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

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Abstract

We study how different sources of fluctuations interact with the micro-structure of trade networks to shape the volatility of exports at the firm-level and in the aggregate. Four shocks affect transactions – a macroeconomic shock and three individual shocks hitting the exporters, their foreign partners, and their matches. We structurally estimate these shocks using data on the transactions connecting French exporters to their individual European buyers. Individual shocks explain half of aggregate fluctuations and the entirety of individual fluctuations. The volatility of sales across firms and countries are well-explained by the cross-sectional heterogeneity in the diversification of their trade networks.

1 Introduction

What explains the resistance of an economy to economic shocks? In this paper, we argue that the microeconomic structure of this economy and the nature of shocks hitting it interact to jointly determine its sensitivity to these shocks, as measured by its volatility. In presence of microeconomic shocks, a more diversified structure of sales reduces the exposure of firms and the economy to shocks which are diversifiable in nature.[1] For instance, a firm expanding the number of markets or buyers served increases diversification of her clients' portfolio, thus reduces her exposure to country-specific or buyer-specific shocks. At the macro level, an economy moving from a fat-tailed to a more uniform distribution of firms gets less "granular", using a term coined by Gabaix (2011), and thus less strongly exposed to firm-specific shocks.

Our paper offers new evidence on the exposure of firms and of the economy to such "diversifiable" shocks. We start by documenting the extent and heterogeneity of diversification in firm-to-firm trade networks. We then structurally estimate the sources of shocks that hit firms' most disaggregated exchanges. Namely, we focus on firms' exports and analyze how the growth of their sales to each client in each destination-country can be decomposed into a variety of shocks. We then analyze how these estimated shocks together with the structure of trade networks shape the volatility in the small – at the exporter-level – and in the large i.e. in the aggregate. We show that individual shocks are the main sources of fluctuations in the small and in the large. Sales' diversification is central to understand this result. Firms' exports most often involve a tiny number of buyers. In addition, the distribution of firm-to-firm transactions is fat-tailed. This lack of diversification makes exports vulnerable to individual shocks. The differences in individual exporters' diversification and in the

[1] Hereafter, a shock is said "diversifiable" if its contribution to the volatility of sales is reduced in more diversified economies. Our empirical contribution is to measure the extent to which shocks that are *potentially* diversifiable are *indeed* diversified. We do not say anything, however, on the *optimality* of such diversification, i.e. our analysis is positive rather than normative.

structure of bilateral trade explain in large part the dispersion in volatility across firms and in totality the dispersion in volatility across markets.

Our strategy requires that we separately identify the shocks that hit the economy. To do so, we present a model-based decomposition of the growth of firm-to-firm exports into micro- and macro-shocks affecting the seller, the buyer, and their match. The empirical counterpart of these firm-to-firm growth rates uses a new source of data measuring the flows of French exports, their exporter, and their precise buyer in Europe over 13 years and 11 countries. This data set offers a unique opportunity to analyze the sources of fluctuations in economic networks, since it provides information on trade relationships at the firm-to-firm level. Then, we structurally estimate the shocks that firms engaged in international trade face, using the specific features of our data together with a set of orthogonality conditions derived from a standard trade model.[2]

More precisely, the model assumes that the growth of firm-to-firm sales is the combination of country-and-sector-specific (macro-economic) shocks, seller-specific idiosyncratic shocks, buyer-specific idiosyncratic shocks, and match (buyer-seller)- specific idiosyncratic shocks. The structural decomposition is derived within a CES import demand system: Foreign buyers purchase French inputs, among other inputs which are combined using a CES aggregator to produce a good sold on the buyer's own market. In such a framework, macro-economic shocks comprise both aggregate technological changes and shocks to the aggregate/sectoral demand, within a destination. Seller-specific shocks comprise idiosyncratic productivity shocks or any other exogenous cost shocks affecting all the seller's clients, both within and across destinations. Buyer-specific shocks capture shifts in demand idiosyncratic to this importer but affecting all its French suppliers. Finally, the match-specific

[2]Our decomposition rests on the use of seller-buyer transactions present at least two consecutive years - what we call the intensive margin. We show that the intensive margin is the main driver of fluctuation in the small and in the large, and discuss the potential survival bias affecting our data in an Appendix.

component captures shifts in demand specifically affecting the match formed by the seller/exporter and its buyer/importer. An example of such shock is an idiosyncratic preference shock; for instance, when a buyer finds a more efficient way to use a seller's input, thus increasing her demand for this particular input.

Armed with our structurally estimated shocks, we then quantify the contribution of these shocks to the volatility in the small – for the seller – and in the large. We then examine whether the differences in the exposure to these shocks account for the dispersion in volatility observed across firms as well as across markets. The relative contribution of different types of shocks to the volatility should be explained by the interaction between the magnitude of these shocks and the natural hedging that the structure of trade networks offers against these shocks. In the small, whereas seller-specific shocks are not diversifiable, by nature, buyer- and seller-buyer shocks may well compensate for each other if the firm's portfolio of clients is sufficiently diversified. In the large, as pointed out by Gabaix (2011), seller-specific shocks can be diversified when the distribution of firm's size is not too-fat tailed. A similar argument applies to the size-distribution of buyers and matches.

The above arguments suggest that some of the shocks that we identify are diversifiable by nature, either in the small or in the large. We however show that they are hardly diversified in our data. In the small, both buyer-specific and match-specific shocks strongly contribute to the volatility of bilateral exports. Muting the buyer-specific and match-specific shocks respectively reduces by 20% and 50% the typical firm's volatility, within a market. Muting seller-specific shocks reduces volatility by 20% while the impact of macro-shocks is negligible. When the volatility of firms' sales is computed across rather than within markets, the contribution of match-specific shocks is reduced whereas seller-specific shocks become relatively more important.

Even though seller-specific shocks cannot be diversified by the seller, a wider portfolio of clients helps attenuate the volatility induced by buyer-related shocks. The sizeable contribution of buyer-related shocks is therefore a direct consequence of French exporters' little-diversified clients' portfolio. Indeed, 42 percent of firms have a single buyer in their typical export destination, and hence are strongly exposed to buyer-specific and match-specific shocks. Even the 10 percent of exporters serving ten or more buyers within a destination, are not perfectly diversified because their sales are skewed towards one or two main clients. The seller's heterogeneity in its diversification across buyers and destinations can be directly related to its volatility. Firms at the first quartile of the distribution of diversification are 30% more volatile than firms at the third quartile, keeping everything else constant. Firm size affects this relation: diversification explains about half of the lower volatility of large firms relative to mid-size firms. However, mid-size firms are less volatile than small firms exclusively because seller-specific shocks are much less volatile for the former than for the latter.

To measure volatility in the large, we aggregate shocks using the realized structure of trade networks. Then, we examine how it relates to the aggregate structure of trade networks. Using counterfactual experiments, we find that muting all individual shocks reduces French multilateral exports volatility by as much as muting all macroeconomic shocks. Here as well, the prevalence of individual shocks is due to the lack of diversification in French exports. French exports are extremely concentrated in the seller, buyer, and match dimensions. The size-distribution of French exporters is more than 200 times what it would be, were exporters equal in size. The distribution of export sales is even more concentrated across buyers and across firm-to-firm transactions than it is across exporters, thus magnifying the amount of granular volatility. For instance, the ten largest seller-buyer pairs within the European area account for 6 percent of French export sales. This granularity contributes to explaining the large contribution of microeconomic shocks to the volatility in the large. We show that when trade is evenly spread across seller-buyer pairs, the counterfactual volatility is three times lower than the realized volatility.

Because we find that macroeconomic shocks (approximately) have the same volatility across destinations, muting individual shocks eliminates the differences in French exports volatility across destinations. In addition, this “across-destinations” heterogeneity due to individual shocks is closely related to the network structure of exports. In destinations where seller-buyer pairs are extremely concentrated, the seller-buyer shocks are key drivers of volatility. Similar correlations are found between cross-seller diversification and seller-shocks, and cross-buyer diversification and buyer shocks.

Our *results* clearly show that both individual firms and the French economy at large are strongly exposed to microeconomic shocks. This exposure comes from the lack of diversification, across buyers and markets within a firm, and across transactions within a market. Firms and markets face different levels of diversification. We also show that the observed differences in sales-diversification are directly linked to the dispersion in volatility across firms and across markets.

This paper contributes to the literature in three dimensions. First, we propose a novel decomposition of firm-to-firm sales growth into different shocks, which we estimate structurally. The method is inspired from the labor literature - see, among many others, Abowd et al. (1999) (AKM hereafter) and Abowd et al. (2002).[3] Whereas the labor literature uses the inter-temporal mobility of workers across firms to separate the employer-, employee- and match-specific determinants of wages, we instead use the cross-sectional network structure of our seller-buyer data to estimate the seller-, buyer- and match-specific components of firm-to-firm growth. Importantly, the decomposition is derived from a structural model which guides our definition of the

[3]Longitudinal employer-employee data have a similar graph structure as that of trade networks. This structure has been exploited to study the determinants of the wage distribution.

estimated equation. The assumptions of the model are exploited to define the orthogonality conditions used to achieve full identification.

Our second contribution 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.[4] 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 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). In line with both strands, our paper identifies the different sources of shocks to firms' growth, coming from idiosyncratic (supply) shocks and customer-related (demand) shocks. We quantify their relative contributions in explaining the volatility of individual sales and their heterogeneity across firms.

Our third, and last, contribution is connected to the recent literature on aggregate "granular" fluctuations. When the distribution of firms' size is fat-tailed (Gabaix, 2011) and when firm-to-firm linkages are sufficiently concentrated (Acemoglu et al., 2012), idiosyncratic shocks can have a substantial effect on macroeconomic outcomes. Here as well, the literature has mostly focused on idiosyncratic supply shocks as a source of granular fluctuations. We expand this framework to identify and incorporate different sources of volatility, as measured at the most disaggregated level. Differences in the structure of trade networks are shown to explain the differences in aggregate volatility. In this respect, the paper is related to Koren and Tenreyro (2007), Caselli et al. (2015), di Giovanni and Levchenko (2012), and di Giovanni et al. (2014). More specifically, Caselli et al. (2015) point out the importance of geographic diversification to mitigate country-specific shocks. We also find

[4] 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.

that geographic diversification is important but mostly as a way to diversify individual rather than aggregate shocks. di Giovanni et al. (2014) show how differences in the micro structure of the economy can affect the magnitude of aggregate fluctuations. In complement to their focus on idiosyncratic supply shocks, our results suggest that the argument extends to other sources of microeconomic shocks.

In addition to the articles cited above, the use of export data naturally draws a link with the trade literature. Several contemporary papers also use firm-to-firm trade data to go deeper into the microeconomic structure of aggregate export flows. In particular, Bernard et al. (2014), Eaton et al. (2013) and Carballo et al. (2013) also provide evidence on the heterogeneity of exporters in terms of the number of buyers they interact with. This dimension of heterogeneity is however interpreted in completely different contexts, to discuss the welfare gains from trade (Carballo et al., 2013), individual and aggregate trade patterns (Bernard et al., 2014), or their dynamics (Eaton et al., 2013). Last, a recent and complementary strand of the literature has studied the structure of economic networks as the outcome of an endogenous process (Oberfield, 2011; Chaney, 2014). In contrast to these papers, we take the structure of the network as given and study how it shapes volatility in trade data.

Our analysis provides a deeper understanding of the sources of fluctuations in individual and aggregate exports than was previously available. Even though data constraints do not allow us to extend our results to domestic sales, we conjecture that our results would not be qualitatively different if we could observe the domestic network of transactions. At the individual level, including the domestic market could only increase the number of partners of French exporters. However, inclusion of this domestic market would also massively increase the number of small (and non-exporting) firms which are unlikely to be well-diversified within their domestic market.

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.[5] 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.[6] For all these countries, we use data for the 1995-2007 period.

Many researchers before us have used individual 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

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

[6]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.

year), the product category (at the 8-digit level of the combined nomenclature) and the value of the shipment. In the analysis, data will be aggregated across transactions within a year, for each exporter-importer pair. This helps focus on the most important novelty in the data, which is the explicit identification of both sides of the markets, the exporter and its foreign partner.[7] 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. Likewise, B_t will denote the set of active buyers/importers b 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 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). Put differently, some of our regressions do not include the smallest exporting firms. 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. There is only one type of flows that we remove. In some cases,

[7] 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 country code is not consistent with the country code that can be recovered from the importer's identifier. This happens when a French firm plays the role of intermediary between two other countries, the first one where the good is produced, the second where it is bought. Since such transactions do not qualify as "French exports" stricto sensu, they are removed from the database.

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_{sbt}, g_{st}, g_{bt} and g_t, respectively for the seller-buyer, the seller, the buyer and the aggregate levels. The growth rate at the seller and aggregate levels will either be defined over destinations, or within an export market, where g_{sct} and g_{ct} will respectively denote the growth rate of firm-level and aggregate exports to destination c.[8] Our measure of 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.[9] Finally, to minimize the effect of outliers on

[8] In Section 4, we focus on the intensive margin, hence on the subset of bilateral pairs active in both $t-1$ and t. Therefore, g_{st} aggregates g_{sbt} for buyers that buy from s in both $t-1$ and t. Appendix A discusses an explicit treatment of the extensive margin and how much this margin contributes to volatility in the small and in the large.

[9] 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

our measures of volatility, we base our estimates in Section 3 on observations for which the seller 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 describe the structure of French firms' international trade networks, as of 2007. Diversification is used as a sufficient summary statistics on the extent to which 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. 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. As already argued in the introduction, different types of shocks have different diversification *potential* depending on their very nature. Macro-economic shocks are hardly diversifiable in the large. Namely, exposure to country-specific shocks is reduced if and only if a country exports to a wider set of destinations. In our sample, not much can be gained in this dimension because exports to EU15 countries are already almost perfectly diversified.[10] In the model of Section 3, "macro-economic shocks" 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 suggest that diversification is relatively high. Depending on the destination country, the Herfindahl index of sales calculated across sec-

volatility based on sub-periods, as is often done in the macroeconomic literature.

[10]The Herfindahl of French exports across destinations is equal to .16, not far from 1/11=.09, the minimum degree of concentration which can be achieved in a sample of 11 countries. The deviation from perfect diversification appears to be correlated with differences in country sizes with France exporting more to larger countries.

tors thus varies between .07 and .11, not far away from the maximum amount of diversification which can be achieved which is 1/35=.03 since we have 35 sectors in our data set.

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. Hence, it is the distribution of sales across firms that determines the prevalence of idiosyncratic supply shocks in aggregate fluctuations (Gabaix, 2011). A similar reasoning applies if idiosyncratic shocks hit the buyer side of the economy. Again, what matters is the distribution of purchases across buyers. Finally, if shocks are specific to seller-buyer transactions, the distribution of sales across transactions is key.

The concentration of exports across sellers, buyers and seller-buyer pairs is illustrated in Table 2, 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 ($Herf/(1/S) = 234$).[11] While always high, this ratio varies significantly depending on the destination country under consideration (column (3), Table 2). It is maximal for French sales in Spain and minimal for exports to Germany.

[11] 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.

The skewness of export distributions 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.

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. As mentioned in the introduction, 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.[12] Finally, buyer-related shocks (buyer- and match-specific 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

[12]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.

sellers' diversification – measured by the number of markets and the number of customers within a destination – in each French exporter's portfolio.

Figure 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. Later in the analysis, we use the Herfindahl of firms' sales as the adequate measure of diversification. 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. 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.

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 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 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.[13] Among the 12% of firms that serve more than 10 buyers, many serve tiny importers with cumulative share less

[13]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.

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 3. We explain firms' degree of diversification using a set of observable characteristics. To measure diversification, Columns (1)-(3) use the number of clients in the exporter's portfolio as left hand-side variable whereas columns (4)-(6) use the Herfindahl index. 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.[14] 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 buyers in proportion to their total purchases.[15] Finally,

[14]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.

[15]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.

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.[16] 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. To measure whether this is the case, our analysis of diversification is not sufficient; we also need to estimate the prevalence of the different shocks that drive volatility. This is what we do in Section 3.

[16]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.

3 Empirical strategy

Having briefly 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 motivate the orthogonality conditions later exploited in the empirical subsection. These conditions allow us to identify and estimate the sources of shocks at the most disaggregated level. These estimated shocks are then aggregated, step by step.

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 producing a consumption good with various imported inputs and selling to a representative consumer. The technology for producing y_b units writes as follows:

$$y_b = \left[z_b \sum_s \left(z_{sb} x_{sb} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where x_{sb} is the demand for the input produced by a seller s, $\sigma > 1$ is the elasticity of substitution between input varieties, z_{sb} is a preference parameter for input s and z_b is a measure of the buyer's productivity. Since we ultimately apply the model to trade data between French exporters and various European buyers, we assume that buyer b uses as sole inputs intermediate goods supplied by French firms.[17]

Given this production function, the buyer minimizes total costs induced

[17] While unnecessary, it is of course straightforward to adjust the model to a more general technology combining other inputs as well as labor and capital.

by the level of production that satisfies market demand:

$$y_b = p_b^{-\eta} A$$

where p_b is the price charged by the buyer to her representative consumer and A 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 with a constant mark-up $\eta/(\eta - 1)$ over her marginal cost c_b.

Cost minimization therefore implies the following (nominal) demand addressed to supplier s:

$$p_{sb} x_{sb} = \left(\frac{p_{sb}}{z_{sb} c_b}\right)^{1-\sigma} c_b \left(\frac{\eta}{\eta - 1} c_b\right)^{-\eta} A z_b^{\sigma} \tag{2}$$

where p_{sb} denotes the price charged by supplier s on her customer b. In equilibrium, the marginal cost writes:

$$c_b = z_b^{\frac{-\sigma}{\sigma - 1}} \left[\sum_s \left(\frac{p_{sb}}{z_{sb}}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

To obtain a demand equation, we define the pricing strategy of input providers. We assume that varieties of inputs are produced using a production function linear in labor. The productivity of labor is assumed to be a function of an aggregate productivity component Z and a firm-specific component z_s. Taking the cost of labor in France as the numéraire and assuming that input providers compete under monopolistic competition, the price set by exporter

s for her sales to buyer b is:[18]

$$p_{sb} = \frac{\sigma}{\sigma - 1} \frac{1}{z_s Z} \tag{3}$$

Plugging equation (3) into (2) and taking the first difference in logs over time gives the predicted equation for the dynamics of trade in the model:

$$\begin{aligned} g_{sbt} &\equiv d \ln p_{sbt} x_{sbt} \\ &= (\sigma - 1) d \ln Z_t + d \ln A_t + (\sigma - 1) d \ln z_{st} \\ &\quad + (\sigma - \eta) d \ln c_{bt} + \sigma d \ln z_{bt} + (\sigma - 1) d \ln z_{sbt} \end{aligned} \tag{4}$$

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

$$\begin{aligned} d \ln c_{bt} &= -\frac{\sigma}{\sigma - 1} d \ln z_{bt} + \sum_s w^b_{st-1} d \ln \left(\frac{p_{sbt}}{z_{sbt}} \right) \\ &= -\frac{\sigma}{\sigma - 1} d \ln z_{bt} - d \ln Z_t - \sum_s w^b_{st-1} (d \ln z_{st} + d \ln z_{sbt}) \end{aligned}$$

with $w^b_{st-1} \equiv \frac{p_{sbt-1} x_{sbt-1}}{\sum_s p_{sbt-1} x_{sbt-1}}$ the share of seller s in buyer b's input cost, in $t-1$.

Equation (4) thus defines the dynamics of trade as a function of the growth of the fundamentals, namely the two supply parameters, z_{st} and Z_t, and the three demand parameters, z_{sbt}, z_{bt} and A_t.[19] The last step consists in specifying how these parameters evolve over time. In what follows, it is assumed that their dynamics is driven by i.i.d. shocks: $Z_t = Z e^{\varepsilon_{Zt}}$, $A_t = A e^{\varepsilon_{At}}$, $z_{st} = z_s e^{\varepsilon_{zst}}$,

[18] Here, we also assume that there is no delivery cost charged on international sales to buyer b. Since we later focus on the dynamics of trade, it would be exactly equivalent to include a time-invariant delivery cost. In the empirical model, variations in the transportation cost will be absorbed into the aggregate shock (if they are common across firms within a sector), or in the match-specific shock (if they are specific to the firm and/or her customer).

[19] 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.

$z_{bt} = z_b e^{\varepsilon_{z_b t}}$, and $z_{sbt} = z_{sb} e^{\varepsilon_{z_{sb} t}}$.

Our structural equation for trade dynamics becomes:

$$\begin{aligned} g_{sbt} \quad &= \quad (\eta - 1)d\varepsilon_{Zt} + d\varepsilon_{At} + (\sigma - 1)d\varepsilon_{z_s t} + \frac{\sigma}{\sigma - 1}(\eta - 1)d\varepsilon_{z_b t} \\ &\quad +(\sigma - 1)d\varepsilon_{z_{sb} t} - (\sigma - \eta)\sum_s w^b_{st-1}(d\varepsilon_{z_s t} + d\varepsilon_{z_{sb} t}) \end{aligned} \tag{5}$$

We now explain how we exploit the structure of the data to estimate the different components of the above equation.

3.2 Identification strategy

As we describe now, we use the graph structure of trade networks to separate between the different components of growth introduced into the model. We take inspiration from the labor literature on the dispersion of wages, notably Abowd et al. (1999), AKM hereafter. This literature seeks to decompose the total cross-sectional distribution of wages into the shares which are attributable to firm-specific variables, worker-specific elements and match-specific determinants. First, we note that our model delivers a similar fixed-effects decomposition.[20] After simple manipulation, Equation (5) rewrites as:

$$g_{sbt} = f_{ct} + f_{st} + f_{bt} \underbrace{-\frac{\sigma - \eta}{\sigma - 1}\sum_s w^b_{st-1}(f_{st} + \nu_{sbt})}_{BSIC_{bt}} + \nu_{sbt} \tag{6}$$

where:

$$\begin{aligned} f_{ct} \quad &= \quad (\eta - 1)d\varepsilon_{Zt} + d\varepsilon_{At} \\ f_{st} \quad &= \quad (\sigma - 1)d\varepsilon_{z_s t} \\ f_{bt} \quad &= \quad \frac{\sigma}{\sigma - 1}(\eta - 1)d\varepsilon_{z_b t} \end{aligned}$$

[20]In AKM, high-dimensional fixed-effects estimators are applied to longitudinal linked employer-employee data. Identification is achieved thanks to the connectivity in employer-employee networks induced by workers' mobility across firms. In the case of trade networks, because sellers are connected to multiple buyers and conversely, identification can be achieved in the cross-section for most effects.

$$\nu_{sbt} \quad = \quad (\sigma - 1)d\varepsilon_{z_{sb}t}$$

are the fixed components and the match-specific residual explaining the cross-sectional dispersion of growth rates. The macro component, f_{ct}, is indexed by the destination country since it comprises aggregate demand shocks ε_{At} which are country-specific. In the empirical analysis, we further assume that it is specific to the firm's industry.

The partial equilibrium model of Subsection (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. The buyer-specific part is itself composed of two terms, the buyer fixed effect f_{bt} and a weighted average of the seller- and match-specific shocks affecting her partners ($BSIC_{bt}$, hereafter). The $BSIC_{bt}$ 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 increases the input cost attenuating the direct impact that the shock has on the demand addressed to that seller. Moreover, this generates externalities on the rest of the buyer's portfolio of partners. The presence of this buyer-specific input cost component in equation (6) is important because it creates a negative correlation between the buyer-specific term and the match-specific residual. Absent this correlation, equation (6) could be estimated using AKM. This endogeneity problem prevents us from directly applying AKM strategy. To solve this problem, we rewrite equation (6) to eliminate the buyer-specific input cost index by adding $\frac{\sigma-\eta}{\eta-1}\sum_s w^b_{st-1} g_{sbt}$ to our growth rate g_{sbt}. Equation (6) then simply becomes:

$$\tilde{g}_{sbt} = (1+\lambda)f_{ct} + f_{st} + (1+\lambda)f_{bt} + \nu_{sbt} \tag{7}$$

where:

$$\begin{aligned}\tilde{g}_{sbt} &= g_{sbt} + \lambda \sum_{s} w^{b}_{st-1} g_{sbt} \\ \lambda &= \frac{\sigma - \eta}{\eta - 1}\end{aligned}$$

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

$$E(\nu_{sbt}|(s,t);(b,t)) = 0 \tag{8}$$

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, namely σ the elasticity of substitution between French inputs, and η the price elasticity of demand addressed to foreign buyers. Up to now, we have not imposed any restriction on these parameters except that they are both larger than one, and homogeneous across buyers. To recover λ, we use an additional orthogonality condition implied by our theoretical model. Namely the model implies:

$$E(f_{st} f_{bt}) = 0 \tag{9}$$

Under the "true" value of λ, condition (9) holds. Note that this model is linear, conditional on λ. It implies that the relationship between λ and the magnitude of the correlation between the sellers and the buyers fixed effects is monotonic (see 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 B gives more details on the estimation procedure.[21]

[21] As detailed in Appendix B, the orthogonality condition (9) 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

To summarize, the estimation procedure consists in:

1. Estimating the components of equation (7) under the exogeneity condition (8) for different values of λ

2. Applying a grid-search algorithm to choose the value for λ which best matches the orthogonality condition (9), and the corresponding estimated components,

3. Recovering the theoretical decomposition in equation (6) which measures the relative contribution of different types of shocks in driving the cross-sectional distribution of firm-to-firm growth rates.

Results for the decomposition are presented in Tables 4 and 5. 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 4 reports the full correlation table of the various estimated effects. 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, as hypothesized in assumption (8). The correlation of the sellers' and the buyers' effects is equal to -.067 which is also what was obtained in the "fake" sample in which we simulated orthogonal shocks given the actual network structure of the data. Based on Abowd et al. (2002), and Andrews et al. (2008), we interpret this negative correlation as spurious due to a "limited-mobility bias" and use it as input in the grid search procedure to estimate λ.[22]

take into account this potential "limited-mobility 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 B.

[22] An estimation error in the buyer effect translates into an estimation error of the opposite sign in the seller effect. Such estimation errors are more likely to exist in not-very-dense networks. In addition, Andrews et al. (2008) show that the absence of observable controls magnifies this bias.

The negative correlation between f_{st} and $BSIC_{bt}$ is consistent with expectations. A positive productivity shock to seller s drives the input cost index of her partners down, which partially counteracts the direct effect that the shock has on the demand for this seller's input. This effect also generates spatial correlation within the set of French sellers connected to the same buyer. The negative correlation between f_{bt} and $BSIC_{bt}$ is not consistent with the theoretical model. It is again a consequence of the "limited-mobility bias". Finally, consistent with our model, the macro-economic shocks are orthogonal to each individual component.

Table 5, 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.[23] 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.

[23]Table 5 provides summary statistics on the contribution of each shock to the annual growth of firm-to-firm exports, which is what is estimated. We have also computed the contribution of each shock to the *volatility* of these growth rates. Results are very similar. The most important source of volatility in the disaggregated data is, by far, the match-specific term, followed by the two individual components. This is almost mechanical given the dimensionality of the data.

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 shock contributes to the volatility of firm-level sales (both within and across destinations). This is done in Section 4 whereas volatility in the large 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 shocks 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 structural shocks, based on a growth decomposition, mechanically excludes from the analysis the entry and exit of buyer-seller pairs. As shown in Appendix A, the intensive margin is the main driver of fluctuations at the individual level. As shown in Appendix C, 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 destination by destination:

$$Var(g_{sct}) = \frac{1}{T}\sum_{t}(g_{sct} - \bar{g}_{sc})^2$$

as well as over total exports:

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

g_{sct} and g_{st} respectively denote the growth rates of seller s (intensive) sales in destination c and overall. $\bar{g}_{sc}$ and $\bar{g}_s$ are their mean growth rates, computed over time.

At the level of individual firms, the volatility of destination-specific 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:

$$\begin{aligned} Var(g_{sct}) &= Var(f_{ct}) + Var(f_{st}) \\ &\quad \underbrace{+Var\left(\sum_{b\in B_{sc}} w^{sc}_{bt-1}(f_{bt}+\nu_{sbt}+BSIC_{bt})\right)}_{Diversifiable\ components} + Cov \end{aligned} \quad (10)$$

where $w^{sc}_{bt-1} \equiv \frac{p_{sbt-1}x_{sbt-1}}{\sum_{b\in B_{sc}} p_{sbt-1}x_{sbt-1}}$ is the weight of buyer b in seller s (intensive) sales in period $t-1$ and country c. B_{sc} is the set of buyers from c connected to seller s in both periods $t-1$ and t ($B_{sc} = B_{sct-1} \cap B_{sct}$). The Cov term 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. $\sum_{b\in B_{sc}} w^{sc}_{bt-1}(f_{bt}+\nu_{sbt}+BSIC_{bt})$).[24]

Equation (10) 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 (10) 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 markets,

[24] In the model and the estimation, f_{st} is neither correlated with f_{bt} nor with ν_{sbt}. While this is true asymptotically, it might not be true within a given pair in the data set. Moreover, orthogonality of f_{bt} (ν_{sbt}) and f_{st} in the cross-section does not necessarily imply that f_{st} is orthogonal to the weighted average of the f_{bt} (ν_{sbt}) terms. Finally, the $BSIC_{bt}$ 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.

as explained below). Moreover, since they hit all exporters uniformly, they do not contribute to the heterogeneity in firm-level volatilities. The second term in equation (10) measures the micro-level volatility induced by shocks that are specific to the seller. This source is also non-diversifiable within a firm (neither within nor across destinations) 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). 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 more diversified portfolio mechanically reduces the firm's exposure to such shocks.

The diversification argument is broader than just described. In our framework, the firm can diversify against buyer-specific shocks, while also smoothing the impact of aggregate shocks, by selling to more markets. With multiple destinations, the variance of export sales indeed writes:

$$\begin{aligned} Var(g_{st}) &= \underbrace{Var\left(\sum_{c\in C_s} w^s_{ct-1}\left[f_{ct} + \sum_{b\in B_{sc}} w^{sc}_{bt-1}(f_{bt} + \nu_{sbt} + BSIC_{bt})\right]\right)}_{Diversifiable\ components} \\ &\quad + Var(f_{st}) + Cov \end{aligned} \tag{11}$$

where w^s_{ct-1} is now the share of destination c in seller s' portfolio, which is computed over the set C_s of its markets. Selling to a broader set of markets is a way for the firm to hedge against country-specific shocks, among which the idiosyncratic shocks to buyers. This possibility is at the root of the argument in Tenreyro et al. (2012), even though they apply it to the volatility *in the large*.

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 (see, among others, Mayer et al., 2014 or Bernard et al., 2011). 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 buyer diversification matters a lot to account for the volatility in the small; more diversified firms display less volatile sales. However, we control for the degree of cross-product diversification whenever possible and show that product diversification does also matter to account for the volatility in the small.

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. First, we compute the distribution of firm-level volatilities and compare it to the distribution one would observe, had one source of fluctuations disappeared. Second, we compute how the contribution induced by diversifiable shocks would change, were firms better diversified. Taken together, these two sets of counterfactual exercises help us understand how the nature of shocks and the structure of trade networks interact to shape the volatility in the small.

Figure 3 displays the relative contribution of each shock to volatility in the small, using our counterfactual analysis. In the exercise, we take as our benchmark the realized dispersion of volatilities, presented as the solid lines in Figure 3. On the same Figure, we present the distributions that would prevail, had one type of shocks disappeared. Because we estimated the full structure of shocks, for each firm, destination, and year, computing such distributions is easily realized by muting each shock in turn. Table 6 further reports the magnitude of the change in volatilities at different points of the distribution. Note that Figure 3 does not report the counterfactual exercise for the macro shocks because the resulting distribution is virtually confounded with the realized one (see the second line in Table 6). Three counterfactual distributions are therefore presented: without seller-specific shocks (dash-dotted line), buyer-specific shocks (long-dashed line), and match-specific shocks (short-dashed line).

We first consider results presented in the top panel of Table 6 and the left graph in Figure 3, showing destination-specific measures of volatility. Eliminating the macro shocks has almost virtually no effect, less than 1% of volatility at all points of the distribution of volatility across individual exporters. By contrast, getting rid of micro shocks has a substantial impact, as shown in Figure 3. The most striking effect is due to the suppression of match-specific components. Eliminating this source of fluctuations reduces the magnitude of firm-level volatility by roughly 50% at all points of the distribution (Table 6). Thus, the density of counterfactual volatilities in Figure 3 is strongly shifted to the left. Muting either seller-specific or buyer-specific shocks also reduces firm-level volatility, though by a smaller amount. The volatility of firm-level sales is reduced by 15 to 25% when either the buyer-specific or the seller-specific shocks are eliminated. Hence, seller-specific, buyer-specific, and match-specific shocks (even though the last two are diversifiable within the firm) are important sources of exporters volatility.

Match-specific shocks have huge effects on the distribution of volatilities because these shocks (as well as the buyer-specific shocks) are little diversified across buyers, within a destination. Diversification is better ensured, albeit still imperfect, when volatility is computed over all countries, as in the right graph of Figure 3 and the bottom panel of Table 6. While getting rid of this source of volatility decreases volatility of firm-level exports, the impact is weaker, 19% of volatility at either the mean or the median firm in the distribution. When seller-specific shocks are eliminated (dash-and-dotted line), the distribution of firm-level volatilities is most strongly affected: the variance of a firm's sales is decreased by more than 30%. As this type of shocks cannot be diversified within the firm, within or across destinations, the impact is similar irrespective of whether volatility is measured within or across countries. However, the potential for diversification against buyer- and match-specific shocks implies that the overall volatility of the typical firm is lower, inducing a larger relative adjustment between the counterfactual and the realized distributions.

As argued before, the prevalence of buyer and buyer-seller shocks as a driver of volatility in the small not only depends on the variance of the shocks, but also on the degree to which they are diversified across customers. Everything else being equal, firms with more diversified sales (with a small Herfindahl index $Herf_{sc}^{B} \equiv \sum_{b \in B_{sc}} {w_b^{sc}}^2$) end up being less volatile because the diversification of their portfolio helps them smooth out the impact of shocks to their individual buyers.

Table 7 shows that this is indeed the case in our data. Namely, we estimate the correlation between volatility at the firm-level and the extent of within and across markets diversification. We regress the (log of the) variance of firm- and destination-specific sales (columns (1) and (2)) and firm-specific sales (column (3)) on a set of explanatory variables, including measures of each firm's diversification. Consistent with our theoretical framework, the left-hand side variable is restricted to the diversifiable component of volatility, i.e. the weighted average of the sum of f_{bt}, ν_{sbt} and $BSIC_{bt}$ in columns (1) and (2) and the weighted average of f_{ct}, f_{bt}, ν_{sbt} and $BSIC_{bt}$ in column (3).

Results confirm that better diversified firms (as measured by their Herfindahl across buyers) display significantly less volatile export sales. This result holds when we control for sector $\times$ destination fixed effects (column (1)) or for firm fixed effects (column (2)). It is robust to the introduction of variables potentially correlated with the Herfindahl and volatility: the diversification of the firm's portfolio of products, size, experience in the destination, or potential intra-firm linkages with the destination.[25] This estimated correlation between the variance and the diversification of exports implies that a firm at

[25]Our results show that large exporters display much less volatile sales, conditional on their degree of diversification. This result confirms the correlation found in the previous literature (Davis et al., 2009; Kelly et al., 2013), though with different data and using different dimensions for identification.

the first quartile of the distribution of Herfindahl indices has sales that are 30% less volatile than those of a firm at the third quartile. Poor diversification of firm-to-firm trade networks does increase firm-level volatility.[26]

Finally, in column (3) of Table 7, we regress the variance of multilateral sales on the (average) degree of diversification across buyers within a destination and the extent of across-destinations diversification of sales. We include the same observable controls (even though they are now defined within-firm across-destinations rather than destination-by-destination). However, because the left hand-side variable has a single observation per firm, we cannot include firm fixed-effects any more. Results confirm those obtained within a destination: firms with better diversified portfolios of clients display significantly less volatile sales. This result holds both within and across destinations; the coefficient on the Herfindahl of sales across destinations is positive and significant. By increasing diversification of her within-destination portfolio of clients from the first to the third quartile of the distribution, a firm would reduce the volatility of her sales by 51%. Similarly, exporting to a less skewed portfolio of destinations (moving again from the first to the third quartile of the distribution of across-destinations diversifications) decreases volatility by an additional 9% .

Since the degree of sales' diversification is correlated with the size of the firm, the lack of diversification of small firms may explain why they display more volatile sales. We explore this view in Figure 4. The dark bars correspond to the median volatility of multilateral sales at each decile of the distribution of firms' size. They confirm the well-known fact that smaller

[26]In a placebo exercise, we use the non-diversifiable component of volatility (the part due to macro and seller-specific shocks) as the variable to explain. The estimated impact of diversification is equal to .34 and .02, when controlling for sector × destination and for firm fixed-effects, respectively. Whereas such coefficients are significantly smaller than in the main regression, they are still significant, which is not consistent with expectations. This inconsistency comes from the estimated correlation between the diversifiable and non-diversifiable components of firm-to-firm growth, due to the "limited-mobility" bias. When we restrict the sample to the more precisely estimated effects, the placebo coefficient are indeed further reduced and become barely significant. Detailed results are available upon request.

firms display more volatility. Our decomposition of firm's growth allows to delve deeper into this result, though. Namely, we can see whether this comes from small firms facing more volatile seller-specific shocks and/or having a portfolio of clients which exposes them to more buyer-specific risks. The light grey bars in Figure 4 show that both explanations are consistent with the data. Namely, the median volatility induced by seller-specific shocks (the "Not diversifiable vol." component in Figure 4) is strongly decreasing over the distribution of firms' size. Seller-specific shocks are 68% less volatile in the 10th decile of the distribution than in the first. This is consistent with supply-side explanations of volatility in the small. The volatility induced by diversifiable shocks is also decreasing in firms' size (the "Diversifiable vol." bars in Figure 4). More specifically, half of the difference in volatility between medium and large 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.[27] However, because their portfolio is imperfectly diversified, even firms in 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 shocks, especially seller-specific and seller-buyer shocks, generate most of the volatility, ii) these shocks also contribute to explain the heterogeneity in the degree of volatility across firms and destination markets, iii) the volatility of sales is (negatively) correlated with firm's size and the degree of diversification of its portfolio of customers. We now turn to the analysis of fluctuations *in the large* and examine whether the above results hold when data are further aggregated.

[27]The correlation between this component of volatility and the median Herfindahl of sales is equal to 99.8% across deciles.

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:

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

or across destinations:

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

where g_{ct} and g_t denote the growth rate of intensive aggregate exports within and across markets, respectively; and where $\bar{g}_c$ and $\bar{g}$ denote the mean growth rates. Here again we focus on the intensive margin of exports. As shown is Appendix A, the intensive margin accounts for the lion's share of fluctuations in the aggregate.

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

$$\begin{aligned} Var(g_{ct}) \quad = \quad & \underbrace{Var\left(\sum_{s\in S_c} w^c_{st-1} f_{st} + \sum_{b\in B_c} w^c_{bt-1}(f_{bt} + BSIC_{bt}) + \sum_{s\in S_c}\sum_{b\in B_{sc}} w^c_{sbt-1}\nu_{sbt}\right)}_{Diversifiable\ components} \\ & + Var(f_{ct}) + Cov \end{aligned} \tag{12}$$

where S_c and B_c respectively denote the set of sellers and buyers in market c in $t-1$ and t, w^c_{st-1} (resp. w^c_{bt-1}, w^c_{sbt-1}) is the share of seller s (resp. buyer b, the pair (s,b)) in (intensive) exports to country c, and Cov is a set of covariance terms between the macro and the individual components.

Equation (12) is the counterpart to equation (10), albeit for volatility in the large. It shows how each type of shocks contributes to the volatility of aggregate trade, in proportion to its volatility and its diversification within the network of firm-to-firm trade flows. As before, macro shocks enter equation (12) in proportion to their volatility because they are non-diversifiable by nature. At the aggregate level, all three micro shocks are, by contrast, diversifiable, though through different dimensions.[28] Seller-specific shocks naturally diversify 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). As shown in Table 2, the distribution of individual sales is highly concentrated as evidenced by the value of the Herfindahl index of sales across sellers $Herf_c^S \equiv \sum_{s\in S_c} {w_s^c}^2$. Thus, idiosyncratic shocks to sellers may well induce granular fluctuations.

Our analysis shows that the argument naturally extends to the concentration of sales across buyers (the inverse of $Herf_c^B \equiv \sum_{b\in B_c} {w_b^c}^2$) and the concentration of transactions across seller-buyer pairs (the inverse of $Herf_c^{SB} \equiv \sum_{s\in S_c}\sum_{b\in B_{sc}} {w_{sb}^c}^2$). Hence, these shocks can be a source of aggregate fluctuations if their variance is large enough or if the distribution of transactions is concentrated enough. Since both Herfindahl indices are large in our trade data (Table 2), we expect the buyer-specific and the seller-buyer shocks to matter for aggregate fluctuations. Using the same reasoning as before, total volatility of multilateral sales aggregate all four types of shocks, across and within markets. Its magnitude thus depends on the relative volatility of each shock and the concentration of sales, both within and across destinations.

[28] To see this, it is convenient to simplify equation (12) by assuming all shocks to be orthogonal to each other and i.i.d. with equal volatility across individuals. Under these assumptions and if the distribution of weights is constant over time, equation (12) becomes:

$$Var(g_{ct}) = \sigma_C^2 + \sigma_{iS}^2 \sum_{s\in S_c} {w_s^c}^2 + \sigma_{iB}^2 \sum_{b\in B_c} {w_s^c}^2 + \sigma_{iSB}^2 \sum_{s\in S_c}\sum_{b\in B_{sc}} {w_{sb}^c}^2 + \phi(BSIC_{bt})$$

where σ_C^2, σ_{iS}^2, σ_{iB}^2 and σ_{iSB}^2 respectively denote the (homogenous) variance of macro, seller, buyer, and seller-buyer shocks, and $\phi(BSIC_{bt})$ is a residual term containing all the variance and covariance components involving $BSIC_{bt}$.

5.2 Empirical results

As in Section 4, we assess the relative contribution of each component using counterfactuals. 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. The remaining columns present the counterfactuals. We first compare the volatility one would observe in the absence of macro shocks (column (2)) and in the absence of all three (diversifiable) micro shocks (column (3)). As expected, the macro-economic shocks matter much more in the large than in the small. Eliminating the macro shocks reduces the volatility of exports by 15 to 70% of the realized variance, depending on the destination. Macro-economic shocks are now more important because the aggregate impact of micro shocks 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 shocks.

Even though macro-economic shocks matter substantially more for volatility in the large, diversifiable micro shocks matter as well, as illustrated in column (3). Muting all three shocks simultaneously reduces the magnitude of aggregate fluctuations, by 73% on average. The strong impact of micro shocks 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.[29] 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, with a correlation coefficient of .98, even though the way they are computed is quite different. Interest-

[29] Namely, we use the existing network of bilateral transactions. Then, rather than using the observed weights when aggregating transactions, the counterfactual uses equal weights.

ingly, the impact of muting individual shocks is positively correlated with the actual level of volatility (see the right panel in Figure 5). Therefore, the counterfactual volatilities shown in column (3) of Table 8, which are entirely attributable to macro shocks, are hardly heterogeneous across countries. Put differently, our results show that most of the heterogeneity between countries in the variance of aggregate exports is due to the heterogeneous impact of individual shocks, whereas the variance induced by macro-economic shocks is fairly similar across countries.

Finally, the last three columns in Table 8 report the aggregate impact of muting one microeconomic shock after the other: seller-specific shocks in column (5), buyer-specific shocks in column (6), and match-specific shocks in column (7). Within a destination, muting the buyer-specific shocks 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.[30] When aggregate exports are considered across countries (last line of Table 8), muting seller-specific shocks matters substantially since these shocks cannot be diversified across countries, in contrast to buyer- and seller-buyer shocks.

In the last exercise of this section, we correlate the contribution of each individual shock to the diversification of trade networks in the corresponding dimension. Results are summarized in Figure 6. As argued in section 5.1, the presence of microeconomic shocks in the aggregate depends on their volatility *and* their diversification across individual firms. Seller-specific shocks can thus be diversified across firms or, conversely, when aggregate flows are more concentrated across sellers, they are more volatile. This is what the upper left graph in Figure 6 confirms. The partial correlation between the correspond-

[30] In Table 8, muting one particular individual shock can sometimes *increase* the volatility of exports. This outcome results from the existence of 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 one, there is another source of diversification, across shocks, which is also muted. Thus the potentially positive impact on the aggregate variance of sales.

ing component of the variance ($Var(\sum_{s\in S_c} w^c_{st-1} f_{st})$) and the Herfindahl of sales across sellers ($Herf^S_c = \sum_{s\in S_c} w^{c\,2}_s$) is positive and strongly significant (equal to 1.6). The same argument holds for buyer-specific shocks, that are diversifiable across buyers. Even though smaller, the partial correlation coefficient between this component of volatility ($Var(\sum_{b\in B_c} w^c_{bt-1} f_{bt})$) and the concentration of sales across buyers ($Herf^B_c = \sum_{b\in B_c} w^{c\,2}_b$) is also significant and positive (equal to .8). Finally, more concentration across seller-buyer pairs also correlates with more volatility induced by the match-specific shocks, $Var(\sum_{s\in S_c}\sum_{b\in B_{sc}} w^c_{sbt-1}\nu_{sbt})$, the partial correlation is now equal to 1.0. Altogether, these three graphs confirm our general finding; the lack of diversification in firm-to-firm trade networks increases countries' exposure to microeconomic shocks.

6 Conclusion

In this paper, we provide a forensic account of the origin of fluctuations in sales at the level of individual firms as well as in the aggregate. We first propose a structural method for identifying different categories of shocks in disaggregated growth data. We show that individual shocks together with the structure of trade networks help explain the volatility of sales and their heterogeneity across firms and markets. In the small, shocks related to customers are an important component of volatility. Differences in the structure of firms' portfolio of buyers are key to account for their differences in volatility. In the large, individual shocks are shown to be the main driving force behind aggregate volatility. The differences in volatility of French exports across countries are mostly due to the effect of the country-specific structure of French trade networks and how they allow the different sources of individual shocks to be absorbed.

The present analysis examines the contribution of various types of estimated shocks on volatility, taking the structure of trade network as given.

Taking the structure of these networks as the endogenous outcome of some dynamic process is a natural extension of our work. This would help us better understand the effects of trade frictions on diversification - and thus on the level and dispersion of volatility in the small and in the large. Another way to make progress in our understanding of the nature and effects of shocks is to use buyers' death to examine how such a shock affects sellers' outcome such as employment, profits or value-added. This would help us measure the international transmission of shocks in novel dimensions.

Table 1: Summary statistics on trade networks

	Value of exports (bil.€)	# French sellers	# foreign buyers	# pairs of buyer-seller
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				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.

Table 3: 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.

Table 4: Correlation matrix of the estimated growth components

	(1) g_{sbt}	(2) f_t	(3) f_{st}	(4) f_{bt}	(5) ν_{sbt}	(6) $BSIC_{bt}$
g_{sbt}	1.0000					
f_{Ct}	.0626	1.0000				
f_{st}	.3028	.0000	1.0000			
f_{bt}	.4751	.0000	-.0679	1.0000		
ν_{sbt}	.7864	.0000	.0000	-.0001	1.0000	
$BSIC_{bt}$	.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 5: Summary statistics on the estimated effects

	(1) Mean	(2) Std.Dev	(3) Count	(4) Contrib.	(5) Partial Corr.
Firm-to-firm growth g_{sbt}	-.0132	.6887	3,834,655		
Macro component f_{ct}	-.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_{bt}	.0000	.3601	933,888	.2142	0.248^a
Match-specific residual ν_{sbt}	.0000	.5417	3,834,655	.6326	0.618^a
Buyer input cost $BSIC_{bt}$	.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. $Med(f_{st}/g_{sbt})$). 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 6: Summary statistics on the actual and counterfactual distributions of firm-level volatilities

	Mean	Median	P5	P95
Destination-specific sales				
Actual variance $Var(g_{sct})$	.352	.276	.136	.486
Volatility induced by muting				
Macro-economic shocks $Var(g_{sct}\|f_{ct}=0)$	.350	.274	.135	.485
Buyer-specific shocks $Var(g_{sct}\|f_{bt}=0)$	.282	.206	.101	.382
Seller-specific shocks $Var(g_{sct}\|f_{st}=0)$	.284	.212	.103	.387
Match-specific shocks $Var(g_{sct}\|\nu_{sbt}=0)$	.168	.122	.063	.221
Multilateral sales				
Actual variance $Var(g_{st})$	.192	.139	.068	.262
Volatility induced by muting				
Macro-economic shocks $Var(g_{st}\|f_{ct}=0)$	.191	.138	.067	.260
Buyer-specific shocks $Var(g_{st}\|f_{bt}=0)$	.169	.118	.056	.224
Seller-specific shocks $Var(g_{st}\|f_{st}=0)$	.112	.078	.040	.145
Match-specific shocks $Var(g_{st}\|\nu_{sbt}=0)$	.157	.113	.056	.209

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. 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 7: Determinants of the volatility of sales at the firm level

	Unilateral	Unilateral	Multilateral
	(1)	(2)	(3)
ln Herfindahl ac. buyers	0.58^a	0.54^a	0.60^a
	(0.005)	(0.006)	(0.009)
ln Herfindahl ac. destinations			0.09^a
			(0.014)
ln Herf. ac. products	-0.01	0.09^a	0.03^c
	(0.005)	(0.009)	(0.014)
ln value of exports	-0.07^a	-0.09^a	-0.02^a
	(0.001)	(0.002)	(0.003)
ln # years	-0.20^a	-0.35^a	-0.12^a
	(0.007)	(0.010)	(0.015)
Entrant	-0.14^a	0.05^a	-0.10^a
	(0.007)	(0.011)	(0.011)
Young exporter	-0.04^a	0.04^a	0.02^c
	(0.007)	(0.009)	(0.011)
$\mathbb{1} = 1$ if HQ in dest.	0.08^a	0.08^a	0.08^a
	(0.017)	(0.018)	(0.016)
$\mathbb{1} = 1$ if aff. in dest.	0.01	-0.02	0.02
	(0.031)	(0.039)	(0.041)
FE *Sect* × *dest.*	Yes	No	No
FE *Firm*	No	Yes	No
Observations	112,056	112,056	29,772
Adjusted R-squared	0.195	0.361	0.214

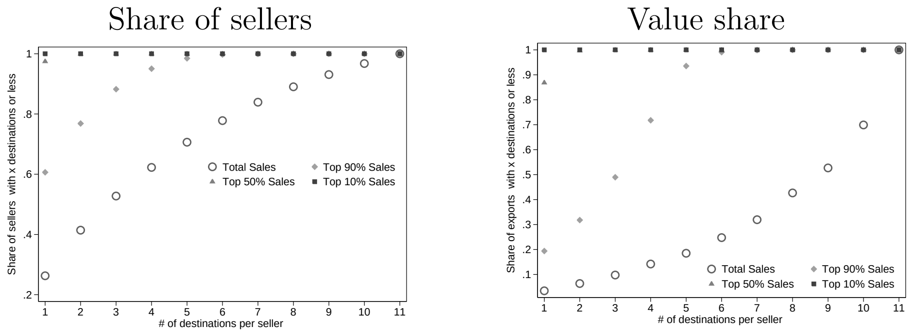
Notes: Robust standard errors in parentheses with ^{a}, ^{b} and ^{c} respectively denoting significance at the 1, 5 and 10% levels. The left-hand side variable is the log of the variance of export growth, induced by the "diversifiable" shocks (i.e. $Var(.|f_{st}, f_{ct} = 0)$). Volatility is measured destination-by-destination in columns (1) and (2) and over all destinations in column (3). "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 (in the destination or overall). "ln # years" is the number of periods the firm is observed (which varies between 4 and 12), in the destination or overall. "Entrant" and "Young exporter" are dummy variables equal to one if the firm just entered the market (just started exporting in column (3)) when observed for the first time, 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.

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

	Var	Var	Var	Var	Var	Var	Var
	(g_{sct})	$(.\|f_{ct}=0)$	$(.\|f_{st},f_{bt},f_{sbt}=0)$	$(.\|w_{sbt}=1/N_{sbt})$	$(.\|f_{st}=0)$	$(.\|f_{bt}=0)$	$(.\|f_{sbt}=0)$
	(1)	(2)	(3)	(4)	(5)	(6)	(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**	**.0004**	**.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. $w^c_{sbt-1} = w^c_{t-1}$, $\forall(s,b)$). Finally, columns (5)-(7) are the counterfactual variations in the absence of seller-specific, buyer-specific and match-specific shocks, respectively.

Figure 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.

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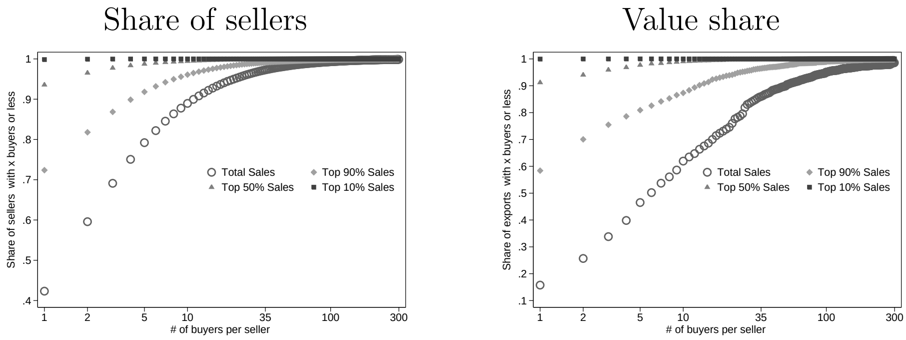
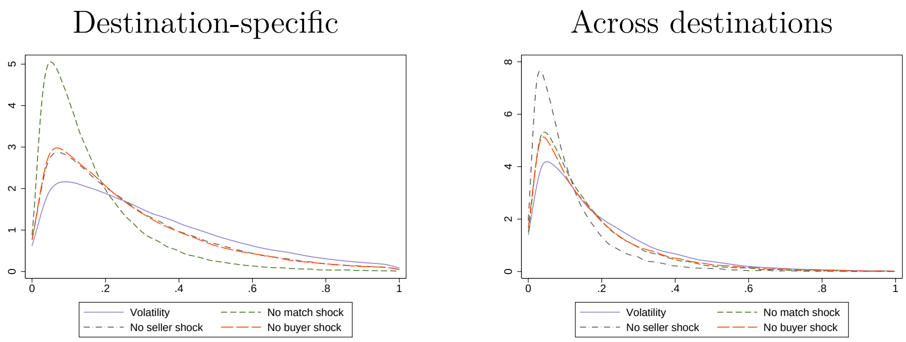
Figure 2: Number of Buyers per Seller-Destination



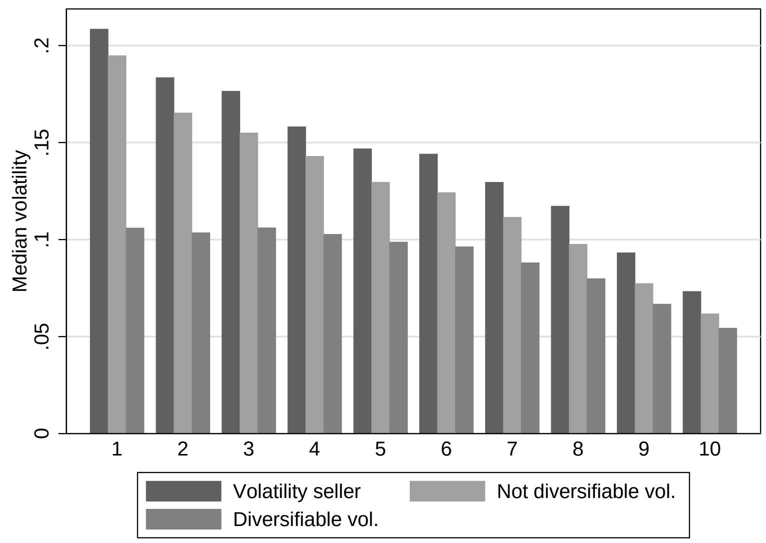
Notes: Proportion of sellers (left panel) and share of trade accounted for by sellers (right panel) that serve x buyers or less in a given destination, in 2007. The "Total Sales" distributions correspond to total exports. The distributions labeled "Top X% Sales" are computed restricting the amount of 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.

Figure 3: Actual and counterfactual distributions of firm-level volatilities



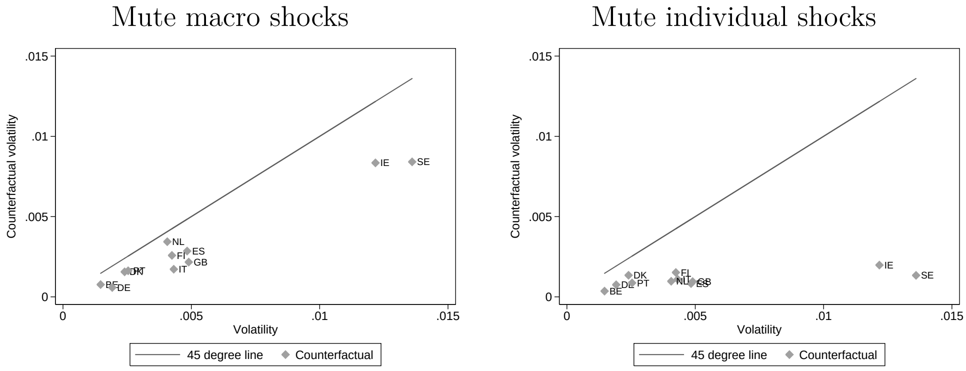
Notes: These graphs represent the actual and counterfactual distributions of volatilities across firms. The left panel is based on the variance of destination-specific export growth. The right panel instead uses the variance of overall sales. The solid line is the actual distribution of volatilities. The other three lines are counterfactual dispersions obtained when muting the seller-specific shocks (dash-dotted line), the buyer-specific shocks (large-dashed line) and the match-specific shocks (small-dashed line). The counterfactual dispersion obtained when muting the macro-economic shocks is not reproduced because it is not distinguishable from the actual distribution.

Figure 4: Volatility, by decile of firms' size



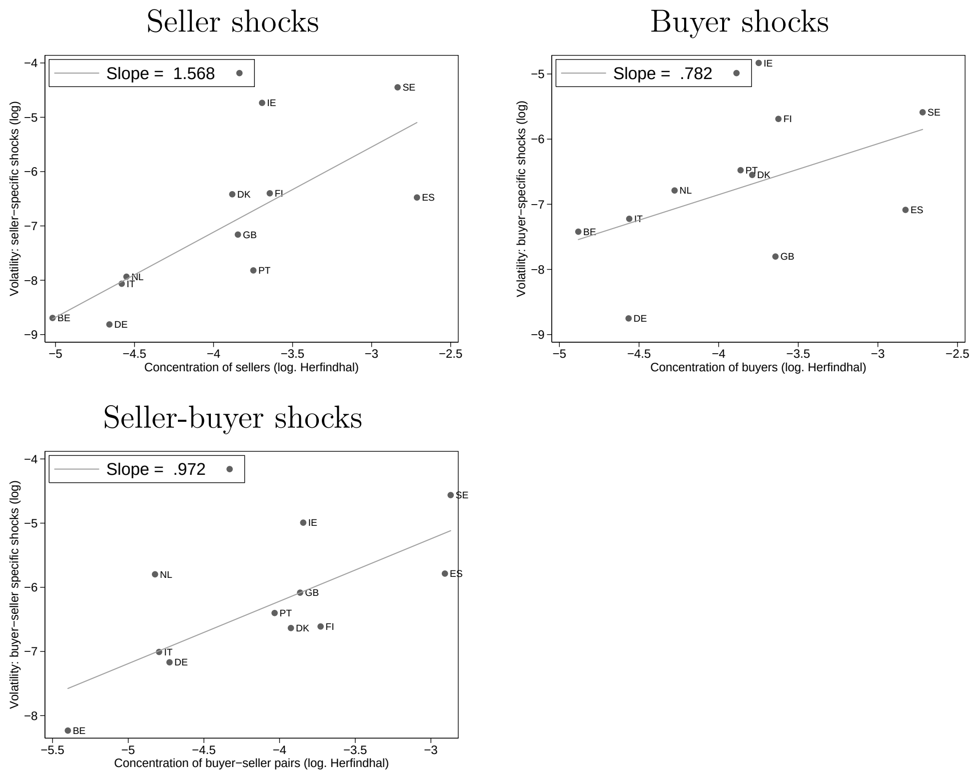
Notes: This figure represents the median volatility of sellers' exports across deciles of sellers' size. Sellers are grouped into size bins based on their initial size, with bin 1 corresponding to the 10% smallest exporters. For each decile, the figure reports the median volatility of sellers ("Volatility seller"), the median volatility attributable to diversifiable shocks ("Diversifiable vol." defined as $Var(\sum_{b\in B_{sc}}(f_{bt}+\nu_{sbt}))$ 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: 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%.

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Appendix

A 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.[31] 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 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 C looks at the structural question.

A.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:

$$g_{sct}^{Tot} \equiv \ln\left(\sum_{b\in B_{sct}} x_{sbt}\right) - \ln\left(\sum_{b\in B_{sct-1}} x_{sbt-1}\right) = g_{sct} + g_{sct}^{Ext.} \qquad \text{(A.1)}$$

where x_{sbt} is the value of exports from seller s to buyer b at date t and B_{sct} the set of buyers from c in seller s' portfolio at date t.

The intensive component

$$g_{sct} = \ln\left(\frac{\sum_{b\in B_{sc}} x_{sbt}}{\sum_{b\in B_{sc}} x_{sbt-1}}\right)$$

is driven by changes in sales to buyers active in the firm's portfolio at dates t and $t-1$ ($d\ln x_{sbt}$ for $b \in B_{sc}$ and $B_{sc} \equiv B_{sct} \cap B_{sct-1}$ the set of incumbent buyers in seller s portfolio). This is the growth component used to compute

[31] 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.

the volatility in the small in Section 4. The extensive component is defined as

$$g_{sct}^{Ext.} = \ln \left(\frac{\sum_{b \in B_{sct}} x_{sbt}}{\sum_{b \in B_{sc}} x_{sbt}} \frac{\sum_{b \in B_{sc}} x_{sbt-1}}{\sum_{b \in B_{sct-1}} x_{sbt-1}} \right)$$

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:

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

g_{ct}^{Tot} represents the growth of aggregate exports to country c:

$$\begin{aligned} g_{ct}^{Tot} &= \ln x_{ct} - \ln x_{ct-1} \\ &= \ln \left(\sum_{s \in S_{ct}} \sum_{b \in B_{sct}} x_{sbt} \right) - \ln \left(\sum_{s \in S_{ct-1}} \sum_{b \in B_{sct-1}} x_{sbt-1} \right) \end{aligned}$$

where S_{ct} is the set of sellers serving destination c at time t.

The intensive component studied in Section 5 is defined as

$$g_{ct} = \ln \left(\frac{\sum_{s \in S_c} \sum_{b \in B_{sc}} x_{sbt}}{\sum_{s \in S_c} \sum_{b \in B_{sc}} x_{sbt-1}} \right)$$

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

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

$$g_{ct}^{Ext-buyer} = \ln \left(\frac{\sum_{s \in S_c} \sum_{b \in B_{sct}} x_{sbt}}{\sum_{s \in S_c} \sum_{b \in B_{sc}} x_{sbt}} \times \frac{\sum_{s \in S_c} \sum_{b \in B_{sc}} x_{sbt-1}}{\sum_{s \in S_c} \sum_{b \in B_{sct-1}} x_{sbt-1}} \right)$$

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

$$g_{ct}^{Ext-seller} = \ln \left(\frac{\sum_{s \in S_{ct}} x_{sct}}{\sum_{s \in S_c} x_{sct}} \times \frac{\sum_{s \in S_c} x_{sct-1}}{\sum_{s \in S_{ct-1}} x_{sct-1}} \right)$$

$g_{ct}^{Ext-seller}$ 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_{sct}^{Tot} and g_{ct}^{Tot}. This is motivated by evidence in Table A2 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.

A.2 Volatility in the small and the extensive margin

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

$$Var(g_{sct}^{Tot}) = Var(g_{sct}) + Var(g_{sct}^{Ext.}) + 2Cov(g_{sct}, g_{sct}^{Ext.}) \tag{A.3}$$

While we focus the analysis on the $Var(g_{sct})$ 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.[32] The extent to which it is indeed the case is an empirical question which Table A3 addresses.

For the median firm, the intensive component of the variance represents 92% of the overall variance (Table A3, Column (3)). 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 fourth column of Table 3 show that both the intensive and the extensive margins contribute to the *dispersion of volatilities across firms*.[33]

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

$$Var(g_{ct}^{Tot}) = Var(g_{ct}) + Var(g_{ct}^{Ext-buyer}) + Var(g_{ct}^{Ext-seller}) + Cov \tag{A.4}$$

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

Adjustments at the buyer or seller extensive margin might contribute to generating fluctuations in aggregate sales. Table A4 quantifies the extent to which it is the case.

At the aggregate level, the buyer extensive margin is clearly a negligible source of fluctuations. Table A4 reports that its variance is thirty times smaller than the overall variance of export growth and it contributes to a tiny share of the dispersion in volatilities across countries. The seller extensive

[32]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.

[33]These results are obtained in the sub-sample of seller-destination pairs for which all variance components can be identified over at least 4 years. If one considers instead all the firm×destinations in our dataset, we find that the intensive margin contributes to about 2/3 of the cross-sectional dispersion in volatilities.

margin is quantitatively more important, but still small in comparison with the intensive component of fluctuations.

B Details on the estimation strategy

The estimated equation takes the following form:

$$\tilde{g}_{sbt} = (1+\lambda)f_{ct} + f_{st} + (1+\lambda)f_{bt} + \nu_{sbt}$$

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 $\tilde{g}_{sbt}$ 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),[34] 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 (7) can be identified in the cross-section of year-specific growth rates. Identification is achieved assuming equation (8) holds or, in matrix format:

$$E(\nu_t|\chi_t, \beta_t) = 0 \tag{B.5}$$

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.[35]

[34] 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.

[35] 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).

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 of growth components through time. Whereas in the model of section 3.1, shocks are implicitly not autocorrelated, estimating equation (7) 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 (B.5) restates the exogeneity condition for our specific case. The residual ν_{sbt} 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 mobility bias". Estimation of this model is simple and has been widely discussed in the literature, starting with Abowd et al. (2002) who were the first to provide the full identification conditions of the fixed effects to be estimated.

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 (9). 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:

$$\begin{aligned} Cov(f_{st}^{\lambda'}, f_{bt}^{\lambda'}) &= Cov\left(f_{st}, (1+\lambda) f_{bt} + (\lambda' - \lambda) \sum_s w_{st-1}^b g_{sbt}\right) \\ &= (\lambda' - \lambda) w_{st-1}^b Var(f_{st}) \end{aligned}$$

where $f_{st}^{\lambda'}$ and $f_{bt}^{\lambda'}$ denote the seller and buyer components of an equation using as left hand side variable $\tilde{g}_{sbt}^{\lambda'} \equiv g_{sbt} + \lambda' \sum_s w_{st-1}^b g_{sbt}$. Misspecifying the LHS variable of equation (7) 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 Mobility 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 (see Andrews et al., 2008, for a more systematic analysis of the problem).[36]

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.[37] 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 mobility bias by targeting this value for $Cov(f_{st}, (1+\lambda)f_{bt})$ instead of the strict orthogonality condition (9).

C 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.[38] Our decomposition of total volatility into its intensive and extensive components presented in Appendix A suggests that our focus, the intensive component, is the main driver of trade fluctuations. **Here we examine the role of the various types of shocks. not sure what you mean**

[36]Since such models were first applied to workers and firms, the more workers moved between firms the more precise the estimates, hence the choice of the "limited mobility" name.

[37]For all three components, the variance of the underlying normal distribution is calibrated using the mean variance estimated when equation (7) is estimated assuming $\lambda = 0$.

[38]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.

C.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, that are 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.

The adopted procedure: Let us denote by s_{sbt} the dummy which equals one when a transaction between seller s and buyer b is observed at date t, and 0 otherwise. Let us denote by $\underline{y}_{sbt}$ the vector of observed variables on the transaction, the buyer, the seller, including some elements about observed past transactions between s and b. Furthermore, let us write $\pi_{sbt} = P(s_{sbt} = 1|\underline{y}_{sbt})$, 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:

$$l(g_{sbt}, s_{sbt}|\underline{y}_{sbt} = l(g_{sbt}|\underline{y}_{sbt})l(s_{sbt}|\underline{y}_{sbt})$$

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:

$$E(g_{sbt}(\theta)) = E\left(\frac{s_{sbt}g_{sbt}(\theta)}{\pi_{sbt}}\right)$$

where θ denotes the parameters to estimate. Now, we see that the moment condition is expressed only in terms of observed components, $s_{sbt}g_{sbt}$ and π_{sbt}. 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.

C.2 Results

Table C1 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 C2, C3, C4, and C5 which are the exact equivalent to Tables 4, 5, 6, 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: 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 under restriction (**??**)	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.

Table A2: 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_t	g_t
	(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 A, equations (A.1) and (A.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 A3: Summary statistics on the margins of firm bilateral exports' volatility

	(1)	(2)	(3)	(4)
	Mean	Std. Dev	Contrib.	Partial Corr.
Variance of				
Firm growth g_{sct}^{Tot}	0.418	0.587		
Intensive component g_{sct}	0.321	0.410	0.923	0.575[a]
Extensive component $g_{sct}^{Ext.}$	0.437	0.5161	0.280	0.508[a]
Covariance term $2Cov(g_{sct}, g_{sct}^{Ext})$	-0.098	0.367	-0.118	-0.082[a]
Count observations	52,831			

Notes: This table gives summary statistics on the variance of firm growth within a market and its extensive and intensive components. The decomposition is based on equation (A.3), where the "Cov" term is the covariance between g_{st} and g_{st}^{Ext}. Column (1) reports the mean variance in the population of firms, Column (2) its standard deviation. Column (3) is the median contribution of each variance component to the total variance (eg. $Med(var(g_{sct})/var(g_{sct}^{Tot})))$. Column (4) is the partial correlation 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 A4: Summary statistics on the margins of aggregate volatility

	(1) Mean	(2) Std. Dev	(3) Contr.	(4) Partial Corr.
Variance of				
Growth $g_{ct}^{Tot.}$	0.0066	0.0076		
Intensive component g_{ct}	0.0065	0.0069	1.073	0.928^a
Extensive comp. seller $g_{ct}^{Ext-seller}$	0.0010	0.0012	0.142	0.155^a
Extensive comp. buyer $g_{ct}^{Ext-buyer}$	0.0005	0.0006	0.128	0.050^a
Covariance term $Cov.$	-0.0015	0.0024	- 0.287	-0.134^a
Count observations	11			

Notes: This table gives summary statistics on the volatility of French bilateral exports and its extensive and intensive components. The decomposition is based on equation (A.4), where the "Cov" term is covariance term involving g_{ct}, $g_{ct}^{Ext-seller}$ and $g_{ct}^{Ext-buyer}$. Column (1) reports the mean variance across destinations, Column (2) its standard deviation. Column (3) is the median contribution of each variance component to the total variance (e.g. $Med(var(g_{ct})/var(g_{ct}^{Tot})))$. Column (4) is the partial correlation 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 C1: 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 C2: Correlation matrix of the estimated growth components, with correction for the attrition bias

	(1) g_{sbt}	(2) f_t	(3) f_{st}	(4) f_{bt}	(5) ν_{sbt}	(6) $BSIC_{bt}$
g_{sbt}	1.0000					
f_{Ct}	.0630	1.0000				
f_{st}	.3023	.0000	1.0000			
f_{bt}	.4646	.0000	-.0674	1.0000		
ν_{sbt}	.7891	.0000	-.0037	-.0139	1.0000	
$BSIC_{bt}$	.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 C3: 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_{sbt}	-.015	.6904	3,478,841		
Macro component f_{ct}	-.054	.0473	3957	.0064	.006***
Seller-specific component f_{st}	.0000	.2705	259564	.0767	.118***
Buyer-specific component f_{bt}	.0000	.3637	845162	.2134	.245***
Match-specific residual ν_{sbt}	.0000	.5461	3478841	.6349	.624***
Buyer input cost $BSIC_{bt}$	.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 C4: Summary statistics on the actual and counterfactual distributions of firm-level volatilities, with correction for the attrition bias

	Mean	Median	P5	P95
Destination-specific sales				
Actual variance $Var(g_{sct})$	.350	.273	.132	.485
Volatility induced by muting				
Macro-economic shocks $Var(g_{sct}\|f_{ct}=0)$	.348	.270	.131	.482
Buyer-specific shocks $Var(g_{sct}\|f_{bt}=0)$	.282	.202	.096	.383
Seller-specific shocks $Var(g_{sct}\|f_{st}=0)$	.279	.204	.097	.382
Match-specific shocks $Var(g_{sct}\|\nu_{sbt}=0)$	.168	.120	.062	.220
Multilateral sales				
Actual variance $Var(g_{st})$	.191	.136	.066	.260
Volatility induced by muting				
Macro-economic shocks $Var(g_{st}\|f_{ct}=0)$	.189	.135	.065	.258
Buyer-specific shocks $Var(g_{st}\|f_{bt}=0)$	.169	.116	.055	.223
Seller-specific shocks $Var(g_{st}\|f_{st}=0)$	.099	.068	.034	.128
Match-specific shocks $Var(g_{st}\|\nu_{sbt}=0)$	.154	.110	.054	.206

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 C5: Summary statistics on the actual and counterfactual levels of volatility in the large, with correction for the attrition bias

	Var (g_{sct}) (1)	Var $(.\|f_{ct}=0)$ (2)	Var $(.\|f_{st}, f_{bt}, f_{sbt}=0)$ (3)	Var $(.\|w_{sbt}=1/N_{sbt})$ (4)	Var $(.\|f_{st}=0)$ (5)	Var $(.\|f_{bt}=0)$ (6)	Var $(.\|f_{sbt}=0)$ (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.