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

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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. In our model, diversifying sales across a larger number of partners reduces the firm's exposure to idiosyncratic demand shocks, thus the volatility of its sales. Being connected with importers that also interact with other sellers creates comovements in sales across sellers. We show that both elements can generate "granular" fluctuations in aggregate exports. Based on highly detailed export data, we show that exporters are little diversified in sales and that trade networks are highly connected across exporters. This participates to explaining the high volatility of bilateral exports in our data.

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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 firm-to-firm linkages that help propagate shocks.[1] According to di Giovanni, Levchenko and Mejean (2012), 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 as well as the structure of the economy in which firms operate are both considered as given. Implicitly, each individual producer is hit by idiosyncratic supply shocks the volatility of which is exogenously given. And the structure of the economy determines the extent to which these supply shocks wash out at the aggregate level. This paper instead introduces the possibility that the volatility of individual sales is driven by a combination of supply *and* demand shocks. In the presence of idiosyncratic demand shocks, the way individual firms spread out their sales across potential buyers matters for their volatility. In particular, firms with more diversified sales (across buyers) hedge against idiosyncratic demand risk. Heterogeneity in the structure of buyers' portfolios thus translates into an heterogeneity in individual volatilities that will further affect aggregate fluctuations in a granular world.[2]

We study how idiosyncratic demand shocks affect individual and aggregate volatility using highly detailed panel data on trade networks. A useful feature of our data is that our records include the identity of both trade partners; the exporting *and* the importing firm. For each French exporter, we observe the allocation of sales over its full portfolio of foreign customers and the way it evolves over time. Essential for our approach, we are able to identify when an importer buys goods from several French firms, i.e. the extent to which trade networks are "connected".

We start with the structure of trade networks as observed in 2005. For each individual exporter, we observe the degree of diversification in sales across for-

[1]Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (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]There are reasons to believe that this source of heterogeneity in volatilities can be important in the data. First, di Giovanni et al. (2012) show that, in French data, larger firms are less volatile. This tends to mitigate the direct granular effect discussed in Gabaix (2011). Second, Chaney (2011) shows that heterogeneity across firms serving a given export market is correlated with the number of customers they serve. Large firms thus serve more customers. In our framework, this reduces their exposure to demand risks and thus the volatility of their sales. Having demand shocks in a model of granular fluctuations can thus help reconcile the predictions of the model with evidence of heterogeneity in volatilities.

eign partners, a measure of exposure to idiosyncratic demand risks. In the data, we show that the amount of heterogeneity in the structure of exporters' trade networks is huge. We also show that more diversified firms tend to display less volatility, on average.[3] In addition, trade networks are shown to be strongly connected, inducing covariance in sales across firms. Firms that share the same buyer face the same demand shocks. Moreover, sharing a buyer creates an indirect link between exporters, that could help propagate shocks. We study these indirect links in detail and show that their number and intensity is correlated with the covariance of sales across firms. We discuss theoretically and empirically how the low level of diversification as well as the connectedness of trade networks generate "granular" fluctuations in bilateral exports.[4]

Up to now, our presentation implicitly assumes that the structure of trade networks is exogenously given. However, shocks are likely to affect these networks; some old links being severed, others being newly created. Based on this intuition, we use the panel dimension of the data to say something on the endogeneity of trade networks and its impact on the long-run contribution of granularity to aggregate fluctuations. Namely, changes over time in the concentration and connectedness of trade networks transmit into larger or smaller granular fluctuations. Our objective here is to identify in the data how exporters adjust their sales to exogenous shocks affecting their network. This endogenous adjustment has consequences for the aggregate structure of the economy and its sensitivity to idiosyncratic shocks. We provide new evidence of such dynamic effects. Our identification assumption is that the death of some buyers in the aftermath of the 2008-2009 crisis can be interpreted as an exogenous shock to the trade network of French exporters. From the point-of-view of the exporter, the death of a buyer mechanically increases the concentration of sales, thus the firm's exposure to idiosyncratic demand shocks. In response to this shock, the firm may reallocate her sales among incumbent consumers and/or new partners, which would mitigate the impact of the initial shock. Finally, firms that are less diversified may be forced out of the market when hit by such shocks. This would increase the concentration of exports across producers, thus the "granularity" of the economy. We study the impact of such shocks both at the microeconomic and aggregate level.

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 con-

[3]The fact that the structure of a firm's portfolio of buyers matters for the volatility of its sales is also discussed in Kelly, Lustig and Nieuwerburgh (2013).

[4]Contrary to most of the literature that studies fluctuations in the aggregate GDP, we focus on the volatility in *bilateral exports*. Our data do not make it possible to identify trade networks in the domestic market of French firms. However, Canals, Gabaix, Vilarrubia and Weinstein (2007) and di Giovanni and Levchenko (2012) argue that the "granular" dimension of aggregate fluctuations is likely to be much more pronounced for export activities. Indeed, the self-selection of firms into export markets makes the distribution of firms selling abroad even more fat-tailed. This suggests that our estimates of how the absence of diversification across buyers generate aggregate fluctuations is an upper limit of what we would observe in total sales.

centration of sales across firms has been discussed by Gabaix (2011) in a closed economy and di Giovanni and Levchenko (2012) in an international framework. More 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; Kelly et al., 2013). We instead study the role of demand shocks and its interaction with the way individual firms allocate their sales across buyers. Some insights on the microeconomic determinants of such choices can be found in the new trade literature. The question of how firms allocate their sales across destination countries is central in such models (see for instance, Melitz, 2003 or Eaton, Kortum, and Kramarz, 2011). More recently, trade economists have started studying additional margins of adjustments, within countries. In particular, the increasing availability of transaction-level trade data makes it possible to test models in which heterogeneous exporters contract with heterogeneous consumers in destination markets. Bernard, Moxnes and Ulltveit-Moe (2013), Carballo, Ottaviano and Volpe Martincus (2013) and Benguria (2011) present models explaining the heterogeneity in the number of buyers that an exporter serves. More closely related to us, Eaton, Eslava, Krizan, Kugler and Tybout (2013), Dragusanu (2013) and Chaney (2011) study the matching process of exporters and importers. To our knowledge, this paper is the first one to infer consequences of these microeconomic decisions on individual and aggregate fluctuations.

The paper starts with a conceptual framework that builds on Gabaix (2011) and di Giovanni et al. (2012). We consider a world in which fluctuations are driven by several types of shocks: aggregate and idiosyncratic shocks to exporters ("supply shocks"), aggregate and idiosyncratic shocks to importers ("demand shocks") and importer- and exporter-specific shocks ("match-specific shocks"). In this framework, the aggregate variance of export growth writes as a weighted average of exporter-specific volatilities and covariances in sales between exporters. As in Gabaix (2011), this variance is larger if sales are more concentrated across exporters because idiosyncratic shocks to large firms do not wash out at the aggregate level. This is how we analyze what we label "diversification in the large".

When considered "in the small", diversification refers to the way individual exporters spread their sales across foreign partners, in a given destination market. When part of the volatility in sales comes from idiosyncratic demand or match-specific shocks, having a more diversified network is a way for individual firms to reduce their exposure, thus the volatility of their sales. In our framework, this materializes into a positive relationship between the volatility of an exporter's sales and the concentration of sales, across buyers.[5]

[5] We know from the trade literature that exporting firms, especially the most productive ones, do produce multiple products (Mayer, Melitz and Ottaviano, 2011). If a firm faces idiosyncratic product-specific shocks, producing multiple products may also be a way to hedge against risk. This dimension is not explicitly introduced in our framework, that focuses on the buyer-seller relationship. However, our empirical results take into account the possibility that firms may produce multiple products.

To evaluate the aggregate effect of diversification in the small, one also needs to take into account the connectedness of trade networks, across exporters. In our framework, the fact that two exporters share the same buyer induces a covariance in the growth rate of their sales, that will show up at the aggregate level. The covariance is generated by two mechanisms. First, these two exporters are exposed to the same idiosyncratic demand shock, a source of positive covariance. Second, shocks affecting one transaction may have spillover effects on the other one, e.g. through a substitution across varieties in the buyer's consumption basket. While the first source of covariance is attributable to different firms facing common shocks, the second source is more closely related to the idea of shocks propagating across connected firms in economic networks.

With this framework in mind, we analyze the structure of exporter-importer networks and its impact on aggregate fluctuations. More specifically, we characterize the degree of diversification in the small and in the large observed in French exports towards Spain, in 2005. As already noticed in the previous literature, the distribution of sales, across exporters, is fat-tailed (see, among others, di Giovanni, Levchenko and Rancière, 2011, on French data). In our data, the Herfindahl of sales across exporters is 500 times larger than it would, if sales were equally shared across exporting firms.[6] Export sales are highly concentrated. This means that there is a potential for granular fluctuations in the bilateral export data we work with.

A feature that is less documented in the literature is the degree of diversification in the small. In the data, exporters are little diversified across buyers, on average. Around 40% of French exporters present on the Spanish market serve a single buyer there. Together, they however account for less than 20% of aggregate exports. This reveals a strong degree of heterogeneity in the structure of trade networks. Exporters in the top quintile of the firm size distribution thus trade with 18 buyers on average while this number is 10 times smaller for exporters in the bottom quintile. Differences in the concentration of sales are less severe, however, because even large buyers do not spread their sales equally across their large number of partners. On average, the Herfindahl index of sales for large exporters is thus .55, still 40% lower than firms in the bottom quintile of the distribution.

This structure of trade networks matters for the volatility of individual firms' exports. Namely, results using external measures of volatility show that exporters with a less diversified foreign network display more volatile export sales, on average. In quantitative terms, reducing the diversification of sales to its minimum level, when all exporters serve a single buyer, increases the mean volatility of individual sales by 11.7%. The effect is stronger once we take into account the relative contribution of firms to aggregate exports. Since large firms tend to be more diversified, forcing all exporters to serve a single buyer reduces the mean volatility of the representative exporter by 20%.

We also provide evidence that individual trade networks are highly connected

[6] Note that this feature of the data is not specific to Spanish imports. Whatever the country, the Herfindahl index computed with our data is at least 20 times larger than the counterfactual value with symmetric exporters.

across firms. The mean buyer with whom an exporter trade is connected with 16 other sellers, on average. This implies that participating to international trade indirectly connects a firm with 16 other exporters in France. Here as well, there is some heterogeneity along the distribution of exporters, with large sellers being connected with buyers that are on average more central in the aggregate network. This explains by some assortativity in the matching of sellers and buyers. On average, large sellers are connected with larger buyers. However, more diversified sellers are also more likely to meet less diversified importers, which tends to counteract the previous effect.

Once again, this connectedness matters for aggregate fluctuations because it introduces a source of covariance between firms. We test this implication of the analytical framework. Namely, our regressions explain the magnitude of the covariance in sales within a pair of exporters on a measure of the connectedness of their trade networks. In our data **to be completed**.

In order to assess the aggregate effect of heterogeneity in the degree of diversification and in the connectedness of trade networks, we run counterfactual exercises. Namely, we compute the aggregate volatility of exports that we would observe in our data if exporters were unable to diversify across buyers, i.e. if each seller was selling the same quantity, to a single importer. The direct effect through individual volatilities would be an increase in the aggregate variance of bilateral exports of **X**%. This increase is attributable to individual exporters being more exposed to idiosyncratic demand risk. As explained before, the effect estimated from this counterfactual experiment is massive because large firms have the more to lose from being unable to diversify. The flip side of exporters being fully specialized in sales, however, is a reduction in the connectedness of trade networks, that reduces their exposure to common shocks. In our counterfactual simulations, we find that forcing the degree of connectedness in trade networks to zero reduces the aggregate volatility by **X**%. This means that, if French exporters were to specialize entirely on sales to a single buyer and this single buyer was committing not to interact with other exporters in France, the total volatility of bilateral exports would **to be completed**.

In the cross-section, the structure of trade networks thus has an impact on diversification in the small as in the large. Our empirical results also provide some insight on the underlying dynamics. In the aftermath of the 2008 crisis, most developed countries, including France, have suffered from a strong reduction in their aggregate exports.[7] The reduction in aggregate exports between 2007 and 2009 is equal to around 15% in France, with some heterogeneity across countries. For sales in Spain, the collapse has been massive, around -28.6%. A large share of this trade collapse is attributable to extensive adjustments, namely a decrease in the number of exporters serving the Spanish market and a decrease in the number of Spanish firms buying French products. As discussed by Eaton, Kortum, Neiman and Romalis (2011b) the sources of the trade collapse in France and in Spain have been quite different. Eaton et al. (2011b) find that

[7]The magnitude of the "trade collapse" is an empirical puzzle that has been discussed in many papers. Baldwin, ed (2011) proposes a collection of contributions on this topic, that covers a large set of countries.

three fourth of the trade collapse in France is attributable to shocks to foreign countries. In contrast, five sixth of the trade collapse in Spain is due to domestic shocks. This suggests that the primary source of the collapse of French bilateral exports to Spain is to be found in shocks hitting Spanish importers. In particular, some Spanish importers have been pushed out of the market. From the point-of-view of French exporters, those exits can be interpreted as exogenous shocks to their trade network.

We use this "natural" experiment to study how the death of buyers changes the diversification of exporters' sales and the concentration of exports across French firms. The endogenous adjustment of the microeconomic structure of the economy to these shocks has consequences for how sensitive to idiosyncratic risk aggregate exports are. Hence, these extensive adjustments following the financial crisis not only matter for explaining the magnitude of the trade collapse but also its persistence over time.

to be completed

The rest of the paper is organized as follows. Section 2 describes the analytical framework we work with. This helps underline the potential effect of idiosyncratic demand shocks on aggregate fluctuations, when individual producers' sales are little diversified across buyers. After having presented our data in Section 3, we analyze the structure of trade networks in Section 4, and its impact on individual and aggregate fluctuations. Section 5 then studies the dynamics of trade networks, which matters for the long-run contribution of idiosyncratic shocks to aggregate fluctuations. Finally, Section 6 concludes.

2 Analytical Framework

In this section, we present the conceptual framework that builds on Gabaix (2011) and di Giovanni et al. (2012), even though we focus on aggregate exports rather than aggregate sales. Using this framework and assuming a general structure of shocks helps understand how the concentration of sales across and within exporters matters for the magnitude of aggregate fluctuations. In this context, adjustments in the structure of the economy modifies the potential for granular fluctuations.

2.1 Diversification in the Large

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. By definition, aggregate exports towards one destination are the sum of firm-specific sales over all firms serving this destination market:

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

where S is the set of sellers and x_{st} the export sales of firm s.[8] As shown by Gabaix (2011), the distribution of sales across exporters is a key determinant of aggregate fluctuations. Taking as given this distribution, one can rewrite the volatility of aggregate exports as:

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

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 destination market. As in Gabaix (2011), if the only source of volatility is attributable to idiosyncratic supply shocks that do no propagate across firms then the second term in equation (1) disappears and the aggregate variance is simply a weighted average of firm-level volatilities. With homogeneous volatilities across firms, equation (1) further simplifies into a linear relationship between the aggregate variance and the Herfindahl index of sales, across exporters ($Herf = \sum_{s \in S} w_s^2$).

In such an economy, aggregate fluctuations are thus larger, given a certain amount of idiosyncratic volatility, the more concentrated the distribution of firms' sales. If volatilities are not homogeneous, the relationship is no longer linear but the distribution of sales across exporters continues to matter for aggregate fluctuations.[9] Finally, the aggregate variance of export growth is further strengthened if individual growth rates covary positively across firms, which is captured by the second term in equation (1). In Acemoglu et al. (2012), such positive covariances arise from input-output linkages across firms. These firm-to-firm linkages help propagate supply shocks from upstream to downstream firms. As we discuss later on, common shocks hitting (several) exporters simultaneously add another source of positive covariance.

[8] In a first step, 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. (2012), we thus consider the aggregate variance, conditional on the distribution of sales observed in a given period τ: $Var(g_{X_t} | \{w_{s\tau}\})$. We however discuss in Section 2.4 how this distribution evolves over time and the impact this has on the long-run aggregate volatility. Said otherwise, the analysis abstracts from the additional volatility induced by the distribution of sales moving over time. What we do take into account, however, is how the structural volatility of aggregate exports evolves when the economy jumps from one distribution of sales to the other.

[9] In di Giovanni et al. (2012) for instance, large firms are less volatile than smaller ones, on average. This mechanically attenuates the magnitude of granular fluctuations. The concentration of sales across producers is however so strong that this counteracting effect does not unable the contribution of granular fluctuations to the total variance of sales to be substantial.

In the empirical section, we study the distribution of sales across exporters $\{w_s\}$ and its link to aggregate fluctuations. A smaller concentration of sales across firms generally reduces the potential for granular fluctuations. We call this effect "diversification in the large". We now explain the sources of "diversification in the small".

2.2 Diversification in the small

Most of the related literature takes the structure of variances and covariances at the microeconomic level as given. In this paper, we exploit the nature of our data to focus on the limits of this assumption. 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).

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.

The decomposition in (2) shows that the way an exporting firm shares her sales across foreign partners matters for the volatility she will face. Namely, diversifying across buyers helps reduce the volatility induced by idiosyncratic shocks to partners. In equation (2), this appears naturally when assuming that the variance of sales at the transaction level is driven by idiosyncratic (demand) shocks and that those shocks are not correlated across buyers. Under these assumptions, the second term in equation (2) disappears. If, on top of this, the variance of bilateral exports is homogeneous across buyers in the exporter's portfolio, then the variance of total sales becomes linear in the Herfindahl of sales, across buyers ($Herf_s \equiv \sum_{b \in B_s} {w_b^s}^2$). The intuition is similar as in Gabaix (2011): More diversification across buyers reduces the exposure of the firm to idiosyncratic demand shocks. Of course, this effect is mitigated if sales are concentrated towards buyers that are little volatile.[10]

[10] An example of such reduction in the firm's exposure concerns firms that allocate a large fraction of their sales to wholesalers abroad. Since wholesalers are themselves intermediaries for a portfolio of final consumers, we should expect that the demand addressed by wholesalers

Another way to reduce its exposure to demand risk is for the exporting firm to diversify sales across buyers which demands are little correlated. This helps reduce the size of the second term in equation (2). If, on the other hand, the set of firms buying goods to exporter s are hit by common shocks, then the covariance of their demand will increase the volatility in exporter s total sales.

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:

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

This decomposition shows that the covariance in sales across exporters is potentially attributable to two sources. First, the covariance induced by sales to buyers that are common to both firms' networks (the set $B_s \cap B_{s'}$). As discussed later, such covariance may arise from shocks to buyers that transmit homogeneously to all firms they are connected with. This source of covariance will be more important in the data if trade networks are more interconnected between exporters (i.e. if $\sum_{b \in B_s \cap B_{s'}} w_b^s w_b^{s'}$ is large). Second, some covariance in sales may arise from the purchase of different buyers in each exporter's network co-varying. Aggregate demand shocks affecting all buyers simultaneously constitute a natural example inducing such covariances.

We summarize the results so far in next section, assuming a structure of shocks that helps identify what type of shocks will affect each element of the aggregate decomposition.

2.3 Assuming a structure of shocks

To give an intuition on the way different types of shocks generate different sources of aggregate fluctuations, we now assume that, at the most disaggregated level, the growth rate of sales can be decomposed as follows:

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

Namely, the growth rate of transactions 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 transaction-specific shock (ε_{sbt}). In the following, shocks that are common across exporters

to French exporters is relatively little volatile. Even if the exporter's sales are little diversified in this example, the firm may be exposed to less risk because its main partner displays less volatility. Such strategy would imply a negative correlation between ${w_b^s}^2$ and $Var(g_{x_{sbt}})$ that reduces the size of the first term in equation (2).

or importers are called "aggregate" shocks.[11] 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. Finally, we let transaction-specific shocks be correlated across transactions and we later discuss which sources of covariance are likely to be the most prevalent in the data.

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.

Given this structure of shocks, the micro-level variances are decomposed as follows:

$$
\begin{aligned}
Var(g_{x_{st}}) = & \underbrace{Var(\varepsilon_{St}) + Var(\varepsilon_{st}) + Var(\varepsilon_{Bt})}_{Non-hedgeable\ risks} \\
+ & \underbrace{\sum_{b \in B_s} {w_b^s}^2 \left[Var(\varepsilon_{bt}) + Var(\varepsilon_{sbt})\right]}_{Across-buyers\ diversifiable\ risk} + \underbrace{\sum_{b \in B_s} \sum_{b' \neq b} w_b^s w_{b'}^s Cov(\varepsilon_{sbt}, \varepsilon_{sb't})}_{Propagation\ across\ buyers}
\end{aligned}
$$

Within firms, the variance of export sales comes from three sources. First, shocks that are common to all buyers in the portfolio, i.e. aggregate and idiosyncratic supply shocks as well as aggregate demand shocks. The volatility of these shocks has a one-to-one effect on the firm's volatility, whatever the structure of its sales. Second, idiosyncratic demand shocks and transaction-specific shocks whose impact on the firm's volatility is increasing in the concentration of sales across buyers. Because these shocks are heterogeneous across buyers in the portfolio, a firm can reduce its exposure using a diversification strategy. In that sense, serving a larger set of buyers is a way for the firm to hedge against idiosyncratic demand risks. Third, shocks that propagate across buyers in the firm's portfolio. The sign and magnitude of this term is difficult to assess, a priori, because it depends on the source of the propagation. One likely source of covariance is due to common shocks having heterogeneous effects on buyers. For instance, a firm reducing its price is likely to benefit from an increase in the demand addressed by all buyers. However, if those buyers have heterogeneous

[11] Here, an "aggregate" shock affects homogeneously all firms contributing to bilateral exports, either on one or the other side of the border. Of course, the decomposition in Section 2.1 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.

price elasticities, the increase in demand will be heterogeneous across buyers. If this is the case, one can expect the $Cov(\varepsilon_{sbt}, \varepsilon_{sb't})$ terms to be either positive, or negative, or zero, depending on the buyers pairs. This suggests that we shall expect this term to be small, in comparison with other sources of volatility. To simplify notations, the rest of the section will assume this term is zero.

Likewise, the covariance across sellers can be decomposed into several components:

$$
\begin{aligned}
Cov(g_{x_{st}}, g_{x_{s't}}) = &\underbrace{Var(\varepsilon_{St}) + Var(\varepsilon_{Bt}) + \sum_{b \in B_s \cap B_{s'}} w_b^s w_{b'}^s Var(\varepsilon_{bt})}_{Covariance\ through\ common\ shocks} \\
+ &\underbrace{\sum_{b \in B_s \cap B_{s'}} w_b^s w_{b'}^s Cov(\varepsilon_{sbt}, \varepsilon_{s'bt})}_{Propagation\ through\ common\ buyers} + \underbrace{\sum_{b \in B_s} \sum_{b' \neq b} w_b^s w_{b'}^{s'} Cov(\varepsilon_{sbt}, \varepsilon_{s'b't})}_{Propagation\ through\ different\ buyers}
\end{aligned}
$$

One source of positive covariance is attributable to different exporters being hit by the same shock. Of course, aggregate (demand and supply) shocks are a source for such covariance. Another source of co-movements, often neglected in the literature, is due to exposure to identical idiosyncratic demand shocks through the connectedness of trade networks. Namely, exporters serving the same customers are naturally hit by the same buyer-specific shocks. This source of covariance is stronger the more connected trade networks. Finally, some covariance in sales may arise from transaction-specific shocks propagating across sellers. The propagation can arise from common buyers, for instance through competitive pressures: If goods sold by exporters s and s' are substitutable then a good performance by exporter s, that drives the demand of buyer b up, may induce a contraction in the demand addressed to seller s'. In this situation, we shall expect $Cov(\varepsilon_{sbt}, \varepsilon_{s'bt})$ to be negative. In principle, the propagation may also arise from different buyers. We however consider this source of little importance, since the economic nature of such co-movements is rather unclear. To simplify notations, we set this term to zero in the rest of the section.

Aggregating up to the country level leads to a decomposition of the total volatility of bilateral exports into 5 components:

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

In standard macroeconomic models, the only source of aggregate volatility is due to aggregate (demand and supply) shocks. This source of fluctuations is captured in the "Macroeconomic volatility" term in the above equation. Under this assumption, aggregate fluctuations are independent from all microeconomic shocks. With a fat-tailed distribution of sales, idiosyncratic shocks no longer disappear at the aggregate level. As in Gabaix (2011), 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" in equation (5). Whereas Gabaix (2011) assumes all firms are similar in terms of the idiosyncratic volatility they face, the concentration of sales across a limited number of buyers is an additional source of "granular" fluctuations in our setup. This is the "Diversifiable granular volatility" term in equation (5). The less diversified the exporters are, especially large ones, the stronger this effect. Then, the network structure of firm-to-firm relationships is an additional source of aggregate fluctuations. The first effect of trade networks being connected is to expose individual exporters to the same demand shocks (the "Pure network volatility" in equation (5)). This source of fluctuations is stronger whenever networks of large enough firms are sufficiently connected. Finally, indirect connections through common buyers also introduce the possibility that shocks propagate along networks, across exporters (the "Propagation through common buyers" term).

In the standard macroeconomic literature, only the "macroeconomic volatility" is considered as a potential source of aggregate fluctuations. Gabaix (2011) has however shown that the "Pure granular volatility" is also important in the data. We ask in the rest of the paper whether more insights on the source of aggregate fluctuations can be derived once one takes into account heterogeneity in the structure of sellers' portfolio of buyers.

2.4 Endogeneity in the structure of trade networks

Up to now, it has been assumed that the structure of sales, across exporters and across buyers within a seller's portfolio (i.e. the distributions of the $\{w_s\}$ and $\{w_b^s\}$ weights), is constant over time. This assumption greatly simplifies the analysis since it implies that aggregate variance and covariance terms can be written as weighted averages of microeconomic variance and covariance terms. Moreover, di Giovanni et al. (2012) show that neglecting fluctuations in the weights does not introduce an important error in the estimation of aggregate fluctuations.

Permanent shocks to the structure of the economy constitutes one reason why changes in these weights matter. More precisely, if buyer- and exporter-specific weights move around a constant value through the influence of idiosyncratic shocks, as is mechanically the case in the model of section 2.3, then we can expect this additional source of volatility to be quantitatively small.[12] However, if the

[12] In the model of Section 2.3, there is mechanically a covariance between the idiosyncratic shocks and the corresponding weights. A positive idiosyncratic supply shock leads to an increase in the share of the exporter in aggregate sales in the next period. Likewise, a positive

economy is hit by a large enough shock that fundamentally alters the structure of the economy, then neglecting these changes will lead to a biased estimate of the aggregate volatility. This is especially true when the shocks have extensive margin effects. Changes in the number of exporters serving a given destination and changes in the number of buyers a given exporter serves will affect the "granularity" of the economy, thus the potential for granular fluctuations.

One candidate for such a persistent shock to the microeconomic structure of the economy is the 2008-2009 world crisis. It is well-known that this crisis has had a huge impact on international trade flows. The trade collapse has notably been documented by Baldwin, ed (2011), Bricongne, Fontagné, Gaulier, Taglioni and Vicard (2012), and Behrens, Corcos and Mion (2013). Most find that the lion share of the trade collapse has been driven by intensive adjustments. But Spain has been more dramatically impacted by the crisis. Bricongne et al. (2012) show that Spain is one of the most harmed destination of French exports during the crisis. Between 2007 and 2009, Spanish imports from France dropped by 29%. In our data, between 2005 and 2009, we observe a net exit of 6,194 Spanish buyers (out of 80,486) and 2,766 French sellers (out of 23,146). As illustrated in Figure 1, a decomposition of the growth rate of bilateral exports shows that the extensive margin (i.e. adjustments in the number of exporters and in the number of buyers per exporter) accounts for a significant share of the French-Spanish trade decline.[13] The crisis in Spain thus constitutes an interesting natural experiment of a large shock having an effect on both the intensive and the extensive margins. In Section 5, we study how this trade collapse has modified the structural volatility of bilateral trade flows.

– Figure 1 about here –

We now describe how permanent shocks at the extensive margin may affect the structural volatility of the economy. In order to be consistent with the empirical exercise, it is assumed that some buyers involved in trade networks are hit by shocks that force them out of the market. Such a shock has a mechanical impact on the variance of firms that were serving this specific market as well as on the covariance between firms that served such buyers. This is turn affects the magnitude of aggregate fluctuations. The total effect of the shock however depends on how exporters adjust and how endogenous adjustments affect the distribution of sales across exporters.

Consider first the mechanical effect of the shock on the variance of sales of an exporter s previously connected to the dead buyer d. Let us denote w^s_{dt-1}

idiosyncratic demand shock tends to inflate the share of the buyer in the exporter's portfolio. On average, these adjustments in weights are however offset if shocks are uncorrelated over time.

[13] For Spain, the total decline of the value of exports is estimated to -27% between 2005 and 2009. Adjustments at the intensive margin (namely, changes in the mean value of a transaction) are almost as big (-25%). Adjustments at the extensive margin (drop in the number of exporters and in the number of partners, by exporter) account for another 19% decrease. The (positive) difference is attributable to net exits being non-random: exits tend to be concentrated in the left-side of the firms' size distribution which mitigates the effect of extensive adjustments.

the share of buyer d in the pre-shock period sales of the exporter. If the demand of other buyers in the firm's portfolio does not adjust to the shock, the exit of buyer d mechanically increases the market share of other firms in the portfolio by a factor $\frac{1}{1-w^s_{dt-1}}$. In general, this mechanically increases the concentration of sales across buyers.[14] Such increase in the concentration of sales pushes the variance of the exporter's sales up. In the short-run, we shall thus expect the death of a buyer to increase the volatility of firm-level exports.

In the short-run, one can also expect the shock to reduce the covariance in sales across exporters. This will be the case whenever dead buyers were creating indirect links between exporters, i.e. whenever $d \in B_s \cap B_{s'}$. If this is the case, then the death of a buyer reduces the connectedness of trade networks. In the model of Section 2.3, it is the connectedness of trade networks that creates covariances in sales. Destructing such indirect links thus attenuates this source of covariance. This effect should be stronger whenever the share of dead buyers in the sales of indirectly connected exporters ($w^s_{dt-1} * w^{s'}_{dt-1}$) was high before the shock.

Each of the short-run effects described above tends to reduce the sources of granular fluctuations, more so when exporters affected by these shocks are large. In order to assess the long-run effect of these shocks, however, it is necessary to take into account the possibility that exporters adjust their portfolio after being hit. In the empirical section, we consider two potential adjustments. First, exporters may be willing to re-balance their sales across remaining buyers in their portfolio. In particular, if they are risk-averse, they may be willing to reallocate sales in favor of the smallest consumers in order to restore their "optimal" degree of diversification.[15] Second, exporters may intensify their search effort in order to substitute a new buyer to the dead one. This will happen if the exporter optimally chooses a number of buyers to serve as long as no search frictions prevents the exporter from reaching this new optimum. On the other hand, in presence of search frictions, the adjustment may take some time. Both kinds of micro-level adjustments in exporters' diversification strategies are

[14]The only circumstances under which the concentration of sales does not increase are those in which the pre-shock sales to the dead buyer are very high in relative terms with respect to other buyers, namely when

$$w_{dt-1} > \frac{2Herf_{st-1}}{1 + Herf_{st-1}}$$

with $Herf_{st-1}$ the pre-shock Herfindahl index of exporter s. If the dead buyer was especially important in the exporter's portfolio, then the Herfindahl index of its sales can decrease after the shock. Likewise, if the dead buyer displayed abnormally high volatility or covariances with other buyers, then we can expect the shock to reduce the volatility that the firm faces. In the rest of this section, we consider situations in which the dead buyer is "normal" in the sense of accounting for an average market share and displaying average variance and covariances with other buyers. This assumption helps derive analytical results. Of course, the empirical section considers heterogeneous responses to shocks depending on the initial size of the dead buyer.

[15]This implicitly assumes that exporters perfectly control how sales are allocated across buyers, without this interacting with demand constraints. This assumption is fairly unlikely and is not expected to be observed frequently in our data. We do not preclude this possibility, however.

expected to counteract the direct effect of the shock. The intensity of such adjustments could thus explain why a given shock may have different effects on the volatilities and covariances of different firms.

To assess the aggregate effect of the shock, we must finally take into account how the distribution of sales across exporters is modified. Mechanically, firms that are hit by a shock decrease in size, with respect to other exporters. If relatively large firms are more likely to face a shock to their network, this will decrease the concentration of the economy. Here again, the direct effect may be modified by endogenous adjustments. A potentially important modification that we consider in the empirical analysis concerns extensive adjustments along the exporter's dimension. Due to the shock, some exporters may be forced out of the market. This will happen if the death of the buyer reduces the present value of serving the destination country by a sufficient amount for the exporter to choose an exit strategy. This is more likely to happen if the size of the shock is important (i.e. if w^s_{dt-1} is big) and if it is difficult for the firm to compensate for the lost value of exports either because search frictions make it difficult to meet new buyers or because the firm's competitiveness is poor and it has difficulties re-balancing its sales. In both circumstances, we shall expect the firm to exit the market in which case the aggregate concentration of sales will increase, thus pushing the aggregate variance up.

While formally assessing the full effect of the shock will require some assumption about the underlying functioning of the economy, Section 5 gives insights about the sources of adjustments that are quantitatively important in the data.

3 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.[16] 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. The cross-sectional results are derived from the 2005 data and we use variations between 2005 and 2009 to investigate the dynamic response of trade networks to the death of some importers.

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. (2011a), Mayer et al. (2011) or Berman, Martin and Mayer (2012). Some papers also use data detailed at the level of the importer, for instance Blaum, Lelarge and Peters (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

[16] 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.

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 of the transaction (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 from the dataset. 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 two additional datasets. Both provide us with additional information on exporters, and can be merged with our data using the Siren identifier. 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).

In the following, we describe the properties of the trade networks at the root of this bilateral export flow, first in cross-section and dynamically.

4 Cross-sectional results

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. We first describe the network from the point of view of the diversification "in the large" before going into the details of the seller-specific trade networks. We further test two insights of our model: the link between diversification and volatility at the individual level and the effect of being connected through common buyers on the comovement of sales between sellers.

4.1 The large in the data

As discussed in Section 2, diversification "in the large" 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. Table 2 reports the concentration of French firms exporting to Spain as measured by the Herfindahl index of total exports. Those Herfindahl can be compared with the counterfactual value one would observe if export flows were symmetric across individuals, i.e. the inverse of the number of individuals (see the last two columns in Table 2).

– Table 2 about here –

The Herfindahl index of sales across exporters is equal to 0.022, to be compared with a counterfactual under symmetric export flows equal to 4.310^{-5}. Sales are thus 500 times more concentrated than in a counterfactual symmetric world.[17] With such a level of concentration, the volatility of aggregate outcomes

[17] As expected, trade is more granular than total sales. Indeed, di Giovanni et al. (2012) reports a Herfindahl of sales for French manufacturing firms of .0035. Concentration of sales across sellers in French exports to Spain is thus 7 times more concentrated than in total sales.

is likely to be impacted by idiosyncratic shocks. Note that the concentration of exports is also important along the distribution of importers (.015) and along the distribution of bilateral transactions (.009).

The concentration of sales across exporters can be further illustrated using the distribution in Figure 2. It illustrates the cumulated value of exports across firms of increasing size. At the top of the distribution, 1% of firms are responsible for 60% of exports.

– Figure 2 about here –

As shown in Section 2.1, the total variance of bilateral exports decomposes into a weighted average of individual volatilities and covariance terms. We close this section by documenting the relative importance of these two terms for the aggregate volatility of French exports to Spain. Namely, we apply the decomposition in Section 2.1 using estimates of individual variance and covariance terms obtained from the time-series of exporter-specific sales available to use annually between 1995 and 2007. Those variance and covariance terms are then aggregated up to the country level using weights observed in the data for 2005.

Results are reported in Table 3. The first line is the actual variance of aggregate sales, computed from export data aggregated year by year. This variance compares with the one reported on the second line, that corresponds to the variance conditional on the distribution of weights observed in 2005. The comparison gives insights on how "wrong" the assumption of the structure of the economy being constant over time is. The mistake is substantial since constraining weights to their value in 2005 overestimates the aggregate variance by 32%. This assumption is nevertheless useful since it helps identify the sources of aggregate fluctuations, namely individual volatilities or the covariance in sales across exporters. In our data, the covariance in sales across exporters is the main source of aggregate volatility.[18]

– Table 3 about here –

4.2 The small in the data

We now turn to the analysis of the diversification in the small. As detailed in section 2, this notion refers to individual firms diversifying their sales across buyers and the degree of interconnection between sellers' trade networks. We investigate this in the next two paragraphs.

Seller's diversification. An important characteristic of a network is the number of connections at each node. In our bipartite network, the number of connections is simply the number of partners a firm trades with, i.e. $Degree_s = \sum_{b \in B_s} a_{sb}$ for sellers, and $Degree_b = \sum_{s \in S_b} a_{sb}$ for buyers (where a_{sb} is a dummy equal to one if firm s trades with partner b). The degree of a firm is a simple measure of its diversification.

[18]Remember that, in raw data, one source of covariance in sales across exporters is aggregate shocks affecting all firms homogeneously.

– Figure 4 about here –

Figure 4 presents the distribution of the number of partners French exporters trade with, in 2005 (top panel) and in 2009 (bottom panel). The left panels represent the share of sellers having at least a certain number of buyers. The right panels present the share of these firms in total exports. In 2005, almost 40% of French sellers export to a single buyer (left top panel). However, these exporters only account for 16% of total sales (right top 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 degree of a firm does not put any hierarchy between transactions, however. Yet, a firm may have many partners but be extremely few 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 4. While the green 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 degree 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.

– Table 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 the total sales of exporter s. Table 4 presents basic statistics (mean and median) about the level of diversification of French exporters. The median exporter trades with 2 Spanish buyers. The corresponding average is larger (7.3 buyers per seller). Diversification as measured by the Herfindahl index is 0.8 for the median firm - and 0.7 on average. Both measures suggest that sellers' exports are highly concentrated. The large gap between the mean and the median diversification of sellers reflects the tremendous heterogeneity in the number of trading partners across firms. We delves into this heterogeneity in Table 5. In this Table, we divide the population of French exporters into 5 quintiles according to the value of their exports. We then study the median and average degree and diversification of sellers in each quintile.

– Table 5 about here –

Whatever the measure of diversification considered, we find that larger firms tend to be more diversified than smaller ones. Namely, firms in the top quintile of the distribution have 9 times more buyers, on average. This does not however 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.

Connectedness of sellers. A second dimension of trade networks that matters for the transmission of idiosyncratic shocks into aggregate fluctuations is the connectedness of the network. The connectedness can be broadly defined as the level of indirect linkages sellers have with each others through the existence of common buyers.

A very broad measure of how connected a network is consists in comparing the actual number of links with the potential number that one would observe if all nodes were connected within the network. In our data, we thus define the density of the network as the number of seller-buyer relationships divided by the product of the number of sellers and the number of buyers.

At the aggregated level, the seller-buyer network is sparse with a density of .00009 $(169,356/(80,486 \times 23,146))$. This definition of the density is however very broad since it implicitly assumes that every seller could trade with every buyer, potentially. We restrict the definition by computing the density of the network at the product level. Under this less stringent definition, density is defined as the number of transactions between sellers and buyers trading a given 8-digit product relative to the number of sellers exporting the product times the number of buyers importing this product. The implicit assumption is that all producers of a given product could potentially export to all buyers of a strictly positive quantity of this good. The distribution of product-level densities is presented in Figure 3. One sees an important mass around zero suggesting that, for many product categories, the number of transactions is low relative to the number of potential transactions. There is however some heterogeneity between products. In a substantial number of product categories (namely, 907 out of 6,974), the density of the network is larger than .5.

– Figure 3 about here –

Another way to assess the level of connectedness of a network is to measure the size of its disjoint components. A network can be decomposed into a collection of disjoint components. Each component consists of buyers and sellers which share no link with buyers and sellers of other components. The number and the size of these components says something about the level of segmentation of trade networks. The French-Spanish network consists mainly of a giant component, as shown in Table 6.

– Table 6 about here –

In 2005, 97.1% of the transactions between French and Spanish firms occurred within this largest component, for a total value of 95.5% of bilateral exports. In principle, the propagation of shocks within this largest component is possible. Instead, disjoint components consisting of only one buyer and one seller are not likely to be a source of propagation: idiosyncratic shocks affecting firms at each side of this component can only be transmitted to its partner. In our data, isolated components are however rare. They account for 1.2% of all transactions and 2% of total trade.

A more direct way of assessing the connectedness of the network is to count the number of indirect links that are created between exporter s and other French exporters, whenever s integrates a buyer in its portfolio. Namely, we define the connectedness of firm s as:

$$Connect_s = \frac{\sum_b (degree_b - 1)}{B_s}$$

where B_s is the number of buyers that firm s serves, and $degree_b$ is the degree of buyer b. Intuitively, connecting with buyers with a larger degree, that are more connected to other French exporters, increases the indirect exposure of the seller to shocks affecting its competitors.

This measure has the advantage of being easy to interpret. However, it presents two drawbacks. First, it is a simple average and thus does not account for differences in the importance of buyers for a seller: Obviously, the exporter should care more about the connectedness of its main partners. Second, it gives a simplistic view of the links between buyers and sellers. To circumvent these issues, we propose a second statistics that is directly inspired from the model of Section 2. Namely, we define

$$WConnect_s = \sum_{b \in B_s} w_b^s \big(\sum_{s' \neq s} w_b^{s'}\big)$$

where w_b^s is the share of buyer b in the sales of seller s. This measures, for each buyer a seller is connected with, the importance of this buyer for other sellers in the network, which is aggregated across buyers taking into account their relative size in the firm's portfolio. Said otherwise, the level of connectedness of two firms having a common buyer depends on the importance of this buyer in the sales of each of the two sellers.

– Table 7 about here –

Table 7 describes these two statistics. The first measure of connectedness shows that the average buyer met by the median seller creates 4.5 indirect links with other sellers in the network. On average, this number increases with the size of the exporter, firms in the fifth quintile being indirectly linked with 5.9 other sellers. Taking the size of transactions into account does not change the whole picture. In particular, it continues to be true that larger firms are more strongly connected with other exporters through common buyers, on average.

One possible explanation for this result would be that large sellers trade with larger buyers, on average. We examine this point in Table 8. We look at the rank correlation of buyer-seller pairs. We consider three characteristics: the size of the firms, their degree, and their Herfindahl index. For each characteristic, we ask whether firms in the top of the distribution of sellers tend to be connected with firms in the top of the distribution of buyers. As expected, our results indicate that large exporters are more likely to trade with large importers. However, we find that more diversified sellers are also more likely to trade with less diversified buyers.

– Table 8 about here –

4.3 Implication for the volatility of exports

Having documented an important amount of heterogeneity in the degree of diversification and connectedness of trade networks, we now ask to what extent these microeconomic structures matter 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 and the covariance in sales between French exporters.

Diversification and volatility. As discussed in Section 2, diversifying its portfolio of buyers is a way for exporters to reduce their exposure to idiosyncratic demand shocks. We now ask whether heterogeneity in this dimension of individual export behaviors matters for the volatility a seller incurs.

To that aim, we regress the variance of firm-level exports, computed using annual data between 1995 and 2007, on the degree and Herfindahl index of the firm's sales, as measured in 2005. We expect a negative coefficient associated with more diversification. Of course, the regression needs to control for other potential sources of volatility. Regressions displayed in Table 9 thus control for the size of the firm and its experience in the Spanish market. Two dummies are also added, that respectively take a value of one if the firm has its headquarter in Spain, which increases the probability that some exports are intra-firm, and if it is located at the border of the Spanish market. Finally, all regressions control for product-level fixed effects that absorb differences across sectors in the volatility of aggregate shocks.

As discussed before, diversifying across buyers is not the only way a firm can hedge against idiosyncratic risk. Another potentially important source of diversification consists in selling multiple products, which reduces the exposure to product-specific shocks. Since it has been documented in the previous literature that a lot of exporters, especially big ones, are multi-product firms (See Mayer et al., 2011), this dimension may be an important source of diversification. In order to control for this possibility, the left-hand side variable is the volatility of seller- *and* product-specific sales. This is the most stringent way of testing the impact of diversification on volatility.

We consider two different samples. The sample of firms present at least three consecutive years between 1996 and 2006, and the sample of continuous exporters, which presents the advantage of having variance terms that are computed on a constant number of periods but restricts the analysis to big enough exporters.

– Table 9 about here –

Results are presented in Table 9. Columns (1) and (2) use the number of buyers of the firm as a measure of diversification. Columns (3) and (4) instead use the Herfindahl index (an inverse measure of diversification). As expected, both measures have a significant effect on the volatility of sales. Within a product category, firms having a larger number of buyers or being less concentrated in sales display less volatile sales. This result is consistent with the analytical framework in this paper and has never been put forward in the literature on the sources of volatility.

In quantitative terms, the impact of being more diversified can be evaluated using counterfactuals. Namely, we predict what would be the variance of a firm's sales in the absence of any diversification across buyers, i.e. with all sales addressed to a single buyer (and thus a Herfindahl index of one). This distribution of individual volatilities can then be compared with the actual distribution. In the full sample used in column (1), reducing the degree of diversification to zero for all exporters increases the variance of sales by 11.7%, on average. The effect on the mean exporter is thus sizeable. A priori, taking into account the relative size of firms in this counterfactual should deliver an even larger number since large firms tend to be more diversified ex-ante. Surprisingly, this is not the case when we average the impact on all firms, weighting each firm by its size in aggregate exports, the estimated effect of reducing diversification is estimated to 10.5%. This surprising result is however triggered by the two largest exporters in our sample, that are both huge in terms of their contribution to aggregate exports and are outliers in terms of their diversification. Indeed, both exporters serve only one buyer per product in the destination market. Anecdotal evidence on these two firms suggest that the buyers they serve in Spain is in fact an affiliate of the firm, which sole function is to distribute the French products in Spain. In that sense, those Spanish importers play the role of intermediaries that potentially hide a large number of buyers. Once those two firms are removed from the calculation, the increase in the mean variance of sales, induced by firms being unable to diversify across buyers is equal to 20%.

Common buyers and comovement. **To be completed**

5 Endogenous adjustments of trade networks

6 Conclusion

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: Concentration of sellers, buyers, and transactions

	Herfindahl index		$1/(\# \text{ obs})(\times 10^5)$	
Year	2005	2009	2005	2009
Seller	.022	.013	4.3	4.9
Buyer	.015	.012	1.2	1.3
Transaction	.009	.006	0.6	0.7

Notes: The Herfindahl index is computed as $Herf_{I_t} = \sum_{i \in I_t} w_{it}^2$ where t is either 2005 or 2009. $i \in I_t$ denotes the individual under consideration, either a seller, or a buyer, or a seller-buyer pair, and w_{it} is the share of individual i in total exports. If market shares were symmetric across individuals in the I_t set, the Herfindahl index would simply be $1/\#_{I_t}$ where $\#_{i_t}$ is the number of individuals in the set I_t. This is what is reported in the last two columns, respectively for 2005 and 2009. The comparison of columns (1)-(2) with columns (3)-(4) tells something about how diversified sales are, in comparison with what they could be.

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Table 3: Volatility of aggregate exports to Spain, 1995-2007

Variable	Formula	Value ($\times 100$)	Share (pct)
Agg. variance (true)	$Var(g_{X_t})$	4.4	100
Agg. variance (cons.weights)	$Var(\sum_s w_s g_{x_{st}})$	5.8	132
Ind. variances	$\sum_{s \in S} w_s^2 Var(g_{x_{st}})$	1.2	27.2
Covariances	$\sum_{s \in S} \sum_{s' \neq s} w_s w_{s'} Cov(g_{x_{st}}, g_{x_{s't}})$	4.6	105

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"). See details in Section 2.1. In real data, many sellers export several 8-digit products. We do take into account this additional dimension. Namely, the set S of sellers is actually the collection of exporter-product pairs that we have in our data: A seller selling two products appears twice and the covariance in sales across products sold by a given firm are included in the "Covariances" term.

Table 4: Diversification of buyers and sellers

Year	2005	2009
Sellers		
Degree: median (mean)	2.0 (7.3)	2.0 (7.4)
Herfindahl: median (mean)	0.8 (0.7)	0.8 (0.7)
Buyers		
Degree: median (mean)	1.0 (2.1)	1.0 (2.0)
Herfindahl: median (mean)	1.0 (0.9)	1.0 (0.9)

Notes: Based on data on French-Spanish trade flows for 2005 and 2009, this table shows summary statistics on the diversification of sellers and buyers. The degree is defined as the number of buyers per seller (resp. the number of sellers per buyer). The Herfindahl index is $Herf_s = \sum_{b \in B_s} {w_b^s}^2$ for sellers and $Herf_b = \sum_{s \in S_b} {w_s^b}^2$ for buyers, where w_b^s is the share of buyer b in exporter s' sales and w_s^b the share of seller s in b's purchases.

Table 5: Diversification of sellers depending on their size

	Degree		**Herfindahl**	
	2005	2009	2005	2009
0-20 quintile	1 (1.6)	1 (1.6)	1 (.87)	1 (.87)
20-40 quintile	2 (3.0)	2 (3.0)	0.9 (.75)	0.9 (.75)
40-60 quintile	2 (5.0)	2 (5.1)	0.7 (.68)	0.7 (.68)
60-80 quintile	3 (8.9)	3 (9.8)	0.6 (.62)	0.6 (.62)
80-100 quintile	5 (18.1)	5 (17.5)	0.5 (.55)	0.6 (.59)
Top 100 firms	6 (18.4)	5 (27.6)	0.7 (.61)	0.8 (.66)

Notes: Based on data on French-Spanish trade flows for 2005 and 2009, 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 per seller (resp. the number of sellers per buyer). The Herfindahl index is $Herf_s = \sum_{b \in B_s} {w_b^s}^2$ for sellers and $Herf_b = \sum_{s \in S_b} {w_s^b}^2$ for buyers, where w_b^s is the share of buyer b in exporter s' sales and w_s^b the share of seller s in b's purchases.

Table 6: Decomposition of the trade network into connected components, Summary statistics

Year	2005	2009
Share in transactions		
Largest component	.971	.972
1-1 components	.012	.020
Share in value		
Largest component	.955	.938
1-1 components	.012	.035

Notes: Using all bilateral transactions between France and Spain, for 2005 and 2009, this table reports summary statistics on the "connected components" of the trade network. The "largest component" is the sub-network that contains the largest number of bilateral transactions. "1-1 components" are sub-networks that contain a single transaction, between one seller and one buyer.

Table 7: Connectedness of sellers, by class of exporters

	Average degree of buyers -1		**Average diversification of buyers**	
	2005	2009	2005	2009
All	4.5 (16.1)	4.2 (14.5)	1.1 (7.8)	1.1 (6.8)
0-20 quintile	3.4 (16)	3.0 (1.6)	0.8 (8.3)	0.8 (6.4)
20-40 quintile	4.0 (15)	4.0 (3.0)	1.0 (7.3)	1.0 (5.9)
40-60 quintile	4.5 (14)	4.0 (5.1)	1.1 (6.4)	1.0 (5.5)
60-80 quintile	5.0 (15)	4.5 (9.8)	1.3 (6.8)	1.2 (6.1)
80-100 quintile	5.9 (19)	6.0 (17.5)	1.7 (10.1)	1.7 (10.1)
Top 100 firms	11.7 (38.6)	8.9 (25.0)	4.3 (22.4)	2.9 (18.0)

Notes: Based on data on French-Spanish trade flows for 2005 and 2009, this table shows summary statistics on the connectedness of sellers' trade networks, 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 "Average degree of buyers -1" column reports statistics on the first measure of connectedness, namely $Connect_s = \frac{\sum_{b \in B_s}(degree_b - 1)}{B_s}$ where $degree_b$ is the number of suppliers of buyer b. The "Average diversification of buyers" column reports statistics on the second measure of connectedness, namely $WConnect_s = \sum_{b \in B_s} w_b^s (\sum_{s' \neq s} w_b^{s'})$ where w_b^s is the share of buyer b in seller s exports.

Table 8: Summary statistics on the seller-buyer matching

Year	2005	2009
Rank correlation		
Value of exports	0.12	0.07
Degree	-0.26	-0.32
Herfindahl index	-0.14	-0.14

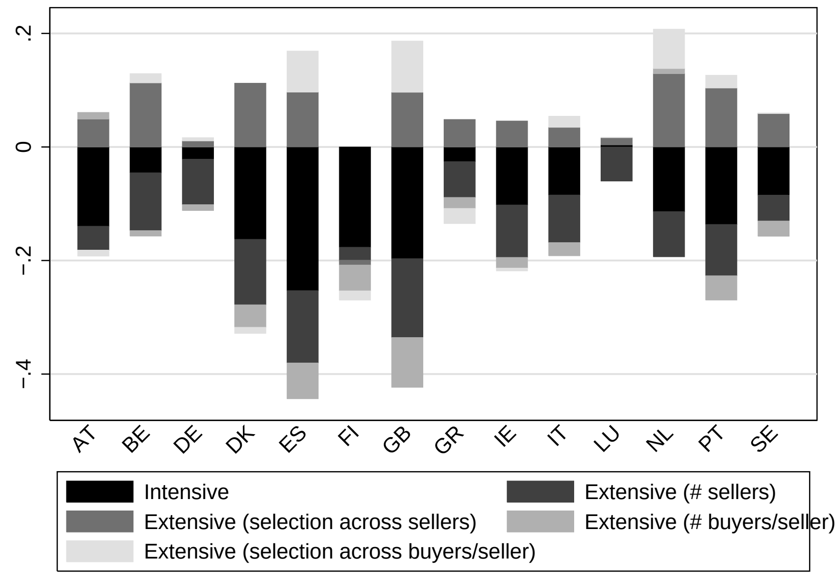
Notes: This table gives rank correlations between characteristics of sellers and characteristics of the buyers they are connected with. The characteristics we consider are their sizes, as measured by the total value of their exports/imports, as well as their degree of diversification, as measured by 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 9: Diversification and volatility of sles at the firm-product level

	Dep.var: ln Variance of export growth			
	(1)	(2)	(3)	(4)
ln # buyers	-0.05***	-0.07***		
	(0.006)	(0.010)		
ln Herfindahl across buyers			0.06***	0.10***
			(0.009)	(0.015)
$\mathbb{1}=1$ if seller is a wholesaler	0.10***	0.19***	0.10***	0.19***
	(0.014)	(0.029)	(0.015)	(0.029)
ln size of the seller	-0.03***	-0.04***	-0.03***	-0.04***
	(0.004)	(0.008)	(0.004)	(0.008)
ln experience in Spain	-0.13***		-0.11***	
	(0.020)		(0.021)	
$\mathbb{1}=1$ if Spanish headquarter	-0.01	0.39	-0.03	0.38
	(0.075)	(0.300)	(0.074)	(0.301)
$\mathbb{1}=1$ if affiliates in Spain	-0.14***	-0.03	-0.10***	-0.02
	(0.033)	(0.060)	(0.035)	(0.060)
Weighted Hefindahl of Buyers	-0.02***	-0.03***	-0.03***	-0.03***
	(0.003)	(0.006)	(0.003)	(0.006)
Sample	All	Contin.	All	Contin.
FE	nc8	nc8	nc8	nc8
# obs.	16,233	5,269	16,229	5,269
R^2	0.010	0.035	0.013	0.033

Robust standard errors in parentheses with ^{a}, ^{b} and ^{c} respectively denoting significance at the 1, 5 and 10% levels.

Figure 1: Decomposition of the trade collapse, by destination country



Notes: This graph shows, for each country of the European Union, the growth rate of exports between 2005 and 2009 and its decomposition into different margins. The decomposition is as follows:

$$\ln\frac{X_t}{X_{t-1}} = \underbrace{\sum_{s\in S} w_{t-1}^{s\in S}\ln\frac{\bar{x}_t^{B^s}}{\bar{x}_{t-1}^{B^s}}}_{Intensive} + \underbrace{\ln\frac{\#_{S_t}}{\#_{S_{t-1}}}}_{Extensive\ (\#\ sellers)} + \underbrace{\ln\frac{\bar{x}_t^{S_t}/\bar{x}_t^{S}}{\bar{x}_{t-1}^{S_{t-1}}/\bar{x}_{t-1}^{S}}}_{Extensive\ (selection\ across\ sellers)}$$

$$+ \underbrace{\sum_{s\in S} w_{t-1}^{s\in S}\ln\frac{\#_{B_t^s}}{\#_{B_{t-1}^s}}}_{Extensive\ (\#\ buyers/seller)} + \underbrace{\sum_{s\in S} w_{t-1}^{s\in S}\ln\frac{\bar{x}_t^{B_t^s}/\bar{x}_t^{B^s}}{\bar{x}_{t-1}^{B_{t-1}^s}/\bar{x}_{t-1}^{B^s}}}_{Extensive\ (selection\ across\ buyers/seller)}$$

$w_{t-1}^{s\in S}$ is the share of seller s in aggregate sales in $t-1$, the aggregation being restricted to the set of incumbent exporters ($S \in S_t \cap S_{t-1}$). $\bar{x}_t^{B^s}$ (resp. $\bar{x}_t^{B_t^s}$) is the mean value of the transaction between seller s and any of the buyers in the set B_s (B_t^s), in period t. $\#_{S_t}$ (resp. $\#_{B_t^s}$) is the number of individuals in the set S_t (resp. B_t^s). Finally, $\bar{x}_t^{S_t}$ (resp. $\bar{x}_t^{S}$) is the mean value of exports of a seller in the set S_t) (resp. S), in period t.

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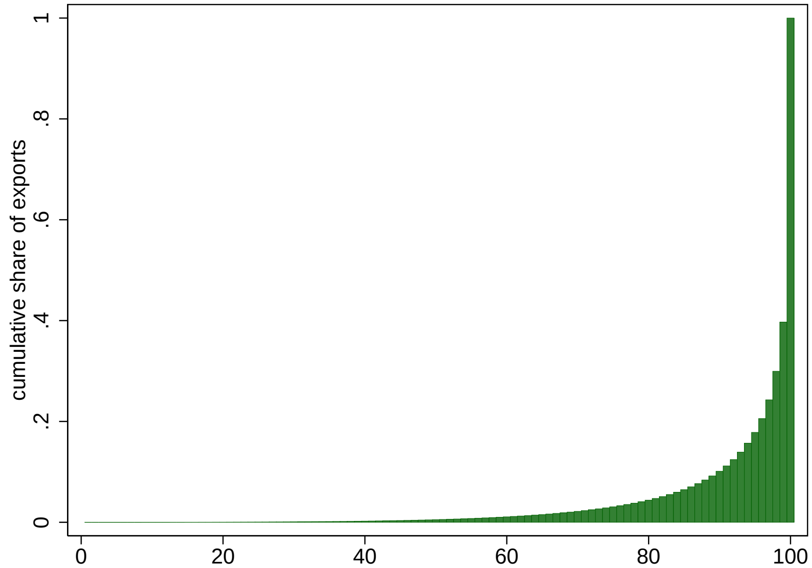
Figure 2: Cumulated share of exporters in the total value of bilateral exports



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%.

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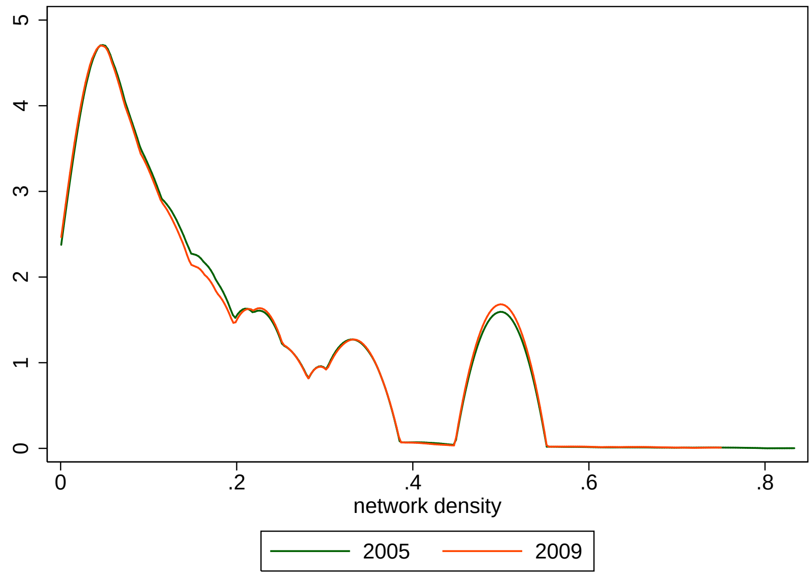
Figure 3: Network density, by 8-digit product



This graph shows the distribution across products, of the network density of trade networks. Density is defined as the number of bilateral transactions falling in the product category divided by the potential number of transactions, i.e. the number of sellers of this product multiplied by the number of buyers.

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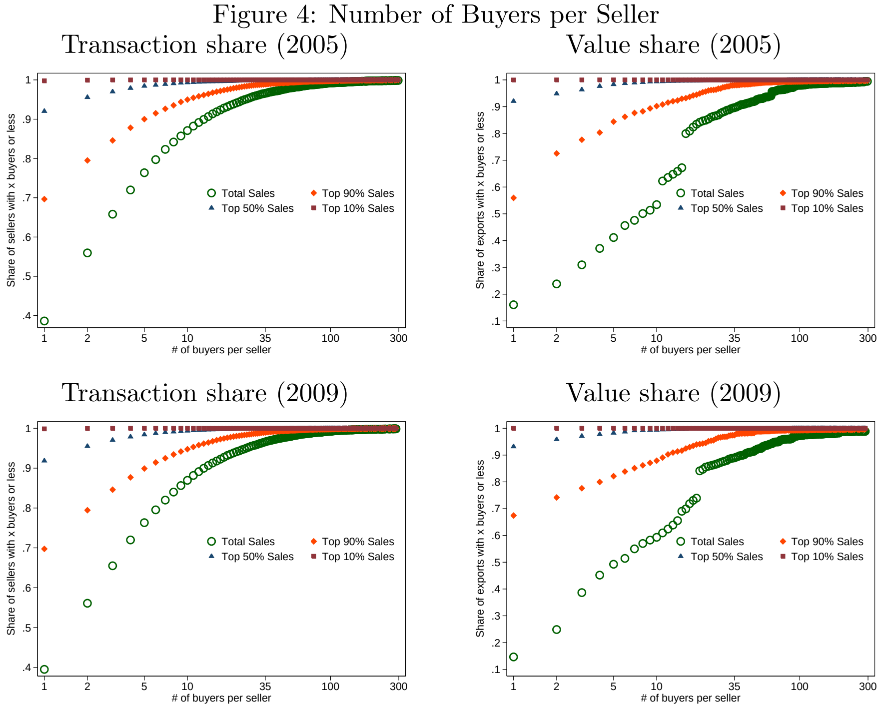
Figure 4: Number of Buyers per Seller



Proportion of sellers (left panel) and share of trade accounted for by sellers (right panel) that serve x buyers or less. 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.