

# From Macro to Micro: Heterogeneous Exporters in the Pandemic\*

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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 economics literature. Changes in the performance of a few large firms can arise due to idiosyncratic shocks to these firms, or due to idiosyncratic reactions to common shocks. This paper provides direct evidence for this second channel. We analyze the response of French firms to a large common demand and supply shock, the Covid-19 pandemic, to document that exports of the largest firms declined substantially more than average. Similar patterns can be observed during the Great Financial Crisis. This overreaction of the largest firms has sizeable aggregate effects: It explains close to half of the -16.3% decline of French exports in 2020.

*Keywords:* exports; firm-level trade data; COVID crisis; lock-down stringency.

*JEL Classification:* F14

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# 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. Changes in the performance of a few large firms can arise due to idiosyncratic shocks to these firms or due to idiosyncratic reactions to common shocks. While the former has been at the center of many models and empirical analyses, we have surprisingly little evidence for the second channel.<sup>1</sup>

This paper uses a large common shock, the 2020 Covid pandemic, to investigate whether there is a role for this second channel in explaining the economy’s aggregate response. We focus on exports, due to the availability of high-frequency firm-level data, which is important given the particular swiftness of both the slump and recovery during this recession. The Pandemic generated a sharp and sizeable drop in international trade flows during the first semester of 2020. The value of French exports fell by 42% between April 2019 and April 2020, movements that were unprecedented in terms of suddenness and depth. We find that the top exporters declined substantially more than average during the recession, which amplified the aggregate response of exports.

We use monthly firm-level trade data from the French Customs office containing monthly exports and imports by country of destination/origin at the 8-digit product level (around 10,000 codes). We complement the trade data with balance sheet data from the dataset FIBEN collected by the Banque de France.

We start with a decomposition of aggregate French exports along the firm extensive and the firm intensive margins. The export collapse of April and May 2020 was almost entirely due to changes in the firm intensive margin. Despite a large drop in the number of exporters (of around one quarter), the extensive margin does not explain much of the collapse because exiters are very small on average.

As in many other countries, the exporter size distribution in France is highly skewed: A few firms account for large shares of aggregate exports. Motivated by this observation, we locate exporters into bins according to their position in the pre-crisis exporter size distribution and study heterogeneity in growth rates during the crisis. A striking result is that the export collapse is disproportionately explained by the small group of “Superstar” exporters. The top 0.1% of exporters contributed 57% to the aggregate

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<sup>1</sup>With the notable exception of [Di Giovanni et al. \(2020\)](#) to which we come back below.

collapse while their pre-crisis share was only 41%. Within the top 0.1%, the 10 largest exporters alone account for around one third of the collapse, while they exported 19% of total pre-crisis values. These facts are not the result of large firms being disproportionably represented in sectors hardest hit by the Pandemic. Importantly, the largest exporters also took more time to recover. By the end of 2020, exports of the top 0.1% were still well below pre-crisis levels while smaller firms had already caught up or even surpassed pre-crisis exports.

Overall, the under-performance of the exporters in the 0.1% with respect to the bottom 99.9% explains almost half of the aggregate export collapse in 2020: aggregate export growth would have been -9.2% instead of -16.3%, had the top exporters grown like the bottom 99.9%.

The relative under-performance of the very large exporters during the Pandemic is the main fact unveiled by our analysis. While the burgeoning literature studying large firms has established that idiosyncratic shocks to large exporters matter for aggregate outcomes, including international trade, the fact that we put forward is related but different: it was the stronger reaction of top exporters to the aggregate shock that explains its large effect.

We then explore potential reasons for the collapse of top exporters. We develop a flexible regression framework allowing us to control for supply and demand factors that may have affected export growth and can be correlated with exporter size. While net entry at the firm level does not matter much for the aggregate, the data shows that entry and exit at the transaction level (that is at the firm-product-destination level) has been very strong during 2020. To incorporate all extensive margin adjustments (firm, product, or destination), we employ midpoint growth rates.

On the supply side, knowing that largest exporters tend also to be amongst the largest imports, one can conjecture that part of their export performance is due to a higher exposure to disruptions in Global Value Chains (GVC) that surged during the Pandemic. We compute measures of GVC intensity at the firm-level by combining data on exports, imports of intermediate goods and balance sheets. We calculate for each firm a measure of GVC intensity as the ratio of imported intermediate inputs to total sales (IIS ratio). The IIS ratio is weakly correlated with firm size, and its inclusion in the growth rate regressions, on its own or interacted with measures of lock-down intensity in exporting countries, does not alter the significance of the size dummies. We interpret the results as GVCs not being the main reason behind

the differential effects across sizes.

To study the impact of demand shocks, we regress mid-point growth rates on the Hale et al. (2021) measure of lockdown stringency in export destinations. The econometric specification compares the export growth of the same exporter across destinations with varying degrees of lockdown stringency, obtaining identification from variation in the timing and strength of sanitary measures across France's trade partners. The detailed firm-level data allows us to include firm  $\times$  month fixed effects, thus fully controlling for contemporaneous supply shocks affecting individual firms that result from both domestic and foreign sanitary measures, as well as for any demand shocks that affect all products by a particular firm (for example, due to changes in the demand for brands). Product-level shocks common to all destinations and exporting firms are absorbed by a product  $\times$  month fixed effects.

Destination-country lock-downs significantly affect export growth: using mid-point growth rates, we find that going from no to full lock-down decreases the growth rate of exports to that market by 0.6. The average effect masks strong heterogeneity across exporter size. In a specification interacting the lockdown variable with the size dummies we find the effect is significantly larger for firms at the top of the export size distribution, whose elasticity to the foreign demand shock was on average twice the elasticity of the smaller firms. Thus, our analysis points to a higher elasticity of large exporters to foreign demand shocks which, given their weight in total French exports, drives a substantial part of the aggregate movement of exports.

The immediate question that pops up is that of how general the above patterns are. Is the larger reaction of top exporters a characteristic present in other large-scale economic events? How much does this differ from the role that top exporters have in determining cyclical fluctuations and the transmission of shocks across borders outside crises?

To make progress on these questions we first compare the evolution in the Great Financial Crisis and find that in that event the largest firms also drove that export collapse (albeit to a lesser extent). We then study the evolution of French exports over a longer time, decomposing aggregate export growth into average firm growth and a granular residual

We find that the granular residual plays an important role in both crisis and non-crisis times and that correlates positively with average firm growth, suggesting that the largest exporters do better than

average in good times but worse than average in bad times. In general, movements in the granular residual can arise from idiosyncratic shocks to large firms or from large firms reacting differently than the average to a macro shock. The positive correlation with the average growth rate suggests that the stronger-than-average response of large firms to common shocks likely plays an important role for the granular residual both during crisis and normal times.

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 documents 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 \(2021a\)](#) 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. \(2020\)](#).

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. We add to these works by focusing on the relationship between GVC and exporter size. We also contribute to papers that document the adjustment of exporters and importers to the Covid using transactional data (e.g. [de Lucio et al. \(2020\)](#) for Spain, [Amador et al. \(2021\)](#) for Portugal).

The rest of the paper is organized as follows. Section 2 presents the French trade and balance sheet data. Section 3 provides a first look at the data by decomposing total French exports across firm extensive and intensive margin, focusing on the role of large exporters. Section 4 looks at whether supply and demand shocks can explain the collapse of large exporters. Section 5 compares the results with the Global Financial Cycle and proposes a long term view. Section 6 concludes.

## 2 Data

### 2.1 Firm-level trade data

We use firm-level trade data from the French Customs office, recorded at a monthly frequency. We have data from January 1994 until December 2020, although most of our analysis will evolve around the period from January 2017 to December 2020. For each firm, uniquely identified by a 9-digit firm identifier called Siren, the data contain the value of exports and imports in current euros, quantities (in kilos or units depending on the product), product code and country of destination/origin. For exports with destination in an EU country (including the UK), the data contains an identifier of the buyer based on VAT records (but anonymized in the dataset). Products are classified at the 8-digit level of the European Combined Nomenclature (CN), which comprises around 10,000 products.<sup>2</sup> The data are exhaustive in the case of extra-EU flows. For intra-EU trade, exporters are required to provide the detailed information described above only if their exports exceed a certain threshold, which vary over time<sup>3</sup>. Exporters whose yearly exports fail to reach the threshold are only required to report the total value of their exports (i.e. summing across products and destinations). Throughout the paper we will exclude observations below the respective threshold. We show in Table A12 of the Appendix that the number of exporting firms subject to no-filing is limited and stable. Furthermore, the overall weight of

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<sup>2</sup>The first six digits of each product code correspond to the Harmonised System (HS) at the six-digit level.

<sup>3</sup>These thresholds are 250k euros from 1994 to 2000, 650k euros in 2001, 150k euros for 2002-2006; 150k for 2007-2010 and 460,000 euros since 2017

those observations in total exports is negligible. Regarding imports, there is no information below the reporting thresholds.

Our main unit of observation is a firm-product-country-month combination. Our baseline dataset contains 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 represent 98% of the total value of exports published in public statistics as shown in Figure [A11](#) in the Appendix.<sup>4</sup>

## 2.2 Firm-level Balance Sheet Data

In some specifications we complement the trade data with balance sheet data collected by the Banque de France called FIBEN. The data contains firms with yearly turnover higher than 750k euros, featuring around 200,000 firms per year. We match the FIBEN and the Customs datasets using the unique firm identifier Siren. Because of the turnover threshold, FIBEN misses small exporters. We will show, as we go along, that the sample obtained by matching both datasets provides a very good representation of the right tail of the export distribution, which is the focus of our analysis.

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<sup>4</sup>Details concerning the construction and of previous contributions that rely on these data are provided in [Bergounhon et al. \(2018\)](#).

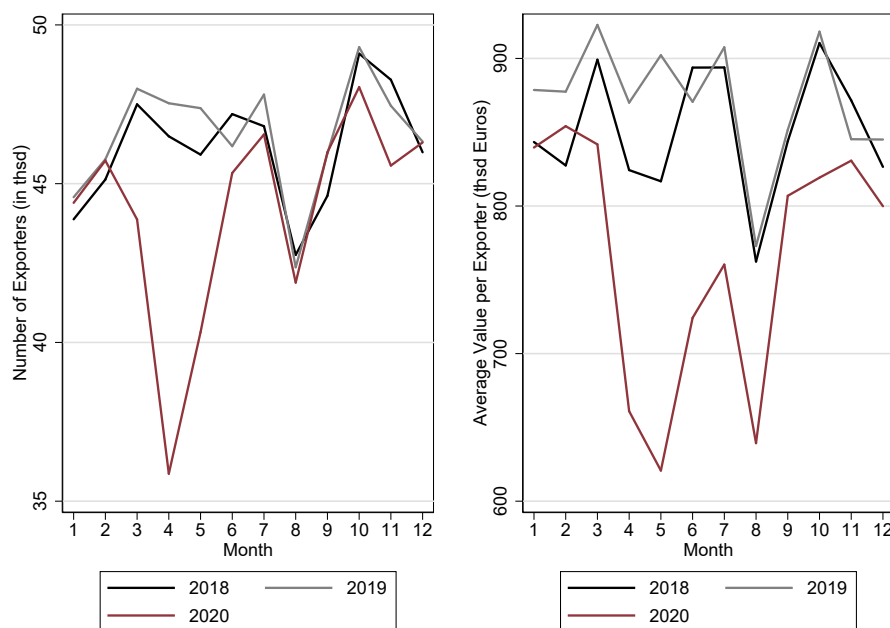
### 3 A first look: exporter size distributions and trade margins

Let us begin with the simplest decomposition of aggregate French exports. 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,  $\bar{x}_t$ :

$$X_t = N_t \bar{x}_t \quad (1)$$

Figure 1 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.<sup>5</sup>

Figure 1: Number of exporters (left) and average value per exporter (right)



Note: Source: French customs, Authors' calculations.

The number of firms with positive exports in April 2020 was roughly 36,000, against 47,000 one year before thus implying 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

<sup>5</sup>The seasonal pattern of French exports is apparent by the fall recorded during August in every year.

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.

In order to quantify the contribution of each margin to the changes in aggregate exports we apply the following decomposition of the year-on-year growth rate of total exports:

$$\frac{\Delta X_t}{X_{t-1}} = \frac{\sum_{f \in S_t} \Delta x_{f,t}}{X_{t-1}} + \frac{\sum_{f \in E_t} x_{f,t} - \sum_{f \in L_t} x_{f,t-1}}{X_{t-1}} \quad (2)$$

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

The results of applying (2) to the 2020 data are provided in Figure 2, 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. It is apparent that almost all of the monthly variation of aggregate exports is accounted for by the firm intensive margin. In spite of the very strong reduction in the number of exporters, the firm extensive margin plays a negligible role in the variation of aggregate exports.

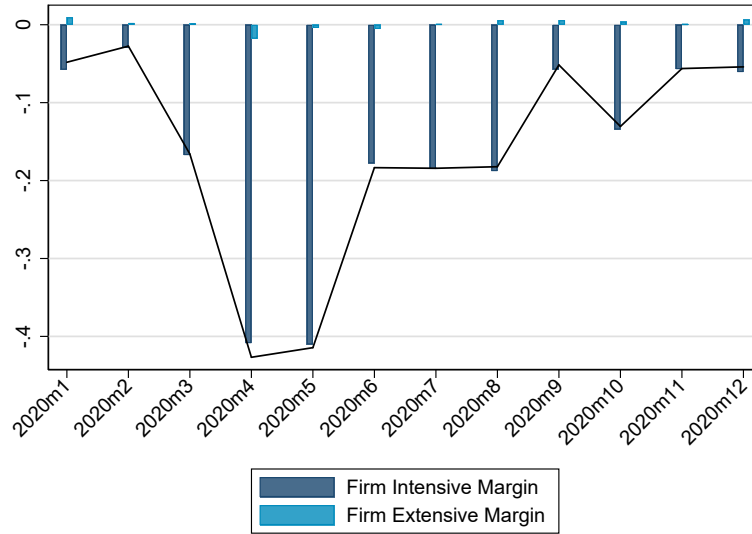
To better understand this result we look at size distributions according to exporter status. We focus on the export collapse that took place during April and May 2020, and consider continuing exporters, exiters and entrants as defined above. The results are provided in Figure 3. The left panel compares the distribution of export values (in common log) of firms that exported in April-May 2019, but exited the export market in April-May 2020, against the distribution of all exports in April-May 2019 (thus the set of firms in the encircled bars is a subset of those present in the light grey bars). It is apparent that exiters are smaller on average than continuing exporters. Average exports of exiters in 2019 equaled 65k Euros, a mere 4.5% of the average of all exporters (1.4m Euros). This substantial size difference is the reason why the exit of exporters, though important in numbers, does not matter much for the decline of aggregate exports.

The right panel looks at the evolution of the size distribution of continuing exporters.<sup>6</sup> The light grey

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<sup>6</sup>In the left panel of figure 3, the mass of continuous exporters is given by the difference between all exporters and exiters.

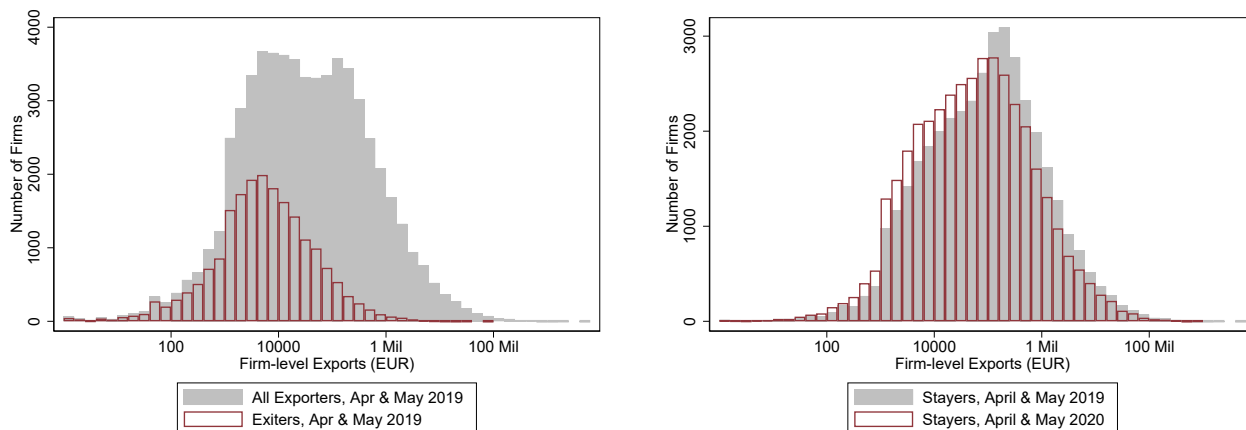
Figure 2: Contributions of the firm intensive and extensive margins



Notes: Horizontal axis, January is month 1; vertical axis: -0.1 stands for a contribution of -10 % of the monthly variation of aggregate exports. *Source:* French customs, Authors' calculations.

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 1. A noteworthy difference lies in the thinner tail right tail of the distribution of stayers in April-May 2020, indicating a truncation of extreme values during the crisis. Such change is likely to have an important impact in the aggregate. We will look further at the role of extreme values in driving the export collapse in the next subsection.

Figure 3: 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 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.<sup>7</sup> Interestingly, looking at exports to countries affected by the 1997 Asian crisis, [Bernard et al. \(2009\)](#) document a starker role for the intense margin with respect to countries not affected by the crisis. However, less is known about the underlying heterogeneities that drive the overall contribution of the intensive margin, and in particular about the role played by individual exporters in the aggregate reaction to large macro shocks. To make progress on that question, we now turn to analysing the variation in export values during the Pandemic along the (pre-pandemic) export size distribution. In particular, we want to look deeper into the role of large exporters, as the size distributions in [Figure 3](#) show that the very large export values were reduced during the crisis.

<sup>7</sup>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.

### 3.1 The Export Collapse along the Exporter Size Distribution

We start by grouping firms into size bins based on their total exports in 2019. We choose particularly fine bins at the top of the distribution because the exporter size distribution in France (as in many other countries) is highly skewed.<sup>8</sup> For instance, the top 1% exporters (roughly 1,000 firms out of a total of 100,000) account for over 60% of total exports.

The black bars in Figure 4 show the share of aggregate exports in April and May 2019 accounted for by each size bin. The top 1% are represented by the sum of the three most right bars. Among the top 1%, the top 0.1% (roughly 100 firms) account for over 40% of aggregate exports. The top 10 firms (top 0.01%) alone account for 19% of total exports in April and May 2019.

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 slump in exports is disproportionately explained by the small group of “Superstar” exporters. The top 0.1% of exporters contributed 57% to the collapse in aggregate exports, while their pre-crisis share was only 41%. 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.

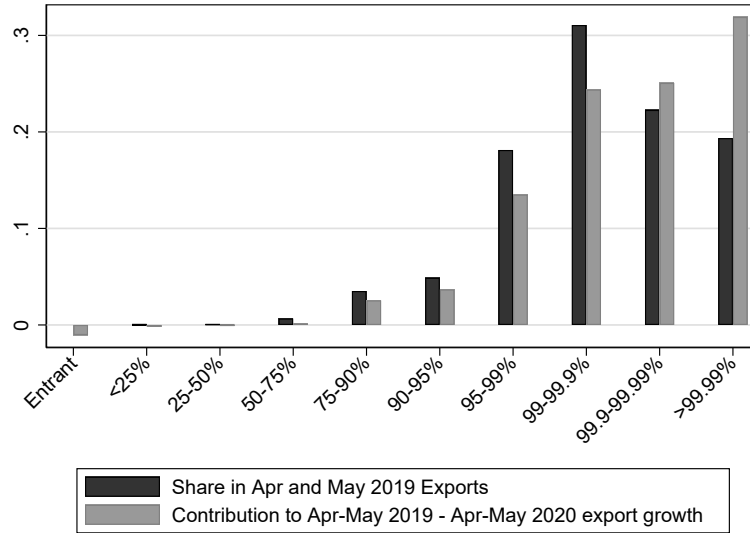
Zooming in on the top firms reveals the existence of a systematic relationship between growth and pre-crisis size. In Figure 5 we place the top 1,000 exporters into 100 bins of 10 firms each and compute for each bin the mid-point growth rate for April/May 2020. We then plot it against the (log) value 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.

The collapse of top exporters is also not driven by differential pre-existing trends across size groups. Figure 6 shows year-on-year growth rates of exports by bins of the exporter size distribution. We collapse firms into four groups, and compute weighted average growth rates within each bin. We begin in July 2019 and focus on continuing exporters, so that the set of firms remains the same within a bin

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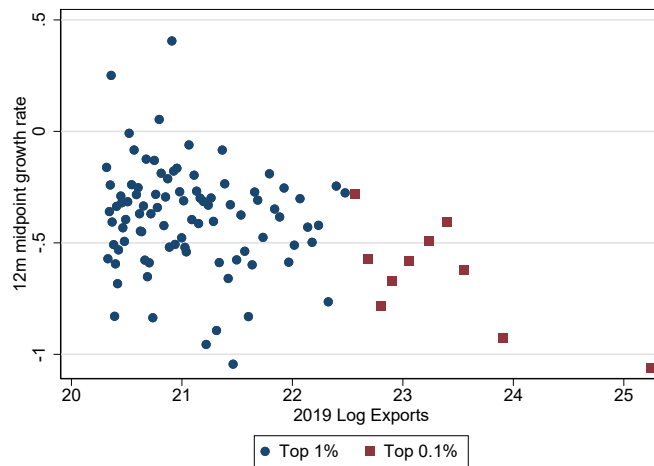
<sup>8</sup>See Freund and Pierola (2015) for a discussion of the role of large exporters in a large sample of countries

Figure 4: Export share *before* Covid and contribution *during* Covid, by size bin



Note: Firms are divided into size bins based on their total exports in 2019. The figure shows the export share of each size bin in April-May 2019 and the contribution of each size bin to the aggregate export collapse from April-May 2019 to April-May 2020.  
 Source: French customs, Authors' calculations.

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

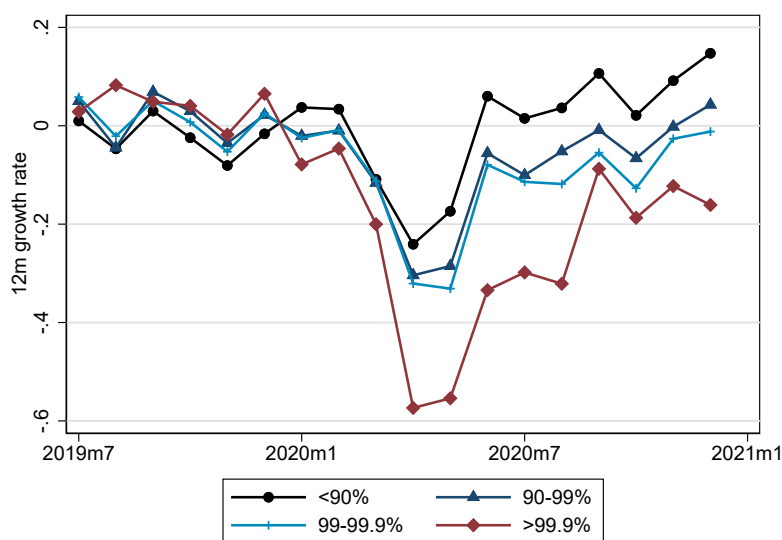


Source: French customs, Authors' calculations.

over time. We find no evidence for different pre-trends. Prior to the export collapse, firms in all bins were growing at very similar (close to zero) rates, with those in the top bin having slightly more positive growth rates. The stronger collapse of top exporters only started at the onset of the crisis.

Figure 6 also shows that the under-performance of top exporters was not restricted to the period of the initial shock in April and May 2020. In the following months, top exporters did not grow faster than the bottom 99.9% to make up for lost exports, but instead slowed down the recovery. By the end of 2020, exports of the top 0.1% were still well below pre-crisis levels, while smaller firms had already caught up or even surpassed pre-crisis exports.

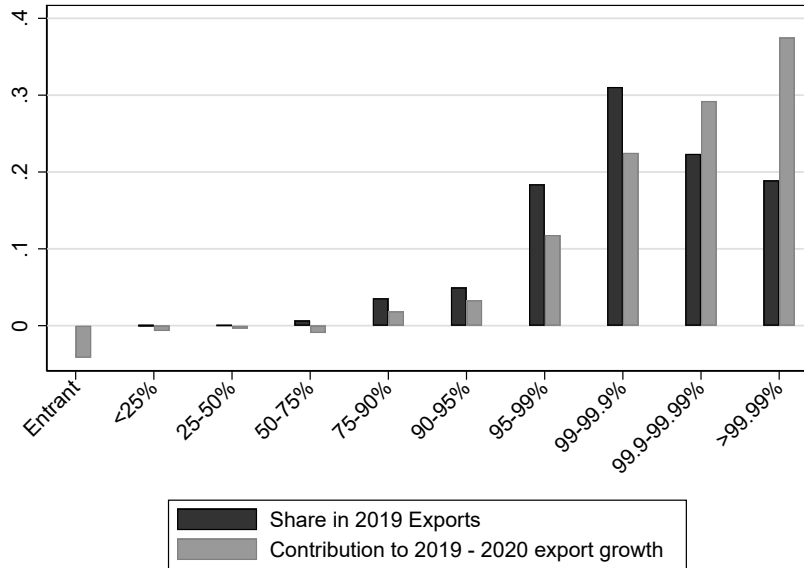
Figure 6: Year-on-year growth rates by exporter size bin: July 2019 - December 2020



Source: French customs, Authors' calculations.

The results in the subsection provide the main fact unveiled in the paper: The collapse of French exports associated with the onset of the Covid crisis was due to a higher adjustment by the very large exporters, which contributed significantly more than their pre-crisis share. This over-adjustment of the top exporters matters for the aggregate collapse: Had the top 0.1% of exporters grown at the same rate as the bottom 99.9%, aggregate year-on-year export growth in April and May 2020 would have been -31%, that is 11 percentage points larger than the observed -42%. Over the whole year, aggregate export growth would have been -9.2% instead of -16.3%. That is, the over-adjustment of top exporters explains almost half of

Figure 7: Export share in 2019 Covid and contribution to 2019-2020 trade growth, by size bin



Source: French customs, Authors' calculations.

the aggregate export collapse in 2020. Given the quantitative importance of this differential adjustment, the rest of the analysis will be devoted to establishing the robustness of this result and digging deeper into the underlying reasons.

This result resonates with an established literature documenting the role of very large individual firms in driving international trade aggregate outcomes, by appealing to the notion of “Granular” economies put forward by the seminal contribution of Gabaix (2011). Freund and Pierola (2015) use data for 32 countries and provide systematic evidence that very large firms, or export “Superstars”, account for the bulk of a country’s exports and can explain sectoral export patterns. This literature argues that idiosyncratic shocks to large firms do not wash out and thus affect aggregate outcomes. The fact that we unveil in this paper is related but different in a subtle way: it was the larger reaction of top exporters to the aggregate shock that explains its large magnitude. Thus, understanding the reaction of aggregate trade to the Covid shock requires taking into account the heterogeneity with which exporters of different sizes reacted to the shock, and in particular the *over-reaction* of the very large exporters with respect to those in the rest of the distribution.

## 4 What is behind the collapse of top exporters?

This section investigates potential reasons for the collapse of top exporters. To do so, we make use of the detailed nature of the export data, and combine them with information on firm-level imports and balance sheets. We also move to a flexible regression framework that will allow us to control for other (supply or demand) factors that may also determine export growth and are potentially correlated with exporter size. Subsection 4.1 describes the methodological approach, using midpoint growth rates and weighted regressions, while subsections 4.2 and 4.3 focus on potential reasons on the supply and demand side, respectively.

### 4.1 Growth rates with high-frequency detailed export data

Moving to the detailed trade data (firm-by-product-by-destination-by-month) immediately poses the problem of how to treat non-continuing transactions. While entry and exit at the *firm*-level does not matter much for the aggregate collapse during the recession, as shown in the previous section, entry and exit of *transactions* plays a more important role. In appendix A.2, we further split up the firm intensive margin into a transaction-intensive margin (year-on-year continuing flows within a firm-product-destination triplet), a product extensive margin (entry and exit of products within a continuing firm), and a destination extensive margin (entry and exit of destinations within continuing firm-products). The transaction-intensive margin remains the most important margin, but only explains about half of the aggregate collapse in April and May 2020.

In order to incorporate all extensive margin adjustments (firm, product, or destination), we employ midpoint growth rates.<sup>9</sup> 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. Specifically, for every firm  $f$ , CN8-product  $k$ , and destination  $j$ , we denote exports (in euros) at time  $t$  (e.g. April 2020) by  $x_{fjk,t}$ . The mid-point growth

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<sup>9</sup>While we use midpoint growth rates to incorporate exiting and entering transactions, our results do not depend on this choice. We also observe a larger collapse of top exporters when we focus on continuing transactions and using log changes.

rate between months  $t$  and  $t - 12$ , is then defined as:

$$g_{fjk,t} = \frac{x_{fjk,t} - x_{fjk,t-12}}{\frac{1}{2}(x_{fjk,t} + x_{fjk,t-12})} \quad (3)$$

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

$$g_t = \frac{X_t - X_{t-12}}{\frac{1}{2}(X_t + X_{t-12})} = \sum_f \sum_j \sum_k \omega_{fjk,t} g_{fjk,t}, \quad (4)$$

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

In the case of small changes, the midpoint growth rate is a very good approximation of the more common log change (see Figure A13 in the Appendix), but avoids extreme values in the case of large year-on-year changes in exports. It is bounded by -2 and +2, the values it takes on in the case of exit or entry of a transaction.

We start with the following model equation, expressing the growth rate  $g_{fjk,t}$  as the average growth rate  $\alpha_{b(f)t}$  of all flows within the same size bin  $b$  (as defined in the previous section), and the deviation from that average.

$$g_{fjk,t} = \alpha_{b(f)t} + \epsilon_{fjk,t} \quad (5)$$

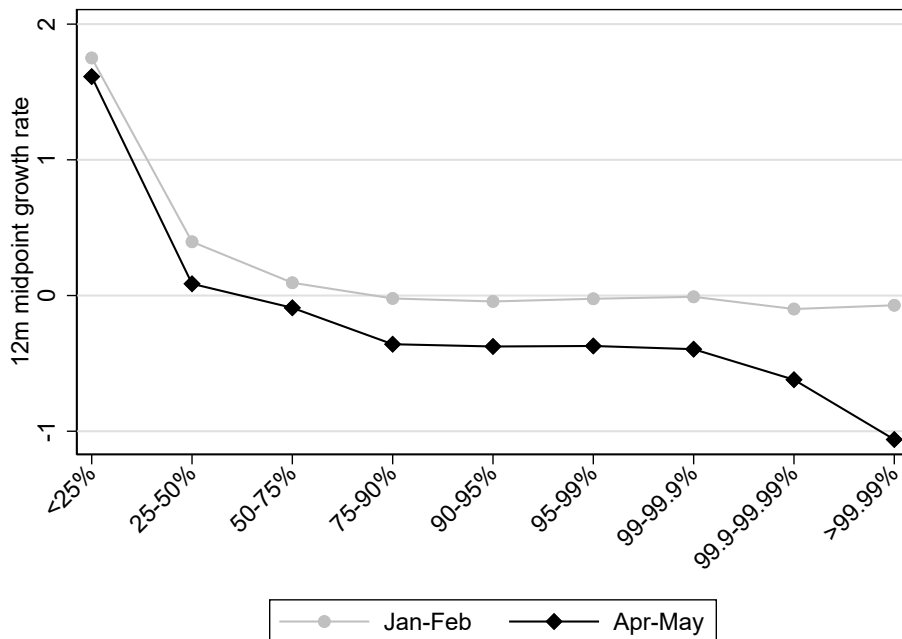
Using weights  $\omega_{fjk,t}$  in a weighted least squares estimation, the coefficient  $\hat{\alpha}_{b(f)t}$  estimates the aggregate midpoint growth rate for bin  $b$  at time  $t$ . Due to the aggregation property of the midpoint growth rate, the aggregate growth rate equals the weighted average of the bin-level growth rates.

We group the data into two-months intervals and estimate the model separately for the time period of January-February 2020, and for April-May 2020. The results are provided in Figure 8. The line for January-February 2020 shows that firms above the 75th percentile grew at essentially the same rates prior to the crisis. The high growth rates at the bottom of the distribution are strongly driven by entering and exiting flows, 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.

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  $g_{fjk,t}$  equalled -0.81 for the top 0.1% of exporters (weighted average of the two rightmost points), compared to -0.35 for exporters within the 75th and 90th percentile of the exporter size distribution. The message provided by Figure 8 is by construction the same as that delivered in Section 3, but presented through a set of estimated growth rates from a regression framework. We will next add controls to this regression framework to test for potential mechanisms that could have led to the collapse of top exporters.

Figure 8: 12-month mid-point growth rate of exports by size bin, January-February and April-May 2020



Source: French customs, Authors' calculations.

## 4.2 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. \(2020\)](#) uses 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 trans-

mission 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. 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 focus in the present section is to understand whether GVC exposure can explain the differential reaction of exports by top exporters to the Pandemic. In particular, 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.

In order to have a picture of international sourcing by French exporters we complement the export data with two additional datasets. First, we match (by firm-month) information on imports by CN8 product and country of origin. 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. Since import data are exhaustive, we set imports of firms that we do not find in the import data to zero. Merging in import data therefore does not lead to any reduction in our sample. We refer to this data as the *Customs sample*. Focusing on firms that export in 2019, this sample comprises roughly 100k firms.<sup>10</sup>

Second, we use firm-level yearly balance sheet data to measure total sales collected by the Banque de France and labeled FIBEN (in French: *Fichier Bancaire des Entreprises*). We match the trade and balance sheet data using the unique firm identifier SIREN. As explained in Section 2, the FIBEN dataset contains information for firms with yearly turnover of over 750,000 Euro, implying that we lose the smaller exporters in the matched sample. Focusing on exporters that are active in 2019 reduces the sample size from roughly 100k to 37k firms.<sup>11</sup> However, these 37k firms account for 71% of total 2019 exports. We refer to this restricted sample as the *Customs-FIBEN sample*. Figure A4 in the appendix gives more detail about match statistics by exporter size bin. We also show that the decline of top

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<sup>10</sup>Among these 100k firms, roughly 25k firms exit from 2019 to 2020. Another 25k firms enter from 2019 to 2020, so that the sample of all exporters that are active at some point in 2019 or 2020 consists of 125k firms.

<sup>11</sup>Including exporters that enter from 2019 to 2020, the sample captures 41k out of 125k firms.

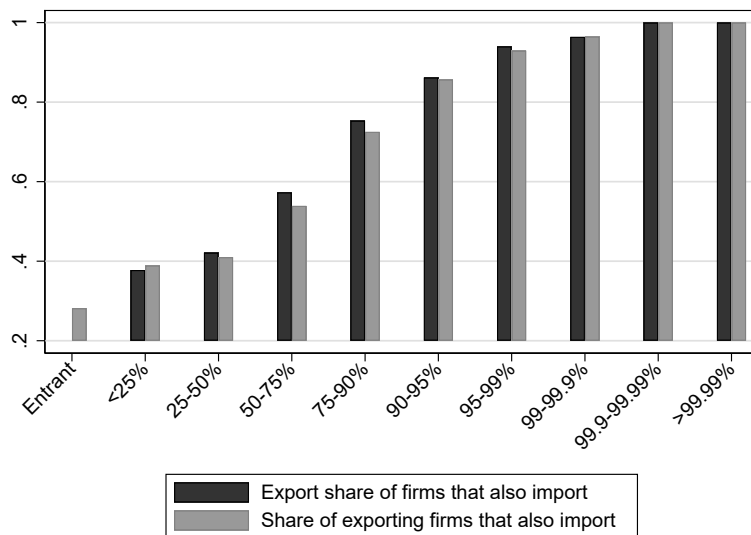
exporters also holds in this restricted sample (see Figure A5). This provides robustness of the already presented patterns and allow us to be confident that the results would carry over to the full sample if data were available.<sup>12</sup>

### Facts on GVC intensity by exporter size

It is well documented that export and import intensity both correlate with firm size, so that large exporters tend to be large importers; see e.g. Amiti et al. (2014) for evidence on Belgium data and Di Giovanni et al. (2020) for France. This feature also holds in our data, as we show now.

Figure 9 plots the share of exporters that are also importers in each bin, together with the share of total exports of that particular bin that is accounted for by exporter-importers. The figure clearly shows that larger exporters are more likely to import. Slightly over 50% of all exporters also import but the share of exporter-importers and their weight in total exports of each bin 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% exporters.

Figure 9: Export share of firms and share of exporting firms that import



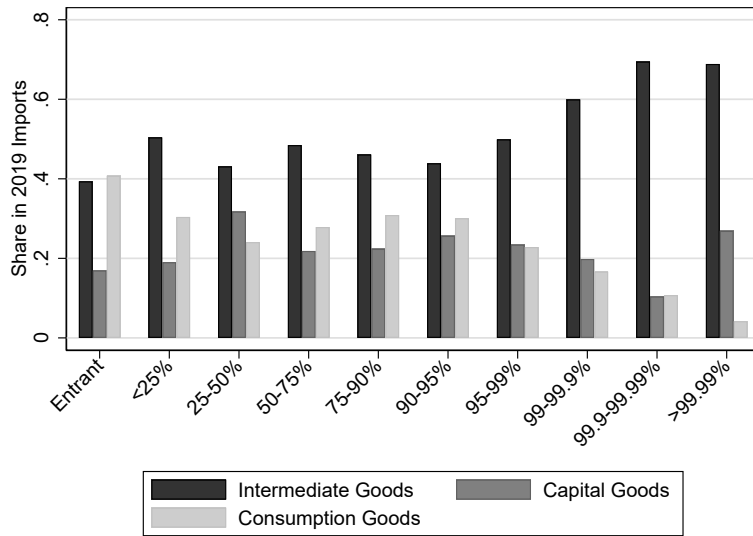
Source: French customs, Authors' calculations.

Focusing on the subset of exporters that also import (54k exporters out of roughly 100k), figure 10

<sup>12</sup>An alternative that we could use is the FICUS-FARE dataset, which provides a slightly better coverage of the left tail of the firm size distribution. Results using FICUS-FARE dataset are very similar to the ones presented here.

documents that the composition of imported goods also 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.<sup>13</sup>

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



Source: French customs, Authors' calculations.

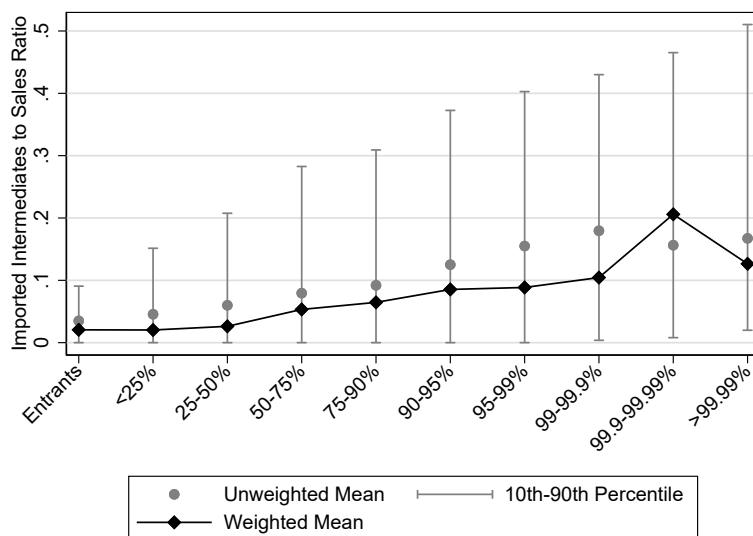
To test whether the collapse of top exporters is due to their higher reliance on imported intermediate inputs, we first compute a *firm-level* measure of dependence on foreign inputs. For that purpose we compute, for each firm in the matched Customs-FIBEN sample, the Imported-Inputs-to-Sales (IIS) ratio as  $IIS_{f,2019} = \frac{M_{f,2019}^{inp}}{Y_{f,2019}}$ , where  $M_{f,2019}^{inp}$  denotes the value of imported intermediate inputs and  $Y_{f,2019}$  total firm sales (including both domestic sales and exports). Both variables are calculated with yearly data for 2019, to capture the potential exposure of firms to the Pandemic-induced supply disruptions based on their pre-existing sourcing choices.

Figure 11 plots, by exporter size bin, the average (sales-weighted) IIS ratio and its within-bin distribution.

<sup>13</sup>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.4

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.

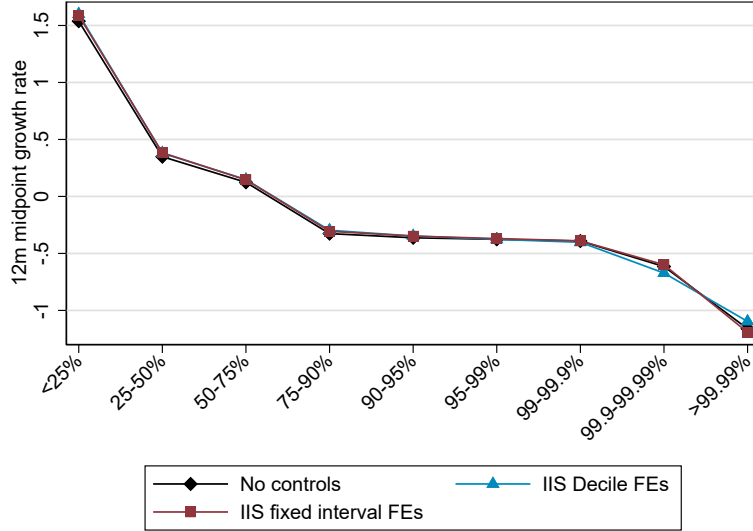
Source: French customs, Authors' calculations.

To test whether GVC exposure can account for the heterogeneous size effects we augment equation (5) with a set of dummies of the IIS ratio, whose effects are captured by  $\gamma_{r(f)t}$ .

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

We use two alternative specifications to create dummies for the IIS ratio, once creating decile dummies, and once creating dummies for intervals of fixed length (0-10%, 10-20%, etc.). We plot the results in Figure 12. 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. This result can be explained by the overall weak correlation between the IIS ratio and firm size reported in Figure 11.

Figure 12: Midpoint growth rate of exports by size bin, controlling or not for the *IIS* ratio



Source: French customs, Authors' calculations.

### Lockdowns in origin countries as supply shocks

Beyond the reliance on imported inputs captured by the *IIS* ratio, large exporters may have been more exposed to foreign supply shocks because of the structure of their imports in terms of origins. This heterogeneity arising from different source countries are not captured by the *IIS* ratio used above. To test for this potential channel, we calculate a firm-level input supply shock as the weighted average of supply restrictions in origin countries, using the share of each origin in total 2019 input imports as weights:  $\text{Supply Shock}_{ft} = \sum_i \frac{M_{fi,2019}^{int}}{M_{f,2019}^{int}} \text{Stringency}_{it}$ , where  $\text{Stringency}_{it}$  is the monthly average of the Oxford Stringency Index in origin country  $i$  at month  $t$  (Hale et al. (2021)).<sup>14</sup> Thus,  $\text{Supply Shock}_{ft}$  is akin to a shift-share instrument that varies over time according to changes in *Stringency* that are weighted by origin country import shares. Assuming that the stringency of lockdowns in origin countries is exogenous to French firms' shocks, and that the import shares in 2019 are uncorrelated with lockdown

<sup>14</sup>The Oxford Stringency index constructed by the University of Oxford for around 180 countries and updated on a daily basis. It is based on 20 indicators with information on several different common policy responses, which are aggregated into a set of four common indices ranging from 0 to 100 and increasing in the measures' stringency: an overall government response index, a containment and health index, an economic support index and the original stringency index. We use as a baseline the composite index that aggregates these four indices. The main indicator – “Stringency index” – is a composite indicator of school closures, workplace closures, cancellation of public events, public transport closures, public information campaigns, stay at home, restrictions on gatherings, restrictions on internal movement and international travel controls.

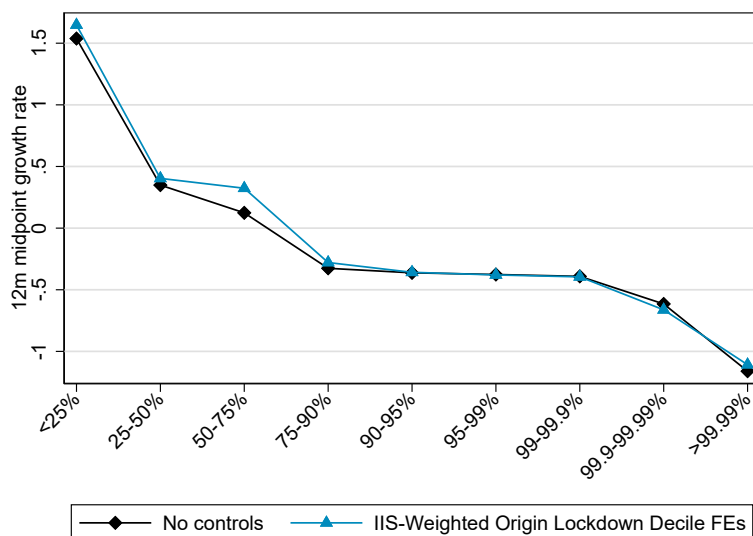
decisions in 2020, the method provides us with exogenous variations in the availability and cost of importing intermediate inputs that can be interpreted as supply shocks.

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

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

We proceed as before, constructing bins of Input Supply Shock $_{ft}$  and introducing them as controls in equation (5). The results are shown in Figure 13. Controlling for exposure to supply chain disruption does not change the coefficient associated with the size dummies. We therefore conclude that larger reliance on imported inputs cannot explain the collapse of top exporters.

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.

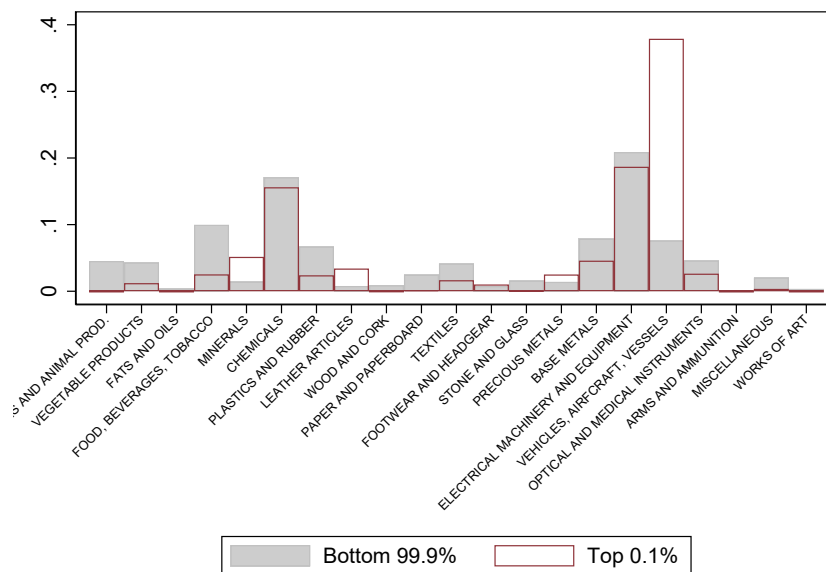
### 4.3 Demand shocks

#### Export composition by exporter size

We now investigate whether different exposure to demand shocks may have contributed to the collapse of top exporters. We start by looking at the sectoral composition of French exports along the exporter size distribution. Figure 14 shows, separately for the bottom 99.9% of exporters and the top 0.1%, the distribution of exports across the 21 sections of the HS code, where one section includes one or more 2-digit HS codes.

While the distributions look broadly comparable, top exporters are clearly over-represented among aircraft exporters. This different sectoral profile could in principle drive our results, especially in the light of the unevenness of the shock across sectors.

Figure 14: Distribution of top exporters across sectors (2019 data)



Source: French customs, Authors' calculations.

Further below we test more systematically for the role of sectoral composition effects by adding sector fixed effects to our regressions. Moreover, 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.<sup>15</sup>

To the extent that the composition of destinations differs by exporter size, top exporters may have also been subject to stronger negative demand shocks. For instance, one characteristic of the Pandemic is that lockdowns were introduced with different intensity and with differences in timing across countries. Thus, it is possible that larger exporters have different export portfolios than smaller ones, and the former were tilted towards destinations that put in place stronger sanitary measures.

To measure exposure to destination-country lockdowns we construct a measure of exposure to demand shocks in destinations, proxied with the stringency of lockdowns. The firm-level demand shock is constructed in an analogous fashion to the firm-level input supply shock of Section 4.2, and defined as the weighted average of lockdowns in destination countries, using the share of each destination in total 2019 exports as weights:

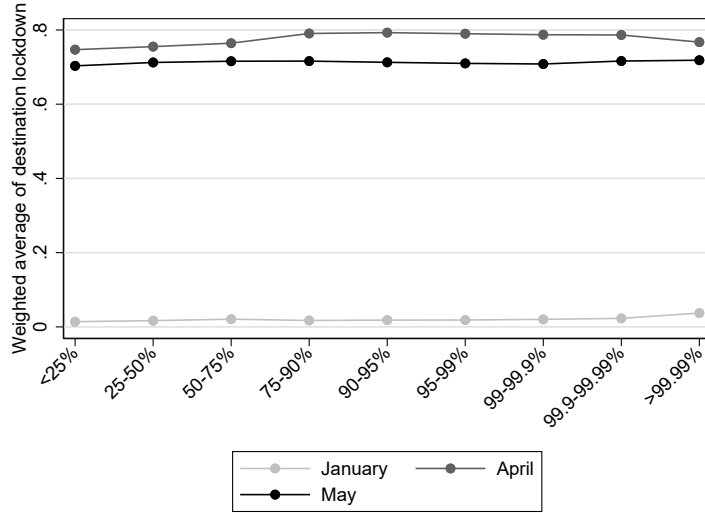
$$\text{Demand Shock}_{ft} = \sum_i \frac{X_{fi,2019}}{X_{f,2019}} \times \text{Stringency}_{it} \quad (8)$$

We then aggregate up the firm-level measures Demand Shock<sub>ft</sub> to the exporter size bin level by using firm-level exports in 2019 as weights, and present the results in Figure 15. It is apparent that there is no systematic relationship between exposure to destination-country lockdowns and firm size.

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<sup>15</sup>Specifically, we exclude all firms for which over 10% of their 2019 exports were classified under HS code 88: Aircraft, spacecraft, and parts thereof.

Figure 15: Export-weighted stringency of lockdown at destination by exporter size



Source: French customs, Authors' calculations.

### Netting out compositional effects

To provide a more stringent test, we now augment the baseline regression using sector and sector-destination fixed effects. That is, we estimate:

$$g_{fjk,t} = \alpha_{b(f)t} + \beta_{s_{jt}} + \epsilon_{fjk,t} \quad (9)$$

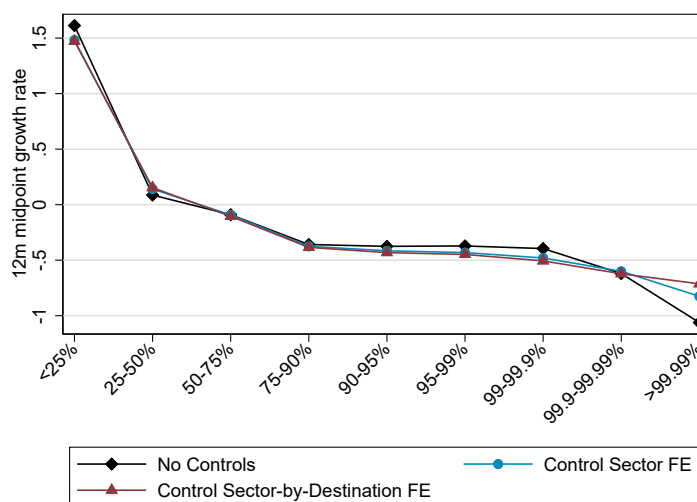
where  $\beta_{s_{jt}}$  reflect either sector ( $\beta_{st}$ ) or sector-destination dummies ( $\beta_{s_{jt}}$ ). Sectors are defined using the 2-digit level of the Harmonised System.

The results are provided in Figure 16. The differential growth rates between the very top exporters and the rest of firms are reduced when the size dummies are estimated within sectors or within sector-destination cells, but those differences remain. Sector composition alone cannot explain the underperformance of large exporters vis-a-vis the smaller firms during the Pandemic.

Notice also that the results using sector (and destination) fixed effects are likely to underestimate the over-adjustment of top exporters. Since the estimations are weighted by exporter size, sector fixed effects reflect the aggregate sectoral midpoint growth rate. In an environment with a few firms that are very

large in the entire economy, and particularly large in their sectors, the strong negative growth of top exporters also largely affects the aggregate growth rate of their sector.<sup>16</sup> 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.

Figure 16: April-May 2020 12-month mid-point growth rates of exports by size bin, controlling for industry and industry-destination characteristics



Source: French customs, Authors' calculations.

## Elasticity differences

The composition of exports by size bin does not explain the stronger reaction of large firms. Another possibility is that the largest exporters have a different elasticity than smaller exporters to a given foreign demand shock. To test for this hypothesis, we proceed as follows. We regress the mid-point growth rate at the firm-by-product-by-destination-by-month level on the stringency of the lockdown at destination. Using the detailed nature of the data is key as it allows us to control for supply and demand shocks using specifications with different sets of fixed effects.

Our estimating equation is:

<sup>16</sup>See also Gaubert and Itshhoki (2021b) who argue that shocks to individual firms can induce comparative advantage reversals in France, due to the dominant position of some large firms in their sector.

$$g_{fik,t} = \alpha \text{Lockdown Stringency}_{i,t} + \beta_{ft} + \gamma_i + \delta_{kt} + \epsilon_{fik,t} \quad (10)$$

where  $g_{fik,t}$  is the mid-point growth rate of exports by firm  $f$  of product  $k$  to destination country  $i$  during month  $t$ , as defined above.  $\text{Lockdown Stringency}_{i,t}$  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  $[0,1]$ . By definition of  $g_{fik,t}$ , the estimation concerns both the extensive and the intensive margin of exports.

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

Results are reported in Table 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 midpoint growth rate of exports to a country in full lockdown (Stringency = 1) is by 0.6 lower than the growth rate to a country without lockdown.

We now test for potential heterogeneous effects according to size, interacting the lockdown effect by dummies for exporter size (constructed using the pre-crisis distribution in Figure 4), and grouping the top exporters into a bin containing the highest 0.1%. We estimate the following baseline equation:

Table 1: Effect of Destination Lockdowns

	(1)	(2)
	Midpoint growth rate of exports	
Lockdown Stringency	-0.580*** (0.128)	-0.599*** (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	✓	✓

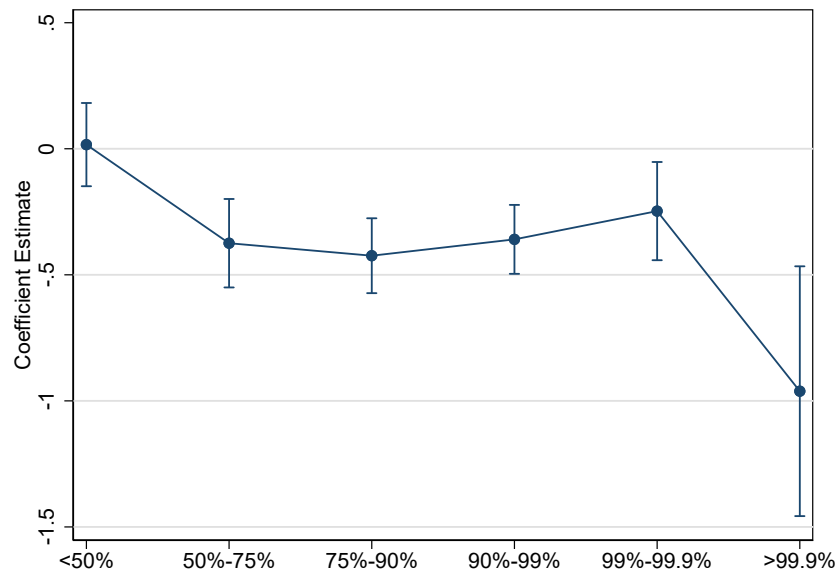
$$g_{fik,t} = \text{Lockdown Stringency}_{i,t} \times \eta_{b(f)} + \beta_{ft} + \gamma_i + \delta_{kt} + \epsilon_{fik,t} \quad (11)$$

where  $\eta_{b(f)}$  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 17 shows that the top exporters have a higher elasticity with respect to foreign demand shocks, that is their exports decline by more.<sup>17</sup> 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”, that is 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.*

<sup>17</sup>In principle, the higher elasticity for top exporters could also mean that these firms reallocate their exports more to low-stringency destination countries. However, we regard this possibility as unlikely, since this reallocation channel would work towards a smaller absolute decline of total exports by the top firms, which is contrary to what we observe.

Figure 17: Effect of Destination Lockdown by Size Bin



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

## 5 Comparison to GFC and a Long-Term View

We now ask how general the results are that we uncovered here. Do top exporters generally play a prominent role in export crises? And to what extent do large exporters drive the (export) business cycle in more normal times?

To study these questions, this section first draws a comparison to the Great Financial Crisis (GFC), arguing that the largest firms also drove that export collapse (albeit to a lesser extent). We then study the evolution of French exports over a longer time period, decomposing aggregate export growth into average firm growth and a granular residual. We find that the granular residual plays an important role in both crisis and non-crisis times. We also find that the granular residual is positively correlated with average firm growth, suggesting that the largest exporters do better than average in good times but worse than average in bad times.

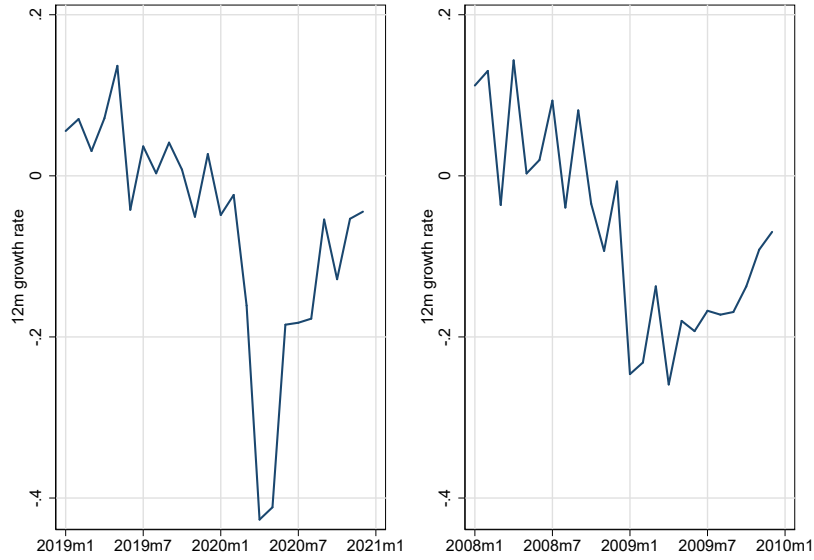
These findings suggests that our main results are not specific to the Covid-pandemic, and instead seem to be more general in that they can also be found during other export collapses, and also during more normal times.

### Comparison to GFC

The only export collapse in our sample (going back to 1993) of comparable magnitude to 2020 happened during the GFC. Figure 18 compares the monthly evolution of the year-on-year growth rates during both periods. The export collapse was much faster during Covid, but the aggregate yearly collapse was very comparable in both episodes: In 2009, aggregate French exports fell by -17.4% (2009 vs 2008), compared to -16.0% during Covid (2020 vs 2019).

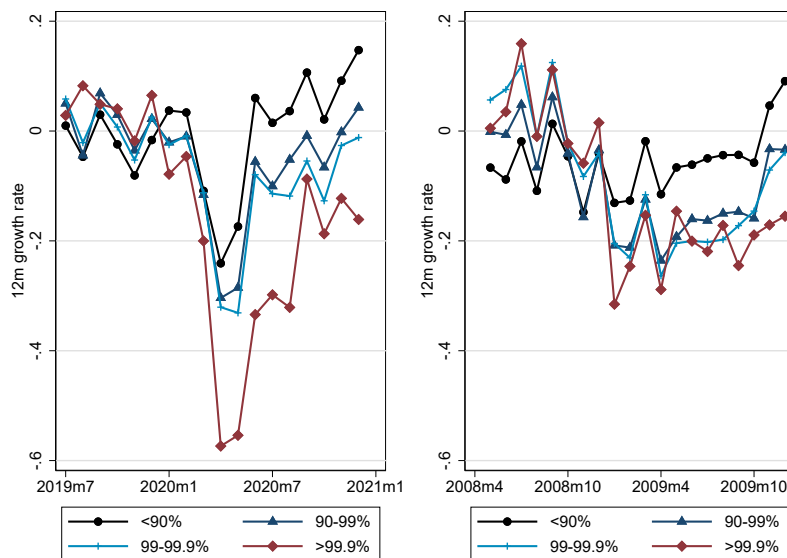
The export collapse during the GFC was also almost entirely driven by continuing exporters (see figure A9 in the appendix). Among the continuing exporters, it was also predominantly the top firms that collapsed by more. Figure 19 replicates figure 6 for the GFC, and plots the two graphs side-by-side. While the difference in growth rates between the top exporters and the rest is stronger during Covid, we observe a qualitatively similar pattern during the GFC.

Figure 18: Aggregate Export Growth, Covid (left) and GFC (right)



Source: Trade Data Monitor, Authors' calculations.

Figure 19: Growth rates of exports during the Covid (left) and GFC (right) crises, by size bin



Source: French customs, Authors' calculations.

## A Long-Term Perspective

We now look at the role of large firms in driving the export cycle over a longer time horizon. In particular, we show that there is an important role for large firms in explaining the export cycle (as measured by the granular residual) and that the granular residual is procyclical.

Studying the behavior of exporters over a longer time horizon (1993-2020) poses the challenge of changing reporting requirements over time. Firms are required to submit their detailed export filings when their total 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.<sup>18</sup> For the purpose of this subsection, we only look at aggregate firm exports. We therefore augment the detailed export filings with separate data on the smallest exporters in order to overcome the problem of changing size thresholds.

We start from 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).<sup>19</sup>

$$g_t = \sum_i \omega_{ft} g_{ft} = \bar{g}_t + Cov_t(\omega_{ft}, g_{ft}) \quad (12)$$

where  $\bar{g}_t$  is the simple average growth rate across exporters, and the granular residual  $Cov(\omega_{ft}, g_{ft})$  is the covariance between exporter size and the growth rate. We divide our data from 1993-2020 into quarters, and then compute the two components of equation 12 using year-on-year growth rates.

Figure 20 plots average export growth and the granular residual over time. We extract two messages from this figure. First, average firm growth and the granular residual contribute roughly equally to fluctuations in aggregate export growth. A simple variance decomposition of the aggregate growth rate gives a share of 58% that comes from average firm growth and a 42% share coming from the granular residual. In non-crisis times, the respective shares are 49% and 51%.

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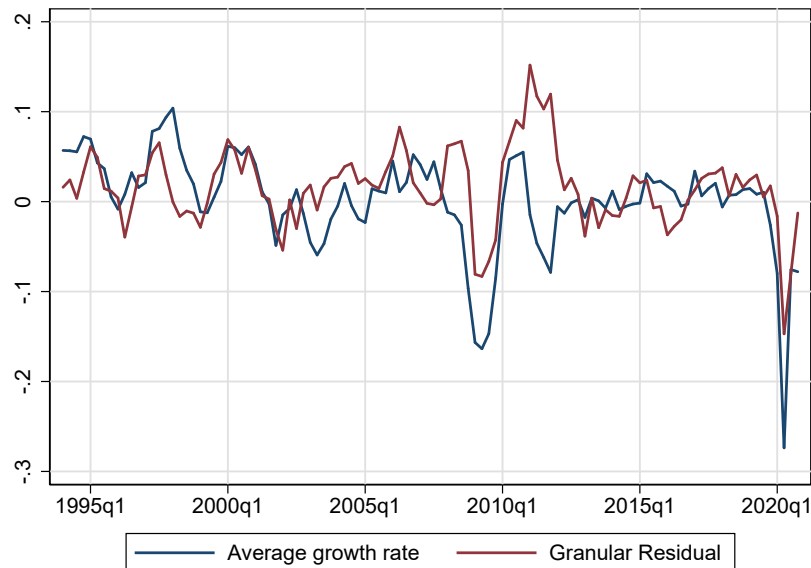
<sup>18</sup>Figure A10 in the appendix shows the number of firms in the detailed export data and the number of small exporters over time. Since the threshold has been raised over time, the share of firms with full information has fallen from over 90% in the 1990s to just over 70% in the most recent data. However, the export share accounted for by firms with full information has stayed close to 100%.

<sup>19</sup>Following these papers, we focus on the growth rate of continuing firms. However, we use the midpoint growth rate instead of the log change. We do this because we find that exports are very volatile within firms over time. This makes that the weighted average of firm-level log changes is not a good approximation for the aggregate log change. This problem is avoided with the midpoint growth rate, since it aggregates up exactly.

Second, average firm growth and the granular residual are positively correlated ( $\rho = 0.46$ ). That is, large exporters are doing worse than the average firm in times of a downturn, and better than average in times of an upturn. This resonates with our main finding that the largest exporters contributed more than proportionately to the export collapse in 2020.

In general, movements in the granular residual can arise from idiosyncratic shocks to large firms or from large firms reacting differently than the average to a macro shock. A first pass at distinguishing these two competing explanations is to look at the correlation between the granular residual and the average growth rate. In the case of idiosyncratic shocks to large firms, there is no immediate reason to believe that the granular residual should be correlated with macro shocks (as measured by average firm growth).<sup>20</sup> If large firms instead overreacted to macro shocks, the granular residual should exhibit a positive correlation with the average growth rate. This second result therefore suggests that the stronger-than-average response of large firms to common shocks likely plays an important role for the granular residual.

Figure 20: Average Firm Export Growth and the Granular Residual



Source: French customs, Authors' calculations.

<sup>20</sup>This is abstracting from cases where idiosyncratic shocks to large firms could affect the average if for instance many small firms supply inputs to large firms.

## 6 Conclusion

This paper provides a systematic study of the role of firm heterogeneity in the collapse of trade during the pandemic. We use detailed French firm-level data from January to June 2020 for exports and imports, with information on the products and countries of destination and origin of exported and imported goods. 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. More importantly, these detailed data clearly indicate a predominant role for the largest firms, whose shipments were reduced more than proportionately. This pattern was also true, albeit to a lesser extent, for exporters during the great financial crisis. 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 major exporters were relatively more affected. 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.

## Bibliography

- Aghion, P., Bergeaud, A., Cette, G., Lecat, R. and Maghin, H. (2019), ‘Coase lecture - the inverted-u relationship between credit access and productivity growth’, *Economica* (C), 86:1–31.
- Amador, J., Melo Gouveia, C. and Pimenta, A. C. (2021), ‘Covid-19, lockdowns and international trade: Evidence from firm-level data’, *mimeo* .
- Amiti, M., Itskhoki, O. and Konings, J. (2014), ‘Importers, exporters, and exchange rate disconnect’, *American Economic Review* **104**(7), 1942–1978.
- Antràs, P. (2020), Conceptual aspects of global value chains, Technical report, World bank policy research working paper 9114.
- Bergounhon, F., Lenoir, C. and Méjean, I. (2018), ‘A guideline to french firm-level trade data’, *Unpublished manuscript* .
- Bernard, A. B., Jensen, J. B., Redding, S. J. and Schott, P. K. (2009), ‘The margins of US trade’, *American Economic Review* **99**(2), 487–93.
- Boehm, C. E., Flaaen, A. and Pandalai-Nayar, N. (2019), ‘Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tohoku earthquake’, *The Review of Economics and Statistics* **101**(1), 60–75.
- Bonadio, B., Huo, Z., Levchenko, A. A. and Pandalai-Nayar, N. (2020), Global supply chains in the pandemic, Technical report, National Bureau of Economic Research.
- Bricongne, J.-C., Carluccio, J., Fontagn, L., Gaulier, G. and Stumpner, S. (2021), ‘The collapse of french exports in the covid crisis: mainly those of large business units’, *Eco Notepad, Blog of the Banque de France* .
- Cahn, C., Duquerroy, A. and Mullins, W. (2020), ‘Unconventional monetary policy and bank lending relationships’, *Proceedings of Paris December 2019 Finance Meeting EUROFIDAI - ESSEC* (C).
- Carvalho, V. M., Nirei, M., Saito, Y. and Tahbaz-Salehi, A. (2016), ‘Supply chain disruptions: Evidence from the great East Japan earthquake’, *Columbia Business School Research Paper* (17-5).
- de Lucio, J., Mínguez, R., Minondo, A. and Requena, F. (2020), Impact of covid-19 containment measures on trade, Technical report, Department of Applied Economics II, Universidad de Valencia.
- Di Giovanni, J., Levchenko, A. A. and Mejean, I. (2014), ‘Firms, destinations, and aggregate fluctuations’, *Econometrica* **82**(4), 1303–1340.
- Di Giovanni, J., Levchenko, A. A. and Méjean, I. (2017), ‘Large firms and international business cycle comovement’, *American Economic Review* **107**(5), 598–602.
- Di Giovanni, J., Levchenko, A. A. and Mejean, I. (2020), Foreign shocks as granular fluctuations, Technical report, National Bureau of Economic Research Working Paper 28123.
- Eaton, J., Eslava, M., Kugler, M. and Tybout, J. (2007), ‘The margins of entry into export markets: evidence from colombia’, *mimeo* .

- Eaton, J., Kortum, S. S. and Sotelo, S. (2012), International trade: Linking micro and macro, Technical report, National bureau of economic research.
- Fernandes, A. M., Klenow, P. J., Meleshchuk, S., Pierola, M. D. and Rodriguez-Clare, A. (2019), ‘The intensive margin in trade: How big and how important?’, *Unpublished manuscript* .
- Freund, C. and Pierola, M. D. (2015), ‘Export superstars’, *The Review of Economics and Statistics* **97**(5), 1023–1032.
- Gabaix, X. (2011), ‘The granular origins of aggregate fluctuations’, *Econometrica* **79**(3), 733–772.
- Gaubert, C. and Itskhoki, O. (2021a), ‘Granular comparative advantage’, *Journal of Political Economy* **129**(3), 871–939.
- Gaubert, C. and Itskhoki, O. (2021b), ‘Granular comparative advantage’, *Journal of Political Economy* **129**(3), 871–939.
- Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S. and Tatlow (2021), ‘A global panel database of pandemic policies (Oxford COVID-19 government response tracker)’, *Nature Human Behaviour* .
- Haltiwanger, J., Jarmin, R. S. and Miranda, J. (2013), ‘Who creates jobs? small versus large versus young’, *Review of Economics and Statistics* **95**(2), 347–361.
- Heise, S. (2020), How did chinas covid-19 shutdown affect u.s. supply chains?, Liberty Street Economics, May 12, Federal Reserve Bank of New York, , <https://libertystreeteconomics.newyorkfed.org/2020/05/how-did-chinas-covid-19-shutdown-affect-us-supply-chains.html>.
- Lafrogne-Roussier, R., Martin, J. and Méjean, I. (2021), Supply-shocks in supply chains: Evidence from the early lockdown in china. Mimeo, CREST.

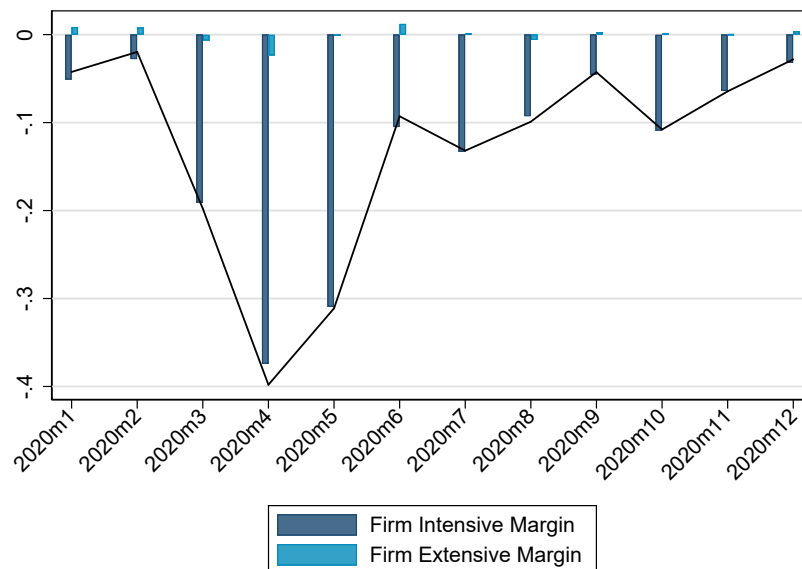
## 7 Appendix

### A.1 Imports

We ask in this Appendix what is the respective contribution of the extensive and intensive margins to the import collapse at the peak of the Covid crisis, and whether top importing firms contributed more than their share to this collapse. The procedure is identical to what has been presented for exporters: we consider the universe of French importers in each month, and observe the value of imports, the product, the origin. Different from the export data, we do not have information on the partner firm for intra-EU imports. Importantly, we do not restrict imports to the population of exporters: we do have importers only.

Figure A1 shows the contribution of the extensive and intensive margins to the collapse of French imports at the peak of the Covid crisis. This confirms what has been observed on the export side: the adjustment took place at the intensive margin rather exclusively. Exits of small importers do not show up in the aggregate given their limited size.

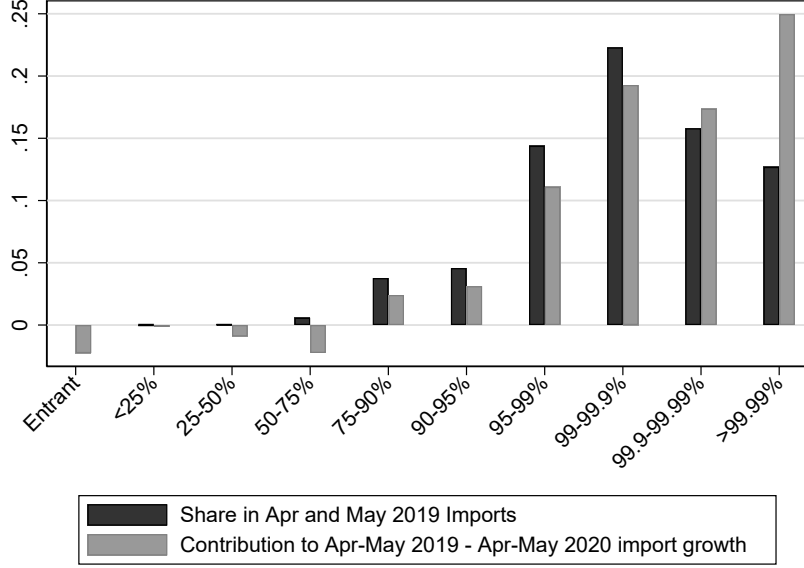
Figure A1: Contributions to imports of the firm extensive and intensive margins



Note: Horizontal axis, January is month 1; vertical axis:  $-0.1$  stands for a contribution of  $-10\%$  of the monthly variation of aggregate exports.  
Source: French customs, Authors' calculations

The next question is whether top importers also contributed more than their share to the collapse. We adopt the same strategy as for exports in Figure A2 and get a similar outcome, suggesting that large firms adjustments are pro-cyclical.

Figure A2: Import share *before* Covid and contribution *during* Covid, by size bin, controlling for industry and industry-destination characteristics



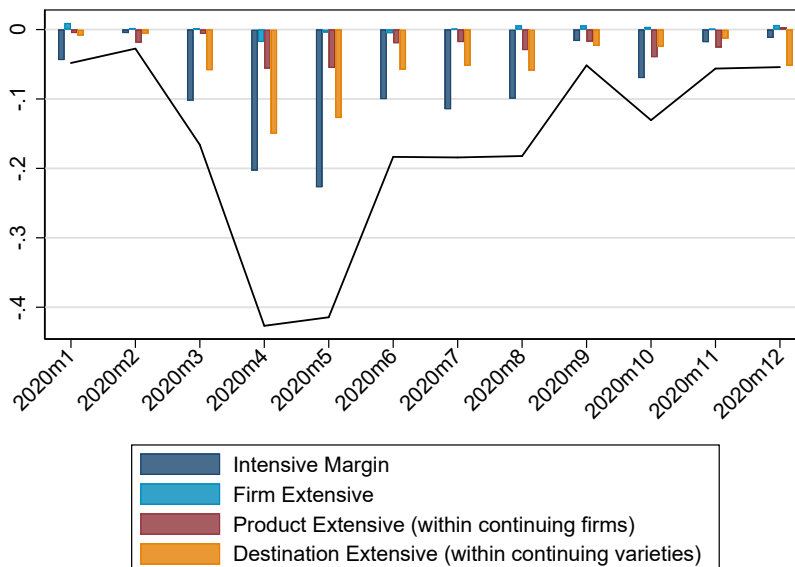
Note: Source: French customs, Authors' calculations

## A.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):

$$\begin{aligned}
\frac{\Delta X_t}{X_{t-1}} = & \underbrace{\frac{\sum_{f \in N} x_{f,t} - \sum_{f \in L} x_{f,t-1}}{X_{t-1}}}_{\text{Firm Extensive}} + \underbrace{\frac{\sum_{f \in S} \sum_{k \in S_f} \sum_{j \in S_{fk}} \Delta x_{fkj,t}}{X_{t-1}}}_{\text{Firm-Product-Destination Intensive}} \\
& + \underbrace{\frac{\sum_{f \in S} (\sum_{k \in N_f} x_{fk,t} - \sum_{k \in L_f} x_{fk,t-1})}{X_{t-1}}}_{\text{Product Extensive}} + \underbrace{\frac{\sum_{f \in S} \sum_{k \in S} (\sum_{j \in N_{fk}} x_{fkj,t} - \sum_{j \in L_{fk}} x_{fkj,t-1})}{X_{t-1}}}_{\text{Destination Extensive}} \quad (13)
\end{aligned}$$

Figure A3: Further decomposing the firm intensive margin



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

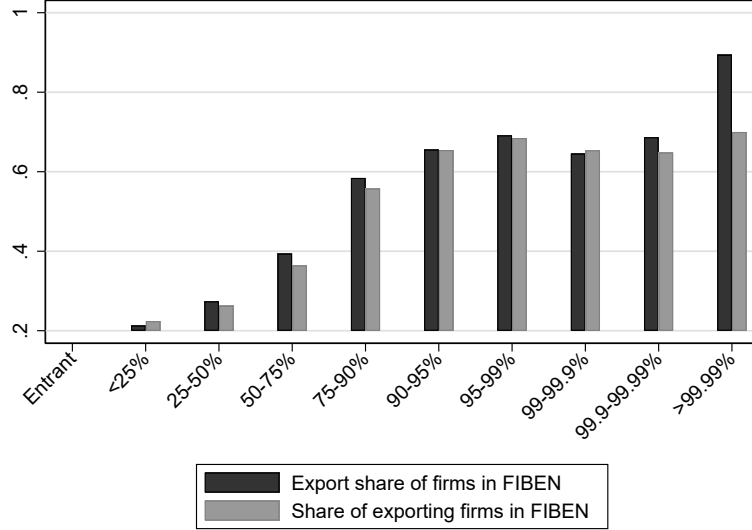
### A.3 Fiben

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

Because of the turnover threshold, the number of firms in the FIBEN dataset is substantially lower than that in the Customs data. Let us first check whether the sample of firms in Fiben is representative. The sample is comprising large exporters as a result of the threshold of turnover (above 750 keuros): 37% of the 2019 exporters have data in Fiben, but they account for 71% of the 2019 export value. And the export share of firms in Fiben reaches 90% in our top bin as shown in [Figure A4](#). The same conclusion holds if one reproduce the previous exercise of computing the 12-month midpoint growth rate of exports

by size bin of exporters for the Fiben sample as shown in Figure A5. We can therefore safely use this subsample to investigate the exporter’s exposure to foreign supply shocks through imported intermediate inputs using the *IIS* ratio as a control in size-estimations.

Figure A4: Share and export share of exporters in Fiben



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

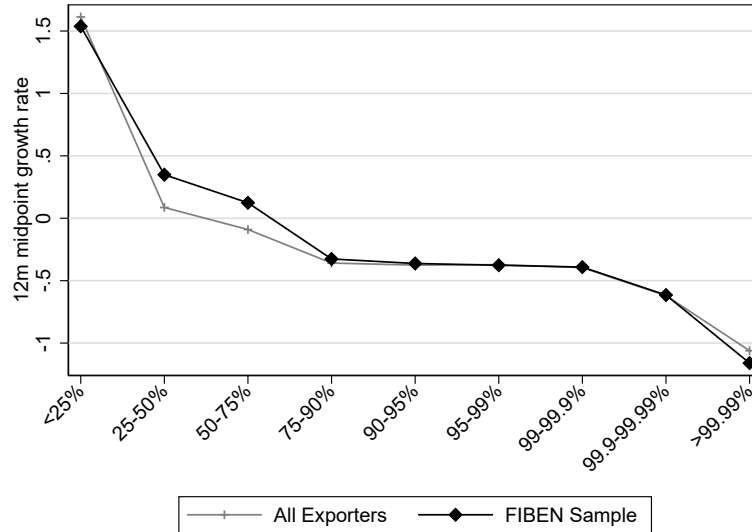
#### A.4 Imports of exporters

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 Mars 2020 and being especially strong during the months of May and June 2020 as show in Figure A6.

The above results show that there were not systematic differences in the exposure to foreign supply shocks depending on the structure of imports by size bin. We now follow the method in Section 4.1 and seek for heterogeneous effects within finely defined markets. We start by regressing the growth rate of imports by exporter, product and origin on a series of fixed effects plus the stringency of lockdown at origin. The equation is:

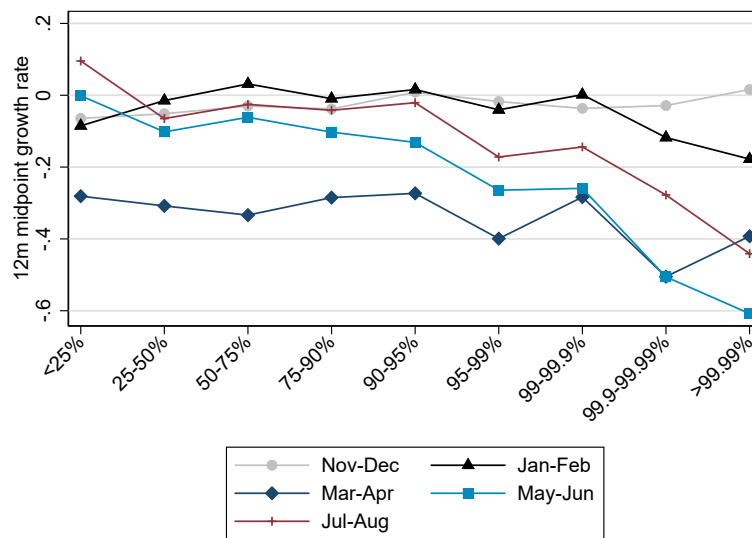
$$g_{fik,t} = \alpha \text{Lockdown Stringency}_{i,t} + \beta_{ft} + \gamma_i + \delta_{kt} + \epsilon_{fik,t} \quad (14)$$

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



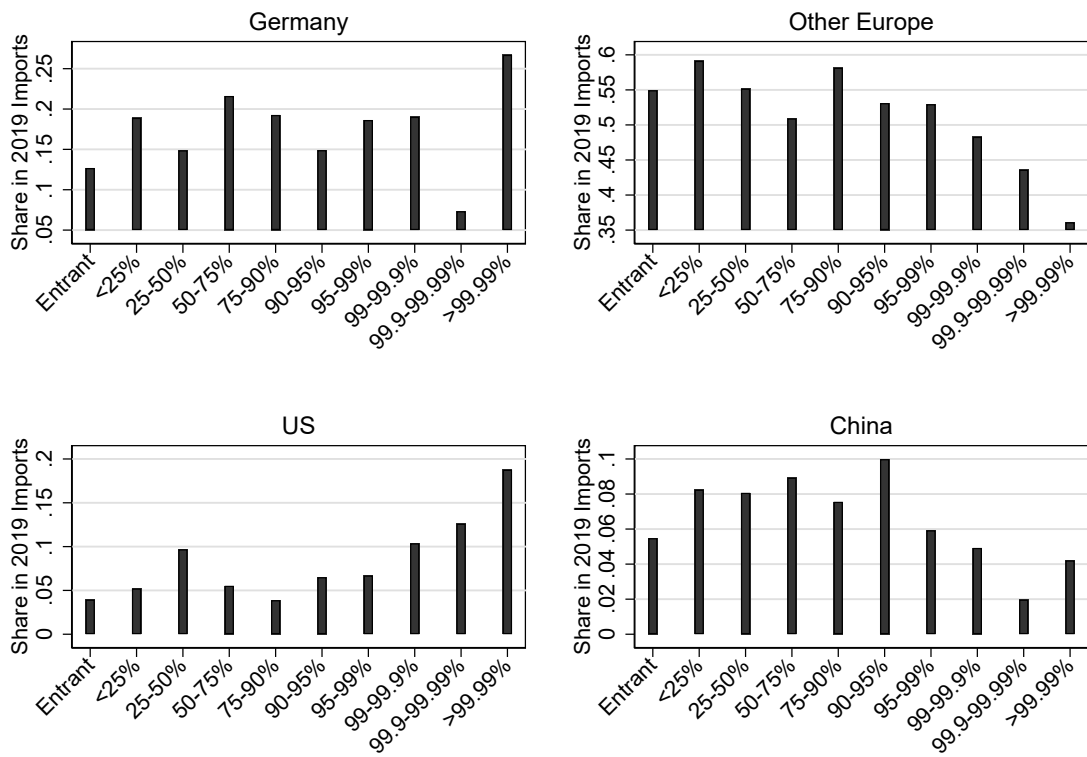
Source: French customs and Fiben Bank of France, Authors' calculations.

Figure A6: Exporter's imports during the Covid crisis (Nov.-Dec. 2019 to July-Aug. 2020)



Source: French customs, Authors' calculations.

Figure A7: Geographic structure of imports of intermediate products, by size bin of exporters (2019)



Source: French customs, Authors' calculations.

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

To look into potential heterogeneous effects according to size, we add size dummies to Equation 14, constructed using the pre-crisis distribution in Figure 4, but grouping the top exporters into a bin containing the highest 0.1%. We estimate the following baseline equation:

$$g_{fik,t} = Lockdown\ Stringency_{i,t} \times \eta_{b(f)} + \beta_{ft} + \gamma_i + \delta_{kt} + \epsilon_{fik,t} \quad (15)$$

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.

So doing we allow for coefficients to vary by size bin, hence capturing a different elasticity of imports to the Covid crisis by size bin of exports.

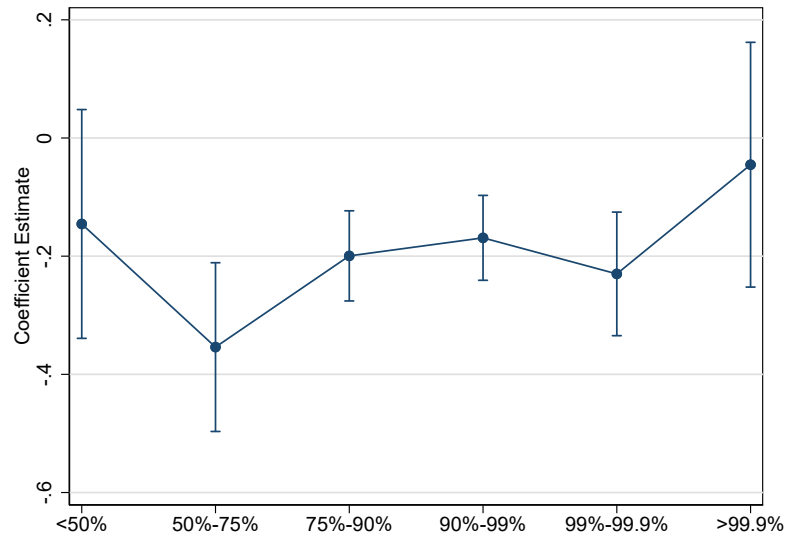
Table A1 shows the results of the estimation of Equation 14. The take home is that the correlation of lockdown stringency at origin with the midpoint growth rate is low. Using our preferred specification of column (2), we find that going from zero to full lockdown in the origin country reduces on average the mid-point growth of imports by 0.2 percentage points only.

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 bins is not statistically different from zero. To conclude, although larger importers did react more to the macroeconomic shock induced by the sanitary crisis, there is no evidence of a larger impact channeling specifically through the lockdowns in the countries of their suppliers.

Table A1: Effect of Origin Lockdowns

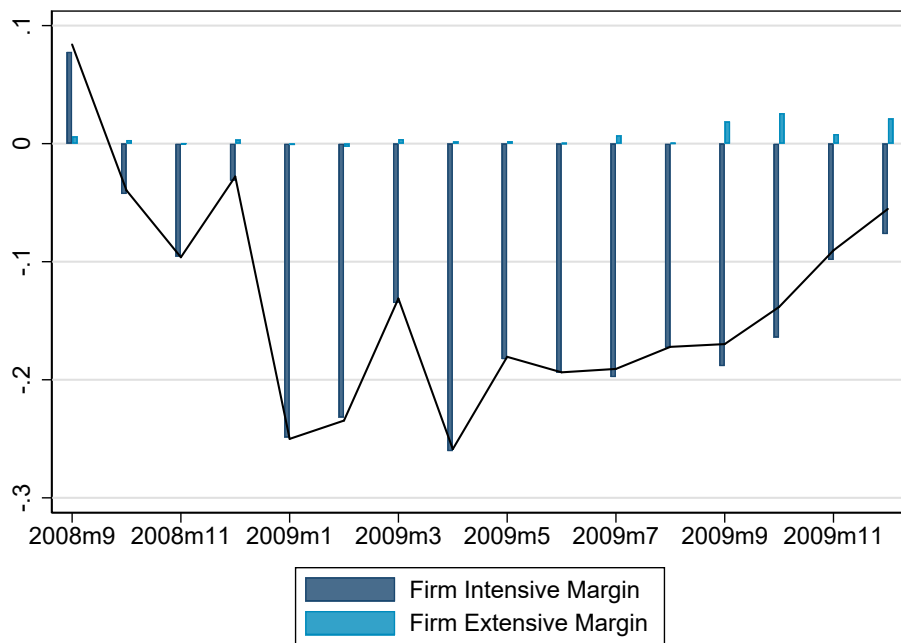
	(1)	(2)
	Midpoint growth rate of imports	
Lockdown Stringency	-0.244*** (0.0446)	-0.202*** (0.0438)
Observations	10,126,825	10,124,779
R-squared	0.379	0.459
Firm x Time	✓	✓
HS2 x Time	✓	✓
Destination	✓	✓
NC8 x Time		✓

Figure A8: Impact of Covid at origin on imports by exporter size



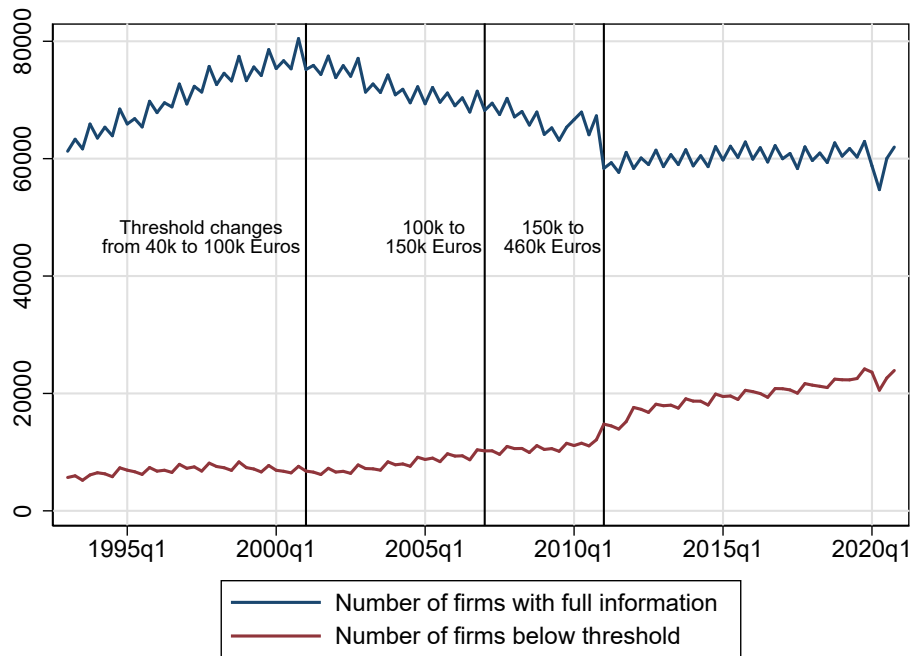
Source: French customs, Authors' calculations.

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



Source: French customs, Authors' calculations.

Figure A10: Number of firms with detailed export information and number of small exporters

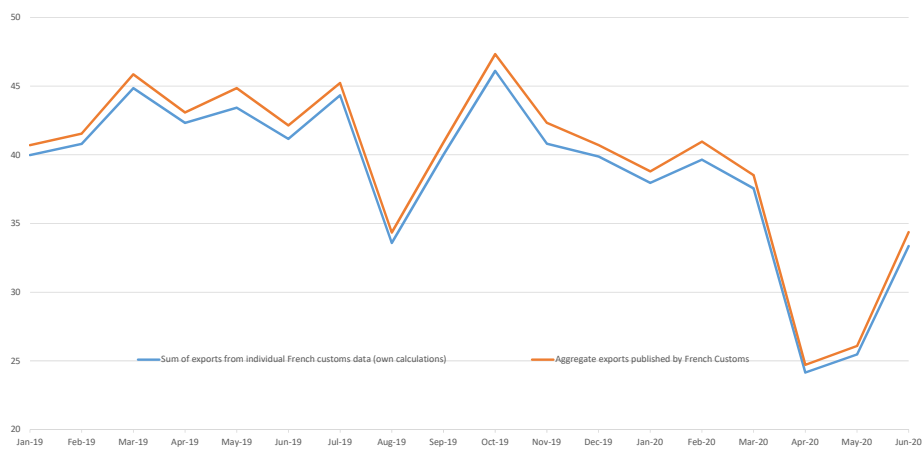


Source: French customs, Authors' calculations.

## A.5 Robustness: Aircrafts

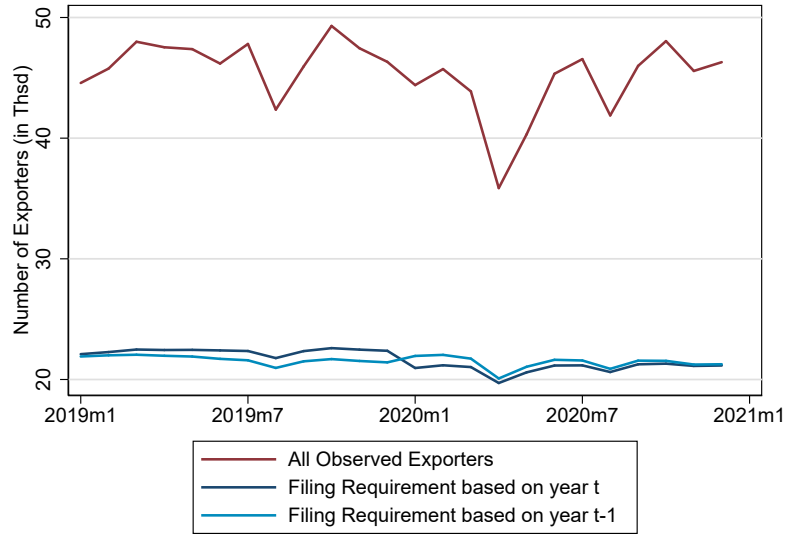
## B Online appendix

Figure A11: Coverage of aggregate statistics with transaction data



*Source:* French customs, Authors' calculations.

Figure A12: Exporters with and without filing obligation (2019-2021)



Source: French customs, Authors' calculations.

Figure A13: Midpoint growth rate vs log change

