# 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 macro shocks; (iii) the stronger reaction of the top 1% exporters to the GFC and Covid crises contributed to the export collapses; (iv) this greater sensitivity is explained by a higher elasticity to large demand shocks, not by different exposure to global value chain shocks. The results show that idiosyncratic reactions of large firms to macro 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 macro 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 macro 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 explains their greater sensitivity to the Covid shock, not a different sensitivity to global value chain shocks.

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 macro 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 top 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 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.

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

We start by studying the micro-dynamics of aggregate exports over the long run. We decompose aggregate export growth into an unweighted average firm export growth rate and a granular residual, which captures the covariance between firm size and firm growth. This exercise provides us with the first *stylized fact*: 40% of the variance of aggregate export growth is accounted for by the granular residual, with the remainder driven by average firm-level growth. Furthermore, both components exhibit a positive correlation (coefficient $\rho = 0.55$). Interpreting average firm growth as a simple measure of macro shocks (see e.g. Di Giovanni et al. (2014)), this correlation points to larger firms reacting more strongly to common macro shocks.

To dig deeper into the relative contributions of macro versus idiosyncratic shocks to aggregate fluctuations, we estimate a parametric factor model in which exporter-level growth rates are determined by both a common factor (captured by the simple average growth rate) and a firm-specific shock, and we allow 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. This approach allows us to compute, at each month in our sample, the component $\lambda_t$ of the granular residual that arises due to idiosyncratic reactions to macro shocks. We document that $\lambda_t$ explains 23% of the variation in aggregate export growth during 1994-2020 (as summarised in our second *stylized fact*). An important part of this contribution transits through the correlation between $\lambda_t$ and the macro shock. This contribution is largest in extreme events such as the GFC and the Pandemic.

In the next subsection we focus on the GFC and the Pandemic, and 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 object of study, they are arguably the clearest examples of macro shocks affecting all firms during our sample period. As such, they provide us with a clean experiment to test for heterogeneous reactions to macro shocks by 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 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 (as mea-

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.

sured 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 mid-point 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, and as such provides an excellent laboratory to study the role of heterogeneous reactions to aggregate shocks.

We conduct our analysis within individual markets (sector-by-destination cells). To look into supply shocks, we augment the flexible regression framework with measures of GVC exposure that combine the imported intermediate inputs to sales (IIS) ratio and supply shock exposure using lockdowns in origin countries. The data reveals that larger exporters tend to be more heavily engaged in GVCs than smaller ones. However, adding GVC measures to our regressions does not affect at all the magnitude of the exporter size-bin dummies: GVC exposure does not explain the underperformance of top exporters during Covid. On the contrary, we do find evidence of a demand channel. We estimate a larger elasticity of large firms to destination-country lockdowns. On average, going from zero to full lockdown reduced the mid-point growth rate by 0.6 point, the effect is twice as large for firms in the top 0.1% (1.0) with respect to the bottom 99.9% (below 0.5). Identification is obtained from variation in export growth of the same firm across destinations with varying degrees of lockdowns, fully controlling for product-level shocks and firm-level supply shocks with firm $\times$ month fixed effects.

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 in 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.

In the same vein, our paper also contributes to our understanding of the drivers of trade collapses. Most of the existing literature has focused on analyzing export collapses along compositional effects in terms of sectors (e.g. manufacturing versus others, consumer durables within manufacturing) or across trade margins at the product- or firm- levels (O'Rourke (2018); Levchenko et al. (2010)). One clear message that arises is the 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. However, we show that compositional effects across firms determine the contribution of the intensive margin itself. We find that large exporters react more to macro 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 a prominent role for global value chains in the transmission of supply shocks generated by the Pandemic, 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. 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. [3]

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) and

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

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 macro 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 shows that top exporters overreact to macro shocks, and this pattern can be seen both during crises and in normal times. It provides a decomposition of aggregate fluctuations of exports quantifying the contribution of the top exporters to the aggregate movement. Section 4 pins down the main reason for this disproportionate reaction of top exporters. Section 5 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. As documented

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))

in Bergounhon et al. (2018), this threshold has changed over time. Firms below this threshold are only obligated 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. Figure A15 shows the number of firms with detailed and restricted filings over time. Since the threshold has been raised over time, the share of firms with full information has fallen from over 90% in the 1990s to just over 70% in the most recent data. However, the export share of firms with detailed filings has stayed close to 100%. 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.

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 as shown in Figure A16 in the Appendix. [5]

Finally, in Section 4 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 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 mid-point 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 mid-point 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 $x_{fjkt-12} = 0$.

5. Details concerning the construction of the data and references to previous contributions that rely on these data are provided in Bergounhon et al. (2018).

The great advantage of mid-point growth rates when using detailed trade data is that they are well-defined in cases of high turnover and entry. Such turnover is very common with highly disaggregated trade data, both during crises and normal times (e.g. Bernard et al. (2009)). For this reason, mid-point growth rates are frequently used in settings where entry/exit is important, e.g. by Haltiwanger et al. (2013) on job creation by establishments, and Eaton et al. (2007) on entry and exit in transaction-level trade data. This approach allows us to incorporate all extensive margin (firm, product, or destination) and intensive margin changes in one single measure. Furthermore, in the case of small changes, the mid-point growth rate is a very good approximation of the more common log change measure (see Figure A18 in the Appendix), but avoids extreme values in the case of large year-on-year changes in exports.

A second very convenient feature of the mid-point growth rate is that, unlike e.g. the log change, it aggregates up exactly. That is, the aggregate growth rate can be expressed as a weighted average of transaction-level growth rates, with no approximation needed:

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

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

In this section we provide evidence that the largest exporters react more strongly to macro shocks and that this amplifies the response of aggregate exports. We show this by first studying a decomposition of aggregate exports over a long horizon, and then by focusing on two large crisis episodes, Covid and the GFC.

### 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*). This decomposition is close to those adopted in previous contributions in the literature on granular firms (Gabaix, 2011; Di Giovanni et al., 2020), although previous papers focused on value added and not on exports as we do here. [6]

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

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

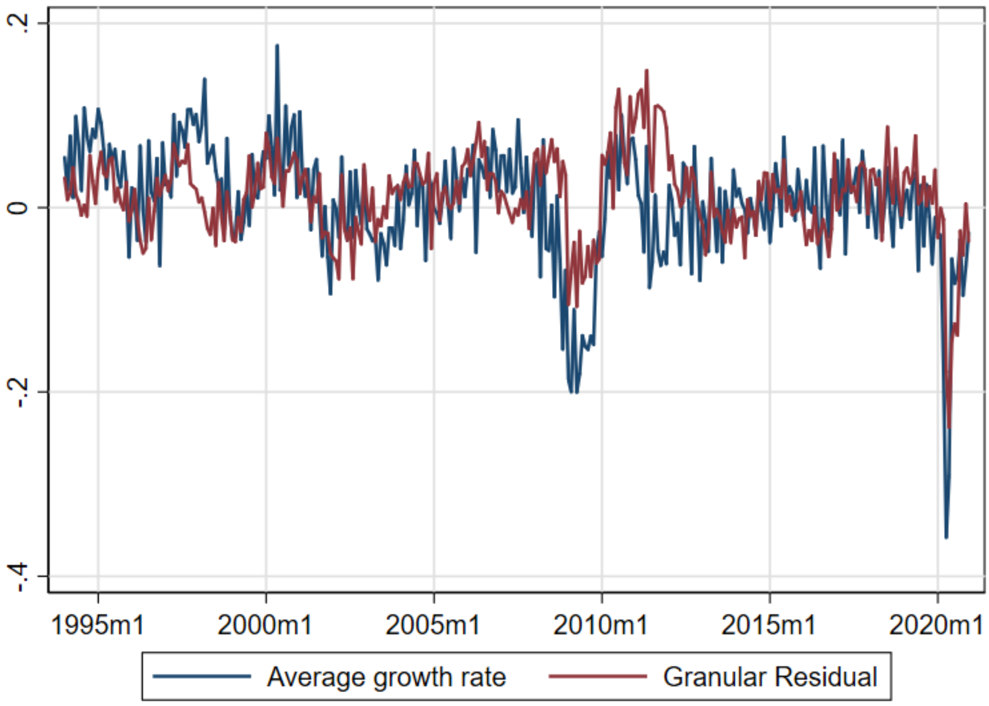
where $\bar{g}_t = \frac{1}{N_t} \sum_f g_{f,t}$ measures the simple average growth rate of continuing exporters (firms that export both in $t$ and $t-12$). This average growth rate is a simple measure of a macro shock that affects all firms. We argue below that the average growth rate across firms during the two major crises of the GFC and the Pandemic capture an underlying common shock to these firms. The granular residual captures the size-weighted deviations of the firm growth rate from this aggregate shock, as it can be easily shown that $Cov_t(\omega_{ft}, g_{f,t}) = \sum_f \omega_{f,t}(g_{f,t} - \bar{g}_t)$, making apparent that $Cov_t(\omega_{ft}, g_{f,t})$ is positive when larger exporters (i.e. those with larger weights $\omega_{ft}$) experience higher growth rates than the average firm and is negative when larger firms do worse than the average firm. If exporter growth was uncorrelated with exporter size, then the covariance and the granular residual would be zero.

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

6. 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.

7. 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.

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 ($\frac{Cov(G_t,\bar{g}_t)}{Var(G_t)}$) and a 40% share coming from the granular residual. Third, average firm growth and the granular residual are positively correlated, with a correlation coefficient $\rho = 0.55$. This positive correlation suggests that large exporters tend to do worse than the average firm in times of a downturn, and better than average in times of an upturn. Such pattern is prominent during major crises as shown below.

We now provide more direct evidence for the cyclical behavior of firms by size. To do so, we start with a simple regression framework, regressing firm-level growth on the average growth rate, and show how these results are related to the previous decomposition. In the following subsection we then generalize this framework to study the cyclical behavior of firms of different size, and measure the contribution of this cyclical heterogeneity for aggregate export volatility.

To start, consider 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, defined as above, and $\bar{g}_t$ is the simple average of all firms with positive values in $t-12$ and $t$ and captures the macro shock.[8] By construction, estimating Equ. 4 without weights on the sample of continuing firms would result in an estimated coefficient of $\hat{\beta} = 1$.

Since we are interested in the behavior of aggregate export growth, we estimate (4) by OLS using midpoint weights as defined earlier: $w_{ft} = \frac{x_{ft}+x_{ft-12}}{X_{ft}+X_{ft-12}}$. Given that mid-point growth rates aggregate up exactly using $w_{ft}$ as weights, the estimated coefficient $\hat{\beta}$ equals the covariance between the aggregate midpoint growth rate and the macro shock, divided by the variance of the macro shock:

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

Using Equ. (3) and the notation $GR_t$ for the *Granular Residual*, we can re-express (5) as follows:

8. This is a standard measure of macro shocks in the granularity literature, see for example Di Giovanni et al. (2014).

$$\hat{\beta} = \frac{Cov(G_t, \bar{g}_t)}{Var(\bar{g}_t)} = 1 + \frac{Cov(GR_t, \bar{g}_t)}{Var(\bar{g}_t)} \tag{6}$$

That is, $\hat{\beta}$ captures the correlation between the granular residual and the macro shock.

Table 1 shows the results, both for continuing firms, defined as those with positive exports in $t$ and $t-12$, and for all firms.[9] Since we have already shown that the macro shock and the granular residual are positively correlated, it must be the case that $\hat{\beta} > 1$. This is what we find in both columns. The aggregate growth rate moves with an elasticity greater than one with respect to the macro shock, since the macro shock and the granular residual are positively correlated.

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

| | (1)<br>g | (2)<br>g |
|---|---|---|
| $\bar{g}_t$ | 1.379***<br>(0.062) | 1.418***<br>(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 mid-point 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 parenthesis. *** implies significance at the 1% level.
*Source*: French customs, Authors' calculations

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 macro shocks affecting all exporters.*

9. We use the same measure $\bar{g}_t$ in both columns, defined as the simple average midpoint growth rate over continuing firms.

### 3.2 A Factor Model Approach

Having established that the correlation between the granular residual and the macro shock is positive and quantitatively important, we next show that this positive correlation arises because the largest firms have a higher sensitivity to macro shocks. We do so by generalizing equation (4), allowing for loadings on the common factor that vary by exporter size.[10]

Consider the following factor model according to which firm-level growth rates are determined by both a common factor – the macro shock – and a firm-specific shock: $g_{ft} = \beta_f \eta_t + \epsilon_{ft}$, where $\eta_t$ is a common shock, $\beta_f$ is a loading factor that is specific to firm $f$, and $\epsilon_{ft}$ is a firm-specific disturbance that is orthogonal to the macro shock. We are interested in the following question: do larger firms have a higher loading on the macro shock? Is yes, how important is the contribution of such higher sensitivity to macro shocks for aggregate fluctuations in comparison with idiosyncratic shocks?

We measure the macro shock as in the previous section, using the simple average growth rate over continuing firms in the sample: $\eta_t = \bar{g}_t$. We construct factor loadings that are a function of firm size. To allow for a flexible specification with potential non-linear effects, we estimate the following regression:

$$g_{ft} = \sum_{b=1}^{B} \alpha_b \mathbb{1}_{b(ft)} + \sum_{b=1}^{B} \beta_b \bar{g}_t \mathbb{1}_{b(ft)} + \epsilon_{ft} \tag{7}$$

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: $\mathbb{1}_{b(ft)}$ equals one if firm $f$ is in bin $b$ at time $t$. The model allows both for bin-specific intercepts $\alpha_b$, that capture average growth rates for each bin, and for bin-specific loadings $\beta_b$. We estimate (7) by weighted OLS using the midpoint weights $w_{ft}$.

We choose a parametric approach in which loadings are a function of firm size, as it will provide us with a more structured view of the role of firm size in driving aggregate fluctuations. The structure of (7) is close to the one developed in Gabaix and Koijen (2020), who use idiosyncratic shocks to large firms to construct GIV's as weighted average of individual shocks, preferring a parametric approach as we do.

We group firms into different size bins based on their total exports in the previous 12 months $t-1$ to

10. While one could argue that the unweighed average $\bar{g}_t$ might be driven by idiosyncratic shocks to large firms that affect smaller ones via production networks, we believe that such concern is to some extent limited by the use of exports data, where smaller firms sell to foreign customer and are less likely to be part of the larger exporters' value chains.

$t-12$. 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. Because the bins are constructed using lagged values, the bin-specific intercepts $\alpha_b$ control for potential reversion to the mean. We build the size bins as follows. We first construct the exporter-size distribution for each year, placing all exporters in a given 12-month period into bins based on their total exports in the time spell under consideration. The exporter-size distribution is very skewed in all periods of our sample. Given this high skewness, to reflect the properties of the actual distribution we construct particularly fine bins at the top. 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%.[11] 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 (as in most similar datasets for other countries, see e.g. Freund and Pierola (2015)).

The results are provided in Table 2. Column 1 restricts attention to continuing firms and Column 2 uses all firms.[12] 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). The estimated coefficients from this model are closely related to the aggregate $\hat{\beta}$ from Equ. (4). In particular, we have $\hat{\beta} = \frac{Cov(G_t, \bar{g}_t)}{Var(\bar{g}_t)} = \sum_b \frac{Cov(\omega_{bt} G_{bt}, \bar{g}_t)}{Var(\bar{g}_t)}$. If the share of size bins is constant over time, $\omega_{bt} = \bar{\omega}_b$, then this simplifies to $\hat{\beta} = \sum_b \bar{\omega}_b \frac{Cov(G_{bt}, \bar{g}_t)}{Var(\bar{g}_t)} = \sum_b \bar{\omega}_b \hat{\beta}_b$.[13]

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.

11. 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.

12. Notice that since both the intercept and the macro 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).

13. In practice, we find that $\hat{\beta} = 1.379$, 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. $\bar{\omega}_b = \frac{1}{T} \sum_t \omega_{bt}$.

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

| | (1) | (2) |
|---|---|---|
| | g | g |
| $\bar{g}_t \times b_1$ | -0.565 | 0.429 |
| | (0.552) | (0.267) |
| $\bar{g}_t \times b_2$ | 0.284** | 0.874*** |
| | (0.123) | (0.293) |
| $\bar{g}_t \times b_3$ | 0.855*** | 1.290*** |
| | (0.308) | (0.196) |
| $\bar{g}_t \times b_4$ | 1.106*** | 1.239*** |
| | (0.030) | (0.032) |
| $\bar{g}_t \times b_5$ | 1.228*** | 1.275*** |
| | (0.045) | (0.044) |
| $\bar{g}_t \times b_6$ | 1.244*** | 1.280*** |
| | (0.037) | (0.038) |
| $\bar{g}_t \times b_7$ | 1.281*** | 1.311*** |
| | (0.056) | (0.058) |
| $\bar{g}_t \times b_8$ | 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 (7). The dependent variable is the year-on-year mid-point growth rate at the firm $\times$ 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 $\omega_{ft}$. Standard errors are twoway-clustered at the firm and time level and reported into parenthesis. *** implies significance at the 1% level.
*Source*: French customs, Authors' calculations

### 3.3 Contribution to aggregate fluctuations of idiosyncratic reactions to macro shocks

The above results will allow us to further decompose changes in the granular residual over time into changes driven by idiosyncratic shocks *versus* idiosyncratic reactions to macro shocks, and shed light on the relative contributions of both to the fluctuations of aggregate exports.

We can re-write the granular residual as the sum of three components:

$$GR_t = \sum_f \omega_{ft}(g_{ft} - \bar{g}_t) = \sum_f \omega_{ft}\hat{\alpha}_b + \sum_f \omega_{ft}(\hat{\beta}_b - 1)\bar{g}_t + \sum_f \omega_{ft}\hat{\epsilon}_{ft} \tag{8}$$

Each component has a clear interpretation:

- $\sum_f \omega_{ft}\hat{\alpha}_b$; captures differences in growth rates depending on size, which are orthogonal to aggregate conditions (due to, e.g., different trends or mean reversion).

- $\sum_f \omega_{ft}(\hat{\beta}_b - 1)\bar{g}_t$ is our main variable of interest, which we define as $\lambda_t \equiv \sum_f \omega_{ft}(\hat{\beta}_b - 1)\bar{g}_t = \sum_b \omega_{bt}(\hat{\beta}_b - 1)\bar{g}_t$.[14] $\lambda_t$ captures, at each point in time $t$, the component of the granular residual that arises due to idiosyncratic reactions to macro shocks. If $\hat{\beta}_b < 1$ then firms in size bin $b$ react less than 1-to-1 to macro shocks and therefore tend to dampen the aggregate response. If on the contrary $\hat{\beta}_b > 1$ then firms in this size bin tend to amplify the aggregate response. If reactions to the macro shock are identical across size bins, then $\hat{\beta}_b = 1 \quad \forall b$ and $\lambda_t = 0$.

- $\sum_f \omega_{ft}\hat{\epsilon}_{ft}$ is the contribution of idiosyncratic shocks at the firm level, properly weighted by the contribution of firm $f$ at time $t$ to the aggregate midpoint growth rate $G_t$.[15]

We find that $\lambda_t$ matters quantitatively for aggregate fluctuations: it explains 27% of the variance of the granular residual, $\frac{Cov(GR_t,\lambda_t)}{Var(GR_t)} = 27\%$, with the remaining 73% coming from idiosyncratic shocks. Even though $\lambda_t$ is less important than idiosyncratic shocks for explaining the volatility of the granular

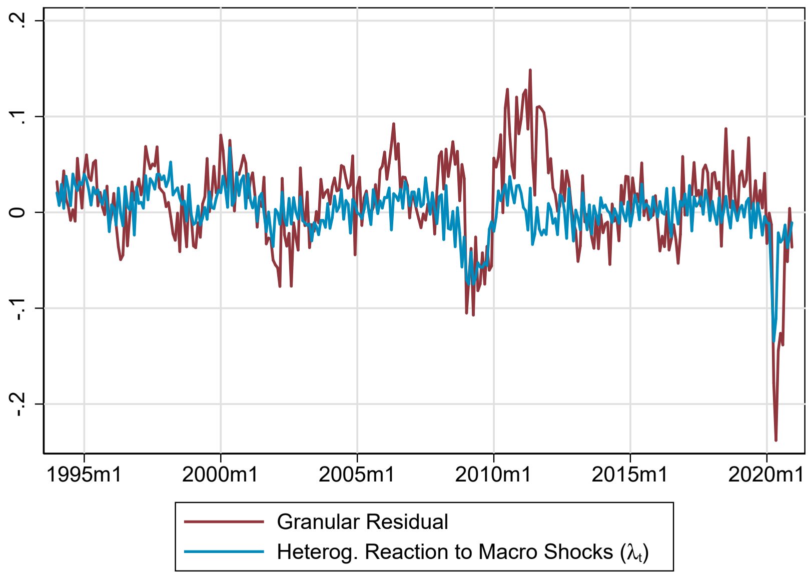
14. If $\omega_{bt}$ is constant over time, then $\hat{\beta} = \sum_b \omega_b\hat{\beta}_b$ and this simplifies to $\lambda_t = (\hat{\beta} - 1)\bar{g}_t$, where $\hat{\beta}$ is the coefficient from Equ. (4).

15. Notice that, by definition of weighted least squares, the weighted average of the error terms summing over both firms and time must be zero: $\sum_t \sum_f \omega_{ft}\hat{\epsilon}_{ft} = 0$. At a given point in time, however, the component capturing idiosyncratic shocks, $\sum_f \omega_{ft}\hat{\epsilon}_{ft}$, can be different from zero.

residual, it is actually *more* important than idiosyncratic shocks for explaining the volatility of aggregate export growth. We find 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 the granular residual). That is, idiosyncratic reactions to macro shocks, $\lambda_t$, account for roughly a quarter of aggregate export fluctuations. The reason is that $\lambda_t$ is particularly important when the macro shock is large, and this adds to the channel's contribution to the variance of aggregate growth.[16]

Figure 2 plots the evolution of $\lambda_t$ over time, together with the granular residual. The figure shows the positive correlation between both variables. It also highlights the latter, and important, point, which is that both variables are linked much more tightly during large macro shocks, as it is apparent for the case of the Great Financial Crisis of 2007/2008 and the Pandemic. We will zoom in on these two episodes later on.

Figure 2: Evolution of $\lambda_t$ and the Granular Residual (1993-2020, monthly data)




*Source*: French customs, Authors' calculations.

We are also interested in which size groups contribute the most to $\lambda_t$. To so do, we further decompose

16. The overall contribution of the granular residual is $\frac{Cov(G_t,GR_t)}{Var(G_t)} = \frac{Var(GR_t)}{Var(G_t)} + \frac{Cov(GR_t,\bar{g}_t)}{Var(G_t)}$. $\lambda_t$ accounts for 27% of the variance of the granular residual $\left(\frac{Cov(GR_t,\lambda_t)}{Var(GR_t)} = 27\%\right)$, but for all of the granular residual's covariance with the macro shock $\left(\frac{Cov(\lambda_t,\bar{g}_t)}{Cov(GR_t,\bar{g}_t)} > 99\%\right)$.

$\lambda_t$ into the contributions of each bin:

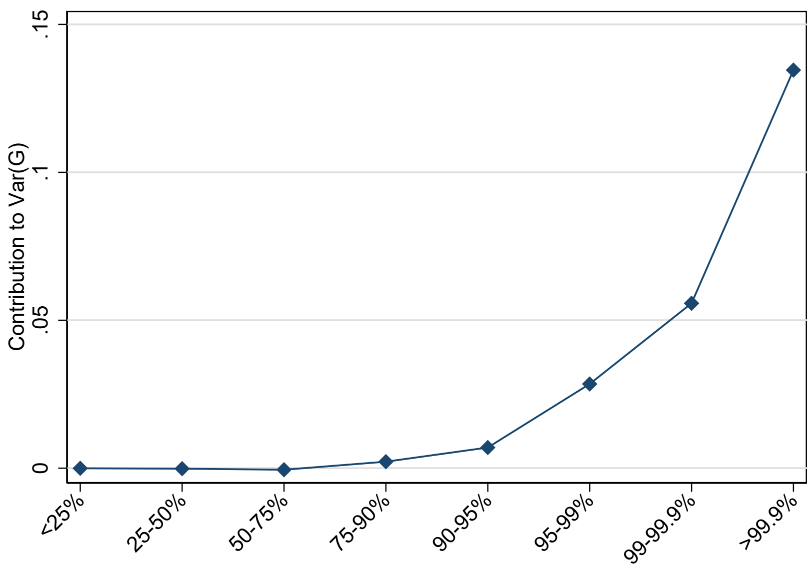
$$\lambda_t = \sum_b \lambda_{bt}, \qquad \text{with} \quad \lambda_{bt} = \omega_{bt}(\hat{\beta}_b - 1)\bar{g}_t$$

We then write

$$\frac{Cov(G_t, \lambda_t)}{Var(G_t)} = \sum_b \frac{Cov(G_t, \lambda_{bt})}{Var(G_t)}$$

Figure 3 shows these contributions by size bin. Out of the 23% of the fluctuations in $G_t$ that are explained by $\lambda_t$, 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 macro shock, as shown in Table 2.

Figure 3: Contribution of size groups to aggregate $\lambda_t$ (1993-2020, monthly data)




*Source*: French customs, Authors' calculations.

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

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

As mentioned, the aggregate relevance of heterogeneity in the sensitivity to macro shocks is larger the larger the shock (that is, the contribution of $\lambda_t$ increases with $\bar{g}_t$). This provides the rationale to study in detail the two major recent macro crises: the Global Financial Crises of 2008/2009 (GFC) and the Pandemic.

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

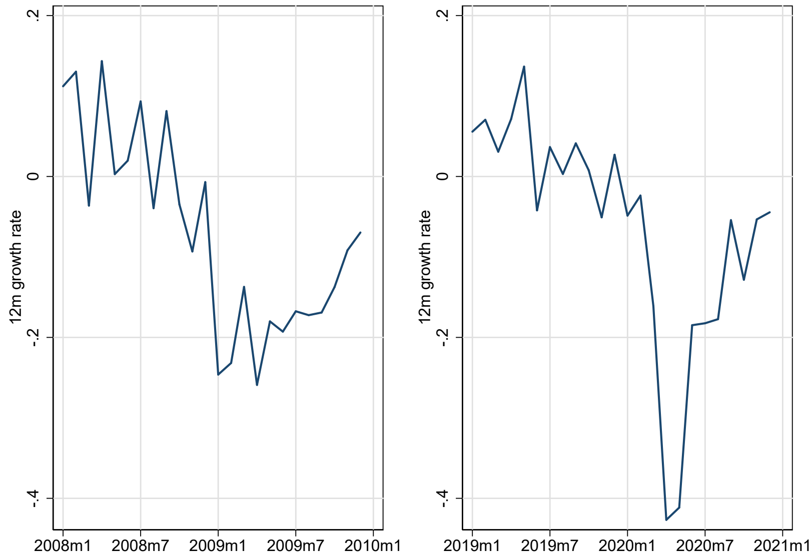
To dig deeper into the macro implications of the stronger reaction of large exporters to macro shocks, we zoom in on the two major shocks that are covered by our sample period: the 2008/2009 Global Financial Crisis and the Covid-19 Pandemic.[17] These two episodes are not only exceptional because of the collapse in aggregate economic activity, but also clearly show up in Figure 1 as the two largest negative macro shocks, evidenced by the fall in the average exporter growth rate. Figure 4 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).

We first construct the exporter-size distribution for each pre-crisis year separately, namely 2008 and 2019, in the same vein as in the previous analysis, placing all exporters in a given year into size bins based on their total yearly exports. The pre-crisis exporter-size distribution is shown in the black bars of Figure 5, which provide the share of aggregate exports accounted for by firms in different size bins in 2008 (left panel) and 2019 (right panel). As mentioned earlier, 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%.[18] The exporter-size distribution for 2007 is remarkably similar, with the top 1% exporters (1057 firms) accounting for 70%

17. A decomposition of the aggregate export growth during both crises into a firm intensive and extensive margin of adjustment in Appendix A.1 shows that both export collapses were almost entirely driven by changes in the export values of continuing exporters (see in particular Figures A3 and A4). The result that short-run aggregate movements in trade are mostly a result of the intensive margin rather than changes in net entry has been documented before, for example by Bernard et al. (2009) using US firm-level data and Eaton et al. (2007) using firm-level data covering all Colombian exporters. Looking at longer time horizons, Fernandes et al. (2019) report that the intensive margin can explain up to 40% of the variation in export values across country pairs on a sample of 50 countries. The relatively small contribution of the extensive margin is explained by the fact that most exiting firms, though sizeable in number, were very small in terms of export value.

18. 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.

Figure 4: Aggregate Export Growth, GFC (left) and Covid (right)



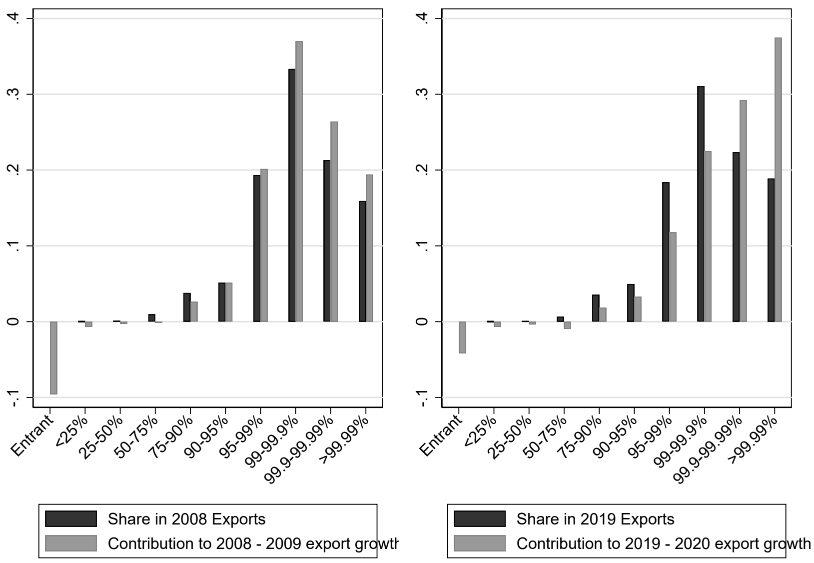

*Source*: Trade Data Monitor, Authors' calculations.

of aggregate exports, and the top 0.1% (105 firms) for 37%. The exporter-size distribution is remarkably stable over the entire period.

The light gray bars in Figure 5 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 disproportionably explained by the small group of "Superstar" exporters. Both panels provide evidence of a correlation between size and the rate of change, basically conveying the same information of the patterns in the long-run that we documented in Figure 1. But both panels 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 $\lambda$, 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.

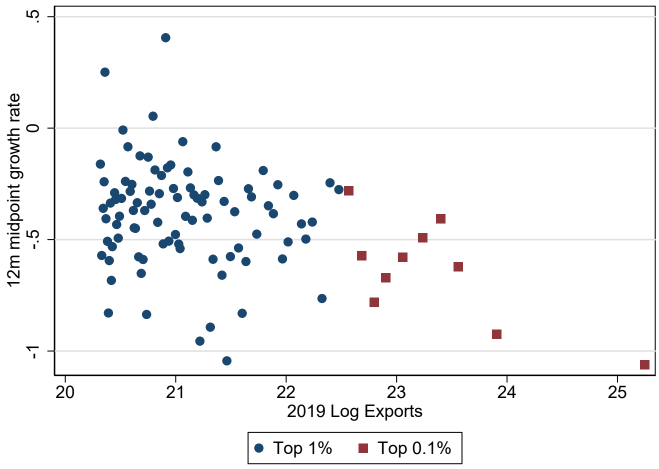
Figure 5: Export Shares and Growth Contribution during the GFC (left) and Covid (right) crises, by size bin




*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 6 we place the top 1,000 exporters into 100 bins of 10 firms each and compute for each bin the mid-point 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 5 could have been the result of a few outliers.

Figure 6: April-May 2020 12-month mid-point growth rate and 2019 exports of the 1,000 largest exporters




*Source*: French customs, Authors' calculations.

### 3.5 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 sector affiliation of the exporter or the particular geographical composition of export revenues. In order to account for potential confounding factors we take full advantage of the highly-detailed data and its monthly frequency. We now consider the 12 month export growth in month $t$ of each exporter $f$ for each destination-product pair $j, k$, namely $g_{fjk,t}$.

We adopt a flexible regression framework to study the dynamic adjustments of exports at the finest level of disaggregation in a transparent manner, allowing us to include several controls as we go along. Our baseline regression is the following:

$$g_{fjkt} = \alpha_{b(f)t} + \epsilon_{fjkt}, \tag{9}$$

where $g_{fjkt}$ is the year-on-year mid-point growth rate defined at the firm $\times$ country $\times$ product level,

$\alpha_{b(f)t}$ is a vector of exporter-size dummies and $\epsilon_{fjkt}$ is an error term. We estimate Equ. (9) by OLS, using weights $\omega_{fjkt}$ as defined in Section 2.2.

We run Equ. (9) on 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.[20] 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 mid-point growth rate as dependent variable.[21]

Figure 7 shows the result of estimating Equ. (9), 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 our nine size bins from Figure 5 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 mid-point growth rates of firms in the bin, which equals the aggregate bin-level mid-point 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.

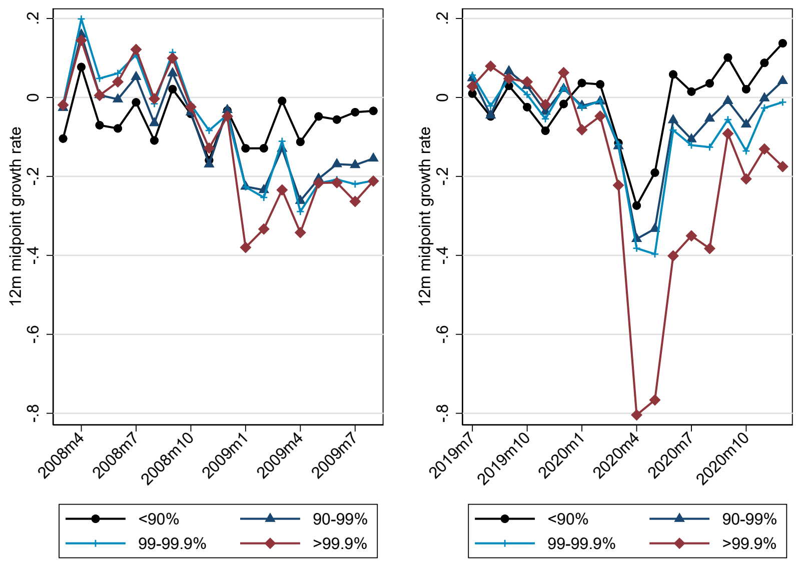
Top exporters led the export collapses of 2009 and 2020. Interestingly, in both episodes the largest exporters were also slower to recover in the months subsequent to the initial shock. Therefore, the lower aggregate yearly export growth rate documented in Figure 5 is the consequence of the combination of a stronger reaction to the initial shock and a slower recovery for the top exporters. Figure A6 in the Appendix A.3 shows a very similar pattern of growth rates across size groups when we use unweighted regressions.[22]

20. 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 A19 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.

21. 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.1.2 in the appendix).

22. For the unweighted regressions, we use a framework without sector-by-destination controls, as in Figure 7. Using sector-by-destination controls would require the use of detailed data, which would imply that we would implicitly weigh firms by their number of transactions.

Figure 7: Export growth during the GFC (left) and Covid (right) crises, by size bin




*Source*: French customs, Authors' calculations.

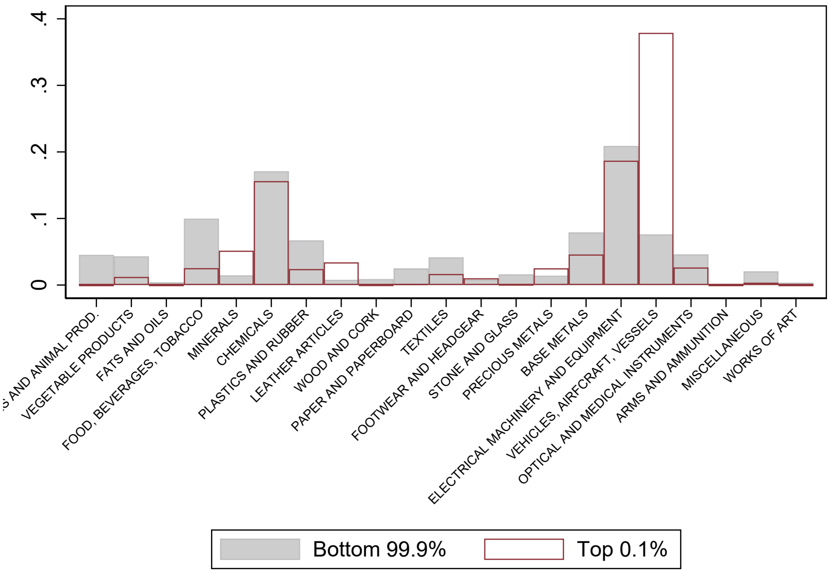
### 3.6 Netting out sectoral composition effects

Composition effects might plague the results, if for example large exporters are relatively more present in sectors more strongly affected during both crises. We illustrate such potential sectoral composition effects looking at the Pandemic in Figure 8. The figure shows, separately for the bottom 99.9% of exporters and the top 0.1%, the distribution of exports in 2019 across the 21 sections of the Harmonised System (HS), where one section includes one or more "Chapters" (2-digit HS codes, of which there are 99). While the distributions look broadly comparable, top exporters are clearly over-represented among aircraft exporters.

To account for the potential bias that would occur if large firms fell by more because of the sector affiliation, we add sector × destination fixed effects to the regressions. [23] In doing so we also control for potential systematic differences in geographical composition of exports by bins. Our main specification is the following: [24]

23. All main results presented here also 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.
24. 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 mid-point growth rate.

Figure 8: Distribution of top exporters across sectors (2019 data)




*Source*: French customs, Authors' calculations.

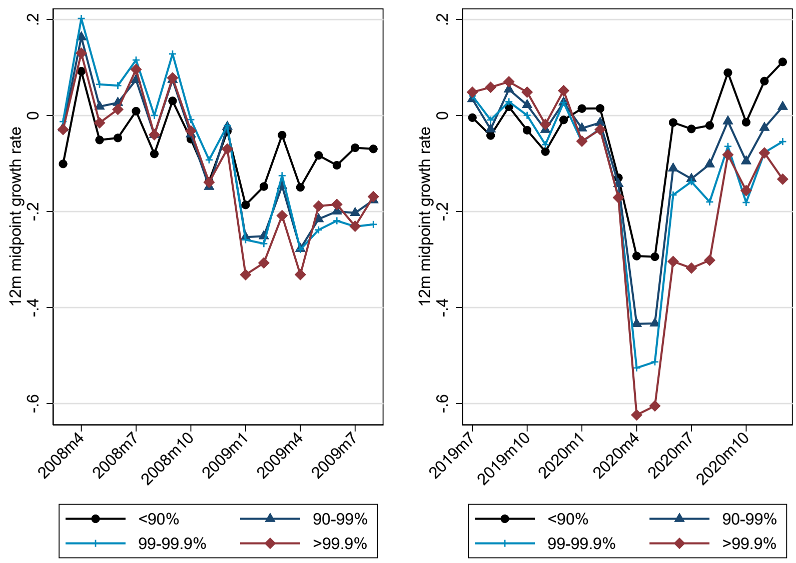
$$g_{fjkt} = \alpha_{b(f)t} + \beta_{jst} + \epsilon_{fjkt}, \tag{10}$$

where $\beta_{jst}$ denotes a time-specific sector $\times$ destination dummy. Sectors are defined using the 2-digit level of the Harmonized System. Results are shown in Figure 9. A comparison with Figure 7 reveals that sector $\times$ destination fixed effect do have some bite. For example, during Covid, the average mid-point growth rate for the top 0.1% bin is reduced from -0.8 to -0.6 when we control for composition. Composition effects seem to be less present during GFC, as the growth rate for the top 0.1% changes from 0.4 to 0.37. Overall, however, the main point of Figure 7 is unchanged: during both the GFC and the Pandemic, the export collapse was driven by the top exporters. [25].

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.

25. Appendix A.4 reports different specifications controlling for size groups, for sectors and for sector-destination.

Figure 9: Export growth during the GFC (left) and Covid (right) crises, by size bin




*Source*: French customs, Authors' calculations.

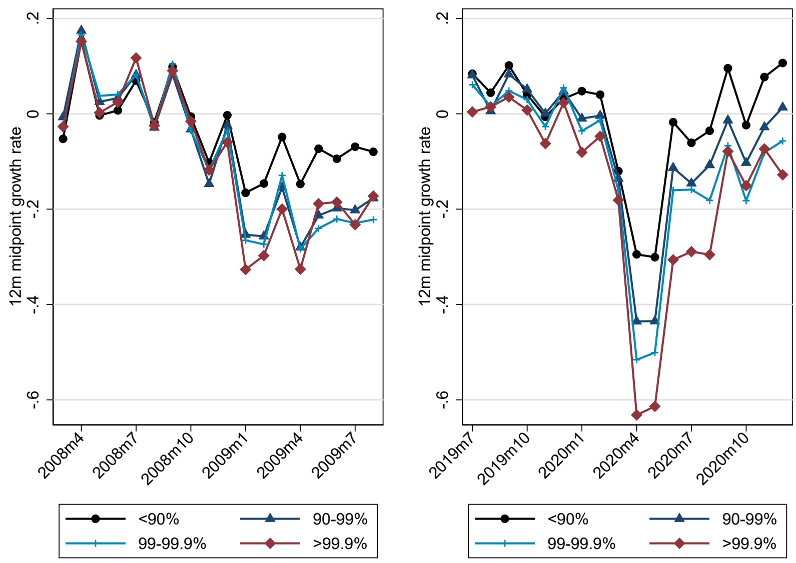
### 3.7 Accounting for reversion to the mean

A second potential problem for our results is reversion to the mean. Mean reversion can plague our results in the case that the largest exporters were growing at a higher rate than the bottom ones in the months prior to the macro shock, and the shock coincides with the reversion of these higher-than-average growth rates to their mean values. In that case, we would be overstating the overreaction of the large exporters to the shock. To control for such potential mean-reversion effects, we add controls for the growth rate before the crises. Specifically, we first calculate pre-crisis firm-level growth rates, using exports from between 2007-2008 for the pre-GFC period and between 2018-2019 for the pre-Covid period. We then construct bins of pre-crisis export growth and add them as controls to the regressions that include sector $\times$ destination fixed effects.[26]

The results are provided in Figure 10, where one can see that accounting for pre-crisis growth does not change the magnitude of the coefficients associated with exporter size.

26. We compute a total of 12 bins, comprising decile dummies among firms that export in both 2007 (resp. 2018) and 2008 (resp. 2019), one bin for entering and one bin for exiting firms.

Figure 10: Export growth during the GFC (left) and Covid (right) crises, by size bin, controlling for pre-crisis growth rates




*Source*: French customs, Authors' calculations.

## 3.8 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. [27]

We ask the following question: what would have been the aggregate export growth rate in 2008/2009 and 2019/2020 had the top exporters 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, presented in Figure 10. 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

27. The magnitude of the 2008 shock and the recovery has been studied by previous literature (REFS), but without a systematic comparison as we do now.

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. We start from the observation that at each point in time the weighted average of the composition-adjusted growth rates (i.e. the growth rate shown in Figure 10) equals aggregate export growth.[28] 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 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 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.

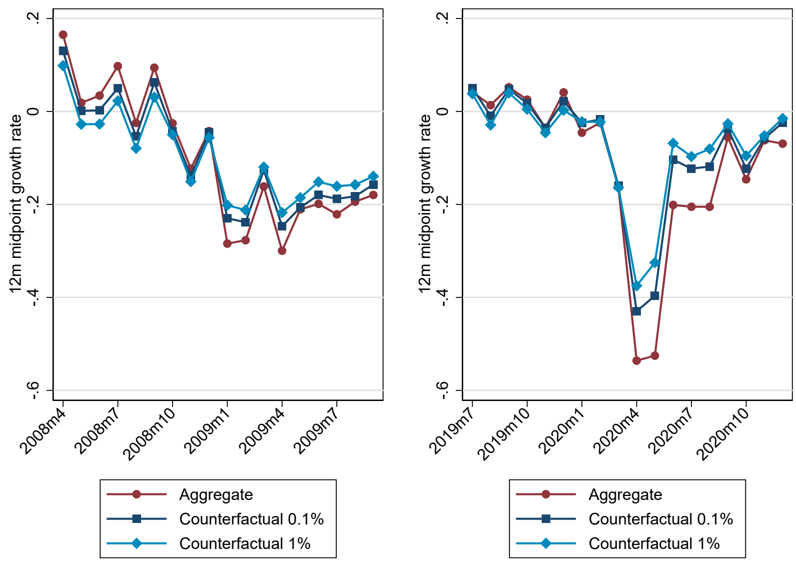
For the Pandemic, the counterfactual using the top 1% implies a year-on-year aggregate growth rate of -10.3%. The actual growth rate was of -16.3%, which implies that the overreaction of the top 1% adds -6.0 percentage points to the aggregate, or alternatively, that the strong reaction of the highest 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 11. We summarise these findings in the third *stylized fact*:

***Fact 3:*** *Larger exporters reacted more strongly than bottom exporters to both the GFC and the Covid*

28. We use the panel of balanced firms for the quantification. Appendix Figure A8 shows that aggregate growth rates using the balanced panel and the full panel are almost identical.

Figure 11: Export growth during the GFC (left) and Covid (right) crises, by size bin, controlling for pre-crisis growth rates




*Source*: French customs, Authors' calculations.

*crises, and such overreaction mattered for explaining the size of the export collapses.*

# 4 Supply *versus* demand

The first three facts uncovered in this paper show that the higher sensitivity of larger exporters **to major macro shocks** has a relevant role in determining the overall aggregate response: "from macro to micro to macro".[29] 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 Covid-19 Pandemic. The Pandemic 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

29. In contrast, Appendix A.7 points to the absence of differential effect for large importers.

and demand shocks.

In the next subsections, we focus on the months of April and May 2020, where aggregate exports recorded the largest fall (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 large demand shocks. We start with supply side explanations.

## 4.1 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 small 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, focusing only on two time periods allows us to turn again to the more detailed size groups used in Figure 5, and also to include all firms (entering, continuing, and exiting). The remainder of the framework is the same as before: we estimate Equ. (10), regressing the year-on-year mid-point growth rate on the (now finer) size-bin dummies and sector-by destination fixed effects, using weights.

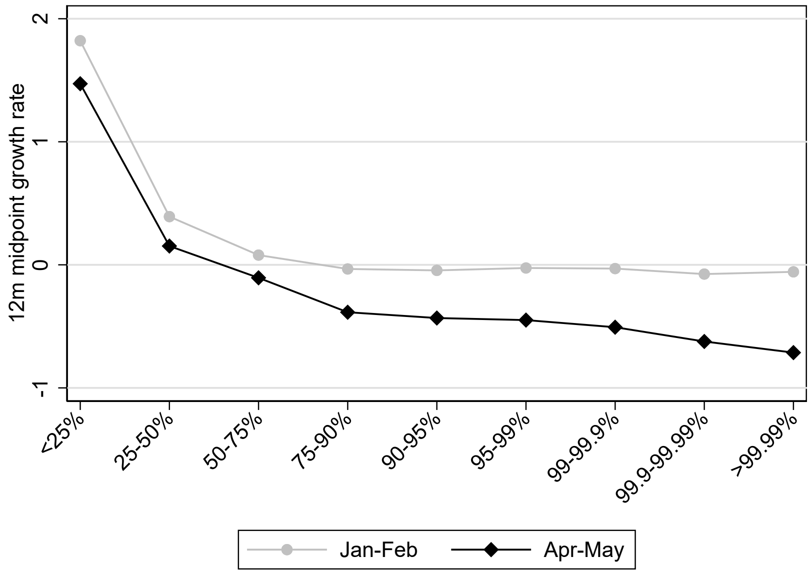
The results are provided in Figure 12. The line for January-February 2020 shows that firms above the 75th percentile grew at essentially the same rates *prior* to the crisis.[30] The line for April-May 2020 shows that at the onset of the crisis, growth rates were significantly lower for the largest exporters. 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. Appendix Table A1 provides details on point estimates and standard errors.

## 4.2 The role of supply shocks

A large literature suggests a prominent role for global value chains in the transition of supply shocks generated by the Pandemic. Bonadio et al. (2020) use a quantitative model of world production and trade, and find that a quarter of the decline of real GDP implied by their model is attributed to transmission

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

Figure 12: Midpoint growth rate by size bin: January-February vs April-May 2020




Note: Sector-destination fixed effects included.

*Source*: French customs, Authors' calculations.

of national labor supply shocks through GVCs. Heise (2020) shows that US imports from China declined by 50% at the onset of the Pandemic compared to the same months in 2019. Lafrogne-Roussier et al. (2022) estimate that French firms that sourced intermediate goods from China before lockdown was imposed in that country, experienced a larger drop in imports and exports than those firms not sourcing from China. Çakmaklı et al. (2021) use an epidemiological Susceptible-Infected-Recovered (SIR) model combined with international production linkages to focus on the role of unequal global vaccinations. In such a framework, advanced economies are shown to bear a large share of the economic costs of the Pandemic (up to 49%) because of the supply disruptions imposed by incomplete vaccinations in developing economies. 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).

Our goal in the present section is to understand whether GVC exposure can explain the differential reaction of exports by top exporters to the Pandemic. 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. We know from the work cited above that GVCs matter for shock transmission. We take a different approach and focus on whether GVC exposure can explain the overreaction by large exporters documented earlier.

#### 4.2.1 Measuring GVC integration of exporters

We construct measures of international sourcing for the exporters in our sample. We complement the export data with two additional datasets. First, for every exporter in our sample we add, by firm × month, information on imports by CN8 product and country of origin coming from the French Customs Office (the same source as the export data, see Section 2). Merging in import data does not lead to any reduction in our sample. We will refer to this dataset as the *Customs sample* from now on. 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. We thus capture engagement in value chains by linking imports and exports at the level of individual firms.[31]

Second, we use firm-level yearly balance sheet data to measure total sales. 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). 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.[32] We refer to the restricted sample as the *Customs-FIBEN sample*.

The reduction in the number of firms comes largely from the turnover threshold in the FIBEN data, which eliminates particularly smaller exporters. Despite the sizable reduction in the number of exporters, however, the *Customs-FIBEN sample* still accounts for 71% of aggregate exports in 2019. Figure A9 in the appendix gives details, by size bin, about the share of firms in the Customs-Sample that can be matched to FIBEN. While we capture few exporters in the bottom 75%, the FIBEN sample gives a reasonable representation of the right tail of the size distribution. In Figure A10 we also replicate the

31. Since the import data are exhaustive, we set imports of exporters that we do not find in the import data to zero. Focusing on firms that export in 2019, this sample comprises roughly 100,000 firms. Among these, roughly 25,000 firms exited exports markets in 2020 with respect to 2019. Another 25,000 entered in 2020 with respect to 2019, so that the sample of all exporters that are active at some point in 2019 or 2020 consists of 125,000 firms.

32. Including exporters that enter from 2019 to 2020, the sample captures 41,000 out of 125,000 firms.

disproportionate collapse of the top exporters from Figure 12 in the Customs-FIBEN sample, and find very similar patterns.

#### 4.2.2 Controlling for GVC Intensity

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 A11 in the Appendix.

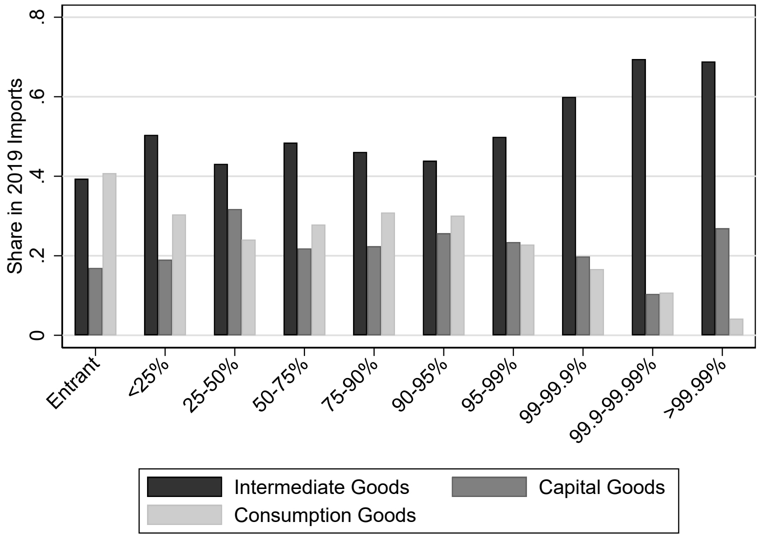
Figure 13 documents that the composition of imported goods changes with exporter size. In particular, imports by the largest exporters are more concentrated among intermediate and capital goods compared to imports by smaller firms: intermediate and capital goods account for over 95% of imports by firms that are placed in the top 0.01% of the export distribution, against 75% for those located in the 50-75% bin.[33]

To study whether the collapse of top exporters was due to their higher reliance on imported intermediate inputs 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 $Y_{f,2019}$ total firm sales (including both domestic sales and exports).[34] Figure 14 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 14. A regression of $IIS_{f,2019}$ on size bin dummies gives an $R^2$ of only 5%.

33. 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.7 and particularly Figure A13

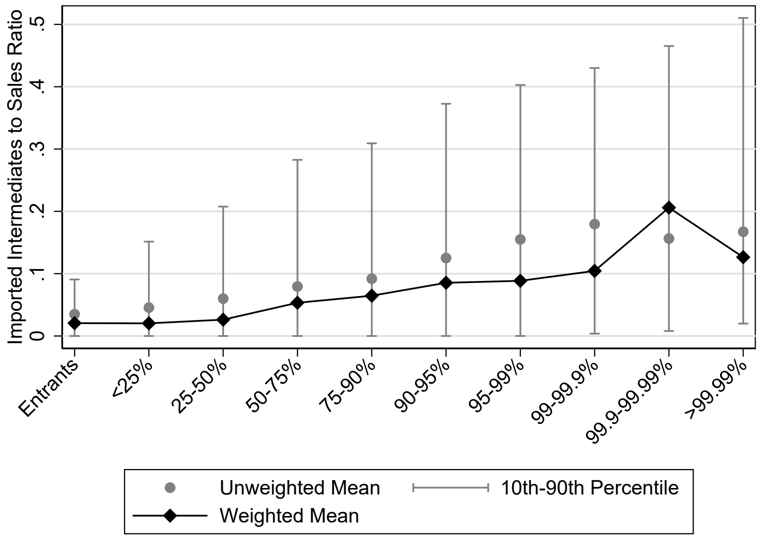
34. Both variables are calculated with yearly data for 2019, to capture the potential exposure of firms to the Pandemic-induced supply disruptions based on their pre-existing sourcing choices.

Figure 13: Share in imports of broad categories of products, by size bin of exporters (2019)




*Source*: French customs, Authors' calculations.

Figure 14: $IIS$ ratio by size bin



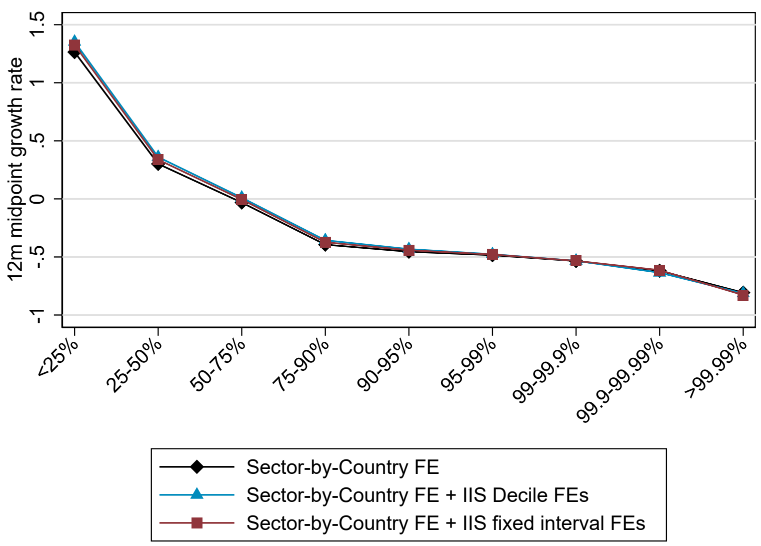

Note: import values as weights.
*Source*: French customs, Authors' calculations.

While this relatively weak correlation already suggests that GVC exposure is unlikely to explain the disproportionate collapse of top exporters, we still test for this possibility in a more explicit way. We augment Equ. (10) with a set of dummies representing the firm's position in the distribution of the *IIS ratio*, whose effects are captured by $\gamma_{r(f)t}$. We control for sector-destination fixed effects.[35]

$$g_{fkjt} = \alpha_{b(f)t} + \beta_{sjt} + \gamma_{r(f)t} + \epsilon_{fkjt} \tag{11}$$

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 15. Within sector-destinations, controlling for systematic differences across firms in terms of dependence on foreign inputs does not affect at all the coefficients associated with the size dummies. We conclude that the reliance on imported inputs (as captured by the *IIS ratio*) did not drive the collapse of superstar exporters.

Figure 15: Midpoint growth rate of exports by size bin, controlling or not for the *IIS* ratio




*Source*: French customs, Authors' calculations.

Beyond the reliance on imported inputs captured, superstar exporters may have been more exposed

35. 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.

to foreign supply shocks because of the geographical structure of imports. To test for this potential channel, 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: $\text{Supply Shock}_{ft} = \sum_i \frac{M^{int}_{fi,2019}}{M^{int}_{f,2019}} \text{Stringency}_{it}$, where $\text{Stringency}_{it}$ is the monthly average of the Oxford Stringency Index in origin country $i$ at month $t$ (Hale et al., 2021).[36] Thus, $\text{Supply Shock}_{ft}$ 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*:

$$\text{Input Supply Shock}_{ft} = IIS_{f,2019} \times \text{Supply Shock}_{ft} \tag{12}$$

We proceed as before, constructing bins of $\text{Input Supply Shock}_{ft}$ and introducing them as controls in Equ. (10). The results are shown in Figure 16: controlling for the exposure to supply chain disruptions does not impact the coefficient associated with the size dummies.

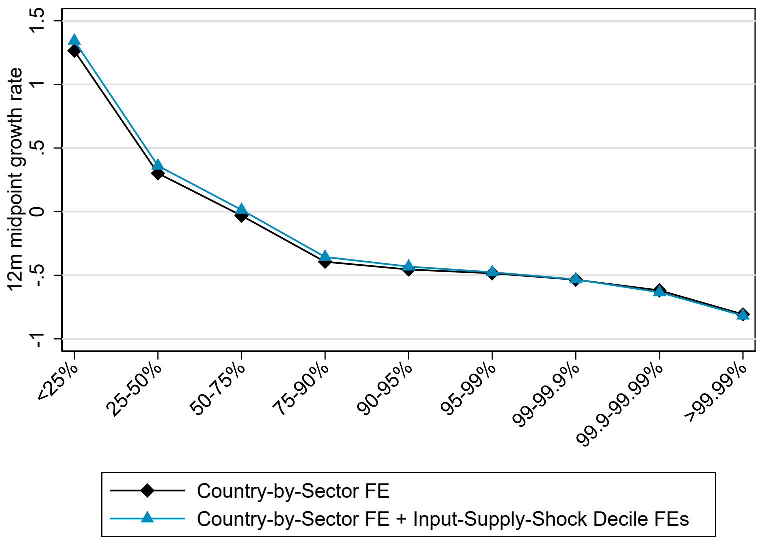
Let us now turn to the potential role of demand shocks.

### 4.3 The role of demand shocks

We now examine whether heterogeneous reactions to demand shocks can explain the stronger reactions of the largest exporters. There are two main possibilities how the largest exporters could suffer more from foreign demand shocks. First, they may be more exposed to foreign demand shocks if their portfolio of

36. 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 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 16: 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.

export destinations is tilted towards countries that happened to have stronger contractions in demand. This composition effect is controlled for by the sector-by-destination fixed effects used in our main specification. Second, the largest exporters may exhibit a higher elasticity to foreign demand shocks. This is the hypothesis we are investigating in this section.

To test for this hypothesis, we proceed as follows. We regress the mid-point 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 mid-point 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 $\alpha$. 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: we compare export growth of the same exporter to destination A (strong lockdown) with its export growth to destination B (weak lockdown), controlling for product-level shocks. Unobservable shocks to firm $f$ are captured by a firm $\times$ time fixed effect $\beta_{ft}$. 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 $\gamma_j$. Finally, product-level shocks common to all destinations and exporting firms are absorbed by a product $\times$ time fixed effect $\delta_{kt}$.

Results are reported in Table 3. 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 mid-point 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 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.

Table 3: 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.

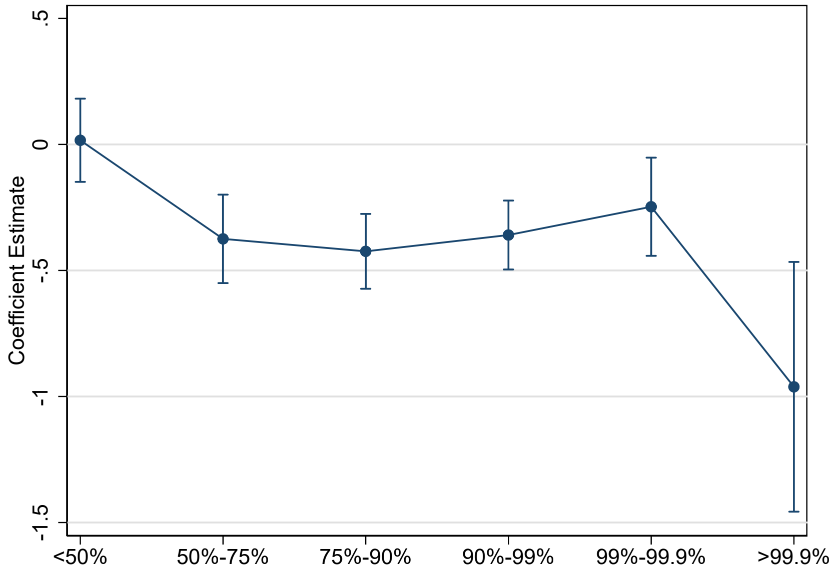
Notes: OLS estimations of (13). The dependent variable is the year-on-year mid-point growth rate at the firm × product × destination × month level. The estimations cover the period from January 2019 to June 2020. Products are defined at the CN8 level of the European Combined Nomenclature. Standard errors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

Figure 17 shows that the top exporters have a higher elasticity with respect to foreign demand shocks. [37] 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. In their empirics (and model), the higher sensitivity of sales to foreign GDP shocks for the largest firms is due to the fact that these firms are more "open", i.e., they have a higher ratio of exports to sales. What we show here is that larger firms are more sensitive to foreign shocks not only because they trade more, but also because they react more to a given shock on their export markets: *the elasticity of exports of larger firms to a severe demand shock is larger.*

Since our results do not reveal a heterogeneous impact of supply-side bottlenecks by size, the above result highlights that the heterogeneous responses to demand shocks explain the overreaction of the largest firms, rather than their vulnerability to supply-side shocks. To provide further evidence of the lack of quantitative effect of supply shocks on exports, in the Appendix we ask whether the imports of larger exporters were more affected than those of smaller exporters as a consequence of foreign supply shocks. While large exporters did reduce their imports relatively more, results from a specification akin to (14), but where imports are regressed on lockdowns in origin countries, show that the effect of lockdowns in origin countries is not statistically different from zero in the case of the top 0.1% exporters, while it

37. 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 17: Effect of Destination Lockdown by Size Bin




*Source*: French customs, Author's calculation.

is negative but small (with an elasticity of around 0.2) for the rest of exporters. Thus, although large exporters reduce their imports more than smaller ones during the period under study (see Figure A12), the data point to a causality running from exports to imports, and not the other way round.

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.*

# 5 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 macro 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 macro 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 macro shocks, as opposed to Global Value Chain 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.

# References


Aghion, P., Bergeaud, A., Cette, G., Lecat, R. and Maghin, H. (2019), 'Coase lecture - the inverted-u relationship between credit access and productivity growth', *Economica* (C), 86:1–31.

Amiti, M., Itskhoki, O. and Konings, J. (2014), 'Importers, exporters, and exchange rate disconnect', *American Economic Review* **104**(7), 1942–1978.

Antràs, P. (2020), Conceptual aspects of global value chains, Technical report, World bank policy research working paper 9114.

Bergounhon, F., Lenoir, C. and Méjean, I. (2018), 'A guideline to French firm-level trade data', *Unpublished manuscript* .

Bernard, A. B., Jensen, J. B., Redding, S. J. and Schott, P. K. (2009), 'The margins of US trade', *American Economic Review* **99**(2), 487–93.

Boehm, C. E., Flaaen, A. and Pandalai-Nayar, N. (2019), 'Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tohoku earthquake', *The Review of Economics and Statistics* **101**(1), 60–75.

Bonadio, B., Huo, Z., Levchenko, A. A. and Pandalai-Nayar, N. (2020), Global supply chains in the pandemic, Technical report, National Bureau of Economic Research working paper 27224.

Brussevich, M., Papageorgiou, C. and Wibaux, P. (2022), Trade and the covid-19 pandemic: Lessons from French firms, Technical report, International Monetary Fund Working paper 22/81.

Cahn, C., Duquerroy, A. and Mullins, W. (2020), 'Unconventional monetary policy and bank lending relationships', *Proceedings of Paris December 2019 Finance Meeting EUROFIDAI - ESSEC* (C).

Çakmaklı, C., Demiralp, S., Kalemli-Özcan, S., Yeşiltaş, S. and Yıldırım, M. A. (2021), The economic case for global vaccinations: An epidemiological model with international production networks, Technical report, National Bureau of Economic Research working paper 28395.

Carvalho, V. M. and Grassi, B. (2019), 'Large firm dynamics and the business cycle', *American Economic Review* **109**(4), 1375–1425.

Carvalho, V. M., Nirei, M., Saito, Y. and Tahbaz-Salehi, A. (2016), 'Supply chain disruptions: Evidence from the great East Japan earthquake', *Columbia Business School Research Paper* (17-5).

Crouzet, N. and Mehrotra, N. R. (2020), 'Small and large firms over the business cycle', *American Economic Review* **110**(11), 3549–3601.

Di Giovanni, J., Levchenko, A. A. and Méjean, I. (2014), 'Firms, destinations, and aggregate fluctuations', *Econometrica* **82**(4), 1303–1340.

Di Giovanni, J., Levchenko, A. A. and Méjean, I. (2017), 'Large firms and international business cycle comovement', *American Economic Review* **107**(5), 598–602.

Di Giovanni, J., Levchenko, A. A. and Méjean, I. (2020), Foreign shocks as granular fluctuations, Technical report, National Bureau of Economic Research Working Paper 28123.

Eaton, J., Eslava, M., Kugler, M. and Tybout, J. (2007), 'The margins of entry into export markets: evidence from Colombia', *mimeo* .

Eaton, J., Kortum, S. S. and Sotelo, S. (2012), International trade: Linking micro and macro, Technical report, National bureau of economic research working paper 17864.

Fernandes, A. M., Klenow, P. J., Meleshchuk, S., Pierola, M. D. and Rodriguez-Clare, A. (2019), 'The intensive margin in trade: How big and how important?', *Unpublished manuscript* .

Freund, C. and Pierola, M. D. (2015), 'Export superstars', *The Review of Economics and Statistics* **97**(5), 1023–1032.

Gabaix, X. (2011), 'The granular origins of aggregate fluctuations', *Econometrica* **79**(3), 733–772.

Gabaix, X. and Koijen, R. (2020), Granular instrumental variables, Technical report, National Bureau of Economic Research working paper 28204.

Galaasen, S., Jamilov, R., Juelsrud, R. and Rey, H. (2020), Granular credit risk, Technical report, National Bureau of Economic Research working paper 27994.

Gaubert, C. and Itskhoki, O. (2021), 'Granular comparative advantage', *Journal of Political Economy* **129**(3), 871–939.

Gertler, M. and Gilchrist, S. (1994), 'Monetary policy, business cycles, and the behavior of small manufacturing firms', *The Quarterly Journal of Economics* **109**(2), 309–340.

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S. and Tatlow (2021), 'A global panel database of pandemic policies (Oxford COVID-19 government response tracker)', *Nature Human Behaviour* .

Haltiwanger, J., Jarmin, R. S. and Miranda, J. (2013), 'Who creates jobs? small versus large versus young', *Review of Economics and Statistics* **95**(2), 347–361.

Heise, S. (2020), How did China's covid-19 shutdown affect U.S. supply chains?, Liberty Street Economics May 12, Federal Reserve Bank of New York, https://libertystreeteconomics.newyorkfed.org/2020/05/how-did-chinas-covid-19-shutdown-affect-us-supply-chains.html.

Kaplan, G. and Violante, G. L. (2018), 'Microeconomic heterogeneity and macroeconomic shocks', *Journal of Economic Perspectives* **32**(3), 167–194.

Lafrogne-Roussier, R., Martin, J. and Méjean, I. (2022), 'Supply-shocks in supply chains: Evidence from the early lockdown in China', *IMF Economic review* . https://doi.org/10.1057/s41308-022-00166-8.

Levchenko, A. A., Lewis, L. T. and Tesar, L. L. (2010), 'The collapse of international trade during the 2008–09 crisis: in search of the smoking gun', *IMF Economic review* **58**(2), 214–253.

Liu, X., Ornelas, E. and Shi, H. (2022), 'The trade impact of the covid-19 pandemic', *The World Economy* **45**(12), 3751–3779.

O'Rourke, K. H. (2018), 'Two great trade collapses: the interwar period and great recession compared', *IMF Economic Review* **66**, 418–439.

Ottonello, P. and Winberry, T. (2020), 'Financial heterogeneity and the investment channel of monetary policy', *Econometrica* **88**(6), 2473–2502.

# 6 Appendix

## A.1 The intensive and extensive margins during Covid and GFC

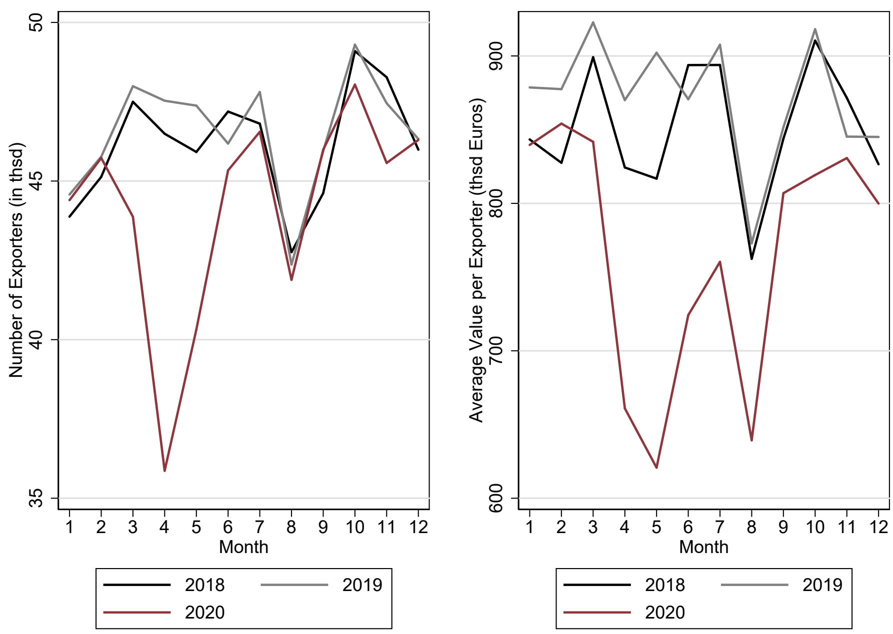
### A.1.1 Firm Intensive and Firm Extensive Margins

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, $\bar{x}_t$:

$$X_t = N_t \bar{x}_t \tag{15}$$

Figure A1 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 A1: Number of exporters (left) and average value per exporter (right)




*Source*: French customs, Authors' calculations.

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

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 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 A2. 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 A2 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 A1. 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.

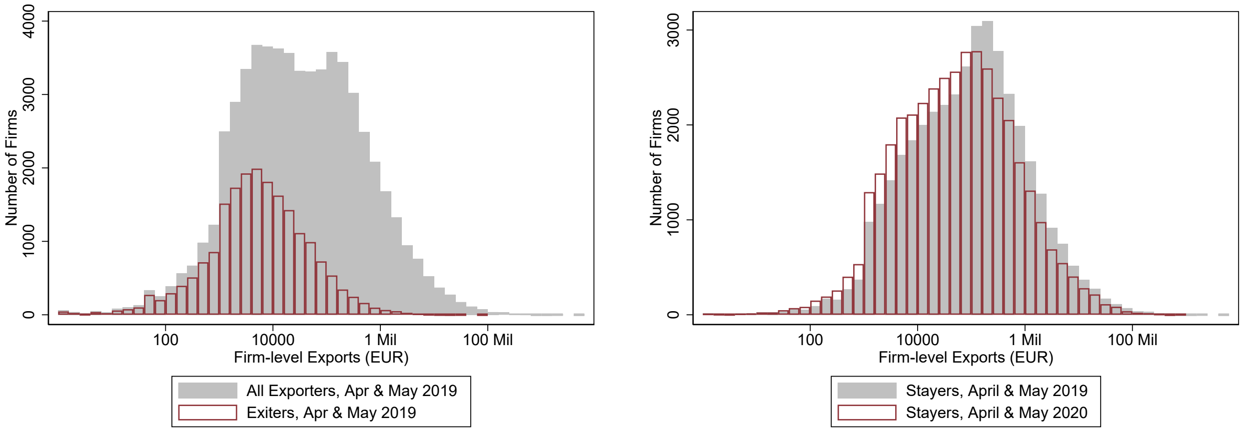
We apply the following decomposition of the year-on-year growth rate of total exports:

$$\frac{\Delta X_t}{X_{t-1}} = \frac{\sum_{f \in S_t} \Delta x_{f,t}}{X_{t-1}} + \frac{\sum_{f \in E_t} x_{f,t} - \sum_{f \in L_t} x_{f,t-1}}{X_{t-1}} \tag{16}$$

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 $t-12$.

39. In the left panel of Figure A2, the mass of continuous exporters is given by the difference between all exporters and exiters.

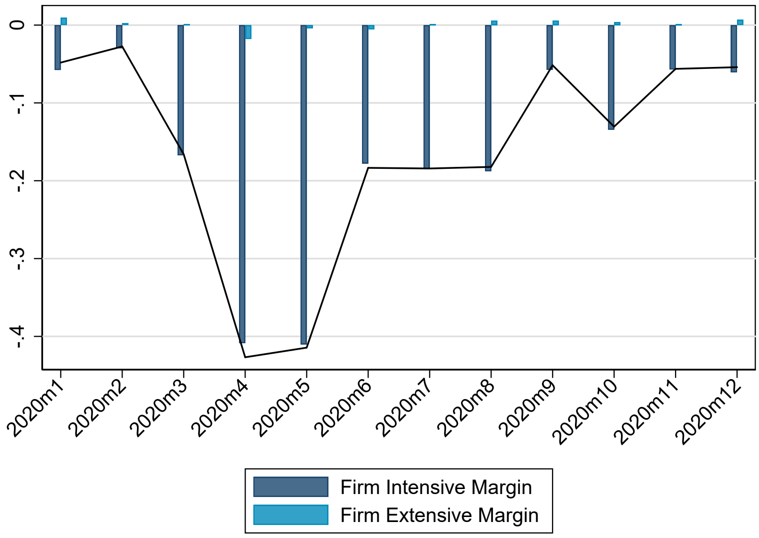
Figure A2: Firm-level export distributions of exiters *vs* continuing exporters: Apr-May '19 vs Apr-May '20




*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.

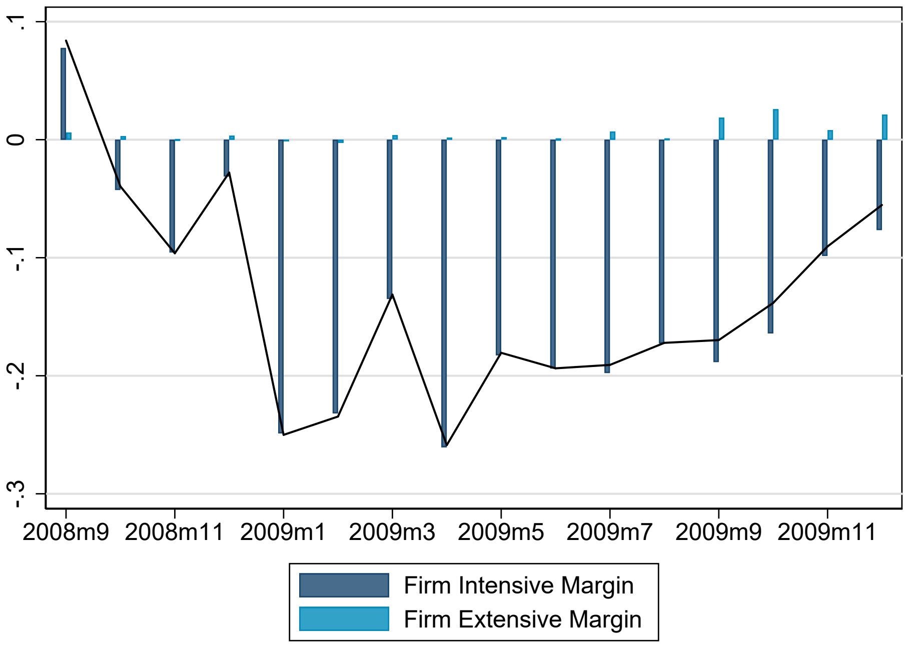
The results of applying (16) to the 2020 data are provided in Figure A3, where $\frac{\Delta X_t}{X_{t-1}}$ is given by the black solid curve. Its two components are represented by the bars: the firm intensive margin is represented in the light blue bars and the firm extensive margin in the dark blue bars. The same exercise is done for the GFC in Figure A4.

Figure A3: 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 A4: Contributions of the firm intensive and extensive margins during the GFC



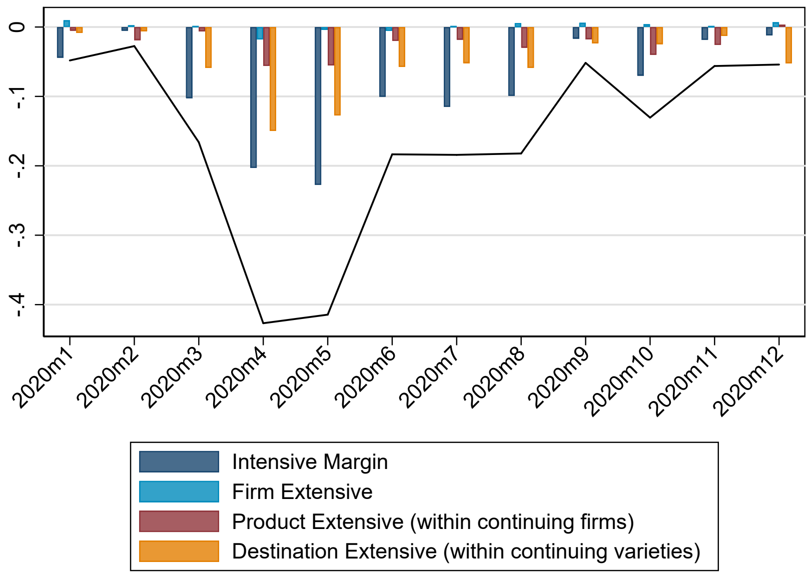

*Source*: French customs, Authors' calculations.

### A.1.2 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 A5 with the following decomposition, that follows Bernard et al. (2009):

$$\frac{\Delta X_t}{X_{t-1}} = \underbrace{\frac{\sum_{f \in N} x_{f,t} - \sum_{f \in L} x_{f,t-1}}{X_{t-1}}}_{\text{Firm Extensive}} + \underbrace{\frac{\sum_{f \in S} \sum_{k \in S_f} \sum_{j \in S_{fk}} \Delta x_{fkj,t}}{X_{t-1}}}_{\text{Firm-Product-Destination Intensive}}$$
$$+ \underbrace{\frac{\sum_{f \in S}(\sum_{k \in N_f} x_{fk,t} - \sum_{k \in L_f} x_{fk,t-1})}{X_{t-1}}}_{\text{Product Extensive}} + \underbrace{\frac{\sum_{f \in S} \sum_{k \in S}(\sum_{j \in N_{fk}} x_{fkj,t} - \sum_{j \in L_{fk}} x_{fkj,t-1})}{X_{t-1}}}_{\text{Destination Extensive}} \quad (17)$$

Figure A5: 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.2 Estimations of size effects on mid-point growth rates

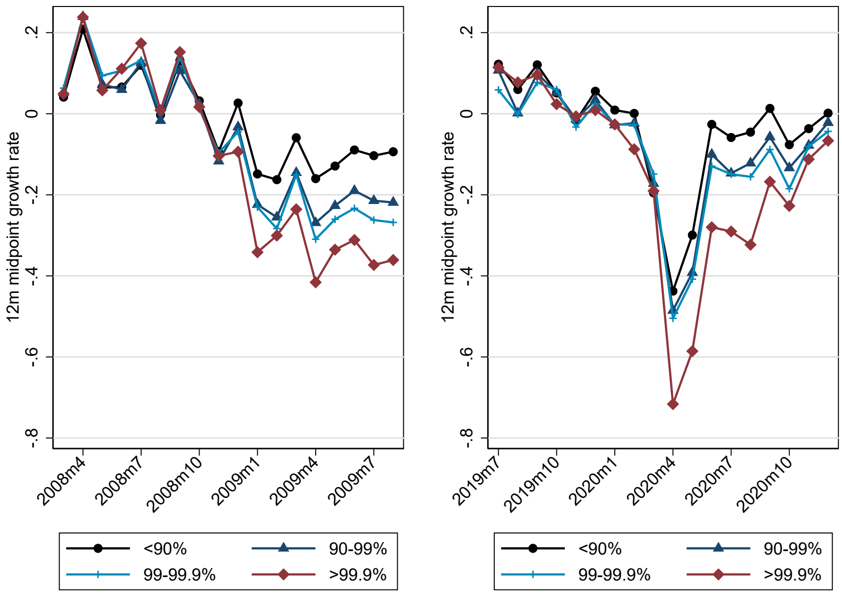
Table A1: Estimations of size effects on mid-point growth rates

| | (1) mid-point 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 mid-point 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 Growth rates across size groups from unweighted regressions

Figure A6: Export growth during the GFC (left) and Covid (right) crises, by size bin (unweighted regressions)

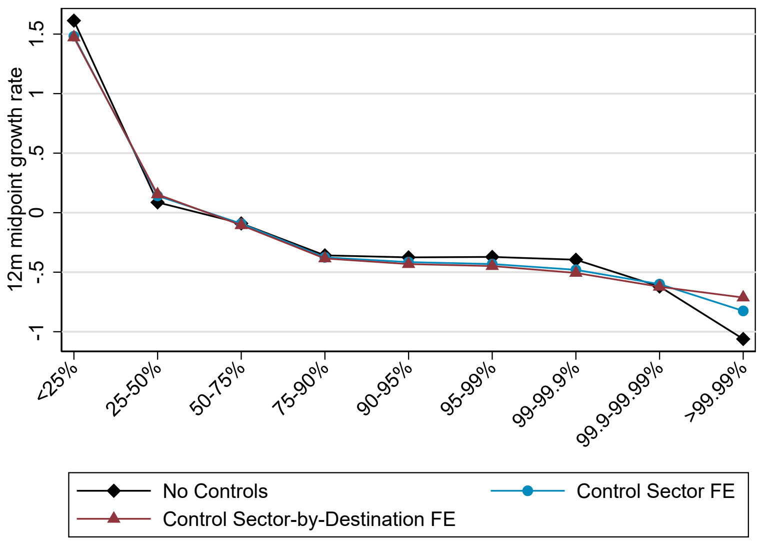



*Source*: French customs and Fiben Bank of France, Authors' calculations.

## A.4 The role of compositional effects

Figure A7 reports different specifications of our main estimation Equ. 10. 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.

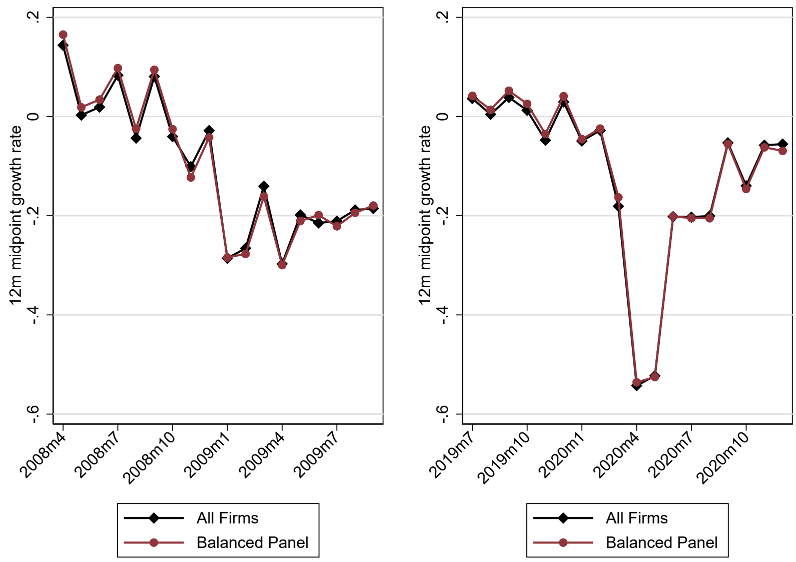
Figure A7: Specifications with and without sector effects




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

## A.5 Aggregate midpoint growth rate using the balanced and the full panel

Figure A8: Export growth during the GFC (left) and Covid (right) crises, by size bin, balanced panel and full panel



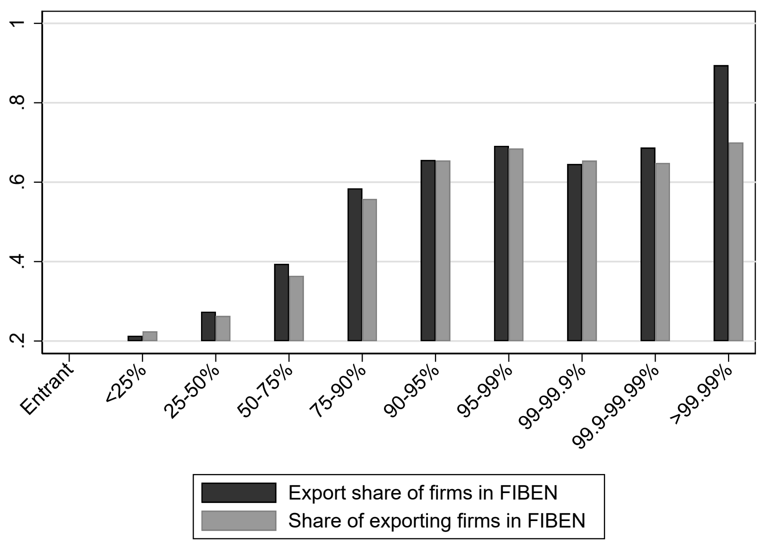

*Source*: French customs, Authors' calculations.

## A.6 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 Bank of 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).

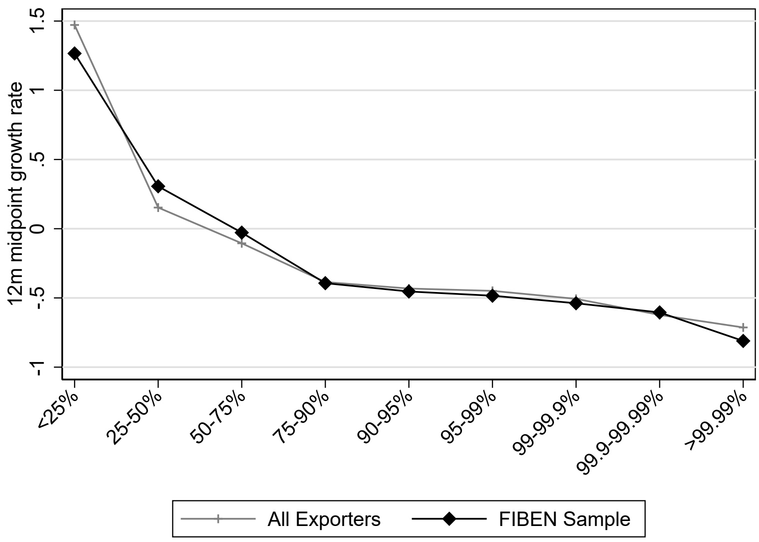
Because of the turnover threshold, the number of firms in the FIBEN dataset is substantially lower than that in the Customs data. Let us first check whether the sample of firms in Fiben is representative. The sample is comprising large exporters as a result of the threshold of turnover (above 750 keuros): 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 A9. The same conclusion holds if one reproduces the previous exercise of computing the 12-month mid-point growth rate of exports by size bin of exporters for the Fiben sample as shown in Figure A10. 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 A9: Share and export share of exporters in Fiben




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

Figure A10: 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.7 Imports of exporters

Large exporters are also large importers as illustrated in Figure A11.

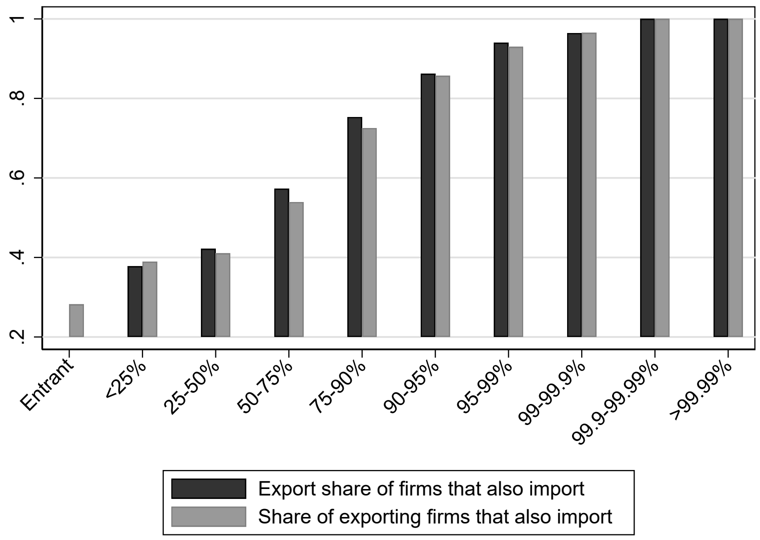
A straightforward motivation to look at supply shocks is provided by the fact that top exporters reduced their imports relatively more than smaller exporters, starting from March 2020 and being especially strong during the months of May and June 2020 as shown in Figure A12.

We now regress the growth rate of imports by exporter, product and origin (as documented in Figure A13) on a series of fixed effects plus the stringency of lockdown at origin, as done in Equ. 13:

$$g_{fik,t} = \alpha Lockdown\ Stringency_{i,t} + \beta_{ft} + \gamma_i + \delta_{kt} + \epsilon_{fik,t} \tag{18}$$

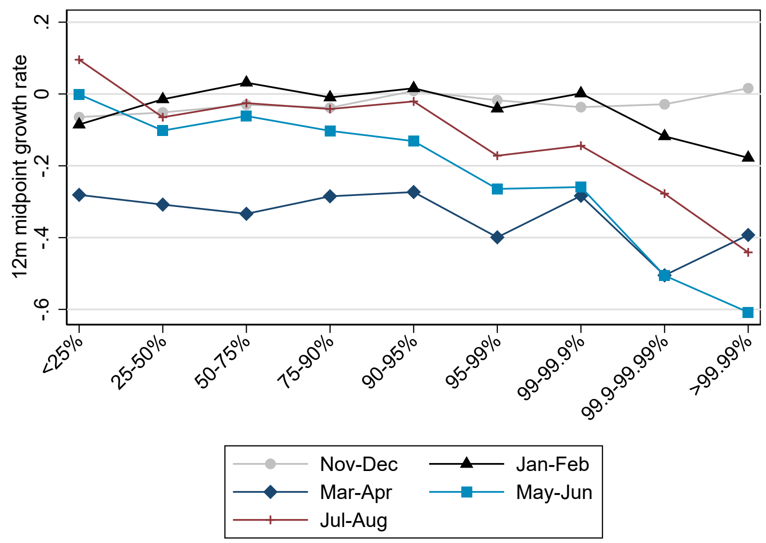
where $g_{fik,t}$ is the mid-point growth rate of imports by exporter $f$ of product $k$ from origin country $i$ during month $t$, as defined above. $Lockdown\ Stringency_{i,t}$ is the value taken by the Oxford Index of stringency in origin country $j$, divided by 100 so that it takes values in the range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

Figure A11: Export share of firms and share of exporting firms that import




*Source*: French customs, Authors' calculations.

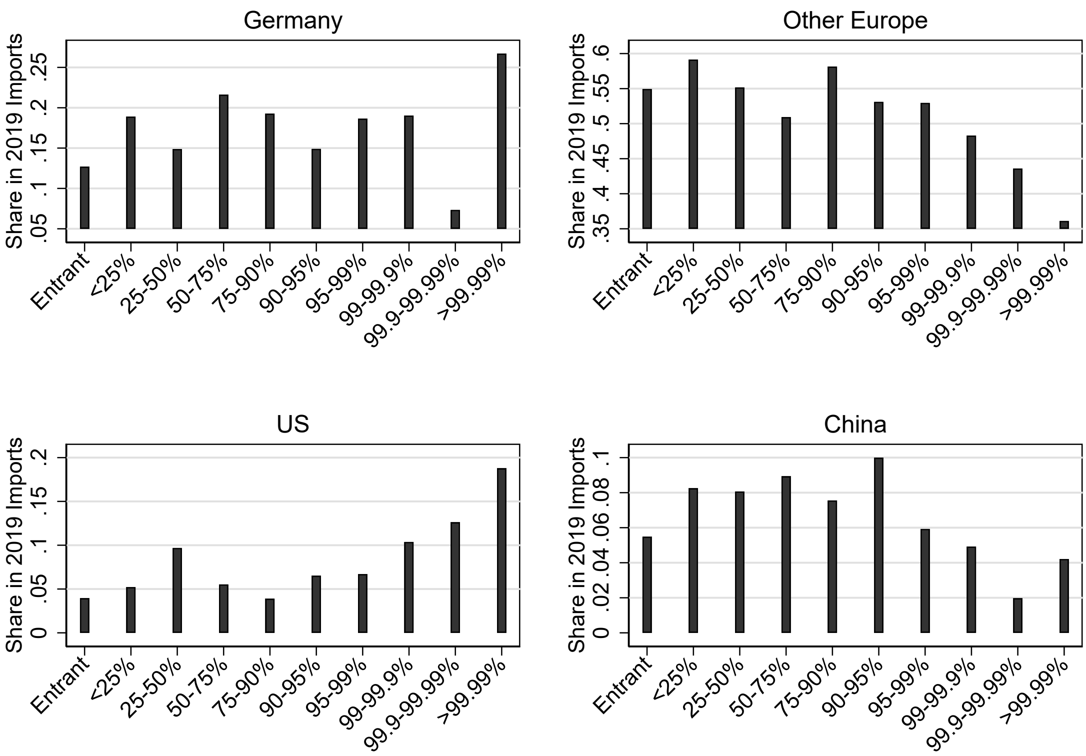
Figure A12: Exporter's imports during the Covid crisis (Nov.-Dec. 2019 to July-Aug. 2020)




*Source*: French customs, Authors' calculations.

unobserved characteristics (France is indeed the destination of all imports) are captured by a vector of origin fixed effect $\gamma_i$, and $\delta_{kt}$ a product-time fixed effect capturing any unobserved product-level shock common to all destinations and exporting firms.

Figure A13: 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 18, grouping the top exporters into a bin containing the highest 0.1%. We estimate the following baseline equation, equivalent to Equ. (14):

$$g_{fik,t} = Lockdown\ Stringency_{i,t} \times \eta_{b(f))} + \beta_{ft} + \gamma_i + \delta_{kt} + \epsilon_{fik,t} \tag{19}$$

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 A2: Effect of Origin Lockdowns

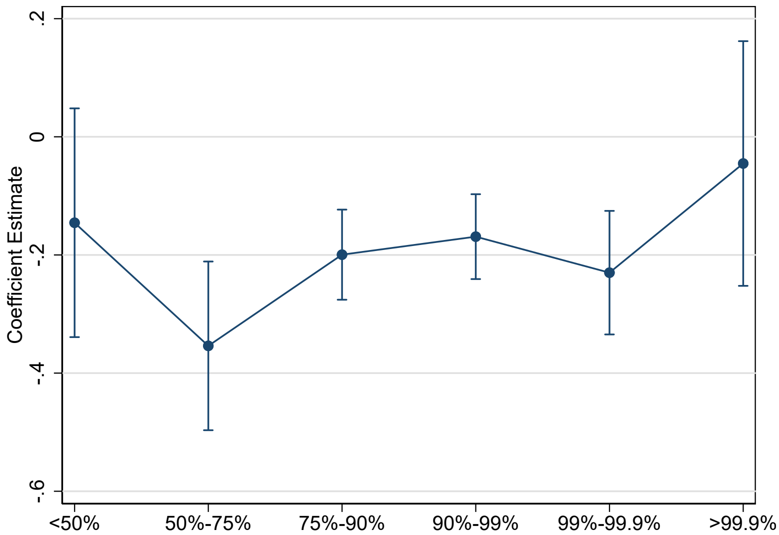
| | (1) | (2) |
|---|---|---|
| | Midpoint growth rate of imports | |
| Lockdown Stringency | -0.244 | -0.202 |
| | (0.0446) | (0.0438) |
| Observations | 10,126,825 | 10,124,779 |
| R-squared | 0.379 | 0.459 |
| Firm x Time | ✓ | ✓ |
| HS2 x Time | ✓ | |
| Destination | ✓ | ✓ |
| NC8 x Time | | ✓ |

Notes: OLS estimations of (13) on the subsample of exporters that report positive import values.The dependent variable is the year-on-year mid-point 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 A2 shows the results of the estimation of Equ.18. The take home is that the correlation of lockdown stringency at origin with the mid-point 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 mid-point growth of imports by 0.2 percentage point only (against 0.6 in the case of exports, see Table 3 in the main text).

Results when interacting with size bins of exporters, shown in Figure A14, 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.

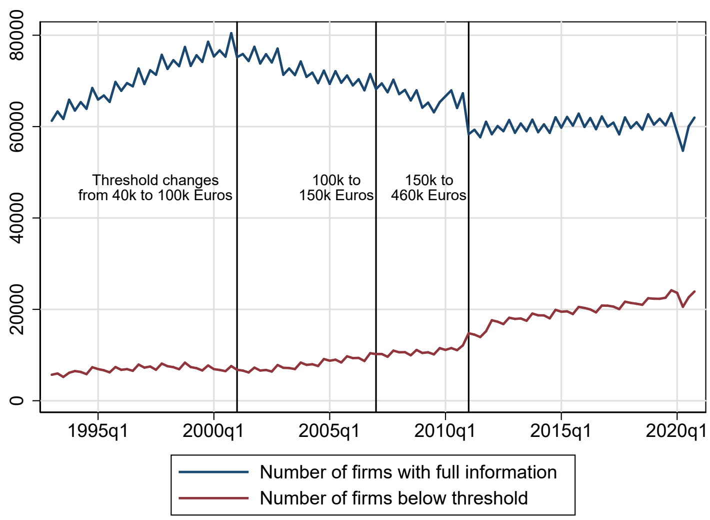
Figure A14: Impact of Covid at origin on imports by exporter size




*Source*: French customs, Authors' calculations.

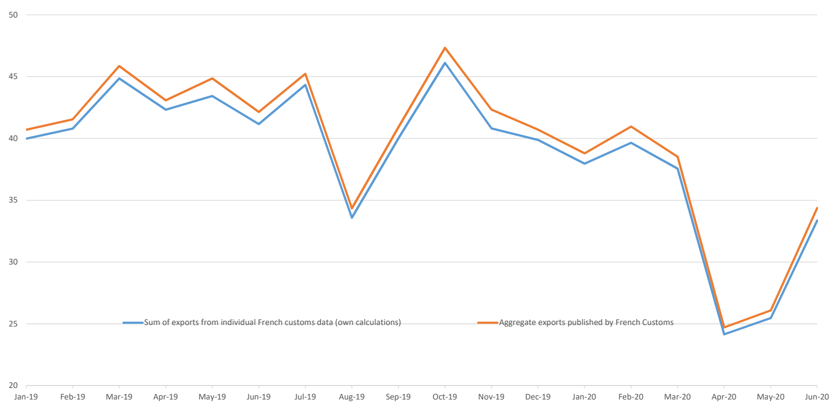
# B Online appendix

Figure A15: Number of firms with detailed export information and number of small exporters



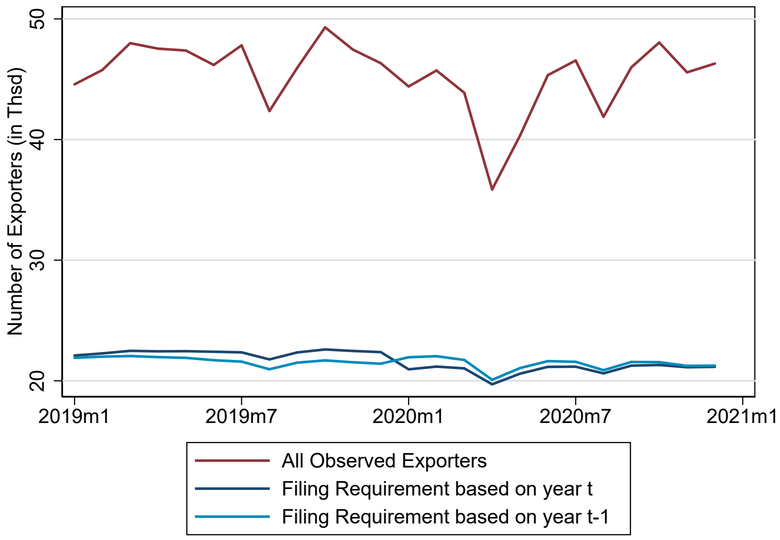

*Source*: French customs, Authors' calculations.

Figure A16: Coverage of aggregate statistics with transaction data




*Source*: French customs, Authors' calculations.

Figure A17: Exporters with and without filing obligation (2019-2021)




*Source*: French customs, Authors' calculations.

Figure A18: Midpoint growth rate vs log change

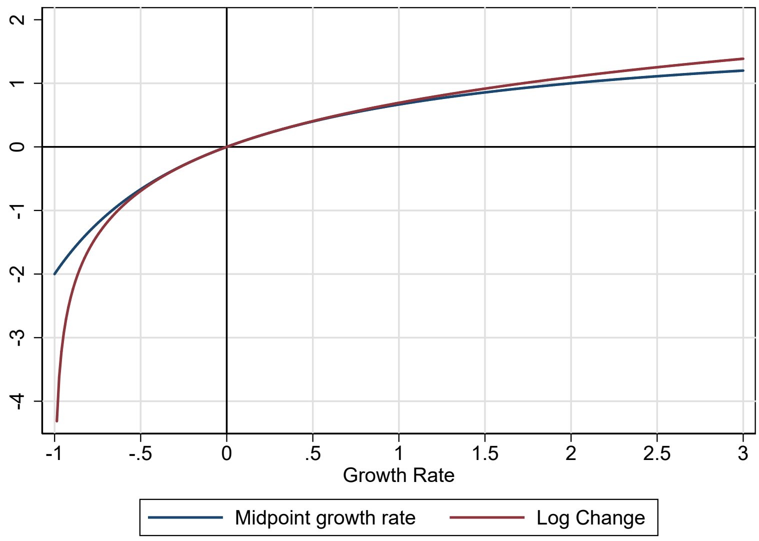


Figure A19: Growth rate for the balanced panel and the aggregate during the GFC and the Pandemic