From Macro to Micro: Large Exporters Coping with Global Crises*

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Abstract

Using monthly firm-level exports and imports over 1993-2020, we uncover four facts: (i) deviations of large exporters from the average growth rate explain a large share of aggregate fluctuations; (ii) an important source for these deviations is the top exporters' higher loadings on common shocks; (iii) the stronger reaction of the top 1% exporters to the GFC and Covid crises contributed to the export collapses; (iv) a higher elasticity to large demand shocks, not a different exposure to global value chain shocks, contributes to this stronger reaction. The results show that idiosyncratic reactions of large firms to common shocks matter for aggregate export fluctuations, and are especially relevant for the trade collapses of the 2008/2009 crisis and the Pandemic.

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1 Introduction

The role of changes in the performance of some very large firms in shaping aggregate outcomes has gained substantial interest in macroeconomics and international economics since Gabaix (2011). Changes in the performance of very large firms may result from idiosyncratic shocks or from idiosyncratic reactions to aggregate shocks affecting all firms. While the former channel has been at the center of a significant body of research on business cycles, comparative advantage, and the international transmission of shocks, we have surprisingly little evidence for the second channel.

In this paper, we leverage monthly-frequency, detailed trade data covering a long period (1993-2020) which includes two major global crises, to uncover four stylized facts about the role of large firms in aggregate exports: i) the *granular residual* of aggregate exports – i.e. the covariance between size and the growth rate of exporters – explains a 40% share of aggregate export fluctuations; ii) larger exporters have higher loadings on common shocks, and such heterogeneity explains one quarter of aggregate export fluctuations during the period under study; iii) the top 1% exporters reacted more strongly than bottom exporters to both the GFC and the Covid crises, and this overreaction mattered for explaining the size of the export collapses; iv) the stronger response of large exporters to foreign demand shocks contributes to their greater sensitivity to the Covid shock, not a different sensitivity to global value chain shocks. Taken together, our results show that idiosyncratic reactions of large firms to common shocks matter for aggregate export fluctuations and were especially relevant for the trade collapses of the 2008/2009 Global Financial Crisis (henceforth GFC) and the Pandemic.

Our analysis uncovers a novel channel leading to a "macro-to-micro-to-macro" approach to cyclical fluctuations that complements the "micro-to-macro" approach based on the role of idiosyncratic shocks to individual firms. The contribution of this novel channel is stronger for larger aggregate shocks, being largest in the two recent global crises (the GFC and the Pandemic), and explaining a sizeable share of the trade collapses observed in such events. Our results can also inform theoretical models of granular firms, in particular the need to incorporate higher sensitivities of the largest firms to demand shocks. [1]

We rely on quasi-exhaustive detailed firm-level export data collected by the French Customs office to draw official international trade statistics. Each observation contains a firm identifier, a finely-defined

1. See Gabaix and Koijen (2020) for an example of such demand heterogeneity in a different context.

product code (8-digits of the Combined Nomenclature), the country of destination and the value and quantity exported. Crucially, the data is available at a monthly frequency and for a long period, spanning 1993-2020.

We start by studying the micro-dynamics of aggregate exports over the long run, using the results from a simple decomposition of the aggregate export growth rate into an unweighted average firm growth rate and a size-growth covariance – the granular residual. Interpreting the average firm growth as a simple measure of common shocks (see e.g. Di Giovanni et al. (2014)), we highlight a first stylized fact: the granular residual accounts for a sizable share of the variance of aggregate export growth and correlates positively with the unweighed average of exporter-level growth rates.

We next show that the positive correlation between the common component and the granular residual arises because the largest firms have a higher sensitivity to common shocks. We estimate a simple factor model allowing for factor loadings to be a function of firm size, in the spirit of Gabaix and Koijen (2020). The data supports the hypothesis that factor loadings increase in (pre-determined) exporter size: larger firms react more strongly to common shocks. We consequently further decompose changes in the granular residual over time into changes driven by idiosyncratic shocks versus idiosyncratic reactions to a common component, and show that higher loadings of larger exporters on common shocks explain one quarter of aggregate export fluctuations.

We then focus on the GFC and the Pandemic to provide detailed evidence for the disproportionate collapse of the largest exporters during both periods. On top of the interest that these events present in themselves as objects of study, they are arguably the clearest examples of common shocks affecting all firms during our sample period. As such, they provide us with a clean experiment to test for heterogeneous reactions to common shocks according to exporter size.

The export collapses during the GFC and the Covid Pandemic were very similar in magnitude: -16.8% in 2009 and -16.3% in 2020. [2] We show that the largest exporters had the highest reduction in exports, contributing disproportionately more compared to their pre-crisis export shares. Furthermore, their recovery was slower. A simple back-of-the-envelope quantification implies that, if the top 1% exporters

2. The figures refer to a balanced panel of firms that we use for the quantification. The aggregate export collapse (including all firms) was very similar in both periods. The number for the GFC refers to the twelve-months period from Oct 2008 to Sep 2009. The number for Covid refers to the period from Jan 2020 to Dec 2020.

(as measured by their pre-crises share) had grown at the same rate as the average exporter, the year-on-year fall in exports would have been -13.9% during the GFC and -10.3% in the Pandemic. These results control for potential composition effects. We develop a flexible estimation framework where we regress the midpoint growth rate in a particular market (defined as a country-sector combination) on a set of exporter size dummies and sector-by-destination (*market*) fixed effects and pre-crisis growth rates to control for mean reversion. The disproportionate collapse of the top exporters holds *within* these finely defined markets.

We then zoom in on the Covid-19 Pandemic to seek for culprits: supply or demand. During the first semester of 2020 the shock was sudden and exogenous, affecting all French exporters. We conduct our analysis within individual markets (sector-by-destination cells). We study supply shocks by augmenting the flexible regression framework with measures of Global Value Chain (GVC) exposure that combine the imported intermediate inputs to sales (IIS) ratio and a measure of supply shock exposure using lockdowns in origin countries. The data reveals larger exporters tend to be more heavily engaged in GVCs than smaller ones. However, adding GVC measures to our regressions does not affect the magnitude of the exporter size-bin dummies: GVC exposure can not explain the underperformance of top exporters during Covid. On the contrary, we do find evidence of a demand channel as large firms yield a higher elasticity to destination-country lockdowns. Greater sensitivity to foreign demand shocks alone cannot explain the overreaction of large firms, but it does have quantitative bite. The difference between the growth rates of large and small firms in regions with high or low demand shocks explains one-fifth of the overreaction of large firms.

Our paper contributes to the literature documenting the role of large firms in international trade. Freund and Pierola (2015) use data for 32 countries and document that exports are very concentrated and shaped by a handful of "Superstar exporters". Gaubert and Itskhoki (2021) develop a theory of granular comparative advantage based on the model of Eaton et al. (2012) and apply it to French individual data. An influential series of papers focuses on the role of large firms in generating business cycle comovement across countries using French data (Di Giovanni et al. (2014); Di Giovanni et al. (2017); Di Giovanni et al. (2020)). The closest to ours is Di Giovanni et al. (2020), who show that foreign shocks translate into granular fluctuations because the largest French firms are those that export and import more from abroad. The mechanism that we put forward takes this one step further as we show that the largest

firms are also hit relatively more by foreign demand shocks within markets. Our results are novel to the literature on granular firms in trade by highlighting that granularity plays a substantial role in trade collapses, an aspect that has been overlooked.

Our paper also contributes to our understanding of the drivers of trade collapses. Most of the existing literature has focused on analyzing compositional effects of export collapses in terms of sectors (e.g. manufacturing versus others, consumer durables within manufacturing) or trade margins such as the product- or firm- levels (O'Rourke (2018); Levchenko et al. (2010)). One clear message that arises is the predominant role of the intensive margin: it is the reduction of exports in continuing units (products or firms) that drives the collapse, with vanishing firms (though large in numbers) contributing very little. However, knowledge about the roots of the intensive margin reaction to large exports collapses is rare. In our data, the dominance of the intensive margin is present both in the GFC and during COVID and we show that compositional effects across firms determine the contribution of this margin. We find that large exporters react more to common shocks during normal times, but this overreaction becomes particularly salient during large crises. Thus, our results point to a link between the concentration in exports in a handful of very large firms and the magnitude of export fluctuations. The literature on the Covid shock suggests play a key role in the transmission of shocks within business networks, notably Bonadio et al. (2020), Heise (2020), Çakmaklı et al. (2021), Lafrogne-Roussier et al. (2022), Brussevich et al. (2022), the last two papers using also French firm-level data for the Pandemic. [3] Our focus is on the disproportionate collapse of the top exporters, not on GVCs per se, and we show that higher GVC exposure does not explain the larger collapse of top exporters. The evidence that we find concerning the respective role of demand and supply shocks echoes the findings of Huremovic et al. (2023) who show, using Spanish firm level data on supplier-customer transactions and bank loans, that bank credit shocks to firms propagate upstream and downstream along the production network, with stronger effects for upstream than downstream propagation.

More broadly, our results inform the literature studying the role of large firms in driving aggregate variables in settings where firm-size distributions are fat-tailed and individual shocks do not average out, the "granular hypothesis" (Gabaix (2011), Carvalho and Grassi (2019), Gabaix and Koijen (2020)

3. In addition, a series of papers have quantified the impact of confinement measures on trade, see for example Liu et al. (2022).

and Galaasen et al. (2020) among others).[4] Our paper also adds another piece of evidence to the literature pointing to heterogeneous responses to aggregate shocks in different settings from ours (see e.g. Kaplan and Violante (2018) for a survey and Ottonello and Winberry (2020) for the role of firm heterogeneity in the response to monetary shocks). While most of the empirical literature is concerned with netting-out common shocks to estimate idiosyncratic shocks (that is, without studying the role of such common shocks), our paper highlights that the contribution of macro shocks to the aggregate matters quantitatively and depends on the reaction of top firms.

The remainder of the paper proceeds as follows. Section 2 briefly describes the data sources. Section 3 analyses the behaviour of exporters along the business cycle paying special attention to the role of size and provides a decomposition of aggregate fluctuations of exports quantifying the contribution of the top exporters. Section 4 focuses on the GFC and the Pandemic. Section 5 studies the reasons for the disproportionate reaction of top exporters, by analysing supply and demand shocks. Section 6 concludes.

2 Data

2.1 Firm-level export data

We use firm-level export data from the French Customs office recorded at a monthly frequency from January 1993 until December 2020. For each firm, uniquely identified by a 9-digit firm identifier called Siren, the data contain the value of exports in current euros, quantities (in kilos or units depending on the product), country of destination, and product code. Products are classified at the eight-digit level of the European Combined Nomenclature (CN), where the first six digits correspond to the Harmonized System (HS) code. At the eight-digit level, the data comprise roughly 10,000 products.

Studying the behavior of exporters over a longer time horizon poses the challenge of changing reporting requirements over time. While the data are exhaustive in the case of extra-EU flows, changing reporting requirements are a problem for intra-EU trade. For intra-EU trade, exporters are required to provide the detailed information described above only if their exports exceed a certain threshold. Firms below

4. This literature is distinct from the debate surrounding the financial accelerator —a greater sensitivity of small firms to the business cycle due to tougher financial constraints (Gertler and Gilchrist (1994); Crouzet and Mehrotra (2020)).

the threshold are only asked to file their total exports, but not detailed by product and destination. In practice, however, we still observe a substantial share of firms with detailed filings even though they are below the size threshold. For the most part of the paper, we focus on firms with detailed filings, because we require information on sector and destination of exports. When that detail is not required (in particular in the beginning of Section 3), we also include firms with more limited information. [5]

Our baseline dataset includes all the firms in the Customs files after dropping invalid firm identifiers, invalid country codes, and invalid product codes. The value of total exports in our dataset represents 98% of the total value of exports published in public statistics. [6]

Finally, in Section 5 we complement the export data with information on firm-level imports and annual balance sheet data. We defer a description of these datasets to the beginning of that section.

2.2 The exporter-size distribution

To study the role that the exporter-size distribution plays in driving aggregate fluctuations we sort firms into size bins, for every given period in our sample. We start by aggregating the export data at the firm-month level to compute firm-level exports of all products to all destinations for every month. The exporter-size distribution is very skewed. For example, in 2019, out of a total of 100,000 firms, 71% of total exports are due to just over 1,000 firms (the top 1%). The top 0.1% (slightly over 100 firms) account for 41% of aggregate exports, and the top 10 firms account for 19%. [7] In 2007, the top 1% exporters (1057 firms) accounted for 70% of aggregate exports, and the top 0.1% (105 firms) for 37%. High skewness is a stable feature of exporter-size distribution that holds in all periods of our sample (as in most similar datasets for other countries, see e.g. Freund and Pierola (2015)).

Throughout the different empirical analyses that follow we will group, for a given year, firms into different size bins based on their total exports in the previous 12 months $t-1$ to $t-12$. That is, for the data point say March 2015, the bins are constructed using the sum of exports per firm for the period from March 2014 to February 2015. This will allow us to study the role that pre-determined size plays in exporters'

5. This threshold has changed over time (see Bergounhon et al. (2018) and Figure A1 in the Online Appendix). However, the export share of firms with detailed filings has stayed close to 100%.

6. See Figure A2 in the Online Appendix. Details concerning the construction of the data and references to previous contributions that rely on these data are provided in Bergounhon et al. (2018).

7. The exact number of firms in these groups are 1011 (top 1%), 101 (top 0,1%) and 10 firms (top 0.01%). To be part of the top 1% / 0.1% / 0.01%, a firm must have had exports of at least 65m / 600m / 3bn Euros in 2019.

reactions to shocks. To reflect the properties of the actual distribution we construct particularly fine bins at the top. We sort firms into eight size bins: the first three bins capture the first three quartiles of the size distribution (0-25%, 25-50%, 50-75%), while the next bins are defined in finer intervals: 75-90% (bin 4), 90-95% (bin 5), 95-99% (bin 6), 99-99.9% (bin 7), >99.9% (bin 8). We will use these bins throughout the analysis that follows, except in some specifications where it will prove convenient to group firms into four bins only as explicitly indicated.

2.3 Growth rates with high-frequency detailed export data

The richness of the detailed trade data will allow us to perform a set of empirical exercises at varying levels of aggregation. Throughout these exercises, unless otherwise specified, we will measure growth using midpoint growth rates. Our lowest level of aggregation is the firm-by-product-by-destination-by-month level. For every firm f, CN8-product k, and destination j, we denote exports (in euro) at month t (e.g., April 2020) with x_{fjkt}. The midpoint growth rate between months t and $t-12$, is defined as:

$$g_{fjkt} = \frac{x_{fjkt} - x_{fjkt-12}}{\frac{1}{2}(x_{fjkt} + x_{fjkt-12})} \tag{1}$$

g_{fjkt} is bounded by -2 and +2. It takes the value -2 when there is exit: $x_{fjkt} = 0$ and $x_{fjkt-12} > 0$. It takes the value of +2 when there is entry: $x_{fjkt} > 0$ and $x_{fjkt-12} = 0$.

Turnover is very common with highly disaggregated trade data, both during crises and normal times (e.g. Bernard et al. (2009)), which suggests using midpoint growth rates. Frequently used in settings where entry and exit is important (Haltiwanger et al., 2013; Eaton et al., 2007), midpoint growth rates allow us to incorporate the extensive margin (firm, product, or destination) and intensive margin changes in one single measure. Furthermore, in the case of small changes, it is a very good approximation of the more common log change measure, but avoids extreme values in the case of large year-on-year changes in exports. [8] A second very convenient feature of the midpoint growth rate is that, unlike the log change, it aggregates up exactly. That is, the aggregate growth rate G_t can be expressed as a weighted average of transaction-level growth rates, with no approximation needed:

8. See Figure A3 in the Online Appendix.

$$G_t = \frac{X_t - X_{t-12}}{\frac{1}{2}(X_t + X_{t-12})} = \sum_f \sum_j \sum_k \omega_{fjkt} g_{fjkt}, \tag{2}$$

where the weights are $\omega_{fjkt} = \frac{x_{fjkt}+x_{fjkt-12}}{X_t+X_{t-12}}$.

This exact aggregation property is very important in a setting like ours with high fluctuations of year-on-year firm-level monthly exports. Given the large volatility of exports within firms over time, the weighted average of firm-level log changes provides a poor approximation for the aggregate log change.

3 The role of large exporters in aggregate export fluctuations: 1993-2020

3.1 The Granular Residual of Aggregate Exports

We first present the results from a simple decomposition of aggregate export growth over a long time series, 1993-2020, which is the longest that our data allows for. We rely on a simple decomposition of the aggregate growth rate into an unweighted average firm growth rate and a size-growth covariance (the *granular residual*). (see e.g. (Gabaix, 2011; Di Giovanni et al., 2020) who focus on value added instead of exports). [9]

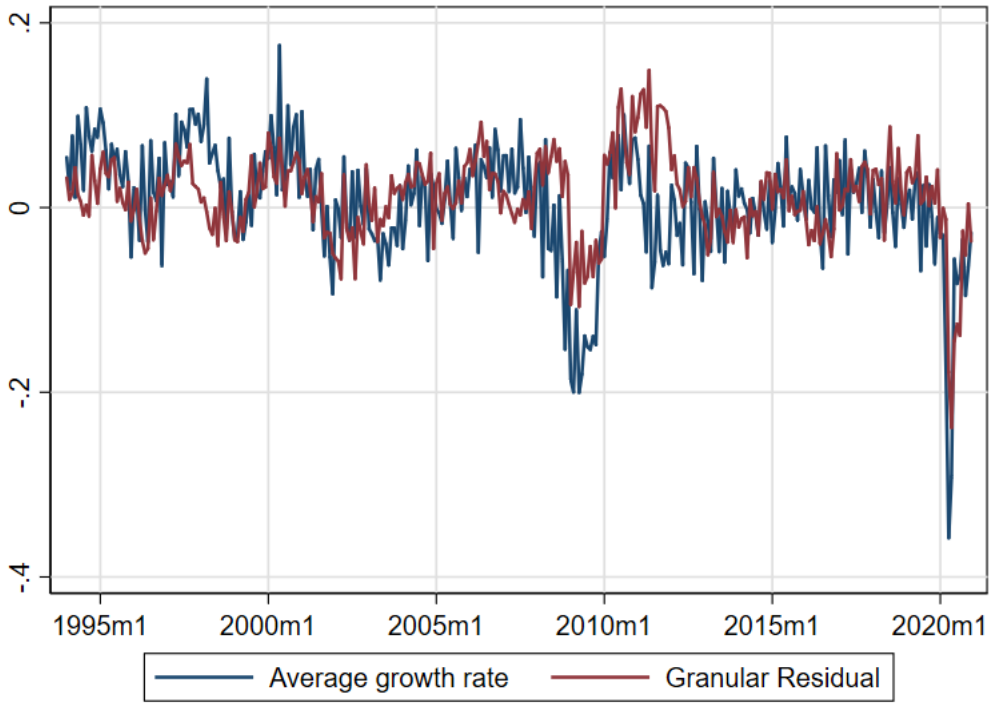
Using weights computed over total firm exports, $\omega_{f,t}$, we define G_t as the monthly year-on-year growth rate of exports (by all firms, products and destinations). We express the decomposition as:

$$G_t = \sum_f \omega_{ft} g_{f,t} = \bar{g}_t + \underbrace{Cov_t(\omega_{ft}, g_{f,t})}_{\text{Granular Residual (GR)}} . \tag{3}$$

where $\bar{g}_t = \frac{1}{N_t} \sum_f g_{f,t}$ measures the simple average growth rate of continuing exporters (firms that export both in t and $t-12$).

9. In this first approach, we consider the 12-month growth rate of total exports of firm f in month t, $g_{f,t}$, pulling together the product k and destination j dimensions. We use data only for firms with complete filings, but find very similar results when we include firms that are below the size threshold. Following the literature, we restrict attention to continuing exporters for this subsection, defined as firms exporting in a given month and also in the same month one year before. The correlation between the aggregate midpoint growth rate using all exporters and that using only continuing exporters is > 0.99.

Figure 1: Average Firm Export Growth and the Granular Residual



Source: French customs, Authors' calculations.

Figure 1 plots both components of Equ. (3) over time. Several messages arise from this exercise. First, the granular residual is not zero: aggregate exports feature granularity. Second, the contribution of granularity to aggregate export fluctuations is large quantitatively. A variance decomposition of the aggregate growth rate gives a share of 60% that comes from average firm growth $\left(\frac{Cov(G_t,\bar{g}_t)}{Var(G_t)}\right)$ and a 40% share coming from the granular residual. Third, average firm growth and the granular residual are positively correlated, with a correlation coefficient $\rho = 0.55$. To provide more structured evidence of the last point we estimate the following basic model at the firm-month level:

$$g_{ft} = \alpha + \beta \bar{g}_t + \epsilon_{ft} \tag{4}$$

where g_{ft} is the firm-level midpoint growth, and $\bar{g}_t$ is the simple average of all firms with positive values in $t-12$ and t and captures a common component. [10] We run a weighted OLS regression using midpoint weights as defined above. Given that midpoint growth rates aggregate up exactly using w_{ft} as weights, the estimated coefficient $\hat{\beta}$ captures the correlation between the granular residual (thereafter noted GR) and the common component. Formally:

$$\hat{\beta} = \frac{Cov(G_t, \bar{g}_t)}{Var(\bar{g}_t)} = 1 + \frac{Cov(GR_t, \bar{g}_t)}{Var(\bar{g}_t)} \tag{5}$$

Results in Table 1 confirm that the aggregate growth rate moves with an elasticity greater than one with respect to the common component, since the latter and the granular residual are positively correlated.

The main insights of the current section can be summarized in the following first *stylized fact*:

Fact 1: *The Granular Residual explains a large share (40%) of aggregate export fluctuations, and it correlates positively with the unweighed average of exporter-level growth rates, the latter measuring common shocks affecting all exporters.*

10. This is a standard measure of common shocks in the granularity literature, see for example Di Giovanni et al. (2014). By construction, estimating Equ. 4 without weights on the sample of continuing firms would result in an estimated coefficient of $\hat{\beta} = 1$.

Table 1: Correlation between the granular residual and the common component (1993-2020, monthly data)

	(1)	(2)
	g	g
$\bar{g}_t$	1.379***	1.418***
	(0.062)	(0.063)
Observations	11,239,482	20,538,465
R-squared	0.024	0.018
Sample	Continuing	All

Notes: OLS estimations of (4). The dependent variable is the year-on-year midpoint growth rate at the firm × month level. $\bar{g}_t$ is the unweighed average of firm-level growth rates in the same period. Column 1 uses only observations for continuing firms (positive exports in t and $t-12$), while column 2 also includes entering and exiting firms. Estimations use midpoint weights that sum to one at each time period t. Standard errors are twoway-clustered at the firm and time level and reported in parentheses. *** implies significance at the 1% level.
Source: French customs, Authors' calculations

3.2 A Factor Model Approach

Having established that the correlation between the granular residual and the common shock is positive and quantitatively important, we next show that it arises because the largest firms have a higher sensitivity to common shocks. We do so by generalizing Equ. (4), allowing for loadings on the common factor that vary by exporter size. [11]

We are interested in the following question: do larger firms have higher loadings on the common component? If this is the case, how important is the contribution of such higher sensitivity for aggregate fluctuations in comparison with idiosyncratic shocks? To answer, we estimate the following regression:

$$g_{ft} = \alpha_{b(ft)} + \beta_{b(ft)}\bar{g}_t + \epsilon_{ft} \tag{6}$$

where firm size is measured with a vector of size dummies that indicate if the firm belongs to a certain location in the exporter-size distribution. The model allows both for bin-specific intercepts α_b, that capture average growth rates for each bin, and for bin-specific loadings β_b. We estimate (6) by weighted

11. While one could argue that the unweighted average $\bar{g}_t$ might be driven by idiosyncratic shocks to large firms that affect smaller ones via production networks, this concern may be limited by the use of exports data, where smaller firms are less likely to be part of the larger exporters' value chains. On the other hand, large multinational enterprises might offer new export opportunities to their (small) local suppliers, such that idiosyncratic shocks to large firms would affect small firms' export growth as well. This channel cannot be investigated in absence on information on firm-to-firm business relations.

OLS using the midpoint weights w_{ft}. The estimated coefficients from this model are indeed closely related to the aggregate $\hat{\beta}$ from Equ. (4): with constant share of size bins over time, we have $\hat{\beta} = \sum_b \bar{\omega}_b \hat{\beta}_b$. [12]

We choose a parametric approach in which loadings are a function of firm size based on their total exports in the previous 12 months $t-1$ to $t-12$, as it will provide us with a more structured view of the role of firm size in driving aggregate fluctuations. [13] The exporter-size distribution is very skewed in all periods of our sample (see Section 2) and thus we construct particularly fine bins at the top. [14] The structure of (6) is close to the one developed in Gabaix and Koijen (2020), who use idiosyncratic shocks to large firms to construct granular instrumental variables as weighted average of individual shocks, preferring a parametric approach as we do.

The results are provided in Table 2. The estimated $\hat{\beta}_b$s are substantially larger for exporters in larger size bins, and particularly larger for the top 0.1%, grouped in bin #8. The size effects are larger in the sample using all firms (Column 2) and a bit more gradual in the sample of continuing exporters (Column 1) for which a larger share of the adjustment comes from the extensive margin of entry/exit. [15]

We can eventually further decompose changes in the granular residual over time into changes driven by idiosyncratic shocks *versus* idiosyncratic reactions to a common component and shed light on the relative contributions of both to the fluctuations of aggregate exports:

$$GR_t = \sum_f \omega_{ft}(g_{ft} - \bar{g}_t) = \sum_f \omega_{ft}(\hat{\beta}_b - 1)\bar{g}_t + \sum_f \omega_{ft}\hat{\alpha}_b + \sum_f \omega_{ft}\hat{\epsilon}_{ft} \tag{7}$$

Each one of the three components has a clear interpretation. Our main focus is on the first one, which we label $\lambda_t = \sum_f \omega_{ft}(\hat{\beta}_b - 1)\bar{g}_t$. It captures, at each point in time t, the value of the granular residual that is due to idiosyncratic reactions to common shocks. If all bins would react equally to common shocks ($\hat{\beta}_b = 1 \forall b$) then $\lambda_t = 0$. The second term, $\sum_f \omega_{ft}\hat{\alpha}_b$, measures the contribution of differences in growth

12. In our sample $\hat{\beta} = 1.379$, and $\sum_b \bar{\omega}_b \hat{\beta}_b = 1.377$, where $\bar{\omega}_b$ is measured as the average over time of the midpoint weight of size bin b, i.e. $\bar{\omega}_b = \frac{1}{T}\sum_t \omega_{bt}$.

13. Because the bins are constructed using lagged values, the bin-specific intercepts α_b control for potential reversion to the mean.

14. High skewness is a stable feature of exporter-size distribution, as in most similar datasets for other countries, see e.g. Freund and Pierola (2015). For example, in 2019, in our sample, out of a total of 100,000 firms, 71% of total exports are due to just over 1,011 firms (the top 1%). The top 0.1% (101 firms) account for 41% of aggregate exports, and the top 0.01% (10) firms account for 19%.

15. Notice that since both the intercept and the common shock are interacted with a full set of non-overlapping size dummies, none of the other estimates changes when we either include or exclude entrants (which are grouped in a distinct size group).

Table 2: Factor loadings by size bin (1993-2020, monthly data)

	(1)	(2)
	g	g
$\bar{g}_t \times b_{1-(0-25\%)}$	-0.565	0.429
	(0.552)	(0.267)
$\bar{g}_t \times b_{2-(25-50\%)}$	0.284**	0.874***
	(0.123)	(0.293)
$\bar{g}_t \times b_{3-(50-75\%)}$	0.855***	1.290***
	(0.308)	(0.196)
$\bar{g}_t \times b_{4-(75-90\%)}$	1.106***	1.239***
	(0.030)	(0.032)
$\bar{g}_t \times b_{5-(90-95\%)}$	1.228***	1.275***
	(0.045)	(0.044)
$\bar{g}_t \times b_{6-(95-99\%)}$	1.244***	1.280***
	(0.037)	(0.038)
$\bar{g}_t \times b_{7-(99-99.9\%)}$	1.281***	1.311***
	(0.056)	(0.058)
$\bar{g}_t \times b_{8-(>99.9\%)}$	1.583***	1.610***
	(0.137)	(0.143)
Observations	11,239,482	20,538,465
R-squared	0.026	0.038
Sample	Continuing	All

Notes: OLS estimations of (6). The dependent variable is the year-on-year midpoint growth rate at the firm × month level. $\bar{g}_t$ is the unweighed average of firm-level growth rates in the same period. $\mathbb{1}_{b(ft)}$ equals one if firm f is in size-bin b at time t. The estimation uses the midpoint weights ω_{ft}. Standard errors are twoway-clustered at the firm and time level and reported in parentheses. *** implies significance at the 1% level.
Source: French customs, Authors' calculations

rates depending across bins which are orthogonal to aggregate conditions (due to, e.g., different trends or mean reversion), and the third one $\sum_f \omega_{ft}\hat{\epsilon}_{ft}$ measures the contribution of idiosyncratic shocks at the firm level. All three terms are properly weighted by the contribution of firm f at time t to the aggregate midpoint growth rate G_t.

We find that λ_t matters quantitatively for aggregate fluctuations: it explains 27% of the variance of the granular residual. [16] Noticeably, λ_t and the GR_t are linked much more tightly during large and plausibly common shocks, which motivates us for zooming in on the two episodes of the GFC and the Pandemic later on. The reason for this magnification effect is that, even though λ_t is less important than idiosyncratic shocks for explaining the volatility of the granular residual, it is actually *more* important than idiosyncratic shocks for explaining the volatility of aggregate export growth: idiosyncratic reactions to common shocks account for roughly a quarter of aggregate export fluctuations. [17]

The next question of interest is which size groups contribute the most to λ_t. We address it by further decomposing λ_t into the contributions of each bin ($\lambda_t = \sum_b \lambda_{bt}$, using weights ω_{bt}), and plot these in Figure 2. Out of the 23% of the fluctuations in G_t that are explained by λ_t, the top 0.1% of firms contribute more than half (13.5%), and the top 1% together account for 19%. This is natural, as it arises from the fact that larger firms have larger weights w_{ft} and larger loadings on the common shock, as shown in Table 2.

The above insights are summarized in the following *stylized fact*:

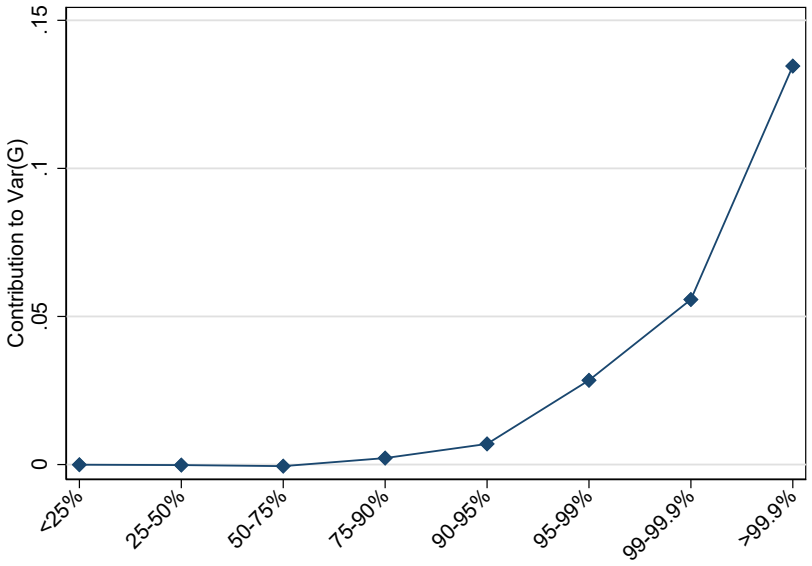
Fact 2: *Larger exporters have higher loadings on common shocks. Such heterogeneity explains one quarter of aggregate export fluctuations over 1994-2020.*

As mentioned, the aggregate relevance of heterogeneity in the sensitivity to common shocks is larger the larger the shock (that is, the contribution of λ_t increases with $\bar{g}_t$). This provides the rationale to study in detail the two major recent crises present in our data: the GFC and the Pandemic.

16. $\frac{Cov(GR_t,\lambda_t)}{Var(GR_t)} = 27\%$. See the evolution of λ_t and the Granular Residual in Figure A11 in the Online Appendix.

17. We observe that $\frac{Cov(G_t,\lambda_t)}{Var(G_t)} = 23\%$ while the contribution of idiosyncratic shocks is 17% (thus summing up to the contribution of 40% of GR). That is, λ_t accounts for roughly a quarter of aggregate export fluctuations, which adds to the channel's contribution to the variance of aggregate growth.

Figure 2: Contribution of size groups to aggregate λ_t (1993-2020, monthly data)



Source: French customs, Authors' calculations.

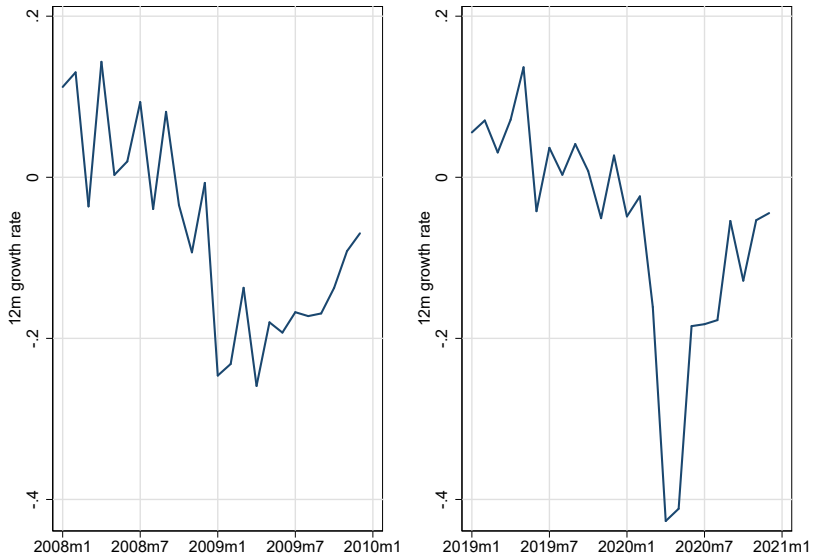
4 Granularity in two large-scale crises: GFC and the Covid-19 Pandemic

4.1 The two largest negative common shocks

The GFC and the Pandemic are not only exceptional episodes because of the collapse in aggregate economic activity, but also clearly show up in Figure 1 as the two largest negative common shocks, as measured by the fall in the average exporter growth rate. We zoom into these two episodes in Figure 3 that compares the monthly evolution of the year-on-year growth rates during both periods. The export collapse was much faster during Covid (right panel) than during the GFC (left panel), but the aggregate yearly collapse was of a similar magnitude in both episodes: in 2009, aggregate French exports fell by -17.4% (2009 vs 2008), compared to -16.0% during Covid (2020 vs 2019). [18]

18. A decomposition of the aggregate export growth during both crises into a firm intensive and extensive margin of adjustment in the Online Appendix A.2 shows that both export collapses were almost entirely driven by changes in the export values of continuing exporters, consistently with previous studies showing that short-run aggregate movements in trade are mostly a result of the intensive margin rather than changes in net entry (Eaton et al., 2007; Bernard et al., 2009; Fernandes et al., 2019).

Figure 3: Aggregate Export Growth, GFC (left) and Covid (right)



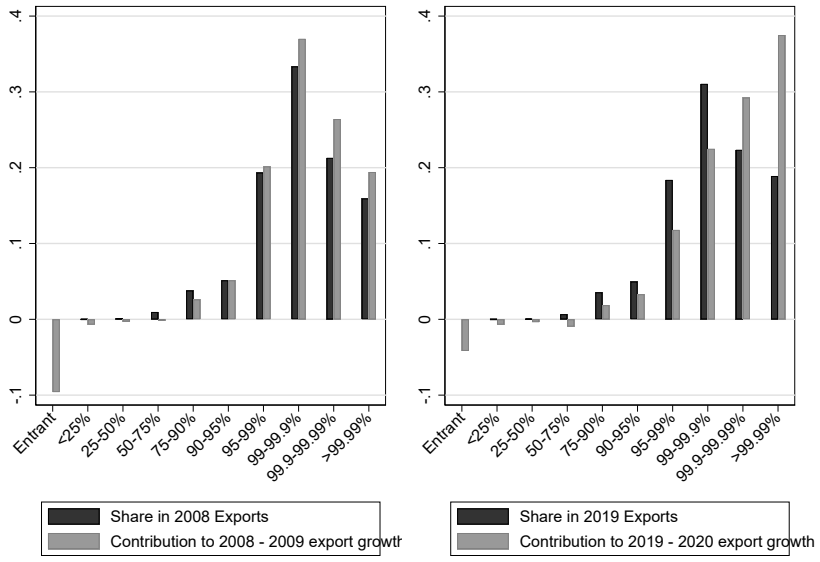
Source: Trade Data Monitor, Authors' calculations.

The pre-crisis exporter-size distribution is shown in the black bars of Figure 4, which provide the share of aggregate exports accounted for by firms in different size bins in 2008 (left panel) and 2019 (right panel) as defined in Section 2.

The light gray bars in Figure 4 provide the contribution of each bin to the change in aggregate exports between the crisis year and the pre-crisis year. The contribution of each size bin is measured as the change in total yearly exports by all firms in a size bin, relative to the change in aggregate exports. If all firms grew at the same rate, the contribution of each bin would equal its pre-crisis share (abstracting from entrants).[19] It is very clear that this is not the case. During both crises, the top exporters *over-reacted*, in the sense that they contributed more than their share to the aggregate yearly export collapse. Overall, both export collapses are disproportionately explained by the small group of "Superstar" exporters. While both panels illustrate the correlation between size and the rate of change that we uncovered above, they also provide additional important information: the export collapse is to a large extent explained by an over-reaction of the exporters located at the very top of the distribution.

19. Including entrants, then the contribution of bin b would be $c_b = \frac{x_{bt-1}}{X_{t-1}} \frac{\lambda}{\lambda + \frac{x_{Et}}{X_{t-1}}}$, if all pre-existing firms grew at the same rate λ, where x_{Et} are exports of entrants in t. While the cumulative contribution of entrants over one year is not unimportant (particularly during the GFC), the main point is that the difference between contribution and pre-crisis share is higher for the top bins than for the bottom bins.

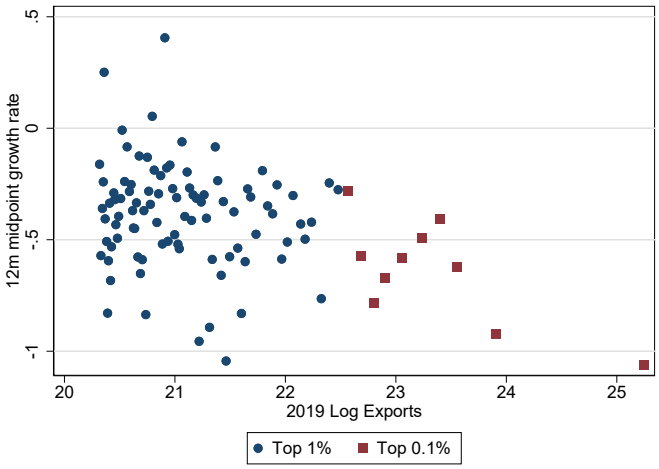
Figure 4: Export Shares and Growth Contribution during the GFC (left) and Covid (right) crises, by size bin



Source: French customs, Authors' calculations.

Zooming in on the top firms confirms the existence of a systematic relationship between growth and pre-crisis size that holds also within the group of top firms. In Figure 5 we place the top 1,000 exporters into 100 bins of 10 firms each and compute for each bin the midpoint growth rate for April/May 2020. We then plot it against the (log) value of total exports of the bin in 2019. The figure shows a clear negative relationship between size before the crisis and adjustment of exports to the crisis that holds also within the set of large exporters, alleviating potential concerns that the patterns depicted in Figure 4 could have been the result of a few outliers.

Figure 5: April-May 2020 12-month midpoint growth rate and 2019 exports of the 1,000 largest exporters



Source: French customs, Authors' calculations.

4.2 A flexible regression framework to estimate the effect of exporter-size on growth

The previous analysis confirms a strong and economically meaningful relationship between pre-determined exporter size and export growth rate. Though informative, the correlations that were revealed were unconditional on any potential factors that could be correlated with exporter size and simultaneously determine growth rates, notably the sector or geographical composition of export revenues. [20]

In order to account for potential confounding factors, we take full advantage of the highly-detailed data and its monthly frequency. We consider the 12-month export growth in month t of each exporter f for each destination-product pair (j, k), namely g_{fjkt}. We adopt a flexible regression framework to study the dynamic adjustments of exports at the finest level of disaggregation in a transparent manner. Our baseline regression is the following:

$$g_{fjkt} = \alpha_{b(f)t} + \beta_{jst} + \epsilon_{fjkt}, \tag{8}$$

20. Top exporters are over-represented among aircraft exporters. Results presented here hold excluding aircraft exports altogether —ie excluding all firms for which over 10% of their 2019 exports were classified under HS code 88: Aircraft, spacecraft, and parts thereof.

where g_{fjkt} is the year-on-year midpoint growth rate defined at the firm $\times$ country $\times$ product level, $\alpha_{b(f)t}$ is a vector of exporter-size dummies, β_{jst} denotes the vector of time-specific sector $\times$ destination dummies and ϵ_{fjkt} is an error term. β_{jst} controls for the potential bias that would occur if large firms fell by more because of the sector affiliation or because of systematic differences in geographical composition of exports by bins. Sectors are defined using the 2-digit level of the Harmonized System. [21]

We estimate Equ. (8) by OLS, using weights ω_{fjkt} as defined in Section 2.3. We use a balanced panel of firms of continuing exporters, defined as those firms that report positive exports for each month at the start and the end of the considered period. [22] By focusing on the intensive margin, we make sure that the results are driven by within-firm changes of growth rates and are not affected by changes in the composition of firms in each bin. Notice nevertheless that, as stated in the end of the previous subsection, aggregate movements are driven by the intensive margin, with firm exit and entry playing a quantitatively limited role. Among continuing exporters, the (sub)extensive margin of products and destinations can play a prominent role, which is taken into account by the use of the midpoint growth rate as dependent variable. [23]

Figure 6 shows the result of estimating Equ. (8), separately for each month, for the periods of March 2008 to August 2009 (left panel), and July 2019 to December 2020 (right panel). For better visibility, and because the bottom firms contribute very little to aggregate exports, we aggregate the initial nine size bins from Figure 4 into four: the bottom 90%, firms in between the 90th and 99th percentile, firms in between the 99th and 99.9th percentile, and the top 0.1%. Each line shows the weighted average midpoint growth rates of firms in the bin, which equals the aggregate bin-level midpoint growth rate. For each size bin, we focus on the set of continuing exporters, keeping the set of exporters in each size bin fixed over time.

Top exporters led the export collapses of 2009 and 2020. Interestingly, in both episodes the largest

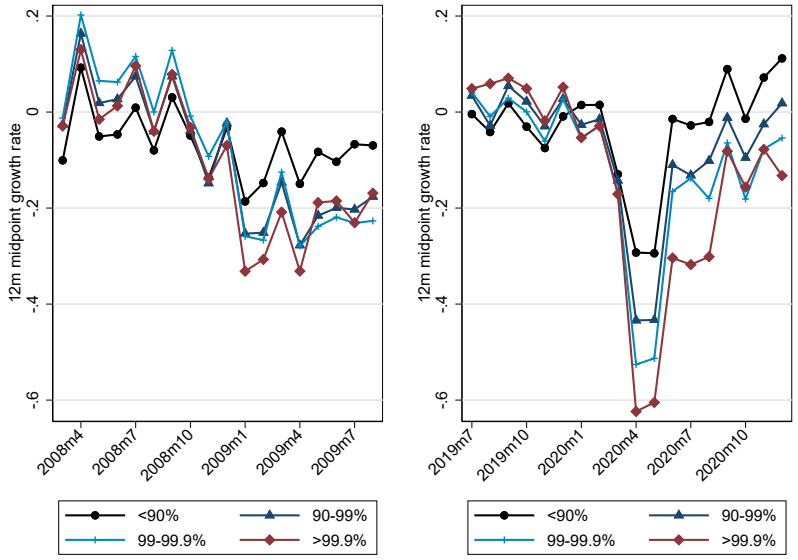
21. Notice that by using sector and destination fixed effects we likely underestimate the over-adjustment of top exporters: since the estimations are weighted by exporter size, sector fixed effects reflect the aggregate sectoral midpoint growth rate. In an environment with a few firms that are very large in the entire economy, and particularly large in their sectors, the strong negative growth of top exporters also largely affects the aggregate growth rate of their sector. This naturally reduces the difference between the growth rate of top exporters and their sectoral aggregate, which is measured by the coefficients on the size bin dummies.

22. All the dynamic graphs present in the paper are done with this balanced panel of firms, so that for a given size group we hold the composition of firms fixed over time. The aggregate growth rate for this balanced panel is very close to the true aggregate growth rate as shown in Figure A12 in the Online Appendix. Notice that, by construction, the aggregate growth rate from the model's predicted values would be identical to the evolution of exports of the balanced panel.

23. The transaction-intensive margin (changes in exports within a firm-product-destination cell) explains about half of the trade collapse during Covid (see section A.2.2 in the Online Appendix).

exporters were also slower to recover in the months subsequent to the initial shock. Therefore, the lower aggregate yearly export growth rate documented in Figure 4 is the consequence of the combination of a stronger reaction to the initial shock and a slower recovery for the top exporters. This result also holds with unweighted regressions. [24]

Figure 6: Export growth during the GFC (left) and Covid (right) crises, by size bin



Source: French customs, Authors' calculations.
We control for time specific H2× sector destination shocks.

Notice that compositional effects do have some bite. For example, during Covid, the average midpoint growth rate for the top 0.1% bin is reduced from -0.8 to -0.6 when we control for compositional effects. Compositional effects seem to be less present during the GFC, as the growth rate for the top 0.1% changes from 0.4 to 0.37. However, composition effects do not explain the main point: during both the GFC and the Pandemic, the export collapse was driven by the top exporters.

24. See Figure A14 in the Online Appendix. For the unweighted regressions, we use a framework without sector-by-destination controls, as in Figure A13. Using sector × destination controls would require the use of detailed data, which would imply that we would implicitly weigh firms by their number of transactions. The results are robust to the addition of controls for the growth rates before crises, which excludes potential problems arising from reversion to the mean. This is shown in Figure A15 in the Online Appendix.

4.3 Quantitative implications

We now use our estimations to quantify the role of granularity in affecting the aggregate outcome during extreme events. We present systematic evidence comparing the role of granular firms in the initial shock and recovery in both the GFC and the Pandemic constructed using our estimates. We seek to study the presence of common patterns across extreme events.

We ask the following question: what would have been aggregate export growth rate in 2008/2009 and 2019/2020 shall the top exporters had grown at the same rate as the average exporter? Comparing the actual growth rate with what one would have obtained in such a counterfactual scenario provides a quantification of the contribution of granularity to the total export collapse. We use the results in the specification that controls for sector $\times$ destination fixed effects and controls for mean reversion. We focus on the effect of the top 1% and the top 0.1%. Given the finding that the under-performance of top exporters was not restricted to the period of the initial shock but extended to the rest of the year in both cases (by the end of both 2009 and 2020, exports of the top 0.1% were still well below pre-crisis levels), we quantify their contribution to the year-on-year change in total exports considering the periods from October 2008 to September 2009 and from January 2020 to December 2020.

We proceed as follows. Using the panel of balanced firms, we start from the observation that, at each point in time, the weighted average of the composition-adjusted growth rates equals aggregate export growth. To focus on the top 1%, we then set their composition-adjusted growth rate equal to the simple average growth rate of continuing firms ($\bar{g}_t$ from the previous section), and then recompute aggregate export growth in the "1%" counterfactual. This counterfactual therefore tells us what aggregate export growth would have been, had the top 1% of firms grown at the same rate as the average firm. We then repeat the exercise focusing on the 0.1% and obtain the corresponding "0.1%" counterfactual aggregate growth rate.

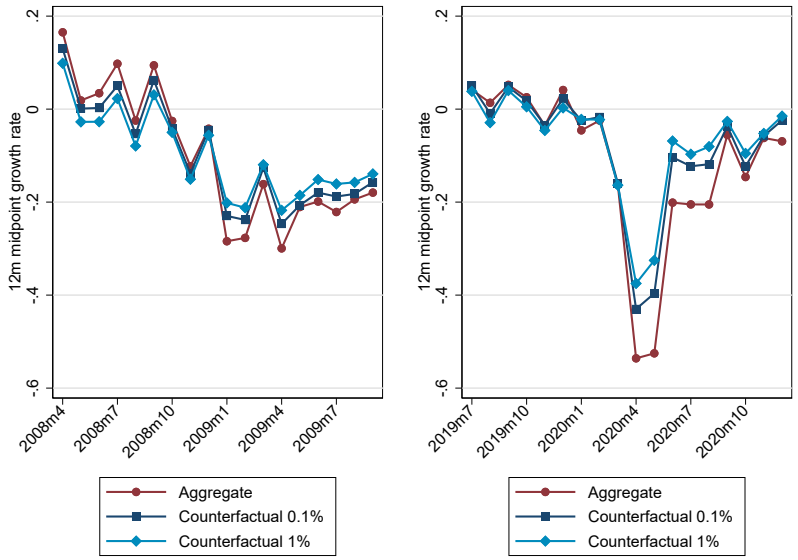
For the GFC, we obtain a year-on-year aggregate growth rate of -13.9% when applying the average growth rate to the top 1%. Given that the actual aggregate growth rate was of -16.8% over this period, this suggests that the reaction of the top 1,000 exporters explains about a sixth $\left(= \frac{16.8-13.9}{16.8}\right)$ of the great trade collapse episode. Focusing on the 0.1% we obtain a counterfactual export growth of -15.1%, indicating that the disproportionate reaction of the top one hundred exporters contributed a tenth of

the export collapse.

For the Pandemic, the counterfactual using the top 1% implies a year-on-year aggregate growth rate of -10.3%. The actual growth rate was of -16.3%, which implies that the overreaction of the top 1% adds -6.0 percentage points to the aggregate, or alternatively, that the strong reaction of the highest 1,000 exporters explains about a third of the total collapse. When re-doing the same exercise for the top 0.1%, we find that in the counterfactual scenario, export growth would have been -12.0%, and that the overreaction of the largest 104 exporters explains around one quarter of the total collapse. These numbers are large in economic terms, especially given the fact that they are driven from the overreaction within finely defined markets.

We show the time series around the shocks of the actual aggregate (the red line) and both counterfactuals (in dark blue for the 0.1% and in light blue for the 1%) in Figure 7. We summarise these findings in the third *stylized fact*:

Figure 7: Actual and Counterfactual Export Growth during the GFC (left) and Covid (right) crises



Source: French customs, Authors' calculations.

Fact 3: *Larger exporters reacted more strongly than bottom exporters to both the GFC and the Covid crises, and such overreaction mattered for explaining the size of the export collapses.*

To what extent are the crises episodes unique events? One way of answering this question is to ask how well the factor model from Section 3.2 explains the drop in aggregate exports, comparing the crises to the rest of fluctuations. To evaluate the performance of the factor model, we ask what aggregate export growth would have been, had firms grown according to the prediction of the factor model. That is, we use the estimated coefficients of the factor model together with monthly data on $\bar{g}_t$ to compute a predicted growth rate for each firm (where firms in the same bin are applied the same bin-specific coefficient), and then compute aggregate export growth. During the GFC (using 10/2008 - 9/2009), predicted aggregate export growth from the factor model was -17.4%, which is very close to actual export growth (-16.8%). During the Pandemic, the factor model predicts aggregate growth of -13.0%, and therefore falls a bit short of actual aggregate growth (-16.3%). However, it can still explain a sizable share of the difference between actual aggregate growth and average growth (-10.2%).

5 Supply *versus* demand

The first three facts uncovered in this paper show that the higher sensitivity of larger exporters to major common shocks has a relevant role in determining the overall aggregate response: "from macro-to-micro-to-macro".[25] The next step is to investigate the reasons behind such effects: why do larger exporters react more strongly to macro shocks? To answer this question, we focus on the Pandemic as it provides an excellent laboratory to study heterogeneous reactions to aggregate shocks. The shock was sudden and exogenous and affected all exporting firms. Moreover, the origins of the shock are well understood, and we have measures of the severity of restrictions on production and consumption across countries, available at high frequencies. While sanitary measures were imposed in most French trade partners, their timing and intensity offers variation that we can exploit to measure both supply and demand shocks.

In the next subsections we focus on the months of April and May 2020, where aggregate exports recorded the largest drop (around 42% year-on-year). We ask to which extent the underperformance of top exporters during Covid is explained by a stronger vulnerability to supply shocks transmitted through global value chains or alternatively by heterogeneous reactions to demand shocks.

25. In contrast, the Online Appendix A.5 points to the absence of differential effect for large *importers*.

5.1 The role of exporter size during the Covid export collapse

To study the reasons for the collapse of the top exporters, we build on the same framework introduced in the previous section, with a few changes. First, we aggregate the data into two-month intervals and compare a crisis-period (April-May 2020) to a pre-crisis period (January-February 2020). Second, this choice allows us to turn again to the more detailed size groups used in Figure 4, and also to include all firms (entering, continuing, and exiting). The remainder of the framework is the same as before: we estimate Equ. (8), regressing the year-on-year midpoint growth rate on the (now finer) size-bin dummies and sector-by destination fixed effects, using weights.

The results are provided in Figure 8. The line for January-February 2020 shows that firms above the 75th percentile grew at essentially the same rates *prior* to the crisis. [26] The line for April-May 2020 shows that at the onset of the crisis growth rates were significantly lower for the largest exporters. The (weighted) average g_{fjkt} equalled -0.66 for the top 0.1% of exporters (weighted average of the two rightmost points), compared to -0.39 for exporters within the 75th and 90th percentile of the exporter size distribution. [27]

We can now focus on the period April-May 2020 and compare it to the same period in 2019 in order to shed light on the respective roles of supply and demand shocks.

5.2 The role of supply and demand shocks

We now investigate the role of GVC exposure in the observed differential reaction of exports by top exporters to the Pandemic, as large firms are more likely to be more engaged in complex GVCs (Antràs, 2020; Di Giovanni et al., 2020) and thus one could expect that these firms are more exposed to foreign shocks. [28]

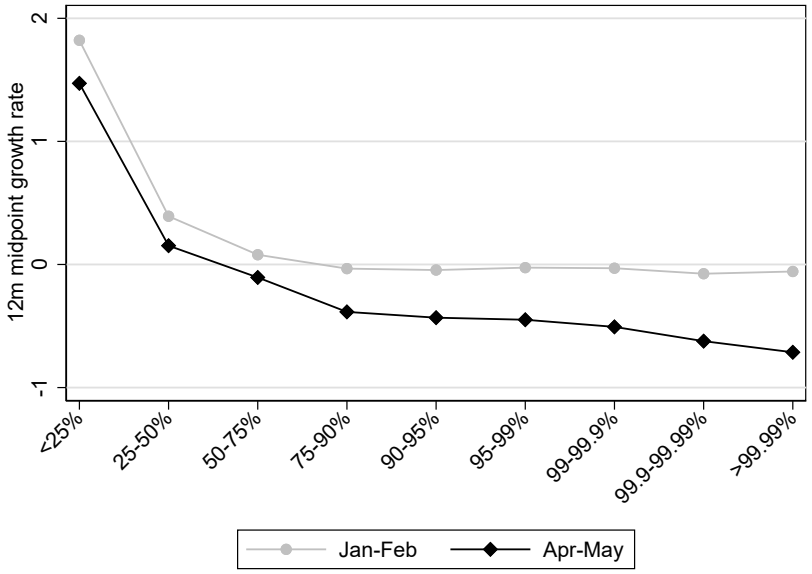
We construct a *firm-level* measure of dependence on foreign inputs using the *Imported-Inputs-to-Sales (IIS) ratio*: $IIS_{f,2019} = \frac{M^{inp}_{f,2019}}{Y_{f,2019}}$, where $M^{inp}_{f,2019}$ denotes the value of imported intermediate inputs and

26. Notice that the high growth rates at the bottom of the distribution are strongly driven by entering and exiting firms. However, as shown previously, firms in the bottom 75% of the exporter size distribution hardly play any role for aggregate exports.

27. Table A1 in the Online Appendix provides details on point estimates and standard errors. Appendix Figure A16 shows the results obtained without fixed effects and using Sector only fixed effects.

28. A large literature suggests a prominent role for global value chains in the transition of supply shocks generated by the Pandemic. See for example Bonadio et al. (2020), Heise (2020), Lafrogne-Roussier et al. (2022), Çakmaklı et al. (2021). More generally, it is well-known that firm-to-firm relationships through value chains are a vehicle for the international transmission of shocks (Carvalho et al., 2016; Boehm et al., 2019).

Figure 8: Midpoint growth rate by size bin: January-February vs April-May 2020



Note: Sector-destination fixed effects included.

Source: French customs, Authors' calculations.

$Y_{f,2019}$ total firm sales (including both domestic sales and exports). [29] We use two additional datasets. First, Customs' data provides us information on imports by CN8 product and country of origin by firm $\times$ month (the same source as the export data, see Section 2). We use the BEC classification to classify products according to their role in the production process, distinguishing among intermediate inputs, capital goods and consumption goods. [30] Second, we use firm-level yearly balance sheet data to measure total sales. [31] We match the trade and balance sheet data using the unique firm identifier SIREN. Focusing on exporters that are present in 2019 in the FIBEN dataset reduces the sample size from roughly 100,000 to 37,000 firms. We refer to the restricted sample as the *Customs-FIBEN sample*. The *Customs-FIBEN sample* accounts for 71% of aggregate exports in 2019. While it captures few exporters in the bottom 75%, the sample gives a reasonable representation of the right tail of the size distribution and we obtain with the *Customs-FIBEN sample* results that are very similar to those obtained on the

29. Both variables are calculated with yearly data for 2019, to capture the potential exposure of firms to the Pandemic-induced supply disruptions based on their pre-existing sourcing choices.

30. See the Online Appendix A.4 for details on the share of imports by broad categories of products and firm size. Since the import data are exhaustive, we set imports of exporters that we do not find in the import data to zero.

31. The data are collected by the Banque de France and labeled FIBEN (in French: *Fichier Bancaire des Entreprises*), which contains firms with yearly turnover $>$ 750,000 euros, featuring around 200,000 firms per year across all sectors of the economy (including non-tradables).

full sample of exporters. [32]

Figure 9 plots, by exporter size bin, the average (sales-weighted) *IIS ratio* and its within-bin distribution. The correlation with exporter size is positive but the *IIS ratio* grows rather weakly with firm size, as the value of imported intermediates increases with exporter size only slightly faster than total sales as we move up the exporter size bins. Moreover, there is a large dispersion within bins as evidenced by the large 10th-90th percentile intervals reported in Figure 9. A regression of $IIS_{f,2019}$ on size bin dummies gives an R^2 of only 5%, a first indication that GVC exposure is unlikely to explain the disproportionate collapse of top exporters (although large exporters' imports tend to be biased towards intermediate goods - see Appendix A.4).

In Equ. (9) we augment Equ. (8) with a set of dummies representing the firm's position in the distribution of the *IIS ratio*, whose effects are captured by $\gamma_{r(f)}$. We also suppress the t subscript, as we now focus on only one time period (Apr-May 2020).

$$g_{fkj} = \alpha_{b(f)} + \beta_{js} + \gamma_{r(f)} + \epsilon_{fkj} \tag{9}$$

We use two alternative specifications to create dummies for the IIS ratio, one creating decile dummies, and one creating dummies for intervals of fixed length (0-10%, 10-20%, etc.). We plot the results in Figure 10. Within sector-destinations, controlling for systematic differences across firms in terms of dependence on foreign inputs does not affect the coefficients associated with the size dummies. [33] We conclude that reliance on imported inputs (as captured by the *IIS ratio*) did not drive the collapse of superstar exporters. [34]

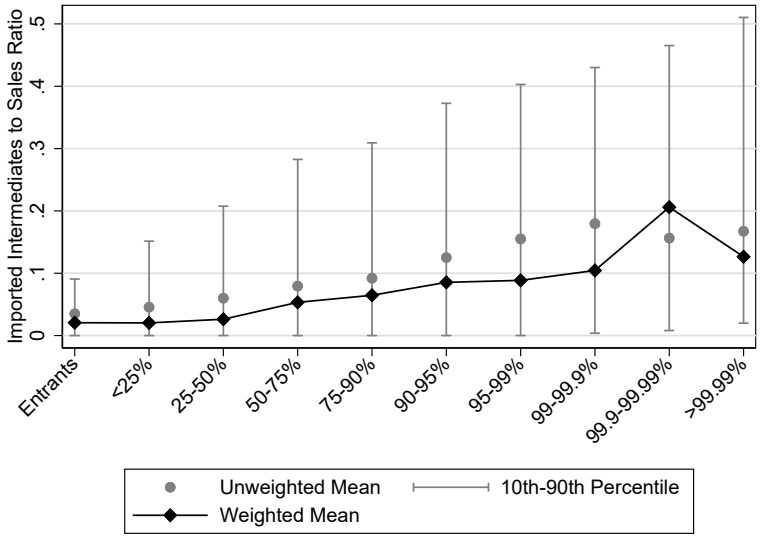
We now turn to the study of demand shocks. The inclusion of sector-by-destination fixed effects rules out compositional effects arising from the largest exporters potentially being more exposed to destinations displayed stronger demand shocks. However, largest exporters might exhibit a higher elasticity to foreign demand shocks (see, for example, Gabaix and Koijen (2020)).

32. See Figure A5 in the Online Appendix that replicates Figure 8 on the *Customs-FIBEN sample*. Including exporters that enter from 2019 to 2020, the sample captures 41,000 out of 125,000 firms. The reduction in the number of firms comes largely from the turnover threshold in the FIBEN data, which eliminates particularly smaller exporters. Figure A4 in the appendix gives details, by size bin, about the share of firms in the Customs-Sample that can be matched to FIBEN.

33. We use dummies to capture potential non-linearities in the impact of the *IIS Ratio* on exports. Introducing the IIS ratio on its own leads to similar conclusions.

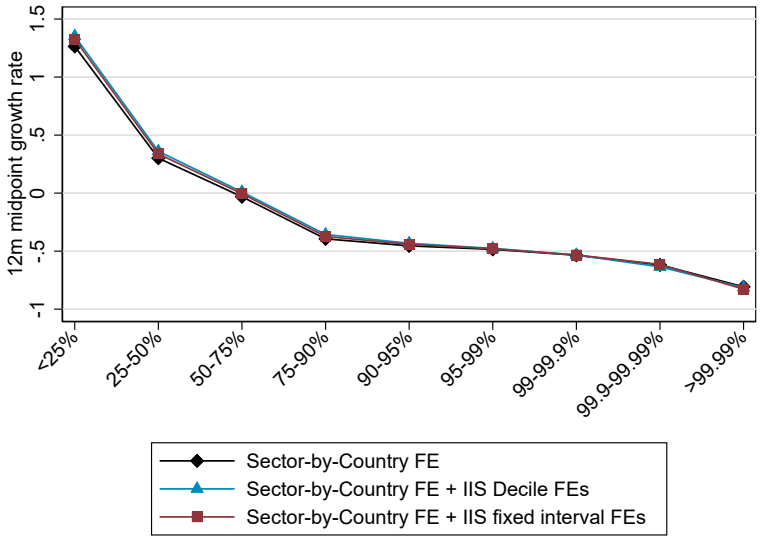
34. In the Online Appendix A.6 we find no evidence of a different exposure to foreign supply shocks due to a different geographical structure of *imports* by the largest exporters.

Figure 9: IIS ratio by size bin



Note: import values as weights.
Source: French customs, Authors' calculations.

Figure 10: Midpoint growth rate of exports by size bin, controlling or not for the IIS ratio

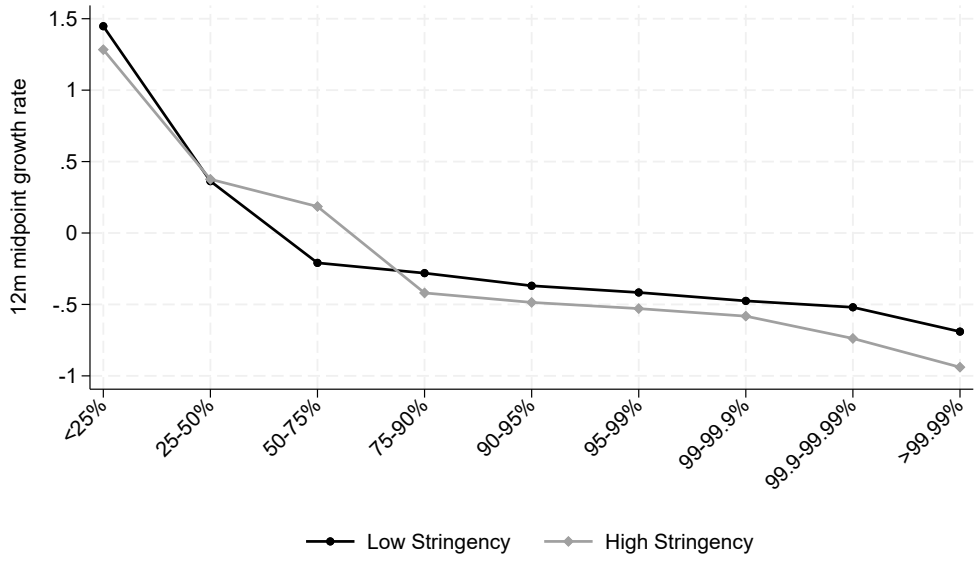


Source: French customs, Authors' calculations.

We measure demand shocks using data on stringency of Covid lockdowns. We want to test whether the overreaction of large exporters is particularly strong in destinations with large adverse demand shocks, that is, whether the growth-by-size relationship in Figure 8 is steeper when we restrict attention to these destinations. To that end, we divide destinations into two groups: those with below-average and those with above-average values for lockdown stringency in April and May 2020. We then re-estimate Equ. 9 (controlling for decile bins of the IIS ratio) separately for each of these country groups.

Results of this exercise are presented in Figure 11. The black line shows export growth to low-stringency destinations while the grey line shows export growth to high-stringency destinations. The difference in growth rates by lockdown intensity are more pronounced for the largest firms, indicating that these firms have a higher sensitivity to common demand shocks. An estimation that uses within-firm variation in export growth to different destinations confirms a higher sensitivity of large firms to foreign demand shocks. [35]

Figure 11: Midpoint growth rate of exports by size bin, by destination lockdown stringency



Source: French customs, Authors' calculations.

We quantify the contribution of the demand channel using counterfactuals. In Section 4.3 we asked which part of the aggregate export decline can be attributed to the overreaction of the largest exporters.

35. See Figure A18 in the Online Appendix.

Focusing on the top 0.1% exporters during the Pandemic, we found that this share roughly equaled one quarter. The goal of this subsection is to ask which part of this channel can be accounted for by heterogeneous reactions to demand shocks. To arrive at an answer, we construct another counterfactual that suppresses heterogeneous reactions to demand shocks according to exporter size, and re-compute aggregate export growth. We then compare the result from this counterfactual to the one that suppresses all overreactions (from Section 4.3), and to actual export growth.

In practice, to compute the counterfactual that suppresses the demand channel, we divide countries each month into high- and low-stringency destinations, and estimate Equ. (9) for each month and country group. We then ask what aggregate export growth would have been, had the difference in growth rates between the top 0.1% and the bottom 90% been the same in the high-stringency destinations as it was in the low-stringency destinations.[36] We obtain that if the difference in growth rates between large and small firms had been the same in regions with high and low demand shocks, the growth of the top 0.1% would have been -20.2% (vs. -22.8% actual growth), and aggregate export growth would have been -16.8% (vs. -18.0% actual).[37]

This scenario needs to be compared to the one that suppresses all overreactions of the top exporters. Since the previous exercise is limited to the *Customs-FIBEN sample*, we re-conduct the counterfactual from Section 4.3 for this subsample. We find that if the top exporters had grown each month at the rate of the average exporting firm, their 2020 growth rate would have been -10.2%, and aggregate export growth would have been -12.1%. Therefore, the overreaction of the top exporters explains about one third $\left(\frac{18.0-12.1}{18.0}\right)$ of the aggregate export decline *Customs-FIBEN sample*, a slightly larger contribution than in the full sample.

The demand channel can thus explain 21.0% $\left(=\frac{22.8-20.2}{22.8-10.2}\right)$ of the overreaction of the largest firms. In the aggregate, exports would have grown at -16.8% in the absence of the demand channel, thus also explaining about one fifth of the gap between a counterfactual where the top exporters grow at the average rate (-12.1%), and actual aggregate export growth (-18.0%).

36. That is, we estimate Equ. 9 separately for each month t, obtaining coefficients $\hat{\alpha}^{C_t}_{b(f)t}$, where $C_t \in \{H, L\}$ denotes the country-group. We then compute counterfactual growth rates for the top 0.1% firms in high-stringency destinations as $\hat{\alpha}^{H,CF}_{top0.1\%,t} = \hat{\alpha}^{H}_{bottom90\%,t} + \hat{\alpha}^{L}_{top0.1\%,t} - \hat{\alpha}^{L}_{bottom90\%,t}$

37. The -22.8% growth of top exporters and -18.0% for aggregate exports are growth rates for the *Customs-FIBEN sample*. We need to restrict attention to this sample, since we also control for the supply channel of imported inputs.

We summarise the findings of the current section in the following stylized fact:

Fact 4: *Top exporters reacted more strongly than bottom exporters to major foreign demand shocks during the Pandemic. In contrast, Global Value Chain shocks can not explain the larger sensitivity of the largest exporters to the Covid shock.*

6 Conclusion

In an economy with few very large firms, idiosyncratic shocks to these firms can have aggregate effects. This has been a topic of intensive research in both macroeconomics and international economics, with important implications for business cycles, comparative advantage, and the international transmission of shocks. We have shown in this paper that the largest firms tend to react more to common shocks, which in turn feeds back into the aggregate response of the economy.

We uncover four stylized facts: i) the *granular residual* of aggregate exports explains a 40% share of aggregate export fluctuations, and the largest firms do better than average in good times and worse in bad times; ii) larger exporters have higher loadings on common shocks, which explains one quarter of aggregate export fluctuations; iii) the top 1% exporters reacted more strongly to both the GFC and the Covid crises, which contributed to the export collapses; and iv) heterogeneous reactions to major demand shocks have explanatory power for the higher sensitivity of the largest exporters to common shocks, as opposed to GVC shocks.

These findings can inform theory to incorporate demand elasticities that are heterogeneous across firms and larger for the top firms as a key ingredient.

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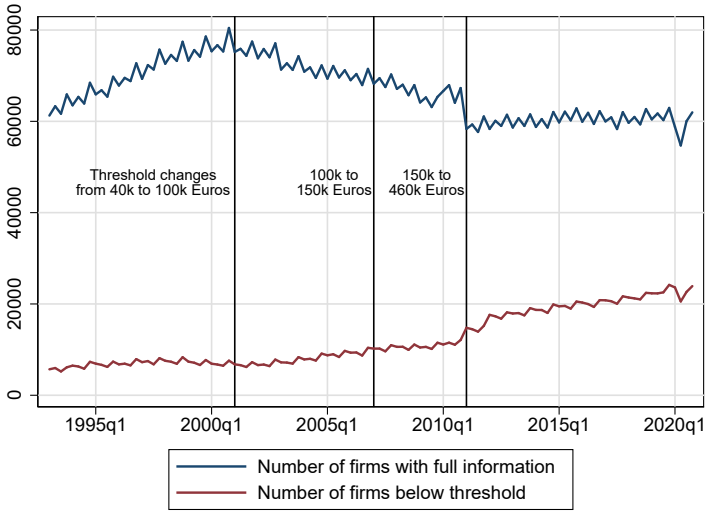
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7 Online Appendix

A.1 Data

Figure A1: Number of firms with detailed export information and number of small exporters



Source: French customs, Authors' calculations.

A.1.1 Coverage

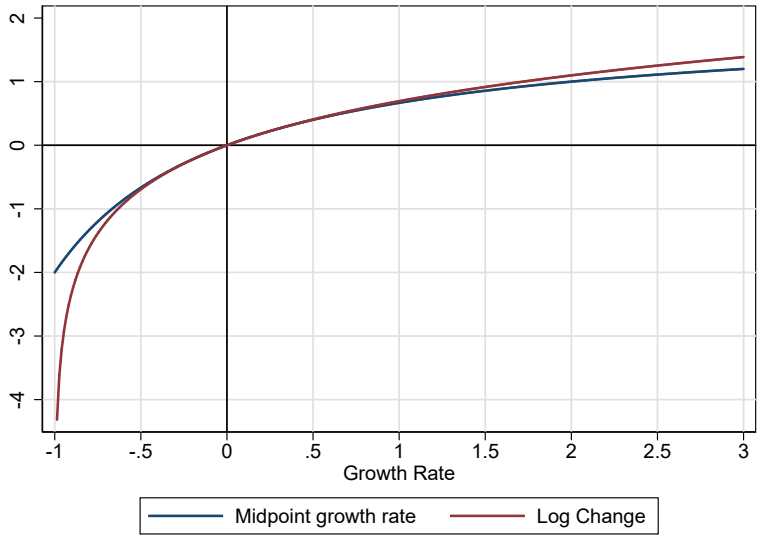
Figure A2: Coverage of aggregate statistics with transaction data



Source: French customs, Authors' calculations.

A.1.2 Midpoint growth rate

Figure A3: Midpoint growth rate vs log change



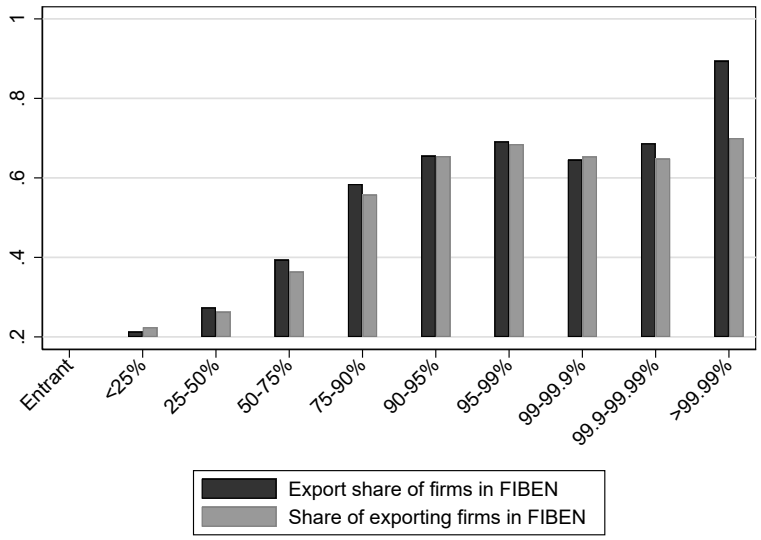
A.1.3 Fiben

The FIBEN dataset provides detailed yearly balance-sheet and income statements for firms with yearly turnover larger than 750,000 euros. The data are collected at a yearly frequency by regional offices of the Banque de France with the purpose of gathering information about firms' credit worthiness. It is collected by the Banque de France since 1988 and the last full set of information available is for 2020. Previous papers using data from FIBEN include Aghion et al. (2019), and Cahn et al. (2020).

Because of the turnover threshold, the number of firms in the FIBEN dataset is substantially lower than that in the Customs data. Let us first check whether the sample of firms in Fiben is representative. The sample is comprising large exporters as a result of the threshold of turnover (above 750 keuros): 37% of the 2019 exporters have data in Fiben, but they account for 71% of the 2019 export value. And the export share of firms in Fiben reaches 90% in our top bin as shown in Figure A4. The same conclusion holds if one reproduces the previous exercise of computing the 12-month midpoint growth rate of exports by size bin of exporters for the Fiben sample as shown in Figure A5. We can therefore safely use this sub-sample to investigate the exporter's exposure to foreign supply shocks through imported intermediate

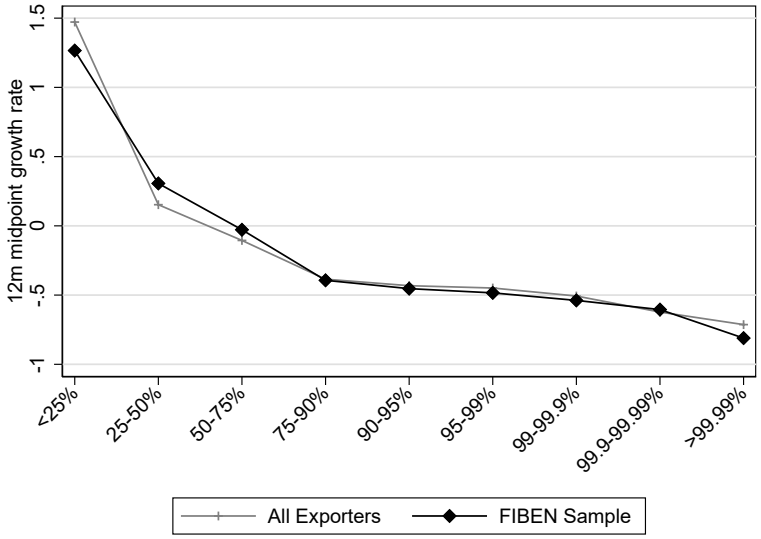
inputs using the IIS ratio as a control in size-estimations.

Figure A4: Share and export share of exporters in Fiben



Source: French customs and Fiben Bank of France, Authors' calculations.

Figure A5: Growth rate of exports by size bin for all exporters and the Fiben sample



Source: French customs and Fiben Bank of France, Authors' calculations.

A.2 The intensive and extensive margins during Covid and GFC

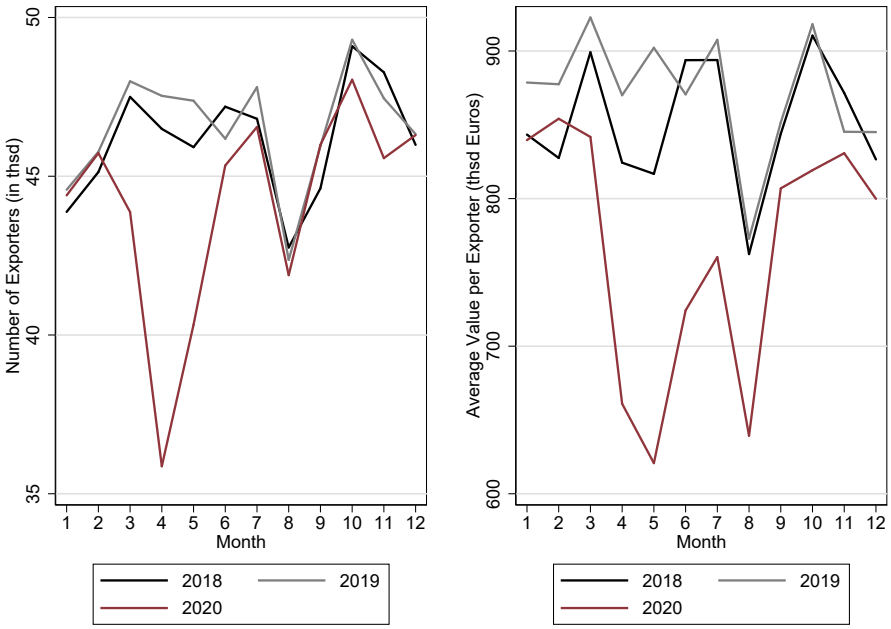
A.2.1 Firm Intensive and Firm Extensive Margins

Denote total French exports in month t as X_t as the product of the number of active exporters, N_t and the average export value per active firm, $\bar{x}_t$:

$$X_t = N_t \bar{x}_t \tag{10}$$

Figure A6 plots the evolution of $\bar{x}_t$ and N_t for the period from January 2018 to December 2020. Both the number of active exporters and average exports recorded a large and sudden drop in the period from March to May 2020, compared to the same period in the two previous years. [38]

Figure A6: Number of exporters (left) and average value per exporter (right)



Source: French customs, Authors' calculations.

The number of firms with positive exports in April 2020 was roughly 36,000, against 47,000 one year before thus implying a drop of around 25%. Similarly, the average value per firm in April 2020 was close

38. The seasonal pattern of French exports is apparent by the fall recorded during August in every year.

to 75% of that recorded the previous April. Both margins were also strongly reduced with respect to the beginning of the year 2020, pointing unambiguously to an effect of the Pandemic. While the size of the initial drop was very similar for both margins, the recovery was much swifter for the extensive margin, with the number of exporters reaching pre-pandemic levels already in the summer of 2020.

We now focus on the export collapse of April-May 2020 and compare the size of continuing exporters ("stayers") and exiters in Figure A7. The left panel compares the distribution of export values (in common log) of firms that exported in April-May 2019, but exited the export market in April-May 2020, against the distribution of all exports in April-May 2019 (thus the set of firms in the encircled bars is a subset of those present in the light grey bars). It is apparent that exiters are smaller on average than continuing exporters. Average exports of exiters in 2019 equaled 65k Euros, a mere 4.5% of the average of all exporters (1.4m Euros). This substantial size difference is the reason why the exit of exporters, though important in numbers, does not matter much for the decline of aggregate exports.

The right panel of Figure A7 looks at the evolution of the size distribution of continuing exporters. [39] The light grey bars show the distribution in April and May 2019, and the encircled bars the distribution in April and May 2020. The distribution during the crisis is shifted to the left: continuing exporters reduced their export values, as already shown in Figure A6. A noteworthy difference lies in the thinner right tail of the distribution of stayers in April-May 2020, indicating a truncation of extreme values during the crisis in line with the facts of Section 3.

We apply the following decomposition of the year-on-year growth rate of total exports:

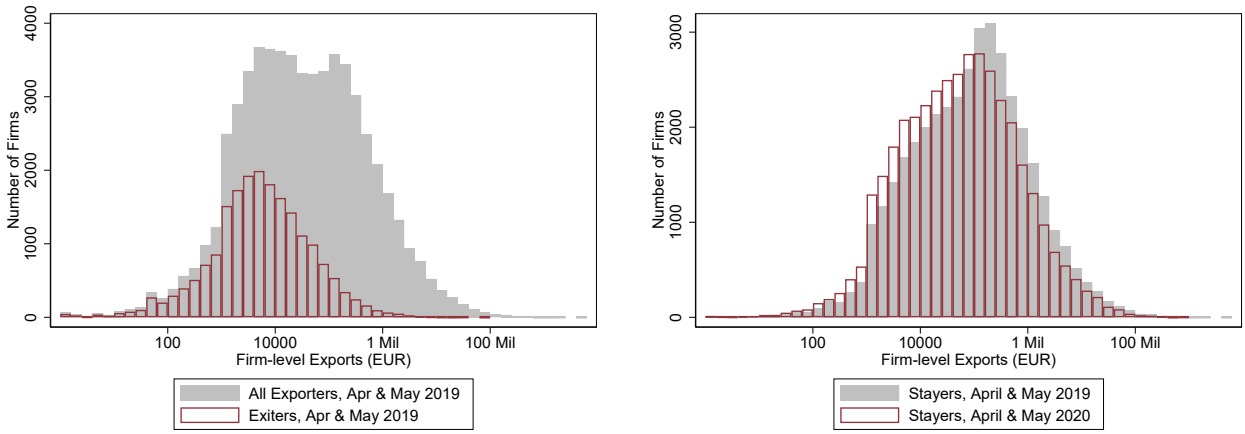
$$\frac{\Delta X_t}{X_{t-1}} = \frac{\sum_{f \in S_t} \Delta x_{f,t}}{X_{t-1}} + \frac{\sum_{f \in E_t} x_{f,t} - \sum_{f \in L_t} x_{f,t-1}}{X_{t-1}} \tag{11}$$

Where S_t is the set of continuing exporters, E_t the set of entrants, defined as firms with positive exports in month t but zero exports in month $t-12$, and L_t the set of exiters, defined as those firms that record positive exports in month t but not in month $t-12$.

The results of applying (11) to the 2020 data are provided in Figure A8, where $\frac{\Delta X_t}{X_{t-1}}$ is given by the black solid curve. Its two components are represented by the bars: the firm intensive margin is represented in

39. In the left panel of Figure A7, the mass of continuous exporters is given by the difference between all exporters and exiters.

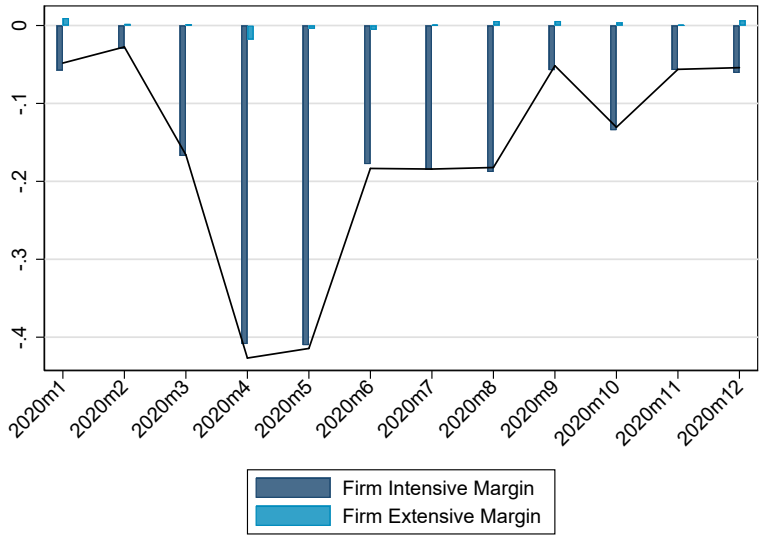
Figure A7: Firm-level export distributions of exiters *vs* continuing exporters: Apr-May '19 vs Apr-May '20



Note: left panel: all firms versus exiters; right panel: continuing exporters. Exiters are defined as firms that export in the period April-May 2019, but do not export in the period April-May 2020.
Source: French customs, Authors' calculations.

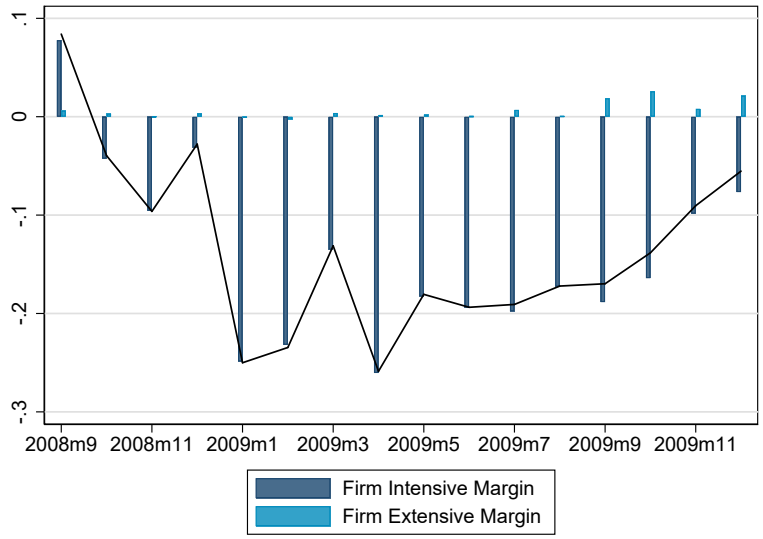
the dark blue bars and the firm extensive margin in the light blue bars. The same exercise is done for the GFC in Figure A9.

Figure A8: Contributions of the firm intensive and extensive margins during the Pandemic



Notes: Horizontal axis, January is month 1; vertical axis: -.1 stands for a contribution of -10 % of the monthly variation of aggregate exports. *Source*: French customs, Authors' calculations.

Figure A9: Contributions of the firm intensive and extensive margins during the GFC



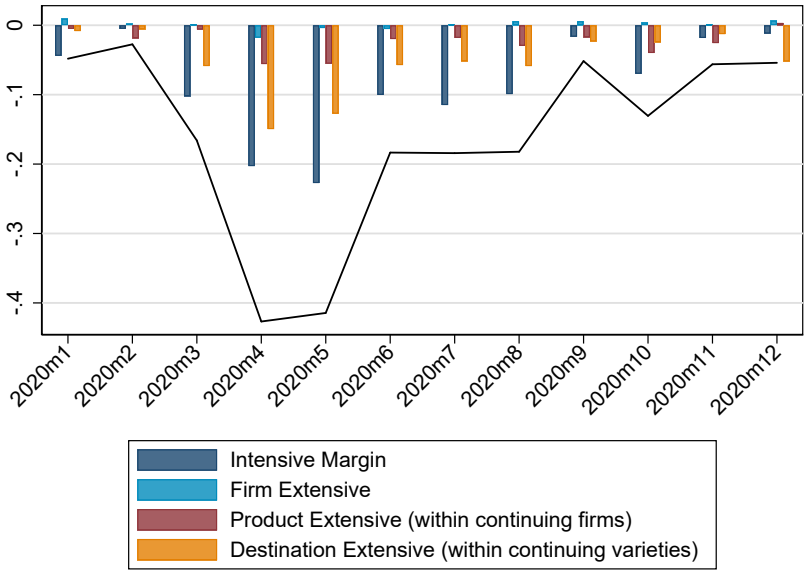
Source: French customs, Authors' calculations.

A.2.2 Decomposing the firm-intensive margin

The firm intensive margin can be further decomposed into a firm-product-destination intensive margin, and two extensive margins capturing the adding/dropping of products and destinations within firms. This is done in Figure A10 with the following decomposition, that follows Bernard et al. (2009):

$$\frac{\Delta X_t}{X_{t-1}} = \underbrace{\frac{\sum_{f\in N} x_{f,t} - \sum_{f\in L} x_{f,t-1}}{X_{t-1}}}_{\text{Firm Extensive}} + \underbrace{\frac{\sum_{f\in S}\sum_{k\in S_f}\sum_{j\in S_{fk}} \Delta x_{fkj,t}}{X_{t-1}}}_{\text{Firm-Product-Destination Intensive}} + \underbrace{\frac{\sum_{f\in S}(\sum_{k\in N_f} x_{fk,t} - \sum_{k\in L_f} x_{fk,t-1})}{X_{t-1}}}_{\text{Product Extensive}} + \underbrace{\frac{\sum_{f\in S}\sum_{k\in S}(\sum_{j\in N_{fk}} x_{fkj,t} - \sum_{j\in L_{fk}} x_{fkj,t-1})}{X_{t-1}}}_{\text{Destination Extensive}} \quad (12)$$

Figure A10: Further decomposing the firm intensive margin

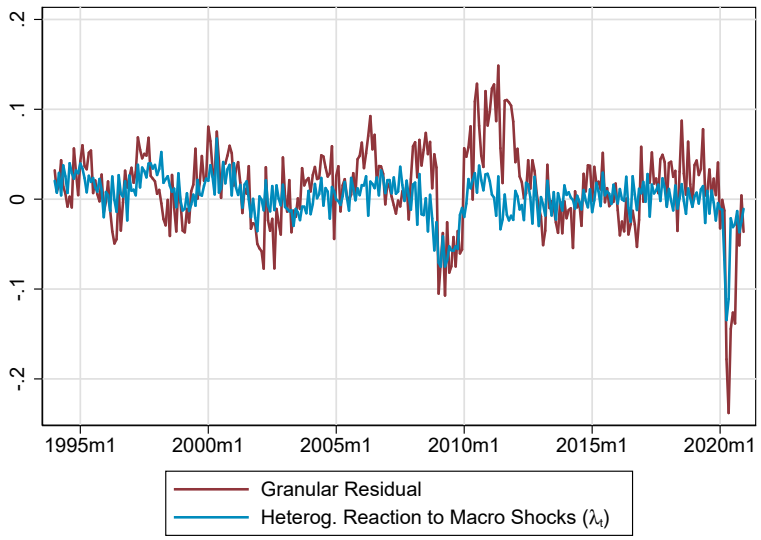


Notes: Vertical axis: -.1 stands for a contribution of -10 % of the monthly variation of aggregate exports.
Source: French customs, Authors' calculations.

A.3 Additional Results

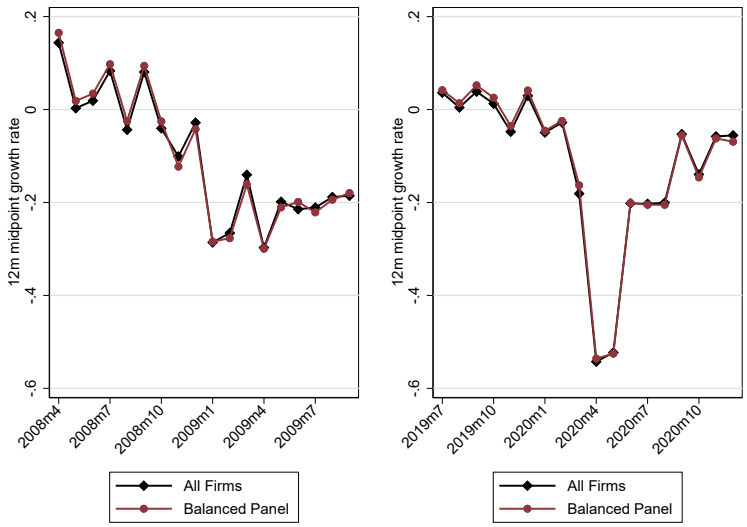
A.3.1 The granular residual

Figure A11: Evolution of λ_t and the Granular Residual (1993-2020, monthly data)



Source: French customs, Authors' calculations.

Figure A12: Growth rate for the balanced panel and the aggregate during the GFC and the Pandemic

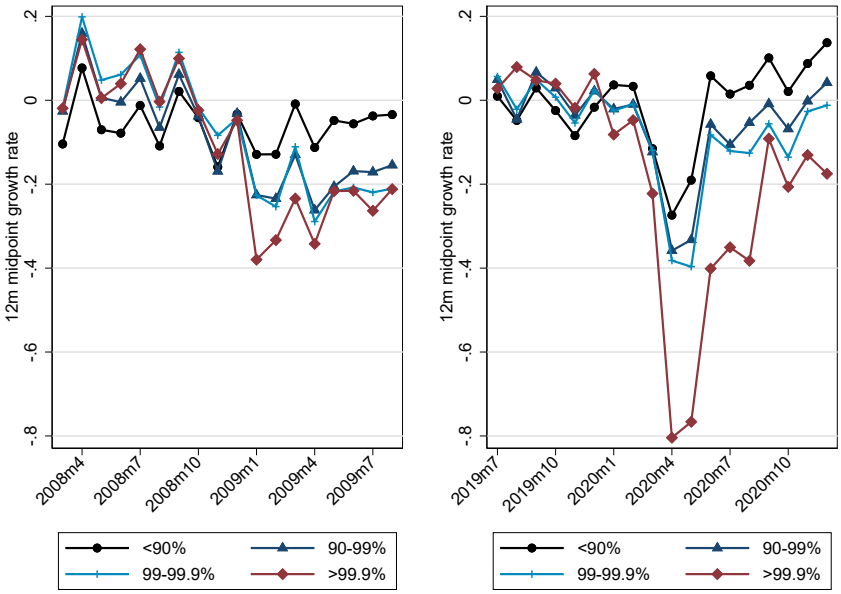


Source: French customs, Authors' calculations.

A.3.2 Aggregate midpoint growth rate using the balanced and the full panel

A.3.3 Growth rates across size groups, not controlling for compositional effects

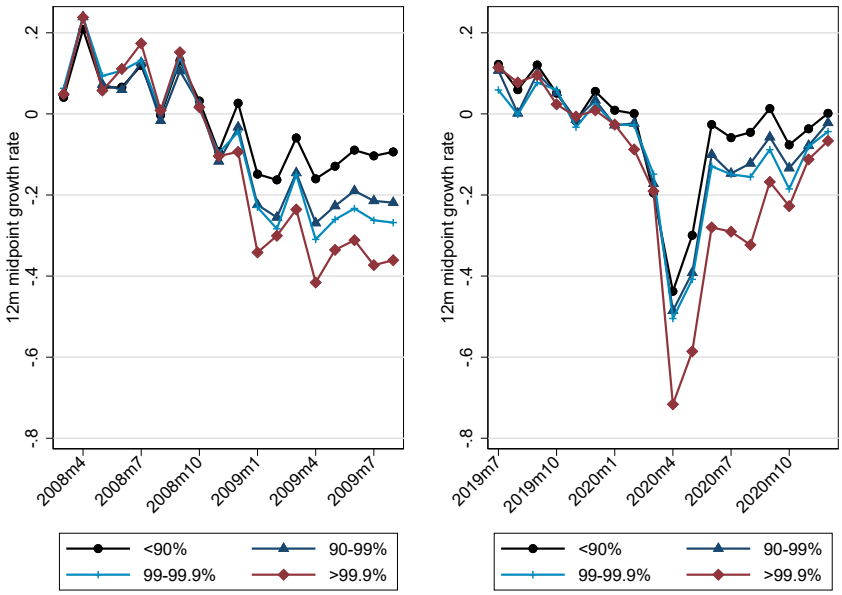
Figure A13: Export growth during the GFC (left) and Covid (right) crises, by size bin



Source: French customs and Fiben Bank of France, Authors' calculations.

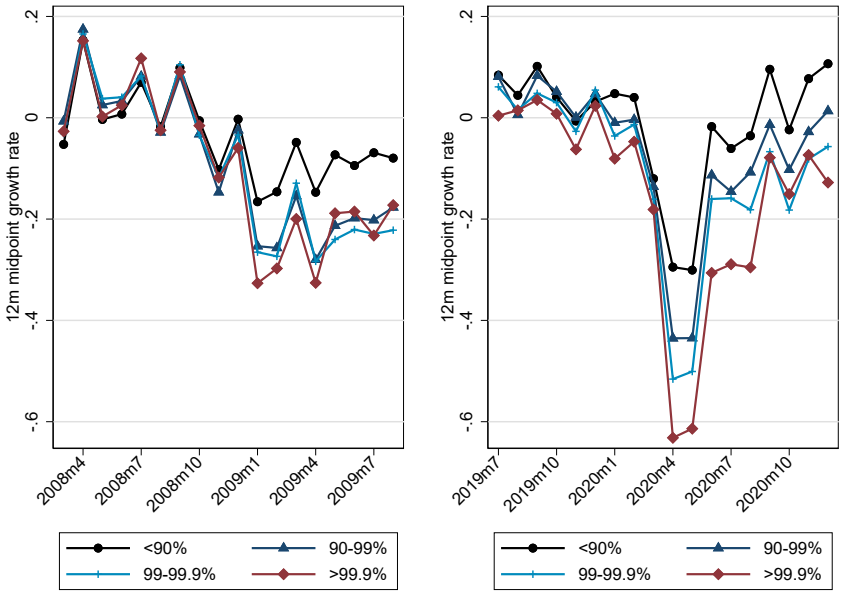
A.3.4 Growth rates across size groups from unweighted regressions

Figure A14: Export growth during the GFC (left) and Covid (right) crises, by size bin (unweighted regressions)



Source: French customs and Fiben Bank of France, Authors' calculations.

Figure A15: Export growth during the GFC (left) and Covid (right) crises, controlling for past growth



Source: French customs and Fiben Bank of France, Authors' calculations.

A.3.5 Size effects during April-May 2020

Table A1: Estimations of size effects on midpoint growth rates

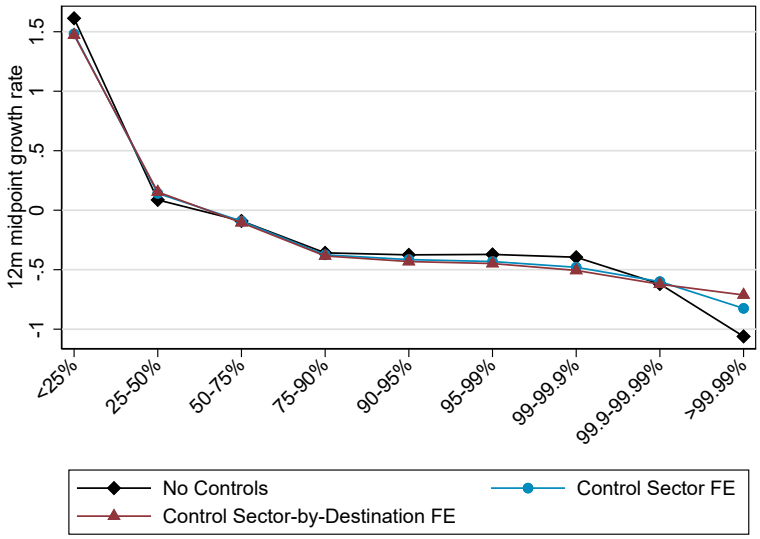
	(1)			
	midpoint growth rate			
Period	Jan-Feb	Jan-Feb	April-May	April-May
FE	None	Sector × Destination	None	Sector × Destination
0-25%	1.7508	1.8213	1.6131	1.4717
	(.1726)	(.1991)	(.2334)	(.2107)
25-50%	.3961	.3919	.0866	.1529
	(.0519)	(.0552)	(.0808)	(.0788)
50-75%	.0943	.0792	-.0903	-.1054
	(.0246)	(.0258)	(.1166)	(.0875)
75-90%	-.0215	-.0336	-.3586	-.3853
	(.0119)	(.0144)	(.0132)	(.0178)
90-95%	-.0435	-.0452	-.3753	-.4323
	(.013)	(.0154)	(.016)	(.0176)
95-99%	-.0238	-.0256	-.3716	-.449
	(.0119)	(.0142)	(.0137)	(.0163)
99-99.9%	-.0093	-.0303	-.3952	-.5068
	(.0172)	(.0196)	(.0216)	(.0206)
99.9-99.99%	-.0992	-.075	-.6201	-.6228
	(.0737)	(.0556)	(.0774)	(.0563)
99.99%-100%	-.0717	-.0571	-1.0609	-.7132
	(.044)	(.0394)	(.1894)	(.0758)

Notes: OLS estimations of Equ. (13). The dependent variable is the year-on-year midpoint growth rate at the firm × product × destination × time level. Time periods are defined as January-February (columns (1) and (2)) and April-May (columns (3) and (4)). Columns (1) and (3) do not include controls and Columns (2) and (4) include sectors × destination fixed effects. Products are defined at the CN8 level of the European Combined Nomenclature and Sector at the Chapter level (2-digits) of the Harmonized System. Standard errors clustered at the firm level are reported into parentheses.

A.3.6 Different fixed effects in the estimation of size effects during April-May 2020

Figure A16 reports different specifications of our main estimation Equ. 8. The black line contains only the size dummies as regressors. The light-blue line adds sector fixed effects, and the red line controls for sector-destination effects. The results show that compositional effects do have some bite, as the effects are milder in the most demanding specification. Nevertheless, it is worth emphasising that growth rates are clearly decreasing in firm size (at a somewhat smoother pace) even when the coefficients are estimated within markets.

Figure A16: Specifications with and without sector effects



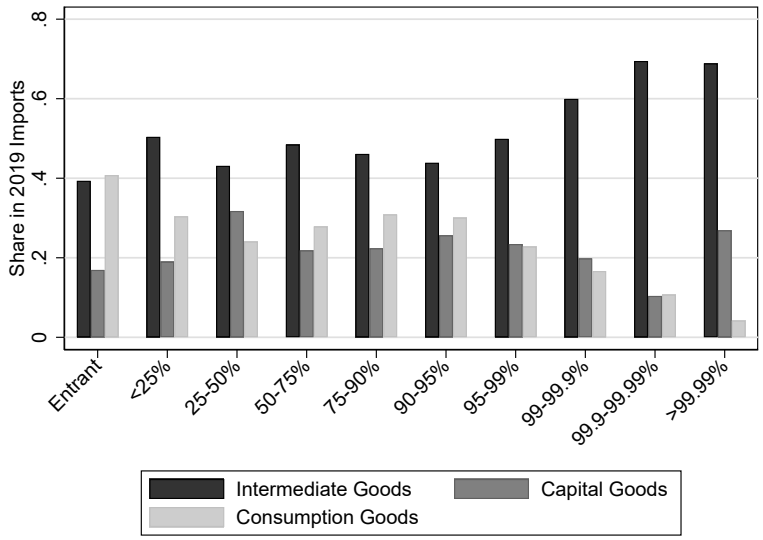
Source: French customs and Fiben Bank of France, Authors' calculations.

A.4 Exposure to GVC shocks by firm size

It is well documented that export and import intensity both correlate with firm size, so that large exporters tend to be large importers; see e.g. Amiti et al. (2014) for evidence on Belgium data and Di Giovanni et al. (2020) for France. This feature also holds in our data. Slightly over 50% of all exporters also import (54,000 out of 100,000 firms), but both the share of exporter-importers in each bin and their weight in total bin-level exports approaches 100% for the exporters in the top 0.1%, and it is higher than 95% for the subset of exporters in the largest 5% - See Figure A19 in the Appendix.

Figure A17 documents that the composition of imported goods changes with exporter size. In particular, imports by the largest exporters are more concentrated among intermediate and capital goods compared to imports by smaller firms: intermediate and capital goods account for over 95% of imports by firms that are placed in the top 0.01% of the export distribution, against 75% for those located in the 50-75% bin. [40]

Figure A17: Share in imports of broad categories of products, by size bin of exporters (2019)



Source: French customs, Authors' calculations.

40. The geographical structure of imports also differs according to firm size. In particular, the top exporters are more reliant on imports of intermediate goods originating in the US and Germany, with those origins together accounting for over 40% of their total imports of intermediate goods. Smaller firms tend to rely more on Eastern Europe and China. It is noteworthy that the share of China in total imports of intermediate goods does not surpass 10% for any bin. See appendix A.5 and particularly Figure A21

A.5 Exporters' export and import growth regressed on Lockdown Stringency

We here regress the midpoint growth rate at the firm-by-product-by-destination-by-month level on the stringency of the lockdown at destination. Using the detailed nature of the data is key as it allows us to control for supply and demand shocks using specifications with different sets of fixed effects. Our estimating equation is:

$$g_{fjkt} = \alpha Lockdown\ Stringency_{jt} + \beta_{ft} + \gamma_j + \delta_{kt} + \epsilon_{fjkt} \tag{13}$$

where $g_{fjk,t}$ is the midpoint growth rate of exports by firm f of product k to destination country j during month t, as defined above. $Lockdown\ Stringency_{j,t}$ is the value taken by the Oxford Index of stringency in destination country j, divided by 100 so that it takes values in the range [0,1]. $Lockdown\ Stringency_{j,t}$ varies both across trade partners and across time, providing us with large variation to identify α. By definition of $g_{fjk,t}$, the estimation includes both the extensive and the intensive margin of exports.

The identification strategy takes advantage of the heterogeneous responses of destination countries to the Covid crisis in terms of timing and intensity of lockdown measures. Unobservable shocks to firm f are captured by a firm $\times$ time fixed effect β_{ft}. Firm $\times$ time fixed effects control for supply shocks to firm f originating both abroad and in France. Importantly, these fixed effects control for the production disruptions that French exporters may have faced due to the domestic lockdown. They also control for demand shocks that affect all products by a particular firm (for example, due to changes in the demand for brands). Time-invariant destination unobserved characteristics are captured by a vector of destination fixed effects γ_j. Finally, product-level shocks common to all destinations and exporting firms are absorbed by a product $\times$ time fixed effect δ_{kt}.

Results are reported in Table A2. Column (1) defines products using 2-digit HS Chapters (corresponding to sectors), while column (2) uses a much finer definition of products, at the 8-digit level of the European Combined Nomenclature. In both cases the reported elasticities are very similar, and imply a strong effect of destination-lockdown stringency on the growth rate of exports at the firm-product-destination level. The value of the coefficient is straightforwardly interpreted. The midpoint growth rate of exports to a country in full lockdown (Stringency = 1) is by 0.6 lower than the growth rate to a country without

Table A2: Effect of Destination Lockdown Stringency

	(1)	(2)
	Midpoint growth rate of exports	
Lockdown Stringency	-0.580	-0.599
	(0.128)	(0.128)
Observations	7,892,770	7,890,184
R-squared	0.345	0.416
Firm-Time FE	✓	✓
HS2-Time FE	✓	
NC8-Time FE		✓
Destination FE	✓	✓

Source: French customs, Authors' calculations.

Notes: OLS estimations of (13). The dependent variable is the year-on-year midpoint growth rate at the firm × product × destination × month level. The estimations cover the period from January 2019 to June 2020. Products are defined at the CN8 level of the European Combined Nomenclature. Standard errors are clustered at the country level and reported into parenthesis. *** implies significance at the 1% level.

lockdown.

We now test for potential heterogeneous effects according to size, interacting the lockdown effect by dummies for exporter size, and grouping the top exporters into a bin containing the highest 0.1%. We estimate the following baseline equation:

$$g_{fjk,t} = \sum_b \alpha_b Lockdown\ Stringency_{j,t} \times D_{b(f)} + \beta_{ft} + \gamma_j + \delta_{kt} + \epsilon_{fjk,t} \tag{14}$$

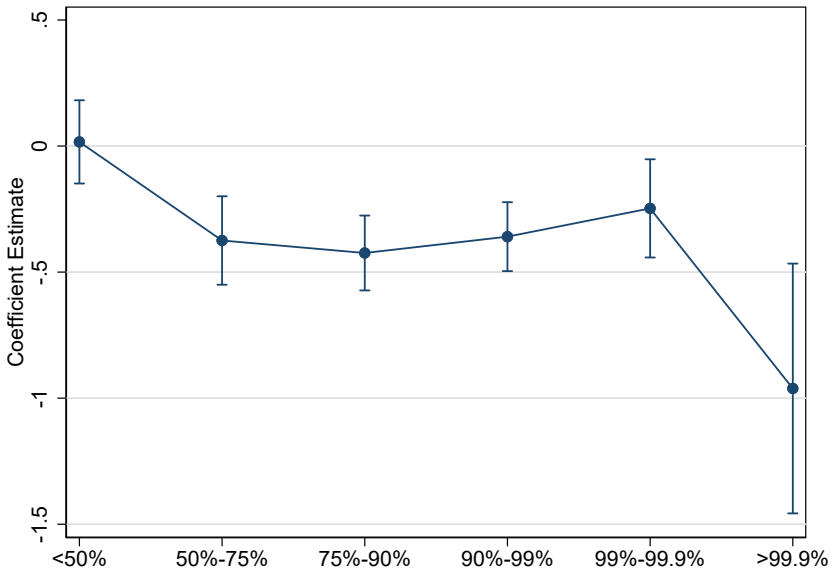
where $D_{b(f))}$ is a set of six complementary size dummies, and the regressions include firm-month, product-month, and destination fixed effects. Standard errors are clustered at the destination-time level.

Figure A18 shows that the top exporters have a higher elasticity with respect to foreign demand shocks. [41] This result is closely related to Di Giovanni et al. (2020) who show for the pre-GFC period (1993-2007) that *sales* of larger French firms are significantly more sensitive to foreign demand variation.

The results illustrate that the heterogeneous responses to demand shocks contributed to the overreaction of the largest firms.

41. In principle, the higher elasticity for top exporters could also mean that these firms reallocate their exports more to low-stringency destination countries. However, we regard this possibility as unlikely, since this reallocation channel would work towards a smaller absolute decline of total exports by the top firms, which is contrary to what we observe.

Figure A18: Effect of Destination Lockdown by Size Bin



Source: French customs, Author's calculation.

Large exporters are also large *importers* as illustrated in Figure A19.

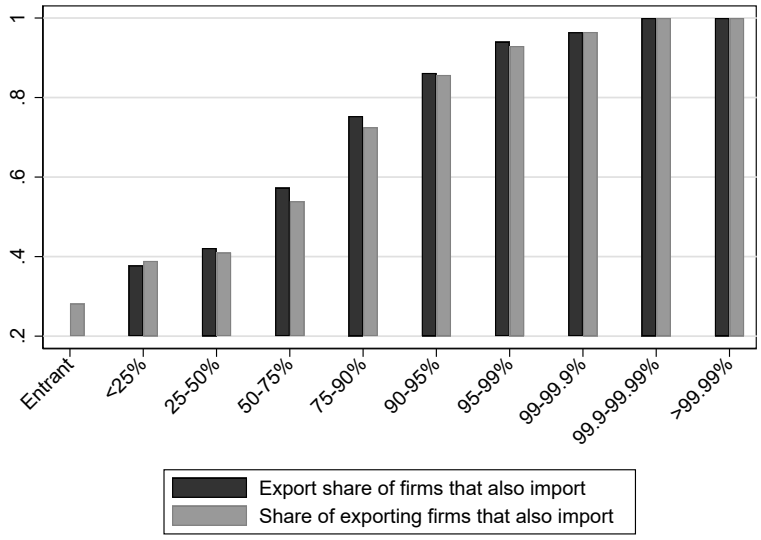
A straightforward motivation to look at supply shocks is provided by the fact that top exporters reduced their imports relatively more than smaller exporters, starting from March 2020 and being especially strong during the months of May and June 2020 as shown in Figure A20.

We now regress the growth rate of imports by exporter, product and origin (as documented in Figure A21) on a series of fixed effects plus the stringency of lockdown at origin, as done in Equ. 13:

$$g_{fik,t} = \alpha Lockdown\ Stringency_{i,t} + \beta_{ft} + \gamma_i + \delta_{kt} + \epsilon_{fik,t} \tag{15}$$

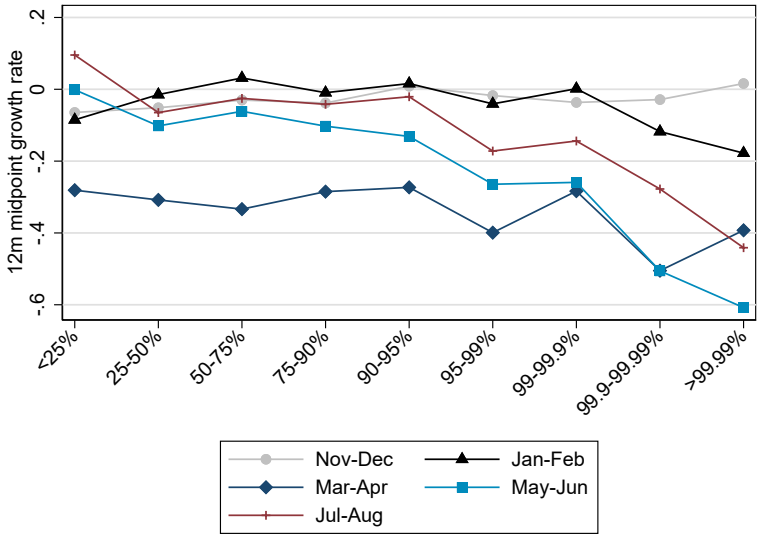
where $g_{fik,t}$ is the midpoint growth rate of imports by exporter f of product k from origin country i during month t, as defined above. $Lockdown\ Stringency_{i,t}$ is the value taken by the Oxford Index of stringency in origin country j, divided by 100 so that it takes values in the range [0,1]. Unobservable shocks to the firm f are captured by a firm-time fixed effect β_{ft}. Time-invariant destination-origin unobserved characteristics (France is indeed the destination of all imports) are captured by a vector of

Figure A19: Export share of firms and share of exporting firms that import



Source: French customs, Authors' calculations.

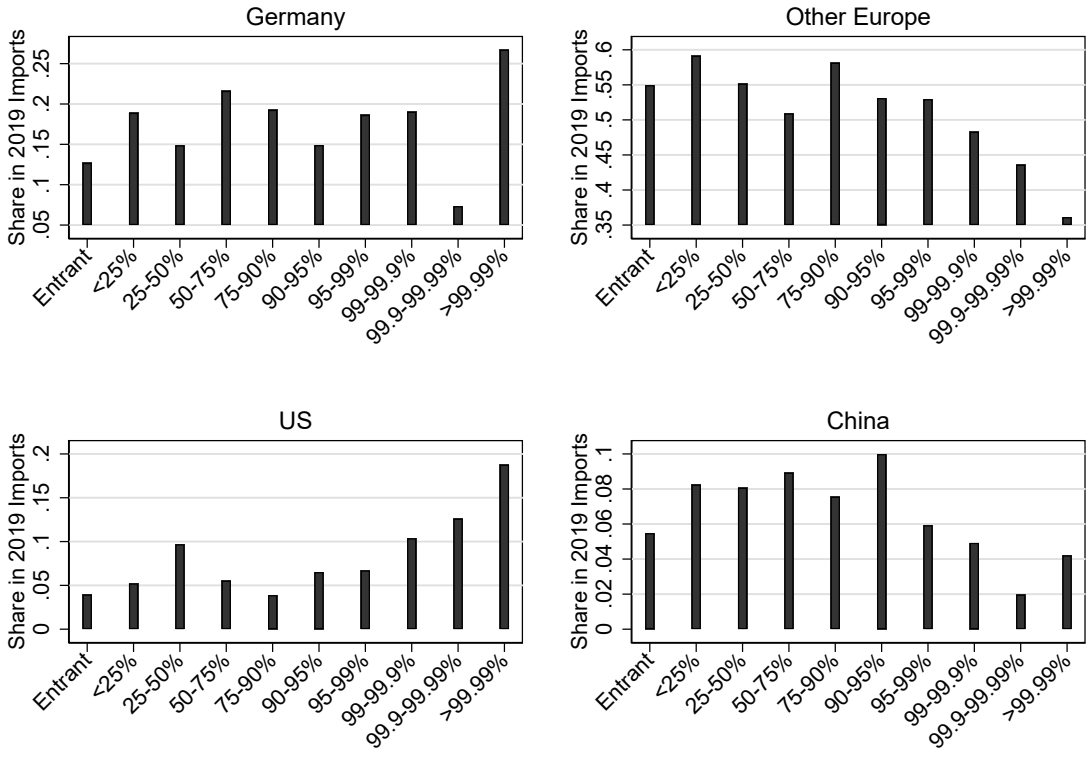
Figure A20: Exporter's imports during the Covid crisis (Nov.-Dec. 2019 to July-Aug. 2020)



Source: French customs, Authors' calculations.

origin fixed effect γ_i, and δ_{kt} a product-time fixed effect capturing any unobserved product-level shock common to all destinations and exporting firms.

Figure A21: Geographic structure of imports of intermediate products, by size bin of exporters (2019)



Source: French customs, Authors' calculations.

To look into potential heterogeneous effects according to size, we add size dummies to Equation 15, grouping the top exporters into a bin containing the highest 0.1%. We estimate the following baseline equation, equivalent to Equ. (14):

$$g_{fik,t} = Lockdown\ Stringency_{i,t} \times \eta_{b(f))} + \beta_{ft} + \gamma_i + \delta_{kt} + \epsilon_{fik,t} \tag{16}$$

where $\eta_{s(f))}$ is a set of six complementary size dummies, and the regressions include firm-month, product-month, and destination fixed effects. Standard errors are clustered at the origin-time level.

Table A3: Effect of Origin Lockdowns

	(1)	(2)
	Midpoint growth rate of imports	
Lockdown Stringency	-0.244	-0.202
	(0.0446)	(0.0438)
Observations	10,126,825	10,124,779
R-squared	0.379	0.459
Firm x Time	✓	✓
HS2 x Time	✓	
Destination	✓	✓
NC8 x Time		✓

Notes: OLS estimations of (13) on the subsample of exporters that report positive import values.The dependent variable is the year-on-year midpoint growth rate at the firm × product × destination × month level. The estimations cover the period from January 2019 to June 2020. Products are defined at the CN8 level of the European Combined Nomenclature. Standard errors are clustered at the country level and reported into parentheses. *** implies significance at the 1% level.

Table A3 shows the results of the estimation of Equ.15. The take home is that the correlation of lockdown stringency at origin with the midpoint growth rate is low. Using our preferred specification of column (2), we find that going from zero to full lockdown in the origin country reduces on average the midpoint growth of imports by 0.2 percentage point only (against 0.6 in the case of exports, see Table A2 in the main text).

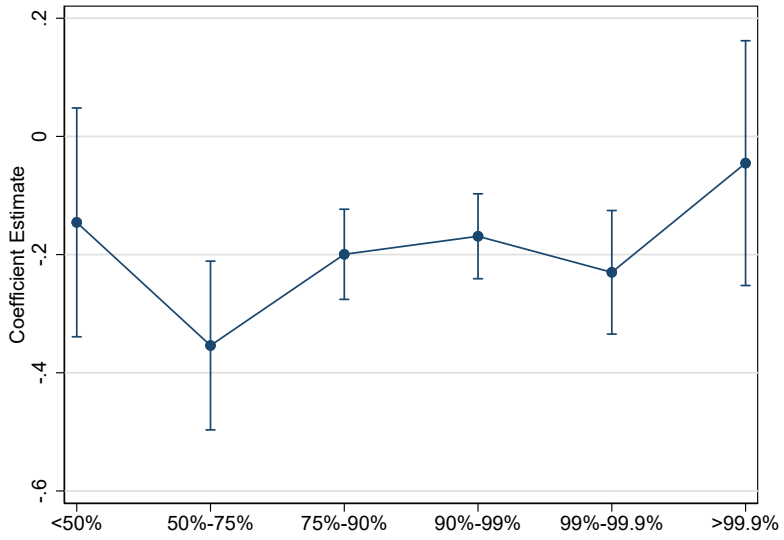
Results when interacting with size bins of exporters, shown in Figure A22, point to the absence of differential effect for large importers: the confidence interval for the estimated parameter tells us that the interaction between *Stringency* and the top size bin is not statistically different from zero.

A.6 Geographical structure of imports channel

To test whether superstar exporters may have been more exposed to foreign supply shocks because of the geographical structure of imports, we calculate a firm-level input supply shock as the weighted average of supply restrictions in origin countries, using the share of each origin in total 2019 input imports as weights: $\text{Supply Shock}_f = \sum_i \frac{M^{int}_{fi,2019}}{M^{int}_{f,2019}} \text{Stringency}_i$, where Stringency_i is the monthly average of the Oxford Stringency Index in origin country i in April-May 2020 (Hale et al., 2021). [42] Thus, Supply Shock_{ft}

42. The Oxford Stringency index constructed by the University of Oxford for around 180 countries is updated on a daily basis. It is based on 20 indicators with information on several different common policy responses, which are aggregated into a set of four common indices ranging from 0 to 100 and increasing in the measures' stringency: an overall government

Figure A22: Impact of Covid at origin on imports by exporter size



Source: French customs, Authors' calculations.

is akin to a shift-share instrument that varies over time according to changes in *Stringency* that are weighted by origin country import shares. Assuming that the stringency of lockdowns in origin countries is exogenous to French firms' shocks, and that the import shares in 2019 are uncorrelated with lockdown decisions in 2020, the method provides us with exogenous variations in the availability and cost of importing intermediate inputs that can be interpreted as supply shocks.

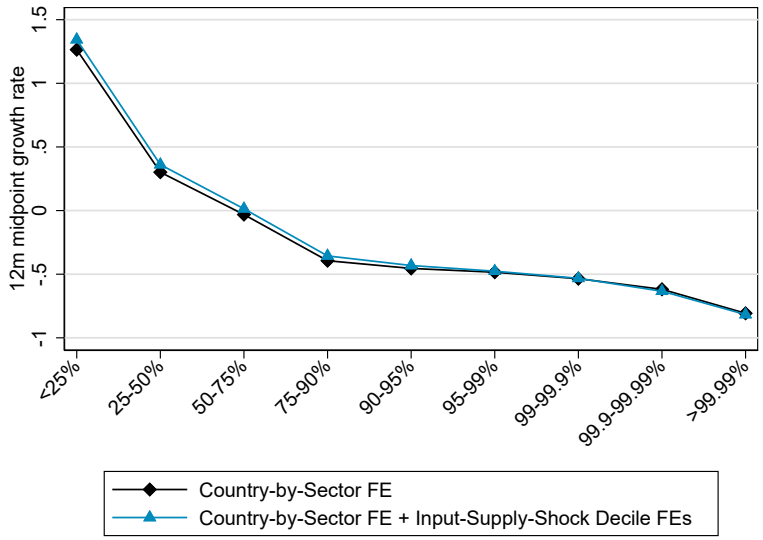
We construct the input supply shock to firm f in month t by scaling the supply shocks measure with the *IIS ratio*:

$$\text{Input Supply Shock}_f = IIS_{f,2019} \times \text{Supply Shock}_f \tag{17}$$

We proceed as before, constructing bins of Input Supply Shock$_{ft}$ and introducing them as controls in Equ. (8). The results are shown in Figure A23: controlling for the exposure to supply chain disruptions does not impact the coefficient associated with the size dummies.

response index, a containment and health index, an economic support index and the original stringency index. We use as a baseline the composite index that aggregates these four indices. The main indicator – "Stringency index" – is a composite indicator of school closures, workplace closures, cancellation of public events, public transport closures, public information campaigns, stay at home, restrictions on gatherings, restrictions on internal movement and international travel controls.

Figure A23: Midpoint growth rate of exports by size bin, controlling or not for the IIS ratio weighted by the stringency of lockdowns in sourcing countries



Source: French customs, Authors' calculations.