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From Macro to Micro: Large Exporters Coping with Common Shocks

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ABSTRACT

Since Gabaix (2011), the role of changes in the performance of some very large firms in shaping aggregate outcomes has been intensively studied in the economic literature. Changes in the performance of a few large firms can arise due to idiosyncratic shocks or idiosyncratic reactions to common shocks. This paper provides direct evidence for the second channel using data on the universe of French firm-level exports and imports over 1993-2020. Granularity matters for the micro-dynamics of aggregate French exports over the long run: the granular residual explains 42% of the variance in aggregate export growth during the period. Moreover, it co-moves with the macro shocks: the largest firms do better than average in good times and worse in bad times. Studying firm-level performance during the Great Financial Crisis and the Pandemic reveals that top exporters contributed to the export collapses disproportionably more than their pre-crisis share of exports, even within finely defined markets. We investigate the reasons for such over-reaction of the top exporters using the Pandemic as a natural experiment. We find that a higher elasticity to demand shocks explains the larger reaction of top exporters to the Pandemic, with GVC exposure having weak explanatory power. Our findings have macro implications, as they help understand the macro reaction to foreign shocks, and micro implications, since they can inform micro models of exports.

Keywords: Granularity; Exports; COVID crisis.

JEL Classification: F14

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NON-TECHNICAL SUMMARY

Changes in the performance of some very large firms matter for aggregate outcomes in granular economies. The "micro to macro" approach, linking micro behaviour to macro outcomes, has considerably advanced our understanding of macro aggregates such as business cycles, comparative advantage, and the international transmission of shocks.

Since changes in the performance of these large firms matter for the macroeconomy, it is paramount to understand their roots. Why do large firms perform differently than the smaller ones? While the literature has focused on the role of idiosyncratic shocks, a complementary view poses that large firms have differential reactions to common shocks affecting all firms. This approach posits that macro shocks lead to heterogeneous reactions, in particular by the largest firms, which in turn determine the macro reaction to the initial shock: i.e. from macro to micro, and back to macro. We analyse the contribution of the largest exporters to aggregate export fluctuations over a long period, spanning 1993-2020. We rely on the universe of detailed firm-level export data collected by the French Customs office, containing export values by destination country at a finely-defined product codes and, crucially, available at a monthly frequency.

A decomposition of aggregate export growth (at quarterly frequency for the sake of readability) into an unweighted average of firm export growth rate and a granular residual captures the covariance between firm size and firm growth. If the response to macro shocks were uncorrelated with firm size, then the granular residual would be zero. The granular residual is not zero and, furthermore, it explains a large share of aggregate export fluctuations: 42% of the variance of aggregate export growth. Moreover, the coefficient of correlation between unweighted average firm growth and the granular residual is close to 0.5. This implies that large exporters tend to do worse than the average exporter in times of downturn, and better than average in times of upturn.

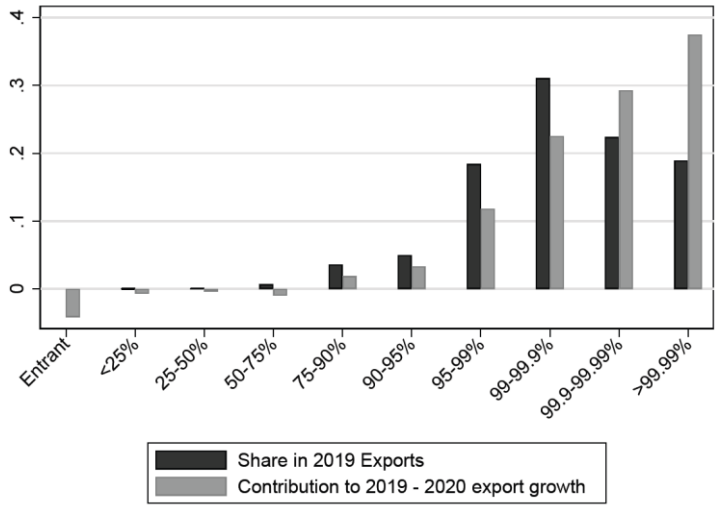
The overreaction of large exporters to macro shocks is sizeable and clearly seen in the case of the two largest macro global shocks of the past decades: the Global Financial Crisis and the Pandemic. Not only are the two export collapses almost entirely explained by the intensive margin (firms that continue to export), but they were also caused by the largest exporters, whose export growth rates were significantly lower than those of the average exporter.

We zoom in the export collapse of April and May 2020 in Figure below. Given the large concentration of exports, we choose particularly fine bins at the top of the distribution. For instance, the top 1% (roughly 1,000 firms out of 100,000) account for over 70% of total exports. The black bars show the share of aggregate exports in April and May 2019 accounted for by each size bin. We then compare the pre-crisis export share of each bin with its contribution to the aggregate export collapse between April and May 2019 and April and May 2020, measured as the change in total exports of a bin divided by the change in aggregate exports. If all firms grew at the same rate, the contribution of each bin would equal its pre-crisis share. The figure shows that the small group of "Superstar" exporters disproportionately explains the slump in exports. Within the top 0.1%, the 10 largest exporters alone account for around one third of the export collapse, while they exported 19% of the total pre-crisis values. Such negative relationship between pre-crisis size and export adjustment to the crisis holds also within the set of 1,000 larger exporters.

Large firms are more likely to be more engaged in complex GVCs. While the data reveals that larger exporters tend to be more heavily engaged in GVCs than smaller ones, adding GVC measures to our regressions does not affect the magnitude and significance of the exporter size-bin dummies. In other words, large exporters overreaction was not due to their deep engagement in GVCs. On the contrary, we do find convincing evidence of a demand channel, which is not driven by the sector or destination

composition of exporters. Instead, we estimate a larger elasticity of large firms to destination-country lock-downs.

Figure: Export share in 2019 Covid and contribution to 2019-2020 trade growth, by size bin



Note: Pre-crisis export share and contribution to the aggregate export collapse between April and May 2019 and April and May 2020. Exporter-size bins are constructed using the 2019 export value by firm.

Du macro au micro : les grands exportateurs confrontés à des chocs communs

RÉSUMÉ

Depuis Gabaix (2011), le rôle des variations de la performance de quelques très grandes entreprises dans le cycle macroéconomique a été largement étudié dans la littérature économique. Les changements dans la performance de quelques grandes entreprises peuvent être dus à des chocs idiosyncratiques ou à des réactions idiosyncratiques à des chocs communs. Cet article met en évidence le second canal en utilisant des données détaillées sur l'ensemble des exportations et des importations des entreprises françaises sur la période 1993-2020. La granularité joue un rôle important dans la dynamique de long terme des exportations françaises totales : le résidu granulaire explique 42 % de la variance de la croissance des exportations agrégées au cours de la période. De plus, elle amplifie les chocs macroéconomiques : les plus grandes entreprises font mieux que la moyenne en période de prospérité et moins bien en période de crise. L'étude des performances des entreprises pendant la grande crise financière et la pandémie révèle que les principaux exportateurs ont contribué à l'effondrement des exportations de manière disproportionnée par rapport à leur part dans les exportations avant la crise, même au sein de marchés finement définis. Nous étudions les raisons de cette réaction amplifiée en utilisant la pandémie comme expérience naturelle. Nous constatons qu'une plus grande élasticité aux chocs de demande explique la réaction plus importante des principaux exportateurs à la pandémie, l'exposition aux chaînes de valeur mondiales ayant un faible pouvoir explicatif.

Mots-clés : granularité ; exportations ; crise du COVID.

1 Introduction

Since the seminal contribution of Gabaix (2011), 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 alike. Changes in the performance of very large firms may result from idiosyncratic shocks or from idiosyncratic reactions to common 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.

This paper provides evidence that the largest firms react more strongly to common macro shocks than smaller firms. We document this fact by studying the evolution of French exporting firms over a long horizon (1993-2020) and by focusing particularly on two large crises, the 2009 Great Financial Crisis (GFC) and the 2020 Covid-19 Pandemic. During both crisis episodes, exports of the top exporters collapsed by more than other firms, controlling for compositional differences linked to sectors and/or destinations and accounting for the effect of potential reversion to the mean in export dynamics. This overreaction of the largest firms amplifies the response of aggregate economic activity to the shock in a quantitatively meaningful way. For example, in the case of Covid, had the top 1% of exporters grown at the same rate as the bottom 99% in 2020, aggregate French exports would have fallen by only 11.2% instead of 16.3%.

To make progress on the underlying causes of the stronger reaction by the largest exporters we zoom in on one particular episode, the Covid-19 Pandemic, where the collapse of economic activity was clearly driven by a common, aggregate shock. Combining data on firm exports, imports, and balance sheets, we explore several hypotheses for the disproportionate collapse of the top exporters. We find no support for a GVC-based view, whereby the top exporters would collapse by more because of their higher dependence on foreign intermediate inputs. Instead, we do find evidence for a demand channel : While the top firms were not differentially exposed to foreign demand shocks, they display a significantly larger elasticity to a given foreign demand shock.

Taken together, our results suggest a novel channel of amplification of macro shocks. The largest exporters exhibit a stronger reaction to common demand shocks than the average exporter and this overreaction matters quantitatively to explain the size of the macro reaction to the shock.

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. We also complement the export data with information on firm-level imports, and balance sheet data (FIBEN) collected by Banque de France.

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 a first set of interesting results. First, the granular residual is not zero : aggregate exports feature granularity. Second, the contribution of granularity to aggregate export fluctuations is sizeable : a variance decomposition of the aggregate growth rate gives a share of 60% that comes from average firm growth and a 40% share coming from the granular residual. Third, average firm growth and the granular residual are positively correlated, with a correlation coefficient $\rho = 0.55$. Since the unweighed average growth rate captures the magnitude of the macro shock, the positive correlation is consistent with the view that movements in the granular residual arise, at least partly, from larger firms reacting more strongly to common macro shocks. This overreaction has important aggregate consequences, as evidenced by the large share of aggregate volatility that is explained by the granular residual.

We then go further by analysing firms' responses to two large macro shocks that are covered by our sample period, the GFC and the Covid Pandemic, during which the export collapse was very similar in magnitude : -17.4% in 2009 and -16.0% in 2020. We show that both export collapses were almost entirely driven by the changes in the export values of continuing exporters (the intensive margin). Among those, the top exporters declined by substantially more than the average exporter. A potential confounding factor is that the largest exporters might have a different composition of activity in terms of sectors and destinations. To control for these compositional effects, we develop a flexible estimation framework where we regress the transaction-level mid-point growth rate on a set of exporter size dummies and sector-by-destination (*market*) fixed effects. The disproportionate collapse of the top exporters holds within these finely defined markets, pointing to heterogenous reactions of the largest firms to the shock. Furthermore, adding pre-crisis growth rates to the regressions as controls does not affect the magnitude of the exporter

size bin dummies, alleviating concerns that part of the effect of firm size could be the consequence of a process of reversion to the mean.

Having established the role of large firms in export fluctuations and their stronger reaction to macro shocks as a prominent explanation, we then zoom in on the Covid-19 Pandemic. [1] We analyze the crisis in detail because it is a clear example of an aggregate shock. 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. To control for heterogeneous reactions along other dimensions that might be correlated with size, most notably industry affiliation, we conduct our analysis within individual markets (sector-by-destination cells).

We move on to test for different explanations for these patterns, through the analysis of supply and demand shocks. We start with supply shocks. Our aim is to understand whether the larger GVC exposure of top exporters can explain their stronger reaction to the shock, not whether GVCs are important per se. We augment the flexible regression framework with measures of exposure to GVCs. For this, we complement the export data with information on firm-level imports and sales. We measure GVC exposure of each exporter with the ratio of imported intermediate inputs to sales (IIS ratio) and supply shock exposure using information on lockdowns in the origin countries of imports. While the data reveals that larger exporters tend to be more heavily engaged in GVCs than smaller ones, adding GVC measures to our regressions does not affect at all the magnitude of the exporter size-bin dummies. GVC exposure of the largest exporters does not explain their underperformance during the Covid crisis.

On the contrary, we do find evidence of a demand channel. This demand channel is not driven by the sector or destination composition of exporters, as we show that there is no significant heterogeneity in the exposure of firms to foreign lockdowns according to size. Instead, we estimate a larger elasticity of large firms to destination-country lockdowns. In particular, we regress the mid-point growth rate at the firm-product-country-month level on the Oxford Stringency Index in the destination country j at month t (Hale et al. (2021). 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 : identification relies on variation in export growth of the same firm across destinations with varying

1. de Lucio et al. (2020) for Spain and Amador et al. (2021) for Portugal document the adjustment of exporters and importers to the Covid crisis using transactional data.

degrees of lockdowns, fully controlling for product-level shocks. The regression includes firm × month fixed effects that fully control for firm-level supply shocks, both originating in France and abroad, as well as demand shocks affecting all products of a given firm (for example, due to brand effects). The results show that, on average, going from zero to full lockdown reduced the mid-point growth rate by 0.6 point. However, the effect is strongly heterogenous, being about twice as large for firms in the top 0.1% (1.0) with respect to the bottom 99.9% (below 0.5).

Our paper speaks 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", so that idiosyncratic shocks to largest exports can reverse revealed comparative advantage. 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. A series of papers focuses on the role of large firms in generating business cycle comovement across countries using the French data. Di Giovanni et al. (2014) show that firm-specific foreign demand shocks affect aggregate fluctuations and Di Giovanni et al. (2017) document that firms with multinational and trading linkages with foreign countries are more affected by shocks to those countries, which important macro implications. The result that the fat-tailed size distribution of exporters coupled with heterogeneous reactions to demand shocks generates aggregate fluctuations resonates well with a recent approach of 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. We show here 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. Our finding suggests that the elasticity of exports of larger firms to a severe demand shock is larger, which tends to reinforce the mechanisms put forward in Di Giovanni et al. (2020).

The literature on the Covid shock suggests a prominent role for global value chains in the transmission 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 the transmission 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. (2021) 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. Relative to that literature, our focus is on the disproportionate collapse of the top exporters, not on GVCs per se, and we show that higher GVC exposure does not explain the larger collapse of top exporters.

The remainder of the paper proceeds as follows. Section 2 briefly describes the data sources. Section 3 presents the main novel stylized fact : top exporters overreact to common shocks, and this pattern can be seen both during crises and in normal times. Section 4 tries to pin down the main reason for this disproportionate reaction of top exporters. Section 5 concludes.

2 Data

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 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 A13 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 A14 in the Appendix. [2]

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.

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 $x_{fjkt-12} = 0$.

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)

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

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 A16 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

In this section we provide evidence that the largest exporters react more strongly to common 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.

A Long-Term Perspective : 1993-2020

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 has been used in previous contributions in the granularity literature, such as Gabaix (2011) and Di Giovanni et al. (2020), although these papers focus on value added and not on exports as we do here. We use the full data, including the information on small

exporters that only have to provide information on their total exports, although results are very similar if we restrict attention to exporters with complete filings.

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. We define g_t as the monthly year-on-year growth rate of exports (all products, all destinations). We express the decomposition as :

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

The average firm growth rate $\bar{g}_t = \frac{1}{N} \sum_f g_{f,t}$ is a simple measure of a macro shock common to all firms. The granular residual captures the size-weighted deviations of the firm growth rate from this aggregate shock.

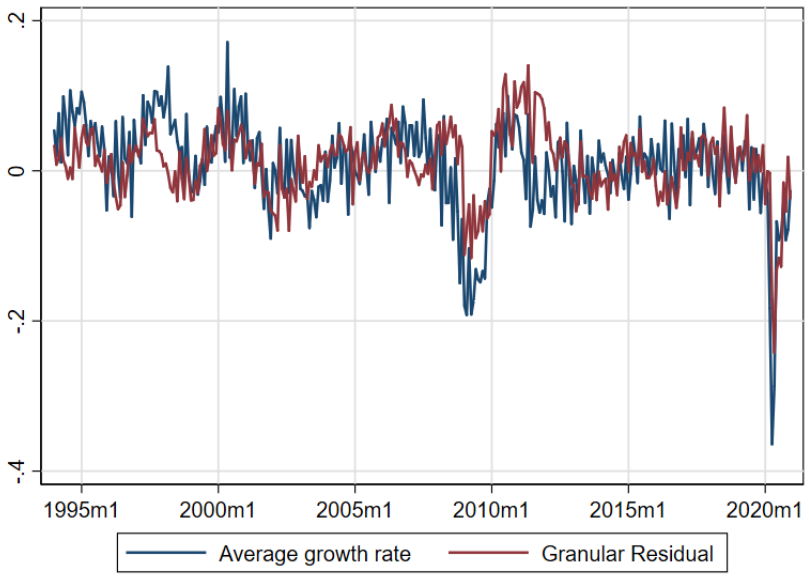
$$Cov_t(\omega_{ft}, g_{f,t}) = \sum_f \omega_{f,t}(g_{f,t} - \bar{g}_t)$$

$Cov_t(\omega_{ft}, g_{f,t})$ is positive when larger exporters experience higher growth rates than the average firm and negative when they do worse than the average firm. If exporter-level growth was uncorrelated with exporter size, then 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 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 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 implies 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.

The positive correlation between both terms is consistent with the idea that larger firms react more strongly to common macro shocks. In turn, this overreaction has important aggregate consequences, as evidenced by the large share of aggregate volatility that is explained by the granular residual. While this evidence is largely suggestive of this channel, it does not rule out the main alternative explanation which

FIGURE 1 – Average Firm Export Growth and the Granular Residual



Source : French customs, Authors' calculations.

is that the granular residual is driven by idiosyncratic shocks to large firms. To make progress, we take advantage of the two large macro shocks covered by our sample period, the Great Financial Crisis and the Covid Pandemic.

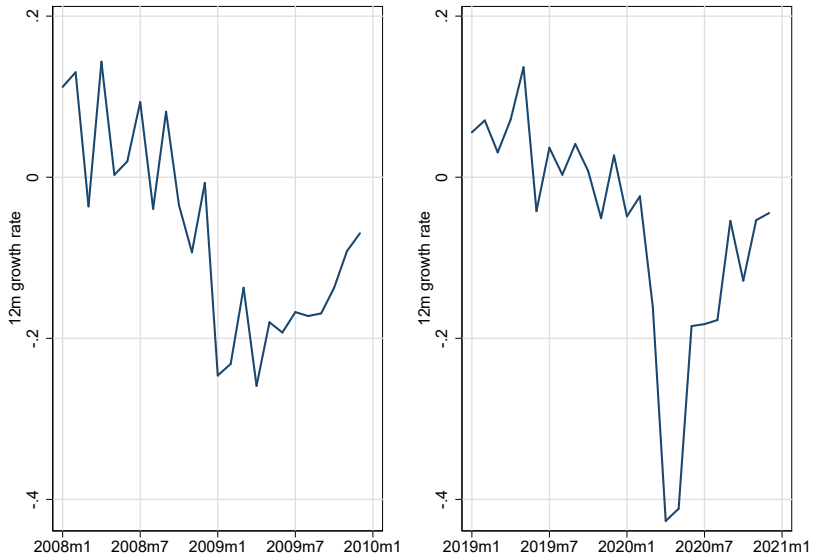
Granularity in two large-scale crises : GFC and the Covid-19 Pandemic

To dig deeper into the macro implications of the stronger reaction of large exporters to common 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. [3] 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, as evidenced by the fall in the average exporter growth rate. Figure 2 compares the monthly evolution of the year-on-year growth rates during both periods. The export collapse was

3. A decomposition of the aggregate export growth during both crises into a firm intensive and extensive margin of adjustment shows that both export collapses were almost entirely driven by changes in the export values of continuing exporters (see Figures A3 and A4 in the Appendix). 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.

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).

FIGURE 2 – Aggregate Export Growth, GFC (left) and Covid (right)



Source : Trade Data Monitor, Authors' calculations.

We proceed as follows. We first construct the exporter-size distribution for each pre-crisis year separately, namely 2008 and 2019. Specifically, we place 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 3, which provide the share of aggregate exports accounted for by firms in different size bins in 2008 (left panel) and 2019 (right panel). As it is the case in virtually all comprehensive firm-level export datasets (e.g. Freund and Pierola (2015)), French exports display strong concentration in the right tail of the distribution. This leads us to choose finer bins at the top of the distribution. In 2019, out of a total of 100,000 firms, 71% of total exports is 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%. [4] The exporter-size distribution for 2007 is remarkably similar, with the top 1% exporters (1057 firms) accounting for 70% of aggregate exports, and the top 0.1% (105 firms) for 37%. A very similar shape is obtained for every (non-crisis)

4. 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.

year of the sample (graphs available upon request), conveying the idea that high skewness is a stable feature of exporter-size distributions.

The light gray bars in Figure 3 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). [5] 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.

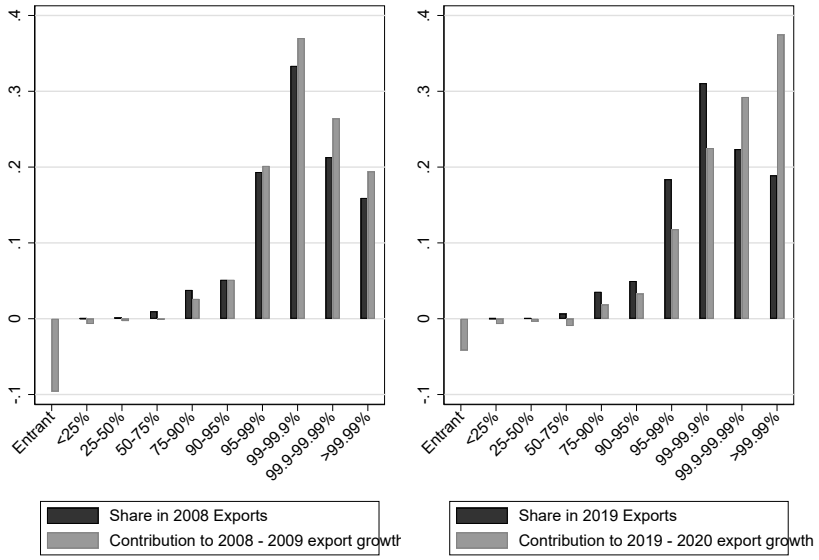
Zooming in on the top firms confirms the existence of a systematic relationship between growth and pre-crisis size that holds also within the group of top firms. In Figure 4 we place the top 1,000 exporters into 100 bins of 10 firms each and compute for each bin the mid-point growth rate for April/May 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 3 could have been the result of a few outliers.

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

The previous analysis reveals a strong and economically meaningful relationship between pre-determined exporter size and export growth. Though informative, the correlations that were revealed were uncondi-

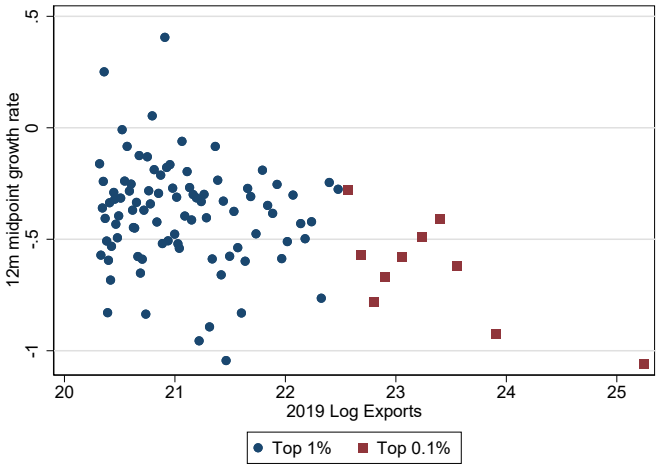
5. Including entrants, then the contribution of bin b would be $c_b = \frac{x_{bt-1}}{X_{t-1}} \frac{\lambda}{\lambda + \frac{x_{Et}}{X_{t-1}}}$, if all pre-existing firms grew at the same rate λ, where x_{Et} are exports of entrants in t. While the cumulative contribution of entrants over one year is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

FIGURE 3 – Export Shares and Growth Contribution during the GFC (left) and Covid (right) crises, by size bin



Source : French customs, Authors' calculations.

FIGURE 4 – April-May 2020 12-month mid-point growth rate and 2019 exports of the 1,000 largest exporters



Source : French customs, Authors' calculations.

tional 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 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 :

$$g_{fjkt} = \alpha_{b(f)t} + \epsilon_{fjkt}, \tag{4}$$

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 ϵ_{fjkt} is an error term. We estimate Equ. (4) by OLS, using weights ω_{fjkt} as defined in Section 2.

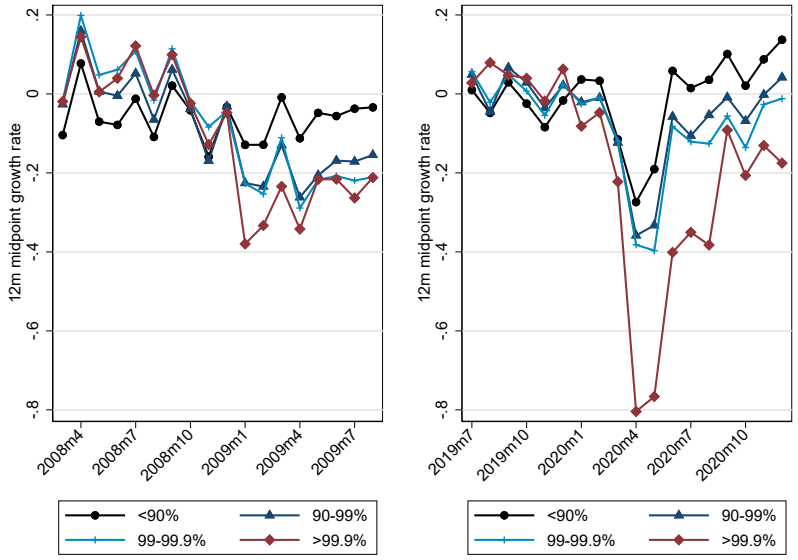
We run Equ. (4) on a balanced panel of firms of continuing exporters, defined as those firms that report positive exports every month. By focusing on the intensive margin, we make sure that the results are driven by within-firm changes of growth rates and are not affected by changes in the composition 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. [6]

Figure 5 shows the result of estimating Equ. (4), 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 3 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.

6. 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).

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 3 is the consequence of the combination of a stronger reaction to the initial shock and a slower recovery for the top exporters.

FIGURE 5 – Export growth during the GFC (left) and Covid (right) crises, by size bin



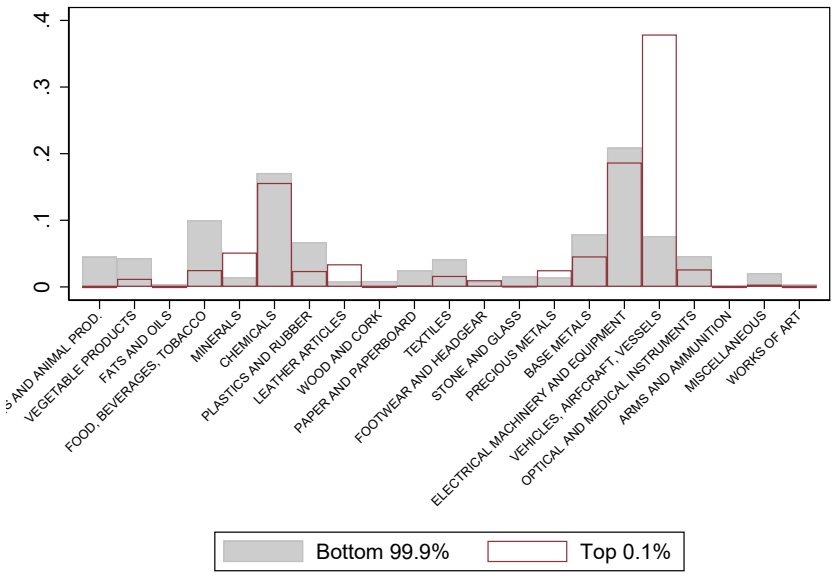
Source : French customs, Authors' calculations.

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 6. 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

FIGURE 6 – Distribution of top exporters across sectors (2019 data)



Source : French customs, Authors' calculations.

affiliation, we add sector × destination fixed effects to the regressions.[7] In doing so we also control for potential systematic differences in geographical composition of exports by bins. Our main specification is the following :[8]

$$g_{fjkt} = \alpha_{b(f)t} + \beta_{jst} + \epsilon_{fjkt}, \tag{5}$$

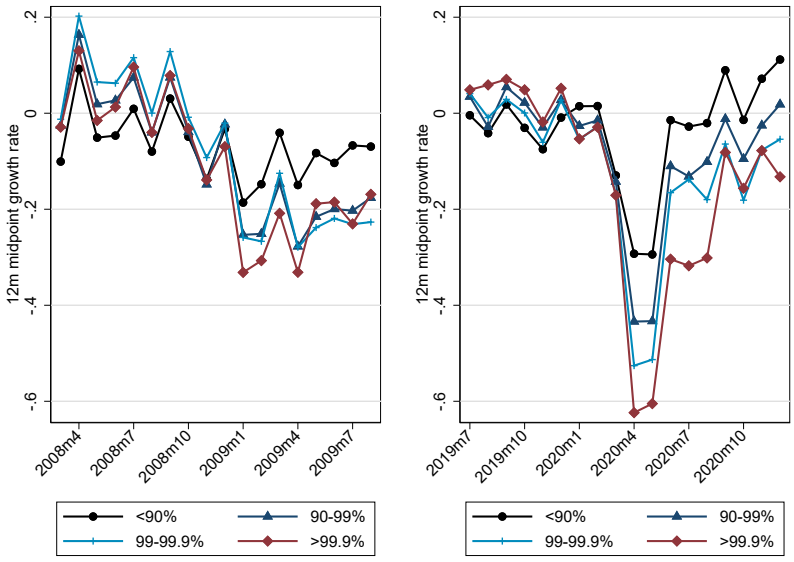
where β_{jst} denotes a time-specific sector × destination dummy. Sectors are defined using the 2-digit level of the Harmonized System. Results are shown in Figure 7. A comparison with Figure 5 reveals that sector × destination fixed effect do have some bite. For example, during Covid, the average mid-point 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

7. In the Appendix and in Bricongne et al. (2021) we provide results from a separate robustness exercise in which we exclude aircraft exports altogether. All main results presented here also hold in this restricted sample. Specifically, we exclude all firms for which over 10% of their 2019 exports were classified under HS code 88 : Aircraft, spacecraft, and parts thereof.

8. 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. 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.

around 0.37. Overall, however, the main point of Figure 5 is unchanged : During both the GFC and the Pandemic, the export collapse was driven by the top exporters.

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



Source : French customs, Authors' calculations.

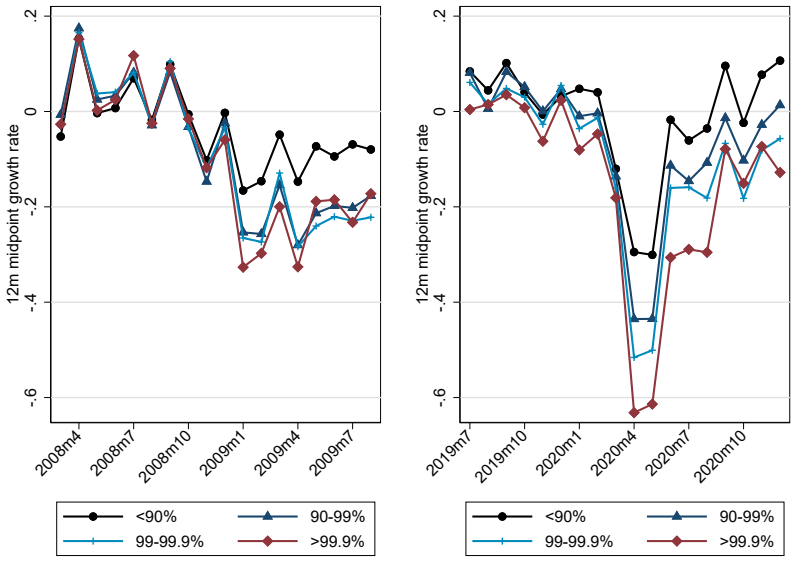
Accounting for reversion to the mean

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 common 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 × destination fixed effects. [9]

9. 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.

The results are provided in 8, where one can see that accounting for pre-crisis growth does not change the magnitude of the coefficients associated with exporter size.

FIGURE 8 – Export growth during the GFC (left) and Covid (right) crises, by size bin, controlling for pre-crisis growth rates



Source : French customs, Authors' calculations.

Quantitative implications

We now use our estimations to quantify the role of heterogeneity in affecting the aggregate outcome. We focus on the 2020 Pandemic and ask the following question : what would have been the aggregate export growth rate, had the top exporters grown at the same rate as the bottom exporters ? 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 × destination fixed effects, presented in the right panel of Figure 7. 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 in April and May 2020 but extended to the rest of the year (by the end of 2020, exports of the top 0.1% were still well below pre-crisis levels), we quantify their contribution to the year on year change in total exports.

We proceed as follows. To focus on the top 1%, we first calculate the average growth rate for the bottom 99% as the export-weighted average of the size-bin coefficients obtained from the estimations. We then apply this growth rate to the top 1%. We obtain a year-on-year aggregate growth rate of -11.2%. The actual growth rate was of -16.3%, which implies that the overreaction of the top 1% (with respect to the bottom 99%) adds -5.1 percentage points to the aggregate. This implies that the strongest reaction of the highest 1,000 exporters, explains about a third of the total collapse. When re-doing the same exercise but imputing the growth rate of the bottom 99.9% to the top 0.1%, we find that in the counterfactual scenario, export growth would have been -13.7%, and that the overreaction of the largest 104 exporters explains around one sixth 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.

4 Supply versus demand

We now seek to explain the determinants of the patterns that we have documented. We ask : why do larger exporters react more strongly to common 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 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 common demand shocks. We start with supply side explanations.

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-months 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 3, and also to include all firms (entering, continuing, and exiting). The remainder of the framework is the same as before : We estimate Equ. (5), 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 9. The line for January-February 2020 shows that firms above the 75th percentile grew at essentially the same rates *prior* to the crisis. [10] 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.

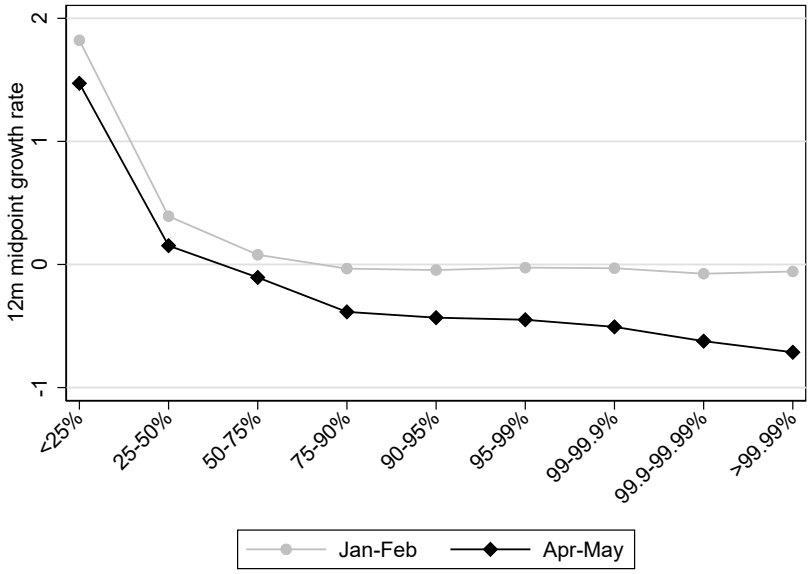
We now turn to seek for explanations of the patterns revealed in Figure 9. We start by studying the role of foreign supply shocks.

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 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. (2021) 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

10. 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 9 – Midpoint growth rate by size bin : January-February vs April-May 2020



Note : Controls for sector-destination fixed effects included. *Source* : French customs, Authors' calculations.

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. It is well known that 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. Thus, our analysis is complementary to these papers.

Measuring GVC integration by exporter

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. [11]

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. [12] 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 A7 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 A8 we also replicate the disproportionate collapse of the top exporters from Figure 9 in the Customs-FIBEN sample, and find very similar patterns.

11. 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.

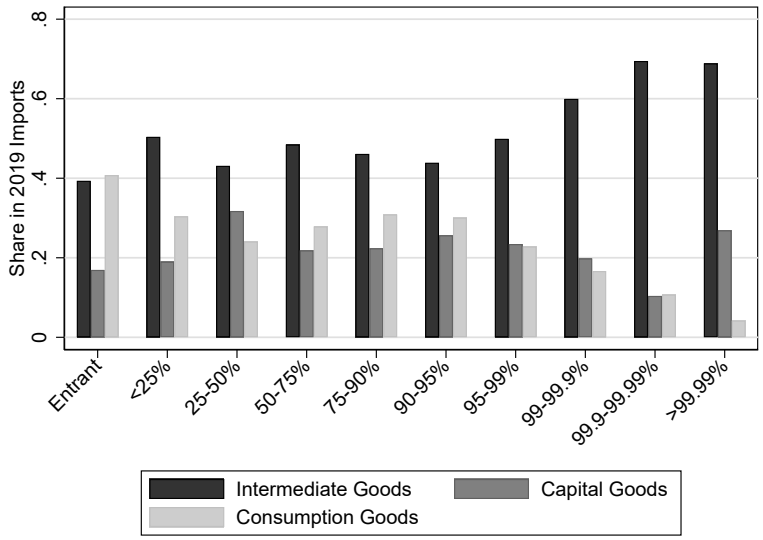
12. Including exporters that enter from 2019 to 2020, the sample captures 41,000 out of 125,000 firms.

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 A9 in the Appendix.

Figure 10 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. [13].

FIGURE 10 – Share in imports of broad categories of products, by size bin of exporters (2019)

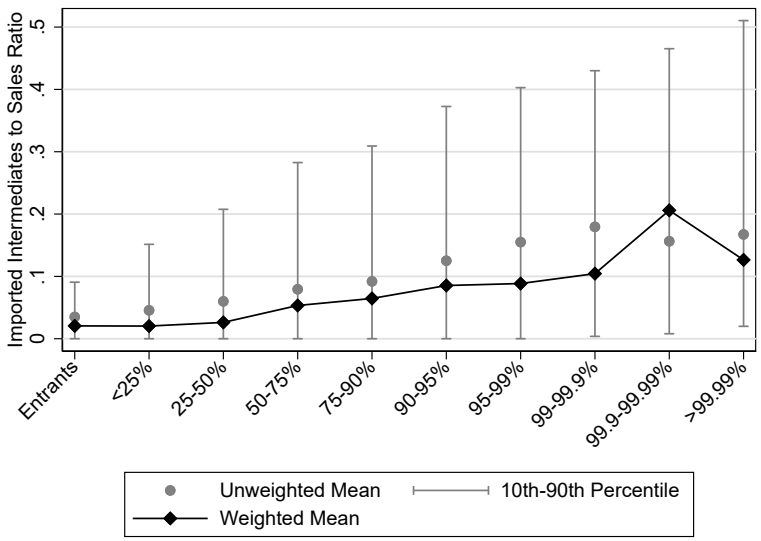


Source : French customs, Authors' calculations.

13. The geographical structure of imports also differs according to firm size. In particular, the top exporters are more reliant on imports of intermediate goods originating in the US and Germany, with those origins together accounting for over 40% of their total imports of intermediate goods. Smaller firms tend to rely more on Eastern Europe and China. It is noteworthy that the share of China in total imports of intermediate goods does not surpass 10% for any bin. See appendix A.5 and particularly Figure A11

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). [14] Figure 11 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 the Figure. A regression of $IIS_{f,2019}$ on size bin dummies gives an R2 of only 5%.

FIGURE 11 – 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. (5) 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. [15]

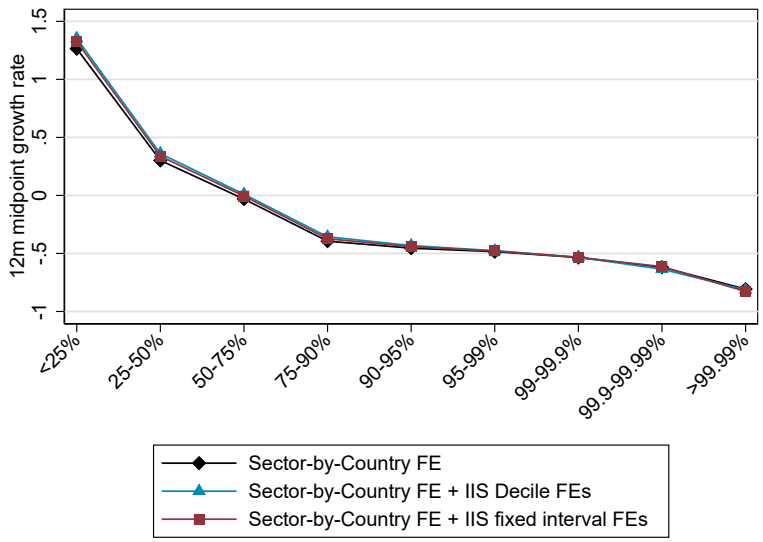
14. Both variables are calculated with yearly data for 2019, to capture the potential exposure of firms to the Pandemic-induced supply disruptions based on their pre-existing sourcing choices.

15. 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.

$$g_{fkjt} = \alpha_{b(f)t} + \beta_{sjt} + \gamma_{r(f)t} + \epsilon_{fkjt} \tag{6}$$

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 12. 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 12 – 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 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 : Supply Shock$_{ft}$ = $\sum_i \frac{M^{int}_{fi,2019}}{M^{int}_{f,2019}}$Stringency$_{it}$, where Stringency$_{it}$ is the monthly average of the Oxford Stringency Index in origin country i at month t (Hale et al. (2021). [16] Thus, Supply Shock$_{ft}$ is akin to a shift-share instrument

16. The Oxford Stringency index constructed by the University of Oxford for around 180 countries is updated on a daily

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* :

$$\text{Input Supply Shock}_{ft} = IIS_{f,2019} \times \text{Supply Shock}_{ft} \tag{7}$$

We proceed as before, constructing bins of Input Supply Shock$_{ft}$ and introducing them as controls in Equ. (5). The results are shown in Figure 13 : controlling for the exposure to supply chain disruptions does not impact the coefficient associated with the size dummies.

We therefore conclude that neither the larger reliance on imported inputs, nor their structure in terms of origins can explain the collapse of top exporters.

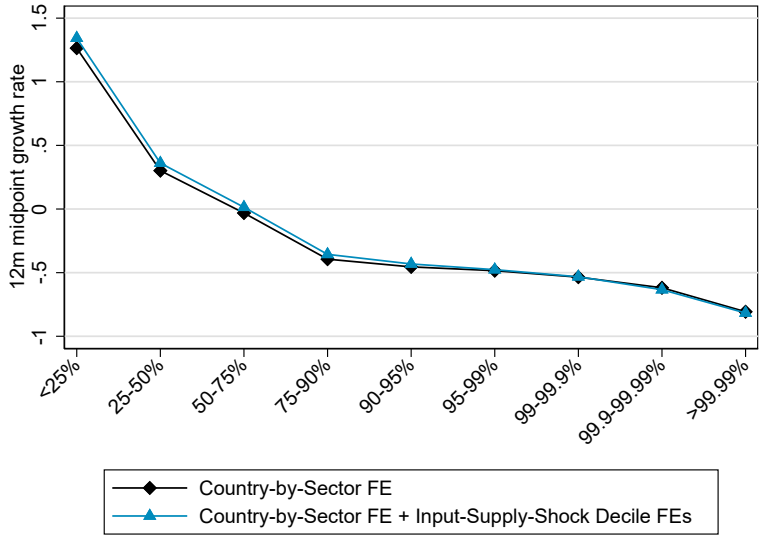
The role of demand shocks

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 export destinations is tilted towards countries that happened to have stronger contractions in demand. This composition effect is controled 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-

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 13 – 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.

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 :

$$g_{fjkt} = \alpha Lockdown\ Stringency_{jt} + \beta_{ft} + \gamma_j + \delta_{kt} + \epsilon_{fjkt} \tag{8}$$

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 α. By definition of $g_{fjk,t}$, the estimation includes both the extensive and the intensive margin of exports.

The identification strategy takes advantage of the heterogeneous responses of destination countries to the Covid crisis in terms of timing and intensity of lockdown measures : 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

TABLE 1 – Effect of Destination Lockdowns

	(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	✓	✓

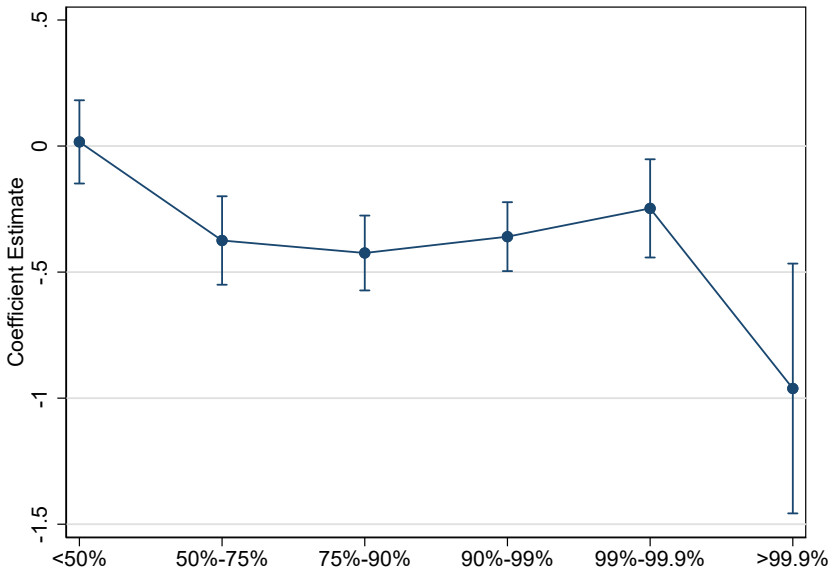
Notes : OLS estimations of (8).The dependent variable is the year-on-year mid-point growth rate at the firm × product × destination × month level. The estimations cover the period from January 2019 to June 2020. Products are defined at the CN8 level of the European Combined Nomenclature. Standard errors are clustered at the country level and reported into parenthesis. *** implies significance at the 1% level.

effect β_{ft}. Firm × time fixed effects control for supply shocks to firm f originating both abroad and in France. Importantly, these fixed effects control for the production disruptions that French exporters may have faced due to the domestic lockdown. They also control for demand shocks that affect all products by a particular firm (for example, due to changes in the demand for brands). Time-invariant destination unobserved characteristics are captured by a vector of destination fixed effects γ_j. Finally, product-level shocks common to all destinations and exporting firms are absorbed by a product × time fixed effect δ_{kt}.

Results are reported in Table 1. 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 :

FIGURE 14 – Effect of Destination Lockdown by Size Bin



Source : French customs, Author's calculation.

$$g_{fjk,t} = \sum_b \alpha_b Lockdown\ Stringency_{j,t} \times D_{b(f)} + \beta_{ft} + \gamma_j + \delta_{kt} + \epsilon_{fjk,t} \tag{9}$$

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

Figure 14 shows that the top exporters have a higher elasticity with respect to foreign demand shocks. [17] 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.*

17. 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.

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 (9), 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 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 A10), the data point to a causality running from exports to imports, and not the other way round.

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 common shocks, which in turn feeds back into the aggregate response of the economy.

Relying on a simple decomposition of the aggregate growth rate into an average growth rate across firms, and a granular residual, as in Gabaix (2011) and Di Giovanni et al. (2020), we have firstly shown that the two latter components contribute roughly equally to fluctuations in aggregate export growth over the business cycle. Importantly, the positive correlation between the average firm growth and the granular residual illustrates that large exporters are doing worse than the average firm in times of a downturn, and better than average in times of an upturn. Our second result is that the largest exporters contributed more than proportionately to the export collapse during the GFC and in 2020. These two results suggest that the magnified response of large firms to common shocks plays an important role for the granular residual in normal and crisis times. This channel is therefore distinct from the already documented one of idiosyncratic shocks to large firms.

Zooming in on the Pandemic, a simple decomposition shows that almost all of the adjustment occurred through the intensive margin of firms, as opposed to the extensive margin, despite a large decline in the number of exporters. These detailed data clearly confirm a predominant role for the largest firms, whose shipments were reduced more than proportionately. With respect to value chains, while the lockdowns in the country of origin of intermediate imports led to a decline in those imports, it is not clear that the large exporters were more severely affected or adjusted their imports more drastically. In contrast, while lockdowns in destination countries affected all firms equally, our econometric results show that the elasticity of exports of larger firms to a severe demand shock is larger. These results open the door to many interesting hypotheses about the type of adjustment of these large exporters, why they contributed more than proportionally to the decline in aggregate exports, and what role they had in the rapid recovery of trade. Overall, this paper provides insight into how the size distribution of exporters and the greater elasticity of response at the tail of the distribution jointly determine the dynamic response of aggregate exports to severe shocks.

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6 Appendix

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

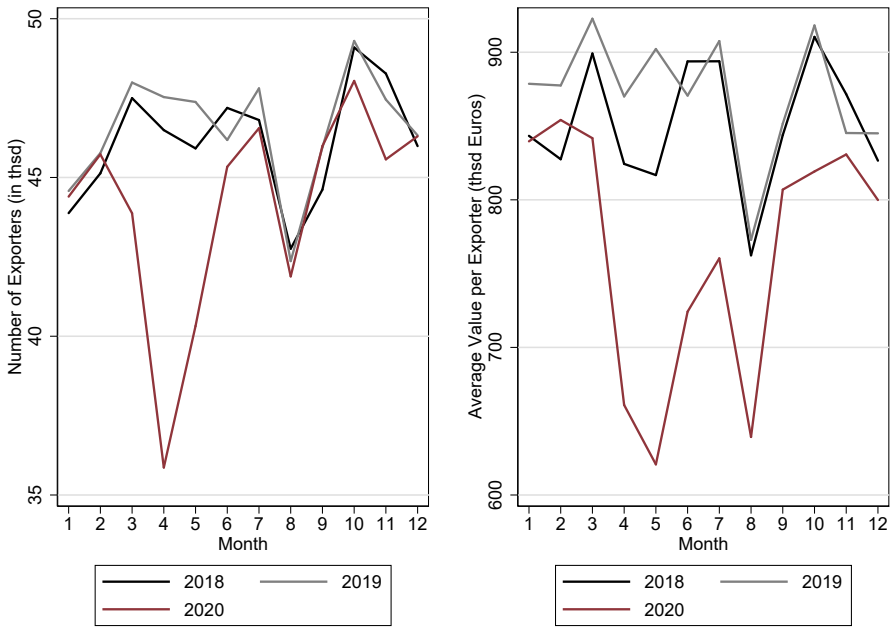
A.1.1 Firm Intensive and Firm Extensive Margins

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, $\bar{x}_t$:

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

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. [18]

FIGURE A1 – Number of exporters (left) and average value per exporter (right)



Source : French customs, Authors' calculations.

18. 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 gray 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. [19] 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.

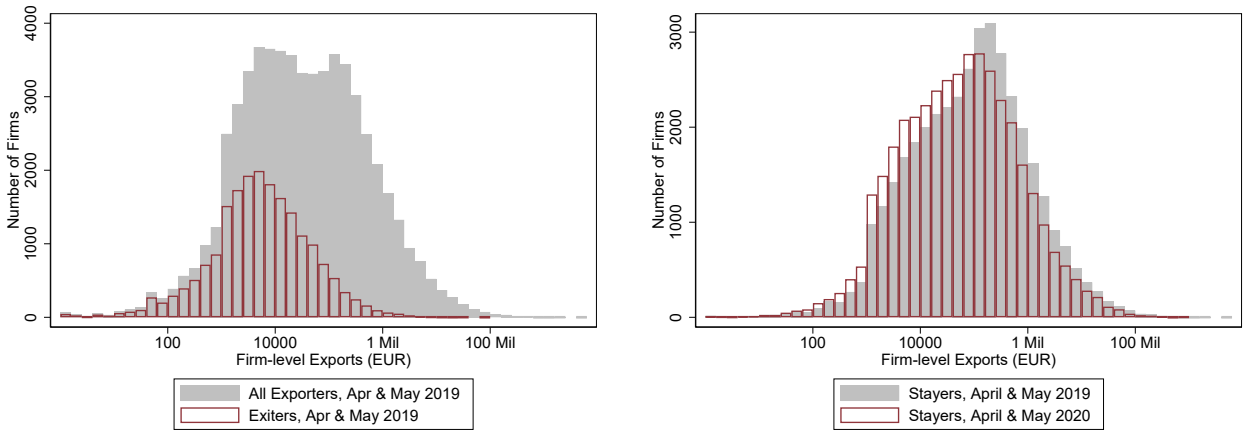
We apply the following decomposition of the year-on-year growth rate of total exports :

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

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

19. 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.

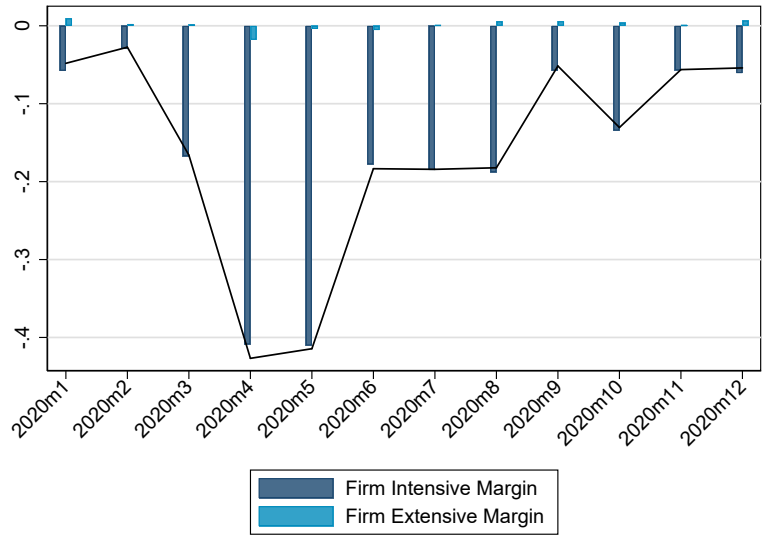
The results of applying (11) to the 2020 data are provided in Figure A3, where $\frac{\Delta X_t}{X_{t-1}}$ is given by the black solid curve. Its two components are represented by the bars : the firm intensive margin is represented in the light blue bars and the firm extensive margin in the dark blue bars.

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 firm. This is done with the following decomposition, that follows Bernard et al. (2009) :

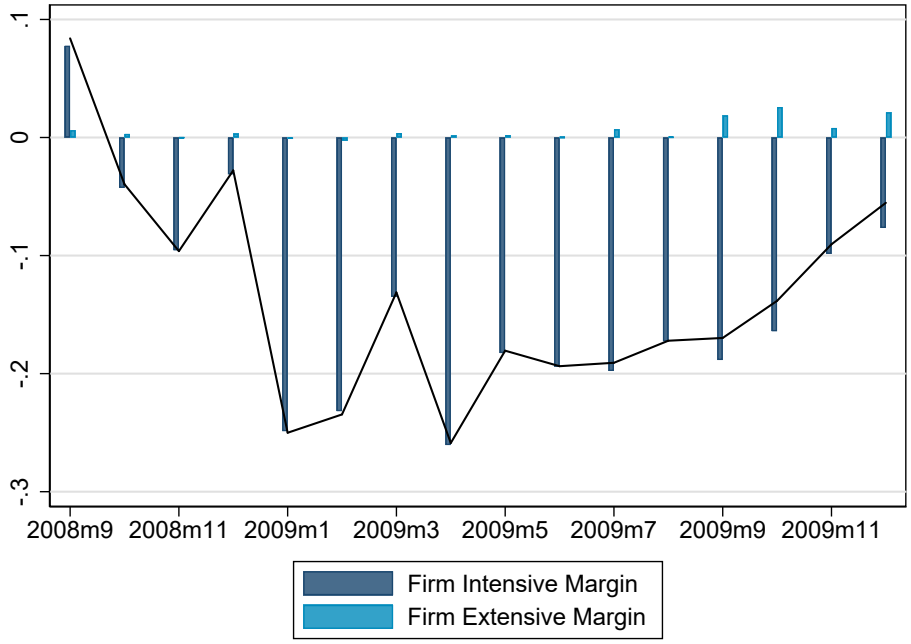
$$\frac{\Delta X_t}{X_{t-1}} = \underbrace{\frac{\sum_{f\in N} x_{f,t} - \sum_{f\in L} x_{f,t-1}}{X_{t-1}}}_{\text{Firm Extensive}} + \underbrace{\frac{\sum_{f\in S}\sum_{k\in S_f}\sum_{j\in S_{fk}} \Delta x_{fkj,t}}{X_{t-1}}}_{\text{Firm-Product-Destination Intensive}} + \underbrace{\frac{\sum_{f\in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

FIGURE A3 – Contributions of the firm intensive and extensive margins



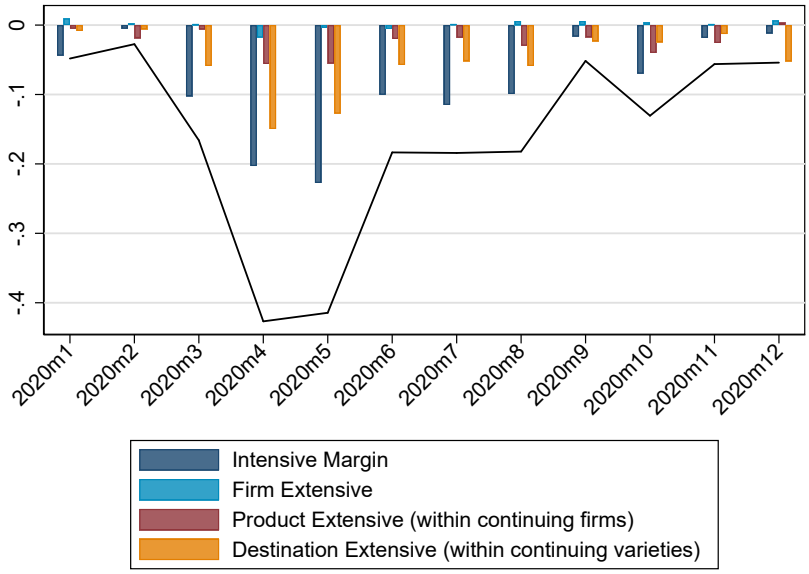
Notes : Horizontal axis, January is month 1 ; vertical axis : -.1 stands for a contribution of -10 % of the monthly variation of aggregate exports. *Source* : French customs, Authors' calculations.

FIGURE A4 – Contributions of the firm intensive and extensive margins during the GFC



Source : French customs, Authors' calculations.

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

A.3 The role of compositional effects

Figure (A6) reports different specifications of our main estimation Equ. (5). 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.

A.4 Fiben

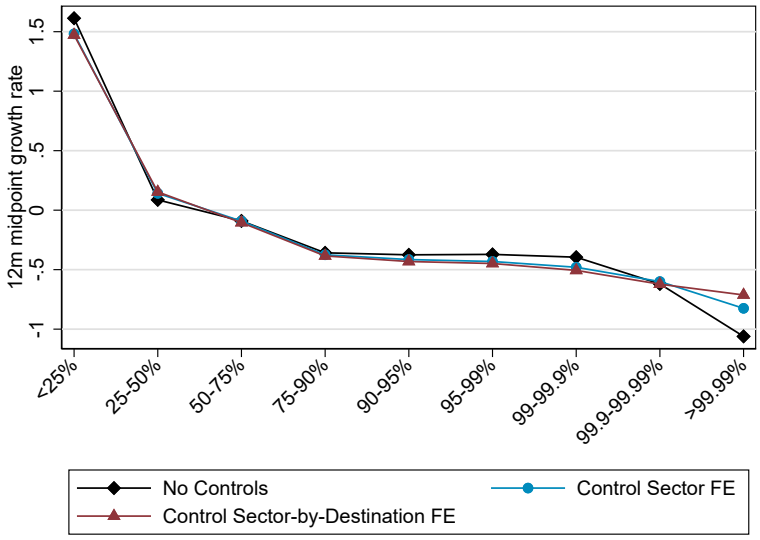
The FIBEN dataset provides detailed yearly balance-sheet and income statements for firms with yearly turnover larger than 750,000 euros. The data are collected at a yearly frequency by regional offices of the Bank of France with the purpose of gathering information about firms' credit worthiness. It is collected

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. (8). 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 parenthesis.

FIGURE A6 – Specifications with and without sector effects



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

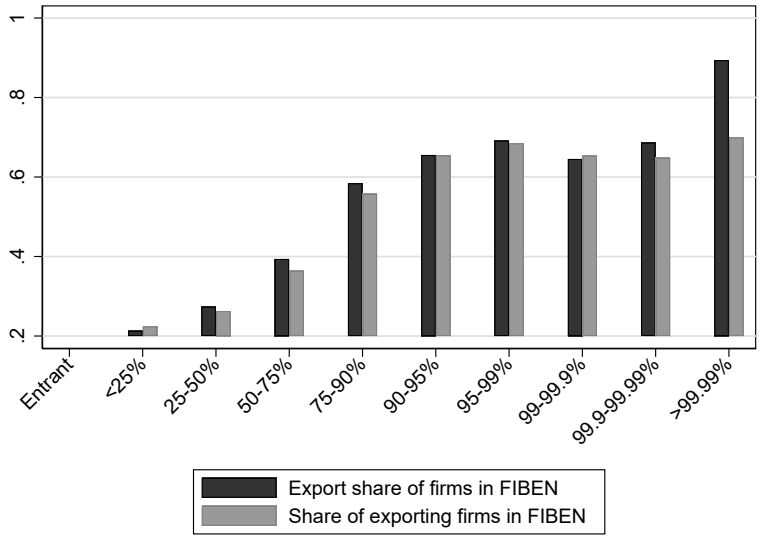
by the Banque de France since 1988 and the last full set of information available is for 2020. Previous papers using data from FIBEN include Aghion et al. (2019), and Cahn et al. (2020).

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 A7. 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 A8. 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.

A.5 Imports of exporters

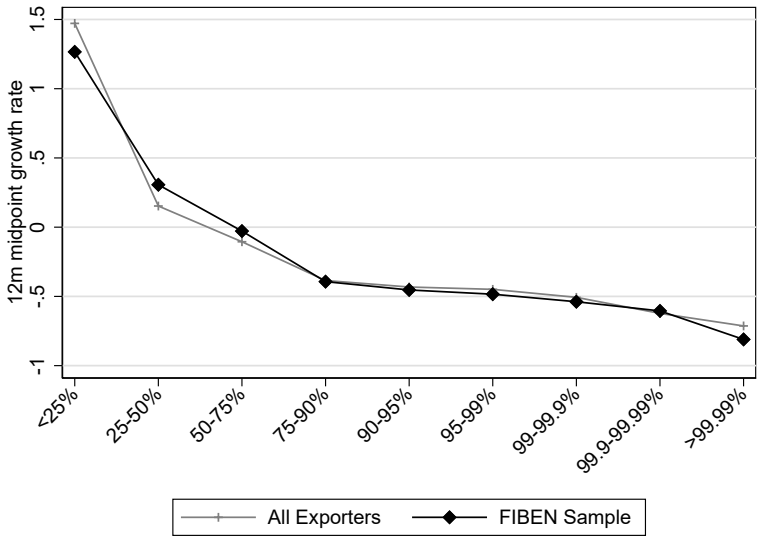
A straightforward motivation to look at supply shocks is provided by the fact that top exporters reduced their imports relatively more than smaller exporters, starting from March 2020 and being especially

FIGURE A7 – Share and export share of exporters in Fiben



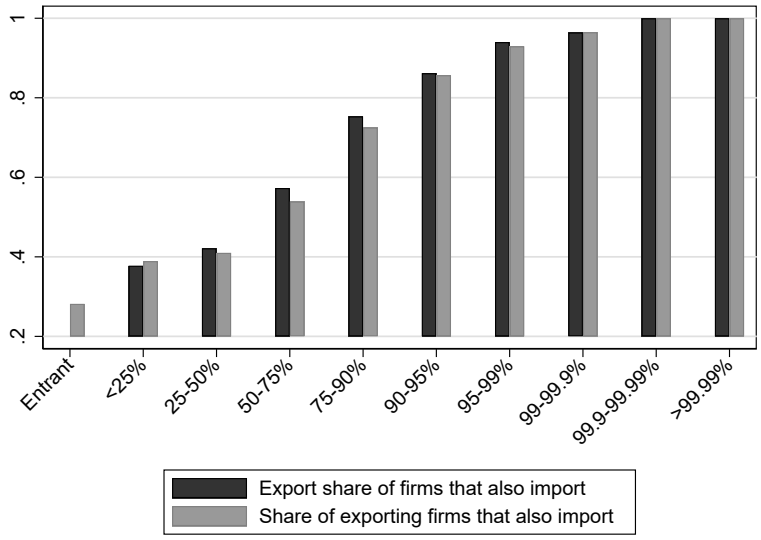
Source : French customs and Fiben Bank of France, Authors' calculations.

FIGURE A8 – Growth rate of exports by size bin for all exporters and the Fiben sample



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

FIGURE A9 – Export share of firms and share of exporting firms that import



Source : French customs, Authors' calculations.

strong during the months of May and June 2020 as shown in Figure A10.

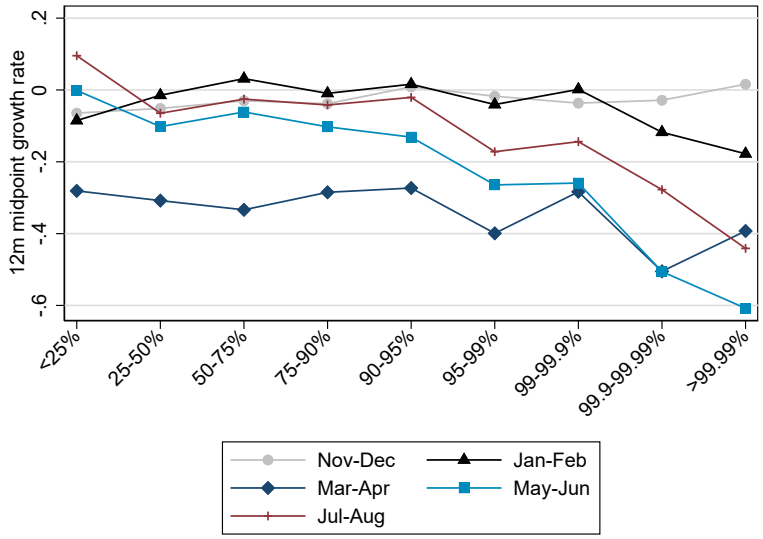
We now regress the growth rate of imports by exporter, product and origin on a series of fixed effects plus the stringency of lockdown at origin, as done in Equ. 8 :

$$g_{fik,t} = \alpha Lockdown\ Stringency_{i,t} + \beta_{ft} + \gamma_i + \delta_{kt} + \epsilon_{fik,t} \tag{13}$$

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 β_{ft}. Time-invariant destination-origin unobserved characteristics (France is indeed the destination of all imports) are captured by a vector of origin fixed effect γ_i, and δ_{kt} a product-time fixed effect capturing any unobserved product-level shock common to all destinations and exporting firms.

To look into potential heterogeneous effects according to size, we add size dummies to Equation 13, grouping the top exporters into a bin containing the highest 0.1%. We estimate the following baseline

FIGURE A10 – Exporter's imports during the Covid crisis (Nov.-Dec. 2019 to July-Aug. 2020)



Source : French customs, Authors' calculations.

equation, equivalent to Equ. (9) :

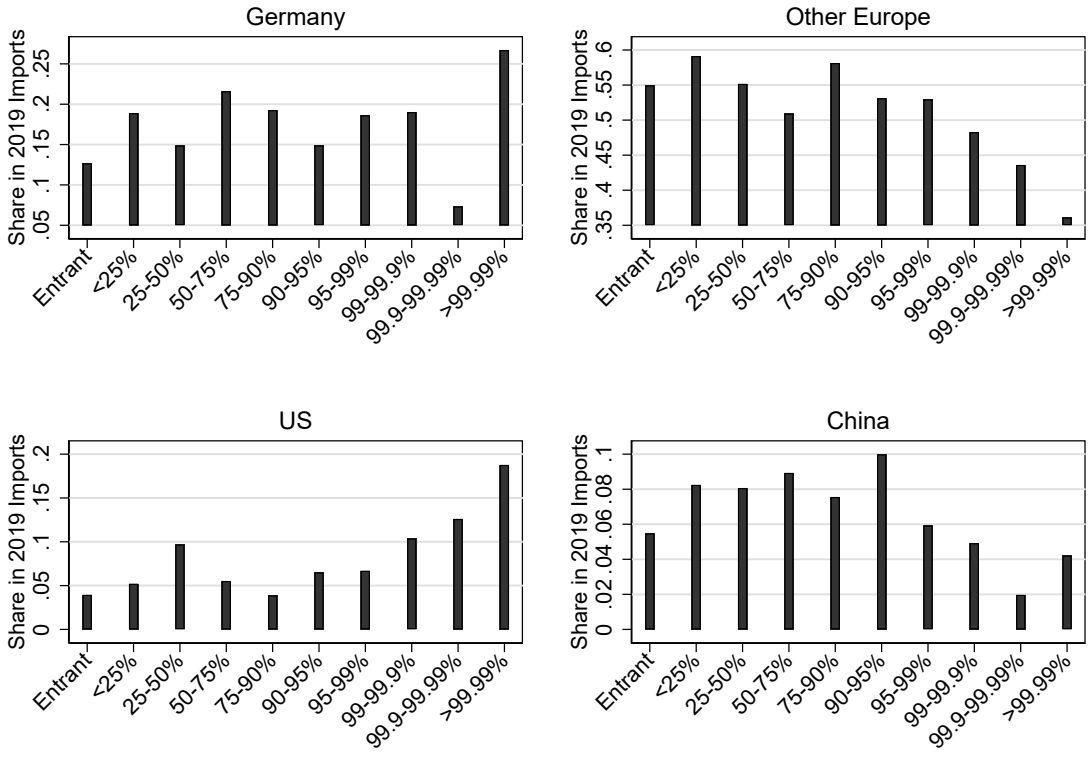
$$g_{fik,t} = Lockdown\ Stringency_{i,t} \times \eta_{b(f))} + \beta_{ft} + \gamma_i + \delta_{kt} + \epsilon_{fik,t} \tag{14}$$

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 shows the results of the estimation of Equ.13. 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 1 in the main text).

Results when interacting with size bins of exporters, shown in Figure **??**, point to the absence of magnification 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 A11 – Geographic structure of imports of intermediate products, by size bin of exporters (2019)



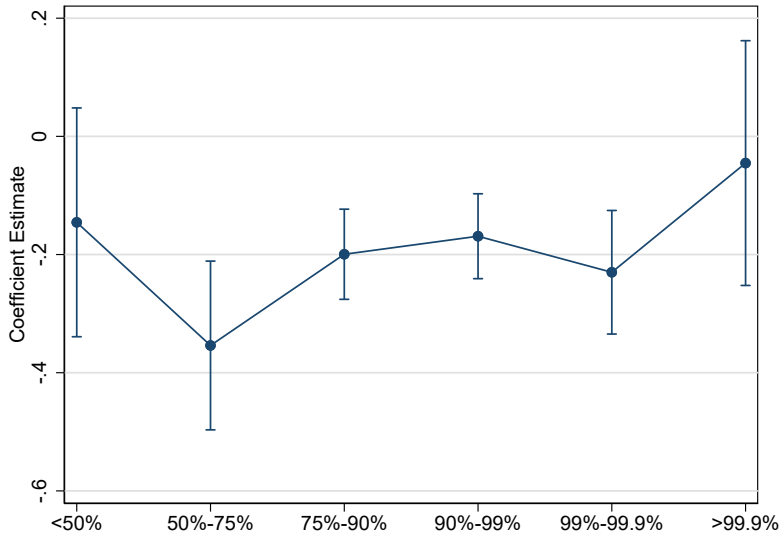
Source : French customs, Authors' calculations.

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		✓

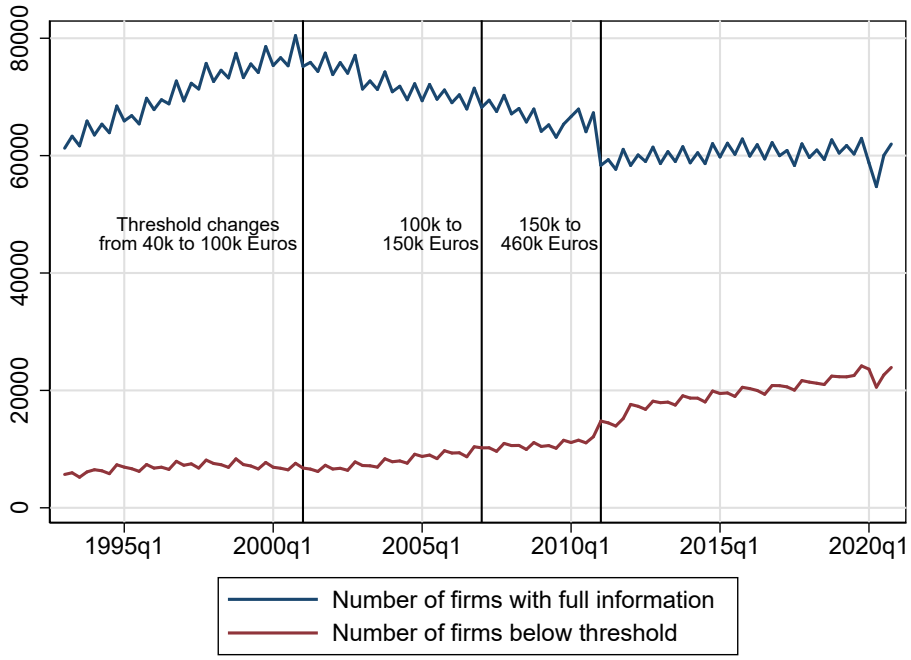
Notes : OLS estimations of (8) on the subsample of exporters that report positive import values.The dependent variable is the year-on-year mid-point growth rate at the firm × product × destination × month level. The estimations cover the period from January 2019 to June 2020. Products are defined at the CN8 level of the European Combined Nomenclature. Standard errors are clustered at the country level and reported into parenthesis. *** implies significance at the 1% level.

FIGURE A12 – Impact of Covid at origin on imports by exporter size



Source : French customs, Authors' calculations.

FIGURE A13 – Number of firms with detailed export information and number of small exporters

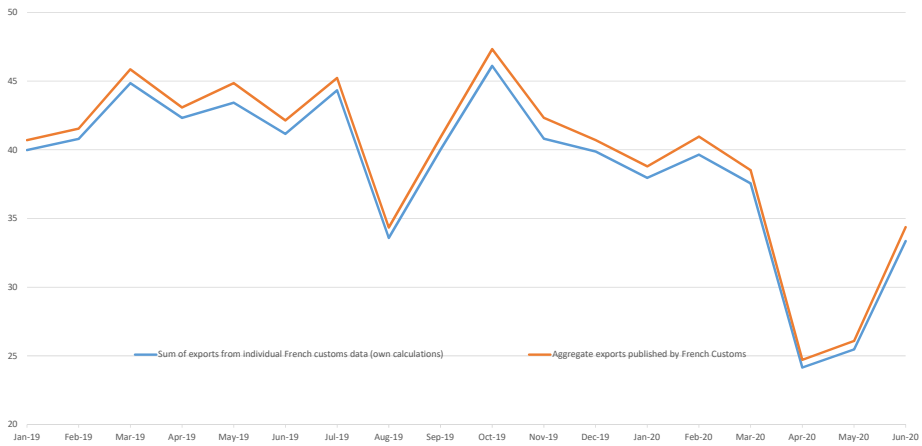


Source : French customs, Authors' calculations.

A.6 Robustness : Aircrafts

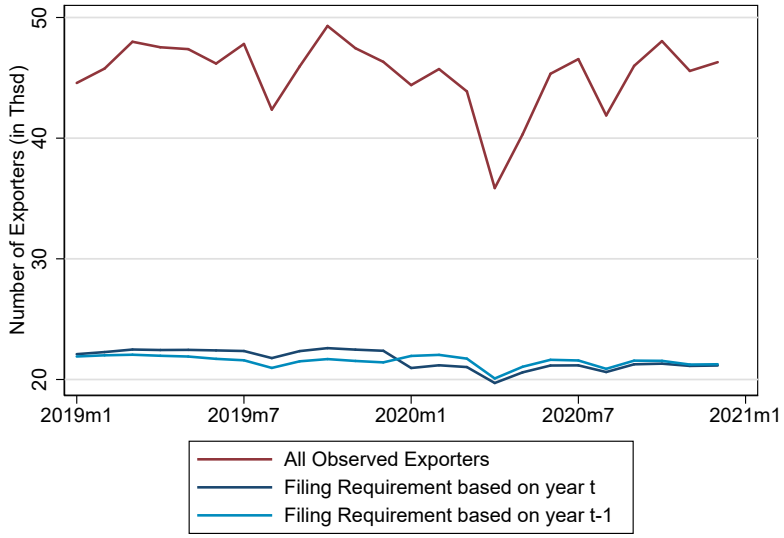
B Online appendix

FIGURE A14 – Coverage of aggregate statistics with transaction data



Source : French customs, Authors' calculations.

FIGURE A15 – Exporters with and without filing obligation (2019-2021)



Source : French customs, Authors' calculations.

FIGURE A16 – Midpoint growth rate vs log change