper is organized as follows. Section 2 provides evidence that the microeconomic structure of trade networks generates granular fluctuations in bilateral trade. More specifically, we first develop an analytical framework that helps isolate the potential sources of granular fluctuations in our data. Then, we provide evidence that the data we have display such statistical features. Finally, we prove that there is indeed a link between the isolated sources of granular fluctuations and the degree of volatility in our data. Section 3 then develops a model in which the above-mentioned features of the data arise endogenously. After having described the main mechanisms of the model, we estimate its parameters and run simulations to analyze the sources of aggregate volatility in trade data. Finally, Section 4 concludes.

2 Granular fluctuations in bilateral trade

2.1 Analytical Framework

In this section, we present the conceptual framework that we use to isolate the relevant statistics characterizing the extent of granular fluctuations in bilateral trade. In doing so, we follow the approach in di Giovanni et al. (2014). Namely, we write the aggregate variance of bilateral export sales assuming that the microeconomic structure of trade flows is constant over time. This is our concept of "aggregate" volatility. We then derive a decomposition of aggregate fluctuations into a weighted average of micro-level variance and covariance

terms. Finally, we posit a structure of shocks at the micro-level and analyze to what extent these shocks show up in aggregate fluctuations, depending on the microeconomic structure of the economy.

Our object of interest is the volatility of aggregate exports, as defined by the variance of export growth:

$$Var(g_{X_t}) = \frac{1}{T}\sum_t (g_{X_t} - \bar{g}_X)^2$$

where g_{X_t} is the growth rate of aggregate exports and $\bar{g}_X$ the mean growth rate over the period under consideration. The geographic indices are neglected to alleviate notations but the focus is on exports from a country j to a destination i. By definition, aggregate exports towards one destination are the sum of firm-specific sales over all firms serving the same destination:

$$X_t = \sum_{s\in S} x_{st}$$

where S is the set of sellers and x_{st} the value of firm s sales. As shown by Gabaix (2011), the distribution of sales across exporters is a key determinant of aggregate fluctuations. Taking this distribution as given, one can rewrite the volatility of aggregate exports as:[7]

$$Var(g_{X_t}) = \sum_{s\in S} w_s^2 Var(g_{x_{st}}) + \sum_{s\in S}\sum_{s'\neq s} w_s w_{s'} Cov(g_{x_{st}}, g_{x_{s't}}) \qquad (1)$$

where w_s is the share of firm s in aggregate exports, $Var(g_{x_{st}})$ is the variance of firm s export growth and $Cov(g_{x_{st}}, g_{x_{s't}})$ is the covariance in growth between firms s and s'. Equation (1) shows that, given a distribution of sales, one can write the aggregate variance in exports as a weighted average of firm-specific volatilities and the set of covariances in growth between any two pairs of firms serving the same destination market.

While most of the related literature takes the microeconomic structure of variances and covariances as given, we further exploit the dimensions available in our data to refine the decomposition. Namely, our data disaggregate the sales of a firm across foreign partners. By definition:

$$x_{st} = \sum_{b\in B_s} x_{sbt}$$

where x_{sbt} is the value of the transaction between exporter s and importer b and B_s the set of foreign partners served by exporter s (say the set of Spanish firms buying goods to exporter s in France).

[7]To simplify the analytical framework, we consider that the set of exporters serving the export market is constant over time, as is the distribution of sales across these exporting firms (i.e. $S_t = S$, $\{w_{st} \equiv \frac{x_{st}}{X_t} = w_s\}$, $\forall\ t$). As in di Giovanni et al. (2014), we thus consider the aggregate variance, conditional on the distribution of sales observed in a given period τ: $Var(g_{X_t}|\{w_{s\tau}\})$. In the empirical exercise, we fix the distribution of sales based on data for 2005 and analyze the variance of trade over the 1996-2007 period, conditional on this distribution of weights.

Using the same logic as before, it is possible to decompose the volatility of exports as measured at the level of an exporting firm into a weighted average of even more disaggregated variance and covariance terms:

$$Var(g_{x_{st}}) = \sum_{b \in B_s} {w_b^s}^2 Var(g_{x_{sbt}}) + \sum_{b \in B_s} \sum_{b' \neq b} w_b^s w_{b'}^s Cov(g_{x_{sbt}}, g_{x_{sb't}}) \qquad (2)$$

where $w_b^s \equiv \frac{x_{sbt}}{x_{st}}$ is the share of buyer b in firm s total exports (that we again assume constant). $Var(g_{x_{sbt}})$ is the variance in the growth of the transaction between s and b and $Cov(g_{x_{sbt}}, g_{x_{sb't}})$ is the covariance in growth between buyers b and b', both served by exporter s.

Finally, given the structure of firm-level exports, one can also write the covariance in sales across exporters, as a function of covariances in their sales to one buyer:

$$Cov(g_{x_{st}}, g_{x_{s't}}) = \sum_{b \in B_s} \sum_{b' \in B_{s'}} w_b^s w_{b'}^{s'} Cov(g_{x_{sbt}}, g_{x_{s'b't}}) \qquad (3)$$

Incorporating equations (2) and (3) into (1) thus implies a full decomposition of aggregate fluctuations into a weighted average of transaction-level variance and covariance terms.

To get more insights from this decomposition, it is convenient to assume a stylized dynamics for transaction-level growth and study what the dynamics implies for aggregate fluctuations. In the rest of the section, we will assume that the growth rate of sales at the most disaggregated level can be decomposed as follows:

$$g_{x_{sbt}} = \underbrace{\varepsilon_{St} + \varepsilon_{st}}_{Supply\ Shocks} + \underbrace{\varepsilon_{Bt} + \varepsilon_{bt}}_{Demand\ Shocks} + \varepsilon_{sbt} \qquad (4)$$

Namely, the dynamics of micro-level trade flows is attributable to three types of shocks: i) Two supply shocks, one that is common across exporters (ε_{St}) and one that is specific to seller s (ε_{st}), ii) Two demand shocks, one that is common across importers (ε_{Bt}) and one that is specific to buyer b (ε_{bt}), iii) A match-specific shock (ε_{sbt}). In the following, shocks that are common across exporters or importers are called "aggregate" shocks while the remaining three shocks are called "idiosyncratic".[8] All types of shocks are assumed orthogonal to each other and non-autocorrelated. This implies that the variance of $g_{x_{sbt}}$ is the sum of the variances of its components. We also assume that the supply and demand "idiosyncratic" shocks are orthogonal across sellers and buyers, respectively, i.e. that all sources of common shocks are encompassed into the "aggregate" shocks (i.e. $Cov(\varepsilon_{st}, \varepsilon_{s't}) = 0 \quad \forall\, s \neq s'$ and $Cov(\varepsilon_{bt}, \varepsilon_{b't}) = 0 \quad \forall\, b \neq b'$).

[8] Here, an "aggregate" shock affects homogenously all firms contributing to bilateral exports, either on one or the other side of the border. Of course, the decomposition of aggregate fluctuations would also apply to bilateral sectoral data, in which case "aggregate" shocks would refer to the combined effect of macroeconomic and sector-specific shocks. In the empirical section, we will mostly focus on the within-sector heterogeneity across sellers. This heterogeneity can only explain by shocks that are idiosyncratic across sellers within sectors, by opposition to sectoral and aggregate shocks.

Finally, we preclude match-specific shocks to be correlated across transactions (i.e. $Cov(\varepsilon_{sbt}, \varepsilon_{s'b't}) = 0 \quad \forall\, (s,b) \neq (s',b')$).[9]

This structure of shocks is useful because it encompasses most types of shocks that are driving business cycles in the literature, notably aggregate supply shocks in RBC models, idiosyncratic supply shocks in the granular literature, and aggregate demand shocks in the new-keynesian literature. Moreover, it helps understand whether and how the microeconomic structure of the economy matters for the final impact of different types of shocks on aggregate fluctuations. Finally, note that it is possible to write a model in which log-linear demand functions deliver a similar decomposition of relation-specific growth rates into different components (see the discussion in di Giovanni et al., 2014).

Plugging this structure of shocks into the decomposition in (1)-(3) implies a structural decomposition of aggregate fluctuations into different components:

$$\begin{aligned} Var(g_{X_t}) \approx\ & \underbrace{Var(\varepsilon_{St}) + Var(\varepsilon_{Bt})}_{Macroeconomic\ volatility} + \underbrace{\sum_{s\in S} w_s^2 Var(\varepsilon_{st})}_{Pure\ granular\ volatility} \\ +\ & \underbrace{\sum_{s\in S} w_s^2 \sum_{b\in B_s} w_b^{s\,2} \left[Var(\varepsilon_{bt}) + Var(\varepsilon_{sbt})\right]}_{Diversifiable\ granular\ volatility} \\ +\ & \underbrace{\sum_{s\in S}\sum_{s'\neq s} w_s w_{s'} \sum_{b\in B_s\cap B_{s'}} w_b^s w_b^{s'} Var(\varepsilon_{bt})}_{Pure\ network\ volatility} \end{aligned} \tag{5}$$

The first component of the decomposition is attributable to “aggregate shocks”, either on the supply or on the demand side. Since these shocks affect all transactions homogenously, their volatility has a one-to-one effect on the magnitude of aggregate fluctuations. In standard macroeconomic models, this is the sole driver of business cycles.

An important contribution of Gabaix (2011) is to show that, under some conditions on the distribution of microeconomic sales (i.e. the distribution of the w_s weights in the above framework), idiosyncratic shocks to firms might also show up in the aggregate. In particular, the more concentrated the distribution of sales across exporters, the larger the contribution of idiosyncratic supply shocks to aggregate fluctuations. This is the “Pure granular volatility” term in equation (5). If we further assume, as Gabaix does, that all individual sellers face the same degree of idiosyncratic risk then $Var(\varepsilon_{st}) = \sigma_{iS}^2 \quad \forall s \in S$ and the “Pure granular volatility” term simplifies into

$$\sum_{s\in S} w_s^2 Var(\varepsilon_{st}) = \sigma_{iS}^2\ Herf$$

[9] Note that it would be straightforward to allow for such cross-correlations in the analytical framework. Those covariances would be at the root of additional sources of volatility within and across exporters. However, the main insights that we want to get from the model can be obtained without introducing such covariance terms and we thus neglect them in the rest of the analysis.

where $Herf \equiv \sum_{s\in S} w_s^2$ is the Herfindahl index of sales, which is increasing in the skewness of the distribution. This conveys the main intuition in Gabaix (2011): The more concentrated is the distribution of sales, the larger the contribution of idiosyncratic shocks to aggregate fluctuations. In particular, under a skewed distribution of sales, shocks affecting the largest exporters in the economy have a substantial impact on aggregate fluctuations.[10]

Taking into account the decomposition of a firm's sales across its different partners adds two additional sources of granular fluctuations. The first one, captured in the "Diversifiable granular volatility" term in equation (5), has to do with the skewness of sales, across buyers within an exporter's portfolio. The idiosyncratic demand and match-specific shocks introduce a novel dimension of idiosyncratic risk that exporters need to deal with. Contrary to idiosyncratic supply shocks, this source of volatility is however "diversifiable". By extending the portfolio of its customers, an exporter can reduce the amount of risk that it faces, since demand and match-specific shocks will partially cancel out. This is the reason why the marginal impact of $[Var(\varepsilon_{bt}) + Var(\varepsilon_{sbt})]$ in equation (5) depends on the way individual exporters share their sales across buyers (i.e. on the distribution of the w_b^s weights). In particular, if we assume that all transactions support the same degree of "demand" risk (i.e. $[Var(\varepsilon_{bt}) + Var(\varepsilon_{sbt})] = \sigma_{iD}^2 + \sigma_{iT}^2 \quad \forall\, s \in S,\ b \in B_s$), the "Diversifiable granular volatility" term simplifies into

$$\sum_{s\in S} w_s^2 \sum_{b\in B_s} {w_b^s}^2 \left[Var(\varepsilon_{bt}) + Var(\varepsilon_{sbt})\right] = (\sigma_{iD}^2 + \sigma_{iT}^2) \sum_{s\in S} w_s^2 Herf_s$$

where $Herf_s \equiv \sum_{b\in B_s} {w_b^s}^2$ is the Herfindahl of sales, computed across buyers for seller s. Firms with more concentrated sales are more volatile, which shows up at the aggregate level in proportion with the (square of the) relative size of the exporter.

The last term in equation (5) (the "Pure network volatility" component) captures the role of trade networks as an amplification mechanism for idiosyncratic shocks. In our analytical framework, there is no direct linkages between exporters, thus no propagation of shocks as in Acemoglu et al. (2012). This does not preclude the possibility that two exporters' sales may covary, however. In particular, any exposure to "common" shocks induces a positive covariance in sales. This is obviously the case of aggregate shocks. This source of covariance is however already taken into account in the "Macroeconomic volatility" term. More interestingly, the connectedness of trade networks among individual exporters is an additional source of comovements. Whenever two exporters interact with the same buyer, they face the same idiosyncratic demand risk and thus mechanically covary positively. Thus, despite the absence of direct linkages between sellers, indirect linkages through common buyers is a source of shocks propagation in the model.[11] Assuming once again that all buyers face the same

[10] Gabaix (2011) thus estimates that one third of variations in US output growth is attributable to the largest 100 firms.

[11] Of course, it is possible that indirect linkages between exporters convey additional sources

amount of risk, the "Pure network volatility" effect simplifies into

$$\sum_{s\in S}\sum_{s'\neq s} w_s w_{s'} \sum_{b\in B_s\cap B_{s'}} w_b^s w_b^{s'} Var(\varepsilon_{bt}) = \sigma_{iD}^2 \sum_{s\in S}\sum_{s'\neq s} w_s w_{s'} Connectedness_{ss'}$$

where $Connectedness_{ss'} \equiv \sum_{b\in B_s\cap B_{s'}} w_b^s w_b^{s'}$ is the degree of connectedness in s and s' trade networks i.e. the share of their sales that is addressed to buyers they have in common. The more connected trade networks, the larger the covariance in sales between exporters, with an end effect on aggregate fluctuations that is proportional to the combined size of the exporters.

Another way to consider the connectedness dimension is to take the point of view of importers. Namely, the "Pure network volatility" term can also be written as:

$$\sum_{s\in S}\sum_{s'\neq s} w_s w_{s'} \sum_{b\in B_s\cap B_{s'}} w_b^s w_b^{s'} Var(\varepsilon_{bt}) \quad = \quad \sigma_{iD}^2 \sum_{b\in B} w_b^2 Connectivity_b$$

where $Connectivity_b = \sum_{s\in S}\sum_{s'\neq s} w_s^b w_{s'}^b = 1 - \sum_{s\in S_b} {w_s^b}^2 = 1 - Herf_b$, w_b is the share of buyer b in aggregate sales and w_s^b the share of seller s in its purchases. $Connectivity_b$ thus measures the extent to which a buyer b "connects" individual sellers together. This statistics is inversely related to the Herfindahl index of the buyer's purchases, a buyer diversifying more connecting a larger number of exporters with each other. Using this approach of the connectedness of trade networks shows that the magnitude of comovements in sales across exporters can potentially be explained by a few large buyers whose purchases are shared among many exporters, thus creating a lot of indirect connections between sellers.

The rest of this section analyzes the trade network data through the lens of this framework. Our objective is to check whether the sources of granular fluctuations just discussed are present in the data.

2.2 Data

The empirical analysis is conducted using detailed export data covering the universe of French exporting firms. The data are provided to us by the French Customs.[12] The full dataset covers all export transactions that involve a French exporter and an importing firm located in the European Union. Most of our analysis however focuses on exports to Spain. For this country, we have data for 1995, 2000, 2005 and 2009. However, most of our results focus on the 2005 cross-section.

of comovements, eventually going in the opposite direction. For instance, if the goods sold by exporters s and s' are substitutable in buyer b's consumption basket, any good performance of buyer s induces a decrease in the demand addressed to s', thus a negative comovement in sales between those exporters. This possibility is ruled out thanks to the simplifying assumption that idiosyncratic match-specific shocks are orthogonal across sellers. In a more general model, the "Pure network volatility" component would also reflect this source of comovements.

[12]We are thankful to the French customs for having kindly accepted to provide the data. Many thanks to Thierry Castagne who took time to explain the specificities of those data.

Many researchers before us have used individual trade data from the French Customs. Most of the time, the data used in empirical exercises are annual data disaggregated at the level of the exporting firm, as in Eaton et al. (2011), Mayer et al. (2011) or Berman et al. (2012). Some papers also use data detailed at the level of the importer, for instance Blaum et al. (2013). An exception is Bricongne et al. (2012) who use data detailed at the transaction level: For each exporting firm, they know how many times a good has been exported to one destination in the year under consideration. In comparison with those papers, our data are even richer since we know the identity of the exporting firm *and* the importer its serves. For each transaction, the dataset specifies the identity of the exporting firm (its name and its SIREN identifier), the identification number of the importer (an anonymized version of its VAT number), the date of the transaction (month and year), the product category (at the 8-digit level of the combined nomenclature), the value and the quantity of the shipment. Most of the time in the analysis, data will be aggregated across transactions within a year, for each exporter-importer-product triplet. An important feature of the data that differentiates us from the previous literature, is that foreign importers are explicitly identified. This is the key feature that makes it possible to measure in the data the extent to which individual exporters' trade networks are interconnected.

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. Those forms are used to repay VAT for transactions on intermediate consumptions. This explains that the data are exhaustive. One caveat of the data, however, is that small exporters are allowed to fill a "simplified" form that does not require the product category of exported goods. This is problematic whenever the empirical strategy controls for sector-specific determinants of the outcome variable since the corresponding transactions can not be included in the dataset. The "simplified" regime concerns firms which total export sales in the European Union in a given year do not exceed 150,000 euros (100,000 euros before 2006). Said otherwise, some of our regressions are based on censored data that do not cover the smallest exporting firms.

Given the quality of the data, little cleaning is necessary to obtain the final dataset. There is only one type of flows that we remove. In some cases, the country code is not consistent with the country code that can be recovered from the importer's identifier. This happens when a French firm plays the role of an intermediary to sell a good produced in a given country bought by a customer in another country. Since those transactions cannot be qualified as "French exports" stricto senso, they are removed from the database.

In 2005, we have information about 46,928 French firms exporting 7,807 8-digit products to 571,149 buyers located in the European Union. Total exports by these firms amounts to 207 billions of euros. Exports to the European Union account for 58% of French total exports. Most of our results are obtained from information on France-Spain bilateral exports. In 2005, this represents 16% of the value of trade in the European Union, disaggregated into 578,864 product-specific transactions between 23,146 exporters and 80,486 importers (see Table

1).

– Table 1 about here –

We complete the information on exporter-specific trade networks using three additional datasets. Each provides us with additional information on exporters, and can be merged with our data using the identifier of the exporter. The first dataset is also provided to us by the French customs. It is a panel of individual export flows, by 8-digit product. This dataset is thus an aggregated version of the previously described dataset, where trade flows are collapsed across importing firms within a country and across months within a year. Contrary to the most detailed data, those export flows are available annually since the beginning of the nineties. We use this additional time-dimension to compute measures of the volatility of sales, at the level of an exporter, and the covariance in export growth, across exporters ($Var(g_{x_{st}})$ and $Cov(g_{x_{st}}, g_{x_{s't}})$, respectively).

Our dataset is also merged with balance-sheet data on exporting firms, provided to us by the French Ministry of Finance. This lets us with additional information on firms, namely their total sales, their sales in France, their employment, their sector of activity and their location (more specifically, the location of their headquarter since those data are detailed at the level of the firm, not the plant).

Lastly, the data are complemented with a firm-level dataset about financial linkages of firm located in France (LiFi). This data is built by the French census (INSEE). It records the ownership of the firms located in France as well as the country of location of their related parties, if any. We use this information to know whether exporters in our data are entities of a Spanish multinational or if they own foreign affiliates in Spain. This helps control for the impact of intra-firm trade on the structure of trade networks and the magnitude of firm-level fluctuations.

2.3 Stylized facts on trade networks

In this section, we describe the trade networks of French firms exporting to Spain, as was in 2005. The presentation of our results follows the thread of the analytical framework. Namely, we study whether i) the distribution of sales across exporters is sufficiently skewed to generate granular fluctuations, ii) within exporters, the distribution of sales is poorly diversified which would expose them to idiosyncratic demand shocks, iii) across exporters, trade networks are sufficiently connected to generate comovements in individual sales.

The concentration of sales across exporters. As discussed in Section 2.1, the main driver of granular fluctuations is directly related to the concentration of sales across exporters. The more concentrated exports, the more likely that idiosyncratic volatility will not wash out at the aggregate level.

– Figure 1 about here –

For exports to Spain, the concentration of exports is illustrated in Figure 1. The figure displays the cumulative value of exports across firms of increasing size. It confirms a well-known stylized fact of the trade literature, namely that the distribution of sales across exporting firms is extremely skewed. At the top of the distribution, 1% of firms are thus responsible for 60% of exports. This extreme skewness shows up in the Herfindahl index which is equal to .022 in our data.[13] While the absolute number is not necessarily meaningful, it represents 500 times the Herfindahl one would observe in a counterfactual world in which all exporters are symmetric in size (and $Herf = 1/S$). This ratio varies slightly depending on the destination country under consideration. It is maximum for sales towards Spain. In our data however, the concentration of bilateral exports is always an order of magnitude higher than the counterfactual, as illustrated in Figure 2. Even Greece, which is relatively less concentrated in comparison with the counterfactual, displays a Herfindahl index that is 75 times larger than would be observed in a symmetric world.

– Figure 2 about here –

As discussed in Section 2.1, the skewness of exporter-specific sales is key to generate granular fluctuations. With a more dispersed distribution of exports, we would expect any source of idiosyncratic volatility to have a negligible impact on the aggregate volatility because idiosyncratic shocks would compensate across exporters. On the contrary, the degree of sales concentration observed in the data makes it very likely that trade displays granular fluctuations. We now further investigate the sources of such fluctuations by studying the likely effect of idiosyncratic demand shocks through the concentration and connectedness of individual exporters' trade networks.

Exporters diversification. In presence of idiosyncratic demand shocks, a source of granularity comes from the extent to which individual exporters diversify their exposure to risk, across clients in their portfolio. As discussed in Section 2.1, the Herfindahl of an exporter's sales, computed across buyers, is positively related to the variance of its sales. Namely, a high Herfindahl index is associated with a poor diversification of idiosyncratic demand risks thus more volatility. We now investigate this dimension of the problem, looking first at the number of clients served by a given exporter. Mechanically, this number is inversely related to the exporter's Herfindahl index.[14]

[13] As expected, trade is more granular than total sales. Indeed, di Giovanni et al. (2014) reports a Herfindahl of sales for French manufacturing firms of .0035. The distribution of sales across French exporters to Spain is thus 7 times more concentrated than the distribution of total sales.

[14] Our dataset has the structure of a bipartite network and can thus be analyzed using the tools of the graph theory. In this network, the number of clients served by a given exporter corresponds to its degree, which is an indicator of how "connected" the exporter is in that network. In the framework of Section 2.1, a high-degree exporter is also expected to display less volatility, because it diversifies demand risks across a larger number of buyers. Likewise, one can compute the "degree" of a buyer, which is simply the number of exporters it is connected

– Figure 3 about here –

Figure 3 presents the distribution of the number of buyers in each French exporter's portfolio. The top panel of Figure 3 (circles line) represents the share of sellers having at least a certain number of buyers. The bottom panel (circles line) presents the share of these firms in total exports, which better takes into account the heterogeneity across sellers of different size. In 2005, almost 40% of French sellers export to a single buyer (top panel). Those sellers are exposed to a maximum level of idiosyncratic demand risk since they do not diversify at all across buyers. However, they only account for 16% of total sales (bottom panel). At the other side of the distribution, around 15% of firms have more than 10 partners in Spain. They are responsible for around 40% of total exports. These distributions thus reveal a huge amount of heterogeneity in the degree of diversification of French exporters with large exporters selling to more buyers, on average.

The number of clients in a firm's portfolio does not put any hierarchy between transactions, however. Yet, a firm may have many partners but be extremely poorly diversified if most of those partners buy tiny amounts. This possibility seems consistent with our data, as shown by the additional lines displayed in Figure 3. While the green circles line computes the number of buyers using the total sales of each exporter, the other lines restrict the analysis to a certain amount of each firm's exports. Namely, for each exporting firm, buyers are ranked in decreasing size and the number of clients is computed excluding from the computation a certain share of exports, to the smallest buyers. Using this strategy, one realizes that, among the 15% of firms that serve more than 10 buyers, many serve tiny importers which cumulated share is less than 10% of the firm's exports. Once those tiny buyers are removed, only 6% of sellers are found to serve at least 10 partners. This number is close to 0 when one concentrates on only half of the firm's sales.

– Figure 4 about here –

To account for such asymmetries in the value of trade flows, within a portfolio, we compute the Herfindahl index at the firm-level: $Herf_s = \sum_{b \in B_s} {w_b^s}^2$, where w_b^s is the weight of partner b in exporter s sales. Results are summarized in Figure 4. Again, the top panel displays the distribution of Herfindahl indices as a share in the total population of exporters and the bottom panel represents numbers in proportion to the total value of exports. By definition, sellers trading with a single buyer have a Herfindahl index of one. This explains why Figures 3 and 4 display similar values for sellers with a degree or a Herfindahl equal to one. With more than one buyer, the Herfindahl index should however reduce dramatically, in proportion to the inverse of the number of clients if sales are equally shared across buyers. As evident from Figure 4, this is not the case in the data. For instance, more than 70% of sellers have a Herfindahl above .5,

to. In our framework, a large degree tends to reinforce granular fluctuations because shocks to strongly connected buyers are a source of comovements in sales across exporters.

the value obtained for sellers with two buyers of equal size. Such high values for the Herfindahl index confirm that exporters' sales are poorly diversified across buyers: Even firms with a rich portfolio of clients concentrate their sales on one or two "main" partners.

– Table 2 about here –

Again, the comparison of the top and bottom panels in Figure 4 provides insights about the heterogeneity in the degree of diversification, across exporters of different sizes. Indeed, the bottom distribution is shifted to the right which means that exporters that represent a larger share of the total value of exports tend to display lower Herfindahl indices. This result is confirmed by statistics in Table 2 (Columns (1) and (2)), concerning the mean and median degree of sales concentration, for firms in different percentiles of the distribution. Whatever the measure of diversification considered (either the inverse of the firm's degree or its Herfindahl index), we find that larger firms tend to be more diversified than smaller ones. Firms in the top quintile of the distribution have 9 times more buyers, on average. This does not transmit into a 90% smaller Herfindahl, which means that their is still a certain amount of heterogeneity across buyers, in the portfolio of large firms. Still, the Herfindahl index of large firms is 40% smaller than firms in the first quintile.

Table 2, Columns (3) and (4), also reports the equivalent statistics, when diversification is considered across products instead of across buyers. A recent literature in trade indeed develops models in which firms grow by extending the range of products they sell (Mayer et al., 2011; Bernard et al., 2011). Since different products are potentially bought by different buyers, such strategy could make us misinterpret the statistics on the diversification of sales across buyers. Appendix A extends the analytical framework of Section 2.1 to multi-product firms and shows that multiplying the number of products in its portfolio is a way for firms to diversify against product-specific idiosyncratic shocks. We explicitly consider the complementarities between diversification across buyers and products later in the text. At that stage, it is worth noting that the same patterns in the data appear when the diversification of sellers' portfolios is considered across products, as in Columns (3) and (4) of Table 2. Namely, large firms not only sell goods to more buyers, they also export a wider range of products.

– Table 3 about here –

Finally, we complete the characterization of individual firms' degree of diversification using a multivariate regression framework. Namely, we explain the variance in the degree of diversification across firms within a sector by a set of observable variables. Results are displayed in Table 3. Columns (1) and (2) use the number of clients in the exporter's portfolio as left hand side variable while columns (3)-(5) use the Herfindahl index. Since both variables are negatively correlated, we expect the coefficients estimated on those two subsets to be of opposite sign.

The first explanatory variable introduced in the regressions is the size of the exporting firm, as measured by its total sales. The coefficients obtained on this variable are systematically significant and confirm that, within sectors, large firms have more clients and display a lower Herfindahl index. We check the robustness of this finding by also including in the list of right hand side variables the experience of the exporter in the Spanish market. The role of this variable is tested following Chaney (2014). In his model, exporters gradually accumulate clients in each destination through random meetings. As a consequence, the number of clients in a firm's portfolio increases over time. Since large firms also tend to have longer experience in export markets, neglecting this explanatory variable could explain the estimated impact of firms size on diversification. Consistent with the expectation, we find that the number of buyers served by a given exporter is increasing in its experience. However, experience is uncorrelated with the firm's Herfindahl. Moreover, the presence of this variable does not turn out the estimated effect of the firm's size.

The second set of explanatory variables has to do with the possibility that firms diversify risks across products rather than across buyers. Columns (1) and (2) regress the number of clients on the number of products the firm has in its portfolio. If it was the case that all the diversification across buyers was due to the firm expanding her range of products, then the coefficient on this variable would be equal to one. This is not the case in our data. While the estimated coefficient is very significant and positive, it is far away from one meaning that firms diversify across buyers, even within products. Qualitatively similar results are obtained when the explained variable is the Herfindahl index computed across buyers and the explanatory variable the number of products (Column (3)) or the Herfindahl of sales across products (Columns (4) and (5)). Here as well, estimation results suggest that diversification across buyers goes hand in hand with diversification across products.

Our regression exercise also controls for other observable characteristics of the firm, which impact on the amount of diversification is less clear however. Namely, we test the possibility that diversification patterns are different for wholesalers in comparison with firms producing and exporting their own products. The estimated coefficients on this variable suggest that wholesalers tend to serve a smaller number of clients, but diversify better across their existing clients. We also control for the observed linkages between the exporting firm and the destination country, within multinational companies. Namely, firms having their headquarter in Spain as well as firms having affiliates there tend to have less clients in their portfolio. This could be due to multinational linkages inducing intra-firm trade between affiliates and their headquarter, a form of trade that does not expose partners to the same type of risks. This result does not seem especially strong, however, since the coefficients on these variables are not systematically significant when the LHS variable is the Herfindahl of sales.

The last element of this table has to do with the heterogeneity across exporters in the *potential* of diversification that they are offered. Depending on the type of products it sells, a firm may indeed face a very large number of potential clients or an oligopsonic demand. Such differences in the *potential* of

diversification may well be at the root of the heterogeneity in the *actual* degree of sales diversification. Column (2) controls for the number of potential clients that an exporter faces, which is calculated based on the observed number of buyers that purchase one specific type of products. Using the firm's observed portfolio of products and the number of potential buyers for each of those products, it is possible to compute the theoretical number of buyers that an exporter could serve, i.e. the supply of clients it is offered. As expected, the variable is positively correlated with the number of buyers in the firm's portfolio, but the correlation is far from perfect. The correlation is stronger with the measure of the *potential* Herfindahl index in column (5), where the potential Herfindahl is calculated as before and assuming that the firm would allocate its sales across all potential buyers in proportion to their relative aggregate demand.

Together, these results suggest that the degree of sales diversification is strongly heterogeneous across firms and systematically correlated with characteristics of the firm, namely its size, the number of potential clients it faces and its experience as an exporter. The model developed in Section 3.1 will come back on those determinants. The objective is to build a model in which those regularities arise endogenously. Before that, however, we complete this section by documenting another source of granular fluctuations in trade, namely the connectedness of individual exporters' networks.

Connectedness of sellers. As discussed in Section 2.1, the connectedness of trade networks across exporters, through common buyers, is another source of granular fluctuations. Such indirect links between exporters induce comovements in sales that amplify the direct effect of shocks on individual volatilities. This dimension of granularity can be apprehended either from the point of view of connected pairs of exporters, through their "connectedness" i.e. the share of the firms' sales addressed to buyers they have in common, or from the point of view of the buyers, through their "connectivity" i.e. the extent to which they create indirect linkages between individual exporters.

– Figures 5 and 6 about here –

Taking the point of view of buyers, Figures 5 and 6 illustrate the connectivity of buyers interacting with French exporters. Figure 5 shows the distribution of the number of sellers per buyer, across Spanish importers. Buyers having more sellers induce more "connectedness" in the aggregate trade network which should increase the magnitude of comovements in sales across exporters. In Figure 6, this transmits into a larger "connectivity", i.e. a smaller Herfindahl index for buyers. In our data, almost 70% of importers display zero connectivity, i.e. they interact with a single exporter in France and are thus unable to create any indirect linkage between exporters (top panels of Figures 5 and 6). However, those "small" buyers represent less than 20% of the aggregate value of French exports (bottom panels of Figures 5 and 6). At the other side of the spectrum, around 5% of buyers have more than 5 sellers, thus generate at least 10 indirect

connections between exporters, and a connectivity above .7. Those buyers are responsible for more than 20% of aggregate trade.

At the very top of the distribution, it is even possible to identify a set of "key" buyers which position in trade networks is central.[15] Summary statistics on these buyers are provided in Table 5. This table focuses on the 9 largest buyers, in terms of the number of sellers in their portfolio. The exercise consists in asking how the density of trade networks would be affected by those buyers' death. Alone, the most strongly connected buyer is responsible for 6.8% of indirect linkages in the network and 5.9% of the value of exports. The second most strongly connected buyer is comparable in importance, with a share in exports of 4.2% and an additional interaction with 5.8% of connected pairs. The remaining 7 buyers are also at the root of a substantial number of indirect linkages. But the size of their purchases is smaller, which implies that their importance as a source of granular comovements is lower. All in all, results in this table suggest that removing a small number of "key" buyers would be sufficient to reduce the aggregate connectedness of trade networks substantially.

– Table 5 about here –

Another way to analyze the connectedness of trade networks is to take the point of view of sellers. For any two exporters, the degree of connectedness of their networks is the combined share of their sales that goes to the same buyers: $Connectedness_{ss'} = \sum_{b \in B_s \cap B_{s'}} w_b^s w_b^{s'}$. A good proxy is also the number of clients that those exporters have in common. Statistics on these dimensions are reported in Table 6. The shortcoming of this indicator is that it can be calculated on a huge number of exporter pairs, almost 268 millions in our data $(23,146 * 23,145/2)$. A vast majority of those pairs (namely 99.8%) display zero connectedness.[16] As a consequence, the mean connectedness of exporters is close to zero in our data. This however does not mean that indirect connections through common buyers is not an important source of covariance. As shown before, the distribution of buyers' connectivity is extremely skewed. A consequence of this skewness is that there are "clusters" of connectedness, namely large groups of exporters' pairs that are indirectly connected through the same "key" buyer. Those clusters are a potential source of large comovements in sales. Conditionally on being connected, the share of their sales that exporters send to buyers they share with other firms is indeed important: 12.25% in the median pair of connected firms and 40.5% on average.

[15] The intuition for the existence of such "key" players is related to evidence on the role of wholesalers and retailers in international trade. Statistics computed by Bernard et al. (2010) suggest that 16% of the value of US imports in 2002 is attributable to "pure" wholesalers and retailers. Since the role of wholesalers and retailers is to aggregate individual demands, one can expect those importers to interact with many exporting firms, eventually selling many different goods, with an end effect on the aggregate connectivity of trade networks.

[16] Presumably, one reason why a lot of exporters are not connected at all through common buyers is because they sell completely different products. In our data, 15% of firms that are connected through common buyers sell goods classified in the same 6-digit product category. However, 46% of connected pairs involve firms that belong to different 1-digit product categories.

– Table 6 about here –

We conclude this section with a last set of stylized facts, in which we analyze the joint characteristics of sellers and buyers that end up interacting with each other. The recent literature working with comparable trade data has indeed documented some degree of "assortative matching" between sellers and the buyers they interact with. Bernard et al. (2014) thus show that there is negative assortative matching among sellers and buyers, with the most connected sellers interacting with little connected buyers, on average. Table 7 examines this dimension in our data using as indicator the rank correlation of buyer-seller pairs. We consider three characteristics of individual buyers and sellers: the size of the firms as measured by the total value of their purchases/sales, their degree, and their Herfindahl index. Our results indicate that large exporters are more likely to trade with large importers, i.e. there is positive assortative matching along the size dimension. With respect to the degree of diversification of firms, our results are however consistent with those in Bernard et al. (2014): More diversified sellers are also more likely to trade with less diversified buyers. This result has important consequences for the likely magnitude of granular fluctuations. In our data, the large sellers which volatility matters a lot in the aggregate tend to be relatively more diversified, thus displaying relatively less exposure to idiosyncratic demand shocks. Moreover, the buyers they are connected with have a low degree, on average, which implies that we should not expect a lot of comovement with other sellers in the aggregate network. All in all, this suggests that the negative assortative matching observed in the data acts against granular fluctuations.

– Table 7 about here –

2.4 Implication for the volatility of exports

Having confirmed that the main sources of granular fluctuations in trade that we identified in the analytical framework are also present in our data, we now ask to what extent the microeconomic structure of trade networks matters for the volatility of exports. More specifically, we run two sets of regressions, where the left-hand side variable is either the volatility of firm-level exports or the covariance in sales between French exporters. We expect those two external measures of how volatile the economy is to be affected by the characteristics of trade networks just identified. We then run counterfactual exercises to quantify the aggregate impact of those microeconomic features.

Diversification and volatility. As discussed in Section 2.1, diversifying their portfolio of buyers is a way for exporters to reduce their exposure to idiosyncratic demand shocks. As a consequence, we shall expect the heterogeneity in the degree of diversification to matter for the volatility of firm-level exports.

To test this prediction of the analytical framework, we regress the variance of firm-level exports, computed using annual growth data between 1996 and 2007,

on the degree and Herfindahl index of the firm's sales, as measured in 2005.[17] We expect a negative coefficient associated with more diversification. Of course, the degree of diversification is not the sole determinant of how volatile a firm is. Regressions displayed in Table 8 thus control for the size of the firm and its experience in the Spanish market, the dummy distinguishing wholesalers from producing firms and the variables capturing the relationship of the exporter with the destination country, within multinationals. Finally, all regressions control for sector-level fixed effects that absorb differences across sectors in the volatility of aggregate shocks.

– Table 8 about here –

Results in Columns (1) and (3) of Table 8 present the benchmark specification. In both regressions, the coefficient obtained on the measure of firm-level diversification is significant and with the expected sign. Namely, firms with a larger number of clients in their portfolio as well as firms displaying a lower Herfindahl index are estimated to have less volatile Spanish sales during the 1996-2007 period. The effect is identified across firms selling goods to the same destination in the same (broad) sector and is thus immune from any source of heterogeneity in the firms' exposure to macroeconomic and sectoral shocks. Our interpretation is thus that the structure of their portfolio of clients matters for the firms' exposure to idiosyncratic shocks.

As discussed before, diversifying across buyers is not the only way a firm can hedge against idiosyncratic risk. Another potential source of diversification consists in selling multiple products, which reduces the exposure to product-specific shocks. In order to control for this possibility, we add the degree and Herfindahl index of sales across products in the list of control variables. Results are displayed in Columns (2) and (4), respectively. They confirm the previous result that diversification across buyers matters for the volatility of their sales. This is also true of a strategy of diversification across products, however. Namely, having more products in its portfolio and a lower Herfindahl of sales across products is also a way for an individual exporter to reduce the volatility of its sales.

Common buyers and comovements. As the analytical framework made it clear, the reason why the connectedness of trade networks matters for aggregate fluctuations is because it is a source of comovements in sales across exporters. We now test this prediction of the model by regressing the magnitude of comovements in sales on the degree of connectedness in the firms' networks. Results are displayed in Table 9. The left hand side variable is the covariance in growth between any two firms, computed on the period from 1996 to 2007. We first use all covariance terms for all possible pairs of firms, before restricting the sample to firms belonging to the same 2-digit sector. Of course, the sample is mechani-

[17] Using the variance of sales as left-hand side variable mechanically restricts the sample to exporters present on the Spanish market for at least two periods over 1996-2007.

cally restricted to the pairs of firms that are present on the Spanish market over two identical years between 1996 and 2007.

– Table 9 about here –

Estimated coefficients are consistent with expectations. Namely, firms that share a larger number of buyers in their respective portfolio display more co-variance in sales (Columns (1) and (2)). Those covariances are also increasing in the share of those common buyers in each firm's portfolio (Columns (3)-(4)). This is consistent with the view that part of the volatility in individual sales is attributable to idiosyncratic demand shocks. In such framework, any connectedness in two firms' trade networks is a source of comovements in sales. Note that the result holds true both between and within sectors.

Implications for aggregate fluctuations. While the previous two paragraphs provide evidence that the structure of trade networks indeed matters for individual variance and covariance terms, they do not say anything about the likely effect on the aggregate volatility of exports. We now use two sets of counterfactual exercises in which the estimation results of Tables 8 and 9 are used to quantify the potential effect of individual firms diversifying better and/or having less connected networks on the aggregate variance of exports.

To this aim, we use the decomposition in equation (1) that we confront to the data using the observed distribution of weights as well as observed and counterfactual values for the individual variance and covariance terms. As discussed in Section 2.1, this decomposition is conditional on the structure of weights observed in a given year (we use 2005). But our panel of firm-level exports makes it possible to measure the actual variance in aggregate export growth as well as the variance conditional on this constant distribution of weights. This comparison conveys insights about the size of the approximation attributable to the use of equation (1) in the counterfactual analysis. Results are displayed in Table 10. The comparison of the first two lines shows that maintaining the weights constant to their 2005 value implies an overestimation of the variance in aggregate export data of about 12.6%.

– Table 10 about here –

The benefit of imposing the assumption is to let us decompose the aggregate variance of exports into the contribution of individual volatilities and of firm-to-firm covariances. This decomposition is performed in the last two lines of Table 10. It shows that about three quarters of the volatility in aggregate exports is due to the covariance terms. Of course, a substantial part of this contribution is due to macroeconomic or sectoral shocks, that trigger the sales of all exposed firms. However, part of it may be due to the propagation of idiosyncratic shocks across individual exporters.

We then use counterfactual scenarios and this decomposition to quantify the impact of the microeconomic structure of trade networks on the aggregate

volatility of exports. Namely, regressions of Tables 8 and 9 are used to simulate an improvement in the diversification of individual exporters' portfolios as well as a reduction in the connectedness of trade networks. After having quantified the impact on individual variance and covariance terms, one can aggregate the effect up to the country level using the actual weight of each firm in aggregate exports. This tells us what the effect would be on aggregate fluctuations. Results are summarized in Table 11.

– Table 11 about here –

The top panel in Table 11 illustrates the likely effect of more diversification in individual firms' trade networks. Namely, we shift the distribution of individual firms' degree of diversification so that, in the counterfactual scenario, all firms display at least as much diversification as the firm at the 90th percentile of the distribution. We then predict the effect that such improvement in the diversification of the less diversified firms would have on individual variances and the aggregate volatility of exports. The effect is estimated to be a decrease in the aggregate variance component of 2 to 8%, depending on the measure of diversification in use. The potential impact on aggregate fluctuations is thus between 0.5 and 2% (since the variance components account for about one quarter of aggregate fluctuations in exports, see Table 10). For comparison purposes, we also simulate the likely effect of having firms better diversified in the product dimension. Again, we shift the distribution of product-level diversification indicators towards more diversification. The estimated effect on the aggregate variance component is estimated between 1.8 and 2.3%. It is notably lower when we use the Herfindahl index as measure of how well-diversified individual firms are because, in our data, even the most diversified firms in the product dimension have a high Herfindahl index. This is consistent with the view that individual exporters specialize in one or two "core" products.

The bottom panel in Table 11 investigates the benefit one would expect from less connectedness in trade networks. Here, the counterfactual scenario is a world in which no foreign buyer interacts with two distinct firms in France, i.e. the connectedness in trade networks is set to zero. The potential effect is substantial, namely a reduction in the variance component of about 5% and a 3.75% drop in aggregate fluctuations.

While the exact number are not especially informative, these counterfactual exercises suggest that the potential effect of firms adjusting the structure of their trade networks towards more diversification and less connectedness is potentially significant. This suggests that the source of aggregate volatility in trade that our paper emphasizes is quantitatively important.

3 Endogenous trade networks

The previous section has documented new patterns in bilateral trade data that generate granular fluctuations. The second step in the paper consists in building a theoretical model in which those patterns arise endogenously. The model can

then be used to study the structural determinants of aggregate fluctuations in trade data.

3.1 A model of matching frictions

In order to replicate the patterns in individual trade networks that were just identified in French data, we build a model of matching between sellers located in a given country and buyers located in a foreign market. While the previous theoretical literature has extensively studied the allocation of individual exporters' sales across countries (Melitz, 2003; Eaton et al., 2011), little is known about the allocation of sales within country, across individual buyers. Two recent exceptions are Bernard et al. (2014) and Carballo et al. (2013) that both build models of two-sided heterogeneity in which heterogeneous exporters meet heterogeneous buyers in international markets. These papers characterize the optimal allocation of sales across buyers in equilibrium. Both models deliver predictions that are qualitatively similar to the ones we obtain, in expectation. However, firm-to-firm matching is purely deterministic in their framework which does not make it well-suited for further structural estimation. Since the objective in this section is to build a model which parameters can be estimated structurally, before being used to simulate and study the sources of granular fluctuations, we instead rely on a probabilistic model.

Our model has N countries indexed by $i = 1, ..., N$ and K goods ($k = 1, ..., K$). In each country, there are buyers and sellers of good k. The market for good k is perfectly competitive and opened to international trade. Firms buy goods to the lowest cost supplier they have access to which is potentially located in any country in the world. In that sense, our model follows the tradition first introduced by Eaton and Kortum (2002). While this strand of the literature implicitly assumes that the process of buyers choosing their supplier is frictionless, we instead introduce the possibility that there are matching frictions between buyers and sellers. The purpose of these matching frictions is to explain why French exporters of the same narrowly defined goods end up being heterogeneous in terms of the number of buyers they serve, within a destination. In the rest of the section, we first present the supply side of the model, which closely follows the above-mentioned tradition, before introducing matching frictions on the demand side.

Supply side. There is a mass of heterogeneous producers of good k in each producing country j. Firms produce with a technology that involves an input bundle paid at cost c_{jk}. The productivity at which they transform this input bundle into a final good is heterogeneous across firms. As standard in the literature, the productivity $z_{s(j)k}$ of a firm located in country j is the realization of a random variable drawn from a Pareto distribution with parameter θ_k so that:

$$Pr[z_{s(j)k} > z | z \geq \underline{z}] = (z/\underline{z})^{-\theta_k}$$

where $\underline{z}$ denotes the (homogenous) minimum efficiency level a firm can draw, that can take values arbitrarily closed to zero. The Pareto assumption implies that the measure of firms that can produce good k with efficiency above z is:

$$\mu_{jk}^{z}(z) = T_{jk} z^{-\theta_k}$$

where $T_{jk} > 0$ is a parameter reflecting the overall measure of firms in country j.[18]

The market for good k is perfectly competitive. Given its productivity level, the CIF price at which firm $s(j)$ serves market i is:

$$p_{s(j)ik} = \frac{d_{ijk} c_{jk}}{z_{s(j)k}}$$

where d_{ijk} denotes the iceberg cost between j and i.

Under these assumptions, the measure of firms from j that can serve market i in good k at a price lower than p is:

$$\mu_{ijk}(p) = \mu_{jk}^{z}\left(\frac{d_{ijk} c_{jk}}{p}\right) = T_{jk}\left(\frac{d_{ijk} c_{jk}}{p}\right)^{-\theta_k}$$

Summing over all producing countries gives the measure of firms that can offer good k to buyers in country i at a price lower than p:

$$\mu_{ik}(p) = p^{\theta_k} \sum_{j=1}^{N} T_{jk} \left(d_{ijk} c_{jk}\right)^{-\theta_k} = p^{\theta_k} \Upsilon_{ik}$$

where $\Upsilon_{ik} \equiv \sum_{j=1}^{N} T_{jk} \left(d_{ijk} c_{jk}\right)^{-\theta_k}$ is a term reflecting the "multilateral resistance" in country i. In Eaton and Kortum (2002), all buyers in country i would simply choose the lowest cost producer in the $\mu_{ik}(p)$ distribution and all other potential producers would be inactive in market i.[19] This however assumes that there is no friction in the matching process, an assumption that we now relax.

Demand side. A buyer $b(i)$ from country i allocates $Y_{b(i)k}$ units of numeraire to the purchase of good k. With perfectly substitutable varieties, a buyer chooses the cheapest possible variety, among the set $S_{b(i)k}$ that it is offered:

$$p_{b(i)k} = min_{s(j) \in S_{b(i)k}} \{p_{s(j)ik}\}$$

In the absence of any search friction, $S_{b(i)k}$ would be the same for all buyers of good k and would simply be the universe of price quotes offered by any

[18] Namely, the total measure of firms in country j is equal to $T_{jk} \times \underline{z}^{-\theta}$.

[19] Another consequence of the frictionless assumption is that, within a producing country, only one potential producer is active in equilibrium, the other ones ending up serving zero buyers in all potential markets. In that sense, Eaton and Kortum (2002) is a model in which the productivity heterogeneity is not across firms but across goods. This is not the case in our model in which even less productive firms within a country can end up serving a strictly positive number of consumers.

producer of good k located in any country in the world, as summarized in $\mu_{ik}(p)$. Following Eaton, Kortum and Kramarz (2014), we however assume that there are search frictions.

Each buyer $b(i)$ of good k meets a countable number of price quotes $D_{b(i)k}$ randomly chosen in the $\mu_{ik}(p)$ distribution. The number of price quotes is itself a random variable distributed Poisson with a parameter $\lambda_{ik}\sum_{j=1}^{N} T_{jk}\underline{z}^{-\theta_k}$. In this framework, $\lambda_{ik} \leq 1$ interprets as the efficiency of the matching between buyers in i and sellers of good k. The higher λ_{ik}, the lower the intensity of matching frictions on market k and country i. In the limit, when $\lambda_{ik} = 1$, all buyers in market i draw as many price quotes as offered in the market. In equilibrium, they all choose the same supplier, as in Eaton and Kortum (2002). Under matching frictions ($\lambda_{ik} < 1$), however, buyers are heterogeneous ex-post in the sample of price quotes they are offered, which explains heterogeneous choices of a supplier, despite perfect substitutability between goods produced by those suppliers.

The Poisson assumption is convenient because it implies that the minimum price at which a buyer $b(i)$ can purchase good k is distributed Weibull with a location parameter $\lambda_{ik}\Upsilon_{ik}$ and a shape parameter θ_k:[20]

$$G_{ik}(p) = 1 - e^{-\lambda_{ik}\Upsilon_{ik}p^{\theta_k}}$$

A larger location parameter (i.e. lower search frictions or tougher competition) means that a lower price is more likely. A higher value for θ_k means that prices are less disbursed.

Implications of the model. In equilibrium, the share of goods produced in j in the total consumption of good k addressed by buyers from i is equal to the sum over all buyers in the economy of demand addressed to buyers in j divided by the total demand:

$$\pi_{ijk} = \frac{\sum_{b(i)=1}^{\#_{ik}} Y_{b(i)k} I_{b(i)j}^{k}}{\sum_{b(i)=1}^{\#_{ik}} Y_{b(i)k}}$$

where $\#_{ik}$ is the (finite) number of buyers of good k in country i and $I_{b(i)j}^{k}$ is a dummy equal to one if the buyer chooses a seller located in country j. This

[20]Under the Pareto assumption, the probability that a buyer having drawn $D_{b(i)k}$ price quotes ends up paying a price above p is:

$$Pr[min_{s(j)\in S_{b(i)k}}\{p_{s(j)ik}\} > p | D = D_{b(i)k}] = \left[1 - \frac{p^{\theta_k}\Upsilon_{ik}}{\sum_{j=1}^{N} T_{jk}\underline{z}^{-\theta}}\right]^{D_{b(i)k}}$$

The unconditional probability is thus:

$$\begin{aligned} Pr[min_{s(j)\in S_{b(i)k}}\{p_{s(j)ik}\} > p] &= \sum_{d=0}^{+\infty}\left[1 - \frac{p^{\theta_k}\Upsilon_{ik}}{\sum_{j=1}^{N} T_{jk}\underline{z}^{-\theta}}\right]^{d}\left[\frac{\left(\lambda_{ik}\sum_{j=1}^{N} T_{jk}\underline{z}^{-\theta}\right)^{d} e^{-\lambda_{ik}\sum_{j=1}^{N} T_{jk}\underline{z}^{-\theta}}}{d!}\right] \\ &= e^{-\lambda_{ik}\Upsilon_{ik}p^{\theta_k}} \end{aligned}$$

expression simplifies a lot if one assumes the number of buyers to be sufficiently large. Under this assumption, the dummy variable can be replaced by the probability that any buyer chooses a k-provider from j, which is constant and homogenous across buyers. Namely:

$$\pi_{ijk} = \frac{\sum_{b(i)=1}^{\#_{ik}} Y_{b(i)k} \frac{\mu_{ijk}(p)}{\mu_{ik}(p)}}{\sum_{b(i)=1}^{\#_{ik}} Y_{b(i)k}} = \frac{\mu_{ijk}(p)}{\mu_{ik}(p)} = \frac{T_{jk}\left(d_{ijk}c_{jk}\right)^{-\theta_k}}{\Upsilon_{ik}}$$

As in Eaton and Kortum (2002), the trade share π_{ijk} is equal to the probability that a given firm from country j is chosen, which only depends on the technology in country j, in relative terms with respect to other countries. This property implies that the gravity structure of the model is maintained, despite additional search frictions:

$$\ln Y_{ijk} = \ln T_{jk} c_{jk}^{-\theta_k} + \ln Y_{ik} - \ln \Upsilon_{ik} - \theta_k \ln d_{ijk} \tag{6}$$

where $Y_{ijk} = \sum_{b(i)=1}^{\#_{ik}} Y_{b(i)k} I_{b(i)j}^{k}$ is the total value of trade between countries j and i in sector k and $Y_{ik} = \sum_{b(i)=1}^{\#_{ik}} Y_{b(i)k}$ is country i's total consumption of good k. This equation can easily be estimated to recover estimates for θ_k.

The ex-post heterogeneity of buyers implies additional predictions concerning the probability that a given supplier ends up being the good k-provider of a buyer in country i, thus the number of buyers that any supplier serves. Namely, the probability that a firm of country j that has drawn a productivity $z_{s(j)k}$ is the lowest cost provider for a buyer $b(i)$ is equal to the probability that $S_{b(i)k}$ contains zero price quotes below the price offered by $s(j)$ times the probability that $s(j)$ ends up in the set of price quotes drawn by $b(i)$ i.e.:[21]

$$Pr(I_{b(i)s(j)}^{k} = 1) = \lambda_{ik} \times e^{-\lambda_{ik}\Upsilon_{ik}\left(\frac{d_{ijk}c_{jk}}{z_{s(j)k}}\right)^{\theta_k}} = \lambda_{ik} \times e^{-\lambda_{ik}\frac{u_{s(j)k}}{\pi_{ijk}}} = \rho_{s(j)ik}$$

where $I_{b(i)s(j)}^{k}$ is a dummy equal to one if $s(j)$ is chosen by $b(i)$ for the input k. $\pi_{ijk} = \frac{Y_{ijk}}{Y_{ik}}$ is the (observed) market share of country j in country i and sector k, and $u_{s(j)k} = T_{jk} z_{s(j)k}^{-\theta_k}$ is the standardized unit cost of seller $s(j)$ - which does not depend on any parameter.

The probability of a seller being chosen as k-provider by any buyer $b(i)$ is decreasing in the extent of matching frictions and the toughness of competition in market k of country j while increasing in the cost competitiveness of country i and the productivity of the firm. It is independent of the identity of the buyer, which means that buyers are homogenous in terms of their expected portfolio of providers.

From this, one can easily derive a prediction about the *expected* number of clients that a producer serves in a given market, which is simply the number of

[21]The probability that any seller offering a price p ends up in the set of price quotes of a buyer is $\frac{\mu_{ik}(p)\lambda_{ik}}{\mu_{ik}(p)} = \lambda_{ik}$.

potential buyers times the probability that any buyer chooses $s(j)$:

$$E(\#_{s(j)ik}) = \#_{ik} \times \lambda_{ik} \times e^{-\lambda_{ik}\Upsilon_{ik}\left(\frac{d_{ijk}c_{jk}}{z_{s(j)k}}\right)^{\theta_k}} = \#_{ik} \times \lambda_{ik} \times e^{-\lambda_{ik}\frac{u_{s(j)k}}{\pi_{ijk}}} \tag{7}$$

where $\#_{ik}$ denotes the number of potential buyers of good k located in country i and $E(\#_{s(j)ik})$ the *expected* number of clients in firm $s(j)$'s portfolio. In expectation, more productive sellers thus have more buyers in their portfolio, a prediction that can also be recovered from Bernard et al. (2014) and Carballo et al. (2013).

In order to match the model with observed moments on the *realization* of the number of clients per seller in our data, it is convenient to compute the expected mass of firms serving a given number of buyers, taking into account all the possible realizations in the number of clients per seller and their relative probabilities. Namely, the probability that a firm $s(j)$ has exactly M clients is:

$$\begin{aligned} Pr(\#_{s(j)ik} = M) &= \binom{M}{\#_{ik}} \left[\lambda_{ik} \times e^{-\lambda_{ik}\Upsilon_{ik}\left(\frac{d_{ijk}c_{jk}}{z_{s(j)k}}\right)^{\theta_k}}\right]^M \left[1 - \lambda_{ik} \times e^{-\lambda_{ik}\Upsilon_{ik}\left(\frac{d_{ijk}c_{jk}}{z_{s(j)k}}\right)^{\theta_k}}\right]^{\#_{ik}-M} \\ &= \binom{M}{\#_{ik}} \left[\rho_{s(j)ik}\right]^M \left[1 - \rho_{s(j)ik}\right]^{\#_{ik}-M} \end{aligned}$$

This probability is conditional on a realization of the firm's productivity level, thus her standardized unit cost. From this, one can derive the expected mass of sellers from j with exactly M clients. It is the integral of the probability of having exactly M clients, computed over the whole distribution of z:

$$\begin{aligned} f(M) &= -\int_{\underline{z}}^{+\infty} \binom{M}{\#_{ik}} \left[\lambda_{ik} \times e^{-\lambda_{ik}\Upsilon_{ik}\left(\frac{d_{ijk}c_{jk}}{z_{s(j)k}}\right)^{\theta_k}}\right]^M \left[1 - \lambda_{ik} \times e^{-\lambda_{ik}\Upsilon_{ik}\left(\frac{d_{ijk}c_{jk}}{z_{s(j)k}}\right)^{\theta_k}}\right]^{\#_{ik}-M} d\mu^z_{jk}(z) \\ &= \frac{\pi_{ijk}}{\lambda_{ik}} \binom{M}{\#_{ik}} \int_{\underline{\rho}_{ijk}}^{\lambda_{ik}} \rho^{M-1}_{s(j)ik} \left[1 - \rho_{s(j)ik}\right]^{\#_{ik}-M} \, d\rho_{s(j)ik} \end{aligned}$$

where $\underline{\rho}_{ijk} = \lambda_{ik} \times e^{-\lambda_{ik}\frac{\bar{u}_{jk}}{\pi_{ijk}}}$ is the probability that the less efficient firm is chosen.

For $M > 0$, this simplifies into:[22]

$$f(M) = \frac{\pi_{ijk}}{\lambda_{ik}} \frac{1}{M} \Big(I_{\lambda_{ik}}(M, \#_{ik} - M + 1) - I_{\underline{\rho}_{ijk}}(M, \#_{ik} - M + 1) \Big)$$

[22] For $M = 0$, the integral becomes:

$$f(0) = \frac{\pi_{ijk}}{\lambda_{ik}} \left[\sum_{i=1}^{\#_{ik}} (-1)^i \binom{\#_{ik}}{i} \frac{\lambda^i_{ik} - \underline{\rho}^i_{ijk}}{i} + \ln(\lambda_{ik}) - \ln(\underline{\rho}_{ijk}) \right]$$

Contrary to the formula discussed in the text, this does depend on non-observed parameters of the model (namely $\underline{\rho}_{ijk}$) and would thus be difficult to confront to the data. This is not necessarily a problem, however, since our dataset covers exporting firms only, thus sellers with at least one buyer.

where $I_{\lambda_{ik}}(M, \#_{ik} - M + 1) \equiv \frac{B(\lambda_{ik}; M, \#_{ik} - M+1)}{B(M, \#_{ik} - M+1)}$ denotes the regularized incomplete beta function. It is straightforward to see that as the minimum productivity ($\underline{z}$) goes to zero, $\underline{\rho}_{ijk}$ goes to zero as well. So assuming that the minimum productivity is sufficiently close to zero, we have:

$$f(M) \approx \frac{\pi_{ijk}}{\lambda_{ik}} \frac{1}{M} I_{\lambda_{ik}}(M, \#_{ik} - M + 1) \tag{8}$$

The mass of firms at each potential realization of the number of clients thus writes as a function of observable variables and the magnitude of matching frictions. This prediction can thus be confronted to the data to estimate λ_{ik}.

3.2 Estimation

3.3 Implication for granular fluctuations

4 Conclusion

A Appendix: Extension to multi-product firms

In this section, we extend the framework of section 2.1 to multi-product firms. More specifically, we now assume that a firm s may be selling several products, each indexed with p, either to the same or to different buyers. At the most aggregated level, the model is unaffected. Namely, the aggregate volatility of sales is still given by:

$$Var(g_{X_t}) = \sum_{s \in S} w_s^2 Var(g_{x_{st}}) + \sum_{s \in S} \sum_{s' \neq s} w_s w_{s'} Cov(g_{x_{st}}, g_{x_{s't}}) \tag{A.1}$$

What is different, however, are the variances and covariances at the level of an exporting firm. Now, the sales of an exporter s decompose as:

$$x_{st} = \sum_{b \in B_s} \sum_{p \in P_s} x_{sbpt}$$

where P_s is the set of products sold by s and x_{sbpt} the value of exports of product p, to buyer b. This implies that the variances and covariances are defined by:

$$Var(g_{x_{st}}) = Var\left(\sum_{b \in B_s} \sum_{p \in P_s} w_{bp}^s g_{x_{sbpt}}\right)$$
$$Cov(g_{x_{st}}, g_{x_{s't}}) = Var\left(\sum_{b \in B_s} \sum_{p \in P_s} w_{bp}^s g_{x_{sbpt}}, \sum_{b \in B_{s'}} \sum_{p \in P_{s'}} w_{bp}^{s'} g_{x_{s'bpt}}\right)$$

where w_{bp}^s is the share of the transaction bp in firm s sales.

The structure of shocks is also enriched with additional product-specific shocks:

$$g_{x_{sbpt}} = \underbrace{\varepsilon_{St} + \varepsilon_{st} + \varepsilon_{pt} + \varepsilon_{spt}}_{Supply\ Shocks} + \underbrace{\varepsilon_{Bt} + \varepsilon_{bt} + \varepsilon_{bpt}}_{Demand\ Shocks} + \varepsilon_{sbt} + \varepsilon_{spbt} \tag{A.2}$$

To simplify, all those shocks are assumed orthogonal to each other and uncorrelated over time and across microeconomic units (i.e. $Cov(\varepsilon_{it}, \varepsilon_{i't}) = 0\ \forall i \neq i'$, $i = s, p, sp, b, bp, sb, spb$).

In this model, there is another dimension in which firms can diversify, namely the product dimension. Intuitively, having more products in its portfolio is a way for the firm to hedge against idiosyncratic risk to products. Using the same kind of reasoning as in the text, the decomposition of the aggregate variance of exports is:

$$\begin{aligned}
Var(g_{X_t}) \approx\ & \underbrace{Var(\varepsilon_{St}) + Var(\varepsilon_{Bt})}_{Macroeconomic\ volatility} + \underbrace{\sum_{s\in S} w_s^2 Var(\varepsilon_{st})}_{Pure\ granular\ volatility} \\
+ & \underbrace{\sum_{s\in S} w_s^2 \sum_{b\in B_s} w_b^{s\,2} \left[Var(\varepsilon_{bt}) + Var(\varepsilon_{sbt})\right]}_{Across-buyer\ diversifiable\ granular\ volatility} + \underbrace{\sum_{s\in S} w_s^2 \sum_{p\in P_s} w_p^{s\,2} \left[Var(\varepsilon_{pt}) + Var(\varepsilon_{spt})\right]}_{Across-product\ diversifiable\ granular\ volatility} \\
+ & \underbrace{\sum_{s\in S} w_s^2 \sum_{b\in B_s} \sum_{p\in P_s} {w_{bp}^{s}}^{2} \left[Var(\varepsilon_{bpt}) + Var(\varepsilon_{sbpt})\right]}_{Across-buyer-product\ diversifiable\ granular\ volatility} \\
+ & \underbrace{\sum_{s\in S} \sum_{s'\neq s} w_s w_{s'} \sum_{b\in B_s\cap B_{s'}} w_b^s w_b^{s'} Var(\varepsilon_{bt})}_{Pure\ network\ volatility\ through\ common\ buyers} + \underbrace{\sum_{s\in S} \sum_{s'\neq s} w_s w_{s'} \sum_{p\in P_s\cap P_{s'}} w_p^s w_p^{s'} Var(\varepsilon_{pt})}_{Pure\ network\ volatility\ through\ common\ products} \\
+ & \underbrace{\sum_{s\in S} \sum_{s'\neq s} w_s w_{s'} \sum_{b\in B_s\cap B_{s'}} \sum_{p\in P_s\cap P_{s'}} w_{bp}^s w_{bp}^{s'} Var(\varepsilon_{bpt})}_{Pure\ network\ volatility\ through\ common\ buyers-products}
\end{aligned} \tag{A.3}$$

Table 1: Summary statistics on the French-Spanish trade network

	2005	2009
Value of exports	3.37e+10	2.52e+10
# of sellers	23,146	20,379
# of buyers	80,486	74,292
# of 8-digit products	6,974	6,869
# of buyer-seller pairs	169,356	150,466
# of buyer-seller-product triplets	578,864	575,606
Completeness	0.00009	0.00010

Notes: Summary statistics computed on 2005 and 2009 data on French exports to Spain. The "Completeness" of the network is defined as the number of bilateral relationships divided by the maximum number of transactions that could be observed (equal to the number of buyers times the number of sellers).

Table 2: Diversification of sellers depending on their size

	Across buyers		**Across products**	
	Degree	**Herfindahl**	**Degree**	**Herfindahl**
	(1)	(2)	(3)	(4)
0-20 quintile	1 (1.6)	1 (.87)	1 (1.9)	1 (.89)
20-40 quintile	2 (3.0)	0.9 (.75)	1 (2.8)	1 (.81)
40-60 quintile	2 (5.0)	0.7 (.68)	1 (4.1)	1 (.94)
60-80 quintile	3 (8.9)	0.6 (.62)	2 (5.9)	.85 (.73)
80-100 quintile	5 (18.1)	0.5 (.55)	4 (13.2)	.70 (.66)
Top 100 firms	6 (18.4)	0.7 (.61)	11 (44.6)	.48 (.51)

Notes: Based on data on French-Spanish trade flows for 2005, this table shows summary statistics on the diversification of sellers, depending on their position in the distribution of individual exports. Each column reports the median value of the statistics and the mean under parentheses. The degree is defined as the number of buyers or nc8-products per seller. The Herfindahl index is defined as $Herf_s = \sum_{b \in B_s} {w_b^s}^2$, where w_b^s is the share of buyer (or product) b in exporter s sales.

Table 3: Determinants of firm level diversification

	ln # buyers	ln # buyers	ln Herfindahl	ln Herfindahl	ln Herfindahl
	(1)	(2)	(3)	(4)	(5)
ln size of the seller	0.02**	0.03***	0.02***	-0.08***	-0.05***
	(0.011)	(0.011)	(0.002)	(0.010)	(0.007)
ln experience in Spain	0.08***	0.08***	0.01	-0.01	0.00
	(0.022)	(0.022)	(0.006)	(0.011)	(0.011)
ln # products	0.40***	0.39***	-0.45***		
	(0.020)	(0.021)	(0.014)		
ln Herfindahl ac. products				0.17***	0.10***
				(0.011)	(0.008)
$\mathbb{1} = 1$ if seller is a wholesaler	-0.10***	-0.11***	-0.05***	-0.19***	-0.10***
	(0.026)	(0.025)	(0.008)	(0.019)	(0.013)
$\mathbb{1} = 1$ if Spanish headquarter	-0.15*	-0.15*	0.03	-0.08	-0.05
	(0.086)	(0.087)	(0.039)	(0.062)	(0.061)
$\mathbb{1} = 1$ if affiliates in Spain	-0.42***	-0.42***	0.07*	-0.19***	-0.06
	(0.112)	(0.112)	(0.037)	(0.062)	(0.046)
ln potential # of buyers		0.06***			
		(0.015)			
ln potential Herfindahl					0.24***
					(0.037)
FE	Main 2-digit sector of the firm				
# obs.	16,661	16,661	16,661	16,661	16,661
R-squared	0.143	0.148	0.696	0.129	0.399

Robust standard errors in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels. "ln potential # of buyers" is the log of a (weighted) average of the number of firms buying at least one variety (whatever the exporter buying it) in each *nc*8 sector in which the exporter is active. "ln potential Herfindahl" is the log of the Herfindahl that the firm would display if it was serving each potential buyer of its *nc*8 products in proportion of their total purchases.

Table 4: Diversification of buyers depending on their size

	Across sellers		**Across products**	
	Degree	**Herfindahl**	**Degree**	**Herfindahl**
	(1)	(2)	(3)	(4)
0-20 quintile	1 (1.1)	1 (.98)	1 (1.8)	1 (.86)
20-40 quintile	1 (1.2)	1 (.94)	2 (3.3)	.94 (.73)
40-60 quintile	1 (1.5)	1 (.88)	2 (5.7)	.71 (.66)
60-80 quintile	1 (2.2)	1 (.81)	3 (9.4)	.63 (.62)
80-100 quintile	2 (4.5)	.82 (.73)	4 (14.3)	.60 (.61)
Top 100 firms	14 (34.3)	.65 (.64)	39 (95.0)	.33 (.40)

Notes: Based on data on French-Spanish trade flows for 2005, this table shows summary statistics on the diversification of sellers, depending on their position in the distribution of individual exports. Each column reports the median value of the statistics and the mean under parentheses. The degree is defined as the number of sellers or nc8-products per buyer. The Herfindahl index is defined as $Herf_b = \sum_{j \in B_j} {w_j^b}^2$, where w_j^b is the share of buyer (or product) j in importer b sales.

Table 5: Impact of the more strongly connected buyers in trade networks

x	Degree	Cumulated share of the x more strongly connected buyers in indirect connections (%)	in the value of exports (%)
1	292	6.8	5.9
2	276	12.6	10.1
3	218	16.8	10.2
4	199	19.9	10.5
5	184	22.7	10.7
6	135	24.1	11.9
7	123	25.3	12.7
8	96	26.1	12.9
9	93	26.7	12.9

This table displays the combined effect of the largest buyers, in terms of how strongly connected they are, as a vector of indirect connections and as a share in the value of imports. The more strongly connected buyers are identified according to the number of sellers they interact with. The buyer corresponding to $x = 1$ is thus the Spanish firm interacting with the largest number of French exporters in 2005 data. Its degree (the number of sellers in its portfolio) is indicated in the second column. Its share in indirect connections is computed by comparing the total number of indirect connections in the network of sellers and the number one would obtain if the largest buyer disappeared from the dataset. Its share in the value of exports is simply equal to the value of its imports relative to the total value of exports from France.

Table 6: Connectedness of pairs of sellers

Connected sellers	
# of connected pairs	584,679
# of common buyers (median)	1
# of common buyers (mean)	1.4
# of potential pairs	2.678×10^8
Share connected	.0022
Conditional probability of pairing in the same:	
8-digit sector	.13
6-digit sector	.15
4-digit sector	.21
2-digit sector	.35
1-digit sector	.54
Connectedness (conditional on being connected)	
Mean($\sum_b w_b^s w_b^{s'}$)	.164
Median($\sum_b w_b^s w_b^{s'}$)	.015
Pair-weighted connectedness (conditional on being connected)	
$\sum_{s,s'} w_s w_{s'} \sum_b w_b^s w_b^{s'}$	.008

Notes: This table gives statistics on the connectedness of sellers in Spain, in 2005. The first panel is the number of indirect connections through common buyers, in comparison with the potential equal to half of the number of sellers times the number of sellers minus 1. It also gives the mean and median number of buyers connecting any pair of sellers. The second panel reports the probability that connected firms belong to the same industry, conditional on being connected. The third panel corresponds to the mean and median value of the connectedness indicator, conditional on the firms being connected. The fourth panel is the weighted average of the connectedness indicator, where the weights correspond to the relative size fo the connected sellers in aggregate exports.

Table 7: Summary statistics on the seller-buyer matching

	Rank correlation
Value of exports	0.12
Degree	-0.26
Herfindahl index	-0.14

Notes: This table gives rank correlations between characteristics of sellers and characteristics of the buyers they are connected with. The characteristics we consider are their sizes, as measured by the total value of their exports/imports, as well as their degree of diversification, as measured by the degree and the Herfindahl index of their sales/purchases. A positive correlation means that sellers tend to match with buyers that tend to be positioned as they are in the distribution of firms.

Table 8: Diversification and volatility of sales at the firm level

	Dep.var: ln Variance of export growth (96-07)			
	(1)	(2)	(3)	(4)
ln # buyers	-0.08***	-0.06***		
	(0.010)	(0.011)		
ln # products		-0.09***		
		(0.009)		
ln Herfindahl ac. buyers			0.09***	0.08***
			(0.013)	(0.014)
ln Herfindahl ac. products				0.08***
				(0.015)
ln size of the seller	-0.06***	-0.05***	-0.07***	-0.07***
	(0.007)	(0.006)	(0.006)	(0.006)
ln experience in Spain	0.12***	0.15***	0.12***	0.14***
	(0.024)	(0.027)	(0.024)	(0.027)
$\mathbb{1} = 1$ if seller is a wholesaler	0.13***	0.17***	0.13***	0.16***
	(0.018)	(0.022)	(0.018)	(0.021)
$\mathbb{1} = 1$ if Spanish headquarter	0.13*	0.10	0.13*	0.09
	(0.068)	(0.075)	(0.070)	(0.075)
$\mathbb{1} = 1$ if affiliates in Spain	-0.23**	-0.21**	-0.23**	-0.24**
	(0.094)	(0.100)	(0.095)	(0.101)
Sample	All	rest1	All	rest1
FE	Main 2-digit sector of the firm			
# obs.	17,164	13,818	17,164	13,818
R^2	0.032	0.051	0.028	0.040

Robust standard errors in parentheses with ^{a}, ^{b} and ^{c} respectively denoting significance at the 1, 5 and 10% levels. Columns (2) and (4) exclude firms with a single product and a single buyer (for these firms the product- and buyer-diversification are the same) - this is the sample called “rest1”.

Table 9: Connectedness and the comovement in sales across exporters

	Dep. var: Covariance in export growth (96-07)			
	(1)	(2)	(3)	(4)
# common buyers	0.013***	0.014***		
	(.001)	(.003)		
Share of common buyers in sales			0.040***	0.031***
			(.004)	(.007)
$\mathbb{1} = 1$ if same group	-0.002	0.010	-0.005	0.008
	(.005)	(.012)	(.005)	(.012)
$\mathbb{1} = 1$ if same hs2 sector	0.002***		0.002***	
	(.000)		(.000)	
Sample	All	Same HS2	All	Same HS2
Observations ($\times 1,000,000$)	10.906	1.130	10.906	1.130
R^2				

Robust standard errors in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels. The left hand side variable is the covariance between the export growth of firms s and s'. "# common buyers" if the number of buyers that exporters s and s' have in common. " Share of common buyers in sales" is the share of those buyers in the firm's sales, on average for s and s'. "$\mathbb{1} = 1$ if same group" is a dummy equal to one if the firms which comovement in sales is measured belong to the same group. "$\mathbb{1} = 1$ if same hs2 sector" is equal to one if they belong to the same 2-digit sector.

Table 10: Volatility of aggregate exports to Spain, 1996-2007

Variable	Formula	Value ($\times 100$)	Share (pct)
Agg. variance (true)	$Var(g_{X_t})$	1.09	100
Agg. variance (cons.weights)	$Var(\sum_s w_s g_{x_{st}})$	1.35	123.9
Ind. variances	$\sum_{s \in S} w_s^2 Var(g_{x_{st}})$	0.35	32.1
Covariances	$\sum_{s \in S} \sum_{s' \neq s} w_s w_{s'} Cov(g_{x_{st}}, g_{x_{s't}})$	1.00	91.7

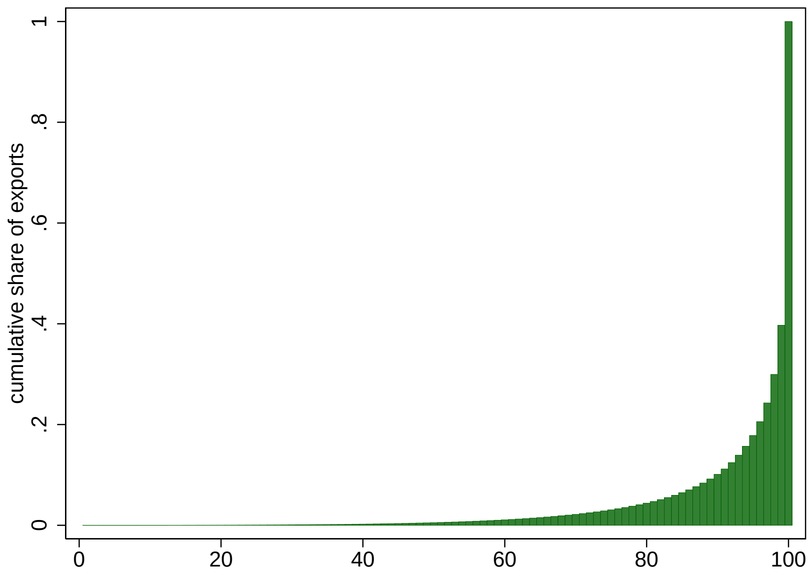
Notes: This table shows the variance of aggregate exports in the data, and its decomposition into the contribution of individual volatilities ("Ind. variances" term) and the contribution of covariances between sellers ("Covariances"). The weights are computed using 2005 data and the individual variance and covariance terms using export flows from 1995 to 2007. See details in Section 2.1.

Table 11: Counterfactual exercise

Variance component	True	Pred.	Count.	% Change
$\sum_s w_s^2 Var(g_{x_{st}})$				
# of buyers equal to p90 or more	.0036	.0034	.0033	-1.8
# of products equal to p90 or more	.0036	.0034	.0033	-2.3
Herfindahl of buyers equal to p10 or less	.0036	.0040	.0037	-8.3
Herfindahl of products equal to p10 or less	.0036	.0040	.0039	-1.8
$\sum_s \sum_{s' \neq s} w_s w_{s'} Cov(g_{x_{st}}, g_{x_{s't}})$				
# of common buyers equal to 0	.0092	.0104	.0099	-4.8
Share of trade to common buyers equal to 0	.0092	.0104	.0100	-4.0

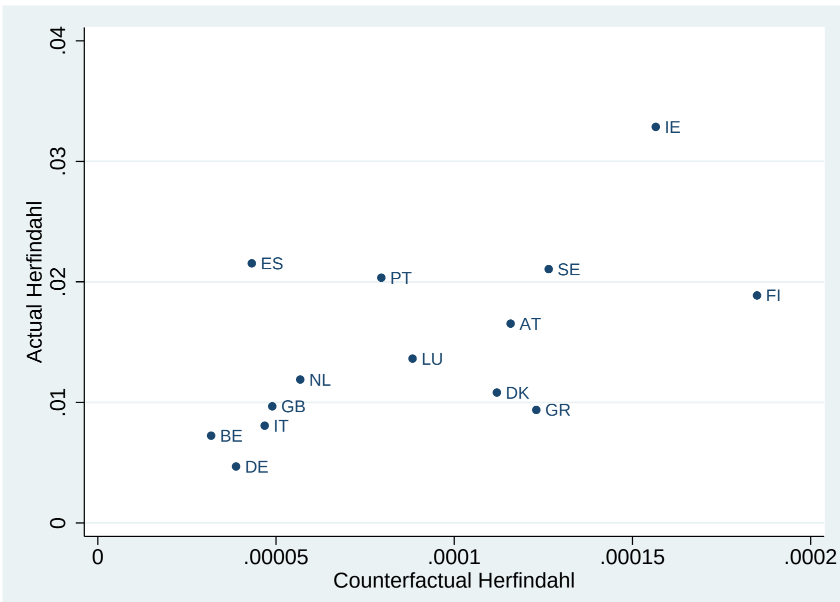
Notes: Based on regressions of Table 8, columns (2) and (4) (top panel) and of Table 9, columns (1) and (3) (bottom panel). The *True* variance component is the 2005-weighted average of individual variance and covariance terms. The *Pred.* variance component is the weighted average of predicted individual variance and covariance terms. The *Count.* variance component is the weighted average of predicted individual variance and covariance terms in the different counterfactual scenarios. In the top panel, the counterfactual scenarios consist in i) increasing the number of buyers of individual exporters in deciles 1-9 to the value observed for firms at the 90th percentile of the distribution and using the predicted variances obtained with coefficients in Column (2), ii) increasing the number of products in individual exporters' portfolio in deciles 1-9 to the value observed for firms at the 90th percentile of the distribution and using the predicted variances obtained with coefficients in Column (2), iii) reducing the Herfindahl index computed across buyers for individual exporters in deciles 2-10 to the value observed for firms at the 10th percentile of the distribution and using the predicted variances obtained with coefficients in Column (4), iv) reducing the Herfindahl index computed across products for individual exporters in deciles 2-10 to the value observed for firms at the 10th percentile of the distribution and using the predicted variances obtained with coefficients in Column (4). In the bottom panel, the scenarios consist in i) setting the number of buyers to zero and using the predicted covariances obtained with coefficients in Column (1), ii) setting the share of sales devoted to common buyers to zero and using the predicted covariances obtained with coefficients in Column (1)

Figure 1: Cumulated share of exporters in the total value of bilateral exports



This graph displays the share of the total value of French exports to Spain that is attributable to the **x**% smallest firms in the economy. For instance, the number that corresponds to the point 80 of the x-axis reads as follows: The cumulated contribution of the 80% smallest exporters is lower than 5%.

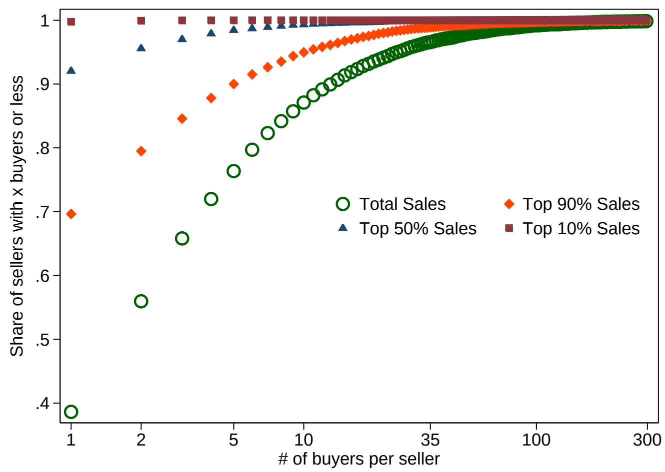
Figure 2: Actual and counterfactual Herfindahl indices for EU member countries



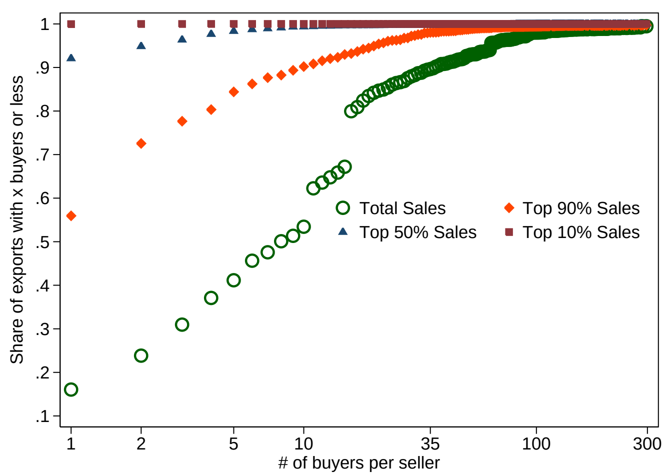
This graph displays the actual Herfindahl of sales, computed across exporters to one destination country, against the counterfactual Herfindahl index one would observe in a symmetric world in which all exporters have the same market share (i.e. one over the number of exporters). Computed with 2005 data on the distribution of exporter-level sales to one destination.

Figure 3: Number of Buyers per Seller

Share of sellers



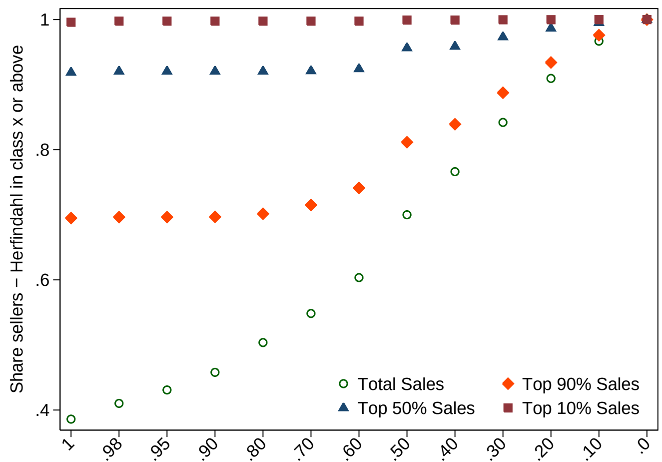
Value share



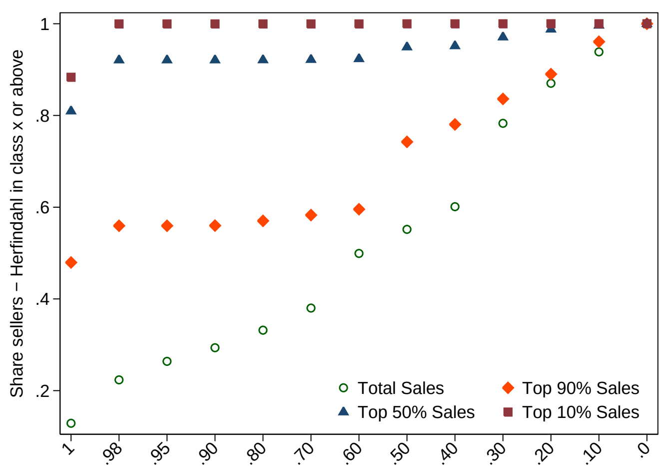
Proportion of sellers (top panel) and share of trade accounted for by sellers (bottom panel) that serve x buyers or less. Statistics based on the France-Spain export flows in 2005. The green circles correspond to total exports. The distributions labeled "Top X% Sales" are computed restricting the amount of each firm's sales to the X first percentiles of the distribution of sales when transactions are ordered by the decreasing share of the buyer in the firm's total sales. The line in red for instance interprets as follows: If, for each exporter, we neglect the set of the smallest buyers contributing to the last 10% of the exporter's sales, more than 70% of exporters have a degree of one buyer while only 5% have 10 buyers or more.

Figure 4: Herfindahl index across buyers, per seller

Share of sellers



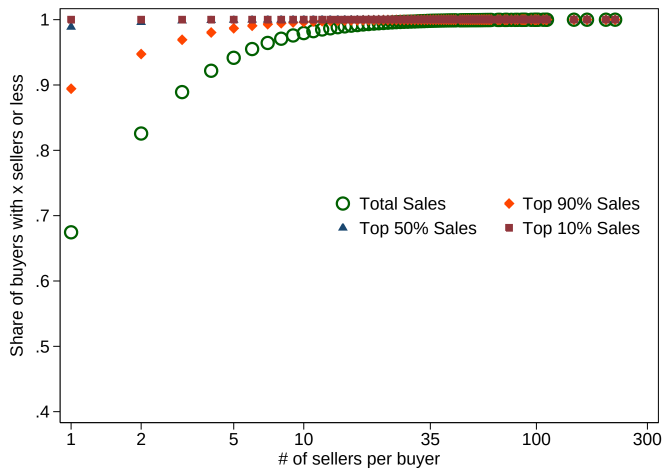
Value share



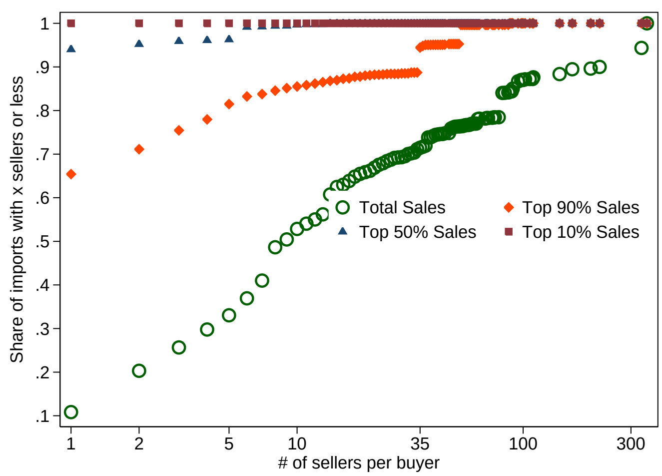
Proportion of sellers (top panel) and share of trade accounted for by sellers (bottom panel) that have a Herfindahl index of sales (across buyers) equal to x or more. The green circles correspond to total exports. The distributions labeled "Top X% Sales" are computed restricting the amount of each firm's sales to the X first percentiles of the distribution of sales when transactions are ordered by the decreasing share of the buyer in the firm's total sales. The line in red for instance interprets as follows: If, for each exporter, we neglect the set of the smallest buyers contributing to the last 10% of the exporter's sales, more than 70% of exporters have a Herfindahl above .80 while only 5% have Herfindahl lower than .10.

Figure 5: Number of Sellers per Buyer

Share of buyers



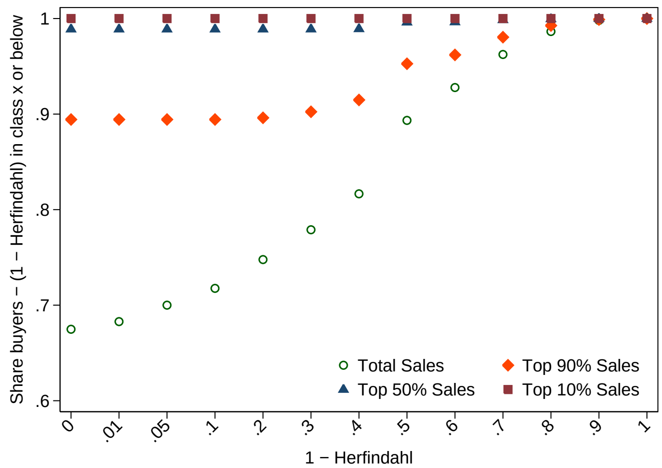
Value share



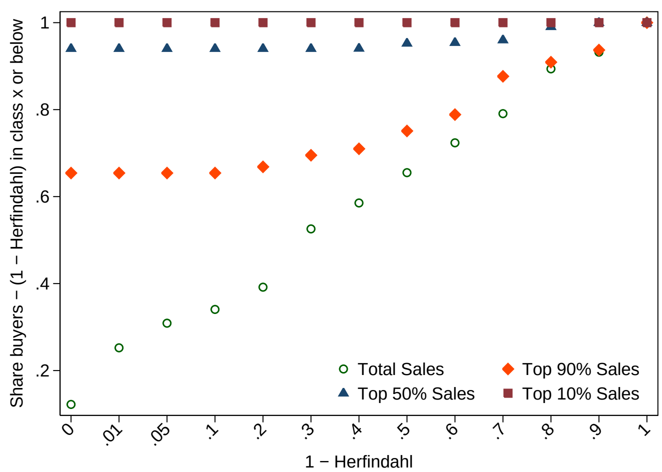
Proportion of buyers (top panel) and share of trade accounted for by buyers (bottom panel) that serve x sellers or less. Statistics based on the France-Spain export flows in 2005. The green circles correspond to total imports. The distributions labeled "Top X% Sales" are computed restricting the amount of each firm's purchases to the X first percentiles of the distribution of purchases when transactions are ordered by the decreasing share of the seller in the firm's total purchases.

Figure 6: Connectivity of buyers

Share of buyers



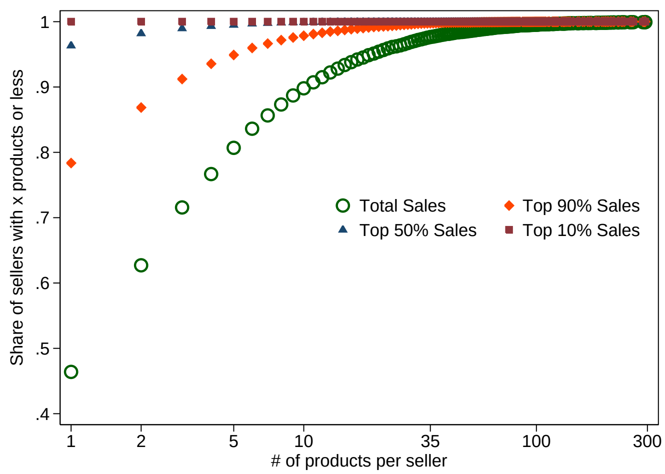
Value share



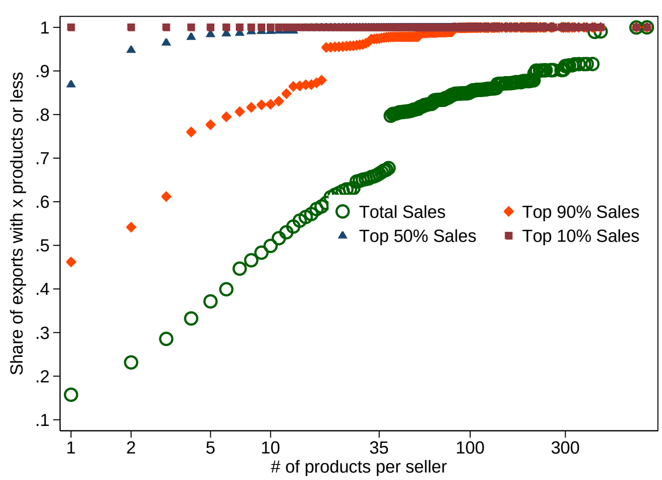
Proportion of buyers (top panel) and share of trade accounted for by buyers (bottom panel) that have a connectivity equal to x or less. A buyer's connectivity is defined as one minus the Herfindahl index of its purchases, computed across sellers it interacts with: $Connectivity_b = \sum_s \sum_{s' \neq s} w_s^b w_{s'}^b = 1 - Herf_b$. A connectivity of zero corresponds to a buyer having a single seller in France, thus creating zero indirect connections between sellers. The green circles correspond to total imports. The distributions labeled "Top X% Sales" are computed restricting the amount of each firm's purchases to the X first percentiles of the distribution of sales when transactions are ordered by the decreasing share of the seller in the firm's total purchases. The line in red for instance interprets as follows: If, for each importer, we neglect the set of the smallest sellers contributing to the last 10% of the importer's sales, more than 70% of importers have a connectivity above .80 while only 5% have a connectivity lower than .10.

Figure 7: Number of Products per Seller **Appendix**

Share of sellers



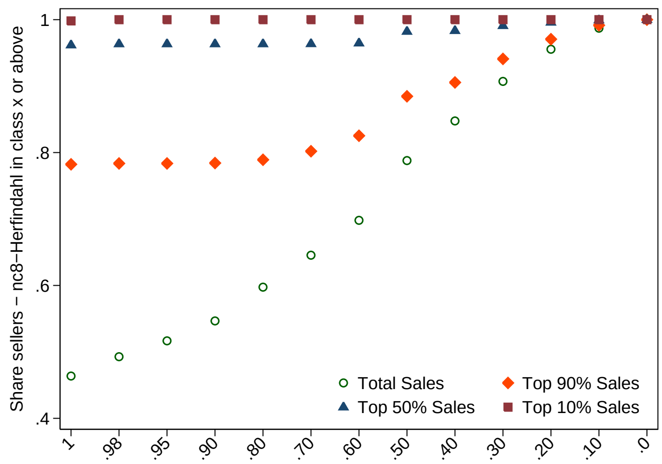
Value share



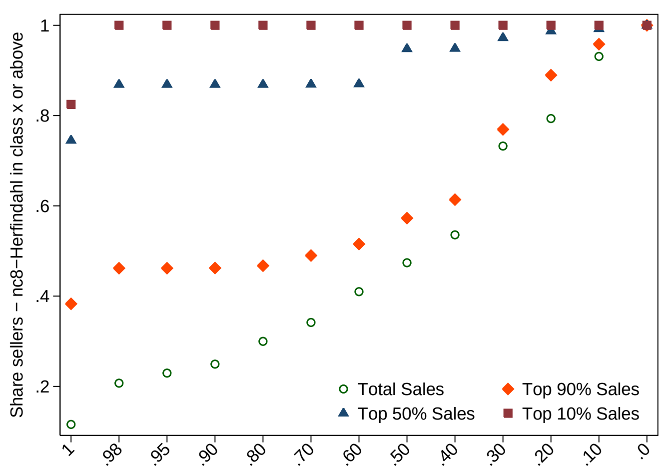
Proportion of sellers (top panel) and share of trade accounted for by sellers (bottom panel) that serve x products or less. Statistics based on the France-Spain export flows in 2005. The green circles correspond to total exports. The distributions labeled "Top X% Sales" are computed restricting the amount of each firm's sales to the X first percentiles of the distribution of sales when transactions are ordered by the decreasing share of the product in the firm's total sales.

Figure 8: Herfindahl index across buyers, per seller**Appendix**

Share in sellers



Value share



Proportion of sellers (top panel) and share of trade accounted for by sellers (bottom panel) that have a Herfindahl index of sales (across products) equal to x or more. The green circles correspond to total exports. The distributions labeled "Top X% Sales" are computed restricting the amount of each firm's sales to the X first percentiles of the distribution of sales when transactions are ordered by the decreasing share of the product in the firm's total sales.

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