Volatility in the Small and in the Large: The Lack of Diversification in International Trade*

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Abstract

Does international trade foster or dampen the risk exposure of firms and countries? Trade induces specialization, thus increasing economies' exposure to idiosyncratic supply shocks. But greater geographic diversification through trade offers natural hedging properties against demand shocks. Key to this debate is the interplay between the sources of shocks hitting firms and countries and their economic diversification. We offer an integrated empirical study of these different dimensions. We quantify the contribution of shocks and the realized structure of trade networks to the volatility of exports, at the firm-level and in the aggregate. Exporters' volatility is shown to directly depend on the (lack of) diversification in their portfolio of clients. Indeed, most exporters, including the largest, have one or two main clients that dwarf the others. This structure of trade networks magnifies aggregate fluctuations.

1 Introduction

Whether international trade fosters or dampens the risk exposure of firms and countries is an ongoing research question. On the one hand, trade induces specialization, that is increasing the concentration of activities across sectors and firms.[1] In the presence of idiosyncratic supply shocks hitting industries or individual producers, this increased specialization of activities should make economies more volatile (di Giovanni and Levchenko, 2009, 2012). On the other hand, trade may be a source of diversification for firms and countries in the presence of demand shocks. If true, greater geographic diversification through trade is associated with lower exposure to country-specific shocks, and lower volatility (Caselli et al., 2015). Likewise, a more diversified portfolio of clients offers natural hedging properties against idiosyncratic demand shocks (Kelly et al., 2013).

Key to this debate is the interplay between the sources of shocks hitting firms and countries and their economic diversification. Whether international trade ultimately induces larger or smaller volatility is an empirical question that depends on i) the prevalence of different types of shocks, ii) the realized structure of trade and production, and the associated residual exposure to different sources of risk. Our paper contributes to this literature by offering an integrated empirical study of these different dimensions. This analysis places a particular emphasis on idiosyncratic demand shocks, which are shown to be an essential source of volatility, both at the level of individual firms and in the aggregate. While these sources of fluctuations could be diversified in international markets, we show that this is *not so* because individual exporters often have a skewed portfolio with a main client and a small number of other clients; all with volatile demands that are almost orthogonal within each exporter's portfolio, resulting in volatile demand for the exporter. This lack of diversification, and the associated volatility, holds for all types of exporters,

[1] See eg. Dornbusch et al. (1977) or di Giovanni et al. (2011).

most strikingly the very large ones. As a consequence, demand shocks hitting exporters drive volatility not only at the firm-level but also in the aggregate. Specialization, with the resulting structure of trade networks, magnifies the impact of exporters' lack of diversification.

The analysis proceeds in three steps. The first step consists in recovering from the data the different shocks hitting firms in international markets. To do so, we make use of newly available data on firm-to-firm trade flows. Our data set measures the flows of French exports, their exporter, and their precise buyer in Europe over 13 years and 11 countries. We develop a simple model to discipline our empirical analysis. In this framework, the growth of export sales between a seller and its client decomposes into four terms: an "aggregate" component that encompasses all the variation in a country's sectoral demand common to all firms active in this market, a seller-specific component which plays the role of an idiosyncratic cost-shifter in the model, and two buyer-related components, one that is specific to the buyer and affects all the sellers she is connected to and one that is specific to the seller-buyer pair, which is akin to an idiosyncratic taste shock. Based on this structural decomposition, we exploit the connectedness in sellers' and buyers' trade networks to back out the different sources of export growth introduced into the model.

Armed with these estimated growth components, we quantify in steps two and three the extent to which different sources of risk contribute to the volatility of French firm-level and aggregate exports. This involves combining the estimated growth components with the actual structure of exports. The architecture of export portfolios determines the extent to which risks that are potentially diversifiable are actually diversified in the data. Because we observe both the sources of risk and the trade portfolios, we can use multiple experiments to study the interplay of both dimensions as a source of risk hedging. In particular, we will use such experiments to quantify the extent to which diversification through trade markets and the concentration of activities induced by specialization shape the nature of export volatility in the data.

Our results can be summarized in two, dual, dimensions: in the small i.e. for firms' exposure; in the large i.e. for countries' exposure. At the level of individual firms, we first show that microeconomic growth components, whether they hit the supply- or the demand-side of the market, account for almost 100% of the volatility of export sales. While seller-specific components are the most important source of volatility in our data, we show that buyer-related growth components also matter substantially. Muting this source of volatility reduces the variance of export sales by almost a third for the median firm in our sample. This is to be compared with a 36% drop in the median volatility obtained when assuming individual supply components away. The reason why buyer-related growth components contribute substantially to the volatility in the small is that they are not much diversified within a firm. Most exporters serve a very limited number of clients in a few destinations. And even the firms with a wider portfolio of foreign partners are left quite exposed to shocks affecting their clients because their sales are skewed towards one or two main clients.[2]

Exposure to buyer-related sources of fluctuations not only helps us explain the *level* of firm volatility, it also contributes to explaining its *heterogeneity* across firms. More specifically, firms with a broader portfolio of clients, within and across destinations, are shown to display significantly less volatility, a result which is consistent with Kelly et al. (2013). Because large firms tend to serve more destinations and clients, this contributes to explaining

[2]Note that interacting with a large number of clients is not a necessary condition for being little exposed to buyer-specific shocks. Individual exporters might end up well-diversified in the buyers' dimension while interacting with a small number of clients if those clients display little volatile purchases and/or if they face negatively correlated shocks. Our empirical analysis is ex-ante agnostic about this possibility since we do not impose any structure on the cross-sectional correlations nor on the amount of volatility and its heterogeneity across individuals. Ex-post, the large volatility of exporters is due to two joint patterns. First, exporters are exposed to a narrow set of clients. Second, the growth rates in these clients' purchases are quite volatile and not sufficiently correlated across buyers for this volatility to wash out in sellers' portfolio. Both patterns imply that French exporters end up relatively exposed to shocks affecting their individual clients.

why they display less volatility, on average. Hence, increasing participation into international trade reduces firms' risk exposure by diversifying individual buyer-related risks. Such diversification can take place within *and* across countries. Our experiments show that both dimensions are almost equally important when it comes to explaining the impact of portfolio diversification on the volatility of individual sales.

In the large, all three microeconomic sources of fluctuations are mechanically diversified across individuals, thus becoming less prevalent. As a consequence, muting all the country-sector components has the same impact on the volatility of multilateral export growth than ignoring the three sources of microeconomic risk. Still, individual growth components continue to matter, as a consequence of the distribution of exports being fat-tailed. Because these large exporters are not perfectly diversified across markets and clients, as seen in the small, shocks affecting these largest exporters show up in the aggregate volatility. Indeed, buyer-related growth components matter almost as much as individual supply components at this aggregate level.[3] Among these buyer-related growth components, the buyer-specific part accounts for a larger share of the aggregate volatility than the seller-buyer one, despite being slightly less volatile, on average. This is a consequence of the connectedness of individual sellers' trade networks: exporters typically interact with the same set of clients, within a destination. Such connectedness induces co-movements in seller-specific exports, thus limiting the extent to which buyer-specific shocks can be smoothed out in the large.

We use various experiments to illustrate how our results are affected by the existing structure of trade networks and the diversification opportunities it offers. Results confirm the view that international markets contribute to

[3]This is consistent with the results in di Giovanni et al. (2014) who show that, even though large firms are less volatile, on average, than smaller firms, the difference in volatilities is not sufficiently strong to overcome the forces towards granularity. We also find that large firms are less volatile, partly because they are less strongly exposed to buyer-related risk. But their exposure to such shocks is still substantial, thus showing up in the aggregate.

reducing volatility through increased diversification opportunities. However, our results show that diversification is neither perfect, nor solely achieved through a wider portfolio of foreign destinations. Namely, having more partners within a country also helps hedging risk. Finally, our experiments confirm that the concentration of firms into international markets is a primary source of volatility. Such concentration increases the economy's exposure to idiosyncratic supply shocks (di Giovanni and Levchenko, 2012). Even the very large firms are exposed to the risk induced by demand shocks – our buyer-related growth components – and this concentration magnifies the aggregate impact of microeconomic demand shocks. Contrasting two large economies, Spain and Germany, with very concentrated trade networks for the former and much less for the latter, the larger aggregate volatility of exports to Spain (2.5 times that of exports to Germany) is largely attributable to the interplay between this concentration and the lack of diversification of French exporters on their demand side, most strikingly among the largest exporters. The lack of diversification on the demand side of economies that are highly specialized and concentrated magnifies volatility.

Our paper is related to several strands of the literature. First, the use of export data naturally draws a link with the international trade literature. Several contemporary papers use comparable firm-to-firm trade data to go deeper into the microeconomic structure of aggregate export flows (Bernard et al., 2017; Eaton et al., 2013; Carballo et al., 2013). While the trade literature typically studies the determinants of the structure of trade, we instead consider its implications for firms and countries' exposure to shocks, as measured by the volatility of export growth.[4]

In this respect, our paper is more closely related to the literature studying the way international trade affects aggregate fluctuations, notably Koren and

[4]A recent and complementary strand of the literature has studied the structure of economic networks as the outcome of an endogenous process. See Oberfield (2011) in the context of a closed economy and Chaney (2014) in an international trade context.

Tenreyro (2007), Caselli et al. (2015) and di Giovanni and Levchenko (2012). Caselli et al. (2015) point out the importance of geographic diversification to mitigate country-specific shocks. We also find that geographic diversification is important but mostly as a way to diversify individual rather than aggregate sources of risk. This finding is in line with the literature on aggregate "granular" fluctuations, which draws a link between the micro structure of the economy and aggregate volatility (Gabaix, 2011; Acemoglu et al., 2012; di Giovanni et al., 2014). In particular, di Giovanni and Levchenko (2012) shows how participation into international markets can strengthen the concentration of activities along the distribution of firms, thus increasing the country's exposure to idiosyncratic supply shocks. Our results suggest that the argument extends to other sources of microeconomic shocks. In comparison with di Giovanni et al. (2014), the additional firm-to-firm dimension allows us to go deeper into the analysis of the microeconomic origins of aggregate fluctuations and statistically separate seller-related and buyer-specific sources of risk. To do so, the different sources of volatility are identified using a rich variance decomposition. A burgeoning and complementary literature instead exploits natural disasters to trace the propagation of well-identified shocks within economic networks (Barrot and Sauvagnat, 2016; Carvalho et al., 2016). While this approach has important advantages when it comes to identifying the propagation of shocks, such a strategy does not attempt to compare the relative importance of several sources of risk, which our approach tries to do.

Finally, the analysis of volatility "in the small" builds upon the literature on firm-level volatility, which documents a large amount of volatility in firm-level data, irrespective of the measure of performance used.[5] Not only is firm-level volatility high on average, it is also strongly heterogeneous across firms (Decker et al., 2014; Fort et al., 2013). Whereas most papers rely on

[5] Comin and Philippon (2006) document the increase in firm volatility using real measures (sales, employment and capital expenditures) as well as financial data (equity returns). See also Comin and Mulani (2006) and Asker et al. (2014) on sales data, Thesmar and Thoenig (2011) based on sales and employment, Campbell (2001) using stock returns.

idiosyncratic supply shocks when explaining such dynamics, recent contributions have pointed out the role of customer-related shocks (Foster et al., 2008, 2012; Arkolakis, 2011; Kelly et al., 2013; Vannoorenberghe et al., 2016). In line with both strands, our paper identifies the different sources of risk affecting firms' growth, coming from exporter-specific (supply) and customer-related (demand) components. We quantify their relative contributions in explaining the volatility of individual sales and their heterogeneity across firms.

The rest of the paper is organized as follows. We start with a description of our data and new stylized facts on trade networks in Section 2. In Section 3, we describe our identification strategy of the growth decomposition at the most disaggregated (seller-buyer) level. Next, we present the results in two distinct steps. We discuss the origin of fluctuations *in the small*, at the level of individual firms, in Section 4. Section 5 instead analyzes the question *in the large*, based on aggregate trade flows. Finally, Section 6 concludes.

2 Data and stylized facts

2.1 Data

The empirical analysis is conducted using detailed export data covering the universe of French firms. The data are provided by the French Customs.[6] The full data set covers all transactions that involve a French exporter and an importing firm located in the European Union. Our analysis however focuses on exports to the fifteen "old" members of the European Union, less Greece, Luxembourg, and Austria.[7] For all these countries, we use data for the 1995-2007 period.

[6] We would like to thank Thierry Castagne who took time to explain the specificities of the data.

[7] The reason for leaving these three countries aside comes from the difficulty, not to say the impossibility, of identifying individual buyers for these destinations. We found breaks in the panel dimension of buyers' identity. We also had to exclude from the analysis the new member states of the European Union because the time dimension was too short in their case.

Many researchers before us have used trade data on individual exporters provided by the French Customs. Our data are richer than the ones used in previous studies since we know, among other characteristics, the identity of the exporting firm *and* the identity of the importer it serves. For each transaction, the data set records the identity of the exporting firm (its name and its SIREN identifier), the identification number of the importer (an anonymized version of its VAT code), the date of the transaction (month and year), the product category (at the 8-digit level of the combined nomenclature) and the value of the shipment. In the analysis, data are aggregated across transactions within a year, for each exporter-importer pair. This helps focusing on the most important novelty of the data, which is the explicit identification of both sides of the markets, the exporter and its foreign partner.[8] In the rest of the analysis, the set of exporters observed at period t will be designated as S_t where $s \in S_t$ is one particular seller. Our data is restricted to sellers located in France and we thus abstract from mentioning their origin, except when needed. On the contrary, individual buyers are characterized by their location, with $b(j)$ denoting a buyer located in country j. B_t will denote the set of active buyers/importers $b(j)$ at time t and B_{st} the subset of buyers interacting with seller s.

While goods are perfectly free to move across countries within the European Union, firms selling goods outside France are still compelled to fill a Customs form. These forms are used to repay VAT for transactions on intermediate consumptions. This explains that the data are exhaustive. One caveat, though: small exporters 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

[8]Notice that, even though we track each sale a seller makes to each country, we cannot do the same for buyers. More precisely, we cannot know if the same buyer buys from two foreign sellers from two different countries. More generally, since we do not have additional information on the buyer, we cannot say whether it is an affiliate of the same (multi-national) firm as the seller or indeed if two buyers in our data are connected through multinational linkages.

the outcome variable since the corresponding transactions cannot be included in the data set. The "simplified" regime concerns firms with total exports in the European Union in a given year below 100,000 euros (150,000 euros since 2006), which are thus dropped from the estimation sample. Since the analysis focuses on "granular" fluctuations, which mostly involve large firms in an economy, we believe this absence to be immaterial. We however checked that the most important stylized facts still prevail if we include the small firms, without controlling for the product dimension.

Given the quality of the data, little cleaning is necessary to construct the final data set. We only remove one type of flows when the country code is not equal to the country code that can be recovered from the importer's identifier. This may happen when a French firm is the intermediary for a transaction between two countries other than France, the first one where the good is produced, the second where it is bought. These transactions are removed from our data set because they do not qualify as "French exports" in a strict sense.

In 2007, we have information on 42,888 French firms exporting to 334,905 individual buyers located in the 11 countries of the European Union. Total exports by these firms amount to 207 billions euros. This represents 58% of French total exports. Detailed summary statistics by destination country are provided in Table 1. Whereas large destination markets naturally involve more firms on both sides of the border, the density of trade networks, as measured by the number of active pairs divided by the potential number of relationships, is instead lower in countries like Germany or Belgium.

The firm-to-firm data are used to describe the structure of trade networks, in the cross-section. We also use the time-dimension to compute measures of sales growth at different levels of aggregation, and their volatility. Let us denote the growth rate between date $t-1$ and t as $g_{sb(j)t}$, g_{st} and g_t, respectively for the seller-buyer, the seller and the aggregate levels.[9] Our measure of

[9] In Section 4, we focus on the intensive margin, hence on the subset of bilateral pairs

volatility is the variance of annual growth rates computed at each level. We restrict our attention to the subset of second-order moments computed on at least four points.[10] Finally, to minimize the effect of outliers on our measures of volatility, we base our estimates in Section 3 on observations for which the seller (log-) growth rate lies in the interval $[-0.8; 4]$. Table A1 in Appendix quantifies how restrictive these constraints are, as measured by the sample coverage.

2.2 Stylized facts on trade networks

In this section, we discuss a new set of stylized facts about the structure of French firms' international trade networks, as of 2007.[11] The extent of sales' concentration is used as a sufficient summary statistics to characterize how easily the existing structure of trade networks *can* help diversify against risks. To assess how much they *do*, we combine this information with the actual structure of shocks in sections 4 and 5.

As explained before, the analysis in this paper is run at two levels of aggregation, "in the small", for individual exporters, and "in the large", for the overall economy. For individual firms, the geographic diversification of exports has natural hedging properties against country-specific risk while having a wider portfolio of buyers, both within and across countries, reduces a firm's exposure to buyer-related shocks. Figure 1 illustrates the extent of such diversification in the data. The left panel shows the cumulated distribution of

active in both $t-1$ and t. Therefore, g_{st} aggregates $g_{sb(j)t}$ for buyers that buy from s in both $t-1$ and t. Appendix B of the Online Appendix discusses an explicit treatment of the extensive margin and how much this margin contributes to volatility in the small and in the large.

[10] Whereas four points may seem a small number for computing measures of volatility, this restriction reveals itself rather constraining once one realizes that it relies on the number of years a given firm serves a specific destination or even the number of years a given seller-buyer pair is active. In our data, about 75% of seller-buyer relationships last less than 4 years. These are tiny transaction accounting for less than 15% of exports. The low average duration of relationships also explains why we do not compute time-varying measures of volatility based on sub-periods, as is often done in the macroeconomic literature.

[11] Section A of the Online Appendix provides a more detailed analysis of the structure of trade networks.

French exporters, ordered by the number of EU destinations they serve. The circles line thus shows the share of French exporters serving x destinations or less, which is naturally equal to 100% when we reach 11 countries, our sample. The right panel illustrates the extent of concentration across buyers, with the circles line measuring the share of exporters serving x buyers or less in a given destination.

On average, between-market diversification is limited in our data, with one seller over four serving a single destination and less than 5% of French exporters active in the eleven EU countries of the data set. As extensively documented in the trade literature, self-selection across firms however implies that these 5% of firms represent a disproportionate share of aggregate exports, around 30% in our data. Serving a large array of countries is not a sufficient condition, however, to be well-diversified in the country dimension. Indeed, a firm may serve all European destinations but be poorly diversified if most of her exports go to one market. Later in the analysis, we use the Herfindahl of firms' sales as the adequate measure of concentration. In Figure 1, we instead compute each firm's number of destination countries, excluding from the calculation the smallest destinations in the firm's portfolio. For instance, the grey diamonds show that 60% of French exporters have at least 90% of their export sales going to a single destination, they represent 20% of French exports.

This suggests that French exporters are hardly diversified in the geographic dimension. The same holds for between-buyers diversification within a market, as illustrated in the right panel of Figure 1. 43% of French sellers export to a single buyer within a destination. At the other side of the distribution, 12% of firms serve at least 10 buyers but account for 40% of total exports. Again, the data reveal a large amount of heterogeneity, across French exporters, with large firms serving more clients on average.[12] However, even large firms are

[12] These results are consistent with those obtained in Carballo et al. (2013) and Bernard et al. (2017). Results in section A of the Online Appendix show that the correlation between

not well-diversified as shown by the additional lines displayed in Figure 1, right panel. Among the 12% of firms that serve more than 10 buyers, the majority of these buyers account for a tiny fraction of the firm's total exports (their cumulative share being below 10%). Once such 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.

We conclude this section with a brief description of the diversification "in the large". All four types of shocks that we later consider are potentially diversifiable in the large, although in different dimensions. Exposure to country-specific shocks is reduced if a country exports to a wider set of destinations. In our sample, such diversification is actually almost perfect, the Herfindahl of French exports across destinations being .16, not far from 1/11=.09, the minimum degree of concentration which can be achieved in a sample of 11 countries.[13] The "aggregate components" that we later estimate encompass both country-specific and sector-specific shocks. Another source of potential diversification is thus the between-sector dimension. In this dimension as well, the data suggests that diversification is relatively high, with an Herfindahl of .09, to be compared with the maximum amount of diversification which is 1/35=.03.

More important for the rest of the analysis is to understand if and how the microeconomic structure of trade networks helps smooth the aggregate impact of *microeconomic* shocks. Here, what matters is the skewness of individual sales (Gabaix, 2011). If the distribution of sales were symmetric, idiosyncratic volatility would have a negligible impact on aggregate fluctuations since individual shocks would compensate one another. The concentration of exports is illustrated in Table 2. These statistics reveal an extreme concentration

firms' size and their number of clients remains significant when one controls for the firm's experience in the destination market, the number of products she sells, the "size" of the destination as measured by the potential number of clients, and the firm's participation to multinational activities.

[13]The deviation from perfect diversification appears to be correlated with differences in country sizes with France exporting more to larger countries.

of French exports, whether across exporters, importers, or exporter-importer pairs. In all three dimensions, the higher decile of the distribution thus accounts for more than 90% of aggregate exports. Overall, the microeconomic structure of French exports induces a strong exposure to idiosyncratic firm-level shocks.

3 Empirical strategy

Having described the main characteristics of the trade networks French exporters are embedded in, we turn to the analysis of trade dynamics within such networks. We first present our theoretical framework, which we use to derive the empirical specification and to motivate our identification strategy. Within this framework, the estimated equation can be interpreted as a decomposition of trade dynamics into various well-identified shocks. Such structural interpretation of course relies on a number of (strong) assumptions. Most of the results that we latter discuss do not critically rely on such structural interpretation, however. Alternatively, one can think of the empirical framework as a rich variance decomposition used to extract from the data various sources of risk affecting firm-to-firm trade growth.

3.1 Sources of firm-to-firm trade growth

In this section, we develop a partial equilibrium model of the demand for imported goods, in which we introduce a variety of fundamental shocks to obtain predictions about the determinants of disaggregated trade growth.

The demand side of the model features a buyer $b(j)$ producing a consumption good in country j with various inputs bought to a finite number of sellers $s(i)$ located in various countries indexed by i. The technology for producing

$y_{b(j)}$ units writes as follows:

$$y_{b(j)} = \left[z_{b(j)} \sum_i \sum_{s(i)\in\Omega_{b(j)i}} \left(z_{s(i)b(j)} x_{s(i)b(j)} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

where $x_{s(i)b(j)}$ is the demand for the input produced by a seller $s(i)$, $\sigma > 1$ is the elasticity of substitution between input varieties, $z_{s(i)b(j)}$ is a preference parameter for input $s(i)$, $z_{b(j)}$ is a measure of the buyer's productivity and $\Omega_{b(j)it}$ is the set of suppliers of buyer $b(j)$ in country i.[14] In general, some of these inputs can be produced in-house, i.e. with the firm's own value added (in which case $s(i) = b(j)$). Such internalized value added only matters to the extent that it can substitute with inputs bought from France, which the empirical framework will later focus on.

Given this production function, the buyer minimizes total costs induced by the level of production that satisfies market demand:

$$y_{b(j)} = p_{b(j)}^{-\eta} A_j$$

where $p_{b(j)}$ is the price charged by the buyer to her representative consumer and A_j an aggregate demand shifter (potentially sector-specific). $\eta > 1$ measures the price elasticity of final demand. The CES demand function implies that the buyer charges her consumer a price $p_{b(j)}$ which is a constant markup $\eta/(\eta-1)$ over her marginal cost $c_{b(j)}$. In equilibrium, the marginal cost writes:

$$c_{b(j)} = z_{b(j)}^{\frac{-\sigma}{\sigma-1}} \left[\sum_i \sum_{s(i)\in\Omega_{b(j)i}} \left(\frac{p_{s(i)b(j)}}{z_{s(i)b(j)}} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

where $p_{s(i)b(j)}$ is the price charged by input supplier $s(i)$ (or the factor cost if the input is produced in-house).

Varieties of inputs are produced using a technology linear in labor. The

[14] The set $\Omega_{b(j)t} = \cup_i \Omega_{b(j)it}$ corresponds to the buyer's sourcing strategy using the term coined by Antràs et al. (2014).

productivity of labor is assumed to be a function of an aggregate productivity component Z_i and a firm-specific term $z_{s(i)}$. Calling ω_i the exogenous cost of labor in country i and assuming that input providers compete under monopolistic competition, the price set by exporter $s(i)$ for her sales to buyer $b(j)$ is:[15]

$$p_{s(i)b(j)} = \frac{\sigma}{\sigma - 1}\frac{\omega_i}{z_{s(i)}Z_i}$$

Note that this pricing rule relies on two strong but important assumptions, namely that technology displays constant returns to scale and that markups are constant. Constant returns to scale insure that the seller's problem is separable across her different clients, which prevents demand shocks to spread within the firm's portfolio. While such propagation of demand shocks is not completely ruled out in the empirical framework, we assume that it is not sufficiently important to induce a systematic correlation between the growth components estimated in the empirical framework.

The constant markup assumption is key for the mapping between estimated growth components and the underlying shocks. Under non-constant markups, (micro and macro) supply shocks might have a non-homogenous impact across the various importers connected to the firm facing the shock. Appendix C accounts for this possibility using several non-structural assumptions. While the solutions proposed do not completely fix the problem, we argue that results are sufficiently consistent over various specifications for the constant markup assumption to be considered as a reasonable proxy.[16]

Together, these assumptions imply that the nominal demand of a variety

[15]For simplicity, we assume no delivery costs in the model. In the empirical analysis, changes in trade costs are absorbed into the sector-destination fixed effect.

[16]More specifically, we show that the results are robust to allowing transactions of different size to adjust differently in the event of a macro shock. We then discuss how a heterogeneous transmission of seller shocks across buyers would affect the interpretation of results. As long as markups are heterogeneous across sellers but homogenous across buyers for a given seller, the estimated decomposition is valid but we cannot interpret the growth components in terms of the underlying shocks as in the constant markup case. If markup adjustments in the event of a seller shock are specific to a seller-buyer pair, the orthogonality conditions at the root of the estimation might be violated.

$s(i)$ bought by buyer $b(j)$ varies over time according to:

$$
\begin{aligned}
g_{s(i)b(j)t} \quad = \quad & (1-\sigma)d\ln\omega_{it} + (\sigma-1)d\ln Z_{it} + d\ln A_{jt} + (\sigma-1)d\ln z_{s(i)t} \\
& +(\sigma-\eta)d\ln c_{b(j)t} + \sigma d\ln z_{b(j)t} + (\sigma-1)d\ln z_{s(i)b(j)t} \qquad (1)
\end{aligned}
$$

where the growth of the marginal cost can be written using a Taylor approximation as in:

$$
\begin{aligned}
d\ln c_{b(j)t} \quad = \quad & \frac{-\sigma}{\sigma-1}d\ln z_{b(j)t} + \left[\sum_{i'} w_{i't-1}^{b(j)} \left(d\ln\omega_{i't} - d\ln Z_{i't}\right)\right] \\
& - \left[\sum_{i'} \sum_{s'(i')\in\Omega_{b(j)i't}} w_{s'(i')t-1}^{b(j)} \left(d\ln z_{s'(i')t} + d\ln z_{s'(i')b(j)t}\right)\right]
\end{aligned}
$$

Here, $w_{s'(i)t-1}^{b(j)}$ is the share of seller $s'(i)$ in buyer $b(j)$'s input cost in $t-1$ and $w_{i't-1}^{b(j)} \equiv \sum_{s'(i')\in\Omega_{b(j)i't}} w_{s'(i)t-1}^{b(j)}$ the share of country i' in buyer $b(j)$'s sourcing strategy.

Equation (1) thus defines the dynamics of trade as a function of the growth of the fundamentals, namely the two price shifters, $z_{s(i)t}$ and Z_{it}, the wage shifter, $d\ln\omega_{it}$, and the three demand variables, $z_{s(i)b(j)t}$, $z_{b(j)t}$ and A_{jt}.[17] The last step consists in specifying how these variables evolve over time. In what follows, it is assumed that their dynamics is driven by non-autocorrelated shocks which are orthogonal to each other in the cross-section, i.e. for each $k = Z_i, A_j, z_{s(i)}, z_{b(j)}, z_{s(i)b(j)}$, $k_t = \bar{k}e^{\varepsilon_{kt}}$ where ε_{kt} denotes the shock affecting (the log of) variable k at time t.

Our data set provides information on the growth of firm-to-firm trade for the sub-sample of input providers located in France and their buyers located in the rest of the European Union (i.e. i =France and j one of the 11 EU

[17] The classification of shocks into supply and demand is somewhat arbitrary in this context. In what follows, all shocks affecting the buyers are called demand shocks, even though they can be driven by changes in the productivity of these firms. From the point of view of the French exporter, such shocks induce an exogenous change in the demand for exports, which justifies this choice of vocabulary.

members covered by our sample). We now explain how we exploit the structure of the data to estimate the different components of the above equation in this sub-sample.

3.2 Identification strategy

As we describe now, we use the graph structure of trade networks to separate between the different components of growth that were introduced into the model. First, we note that our model delivers a fixed-effects decomposition. After simple manipulation, Equation (1) rewrites as:

$$g_{s(i)b(j)t} = f_{c(ij)t} + f_{s(i)t} + f_{b(j)t} + BSIC_{b(j)t} + \nu_{s(i)b(j)t} \tag{2}$$

where:

$$\begin{aligned}
f_{c(ij)t} &= (\sigma-1)d\varepsilon_{Z_it} + d\varepsilon_{A_jt} + (1-\sigma)d\ln\omega_{it} \\
f_{s(i)t} &= (\sigma-1)d\varepsilon_{z_{s(i)}t} \\
f_{b(j)t} &= \frac{\sigma}{\sigma-1}(\eta-1)d\varepsilon_{z_{b(j)}t} + (\sigma-\eta)\sum_{i'} w^{b(j)}_{i't-1}(d\ln\omega_{i't} - d\ln Z_{i't}) \\
BSIC_{b(j)t} &= -\frac{\sigma-\eta}{\sigma-1}\sum_{i'}\sum_{s'(i')\in\in\Omega_{b(j)i't}} w^{b(j)}_{s'(i')t-1}(f_{s'(i')t} + \nu_{s'(i')b(j)t}) \\
\nu_{s(i)b(j)t} &= (\sigma-1)d\varepsilon_{z_{s(i)b(j)}t}
\end{aligned}$$

The partial equilibrium model of Section 3.1 therefore delivers a decomposition of firm-to-firm trade growth into four terms, a macroeconomic component, a seller-specific term and a buyer-specific effect, plus a residual term specific to the seller-buyer match. Note that the buyer-specific component is composed of two terms, the buyer fixed effect $f_{b(j)t}$ and a weighted average of the seller- and match-specific shocks affecting her partners ($BSIC_{b(j)t}$, hereafter). The $BSIC_{b(j)t}$ term arises from the response of the buyer-specific input cost index to price adjustments made by each of her partners. A negative productivity shock to seller $s(i)$ increases the input cost attenuating the direct impact that the shock has on the demand addressed to that seller. Moreover, this effect propagates to the rest of the buyer's portfolio of partners. The presence of this buyer-specific input cost component in equation (2) is important because it creates a negative correlation between the buyer-specific term and the match-specific residual, which is stronger when the seller represents an important share of the buyer's input purchases.[18] Absent this correlation, equation (2) could be estimated using a two-way fixed effect estimator, as in Abowd et al. (1999).

We propose to control for the endogeneity bias just described using an additional assumption, namely that foreign buyers concentrate their input purchases on French suppliers, $w_{Ft-1}^{b(j)} = 1 \ \forall \ b(j)$.[19,20] Under this assumption, one can show that it is possible to rewrite equation (2) as follows:

$$\tilde{g}_{s(i)b(j)t} = \tilde{f}_{c(ij)t} + f_{s(i)t} + \tilde{f}_{b(j)t} + \nu_{s(i)b(j)t} \tag{3}$$

[18]Namely,

$$Corr\left(f_{b(j)t} + BSIC_{b(j)t}, \nu_{s(i)b(j)t}\right) = -\frac{\sigma - \eta}{\sigma - 1} w_{s(i)t-1}^{b(j)} Var(\nu_{s(i)b(j)t-1})$$

.

[19]The strategy that we adopt to recover the different components of equation (2) still applies if we instead assume the share of French exporters in all buyers' input purchases to be homogenous, i.e. $w_{Ft-1}^{b(j)} = \bar{w}_{Ft-1} \ \forall \ b(j)$. Under this (less stringent) assumption, the estimated buyer-specific effect encompasses shocks to the buyer's productivity $\varepsilon_{z_{b(j)t}}$ and an average of shocks affecting her clients located outside France.

[20]Another conceivable strategy consists in neglecting the endogeneity issue arising from seller- and match-specific shocks affecting the buyer's input price index. This strategy corresponds to the case in which elasticities at the intermediate and final good levels are calibrated with the same value (namely $\sigma = \eta$). Ignoring endogeneity is also a good approximation of what will happen if no single French firm represents a large enough share of her buyer's marginal cost (i.e. $w_{s(F)t-1}^{b(j)} \approx 0 \ \forall (s(F), b(j))$ and thus $w_{Ft-1}^{b(j)} \approx 0$). Unfortunately, we do not have any information on these shares in our dataset but outside evidence based on firm-level data suggest that the share of foreign value added in output is typically relatively small (e.g. below 40% on average and closer to 15-20% for most firms in the case of France described in Blaum et al. (2016)). A low foreign content in output de facto implies that no single foreign input provider has a substantial impact on her client's marginal cost. Section C of the Online Appendix shows that neglecting endogeneity issues does not affect the main results obtained in the core of the paper.

where:

$$
\begin{aligned}
\tilde{g}_{s(i)b(j)t} &= g_{s(i)b(j)t} + \lambda \sum_{s'(F) \in \Omega_{b(j)t}} w^{b(j)}_{s'(F)t-1} g_{s'(F)b(j)t} \\
\lambda &= \frac{\sigma - \eta}{\eta - 1} \\
\tilde{f}_{c(ij)t} &= (1+\lambda) \left[(\eta - 1) d\varepsilon_{Z_i t} + d\varepsilon_{A_j t} + (1-\eta) d \ln \omega_{it} \right] \\
\tilde{f}_{b(j)t} &= \sigma d \ln \varepsilon_{z_{b(j)t}}
\end{aligned}
$$

to which the Abowd et al. (1999) estimator straightforwardly applies under the following exogeneity condition (see details in Appendix A):

$$E(\nu_{s(i)b(j)t} | (s(i), t); (b(j), t)) = 0$$

Equation (3) thus delivers a fixed-effects decomposition which terms can be estimated under the structural assumptions of the model to recover the contribution of various families of shocks to the growth of firm-to-firm trade flows. In this equation, the "macroeconomic" component captures the contribution to firm-to-firm growth of all the supply and demand shocks that are common across all sellers and buyers within a destination. In the empirical analysis, we further assume that it is specific to the seller's industry, thus absorbing sector-specific shocks as well. The buyer-specific term captures the impact on firm-to-firm growth of buyer-specific demand shifters, the buyer's productivity shock $\varepsilon_{z_{b(j)t}}$ in the model of Section 3.1. Finally, the seller component is driven by seller-specific productivity shocks $\varepsilon_{z_{s(i)t}}$ while the seller-buyer residual absorbs the impact of taste shocks $\varepsilon_{z_{s(i)b(j)t}}$. In presence of non-constant markups, the cross-sectional variation in these components would also reflect differences in sellers' cost pass-through. Therefore what we loosely label a seller shock is in fact the ex-post impact of the primitive seller-specific shock onto the growth of the seller sales. Likewise, the seller-buyer residual also absorbs any seller-buyer-specific impact of a more aggregated shock.

Such structural interpretation is useful inasmuch as it helps interpreting the growth components that we later estimate. However, applying this strategy requires that we take a stand on the value of λ, a function of the two demand elasticities of the partial equilibrium model. To recover λ, we use an additional orthogonality condition in line with the theoretical model:

$$E(f_{s(i)t}\tilde{f}_{b(j)t}) = 0$$

Under the "true" value of λ, the above orthogonality condition holds. Since the model is linear, conditional on λ, the relationship between λ and the magnitude of the correlation between the sellers and the buyers fixed effects is monotonic (Blundell and Robin, 1999). As these authors suggest, we implement a grid-search algorithm on all the possible values of λ and pick the value which best satisfies the model-implied orthogonality condition. Appendix A gives more details on the estimation procedure.[21,22] Results for the decomposition are presented in Tables 3 and 4. They are obtained for $\hat{\lambda} = 0.77$ which is consistent with the price elasticity of demand for French inputs being slightly above the price elasticity that buyers face on their own market (eg. 0.77 is consistent with $\eta = 3$ and $\sigma = 4.5$). A positive value is also consistent with the view that markups increase along the production chain ($\sigma > \eta$).

Table 3 reports the full correlation table of the various estimated effects.

[21] As detailed in Appendix A, the orthogonality condition (3.2) relies on the asymptotic properties of the model. Given that the actual network is relatively sparse, it may be that we do not achieve orthogonality between the seller and buyer components because of measurement errors on some of the estimated components of the shocks. We explicitly take into account this potential "limited-connectivity bias" in the estimation of λ. Namely, we quantify the magnitude of the bias using a numerical simulation and target a value for the correlation that is consistent with the results of the simulation. See details in Appendix A.

[22] Note that the above correction rests on the assumption that the share of French inputs in buyers' purchases is equal to one, which is arguably a strong assumption. If buyers instead purchase inputs from several source countries, the correction might overstate the endogeneity issue induced by match-specific shocks affecting the buyer's input cost index. One can show however that the correction reduces the endogeneity, in comparison with a solution that would ignore the problem, whenever the share of French inputs in the buyer's costs is sufficiently large.

Notice that the correlations are not corrected for the part due to estimation errors. We see that the residual is indeed orthogonal to the buyer and the seller effects. The correlation of the sellers' and the buyers' effects is equal to -.067, our target in the grid-search algorithm.

Table 4, columns (1)-(3), reports the mean effects, their standard deviations and the number of estimated components. Column (4) reports the median contribution of each component to the overall growth *level* while column (5) reports the partial correlation coefficient; a measure of the contribution of each component to the cross-sectional *dispersion* of firm-to-firm export growth rates.The number of observations for which we can identify all three individual components is equal to 3.8 millions. There are 12 years, 11 countries and 35 2-digit industries, hence more than 4,300 macro shocks. Finally, we are in position to identify more than 200,000 seller (time) effects, using an average of 13 observations per effect and 930,000 buyer (time) effects, using on average 4 observations per effect. Without much surprise, the residual match-specific component is the most important component, explaining more than 60% of the level *and* dispersion of firm-to-firm growth rates. The other two individual components, namely the seller-specific and the buyer-specific terms, also contribute substantially to the heterogeneity in the data, respectively accounting for 12% and 25% of the dispersion. As expected given the dimensionality of the data, aggregate shocks do not explain much.

Having estimated the structural drivers of trade growth using the firm-to-firm data, it is now possible to assess the extent to which each growth component contributes to the *volatility* of firm-level sales. This is done in Section 4. Volatility "in the large", of aggregate exports, is discussed in Section 5.

4 Volatility in the small

In this section, our analysis is carried out at the exporter (seller) level and implies aggregating trade flows across buyers within a seller's portfolio. Aggregation within a seller's portfolio of buyers is the key reason for the estimated growth components to interact with the realized structure of trade networks in shaping the volatility of export sales.

In the following analysis, we focus on the *intensive* margin of trade volatility. Our strategy for identifying the different sources of risk, based on a growth decomposition, mechanically excludes from the analysis the entry and exit of buyer-seller pairs. As shown in Appendix B of the Online Appendix, the intensive margin is the main driver of fluctuations at the individual level. Appendix D further shows that accounting for survivor bias does not alter the main conclusions of our structural estimation strategy.

4.1 Theoretical framework

The volatility of a firm's sales, our object of main interest, can be defined as follows:

$$Var(g_{st}) = \frac{1}{T}\sum_{t}(g_{st} - \bar{g}_s)^2$$

where g_{st} denotes the growth rate of seller s (intensive) sales and $\bar{g}_s$ its mean, computed over time. Since our data solely covers sellers in France, we abstract from their location identifier in what follows.

At the level of individual firms, the volatility of export sales is a weighted average of the variances and covariances of firm-to-firm growth rates, observed in the sub-sample of trade flows involving a single exporter. Using the decomposition derived in Section 3:

$$Var(g_{st}) = \underbrace{Var\left(f_{st}\right)}_{Non-Diversifiable} + \underbrace{Var\left(\sum_{j\in C_s} w^s_{jt-1} f_{c(Fj)t}\right)}_{Diversifiable\ ac\ countries}$$
$$\underbrace{+Var\left(\sum_{b(j)\in B_s} w^s_{b(j)t-1}(f_{b(j)t} + \nu_{sb(j)t} + BSIC_{b(j)t})\right)}_{Diversifiable\ across\ and\ within\ countries} + Cov \tag{4}$$

where $w^s_{b(j)t-1}$ is the weight of buyer $b(j)$ in seller s (intensive) sales in period $t-1$. C_s and B_s respectively denote the set of countries and buyers connected to seller s in both periods $t-1$ and t. The Cov component represents a sum of covariance terms across the macro-economic shocks, the seller-specific shocks and the residual growth induced by the combined effect of the diversifiable components, not diversified within the firm (i.e. $\sum_{b(j)\in B_s} w^s_{b(j)t-1}(f_{b(j)t} + \nu_{sb(j)t} + BSIC_{b(j)t})$).[23]

Equation (4) summarizes the main insight of this Section. In presence of multiple sources of volatility, the variance in the small can be thought of as the sum of multiple variance and covariance terms, each depending on one specific source of volatility. Namely, the first term in equation (4) measures the micro-level volatility induced by shocks that are specific to the seller. This source is non-diversifiable within a firm but can be of heterogeneous magnitude across sellers, thus contributing to the cross-sectional dispersion in firm-level volatilities (Gabaix, 2011, Section 2.5 for instance). The second term can be interpreted as the aggregate component of volatility in the small. Such shocks are not diversifiable within a firm and a market but are diversifiable across

[23]In the model and the estimation, f_{st} is neither correlated with $f_{b(j)t}$ nor with $\nu_{sb(j)t}$. While this is true asymptotically, it might not be true within a given pair in the data set. Moreover, orthogonality of $f_{b(j)t}$ ($\nu_{sb(j)t}$) and f_{st} in the cross-section does not necessarily imply that f_{st} is orthogonal to the weighted average of the $f_{b(j)t}$ ($\nu_{sb(j)t}$) terms. Finally, the $BSIC_{b(j)t}$ terms are expected to be correlated with f_{st} in the model. Taken together, Cov comprises many elements. Empirically, they do not strongly contribute to the overall volatility of individual sales. Hence, they are not further commented in the rest of the text, although their impact is systematically taken into account.

markets. Selling to a broader set of markets is a way for the firm to hedge against country-specific shocks. This possibility is at the root of the argument in Caselli et al. (2015), even though they apply it to the volatility *in the large*. Finally, the third term captures the impact of buyer- and seller-buyer shocks, as well as the variance of the buyer-specific input cost index. The reason why these terms are grouped together is that they are *diversifiable* in nature, i.e. their impact depends on the structure of the firm's portfolio of clients. A less concentrated portfolio mechanically reduces the firm's exposure to such shocks. Of course, having a less concentrated portfolio is not the only source of risk hedging in this set-up. A firm might be little exposed to buyer-related shocks if she interacts with little volatile partners and/or if her portfolio is made of partners that comove negatively. This is the reason why both the structure of portfolios (as measured by the weighting parameters) and the individual growth components jointly determine the size of this component.

Before concluding, we note that the product dimension offers another diversification margin. In presence of product-specific (supply and demand) shocks, a firm may dampen the volatility of her sales by producing a broader portfolio of products. The trade literature has recently emphasized this margin of international trade (Mayer et al., 2014; Bernard et al., 2011, among others). However its role on the volatility of sales has not yet been analyzed. In what follows, we focus on the buyer diversification margin and show that it matters a lot to account for the volatility in the small; more diversified firms display less volatile sales. Whenever possible, we also control for the degree of cross-product diversification and show that it hardly adds anything to the analysis. This effect is however difficult to identify separately from the impact of across-buyer diversification since firms often sell their different products to different buyers.

4.2 Empirical results

In order to analyze the respective contributions of the different shocks to volatility in the small, we run a number of *counterfactual* exercises.[24] First, we compute the distribution of firm-level volatilities and compare it to the distribution of volatilities computed by muting one source of fluctuations. Second, we compute the distributions under alternative structures for trade networks. Taken together, these two sets of thought experiments help us understand how the nature of shocks and the structure of trade networks interact to shape the volatility in the small.

Figure 2 illustrates the relative contribution of each type of shocks to the volatility in the small. In this exercise, we take as our benchmark the realized dispersion of volatilities, presented as the solid line in Figure 2. We then present the distributions obtained when one source of volatility disappears. Because we estimated the full structure of shocks, for each firm, destination, and year, computing such distributions is easily realized by muting the corresponding growth components. Table 5 further reports the magnitude of the change in volatilities at different points of the distribution. In all such exercises, we not only account for the direct effect of the shocks but also their indirect effect through the buyer price index. Furthermore, muting a source of fluctuations also implies setting to zero all the covariance terms linked to this component.

As is often assumed in the related literature, seller-specific growth components are a major source of volatility in the small. Namely, removing this source of risk reduces the volatility of export growth by about a third, at every point of the distribution (large-dashed line in Figure 2). That microeconomic buyer-related components also represent a significant source of risk for exporters is less well-known though. Namely, muting both the buyer-specific

[24] We are well aware that the term "counterfactual" is not fully appropriate since we do not account for general equilibrium effects in our strategy. However, we were not able to come up with a better term. Hence we write it *counterfactual* to remind the reader of this limitation.

and the match-specific components has almost the same impact on individual volatilities than removing the seller-specific terms (short-dashed line in Figure 2). This is true even though this source of risk is diversifiable, contrary to the risk induced by idiosyncratic supply shocks. The reason why these terms contribute significantly to the volatility in the small is that i) they are relatively volatile, as shown in Table 4 and ii) they are poorly diversified in firms' export portfolios as established in Section 2.2. Finally, note that sector-country components do not contribute much to the volatility in the small, although they are not well diversified within firms' portfolios either. Indeed, these shocks are an order of magnitude less volatile than individual perturbations.

We further emphasize the role of (the lack of) diversification of firms' export portfolios by running three additional experiments. Instead of muting one source of growth after another, we directly assess the role of the structure of individual portfolios on volatility. Results are summarized in Figure 3 and Table 6. First, we simulate the *counterfactual* volatility that each firm would have faced in the absence of cross-country diversification of the country-sector shocks. This is equivalent to assuming that all the firm's buyers are located in the same country. Since country-sector components are a negligible source of volatility in the data, it is not surprising that such *counterfactual* lets the distribution of volatilities almost unchanged (see the short-dashed line in Figure 3 which lies above the actual distribution).

More interesting are the other two *counterfactuals* which examine a world in which firms cannot diversify risks within countries (large-dashed line in Figure 3) as well as between countries (dash-dotted line). In the "No within-country diversification" case, each firm's trade network is restricted to her main client in each destination. In the "No between-country diversification" case, it is instead assumed that her network is restricted to buyers located in her main export destination. In both cases, the distribution of firm-level volatilities is significantly shifted to the right. Diversification of buyer-related risks indeed allows firms to reduce the volatility of their export growth. Interestingly, the largest effect is obtained in the 'No between-country diversification case". Although we find little evidence that exporting to a wider set of countries allows firms to reduce their exposure to aggregate demand shocks, the geographic diversification of a firm's exports is still found to be associated with significantly less volatility, because it allows the firm to reduce her exposure to microeconomic demand shocks.

As argued before, buyer and buyer-seller growth components drive volatility in the small because of sellers' lack of diversification. We now show that this dimension also contributes to the between-firms *heterogeneity* in firm-level volatilities. Namely, firms that have less concentrated export portfolios display significantly less volatile exports. To do so, we regress the (log of the) variance of firm-level sales on a set of control variables, including measures of sales concentration. Results are presented in Table 7. Column (1) shows the benchmark regression in which the observable variables are measures of firm's size, her experience as an exporter, and two indicators capturing the existence of multinational linkages between the exporter and the markets it serves. It confirms a well-documented result of the literature, namely that larger exporters display significantly less volatility (Davis et al., 2009; Kelly et al., 2013). This is also true of more experienced exporters while the role of multinational linkages is ambiguous.

Column (2) augments the benchmark regression with various measures of export diversification, namely Herfindahl indicators of sales across buyers within a market, across markets and across products. Results clearly indicate a correlation between these measures of diversification and the firm's volatility. Better-diversified firms display significantly less volatility. By reducing the concentration of her within-destination portfolio of clients from the third to the first quartile of the distribution, a firm would reduce the volatility of her sales by 27%. Similarly, exporting to a less skewed portfolio of destinations (moving again from the third to the first quartile of the distribution of across-destinations Herfindahl indices) decreases volatility by an additional 8%. Finally, having a more diversified portfolio of products does not significantly affect volatility.

Interestingly, adding these control variables significantly increases the explanatory power of the regression and reduces the conditional correlation between size and volatility. Large firms display less volatility in part because they are better diversified. Column (3) provides further support for this interpretation. Namely, the specification in Column (2) is replicated using as left-hand side variable the component of export volatility that is driven by diversifiable buyer-related microeconomic growth components. As expected, the conditional correlation between volatility and the extent of diversification across buyers is reinforced and the correlation with the exporter's size further reduced. Finally, results in Column (4) show that the impact of diversification on volatility also holds when identified *within* a firm, across destination markets. In this specification, volatility is measured at the firm level, destination-by-destination, and the estimated equation is augmented with firm and sector-destination fixed effects. Here as well, the impact of between-buyers diversification is significant: firms' sales are less volatile in those markets in which the firm's portfolio of clients is less concentrated.

Figure 4 shows variations in the volatility of firms at different points of the size distribution, where the size of a firm is defined by the value of her exports at entry into the sample. This confirms that smaller firms display more volatility. It also shows that volatility is decreasing with size because small firms face more volatile seller-specific shocks and have a portfolio of clients that exposes them to more buyer-specific risks. Seller-specific shocks are 68% less volatile at the 10th decile of the distribution than at the first. This is consistent with supply-side explanations of volatility in the small. But the "Diversifiable vol." bars in Figure 4 also show that half of the difference in volatility between medium-size and large-size firms is due to the diversifiable volatility. This result is driven by diversification in the small: Large firms are less exposed to buyer-related shocks, thus less volatile, because their portfolio of clients is better diversified.However, because their portfolio is so imperfectly diversified, even firms at the tenth decile of the distribution (of Herfindahl indices) display a significant amount of buyer-specific risk.

To summarize our analysis of volatility in the small, we have shown that i) individual growth components generate most of the volatility, ii) buyer-related growth components are almost as important as supply components as a source of volatility in the small, iii) these sources of risk also contribute to explain the heterogeneity in the degree of volatility across firms and destination markets, iv) the volatility of sales is (negatively) correlated with firm's size and the degree of diversification of its portfolio of customers, v) however, even the largest firms are often not well-diversified. We now turn to the analysis of fluctuations *in the large* and examine whether the above results hold when data are further aggregated.

5 Volatility in the large

5.1 Theoretical framework

In this section, the object of interest is the volatility of aggregate exports. This aggregate volatility may be defined country-by-country:

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

or across destinations:

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

where g_j and g_t denote the growth rates of intensive aggregate exports within and across markets, respectively; and where $\bar{g}_j$ and $\bar{g}$ denote the mean growth rates. Here again we focus on the intensive margin of exports. As shown is Appendix B, the intensive margin accounts for a substantial share of fluctuations in the aggregate.

As in Section 4, the variance of aggregate sales is decomposed into its structural drivers (as identified in Section 3):

$$
\begin{aligned}
Var(g_t) = Cov + & \underbrace{Var\left(\sum_j w_{jt-1} f_{c(Fj)t}\right)}_{Diversifiable\ ac.\ countries} + \underbrace{Var\left(\sum_s w_{st-1} f_{st}\right)}_{Diversifiable\ ac.\ sellers} \\
+ \quad & \underbrace{Var\left(\sum_{b(j)} w_{b(j)t-1}(f_{b(j)t} + BSIC_{b(j)t})\right)}_{Diversifiable\ ac.\ buyers} + \underbrace{Var\left(\sum_s \sum_{b(j)} w_{sb(j)t-1} \nu_{sb(j)t}\right)}_{Diversifiable\ ac.\ seller-buyer\ pairs}
\end{aligned} \tag{5}
$$

where $w_{kt-1},\ k = j, s, b(j), sb(j)$ is the share of unit k in overall (intensive) exports in $t-1$, and Cov is a set of covariance terms between the macro and the individual components.

Equation (5) is the counterpart to equation (4), albeit for volatility in the large. It shows how each family of growth components contributes to the volatility of aggregate trade, in proportion to its volatility and its diversification within the network of firm-to-firm trade flows. Macro components enter equation (5) in proportion to their share in overall exports, meaning that geographic diversification reduces the country's exposure to these shocks (Caselli et al., 2015). Seller-specific components are naturally diversified across sellers. Their aggregate impact is thus reduced if the distribution of sellers' size is less fat-tailed. This is the argument for "granular fluctuations" in Gabaix (2011). Our analysis shows that the argument naturally extends to the concentration of sales across buyers (as measured by the inverse of the Herfindahl index across buyers, $Herf^B \equiv \sum_{b(j)} {w_{b(j)}}^2$) and the concentration of transactions across seller-buyer pairs (the inverse of $Herf^{SB} \equiv \sum_s \sum_{b(j)} {w_{sb(j)}}^2$). Hence, these microeconomic growth components can be a source of aggregate fluctuations if their variance is large and the distribution of transactions concentrated enough, which is the case in our data (see Tables 2 and 4).

5.2 Empirical results

As in Section 4, we assess the relative contribution of each growth component using *counterfactual* experiments. Results are summarized in Figure 5 and Table 8, destination-by-destination as well as for multilateral sales. The first column in Table 8 presents the actual variance of sales in the data reproduced on the x-axes in Figure 5. The remaining columns present the *counterfactuals*. We first compare the volatility one would observe in the absence of country-sector growth components (column (2) and left panel of Figure 5) and in the absence of all three (diversifiable) micro shocks (column (3) and right panel of Figure 5). As expected, the macro-economic components matter much more in the large than in the small. Eliminating this source of growth reduces the volatility of exports by 15 to 70% of the realized variance, depending on the destination. Macro-economic components are now more important because the aggregate impact of micro terms is reduced, through diversification across individuals. Hence, the 70% reduction found for exports to Germany does not come from macro shocks being especially volatile there but from the small overall variance induced by well-diversified micro components.

Even though macro-economic components matter substantially more for volatility in the large, diversifiable micro shocks matter as well, as illustrated in column (3). Muting all three individual components simultaneously reduces the magnitude of aggregate fluctuations, by 73% on average. The strong impact of micro components essentially comes from the imperfectly diversified structure of trade networks. To further illustrate this point, column (4) in Table 8 summarizes the result of another *counterfactual* exercise in which the distribution of seller-buyer pairs is assumed to be uniform, i.e. when granularity is muted.[25] Results show that the volatility of exports is divided by at least a factor two in such a "symmetric" world. Such a distribution of trade flows prevents individual shocks from showing up in the aggregate. This explains why the *counterfactual* volatilities in columns (3) and (4) are highly correlated even though the way they are computed is quite different.

The *counterfactual* volatilities shown in column (3) of Table 8, which are entirely attributable to macro components, are hardly heterogeneous across countries. Indeed, the right panel of Figure 5 makes it clear that most of the heterogeneity between countries in the variance of aggregate exports is due to the heterogeneous impact of individual components, whereas the variance induced by macro-economic shocks is fairly similar across countries. Note that this result might be quite specific to the estimation sample, which is composed of fairly homogenous countries, including eight countries belonging to the same monetary union as France. This tends to drive the amount of cross-country correlation in country-sector shocks up.

Finally, the last three columns in Table 8 report the aggregate impact of muting one microeconomic component after the other: seller-specific components in column (5), buyer-specific components in column (6), and seller-buyer residuals in column (7). Within a destination, muting the buyer-specific components has the largest impact, reducing export fluctuations by 37% on average. The impact is smaller, and sometimes positive, when either the seller- or the match-specific effects are turned off.[26] When aggregate exports are examined across countries (last line of Table 8), muting seller-specific components matters substantially since these shocks cannot be diversified across countries, in contrast to buyer- and seller-buyer shocks.

[25]To do so, we use the existing network of bilateral transactions. Then, rather than using the observed weights when aggregating transactions, this *counterfactual* uses equal weights.

[26]In Table 8, muting one particular individual component can sometimes *increase* the volatility of exports, because of the negative correlations between individual shocks. When a shock is muted, the direct impact on the volatility of sales is mechanically negative. However, if this shock is negatively correlated with another shock, then another source of diversification, across shocks, is also muted. Thus the potentially positive impact on the aggregate variance of sales.

Among microeconomic "demand" components, the impact of muting buyer-specific terms is systematically found larger than when seller-buyer residuals are ignored (see the comparison of columns (6) and (7) in Table 8 and the corresponding percentage change in Figure 6). This comes from the connectedness in French exporters' trade networks: Since buyer-specific components are spread across all the firm's input providers, sharing the same clients induces some comovements across sellers, thus more volatility in the large.[27] The connectedness of individual trade networks is illustrated in Figure 7. Namely, the dark bars represent the median "connectedness" in French sellers' networks, by decile of size. Connectedness is measured by the mean degree of French sellers' partners. If, on average, French sellers export goods to foreign buyers who themselves interact with a sufficiently large number of French exporters, shocks affecting those buyers will create a substantial amount of comovement between individuals, thus more volatility in the large. As shown in Figure 7, this is actually the case. Namely, the median exporter in our sample interacts with foreign buyers who on average have eight partners in France. This number is slightly increasing in the size of the exporter, meaning that large French sellers, those that matter the most for the volatility in the large, tend to be even more (indirectly) connected to other French sellers than smaller ones. The correlation is found stronger when the weight of each buyer in sellers' trade networks is taken into account. As the light grey bars in Figure 7 show, the weighted connectedness tends to be larger than the unweighted indicator, for firms above the median size. These firms thus sell relatively more to the buyers that are relatively more connected to other French sellers. All in all, these statistics show that French sellers' trade networks tend to be connected to each others through the buyers they have in common. This contributes to

[27] Note that the connectedness of individual trade networks is in part driven by the estimation strategy that excludes from the analysis those buyers that are connected with a single French exporter. As shown in Figure 7, the mean degree of connectedness is substantially above two meaning that, on average, French sellers' clients are connected with more than two French sellers.

amplifying the impact that buyer-specific shocks have in the aggregate.

To conclude this section, we study how diversification in firm-to-firm trade networks affects countries' exposure to microeconomic shocks. Figure 8 shows the correlation between the contribution of each individual growth component and the concentration of trade networks in the corresponding dimension, destination-by-destination. Whatever the microeconomic source of volatility - namely seller-specific effects in the top-left panel, buyer-specific components in the top-right panel and seller-buyer residuals in the bottom panel- there is a strong positive correlation. The contribution of all three types of shocks is larger in more concentrated trade networks.

We gain further insights on the link between volatility in the large and the diversification of exports using various experiments. First, we quantify the impact of the geographic diversification of exports using two scenarios. In the first one, we simulate what would happen to the volatility in the large would French firms be unable to diversify their exposure to aggregate (country-sector) shocks. In practice, it is assumed that the existing foreign partners of French firms are all located in the same country, we arbitrarily chose Germany, the largest destination of French exports. In the absence of such "macroeconomic" diversification, we find the volatility of French exports to be 13% higher. This number is significant despite the correlation of country-sector growth components in our data because the structure of French exports in Europe is actually quite diversified. This experiment however underestimates the gains, in terms of volatility, associated with the geographic diversification of exports because such diversification not only helps smooth the impact of aggregate demand shocks but also mechanically affects the concentration of sales across buyers located in different countries. When this dimension is taken into account, the estimated impact of geographic diversification is doubled. The volatility of French exports would be 26% higher under full concentration of exports in Germany.[28]

[28]In practice, we simulate what would happen would France exports solely to Germany,

Second, we quantify what gains, in terms of volatility, is induced by firms' within-country diversification. This dimension is typically neglected in the literature that assumes foreign demand is well-represented by the preferences of a representative consumer. We instead show that diversification of firms' portfolios within a country significantly reduces the amount of volatility. To do so, we simulate a world in which each firm solely interacts with her main partner in each destination market. In such *counterfactual* world, the volatility of export sales is increased by 13%.

Diversification across trading partners allows countries to reduce their exposure to demand-related shocks. Instead, the specialization of activities triggered by the participation of firms into foreign markets has the opposite effect (di Giovanni and Levchenko, 2009, 2012). In our framework, this amplifies the aggregate impact that all three idiosyncratic shocks have in the aggregate. To quantify this effect we borrow a strategy from di Giovanni and Levchenko (2012) by simulating the distribution of French exporters, and the associated volatility of exports, in a world in which the firm size distribution is not skewed by their export activity. This is equivalent to assuming that the distribution of exporters' sales mimics that of domestic firms.[29] In such a (less concentrated) world, the *counterfactual* volatility is found to be 2.5% lower. The impact is relatively limited because i) the exercise does not take into account adjustments at the extensive margin, ii) the contribution of country-sector shocks is left unaffected in the exercise,[30] and iii) the *counterfactual* distribution of

thus interacting with a smaller set of foreign clients. Of course, the experiment is somewhat artificial since it assumes everything else is left unaffected. In particular, the network of French exporters in Germany is assumed to be the same, whether firms also export in the rest of the European Union or not.

[29] We calibrate firms' exports under autarky to be such that the *change* in the distribution between trade and autarky mimics the one estimated by di Giovanni et al. (2011). More specifically, we use the fact that, under the assumption that sales are Pareto-distributed, the change in sales can be backed out using the rank size of firms and the parameter governing the distribution of firm size : $\frac{log(sales_i^{trade})}{log(sales_i^{autar})} = \frac{\beta^{autar}}{\beta^{trade}} \frac{log(rank_i - 0.5) - \alpha^{trade}}{log(rank_i - 0.5) - \alpha^{autar}}$ where β and α are the constant and the coefficient on size estimated by regressing the log of firm's rank - 0.5 on the log of firm size. We use the coefficients estimated by di Giovanni et al. (2011) to compute the *counterfactual* value of exports under autarky.

[30] If we instead calculate the impact of less concentration on the volatility induced by

firms in the domestic market is itself relatively concentrated. If we instead mute granular forces entirely by assuming the distribution of exporters to be homogenous, volatility is found to decrease by 67%. All in all, this exercise confirms the evidence in di Giovanni and Levchenko (2012) that the increasing concentration of activities driven by international trade amplifies the aggregate impact of idiosyncratic supply shocks. What our analysis adds to this literature is that the concentration of exports, when combined with an imperfect diversification of firms' portfolios, also amplifies the aggregate effect of microeconomic demand shocks.

6 Conclusion

In this paper, we provide a forensic account of the origin of fluctuations in exports at the level of individual firms as well as in the aggregate. We first propose a structural method for identifying different sources of fluctuations in sellers-buyers data. We then show that microeconomic sources of fluctuations together with the structure of trade networks help us explain the volatility of sales and their heterogeneity across firms and markets. Our emphasis on buyer-related shocks as a key driver of fluctuations is, we believe, a novel contribution. Even though entering foreign markets (almost mechanically) reduces the volatility of individual exports and therefore allows firms to diversify this buyer-related source of risk, differences in the diversification of individual exporters remain a key driver of these firms' heterogeneous volatility. Furthermore, even the largest exporters are little diversified and end up being exposed to microeconomic demand risks. In turn, these large firms bring a large amount of "granular" risk to the overall economy, through their exposure to idiosyncratic supply and demand shocks. Since international

idiosyncratic supply shocks, the change in volatility increases to 7.7%. It is marginally smaller, at 5.8%, if we consider the residual effect of all three idiosyncratic shocks. This can be explained by large firms being relatively better diversified across buyers, which somewhat counteracts the impact of granularity.

trade tends to increase the importance of these large firms in the aggregate, this combined mechanism increases the amount of macroeconomic volatility and explain why individual-level foreign demand shocks remain an important source of aggregate fluctuations. Hence, differences in the structure of trade networks also help explain differences in aggregate export volatility across foreign destinations.

References

Abowd, J.M., B. Crepon, and Kramarz F., "Moment Estimation With Attrition: An Application to Economic Models," *Journal of the American Statistical Association*, December 2001, *96*, 1223–1231.

Abowd, John, Francis Kramarz, Paul Lengermann, and Perez-Duarte Sebastien, "Are Good Workers Employed by Good Firms? A Simple Test of Positive Assortative Matching Models for France and the United States," mimeo, CREST 2004.

Abowd, John M., Francis Kramarz, and David N. Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, March 1999, *67* (2), 251–334.

_ , Robert H. Creecy, and Francis Kramarz, "Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data," Longitudinal Employer-Household Dynamics Technical Papers 2002-06, Center for Economic Studies, U.S. Census Bureau March 2002.

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, "The Network Origins of Aggregate Fluctuations," *Econometrica*, September 2012, *80* (5), 1977–2016.

Andrews, M. J., L. Gill, T. Schank, and R. Upward, "High wage workers and low wage firms: negative assortative matching or limited mobility bias?," *Journal of the Royal Statistical Society Series A*, 2008, *171* (3), 673–697.

Antràs, Pol, Teresa C. Fort, and Felix Tintelnot, "The Margins of Global Sourcing: Theory and Evidence from U.S. Firms," Working Paper 20772, National Bureau of Economic Research December 2014.

Arkolakis, Costas, "A Unified Theory of Firm Selection and Growth," NBER Working Papers 17553, National Bureau of Economic Research, Inc October 2011.

Asker, John, Allan Collard-Wexler, and Jan De Loecker, "Dynamic Inputs and Resource (Mis)Allocation," *Journal of Political Economy*, 2014, *122* (5), pp. 1013–1063.

Barrot, Jean-Noël and Julien Sauvagnat, "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks," *The Quarterly Journal of Economics*, 2016, *131* (3), 1543–1592.

Bernard, Andrew, Andreas Moxnes, and Karen Helene Ulltveit-Moe, "Two-sided Heterogeneity and Trade," *Review of Economics and Statistics*, 2017, *Forthcoming.*

Bernard, Andrew B., Stephen J. Redding, and Peter K. Schott, "Multiproduct Firms and Trade Liberalization," *The Quarterly Journal of Economics*, 2011, *126* (3), 1271–1318.

Blaum, Joaquin, Claire Lelarge, and Michael Peters, "The Gains from Input Trade with Heterogeneous Importers," CEPR Discussion Papers 11721, C.E.P.R. Discussion Papers December 2016.

Blundell, Richard and Jean Marc Robin, "Estimation in Large and Disaggregated Demand Systems: An Estimator for Conditionally Linear Systems," *Journal of Applied Econometrics*, May-June 1999, *14* (3), 209–32.

Campbell, John Y., "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk," *Journal of Finance*, 02 2001, *56* (1), 1–43.

Carballo, Jerónimo, Gianmarco Ottaviano, and Christian Volpe Martincus, "The Buyer Margins of Firms' Exports," CEPR Discussion Papers 9584, C.E.P.R. Discussion Papers August 2013.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Alireza Tahbaz-Salehi, "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake," Cambridge Working Papers in Economics 1670, Faculty of Economics, University of Cambridge December 2016.

Caselli, F., M. Koren, M. Lisicky, and S. Tenreyro, "Diversification through Trade," 2015.

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

Comin, Diego A. and Thomas Philippon, "The Rise in Firm-Level Volatility: Causes and Consequences," in "NBER Macroeconomics Annual 2005, Volume 20" NBER Chapters, National Bureau of Economic Research, Inc, March 2006, pp. 167–228.

Comin, Diego and Sunil Mulani, "Diverging Trends in Aggregate and Firm Volatility," *The Review of Economics and Statistics*, 2006, *88* (2), 374–383.

Davis, Steven J., John C. Haltiwanger, and Scott Schuh, *Job Creation and Destruction*, Vol. 1 of *MIT Press Books*, The MIT Press, June 1998.

_ , John Haltiwanger, Ronald S. Jarmin, C.J. Krizan, Javier Miranda, Alfred Nucci, and Kristin Sandusky, "Measuring the Dynamics of Young and Small Businesses: Integrating the Employer and Nonemployer Universes," in "Producer Dynamics: New Evidence from Micro Data" NBER Chapters, National Bureau of Economic Research, Inc, March 2009, pp. 329–366.

Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda, "The Role of Entrepreneurship in US Job Creation and Economic Dynamism," *Journal of Economic Perspectives*, 2014, *28* (3), 3–24.

di Giovanni, Julian and Andrei A. Levchenko, "Trade Openness and Volatility," *The Review of Economics and Statistics*, August 2009, *91* (3), 558–585.

— and — , “Country Size, International Trade, and Aggregate Fluctuations in Granular Economies,” *Journal of Political Economy*, 2012, *120* (6), 1083 – 1132.

— , — , and Isabelle Mejean, “Firms, Destinations, and Aggregate Fluctuations,” *Econometrica*, 07 2014, *82* (4), 1303–1340.

— , — , and Romain Rancière, “Power laws in firm size and openness to trade: Measurement and implications,” *Journal of International Economics*, September 2011, *85* (1), 42–52.

Dornbusch, R., S. Fischer, and P. A. Samuelson, “Comparative Advantage, Trade, and Payments in a Ricardian Model with a Continuum of Goods,” *The American Economic Review*, 1977, *67* (5), 823–839.

Eaton, Jonathan, Marcela Eslava, C. J. Krizan, Maurice Kugler, and James Tybout, “A Search and Learning Model of Export Dynamics,” 2013.

Fort, Teresa C, John Haltiwanger, Ron S Jarmin, and Javier Miranda, “How Firms Respond to Business Cycles: The Role of Firm Age and Firm Size,” *IMF Economic Review*, 2013, *61* (3), 520–559.

Foster, Lucia, John C. Haltiwanger, and Chad Syverson, “The Slow Growth of New Plants: Learning about Demand?,” NBER Working Papers 17853, National Bureau of Economic Research, Inc February 2012.

— , John Haltiwanger, and Chad Syverson, “Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?,” *American Economic Review*, March 2008, *98* (1), 394–425.

Gabaix, Xavier, “The Granular Origins of Aggregate Fluctuations,” *Econometrica*, 05 2011, *79* (3), 733–772.

Kelly, Bryan, Hanno Lustig, and Stijn Van Nieuwerburgh, “Firm Volatility in Granular Networks,” NBER Working Papers 19466, National Bureau of Economic Research, Inc September 2013.

Koren, Miklós and Silvana Tenreyro, “Volatility and Development,” *The Quarterly Journal of Economics*, 02 2007, *122* (1), 243–287.

Mayer, Thierry, Marc J. Melitz, and Gianmarco I. P. Ottaviano, “Market Size, Competition, and the Product Mix of Exporters,” *American Economic Review*, February 2014, *104* (2), 495–536.

Melitz, Marc J., “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity,” *Econometrica*, November 2003, *71* (6), 1695–1725.

Oberfield, Ezra, “Business networks, production chains and productivity: A theory of input-output architecture,” Working Paper Series WP-2011-12, Federal Reserve Bank of Chicago 2011.

Thesmar, David and Mathias Thoenig, “Contrasting Trends in Firm Volatility,” *American Economic Journal: Macroeconomics*, 2011, *3* (4), 143–80.

Vannoorenberghe, Gonzague, Zheng Wang, and Zhihong Yu, “Volatility and diversification of exports: Firm-level theory and evidence,” *European Economic Review*, 2016, *89* (C), 216–247.

Wooldridge, Jeffrey, "Inverse probability weighted M-estimators for sample selection, attrition, and stratification," *Portuguese Economic Journal*, 2002, *1*, 117–139.

Table 1 – Summary statistics on trade networks

	Value of exports (bil.€)	# French sellers	# foreign buyers	# pairs of buyer-seller
	(1)	(2)	(3)	(4)
Belgium	26.6	29,941	74,427	225,823
Denmark	2.8	8,567	9,248	22,008
Finland	1.85	5,420	5,379	12,243
Germany	50.2	25,078	122,568	249,197
Ireland	2.54	6,508	6,857	16,804
Italy	32.0	20,565	100,115	192,628
Netherlands	15.5	16,851	35,080	73,568
Portugal	4.59	11,980	20,331	44,957
Spain	35.5	22,038	80,178	166,738
Sweden	5.08	7,896	10,757	21,832
United Kingdom	30.6	19,289	52,596	115,992
EU11	207	42,888	334,905	1,141,326

Notes: Summary statistics computed on 2007 data describing French bilateral exports. The last line corresponds to the 11 members of the European Union pooled together. The table does not include the transactions for which the CN8 product code is not reported (19,803 sellers accounting for less than 0.05% of exports). Column (1) reports the value of the aggregate trade flow, in billions euros. Columns (2)-(4) respectively report the number of sellers, buyers, and seller-buyer pairs involved in this aggregate trade flow.

Table 2 – Concentration of trade flows, by destination

	Concentration across		
	sellers	buyers	seller-buyer pairs
	(1)	(2)	(3)
Herfindahl Index			
Absolute value	0.005	0.001	0.001
Relative to symmetry	234	497	755
Share in aggregate of			
Top 10%	90%	94%	94%
10 largest	15%	7%	6%

Notes: Summary statistics computed on 2007 data describing French multilateral exports. This table reports statistics regarding the concentration of exports across French exporters (column (1)), foreign importers (column (2)) and the pairs they form (column (3)). Concentration of export sales is measured by i) the Herfindahl index, either expressed in absolute value or in relative terms with the value one would obtain would existing individuals be symmetric in size (computed as the Herfindahl times the number of individuals), ii) the share in aggregate exports of the top decile of the distribution or the 10 largest individuals.

Table 3 – Correlation matrix of the estimated growth components

	(1)	(2)	(3)	(4)	(5)	(6)
	$g_{sb(j)t}$	$f_{c(Fj)t}$	f_{st}	$f_{b(j)t}$	$\nu_{sb(j)t}$	$BSIC_{b(j)t}$
$g_{sb(j)t}$	1.0000					
$f_{c(Fj)t}$	.0626	1.0000				
f_{st}	.3028	.0000	1.0000			
$f_{b(j)t}$	.4751	.0000	-.0679	1.0000		
$\nu_{sb(j)t}$	.7864	.0000	.0000	-.0001	1.0000	
$BSIC_{b(j)t}$	.0517	-.0281	-.2523	-.1027	.0000	1.0000

Notes: This table gives the correlation matrix between the growth components, in the panel of firm-to-firm growth rates.

Table 4 – Summary statistics on the estimated effects

	(1) Mean	(2) Std.Dev	(3) Count	(4) Contrib.	(5) Partial Corr.
Firm-to-firm growth $g_{sb(j)t}$	-.0132	.6887	3,834,655		
Macro component $f_{c(Fj)t}$	-.0519	.0471	4,310	.0055	0.006^a
Seller-specific component f_{st}	.0000	.2688	283,032	.0757	0.118^a
Buyer-specific component $f_{b(j)t}$	.0000	.3601	933,888	.2142	0.248^a
Match-specific residual $\nu_{sb(j)t}$	.0000	.5417	3,834,655	.6326	0.618^a
Buyer input cost $BSIC_{b(j)t}$	.0387	.1417	933,888	.0039	0.010^a

Notes: This table gives the mean (column (1)) and standard deviation (column (2)) of each of the component of seller-buyer growth rates, over the population of estimated effects. The number of estimated effects is displayed in column (3). Column (4) is the median contribution of each growth component to the seller-buyer growth (e.g. $Med(f_{st}/g_{sb(j)t})$). The last column is the regression coefficient of each component on the firm-to-firm growth rate. ^{a} indicates significance at the 1% level.

Table 5 – Summary statistics on the actual and *counterfactual* distributions of firm-level volatilities: Muting shocks

	Mean	Median	P5	P95
Actual variance $Var(g_{st})$	.192	.139	.068	.262
Change in the volatility induced by muting				
Seller-specific shocks				
$Var(.\|f_{st} = 0)$	-.305	-.363	-.357	-.357
Buyer-related shocks				
Micro $Var(.\|f_{b(j)t}, \nu_{sb(j)t} = 0)$	-.295	-.329	-.354	-.317
Micro & macro $Var(.\|f_{c(Fj)t}, f_{b(j)t}, \nu_{sb(j)t} = 0)$	-.301	-.336	-.364	-.322
One buyer-related shock after the other				
Macro $Var(.\|f_{c(Fj)t} = 0)$	-.007	-.008	-.023	-.008
Buyer-specific $Var(.\|f_{b(j)t} = 0)$	-.127	-.155	-.187	-.151
Match-specific $Var(.\|\nu_{sb(j)t} = 0)$	-.192	-.190	-.165	-.213

Notes: This table gives summary statistics on the actual and *counterfactual* dispersions of firm-level volatilities, when the *counterfactuals* are obtained by muting different shocks one after the other. The *counterfactual* results are expressed in percentage deviation from the actual distribution. P5 and P95 denote the variance at the 5th and 95th percentile of the distribution, respectively.

Table 6 – Summary statistics on the actual and *counterfactual* distributions of firm-level volatilities: Changing the structure of trade networks

	Mean	Median	P5	P95
Actual variance $Var(g_{st})$	.192	.139	.068	.262
Change in the volatility induced by making firms unable to				
Diversify country-sector risks				
across countries	.000	.000	.000	.000
Diversify across countries	.426	.532	.539	.432
Diversify within countries	.288	.360	.407	.283

Notes: This table gives summary statistics on the actual and *counterfactual* dispersions of firm-level volatilities, when the *counterfactuals* are obtained by modifying the structure of individual trade networks. The *counterfactual* results are expressed in percentage deviation from the actual distribution. P5 and P95 denote the variance at the 5th and 95th percentile of the distribution, respectively. To simulate what would have happened if the firm was unable to diversify country-sector risks across markets, we force all the firm's existing buyers to be located in the same country. We then compute the volatility one would have observed if the firm's trade network was restricted to her main partner country. Finally, we simulate the case without any diversification within countries by computing the volatility driven by each firm's main client in each destination served.

Table 7 – Determinants of the volatility of sales at the firm level

	Multilateral Total (1)	Multilateral Total (2)	Multilateral Diversifiable (3)	Unilateral Total (4)
ln Herfindahl ac. buyers		0.34***	0.60***	0.17***
		(0.010)	(0.009)	(0.003)
ln Herfindahl ac. destinations		0.11***	0.09***	
		(0.015)	(0.014)	
ln Herf. ac. products		0.01	0.03*	0.04***
		(0.015)	(0.014)	(0.004)
ln value of exports	-0.13***	-0.09***	-0.02***	-0.06***
	(0.003)	(0.003)	(0.003)	(0.001)
ln # years	-0.56***	-0.43***	-0.12***	-0.14***
	(0.015)	(0.015)	(0.015)	(0.005)
Entrant	-0.03**	-0.00	-0.10***	0.03***
	(0.011)	(0.011)	(0.011)	(0.006)
Young exporter	0.00	-0.02*	0.02*	0.01**
	(0.011)	(0.011)	(0.011)	(0.005)
$\mathbb{1} = 1$ if HQ in dest.	0.11***	0.05***	0.08***	0.02**
	(0.018)	(0.018)	(0.016)	(0.009)
$\mathbb{1} = 1$ if aff. in dest.	-0.11**	-0.10**	0.02	-0.02
	(0.048)	(0.045)	(0.041)	(0.020)
Sector × country FE	No	No	No	Yes
Firm FE	No	No	No	Yes
Observations	29,772	29,772	29,772	106,037
Adjusted R-squared	.149	.213	.227	.491

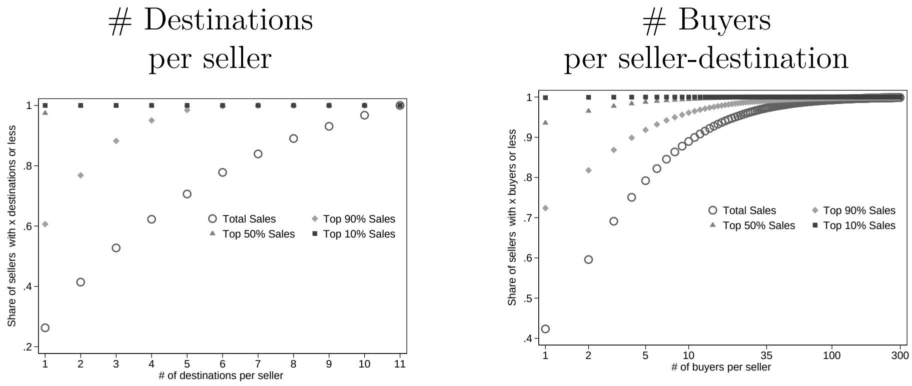
Notes: Robust standard errors in parentheses with $***$, $**$ and $*$ respectively denoting significance at the 1, 5 and 10% levels. The left-hand side variable is the log of the variance of multilateral export growth (columns (1) and (2)), the log of the residual variance attributable to "diversifiable" shocks (i.e. $Var(.|f_{st}, f_{c(Fj)t} = 0)$) (column (3)) or the log of the variance of unilateral export growth (column (4)). "ln Herfindahl ac. buyers" is the Herfindahl of sales across buyers, computed the first year the firm appears in the data. "ln Herfindahl ac. destinations" is the Herfindahl index across destination markets and "ln Herfindahl ac. prod." is the Herfindahl across products. "ln value of exports" is the (initial) trade value (overall or in that destination). "ln # years" is the number of periods the firm is observed (which varies between 4 and 12), overall or in the destination. "Entrant" and "Young exporter" are dummy variables equal to one if the firm just started exporting (just entered the market in column (4)), or entered it less than two years before. The coefficients are identified in relative terms with respect to mature exporters. "$\mathbb{1} = 1$ if HQ in dest." and "$\mathbb{1} = 1$ if aff. in dest." proxy the extent of intra-firm trade flows by dummy variables identifying firms which are part of a multinational with either affiliates or the headquarter located in the destinations covered by the sample.

Table 8 – Summary statistics on the actual and *counterfactual* levels of volatility in the large

	Var (g_{jt}) (1)	Var $(.\|f_{c(Fj)t}=0)$ (2)	Var $(.\|f_{st}, f_{b(j)t}, \nu_{sb(j)t}=0)$ (3)	Var $(.\|w_{sb(j)t-1}=1/N)$ (4)	Var $(.\|f_{st}=0)$ (5)	Var $(.\|f_{b(j)t}=0)$ (6)	Var $(.\|\nu_{sb(j)t}=0)$ (7)
Destination-specific sales							
Belgium	.0015	.0008	.0004	.0003	.0013	.0007	.0013
Germany	.0019	.0006	.0008	.0006	.0016	.0014	.0015
Denmark	.0024	.0016	.0013	.0011	.0021	.0022	.0029
Spain	.0048	.0029	.0008	.0008	.0040	.0028	.0038
Finland	.0042	.0026	.0015	.0016	.0043	.0040	.0035
UK	.0049	.0022	.0010	.0008	.0043	.0032	.0029
Ireland	.0122	.0083	.0020	.0018	.0105	.0047	.0174
Italy	.0043	.0017	.0011	.0010	.0036	.0027	.0029
Netherands	.0041	.0034	.0010	.0009	.0030	.0020	.0028
Portugal	.0025	.0016	.0009	.0008	.0024	.0020	.0022
Sweden	.0136	.0084	.0013	.0011	.0172	.0048	.0135
Median	**.0042**	**.0022**	**.0010**	**.0009**	**.0036**	**.0027**	**.0029**
Multilateral	**.0015**	**.0005**	**.0005**	**.0005**	**.0008**	**.0011**	**.0013**

Notes: Column (1) reports the variance of aggregate export growth computed country-by-country or using multilateral sales ("Multilateral" line). Columns (2) and (3) are the *counterfactual* variances one would observe in the absence of macro-economic shocks and in the absence of all three individual shocks, respectively. Column (4) is the *counterfactual* variance computed using all four shocks but assuming individual transactions to be symmetric in size (i.e. $w^j_{sb(j)t-1} = w^j_{t-1}$, $\forall(s, b(j))$). Finally, columns (5)-(7) are the *counterfactual* variations in the absence of seller-specific, buyer-specific and match-specific shocks, respectively.

Figure 1 – Diversification of exporters, across destinations and buyers



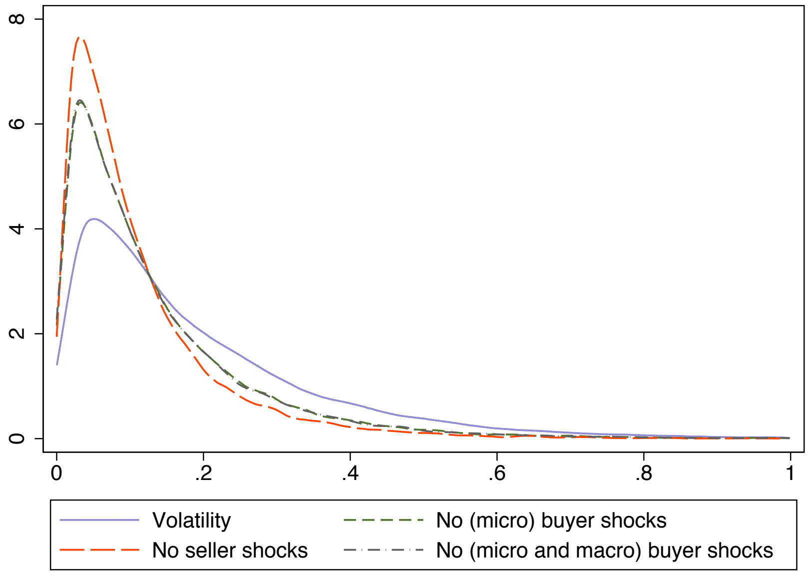
Notes: The left panel displays the proportion of sellers that serve x destination markets or less, in 2007. The right panel corresponds to the share of seller that serve x buyers or less in a given destination, also in 2007. The "Total Sales" distributions correspond to total exports. The distributions 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 their decreasing share in the firm's total sales. In the left panel, the grey diamonds for instance interprets as follows: If, for each exporter, we neglect the set of the smallest markets contributing to the last 10% of the exporter's sales, more than 60% of exporters have a degree of one market while less than 1% serve 6 countries or more.

Table A1 – Coverage

	Value of exports (billion euros)	# of observations
All	2,180	14,069,787
Enough obs to compute g_{sct}	1,960	12,093,470
Intensive margin	1,800	7,209,663
Excluding outliers ($g_{sct} \in [-0.8; 4]$)	1,670	6,025,288
All shocks identified	1,560	5,811,303
Enough obs to compute $Var(g_{sct})$	892	3,085,338

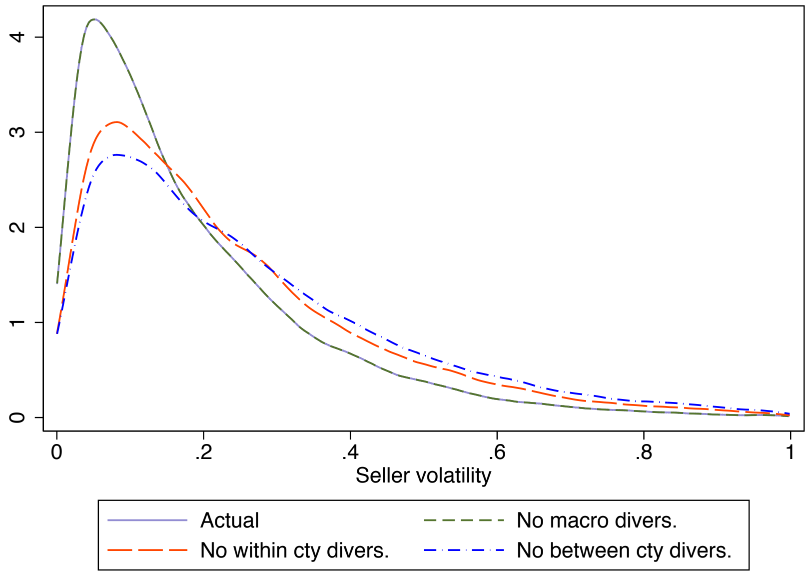
Notes: This table gives the coverage of the sample used in the empirical analysis depending on the restrictions we apply.

Figure 2 – Actual and *counterfactual* distributions of firm-level volatilities: Muting shocks



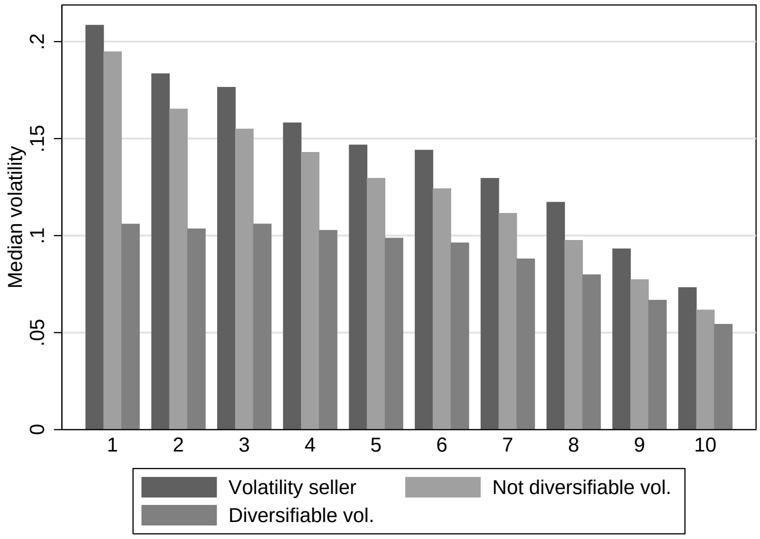
Notes: This graph represents the actual and *counterfactual* distributions of volatilities across firms. The solid line is the actual distribution of firm-level volatilities. The other three lines are *counterfactual* dispersions obtained when muting the seller-specific shocks (large-dashed line), the microeconomic buyer-related shocks (small-dashed line) and the micro and macro buyer-related shocks (dash-dotted line, virtually indistinguishable from the small-dashed line).

Figure 3 – Actual and *counterfactual* distributions of firm-level volatilities: Changing the structure of trade networks



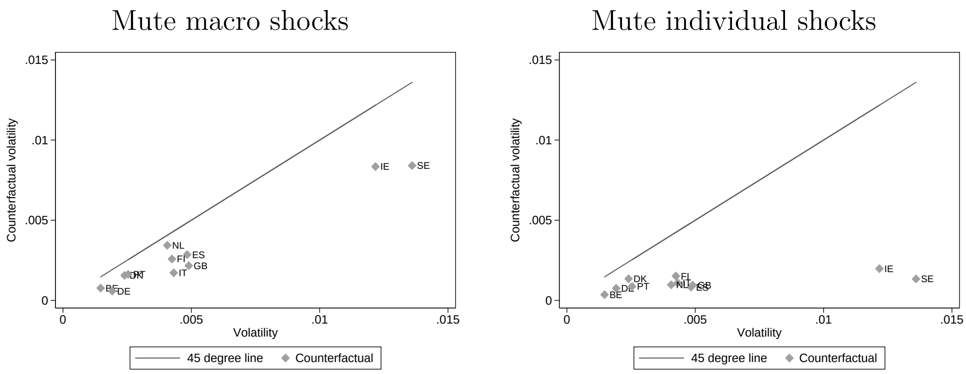
Notes: This graph represents the actual and *counterfactual* distributions of volatilities across firms. The solid line is the actual distribution of firm-level volatilities. The other three lines are *counterfactual* dispersions obtained when muting diversification of the country-sector shocks across markets ("No macro divers." line, virtually indistinguishable from the "Actual" line), when restricting the firm's network to her main client in each destination ('No within cty divers." line) and when restricting the firm's network to the buyers in her main destination ("No between cty divers.").

Figure 4 – Volatility, by decile of firms' size



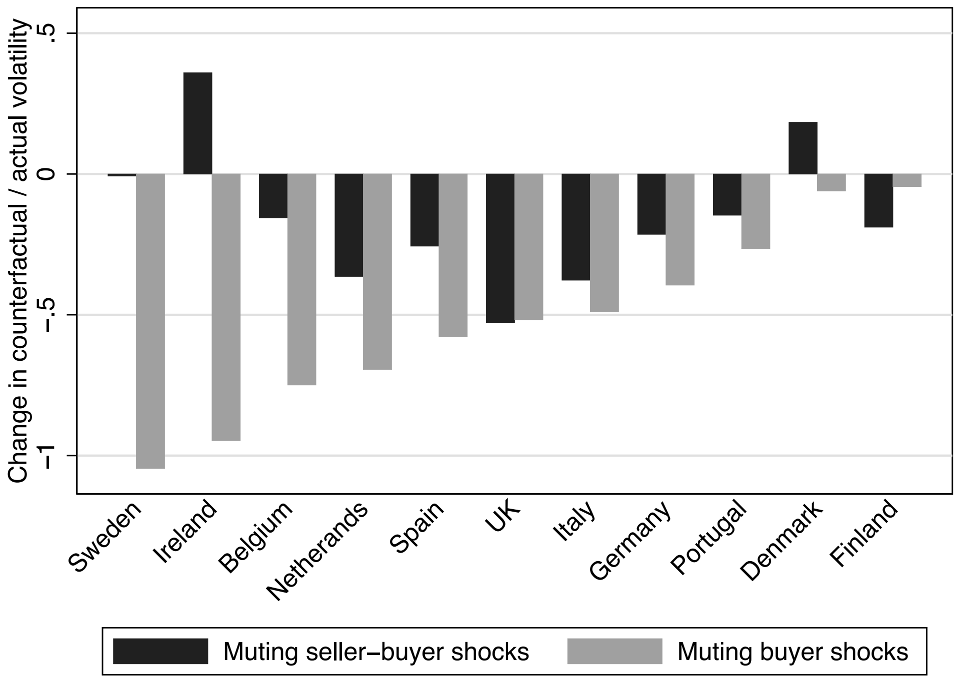
Notes: This figure represents the median volatility of sellers' exports across deciles of sellers' size. Sellers are grouped into size bins based on their initial size, with bin 1 corresponding to the 10% smallest exporters. For each decile, the figure reports the median volatility of sellers ("Volatility seller" defined as $Var(g_{st})$), the median volatility attributable to buyer-related microeconomic shocks ("Diversifiable vol." defined as $Var(\sum_{b(j)\in B_s}(f_{b(j)t} + \nu_{sb(j)t}))$ and the median volatility induced by seller-specific shocks ("Not diversifiable vol." defined as $Var(f_{st})$).

Figure 5 – Actual and *counterfactual* levels of volatility in the large



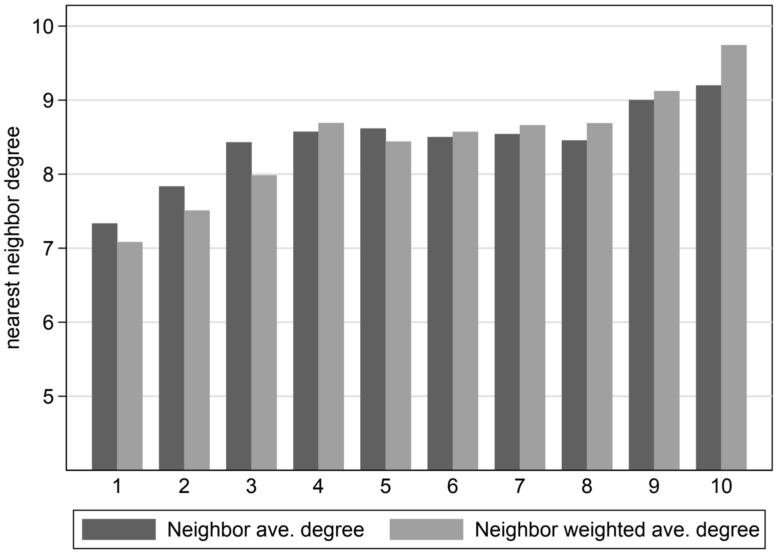
Notes: The graphs plot the volatility of bilateral French exports against their *counterfactual* volatility when muting either macro shocks (left panel) or all three individual shocks (right panel). The line corresponds to the 45-degree line.

Figure 6 – Muting buyer-specific and seller-buyer effects



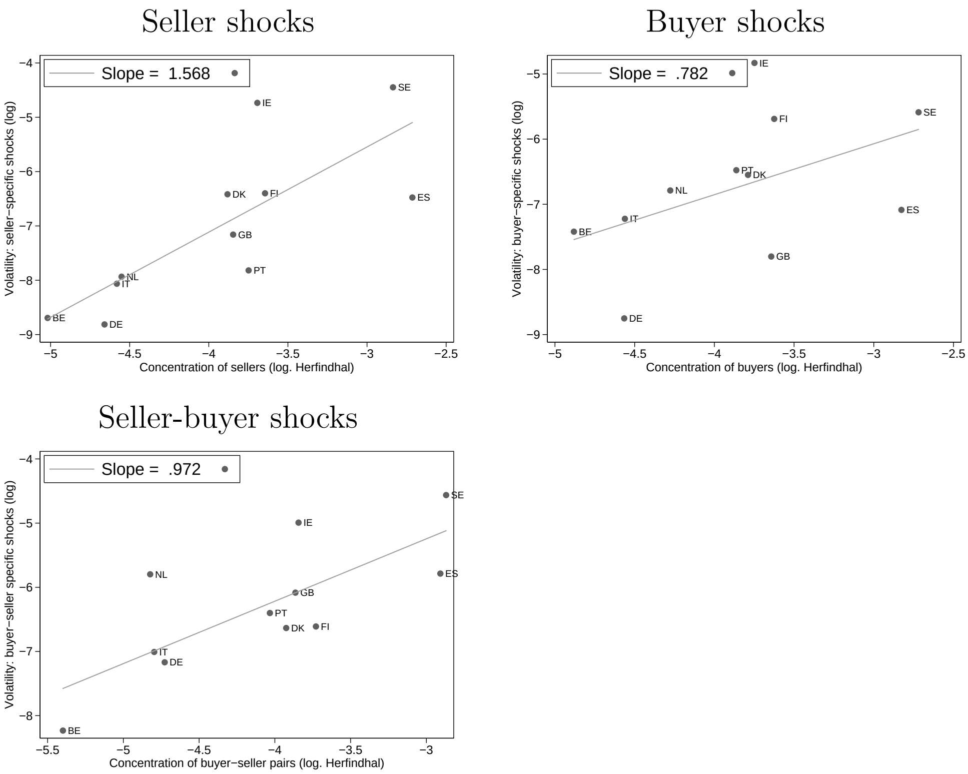
Notes: The graph plots the percentage change in the volatility of unilateral export growth induced by muting i) the buyer-specific shocks (grey bars) and ii) the seller-buyer residuals (black bars).

Figure 7 – Connectedness in sellers' trade networks along the size distribution



Notes: The graph plots the median connectedness of sellers' networks, by decile of the size distribution. Connectedness, also called nearest neighbor degree, is measured by the mean number of sellers a firm's partners interact with (i.e. $Connectedness_s = \frac{1}{\#_s} \sum_{b(j)} degree_{b(j)}$ where $\#_s$ is the number of buyers seller s interacts with and $degree_{b(j)}$ the number of sellers that buyer $b(j)$ purchases from). The weighted version of the indicator is a weighted average of the partners' degree, where each of the seller's partners is weighted by her share in the seller's total sales (i.e. $Connectedness^w_s = \sum_{b(j)} w^s_{b(j)} degree_{b(j)}$). Connectedness is computed using 2007 data.

Figure 8 – Concentration of trade flows and granular components



Notes: The graphs plot each of the components of the variance in the large induced by one type of individual shocks against the concentration of sales in the corresponding dimension. The slope of the regression line is reported in the legend. The slope coefficients for seller and seller-buyer shocks are significant at the 1% level. The slope coefficient for buyer shocks is significant at 13%.

A Details on the estimation strategy

The estimated equation takes the following form:

$$\tilde{g}_{s(i)b(j)t} = \tilde{f}_{c(ij)t} + f_{s(i)t} + \tilde{f}_{b(j)t} + \nu_{s(i)b(j)t}$$

or, in matrix format:

$$G_t = \alpha_t f_t^C + \chi_t f_t^S + \beta_t f_t^B + \nu_t$$

where G_t is the vector that contains the $\tilde{g}_{s(i)b(j)t}$ terms ($N_t \times 1$, where N_t is the number of observations for year t), α_t is the design matrix for the year-t country-sector effects ($N_t \times N_t^C$, where N_t^C is the number of country-sector for year t),[31] χ_t is the design matrix for the year-t seller effects ($N_t \times N_t^S$, where N_t^S is the number of sellers for year t), β_t is the design matrix for the year-t buyer effects ($N_t \times N_t^B$, where N_t^B is the number of buyers b, at date t), and ν_t is the vector of residuals ($N_t \times 1$).

Given a value for λ, the components of equation (3) can be identified in the cross-section of year-specific growth rates. Identification is achieved assuming equation (3.2) holds or, in matrix format:

$$E(\nu_t|\chi_t, \beta_t) = 0 \tag{A.1}$$

These assumptions are exactly identical to those in AKM. Notice here that there is no explanatory variable, X, in the above model (except the α_t, the country-industry-year effects). To reach identification of the seller and buyer components, the buyers and sellers must be connected in the sense of belonging to a connected group (Abowd et al., 2002). For each connected group, all the buyer and seller effects but one are identified. To have comparable effects, we focus our analysis on the largest component. Since trade networks are extremely well connected, this restriction does not affect our conclusions since the largest component comprises more than 95% of all observations.[32]

Before explaining how we implement the estimation in practice, note that the above equation could be estimated in the panel dimension. Since the ultimate objective is to use the estimated effects to discuss the sources of *volatility* in the data, we decided to estimate the model year-by-year, relying exclusively on the cross-sectional dimension to identify the estimated effects. This strategy allows us to avoid imposing undue structure on the correlation

[31] Because some of our firms sell multiple products, the definition of the firm's "industry" is not necessarily straightforward. We chose to affect each seller-buyer pair to the "industry" that corresponds to the most important product constituting the corresponding trade flow. Industries are defined by the 2-digit level of the HS nomenclature.

[32] In a previous version of this paper, we adopted a slightly different version of the model, in which seller effects where country-specific. Therefore, the equation above could be estimated country by country. In this version, a seller is endowed with a unique seller-effect in the year common to all its destinations. Obviously, buyers are all country-specific since there is no common identifier. The benefits of this new strategy are clear on at least two grounds. First, the network is denser and many more observations are now "connected"; hence with identified effects. Second, because we have more available observations to estimate each of the seller effects (at least for those sellers that export to at least two countries), the precision of the estimated seller effects is increased (Abowd et al., 2002).

of growth components through time. Whereas in the model of section 3.1, shocks are implicitly not autocorrelated, estimating equation (3) year-by-year does not impose any restriction on the correlation over time of the various components; the only constraints are imposed on the cross-sectional dimension of the growth components through the moment conditions used in the AKM estimation.

Equation (A.1) restates the exogeneity condition for our specific case. The residual $\nu_{s(i)b(j)t}$ is orthogonal to the buyer×time and the seller×time effects, conditional on the other effects. Two things are worthy of note. First, the condition holds at every time period. Second, even though a buyer's identity is country-specific, this is not the case for the sellers since they may sell in all countries. Hence, the assumption holds across all observations of a given seller to her buyers in the 11 countries in the data. This last remark is important in view of our discussion of the so-called "limited-connectivity bias".

Estimation of λ : Estimating the above equation using Abowd et al. (1999) requires that we first estimate the λ parameter. As explained in the text, we identify the parameter using an additional orthogonality condition suggested by the theoretical model, namely equation (3.2). Under the true value of λ, the model tells us that the seller and buyer components should be orthogonal to each other. For any $\lambda' \neq \lambda$, we have instead:

$$
\begin{aligned}
Cov(f^{\lambda'}_{s(i)t}, \tilde{f}^{\lambda'}_{b(j)t}) &= Cov\left(f_{s(i)t}, \tilde{f}_{b(j)t} + (\lambda' - \lambda) \sum_{s(i) \in \Omega_{b(j)t}} w^{b(j)}_{s(i)t-1} g_{s(i)b(j)t} \right) \\
&= (\lambda' - \lambda) w^{b(j)}_{s(i)t-1} Var(f_{s(i)t})
\end{aligned}
$$

where $f^{\lambda'}_{s(i)t}$ and $\tilde{f}^{\lambda'}_{b(j)t}$ denote the seller and buyer components of an equation using as left hand side variable $\tilde{g}^{\lambda'}_{s(i)b(j)t} \equiv g_{s(i)b(j)t} + \lambda' \sum_{s \in \Omega_{b(j)t}} w^{b(j)}_{s(i)t-1} g_{s(i)b(j)t}$. Misspecifying the LHS variable of equation (3) thus augments the buyer-specific component with an additional term which is systematically correlated with the (theoretical) seller-specific effect. This shall induce a covariance between the estimated seller and buyer effects. The algorithm implemented to estimate λ uses this prediction of the model and selects the value for λ which satisfies the orthogonality condition implied by the model. Note that the algorithm is straightforward to implement since the value of the covariance is monotonous in $(\lambda' - \lambda)$: Any value of $\lambda' < \lambda$ (resp. $\lambda' > \lambda$) implies a negative (resp. positive) covariance between the estimated seller and buyer components.

Limited Connectivity Bias: Abowd et al. (2004) were the first to note that, in models with two-way effects, even when data were simulated with no correlation between the individuals at each side of the graph (here, between buyers and sellers), estimating these effects and then computing the correlation between the resulting effects yielded a negative correlation. This finding has been found multiple times in various types of data sources for which these two-way effects were relevant modeling tools. The intuition for this result is quite straightforward. In such additive models, when an estimation error is made on one effect, there is a corresponding estimation error of the opposite sign on the other effect. Because the standard error of these effects decreases as the number of observations used to estimate them increases, the larger the number of buyers connected to a seller, or conversely the number of sellers connected to a buyer, the more precise these effects become (Andrews et al., 2008, for a more systematic analysis of the problem).

Based on these results, we argue that the structure of the network by itself might induce a bias in the estimated seller and buyer effects. To quantify the magnitude of this bias, we generate uncorrelated seller and buyer effects from a normal distribution with fixed, known variance for each node of the network, as well as a residual, also drawn in a normal distribution.[33] Adding these effects, we generate simulated growth rates. These growth rates are used to estimate the seller and buyer effects using the AKM procedure and, then, compute the associated correlation between the two. This procedure is repeated 100 times. This yields a distribution of the bias using our simulated effects and the realized structure of the network since, by construction, the *true* correlation between these effects is equal to zero. We select the mean of this distribution as our target bias, which is -0.0670 in our data. We then take into account the limited connectivity bias by targeting this value for $Cov(f_{s(i)t}, \tilde{f}_{b(j)t})$ instead of the strict orthogonality condition (3.2).

[33] For all three components, the variance of the underlying normal distribution is calibrated using the mean variance estimated when equation (3) is estimated assuming $\lambda = 0$.

Online Appendix, Not for Publication

A More stylized facts on trade networks

In this section, we describe the structure of French firms' international trade networks, as of 2007. The concentration of export sales is used as a sufficient summary statistics on the extent to which the existing structure of trade networks *can* help diversify against risks. We first describe the distribution of trade flows *across* firms. We coin it the diversification in the large. We then present the diversification in the small. This corresponds to the distribution of trade flows *within* firms across trade partners.

Diversification in the large. Different types of shocks have different diversification *potential* depending on their very nature. As explained in the main text, the country-sector components can and actually are diversified across countries and/or sectors. Microeconomic components compensate along the distribution of individuals, more so if the distribution of their sales/purchases is more uniform. Here, what matters is thus the skewness of individual sales (Gabaix, 2011). The concentration of exports across sellers, buyers and seller-buyer pairs is illustrated in Table A1, columns (2)-(5), (6)-(9) and (10)-(13), respectively. Different measures of concentration are reported, destination-by-destination, and for the EU15 as a whole.

Columns (2) to (5) confirm 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, 10% of firms are responsible for about 90% of exports. This extreme skewness shows up in the Herfindahl index, equal to .005 in our data, 234 times the Herfindahl one would observe in a *counterfactual* world with S exporters symmetric in size ($Herf/(1/S) = 234$).[1] While always high, this ratio varies significantly depending on the destination country under consideration (column (3), Table A1). It is maximal for French sales in Spain and minimal for exports to Germany.

The skewness of the distribution of individual exports has already been documented in the trade literature. Less well-known is the extreme concentration of imports (columns (6)-(9)) and, above all, of the distribution of sales across exporter-importer pairs (columns (10)-(13)). At the top of the distribution, 10% of importers are responsible for about 94% of imports. And for some destination countries, the ten largest transactions can account for as much as 20 to 30% of French exports. In these dimensions as well, Herfindahl indices are an order of magnitude larger than they would be in a symmetric world. Interestingly, the data however display some heterogeneity across destinations. For instance, the concentration of trade seems especially pronounced in Spain but more evenly spread across firms for small destinations such as Finland or Denmark.

[1] 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 is almost twice as concentrated as the distribution of total sales.

Overall, this analysis of diversification in the large suggests that exposure to macro-economic shocks is quite limited in the data since the composition of exports across countries and sectors is not too skewed. On the contrary, the microeconomic structure of French exports implies a strong exposure to idiosyncratic firm-level shocks, whether they hit the sellers, the buyers, or the matches they form. We now take the perspective of individual exporters and document their individual exposure to these shocks.

Diversification in the small. In our framework, the magnitude of fluctuations in individual sales depends on the structure of individual exporters' clientele. If firm-specific shocks cannot be diversified within a firm, exporters can reduce their exposure to country-specific shocks by selling to more markets.[2] Finally, buyer-related growth components (buyer- and match-specific shocks in the framework of section 3) can be diversified both within and across destinations, through a wider portfolio of clients. We now describe the extent of sellers' diversification – measured by the number of markets and the number of customers within a destination – in each French exporter's portfolio.

Figure A.1 summarizes the extent of diversification across destination markets. To document both the level of diversification and the heterogeneity across exporters, we plot the distribution of the *number of destinations* that each French firm serves in Europe (left panel) and the share that each category of firms represents in total exports (right panel). Consider first the left panel. The circles line shows the share of French exporters serving x destinations or less, which is naturally equal to 100% when we reach 11 countries, our sample. In 2007, around 25% of French exporters serve a single European destination and are thus exposed to a maximum amount of macro-economic risk. These firms are small on average, since they represent less than 2% of French exports (right panel). At the other side of the spectrum, less than 20% of firms serve more than 7 destinations, but they represent almost 70% of exports. Diversification across markets is thus heterogeneous across firms with large firms being more diversified on average, a result consistent with Melitz (2003).

Serving a large array of countries is not a sufficient condition, however, to be well-diversified in the country dimension. Indeed, a firm may serve all European destinations but be poorly diversified if most of her exports go to one market. In the core of the paper, we use the Herfindahl of firms' sales as the adequate measure of diversification. In Figure A.1, we instead compute each firm's number of destination countries, excluding from the calculation the smallest destinations in the firm's portfolio. For instance, the grey diamonds show that 60% of French exporters have at least 90% of their export sales going to a single destination, they represent 20% of French exports. These numbers jump to more than 90% if we focus on firms with at least 50% of their export sold to a single destination (grey triangles). These results are in sharp contrast with those obtained in the large, where the distribution of exports across destinations was more or less symmetric. Instead, individual firms have geographically concentrated sales, leaving them exposed to country-specific shocks.

[2] In the previous paragraph, it was argued that macro-economic shocks, when defined as in the rest of the paper, can also be diversified in the between-sector dimension. This is not possible, however, in the small since the sector is, by definition, a unique attribute of the firm. One dimension of diversification which is not treated explicitly in this section but is also conceivable, is the product-dimension. A firm might diversify against product-specific shocks by producing more products. We come back to this issue later on.

In contrast with macro shocks, buyer-related (buyer- and match-specific) shocks can be diversified *both across and within* destinations. To document the extent of such diversification, Figure A.2 presents the distribution of the number of buyers in each French exporter's portfolio, within a given destination country. Again, the left panel (circles line) represents the share of sellers having at least a given number of buyers in a given destination and the right panel (circles line) their share in total exports. 43% of French sellers export to a single buyer within a destination (left panel). These sellers are exposed to a maximum level of idiosyncratic demand risk since they are not diversified at all against buyer- and match-specific shocks. Such sellers only account for 18% of total sales, however (right panel). At the opposite side of the distribution, 12% of firms have more than 10 partners in their typical European market and represent 40% of total exports. Again, the data reveal a large amount of heterogeneity, across French exporters, with large firms serving more clients on average. In Carballo et al. (2013), the heterogeneity comes from large or highly productive firms being more likely to pay the cost of adapting their products to the tastes of a wide range of buyers.

Here as well, the number of clients is not sufficient to fully assess a seller's degree of diversification; the skewness of sales, across clients, is important as well. As shown by the additional lines displayed in Figure A.2, French exporters tend to skew their export sales towards their "main" partner. When the analysis is restricted to sales above a given share within each firm's exports, the number of buyers shrinks rapidly.[3] Among the 12% of firms that serve more than 10 buyers, many serve tiny importers with cumulative share less than 10% of the firm's exports. Once such 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. These findings indicate that exporters' sales are not well-diversified across buyers: even large firms with a rich portfolio of clients tend to concentrate their sales on one or two "main" partners.

We complement this description of individual firms' degree of diversification using a multivariate linear regression analysis, based on our data sources. Results are presented in Table A2. We correlate firms' concentration of export sales using a set of observable characteristics. We use two measures of concentration, the number of clients in the exporter's portfolio in Columns (1)-(3) and the Herfindahl index in Columns (4)-(6). Since both variables are negatively correlated, we expect the estimated coefficients to be of opposite sign. The regressors include firm-level characteristics: the value of the firm's exports, her experience in the destination, the number of products/Herfindahl of her sales across products, and two indicator variables for firm's linkage to the destination.[4] We also control for the diversification potential. Depending on the type of products it sells, a firm may indeed face a very large number of potential clients or an oligopsonic demand. This diversification potential is measured either as the total number of buyers of the goods she exports or the potential Herfindahl index that would be achieved by serving all such

[3] Namely, for each exporting firm, buyers are ranked according to their (decreasing) size and the number of clients is computed by excluding from the computation the smallest buyers representing this given share of exports.

[4] The value of exports is directly computed from the Customs data. The experience of the firm in the destination is computed using historical firm-level export data and defined as the log of the number of years for which the firm has been active in the destination (the first year being 1993). The indicators for the linkages are obtained using the INSEE-Lifi database and are equal to one if the firm has an affiliate / is the affiliate of a firm located in the destination country.

buyers in proportion to their total purchases.[5] Finally, regressions include sector*destination fixed-effects (columns (1), (3), (4) and (6)) and/or exporting firm fixed-effects (columns (2), (3), (5) and (6)).

Results show that the relationship between firm's size as measured by exports and its diversification is concave: large firms tend to be better diversified, up to a threshold.[6] Consistent with Chaney (2014), the number of buyers served by a given exporter and the diversification of sales (as measured by the inverse of the exporter's Herfindahl) are increasing in experience in the market. Diversification across buyers is potentially correlated with diversification across products. Still, we find that firms diversify across buyers, even within products. When a firm is an affiliate of a foreign MNE located there (variable called "$\mathbb{1} = 1$ if HQ from dest.") or has affiliates in the destination (variable called "$\mathbb{1} = 1$ if affiliates in dest."), export flows are less diversified (across buyers). This result is to be expected if MNE linkages are correlated with intra-firm trade, which does does not expose related parties to the same type of risks as between-firms trade. Finally, the potential for diversification measured by the total number of potential buyers is positively correlated with the number of buyers in the firm's portfolio, but the correlation is far from perfect. The correlation is also positive, but small, between the *actual* and the *potential* Herfindahl index of sales in columns (4)-(6).

Together, these results suggest that the degree of sales diversification is strongly heterogeneous across firms and systematically correlated with the characteristics of the firm, namely its size, the number of potential clients it faces, and its experience as an exporter. The coefficients on multinational linkages and firm's size suggest that the largest firms are not the most diversified. Individual shocks affecting their transactions might have sizable aggregate implications.

B Role of extensive adjustments

The analysis in the text has not considered entry or exit of buyers, sellers, or matches as a potential source of fluctuations. Instead, the analysis is confined to the intensive margin of trade.[7] The overall distribution of exports across sellers, buyers and seller-buyer pairs exhibit little variations over the 1995-2007 period. Within a year, however, a substantial share of the action takes place at the extensive margin. At the seller-level, the net entry of buyers in firms' portfolio of customers contributes to the growth of their exports. At the aggregate level, the effect is reinforced by entries and exits of sellers

[5]The variable is computed using the observed number of buyers that purchase one specific type of product in the destination. 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. The potential Herfindahl index is calculated similarly, by weighting each potential buyer by the squared value of its actual purchases.

[6]Increasing size has a positive impact on firm's diversification for exports below the 80^{th} percentile. Then, increasing size is associated with a reduction in the level of diversification.

[7]More precisely, our analysis does not take into account the impact of extensive adjustments, *the year when they take place*. However, the sample under consideration does evolve throughout the period, i.e. we do not need to restrict our attention to those firm-to-firm relationships which are present over the whole period. This would be a much more constraining restriction.

into different destination markets. To assess the economic importance of such adjustments, we compute the relative contributions of the intensive and the extensive margins to the volatility of sales. Because our strategy has both descriptive and structural components, this Appendix provides essentially descriptive elements when Appendix D looks at the structural question.

B.1 The intensive and extensive margins of export growth

At the level of individual firms, the overall growth rate of destination-specific sales can be decomposed into an intensive and an extensive components as follows:

$$g_{st}^{Tot} \equiv \ln\left(\sum_{j\in C_{sjt}} \sum_{b(j)\in B_{sjt}} x_{sb(j)t}\right) - \ln\left(\sum_{j\in C_{sjt}} \sum_{b\in B_{sjt-1}} x_{sb(j)t-1}\right) = g_{st} + g_{st}^{Ext.} \tag{B.1}$$

where $x_{sb(j)t}$ is the value of exports from seller s to buyer $b(j)$ at date t C_{sjt} is the set of destinations served by s at time t and B_{sjt} the set of buyers from j in seller s' portfolio at date t.

The intensive component

$$g_{st} = \ln\left(\frac{\sum_{j\in C_s}\sum_{b(j)\in B_{sj}} x_{sb(j)t}}{\sum_{j\in C_s}\sum_{b(j)\in B_{sj}} x_{sb(j)t-1}}\right)$$

is driven by changes in sales to buyers active in the firm's portfolio at dates $t-1$ and t ($d\ln x_{sb(j)t}$ for $b(j) \in \sum_{j\in C_s} B_{sj}$ where $C_s \equiv C_{st}\cap C_{st-1}$ is the set of destinations served in $t-1$ and t and $B_{sj} \equiv B_{sjt}\cap B_{sjt-1}$ the set of incumbent buyers in seller s portfolio).

This is the growth component used to compute the volatility in the small in Section 4. The extensive component is defined as

$$g_{st}^{Ext.} = \ln\left(\frac{\sum_{j\in C_{st}}\sum_{b(j)\in B_{sjt}} x_{sb(j)t}}{\sum_{j\in C_s}\sum_{b(j)\in B_{sj}} x_{sb(j)t}}\frac{\sum_{j\in C_s}\sum_{b(j)\in B_{sj}} x_{sb(j)t-1}}{\sum_{j\in C_{st-1}}\sum_{b(j)\in B_{sjt-1}} x_{sb(j)t-1}}\right)$$

It thus measures the contribution to sales growth of new entrants, in relative terms with respect to the contribution of buyers that have stopped importing from s between $t-1$ and t.

In the aggregate, the growth of exports decomposes as follows:

$$g_{jt}^{Tot} = g_{jt} + g_{jt}^{Ext-buyer} + g_{jt}^{Ext-seller} \tag{B.2}$$

g_{jt}^{Tot} represents the growth of aggregate exports to country j:

$$\begin{aligned} g_{jt}^{Tot} &= \ln x_{jt} - \ln x_{jt-1} \\ &= \ln\left(\sum_{s\in S_{jt}} \sum_{b(j)\in B_{sjt}} x_{sb(j)t}\right) - \ln\left(\sum_{s\in S_{jt-1}} \sum_{b(j)\in B_{sjt-1}} x_{sb(j)t-1}\right) \end{aligned}$$

where S_{jt} is the set of sellers serving destination j at time t.

The intensive component studied in Section 5 is defined as

$$g_{jt} = \ln\left(\frac{\sum_{s\in S_j}\sum_{b(j)\in B_{sj}} x_{sb(j)t}}{\sum_{s\in S_j}\sum_{b(j)\in B_{sj}} x_{sb(j)t-1}}\right)$$

It is driven by changes in the sales of seller-buyer transactions present at dates t and $t-1$ (the set $(s, b(j)) \in \bigcup_{s\in S_j} B_{sj}$), which itself is defined on the subset of incumbent exporters $S_j = S_{jt} \cap S_{jt-1}$.

At the aggregate level, the extensive margin can be decomposed into a buyer and a seller components. The buyer component of the extensive margin is defined as

$$g_{jt}^{Ext-buyer} = \ln\left(\frac{\sum_{s\in S_j}\sum_{b(j)\in B_{sjt}} x_{sb(j)t}}{\sum_{s\in S_j}\sum_{b(j)\in B_{sj}} x_{sb(j)t}} \times \frac{\sum_{s\in S_j}\sum_{b(j)\in B_{sj}} x_{sb(j)t-1}}{\sum_{s\in S_j}\sum_{b(j)\in B_{sjt-1}} x_{sb(j)t-1}}\right)$$

It represents the weight of new buyers in total sales of incumbent sellers, in relative terms with respect to the weight of purchases by buyers that exit the portfolio between $t-1$ and t. The seller component of the extensive margin is in turn

$$g_{jt}^{Ext-seller} = \ln\left(\frac{\sum_{s\in S_{jt}} x_{sjt}}{\sum_{s\in S_j} x_{sjt}} \times \frac{\sum_{s\in S_j} x_{sjt-1}}{\sum_{s\in S_{jt-1}} x_{sjt-1}}\right)$$

$g_{jt}^{Ext-seller}$ thus measures the weight of new sellers in total exports relative to the weight of sellers that exited the market.

The analysis in the main body of the text focuses on fluctuations in the intensive components of g_{st}^{Tot} and g_{jt}^{Tot}. This is motivated by evidence in Table B.1 that intensive flows are the most important source of growth in our data. We now discuss the extent to which the neglected extensive adjustments further amplify fluctuations in the small and in the large.

B.2 Volatility in the small and the extensive margin

Volatility in the small: Using equation (B.1), the overall volatility of firm-level sales decomposes as follows:

$$Var(g_{st}^{Tot}) = Var(g_{st}) + Var(g_{st}^{Ext.}) + 2Cov(g_{st}, g_{st}^{Ext.}) \qquad \text{(B.3)}$$

While we focus the analysis on the $Var(g_{st})$ component, adjustments at the (buyer) extensive margin might contribute to generating fluctuations in firm-specific sales. This is especially likely to be the case if extensive adjustments correlate positively with fluctuations at the intensive margin.[8] The extent to which it is indeed the case is an empirical question which Table B.2, columns (1)-(2), addresses.

For the median firm, the intensive component of the variance represents 88% of the overall variance (Table B.2, Column (1)). Contrary to expectations, the covariance between the intensive and extensive components is negative, on average. This contributes to reducing the overall variance. However, the magnitude of this term substantially varies across firms, which precludes any strong interpretation. While the intensive margin is the most important source of volatility, results in the second column of Table B.2 show that both the intensive and the extensive margins contribute to the *dispersion of volatilities across firms*.

Volatility in the large: Using equation (B.2), the overall volatility of aggregate sales in turn decomposes as follows:

$$Var(g_{jt}^{Tot}) = Var(g_{jt}) + Var(g_{jt}^{Ext-buyer}) + Var(g_{jt}^{Ext-seller}) + Cov \quad \text{(B.4)}$$

where Cov now includes all covariance terms involving one of the three components of (B.2).

Adjustments at the buyer or seller extensive margin might contribute to generating fluctuations in aggregate sales. Table B.2, columns (3) and (4), quantifies the extent to which it is the case. At the aggregate level, the intensive component is clearly a major source of volatility and of the cross-country dispersion in volatilities. The seller and buyer extensive margins each contribute to around 10-15% of the overall variance.

C Sensitivity to the identification strategy

C.1 Calibrating λ to zero

The baseline regression presented in the text uses the following decomposition:

$$\tilde{g}_{s(i)b(j)t} = \tilde{f}_{c(ij)t} + f_{s(i)t} + \tilde{f}_{b(j)t} + \nu_{s(i)b(j)t} \quad \text{(C.5)}$$

[8]Note that this is likely to be the case in a dynamic model with a fixed cost of serving a buyer. In such model a negative productivity shock to a seller would reduce sales to each of its partners, and eventually force it to stop serving some of these buyers, if the operational profits their demand generates is not sufficient to cover the fixed cost.

where:

$$\begin{aligned}
\tilde{g}_{s(i)b(j)t} &= g_{s(i)b(j)t} + \lambda \sum_{s'(F)\in\Omega_{b(j)t}} w^{b(j)}_{s'(F)t-1} g_{s'(F)b(j)t} \\
\lambda &= \frac{\sigma-\eta}{\eta-1} \\
\tilde{f}_{c(ij)t} &= (1+\lambda)\left((\eta-1)d\ln Z_{it} + d\ln A_{jt} + (1-\eta)d\ln\omega_{it}\right) \\
\tilde{f}_{b(j)t} &= \sigma d\ln z_{b(j)t}
\end{aligned}$$

The decomposition is estimated following Abowd et al. (1999) augmented with an additional orthogonality condition, between the seller and buyer fixed effects, which allows recovering λ.

An alternative strategy consists in calibrating $\lambda = 0$, which amounts to neglecting the potential endogeneity induced by match-specific shocks affecting the buyer-specific input cost index. This case is consistent with any calibration assuming $\sigma = \eta$.[9] Neglecting endogeneity is irrelevant in the limit when no single French firm has a significant weight in her clients' input purchases. From that point of view, such calibration is a good comparison point with results in the text, which are based on the opposite assumption that French exporters represent 100% of the buyer's input purchases. Although there are a lot of non-linearities running around, we suspect that assumptions in between those two extremes would not imply dramatically different results.

Table C.1 displays the actual and *counterfactual* volatilities computed for individual and aggregate exports using the decomposition assuming $\lambda = 0$.[10] It shows that setting λ to zero does not change the main conclusion of the analysis. The macro shock has a negligible impact on the volatility of individual exporters but matters substantially in the large. Namely, the volatility of bilateral aggregate exports is halved and the volatility of multilateral exports is divided by three when muting macro shocks. The micro shocks accounts for the bulk of individual fluctuations and a significant part of the volatility of aggregate export growth. Buyer-related shocks continue to be a major source of fluctuations, both in the small and in the large.

C.2 Variable markups

The structural decomposition at the root of the estimation crucially relies on a constant markup assumption. While this assumption is obviously at odds with the evidence, integrating variable markups in a tractable and general setup is well-known to be difficult. In this section, we discuss how some forms

[9] While such calibration might seem arbitrary, there is little evidence that elasticities are significantly different at different stages of the production process. From that point of view, imposing $\lambda = 0$ is not completely at odds with previous evidence.

[10] Here, the variance decomposition is estimated in three steps: i) individual export growth is regressed on macro fixed effects, ii) the residual of the first step is regressed against buyer fixed effects, iii) the residual of the second step is regressed against seller fixed effects. This ensures that the different components are close to the orthogonality imposed in the benchmark case. Switching steps ii) and iii) marginally affects the results. When estimated within the same stage, the seller and buyer components are negatively correlated. Note that the model instead predicts the correlation to be positive whenever shocks to adjusted prices have a significant impact on the buyer's input cost index.

of markup adjustments can be taken into account within our framework while others can not.

The variance decomposition exercise proposed in our paper can control for one particular type of mark-up adjustments, namely those inducing a heterogeneous response of firms to the same aggregate shock (see also di Giovanni et al. (2014)). This involves interacting the "macro" components of the estimated equation with observable characteristics on the individuals facing those shocks. We tested two such augmented specifications, one that allows small and larger exporters to display heterogeneous responses to the same shock and one that permits individual sellers to discriminate across their buyers when facing the same macro shock. Results are summarized in Table C.2. In the first augmented specification, called "Heterogeneity across sellers" in Table C.2, the country-sector components are interacted with dummy variables for small, medium, and large sellers. The size classes correspond to the first, second and third bins of the overall distribution of firms' exports in our data. In the second augmented specification, firm-to-firm transactions are spread into three classes, for small, medium and large transactions, which are later interacted with the country-sector shocks. Since the identification of coefficients is within a seller, this amounts to authorizing country-sector shocks to be passed differently across buyers of various size, within a seller's portfolio. The corresponding results are labeled "Heterogeneity across buyers" in Table C.2.

In both augmented specifications, the importance of the macro shocks increases slightly at the individual level and more substantially in the aggregate. This is to be expected since ignoring such heterogeneity amounts to attributing part of the impact of macro shocks to the individual components. In the small, muting the macroeconomic components reduces the volatility of exports by 2% which is small but larger than in the baseline specification where the impact was virtually zero. In the large, muting the country-sector components leads to a 5-time lower volatility, to be compared with a reduction by a factor of three in the baseline case. Importantly, individual components remain the key drivers of export volatility, both in the small and in the large. The relative importance of the seller, buyer, and seller-buyer shocks is also consistent with the baseline results. We conclude from these that the main results are robust to allowing for heterogeneous adjustments of sellers and seller-buyer pairs to macro shocks.

Variable markups may also induce sellers to adopt different pass-through rates of shocks affecting their own productivity. If such heterogeneity affects all buyers connected to the same exporter homogenously, the problem is limited since the decomposition in equation (2) is left unaffected. Note however that this affects the interpretation of the decomposition since the elasticity of the seller component to the underlying productivity shock now involves the (seller-specific) pass-through rate. The transmission of seller-specific shocks might also differ within a seller's portfolio, across her different clients, however. If this is the case, part of the volatility captured in seller-buyer residuals in fact reflects the heterogeneous impact of sellers' shocks on her clients. Unfortunately, this form of heterogeneity can not be controlled for due to a lack of variability within a seller's portfolio. The analysis has established that sellers interact with a limited number of clients. Such lack of diversification precludes us from controlling for the heterogeneous impact of sellers' shocks at different points of the seller's portfolio. The possibility that sellers might adopt different pass-through rates of their own supply shocks onto their clients complicates the interpretation of the growth components in terms of well-identified structural shocks. Note however that such structural interpretation is not key for a number of results in the text. In particular, the fact that the seller-buyer residual cannot be fully attributable to a seller-buyer idiosyncratic shock does not change the intuition that such residual source of firm-to-firm growth is potentially diversifiable within a seller's portfolio.

D The Identification of Shocks with Entry and Exit

In this Appendix we discuss how our estimation strategy can be modified to include extensive adjustments. However, the method being essentially statistical because we do not model the underlying process that governs exit and entry, we will refrain from providing a structural interpretation of these results.[11] Our decomposition of total volatility into its intensive and extensive components presented in Appendix B suggests that our focus, the intensive component, is the main driver of trade fluctuations.

D.1 Survival bias and potential correction strategies

The focus on the intensive margin implies a potential survival bias. Namely, the use of growth rates as LHS variable implies that we de facto neglect all combinations of shocks which destroy the relationship, either because the seller dies, or because it is the buyer which exits the market, or simply because both nodes stay active but no longer trade together. Since such combinations of shocks are probably not randomly drawn from the distribution of all possible combinations, neglecting such observations is likely to induce a bias. In Abowd et al. (2001), it is shown that a valid procedure for the type of data at hand consists in weighting each observation by the inverse of the death probability of the observation (hence, of the trade relationship). The main problem in implementing this approach with the data at hand is that we do not know much about sellers (in terms of observables), not to mention buyers for which we know close to nothing except the products they buy, their past purchases, and the country in which they operate. In what follows, we estimate shocks using this procedure and the resulting volatility. Our conclusions are not altered when we weight each transaction by its survival probability.

This procedure is easy to implement but rests on relatively strong assumptions, described below. In theory, an alternative way to deal with this issue would be to estimate a selection model. In practice, this strategy has never been applied in a satisfactory way when entry and exit must be simultaneously taken into account. In addition, estimation of such models with high dimensional fixed effects is even harder. Another avenue to deal with this issue is to develop a model with endogenous entry and exit of sellers and buyers as in Oberfield (2011), then estimate it structurally. We do not know of any paper having successfully accomplished this type of task.

[11] One could also think about using Davis et al. (1998) growth rates, which take into account adjustments at the intensive and the extensive margins, within our estimation approach. This would however break the link between the structural model and the estimated equation, since the structural model does not take net entries into consideration. Since having a structural interpretation is key to our general strategy, we decided to restrict the analysis to the intensive margin and treat the case of extensive adjustments separately using a statistical approach.

The adopted procedure: Let us denote by $s_{sb(j)t}$ the dummy which equals one when a transaction between seller s and buyer $b(j)$ is observed at date t, and 0 otherwise. Let us denote by $\underline{y}_{sb(j)t}$ the vector of observed variables on the transaction, the buyer, the seller, including some elements about observed past transactions between s and $b(j)$. Furthermore, let us write $\pi_{sb(j)t} = P(s_{sb(j)t} = 1|\underline{y}_{sb(j)t})$, the probability of observing the transaction conditional on the vector of observable variables. If we denote as $l(a|b)$ the distribution of a conditional on b, then missing at random conditional on observables means that:

$$l(g_{sb(j)t}, s_{sb(j)t}|\underline{y}_{sb(j)t}) = l(g_{sb(j)t}|\underline{y}_{sb(j)t})l(s_{sb(j)t}|\underline{y}_{sb(j)t})$$

Put otherwise, conditional on the observed variables, the growth of sales process and the survival process are independent. This implies that, applied to our moment conditions, we have:

$$E(g_{sb(j)t}(\theta)) = E\left(\frac{s_{sb(j)t}g_{sb(j)t}(\theta)}{\pi_{sb(j)t}}\right)$$

where θ denotes the parameters to estimate. Now, we see that the moment condition is expressed only in terms of observed components, $s_{sb(j)t}g_{sb(j)t}$ and $\pi_{sb(j)t}$. Notice also that we do not fully apply the framework developed in Abowd et al. (2001) but a setup also close to Wooldridge (2002)'s. The procedure therefore implies to weight moment conditions by the inverse of the probability of a transaction being present in the sample.

D.2 Results

Table D.1 presents the results of the first step, estimating the probability of a transaction being active at date t, conditional on the transaction being active the previous year. The presence of a transaction (in fact its absence in the Table) is explained by the size of the flow (in logs) in the previous year (and its square), the seller's degree, the buyer's degree, and their interaction (all in logs, in the previous year), the seniority of the transaction (with indicator functions for 1 year (omitted), 2 to 4 years, and 5 years and more). Survival of a transaction is more likely the larger the previous year transaction, the longer the relation between the two partners. Interpreting the degrees impact is more complex. Our results show that conditional on the previous variables, the more relations a buyer (resp. a seller) has, the less stable the transaction. The effect is however attenuated if both firms involved in the transaction are well connected, suggesting the existence of some kind of complementarity between partners.

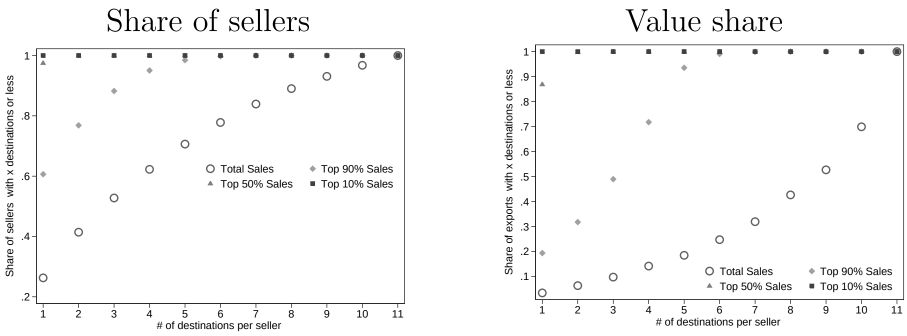
The inverse survival probability of the transaction is then used to weight the moments and estimate our decomposition. Results are presented in Tables D.2, D.3, D.4, and D.5 which are the exact equivalent to Tables 3, 4, 5, and 8. A visual inspection of the two sets of Tables yields a clear conclusion: weighting has essentially no impact on the results. From this we conclude that the attrition bias does not affect our results and conclusions.

Table A1 – Concentration of trade flows, by destination

		Concentration across sellers				Concentration across buyers				Concentration ac. seller-buyer pairs			
	Export value	Herf. ac. sellers	Herf. × # sellers	Top 10%	10 largest	Herf. ac. buyers	Herf. × # buyers	Top 10%	10 largest	Herf. ac. pairs	Herf. × # pairs	Top 10%	10 largest
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Belgium	26.6	0.007	196	88%	19%	0.007	493	97%	20%	0.005	1178	94%	18%
Germany	50.2	0.003	83	90%	12%	0.003	358	97%	12%	0.002	455	95%	9%
Denmark	2.76	0.009	79	87%	19%	0.010	93	90%	20%	0.009	188	90%	18%
Spain	35.5	0.018	404	89%	27%	0.013	1026	96%	29%	0.007	1219	94%	22%
Finland	1.85	0.011	57	87%	24%	0.012	62	91%	25%	0.009	116	90%	23%
UK	30.6	0.009	179	90%	20%	0.007	368	96%	21%	0.006	661	94%	17%
Ireland	2.54	0.030	198	90%	40%	0.031	210	93%	39%	0.030	497	93%	39%
Italy	32.0	0.005	107	90%	16%	0.004	365	95%	15%	0.003	614	93%	14%
Netherlands	15.5	0.009	144	90%	24%	0.006	225	95%	21%	0.005	384	94%	19%
Portugal	4.59	0.015	177	87%	24%	0.009	187	93%	24%	0.007	330	92%	22%
Sweden	5.08	0.024	191	90%	32%	0.028	302	94%	37%	0.023	496	93%	29%
EU11	207	0.005	234	90%	15%	0.001	497	94%	7%	0.001	755	94%	6%

Notes: Summary statistics computed on 2007 data describing French bilateral exports. The first column is the value of aggregate exports, in billion euros. Column (2) is the Herfindahl index across exporters, computed as $Herf_c^S = \sum_{s \in S_c} {w_s^c}^2$ where w_s^c is the share of exporter s in the total bilateral flow. Column (3) rescales this number by the number one would expect from a uniform distribution of exporters (i.e. $1/S_c$). Columns (4) and (5) report the share of aggregate exports that is attributable to the top 10% and the largest 10 exporters. Column (6) is the Herfindahl index across importers, computed as $Herf_c^B = \sum_{b \in B_c} {w_b^c}^2$ where w_b^c is the share of importer b in the total bilateral flow. Column (7) rescales this number by the number one would expect from a uniform distribution of importers (i.e. $1/B_c$). Columns (8) and (9) report the share of aggregate exports that is attributable to the top 10% and the largest 10 importers. Column (10) is the Herfindahl index across exporter-importer pairs, computed as $Herf_c^{SB} = \sum_{(s,b) \in N_c} {w_{sb}^c}^2$ where w_{sb}^c is the share of the pair in the total bilateral flow. Column (11) rescales this number by the number one would expect from a uniform distribution of pairs (i.e. $1/N_c$). Columns (12) and (13) report the share of aggregate exports that is attributable to the top 10% and the largest 10 pairs. Each line corresponds to a destination country and the last line pools the 11 members of the European Union together.

Figure A.1 – Number of Destinations per Seller



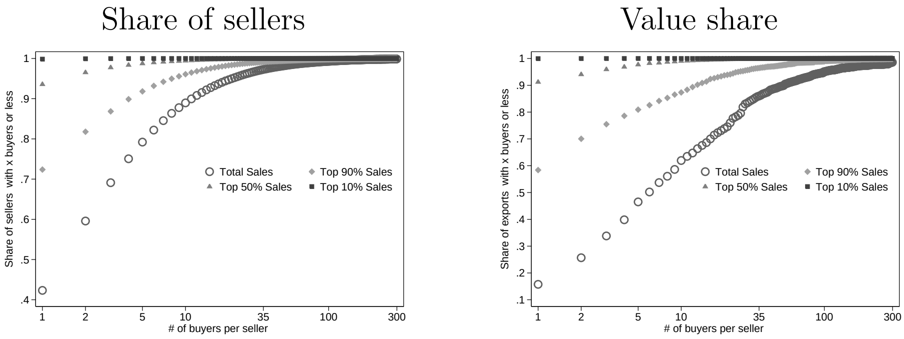
Notes: Proportion of sellers (left panel) and share of trade accounted for by sellers (right panel) that serve x destination markets or less, in 2007. The "Total Sales" distributions correspond to total exports. The distributions labeled "Top X% Sales" are computed restricting the amount of each firm's 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 grey diamonds for instance interprets as follows: If, for each exporter, we neglect the set of the smallest markets contributing to the last 10% of the exporter's sales, more than 60% of exporters have a degree of one market while less than 1% serve 6 countries or more.

Table A2 – Determinants of firm-level diversification within a country

	ln # **buyers**			ln **Herfindahl**		
	(1)	(2)	(3)	(4)	(5)	(6)
ln value of exports	0.22^a	0.21^a	0.28^a	-0.08^a	-0.10^a	-0.13^a
	(0.022)	(0.010)	(0.015)	(0.013)	(0.006)	(0.010)
(ln value of exports)^2	-0.01^a	-0.01^a	-0.01^a	0.01^a	0.01^a	0.01^a
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
ln experience in dest.	0.11^a	0.34^a	0.13^a	-0.06^a	-0.22^a	-0.10^a
	(0.008)	(0.020)	(0.019)	(0.005)	(0.012)	(0.013)
ln # products	0.40^a	0.74^a	0.53^a			
	(0.013)	(0.020)	(0.023)			
ln Herfindahl ac. prod.				0.27^a	0.39^a	0.35^a
				(0.010)	(0.014)	(0.014)
$\mathbb{1}$ = 1 if HQ in dest.	-0.19^a	-0.01	-0.02	0.16^a	0.02	0.04^a
	(0.033)	(0.032)	(0.024)	(0.018)	(0.015)	(0.014)
$\mathbb{1}$ = 1 if affiliates in dest.	-0.19^a	-0.04	-0.18^a	0.13^a	0.03	0.13^a
	(0.052)	(0.086)	(0.060)	(0.034)	(0.051)	(0.040)
ln potential # of buyers	0.04^a	0.00	0.00			
	(0.006)	(0.003)	(0.004)			
ln potential Herfindahl				0.03^a	0.09^a	0.03^a
				(0.004)	(0.014)	(0.006)
FE *Sect* × *dest.*	Yes	No	Yes	Yes	No	Yes
FE *Firm*	No	Yes	Yes	No	Yes	Yes
# obs.	158,239	158,239	158,239	158,239	158,239	158,239
R^2	0.184	0.294	0.676	0.100	0.139	0.556

Notes: Standard errors in parentheses clustered in the *destination* × *sector* dimension with ^{a}, ^{b} and ^{c} 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.

Figure A.2 – Number of Buyers per Seller-Destination



Notes: Proportion of sellers (left panel) and share of trade accounted for by sellers (right panel) that serve x buyers or less in a given destination, in 2007. The "Total Sales" distributions 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 market-specific sales, more than 70% of exporters have a degree of one buyer while only 5% have 10 buyers or more.

Table B.1 – Contribution of the intensive and extensive margins to export growth

	Contribution to			
	Individual growth		Aggregate growth	
	Mean	Median	Mean	Median
	g_{st}	g_{st}	g_{jt}	g_{jt}
	(1)	(2)	(3)	(4)
Intensive	0.791	1.000	0.654	0.645
Extensive	0.209	0.000	0.346	0.273
of which:				
Buyer margin			-0.046	0.153
Seller margin	0.209	0.000	0.392	0.120
# of obs.	1,570,494		132	

Notes: Statistics on the decomposition of the total growth into the intensive and extensive margins. The formula are detailed in Appendix B, equations (B.1) and (B.2). Columns (1) and (2) decompose firm-level destination-specific growth rates while Columns (3) and (4) decompose the growth of aggregate bilateral sales. Growth rates are computed annually on the period 1996-2007. The first and third columns give the mean contribution computed on the corresponding sample of yearly growth rates. The second and fourth columns give the median contributions.

Table B.2 – Summary statistics on the margins of firm bilateral exports' volatility

	Decomposition of			
	Firm-level Volatility		Aggregate Volatility	
	(1)	(2)	(3)	(4)
	Contr.	Partial Corr.	Contr.	Partial Corr.
Var Intensive component	0.877	0.498^a	1.073	0.928^a
Var Extensive comp. buyer	0.308	0.362^a	0.128	0.050^a
Var Extensive comp. seller	.	.	0.142	0.155^a
Covariance term	-0.129	0.139^a	-0.287	-0.134^a
Count observations	29,772		11	

Notes: This table gives summary statistics on the variance of firm-level and aggregate growth (respectively in (1)-(2) and columns (3)-(4)) and how it decomposes into its extensive and intensive components. The decomposition is based on equations (B.3) and (B.4). Columns (1) and (3) report the median contribution of each variance component to the total variance (eg. $Med(Var(g_{sct})/Var(g^{Tot}_{sct})))$. Columns (2) and (4) are the partial correlations between each variance component and the overall variance. The sample is restricted to variances computed on at least four growth rates. ^{a} indicates significance at the 1% level.

Table C.1 – Summary statistics on the actual and *counterfactual* distributions of firm-level volatilities: $\lambda = 0$

	Small	**Large**	
	Individual exports	Median ac destinations	All destinations
	(1)	(2)	(3)
Actual volatility $Var(.)$	.1389	.0042	.0015
Volatility when muting			
Macro shocks			
$Var(.\|f_{c(Fj)t} = 0)$	.1378	.0019	.0004
Micro shocks			
$Var(.\|f_{st}, f_{b(j)t}, \nu_{sb(j)t} = 0)$	.0000	.0014	.0006
One micro shock after the other			
Seller-specific $Var(.\|f_{st} = 0)$	.0751	.0038	.0008
Buyer-specific $Var(.\|f_{b(j)t} = 0)$	.1057	.0028	.0012
Match-specific $Var(.\|\nu_{sb(j)t} = 0)$	.1090	.0030	.0014

Notes: This table gives summary statistics on the actual and *counterfactual* distributions of firm-level and aggregate volatilities. The *counterfactuals* are obtained by muting different shocks one after the other. Column (1) reports the median variance of individual export growth. Column (2) reports the median variance of aggregate bilateral export growth, computed aross countries. Column (3) reports the variance of aggregate export growth computed using multilateral sales.

Table C.2 – Volatility in the small and in the large with heterogeneous markups

	Var	Var	Var	Var	Var	Var
	$(.)$	$(.\|f_{c(Fj)t}=0)$	$(.\|f_{st},f_{b(j)t},\nu_{sb(j)t}=0)$	$(.\|f_{st}=0)$	$(.\|f_{b(j)t}=0)$	$(.\|\nu_{sb(j)t}=0)$
	(1)	(2)	(3)	(4)	(5)	(6)
			Volatility of individual exports (median)			
Heterogeneity :						
Across sellers	.139	.137	.000	.078	.118	.113
Across buyers	.139	.136	.000	.079	.118	.114
			Volatility of aggregate exports			
Heterogeneity :						
Across sellers	.0015	.0004	.0006	.0010	.0012	.0014
Across buyers	.0015	.0004	.0008	.0012	.0012	.0014

Notes: The top panel focuses on the volatility of individual firms and the bottom panel reports the volatility of aggregate exports. The rows labeled "Heterogeneity across sellers" display the results based on a growth decomposition allowing for small and large firms to respond differently to common shocks. The rows labeled "Heterogeneity across buyers" display the results obtained when the growth decomposition allows small and large bilateral transactions to display different responses to common shocks, within a seller's portfolio. Column (1) reports the variance of export growth computed country-by-country or using multilateral sales ("Multilateral" line). Columns (2) and (3) are the *counterfactual* variances one would observe in the absence of macro-economic shocks and in the absence of all three individual shocks, respectively. Finally, columns (4)-(6) are the *counterfactual* variations in the absence of seller-specific, buyer-specific and match-specific shocks, respectively.

Table D.1 – Logistic analysis of the probability of survival

	LPM (1)	Logit (2)
Size of the flow (log)	0.088***	0.268***
	(0.000)	(0.002)
Size^2 (log)	-0.001***	0.002***
	(0.000)	(0.000)
Seller's degree (log)	-0.128***	-0.505***
	(0.036)	(0.163)
Buyer's degree (log)	-0.282***	-1.200***
	(0.043)	(0.192)
Interacted degrees (log)	0.021***	0.090***
	(0.003)	(0.014)
2-4 years transactions	0.035***	0.152***
	(0.001)	(0.002)
5+ years transactions	0.087***	0.388***
	(0.000)	(0.002)
Constant	0.496	3.987*
	(0.503)	(2.265)
Observations	12,926,164	12,926,164
R-squared	0.105	
Tjur discrimination coef		0.10

Notes: This table displays the results of an estimate of the determinants of the death probability of a seller-buyer transaction. Column (1) reports the results of a Linear Probability Model while Column (2) reports the results of a logistic model. The left-hand side variable is a dummy equal to one if the seller-buyer transaction was active the previous year and is still active the current year. Survival is explained by the log value of the (past) transaction and its squared value, the degree of the seller and the buyer (in log), an interaction between the log degree of the seller and the degree of the buyer, an indicator equal to one if the transaction had been active for more than one year but less than 5 years, and an indicator equal to one if the transaction had been active for more than 5 years. Robust standard errors in parentheses with ***, ** and * respectively denoting significance at the 1, 5 and 10% levels.

Table D.2 – Correlation matrix of the estimated growth components, with correction for the attrition bias

	(1) $g_{sb(j)t}$	(2) $f_{c(Fj)t}$	(3) f_{st}	(4) $f_{b(j)t}$	(5) $\nu_{sb(j)t}$	(6) $BSIC_{b(j)t}$
$g_{sb(j)t}$	1.0000					
$f_{c(Fj)t}$	.0630	1.0000				
f_{st}	.3023	.0000	1.0000			
$f_{b(j)t}$	.4646	.0000	-.0674	1.0000		
$\nu_{sb(j)t}$	.7891	.0000	-.0037	-.0139	1.0000	
$BSIC_{b(j)t}$	.0438	-.0290	-.2680	-.1297	.0357	1.0000

Notes: This table gives the correlation matrix between the growth components, in the panel of firm-to-firm growth rates, with correction for the attrition bias.

Table D.3 – Summary statistics on the estimated effects, with correction for the attrition bias

	(1) Mean	(2) Std.Dev	(3) Dimension	(4) Contrib.	(5) Partial Corr.
Firm-to-firm growth $g_{sb(j)t}$	-.015	.6904	3,478,841		
Macro component $f_{c(Fj)t}$	-.054	.0473	3957	.0064	.006***
Seller-specific component f_{st}	.0000	.2705	259564	.0767	.118***
Buyer-specific component $f_{b(j)t}$	.0000	.3637	845162	.2134	.245***
Match-specific residual $\nu_{sb(j)t}$	.0000	.5461	3478841	.6349	.624***
Buyer input cost $BSIC_{b(j)t}$	.0391	.1318	845162	.0025	.007***

Notes: This table gives the mean (column (1)) and standard deviation (column (2)) of each of the component of seller-buyer growth rates, over the population of estimated effects, with correction for the attrition bias. The number of estimated effects is displayed in column (3). Column (4) is the median contribution of each growth component to the seller-buyer growth (e.g. $Med(f_{st}/g_{sbt})$). The last column is the regression coefficient of each component on the firm-to-firm growth rate. *** indicates significance at the 1% level.

Table D.4 – Summary statistics on the actual and *counterfactual* distributions of firm-level volatilities, with correction for the attrition bias

	Mean	Median	P5	P95
Actual variance $Var(g_{st})$	.191	.136	.066	.260
Change in the volatility induced by muting				
Seller-specific shocks $Var(.\|f_{st} = 0)$	-.482	-.500	-.485	-.508
One buyer-related shock after the other				
Macro $Var(.\|f_{c(Fj)t} = 0)$	-.010	-.007	-.015	-.008
Buyer-specific $Var(.\|f_{b(j)t} = 0)$	-.115	-.147	-.167	-.142
Match-specific $Var(.\|\nu_{sb(j)t} = 0)$	-.194	-.191	-.182	-.208

Notes: This table gives summary statistics on the actual and *counterfactual* dispersions of firm-level volatilities, when the *counterfactuals* are obtained by muting one shock after the other, with correction for the attrition bias. Individual shocks are estimated by weighting seller-buyer observations by the inverse of the probability to stay active. The first panel uses firm- and destination-specific measures of volatility while the second panel is based on multilateral measures. We report summary statistics on the actual distribution of volatilities. We then report the corresponding *counterfactual* variances when each of the four structural shocks is muted. P5 and P95 denote the variance at the 5th and 95th percentile of the distribution, respectively.

Table D.5 – Summary statistics on the actual and *counterfactual* levels of volatility in the large, with correction for the attrition bias

	Var (g_{jt}) (1)	Var $(.\|f_{c(Fj)t}=0)$ (2)	Var $(.\|f_{st}, f_{b(j)t}, \nu_{sb(j)t}=0)$ (3)	Var $(.\|w_{sb(j)t}=1/N_{sb(j)t})$ (4)	Var $(.\|f_{st}=0)$ (5)	Var $(.\|f_{b(j)t}=0)$ (6)	Var $(.\|\nu_{sb(j)t}=0)$ (7)
Destination-specific sales							
Belgium	.0016	.0008	.0003	.0003	.0014	.0007	.0014
Germany	.0020	.0006	.0007	.0006	.0016	.0014	.0015
Denmark	.0026	.0017	.0014	.0012	.0021	.0021	.0032
Spain	.0053	.0031	.0009	.0008	.0047	.0031	.0035
Finland	.0047	.0027	.0015	.0016	.0049	.0040	.0038
UK	.0051	.0023	.0009	.0009	.0043	.0034	.0029
Ireland	.0134	.0091	.0022	.0020	.0123	.0033	.0165
Italy	.0046	.0018	.0012	.0011	.0038	.0027	.0032
Netherands	.0030	.0011	.0009	.0008	.0020	.0020	.0027
Portugal	.0027	.0018	.0009	.0008	.0027	.0017	.0021
Sweden	.0142	.0091	.0012	.0010	.0122	.0048	.0138
Median	**.0046**	**.0018**	**.0009**	**.0009**	**.0038**	**.0027**	**.0032**
Multilateral	**.0017**	**.0005**	**.0005**	**.0005**	**.0009**	**.0012**	**.0012**

Notes: Column (1) reports the variance of aggregate export growth computed country-by-country or using multilateral sales ("Multilateral" line), with correction for the attrition bias. Columns (2) and (3) are the *counterfactual* variances one would observe in the absence of macro-economic shocks and in the absence of all three individual shocks, respectively. Column (4) is the *counterfactual* variance computed using all four shocks but assuming individual transactions to be symmetric in size (i.e. $w^c_{sbt-1} = w^c_{t-1}, \forall(s,b)$). Finally, columns (5)-(7) are the *counterfactual* variations in the absence of seller-specific, buyer-specific and match-specific shocks, respectively.