Large Exporters, Industrial Composition, and Aggregate Exposure to External Shocks

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Abstract

Using monthly Mexican firm-level export data, I show that the larger declines of large exporters (top 1 percent by export value) during the COVID-19 trade collapse reflect their greater exposure to harder-hit industries, rather than greater sensitivity to fluctuations within the same industry. While large exporters' exports were disproportionately represented in a few durable manufacturing industries, other exporters' exports were spread more broadly across industries. Assigning the top 1 percent of exporters the industrial composition of the remaining 99 percent reduces Mexico's cumulative export shortfall in 2020Q2 by about one-quarter. Contractions varied even among these durable industries, and U.S. demand conditions are closely aligned with this cross-industry variation. These findings explain why large exporters appear more sensitive in aggregate and show how their industrial composition can amplify the aggregate effect of foreign demand conditions.

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1 Introduction

International trade contracts sharply during major downturns. During both the Global Financial Crisis (GFC) and the COVID pandemic, trade fell substantially more than GDP did, motivating a large literature on trade collapses. A central explanation is that internationally traded goods are concentrated in durable-goods industries whose demand is particularly cyclical (Eaton et al. (2016), Behrens et al. (2013), Engel and Wang (2011), Levchenko et al. (2010)).

Trade is concentrated not only across industries but also across firms. A small number of large exporters account for most aggregate exports. Recent evidence finds that the largest exporters decline more sharply than smaller exporters during major recessions and attributes this pattern to their greater sensitivity to demand conditions. As a result, their contributions to aggregate export fluctuations exceed their shares of exports (Bricongne et al. (2025), di Giovanni et al. (2024)). This pattern is puzzling because large firms are generally thought to be less sensitive to aggregate fluctuations and more resilient to external shocks than smaller firms (Gertler and Gilchrist (1994), Crouzet and Mehrotra (2020), Khwaja and Mian (2008)). Why, then, do large exporters experience larger declines than smaller exporters? Do they respond more strongly because of characteristics associated with firm size, or are their exports more exposed to industries that contract sharply? This paper examines whether the industries in which large exporters are disproportionately represented explain their larger declines. If those industries contract more sharply, large exporters can contribute disproportionately to an aggregate trade collapse even when they are no more responsive than smaller exporters within the same industry.

I study this mechanism using the collapse of Mexican exports during the COVID pandemic. Mexico provides a particularly useful setting because its exports are highly concentrated across both firms and industries. The top 1 percent of exporters account for approximately 70 percent of aggregate exports, durable manufacturing accounts for roughly three-quarters of exports, and approximately 80 percent of exports are shipped to the United States. This setting makes it possible to examine how the allocation of large exporters across industries shapes aggregate exposure to heterogeneous industry-level and foreign demand conditions.

I begin by documenting that the largest exporters experienced sharper declines than smaller exporters during Mexico's export collapse in 2020 and contributed more to the aggregate decline than their pre-pandemic export share would suggest. In 2019, the top

1 percent of exporters accounted for 70 percent of Mexico's exports, but they accounted for 99 percent of the decline from 2019 to 2020. I then test whether larger exporters are more responsive to common fluctuations at the aggregate firm level, as Bricongne et al. (2025) find for French exporters. I find the same pattern for Mexico. If this pattern reflects greater sensitivity to foreign demand conditions among large exporters, the positive size gradient should remain when exporters are compared within the same industry. While prior studies control for industry or destination but still measure firms' responses to an aggregate common fluctuation, I define the common fluctuation separately for each industry and compare large and small exporters' responses to that industry's movement. I find no systematic positive size gradient in these within-industry responses. This result suggests that the larger decline of large exporters may reflect their industrial composition rather than greater sensitivity associated with firm size.

I next examine the industrial allocation underlying this result. The top 1 percent of exporters' export values were disproportionately concentrated in a small number of industries, particularly motor vehicles, computer and electronics, and petroleum. These industries experienced heterogeneous contractions during the COVID collapse. Motor vehicles and petroleum contracted sharply, while the decline in computer and electronics was relatively modest. The aggregate exposure of large exporters therefore depended on how their industrial composition aligned with these heterogeneous industry-level contractions.

I quantify the aggregate importance of the two channels using two counterfactuals. The first assigns the top 1 percent of exporters the industry-specific growth rates of the remaining 99 percent, adjusted for pre-COVID differences in growth, removing within-industry differences in response while preserving their industrial allocation. This counterfactual leaves the aggregate collapse essentially unchanged. The second assigns the top exporters the pre-COVID industrial composition of the remaining 99 percent, removing differences in industrial allocation while preserving their own industry-specific growth rates. This counterfactual reduces Mexico's cumulative export shortfall in 2020Q2 from 37.2 percent to 28.6 percent, eliminating about 23.2 percent of the observed decline. The industrial composition of top exporters therefore had substantial aggregate consequences, even though top exporters did not respond more strongly than other exporters within industries.

I then examine U.S. demand conditions as a potential contributor to the heterogeneous industry-level contractions. I construct U.S. industry-level demand conditions using a sign-restricted vector autoregression (VAR) with industrial production from the Federal Reserve Board and inventories from the Census Bureau. I map them to Mexican industries through

predetermined global input-output linkages. The transmitted U.S. demand conditions are closely aligned with the cross-industry variation in Mexican export growth. Motor vehicles faced the sharpest deterioration in transmitted U.S. demand conditions and one of the largest export contractions, while computer and electronics experienced relatively modest declines in both.

Applying the same industrial-composition counterfactual to the aggregate growth component associated with U.S. demand conditions eliminates approximately 38.1 percent of its cumulative decline in 2020Q2. The larger composition effect for this component indicates that top exporters' exports were particularly concentrated in industries exposed to adverse U.S. demand conditions. This larger reduction suggests that top exporters' industrial composition mattered especially for the part of the export collapse associated with U.S. demand conditions.

This paper offers an explanation for the apparent contrast in findings on how large firms respond to aggregate fluctuations. Studies of domestic firms generally find that larger firms are less sensitive to business cycles (Gertler and Gilchrist (1994), Crouzet and Mehrotra (2020)), while other studies find that larger firms are more sensitive to aggregate export fluctuations or foreign GDP growth (Bricongne et al. (2025), di Giovanni et al. (2024)). I show that industrial composition can account for this apparent contrast. In firm-level regressions on aggregate fluctuations, Mexico's large exporters declined more sharply during COVID and appear more responsive to common fluctuations. Within the same industry, however, they are not systematically more responsive than smaller exporters to the same industrial fluctuation. Their greater aggregate decline partly reflects the industries in which they export rather than greater sensitivity associated with firm size.

This finding also connects firm-level heterogeneity to the literature on trade collapses. A large literature attributes the trade collapse during the GFC to falling demand for durable goods (Eaton et al. (2016), Engel and Wang (2011), Behrens et al. (2013), Levchenko et al. (2010)). Yet little attention has been paid to how a decline in durable-goods demand affects large and small exporters differently. I show how an industry-level trade collapse can produce larger declines among large exporters when their exports are disproportionately represented in the industries hit hardest.

This paper also contributes to the literature on the granular origins of aggregate fluctuations. When economic activity is concentrated among a few large firms, differences in their growth can have disproportionate aggregate effects (Gabaix (2011), di Giovanni and Levchenko (2012)). I ask why large exporters' growth differs from that of smaller exporters

during a trade collapse. The sectoral literature emphasizes that aggregate fluctuations also depend on where activity is located across industries and which industries are hit (Koren and Tenreyro (2007), di Giovanni and Levchenko (2009), Casal and Guntin (2025)). I connect these views by showing that large exporters' aggregate contribution depends on both their export share and the industries in which their exports are represented.

Finally, the paper contributes to work on global production networks and the international transmission of shocks. Existing studies show that input-output linkages and global supply chains transmit shocks across countries and sectors (Acemoglu et al. (2015), Carvalho et al. (2021), Huo et al. (2019)). I show that the aggregate consequences of this transmission also depend on the industrial allocation of a country's largest exporters. When large exporters' exports are concentrated in the industries most exposed to a foreign demand contraction, their allocation amplifies its transmission to aggregate exports.

The rest of the paper proceeds as follows. Section 2 describes the data and the construction of exporter size groups and industries. Section 3 documents heterogeneous exporter responses, shows that the positive aggregate size gradient does not persist systematically within industries, and examines the industrial composition of large exporters and heterogeneous industry-level contractions. It then quantifies the aggregate consequences of large exporters' industrial allocation using counterfactual exercises. Section 4 examines U.S. demand conditions as a potential source of industry-level heterogeneity and quantifies how the industrial allocation of large exporters shapes their transmission to aggregate Mexican exports. Section 5 concludes.

2 Data

2.1 Data Source

2.1.1 Export Data

Mexican firm-level export data are obtained from Panjiva, a platform that provides detailed information on global trade, including import and export activities across multiple countries. It is a product of S&P Global Market Intelligence. The Mexican export data are monthly and transaction-level, covering the period from 2012 to 2020. They include information on the exporter, export value, quantity, shipment date, importer, destination, the 8-digit Harmonized System (HS) code, and transport mode. To ensure that the data reflect international trade, I exclude observations where the destination is Mexico.

2.1.2 OECD ICIO

The OECD Inter-Country Input-Output (ICIO) tables are a dataset developed by the Organisation for Economic Co-operation and Development (OECD) to track the flow of goods and services across industries and countries in the global economy. They show how industries in one country use inputs from other industries, both domestically and internationally, and how shocks can spill over through global value chains. The 2025 edition covers 80 countries and 50 industries (based on the International Standard Industrial Classification (ISIC)) and is available on an annual basis throughout the sample period (2012–2020). I use the OECD ICIO tables to map HS codes to industries and to measure Mexican industries' exposure to U.S. demand conditions through pre-COVID input-output linkages.

2.1.3 Industrial Production and Inventories

I measure U.S. industry output using the industrial production (IP) index from the Federal Reserve Board's G.17 statistical release, Industrial Production and Capacity Utilization. The IP index tracks the real output of U.S. manufacturing industries at a monthly frequency and is seasonally adjusted. It is constructed from physical product data, deflated shipments, and production-worker hours, and is reported by North American Industry Classification System (NAICS) industry. I use the indexes for ten durable manufacturing industries over 2004–2020 and map them to OECD ICIO sectors. Table E.1 in Appendix lists the industries and their ICIO counterparts.

I measure inventories using the Manufacturers' Shipments, Inventories, and Orders (M3) survey published monthly by the U.S. Census Bureau. Its panel includes nearly all manufacturing companies with annual shipments of $500 million or more, along with a sample of smaller firms. The survey reports end-of-month inventories by stage of fabrication, and I use finished goods inventories for most durable goods industries. All series are seasonally adjusted, reported in millions of current dollars, and deflated by the corresponding industry Producer Price Index (PPI) published monthly by the U.S. Bureau of Labor Statistics (BLS).

2.2 Data construction

2.2.1 Size Group

I classify firms into three size groups based on their previous-year export values. For each year, I rank exporters by their export values in the preceding year. Size group 1 comprises the bottom 90 percent, size group 2 the 90th to 99th percentiles, and size group 3 the top 1 percent. Grouping the bottom 90 percent as small exporters and dividing the top 10 percent into finer size groups is common in studies of heterogeneous sensitivity.[1] Export values by percentile in 2019 also begin to rise sharply above the 90th percentile, while those of the top 1 percent stand out from the rest, further supporting this size-group classification (Appendix Figure A.1).

Classifying firms by their previous-year export values follows an approach similar to that of Crouzet and Mehrotra (2020), who classify firms using percentiles of the previous year's book assets. It differs, however, from the approach of Bricongne et al. (2025), who reclassify firms each month t.[2] With a rolling measure of firm size, the collapse in exports could change a firm's size group, so its response to the collapse would be measured using a size group affected by that same collapse. Using 2019 export values holds the size-group assignments fixed during 2020 and limits reclassification driven by the collapse.[3]

Figure 1a shows the share of Mexico's export value by size group from 2012 to 2020. The distribution of export value is highly skewed. Size group 3, the top 1 percent of exporters, accounts for approximately 70 percent of total exports throughout the period. In contrast, the bottom 90 percent of exporters account for less than 5 percent.

2.2.2 Industry

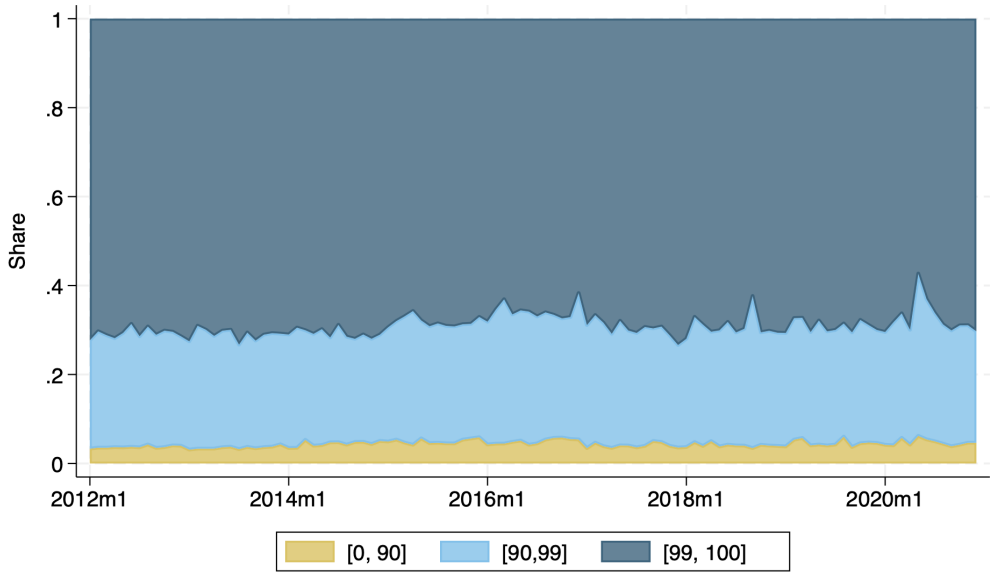
I define industries at the two-digit ISIC level and group them into four broad sectors: agriculture, mining, nondurable manufacturing, and durable manufacturing.[4] Panjiva pro-

[1] Bricongne et al. (2025) divide exporters into the 0–90th, 90th–99th, 99th–99.9th, and 99.9th–100th percentile groups; Crouzet and Mehrotra (2020) use the 0–90th, 90th–99th, 99th–99.5th, and 99.5th–100th percentile groups.

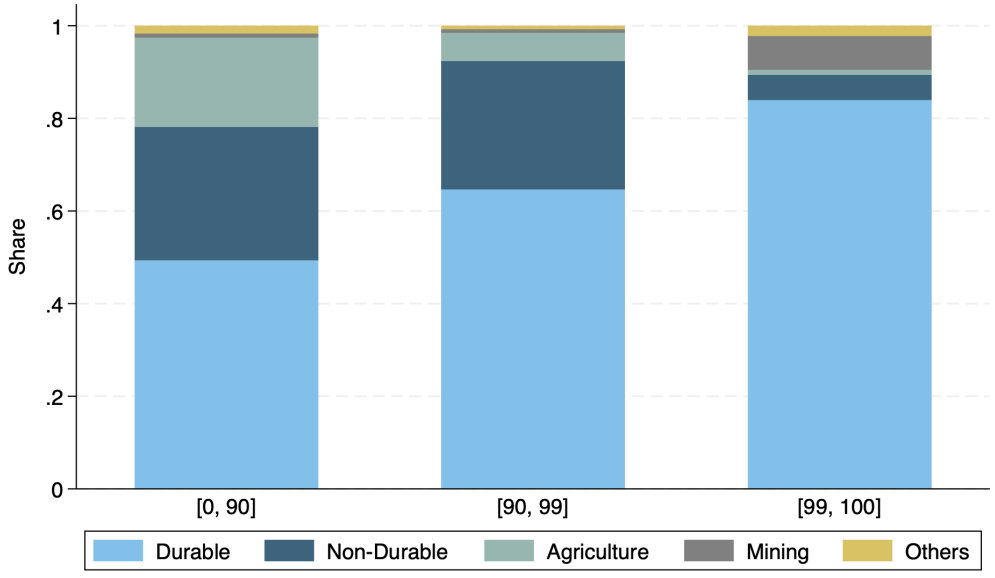
[2] Let x_{ft} denote exporter f's export value in month t. Monthly size groups are based on exports over the preceding 12 months, $\sum_{i=1}^{12} x_{ft-i}$.

[3] This annual classification is used in the regression analyses. In the accounting identity and counterfactual analyses in Sections 3.4 and 3.5, I instead fix each exporter's type at its 2019 size group and apply it to both 2019 and 2020, so that the same set of exporters is compared between $t-12$ and t. See also footnote 11.

[4] Table 5 in Section 3.3 lists the ICIO industries and their sector classifications. I classify C16 (wood products) as durable manufacturing because the Census M3 Survey classifies wood products as durable



(a) Share of Export Value by Size Group



(b) Share of Industry by Size Group

Figure 1: Share of Export Value and Industry by Size Group

Notes: Panel (a) displays the share of export value by size group from January 2012 to December 2020. Panel (b) displays the share of industry in each size group as of December 2019.

Table 1: Share by Industry and Destination

	Share	St. Dev.
Panel A. Industry		
Agriculture	0.025	1.609
Durable	0.745	1.618
Mining	0.079	1.691
Non-durable	0.136	1.587
Panel B. Destination		
US	0.792	1.573
non-US	0.208	1.741

Notes: This table shows the share of export value and standard deviation by industry and destination from 2012 to 2020. Standard deviation is that of firm-industry growth rates broken down by industry, and firm-industry-destination growth rates broken down by destination.

vides 10-digit HS codes but does not include industry classifications. HS codes are defined at the product level, while the ICIO tables are defined at the industry level, so each HS code must be mapped to an industry. The 6-digit HS code is internationally standardized, while digits beyond the sixth are country-specific. Therefore, I use 6-digit HS codes to map products to industries. A single HS code can correspond to multiple industries. In such cases, I assign weights to each industry at the destination-year level using the ICIO table. Specifically, when an HS code maps to multiple industries, its export value is split across those industries according to the assigned weights. Appendix subsection B provides matching details.

Figure 1b shows the distribution of industries by size group as of December 2019. The smallest firms (bottom 90 percent) are primarily involved in agriculture, non-durable manufacturing, and durable manufacturing. As firm size increases, the shares of agriculture and non-durable manufacturing decline, while the shares of durable manufacturing and mining increase. The largest firms (top 1 percent) are mostly engaged in durable manufacturing, with a smaller presence in mining, where they nevertheless play a dominant role.

Table 1 presents the distribution of industries and destinations over the sample period. The durable manufacturing sector accounts for the largest share, comprising approximately

manufacturing, whereas its nondurable manufacturing category does not include wood products. I exclude the "Others" sector from subsequent analyses because the top 1 percent of exporters cannot be identified in many of its industries.

75 percent of total exports. Across firm-size groups, most exports are directed to the United States, which receives about 80 percent of Mexico's exports. All industries exhibit similar levels of volatility, but exports to the United States are less volatile than exports to non-U.S. destinations. Overall, Mexican exports are highly concentrated in durable goods destined for the U.S. market.

3 Exporter Size and Industry Exposure

3.1 Large Exporters and Aggregate Fluctuations

During the trade collapse in Mexico in 2020, large exporters contributed disproportionately to the decline relative to their share of exports in 2019. Table 2 reports each size group's share of exports in 2019 and its contribution to the 2019–2020 change. The top 1 percent of exporters accounted for 70 percent of total exports in 2019 and contributed 99 percent of the net decline in exports from 2019 to 2020.

Table 2: Export Shares and Contributions to the 2019–2020 Change

Size group	(1) 2019 export share	(2) Share of 2019–2020 change
$[0, 90]$	0.034	-0.075
$[90, 99]$	0.261	0.087
$[99, 100]$	0.704	0.988

Notes: Column (1) reports each size group's share of aggregate exports in 2019, $X^{(b)}_{2019}/X_{2019}$, where $X^{(b)}_y$ denotes exports by size group b in year y and $X_y = \sum_b X^{(b)}_y$. Column (2) reports each group's contribution to the change in aggregate exports from 2019 to 2020, $(X^{(b)}_{2020} - X^{(b)}_{2019})/(X_{2020} - X_{2019})$.

Large exporters' disproportionate contribution to trade decline arises because large exporters contracted substantially more than small exporters. Figure 2 provides complementary evidence. Continuing large exporters had lower average year-over-year growth than continuing smaller exporters during the collapse. Together with their large initial export share, this pattern is consistent with their disproportionate contribution in Table 3.

Previous literature provides contradictory evidence on how firms of different sizes respond during recessions. Using U.S. manufacturing data, Gertler and Gilchrist (1994) and

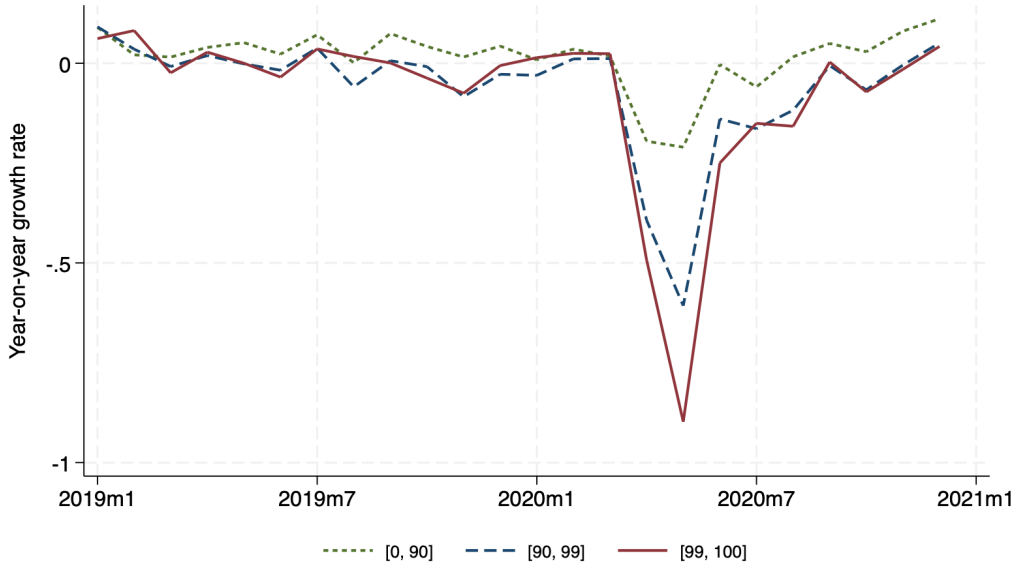


Figure 2: Average Export Growth by Exporter Size

Notes: Each line shows the unweighted average year-over-year midpoint export growth rate of continuing exporters in a size group. Continuing exporters have positive exports in both month t and month $t-12$. Firms are assigned to size groups using their export values in the previous year: the bottom 90%, the 90th–99th percentiles, and the top 1%.

Crouzet and Mehrotra (2020) find that large firms are less cyclical. Using Pakistan domestic firm-bank data, Khwaja and Mian (2008) also find that large firms are more resilient to external financial shock. Then why do large exporters exhibit the opposite pattern? Using French firm-level export data, Bricongne et al. (2025) argue that greater sensitivity to common movements reflects firm size, meaning sensitivity increases with exporter size. I therefore first test whether large Mexican exporters are also more responsive to the common movement.

Let x_{ft} denote firm f's exports in month t. Define the year-over-year midpoint growth rate as[5]

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

[5]Throughout this paper, I use the midpoint growth rate, following Bricongne et al. (2025). As noted in their study, the midpoint growth rate allows individual firms' growth rates to aggregate exactly to the aggregate growth rate. It also assigns well-defined growth rates to entering and exiting firms such that $g_{ft} = 2$ for entry and $g_{ft} = -2$ for exit.

I focus on continuing exporters, defined as firms with positive exports in both t and $t-12$, so that entry and exit do not enter the aggregate growth.[6] Let $\mathcal{C}_t$ denote the set of continuing exporters at time t, with $N_t = |\mathcal{C}t|$ and total exports $X_t = \sum_{f \in \mathcal{C}t} x_{ft}$. Building on the common-movement measure of Gabaix (2011) and Bricongne et al. (2025), I construct a leave-one-out version for each firm f, defined as the unweighted average growth rate of all other continuing firms at time t:[7]

$$\bar{g}_t^{-f} = \frac{1}{N_t - 1} \sum_{\substack{f' \in \mathcal{C}_t \\ f' \neq f}} g_{f't}. \tag{2}$$

Defining the common movement as a leave-one-out average avoids a mechanical correlation between a firm's growth and an average that includes its own growth. This concern is particularly relevant because exports are highly concentrated among the largest exporters and the growth rate of a single large exporter can substantially affect the average growth rate.

$$g_{ft} = \sum_b (\alpha_b + \beta_b \bar{g}_t^{-f}) \mathbf{1}\{f \in I_t^{(b)}\} + \varepsilon_{ft} \tag{3}$$

Equation (3) measures the responsiveness of each size group to the leave-one-out common movement. The set $I_t^{(b)}$ is a size group. For instance, exporters below the 90th percentile of the distribution of export sales in previous year are denoted by $f \in I_t^{(1)}$. The coefficient α_b captures the average growth rate for each size group, while β_b measures the differential response of firms in size group b to the common movement. A larger β_b indicates that exporters in size group b fluctuate more with the common movement. β_b is the coefficient of interest.

Table 3 reports weighted OLS estimates for continuing exporters, using the weight $w_{ft} = (x_{ft} + x_{f,t-12})/(X_t + X_{t-12})$.[8] The base group is the bottom 90 percent of exporters, so the coefficients on the interaction terms represent the difference in loadings of size group b relative to the bottom 90 percent exporters (i.e. $\beta_{[90,99]} - \beta_{[0,90]}$ and $\beta_{[99,100]} - \beta_{[0,90]}$).

[6] Appendix Table C.1 shows that most aggregate export fluctuations arise from the intensive margin, while the extensive margin makes a quantitatively small contribution throughout the sample period.

[7] Gabaix (2011) defines $g_{ft} - \bar{g}_t$ as a firm-specific idiosyncratic shock, where $\bar{g}_t$ is the unweighted average growth rate across firms. Bricongne et al. (2025) treats $\bar{g}_t$ as a common fluctuation shared by all exporters and measures how responsiveness to this fluctuation varies with firm size.

[8] Estimates including all exporters are reported in Appendix D.1 and are similar.

Table 3: Exporter Size and Aggregate Export Fluctuations

	(1)
	g_{ft}
$\bar{g}_t^{-f}$	0.987***
	(0.198)
$[90, 99] \times \bar{g}_t^{-f}$	0.172
	(0.211)
$[99, 100] \times \bar{g}_t^{-f}$	0.786**
	(0.360)
Adjusted R^2	0.049
Observations	981,536
Clustering	Firm, Date
Number of Cluster	96

Notes: Weighted OLS estimations of Equation (3) during 2013-2020, with weights given by w_{ft}. The dependent variable is the year-on-year midpoint growth rate at the firm-by-month level, g_{ft}. $\bar{g}_t^{-f}$ is the unweighted average of growth rate of all other continuing firms at date t. Base group is exporters at bottom 90%, and the coefficient on each interaction term represents the estimated difference in response from the base group. Standard errors are two-way clustered at the firm and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The result shows that the top 1 percent have a significantly higher loading than the bottom 90 percent. In the reported specification, a one-percentage-point decline in the midpoint growth of the leave-one-out common movement is associated with an additional 0.786-percentage-point decline in the midpoint growth of the top 1 percent relative to the bottom 90 percent. The size gradient on loadings is most apparent between the smallest exporters and the largest exporters, and I do not find evidence for a structural break on loadings between the pre-COVID and COVID periods (Appendix D.2). This greater sensitivity of large exporters to common fluctuation is consistent with Bricongne et al. (2025).

3.2 Exporter Size and Responsiveness Within Industries

During the trade collapse in 2020Q2, durable-manufacturing and mining sectors contracted the most. Figure 3 plots growth rate of each sector from January 2019 to December 2020. At the trough of the collapse in May, midpoint growth was about -1.0 in mining and

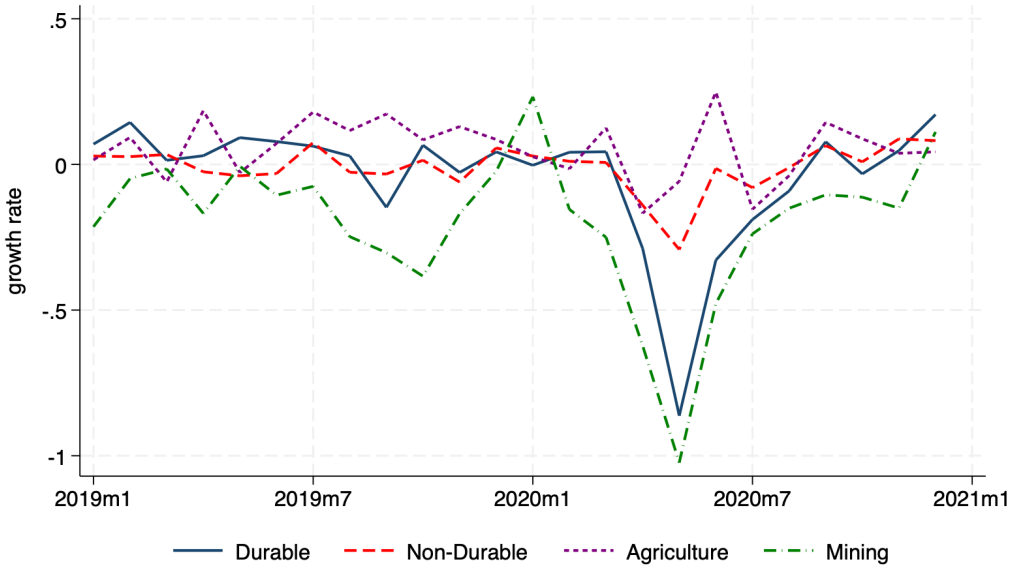


Figure 3: Growth Rate By Industry

Notes: This figure displays midpoint growth rate of each industry from January 2019 to December 2020. The durable manufacturing and mining industries were the most severely affected.

-0.86 in durable manufacturing. These sectors account for a substantial share of top exporters' total exports (Figure 1b). While Bricongne et al. (2025) find that higher sensitivity of larger exporters to aggregate fluctuation persists even after controlling for product-by-destination, the concentration of the largest exporters' exports in the hardest-hit sectors raises the question of whether their stronger response reflects industry composition.

Large exporters may decline more for two reasons. They may be concentrated in industries that contract more sharply (the industry-composition channel), or they may respond more strongly than smaller exporters to fluctuations within the same industry (the firm-size channel). If the aggregate size gradient reflects industrial composition, the positive gradient in Table 3 should weaken or disappear when exporters are compared within industries. If it reflects a stronger response associated with firm size, it should persist within industries.

Equation (4) disaggregates Equation (3) into industry i level, where industry denotes the ICIO industry defined in Section 2,

$$g_{fit} = \sum_b (\alpha_b + \beta_b \bar{g}_{it}^{-f}) \mathbf{1}\{f \in I_t^{(b)}\} + \varepsilon_{fit}. \tag{4}$$

g_{fit} denotes the midpoint growth rate at firm-industry-time level. $\bar{g}_{it}^{-f}$ denotes the industry-level common movement, defined for each firm f as the unweighted average growth rate of all other continuing firms in industry i at time t.

$$\bar{g}_{it}^{-f} = \frac{1}{N_{it} - 1} \sum_{\substack{f' \in \mathcal{C}_{it} \\ f' \neq f}} g_{f'it} \tag{5}$$

where $\mathcal{C}_{it}$ is the set of continuing exporters in industry i at t and $N_{it} = |\mathcal{C}_{it}|$. Equation (4) compares how exporters of different sizes respond to common fluctuations within the same industry.

Table 4 reports the weighted OLS estimates for Equation (4) for continuing exporters, with weights given by $w_{fit} = (x_{fit} + x_{fi,t-12})/(X_t + X_{t-12})$.[9] Column (1) reports pooled regression estimates for all industries, and column (2) includes manufacturing sector only. The interaction term represents the difference in loadings on the common industry-fluctuation relative to the bottom 90 percent group.

In contrast to the firm-level aggregate analysis in Table 3, the estimates show no systematic positive size gradient when exporters are compared within industries. In the all-sector sample, the loading of the top 1 percent of exporters is 0.765 lower than that of the bottom 90 percent. In manufacturing, the estimated difference is 0.198 and is not statistically significant. The positive point estimate could reflect industry composition effects that remain within broad two-digit ISIC industries. The results using alternative industry definitions are consistent with this possibility. In Appendix D.3, I report the results of Equation (4) with alternative industry classifications: two-digit and three-digit HS codes. Although none of the interaction coefficients is significant, the interaction coefficients are positive at the two-digit HS level, which suggests higher loadings for larger exporters. In contrast, the interaction coefficients are negative at the three-digit HS level, which suggests lower loadings for larger exporters. This implies that the difference in loadings depends

[9] The weight is simply w_{fit} even after considering the within-industry firm weight because it is canceled out. $w_{fit} = \{(x_{fit} + x_{fi,t-12})/(X_{it} + X_{i,t-12})\}\{(X_{it} + X_{i,t-12})/(X_t + X_{t-12})\}$ where X_{it} denotes the export value of industry i at t, $X_{it} = \sum_f x_{fit}$. For column (2) manufacturing only analysis, the denominator is $X_t^{Manu} + X_{t-12}^{Manu}$ where $X_t^{Manu} \equiv \sum_f \sum_i x_{fit}$ where $i \in$ Manufacturing.

Table 4: Exporter Size and Common Industry Fluctuation

	(1) g_{fit}	(2) g_{fit}
	All Sectors	Manufacturing
$\bar{g}_{it}^{-f}$	0.886***	0.941***
	(0.188)	(0.238)
$[90, 99] \times \bar{g}_{it}^{-f}$	0.116	0.146
	(0.204)	(0.250)
$[99, 100] \times \bar{g}_{it}^{-f}$	-0.765***	0.198
	(0.211)	(0.340)
Industry FE	✓	✓
Adjusted R^2	0.022	0.048
Observations	2,192,317	2,003,066
Cluster	Firm, Date	Firm, Date
Number of Clusters	96	96

Notes: Weighted OLS estimations of Equation (4) during 2013-2020, with weights given by w_{fit} ($i \in$ Manufacturing for column (2)). The dependent variable is the year-on-year midpoint growth rate at the firm-by-industry-by-month level. $\bar{g}_{it}^{-f}$ is the unweighted average of growth rate of all other continuing firms in industry i at time t. Fixed effect is industry i level. Column (1) includes all industries, and column (2) includes durable manufacturing and non-durable manufacturing sector only. Standard errors are two-way clustered at the firm and date level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

on the level of industry aggregation. At coarser industry classifications, large exporters appear more sensitive, but at finer classifications, they are no more sensitive than smaller exporters. Overall, the estimates provide no evidence that responsiveness systematically increases with exporter size within industries. I find no evidence that the differences in loadings changed between the pre-COVID and COVID periods; the results are reported in Appendix D.2. The findings are also robust to alternative standard error clustering, as shown in Appendix D.4.

This result offers a different interpretation of the findings in Bricongne et al. (2025). They find that larger exporters have higher loadings on common fluctuations even after including industry and destination fixed effects. I instead compare the loadings of large and small exporters on fluctuations within the same industry. In this setting, I find no systematic evidence that larger exporters have higher loadings. This pattern is more consistent

with Crouzet and Mehrotra (2020), who find that large firms in U.S. manufacturing are less sensitive to business cycles. The within-industry results point to industrial composition as a possible explanation for why large exporters contracted more during COVID-19. I examine this possibility in the next section.

3.3 Industrial Composition of Large and Small Exporters

The within-industry results provide no evidence that large exporters respond more strongly to industry-level fluctuations. I next describe how the industrial composition of large exporters differs from that of other exporters and how export growth varied across industries during the COVID-19 collapse. The following sections examine how these patterns combine to affect aggregate export growth.

To compare industrial composition across exporter sizes, I divide exporters into two groups for simplicity. Top exporters are the top 1 percent based on export values in the previous year; other exporters are the remaining 99 percent. Let X_{it}^T denote the export value accounted for by top exporters in industry i, $X_{it}^T \equiv \sum_{f \in T_t} x_{fit}$, and let X_t^T denote the total export value accounted for by top exporters, $X_t^T \equiv \sum_i X_{it}^T$. Similarly, for other exporters, $X_{it}^O \equiv \sum_{f \in O_t} x_{fit}$ and $X_t^O \equiv \sum_i X_{it}^O$. I then measure each exporter type's industrial composition as the share of its total exports accounted for by industry i:

$$s_{it}^T = \frac{X_{it}^T}{X_t^T}, \qquad s_{it}^O = \frac{X_{it}^O}{X_t^O}. \tag{6}$$

These shares describe how each group's exports are distributed across industries. They do not measure the industrial portfolio of an individual exporter or each group's share of exports within an industry.

Table 5 compares the industrial composition of top and other exporters in 2019. Columns (1) and (2) report each industry's share of the two groups' exports, and column (3) reports the difference between these shares. Column (4) reports each industry's share of aggregate Mexican exports. Top exporters' exports are concentrated in a few industries. Motor Vehicles (C29) accounts for 39 percent of their exports, compared with 14 percent of other exporters' exports, and Computer and Electronics (C26) accounts for 23 percent, compared with 6 percent. Top exporters also have a larger share in Crude Petroleum and Natural Gas (B06). Other exporters' exports are more evenly distributed across a wider range of industries.

Table 5: Industrial Composition in 2019

ICIO industry	Description	(1) s_{it}^T	(2) s_{it}^O	(3) $s_{it}^T - s_{it}^O$	(4) X_{it}/X_t
Agriculture					
A01	Agriculture and Hunting	0.01	0.07	-0.06	0.03
A02	Forestry and Logging	0.00	0.00	0.00	0.00
A03	Fishing and Aquaculture	0.00	0.00	0.00	0.00
Mining					
B05	Coal and Lignite Mining	0.00	0.00	0.00	0.00
B06	Crude Petroleum and Natural Gas	0.07	0.00	0.07	0.05
B07	Metal Ore Mining	0.01	0.01	0.01	0.01
B08	Other Mining and Quarrying	0.00	0.00	0.00	0.00
Non-Durable					
C10T12	Food, Beverages, and Tobacco	0.02	0.10	-0.08	0.05
C13T15	Textiles and Apparel	0.00	0.05	-0.05	0.02
C17T18	Paper, Printing, and Publishing	0.00	0.02	-0.01	0.01
C19	Coke and Refined Petroleum	0.01	0.00	0.01	0.01
C20	Chemicals	0.02	0.05	-0.03	0.03
C21	Pharmaceuticals	0.00	0.01	-0.01	0.01
C22	Rubber and Plastics	0.01	0.05	-0.05	0.02
Durable					
C16	Wood Products	0.00	0.00	0.00	0.00
C23	Non-Metallic Minerals	0.00	0.03	-0.02	0.01
C24	Primary Metals	0.02	0.03	-0.01	0.02
C25	Fabricated Metals	0.01	0.05	-0.04	0.02
C26	Computer and Electronics	0.23	0.06	0.17	0.18
C27	Electrical Equipment	0.08	0.11	-0.04	0.09
C28	Machinery	0.05	0.09	-0.04	0.07
C29	Motor Vehicles	0.39	0.14	0.25	0.32
C30	Other Transportation	0.04	0.05	-0.01	0.04
C31T33	Other Manufacturing	0.03	0.07	-0.04	0.04
	Mean	0.04	0.04	0.00	0.04
	Standard Deviation	0.09	0.04	0.07	0.07

Notes: This table reports the average industrial composition of top and other exporters in 2019. $s_{it}^T = X_{it}^T/X_t^T$ and $s_{it}^O = X_{it}^O/X_t^O$ denote the shares of top and other exporters' total export values accounted for by industry i, respectively. Thus, these measures characterize the cross-industry allocation of each exporter group and do not measure the within-industry shares of top or other exporters. Industry classifications follow the OECD ICIO framework.

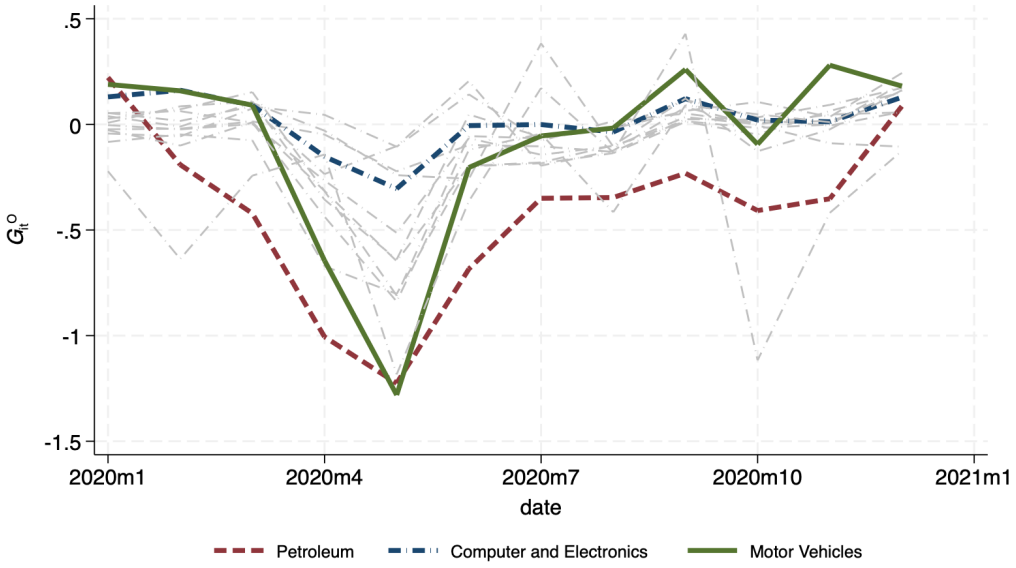


Figure 4: Industry-Level Export Growth in 2020

Notes: This figure plots industry-level midpoint growth rates of bottom 99% exporters, G^O_{it}, during 2020. For Petroleum, the midpoint growth rate of all exporters is used because bottom 99% exporters account for a negligible share of industry exports. Industries with an average aggregate export share below 0.01 in 2019 are omitted for readability.

Figure 4 plots the year-over-year growth rate of other exporters' total exports within each industry, G^O_{it}, in 2020.[10] Motor Vehicles (C29) and Crude Petroleum and Natural Gas (B06) accounted for large shares of top exporters' exports, and both contracted sharply. Computer and Electronics (C26) also accounted for a large share, but its decline was relatively modest. Top exporters were therefore heavily exposed to some of the hardest-hit industries, while industry contraction differed even among the industries toward which their exports were tilted. The next section examines how these differences affected aggregate export growth.

[10] $G^O_{it} = 2(X^O_{it} - X^O_{i,t-12})/(X^O_{it} + X^O_{i,t-12})$ will be defined in the next section precisely. Plotting G^O_{it} is intended to distinguish the industry-level contraction from large-exporters' contraction. For Petroleum and Natural Gas (B06), however, the industry-level growth rate for all firms, $G_{it} = 2(X_{it} - X_{i,t-12})/(X_{it} + X_{i,t-12})$, is plotted instead of G^O_{it}, because top 1% exporters account for nearly the entire export value in this industry. Also, the figure includes only industries with industry weights to aggregate exports (X_{it}/X_t) greater than 0.01 in Table 5 for readability.

3.4 Accounting Identity

The industrial composition of large exporters affects aggregate export growth through both the industries in which their exports are represented and the growth rates of those industries. To see how these patterns affect aggregate export growth, I use an accounting identity that combines top exporters' share of total exports, their industrial composition, and industry growth. This approach is related to the micro-to-aggregate accounting decompositions of Foster et al. (2001).

As defined in the previous section, X_{it}^T and X_{it}^O are the exports of top and other exporters in industry i. X_t^T and X_t^O are the total exports of each type, and aggregate exports, X_t, are the sum of X_t^T and X_t^O. Let λ_t denote the top exporters' midpoint share in total exports, and it is defined as

$$\lambda_t = \frac{X_t^T + X_{t-12}^T}{X_t + X_{t-12}}. \tag{7}$$

λ_t measures top exporters' share of aggregate exports using the combined export values at $t-12$ and t.[11] Accordingly, $1-\lambda_t$ is the corresponding share for other exporters. Because top and other exporters' exports sum to aggregate exports at each date, aggregate midpoint growth, $G_t = 2(X_t - X_{t-12})/(X_t + X_{t-12})$, can be written exactly as a weighted sum of their midpoint growth rates:[12]

$$G_t = \lambda_t G_t^T + (1-\lambda_t) G_t^O. \tag{8}$$

Next, to account for changes in the industry composition of each exporter type between $t-12$ and t, I use midpoint industry shares in place of the level shares s_{it}^T and s_{it}^O defined in Equation (6). Let w_{it}^T denote industry i's midpoint share of top exporters' total export value between $t-12$ and t. The corresponding midpoint share for other exporters is denoted by w_{it}^O.

$$w_{it}^T = \frac{X_{it}^T + X_{i,t-12}^T}{X_t^T + X_{t-12}^T}, \quad w_{it}^O = \frac{X_{it}^O + X_{i,t-12}^O}{X_t^O + X_{t-12}^O} \tag{9}$$

[11] The analysis focuses on $t \in 2020$, so that $t-12$ falls in 2019. Because exporter types are assigned annually, I fix each exporter's type at its 2019 classification, i.e., at $t-12$, and apply it to t as well. Thus, X_{t-12}^T is the export value 12 months earlier of the same exporters included in X_t^T, and changes in exporter type between $t-12$ and t are not reflected by construction.

[12] $G_t^T = 2(X_t^T - X_{t-12}^T)/(X_t^T + X_{t-12}^T)$ and $G_t^O = 2(X_t^O - X_{t-12}^O)/(X_t^O + X_{t-12}^O)$

w_{it}^T captures how strongly top exporters' exports are tilted toward industry i between $t-12$ and t, and w_{it}^O captures the same pattern for other exporters.

Industry-level midpoint growth rate by exporter type is defined as

$$G_{it}^T = \frac{X_{it}^T - X_{i,t-12}^T}{\frac{1}{2}(X_{it}^T + X_{i,t-12}^T)}, \quad G_{it}^O = \frac{X_{it}^O - X_{i,t-12}^O}{\frac{1}{2}(X_{it}^O + X_{i,t-12}^O)} \tag{10}$$

where

$$G_t^T = \sum_i w_{it}^T G_{it}^T, \quad G_t^O = \sum_i w_{it}^O G_{it}^O \tag{11}$$

By Equations (8) and (11), aggregate export growth can be decomposed as

$$G_t = \lambda_t \sum_i w_{it}^T G_{it}^T + (1-\lambda_t) \sum_i w_{it}^O G_{it}^O. \tag{12}$$

The first term in equation (12) shows that top exporters' contribution to aggregate export growth depends on their share of total exports, λ_t, their industrial composition, w_{it}^T, and growth in each industry, G_{it}^T. Their industrial composition can therefore amplify a trade decline when a larger share of their exports comes from industries that contract sharply.

3.5 Counterfactuals

I use two counterfactuals to assess why top exporters contributed so much to the COVID-19 export decline. First, I keep their industrial composition fixed but give them other exporters' growth rates within each industry, adjusted for pre-COVID differences in growth. If large exporters' larger declines reflect a firm characteristic that makes them more responsive even within the same industry, they would have experienced larger within-industry declines, and this counterfactual would substantially change aggregate export growth. Second, I keep top exporters' observed growth rates in each industry but give them other exporters' pre-COVID industrial composition. If their larger decline reflects greater representation in harder-hit industries, this counterfactual would also differ substantially from observed aggregate export growth. I then compare the two counterfactuals

to assess which channel accounts for more of the aggregate trade collapse.[13]

3.5.1 Counterfactual 1

I hold top exporters' baseline industry-level exports and other exporters' outcomes fixed, and assign top exporters the growth rate of other exporters within each industry, adjusted for pre-COVID differences in growth:

$$G_{it}^{T,CF1} = G_{it}^{O} - \left(\bar{G}_{i}^{O} - \bar{G}_{i}^{T}\right), \quad t \in 2020, \tag{13}$$

where $\bar{G}_{i}^{O}$ and $\bar{G}_{i}^{T}$ are the 2019 averages of G_{it}^{O} and G_{it}^{T}. For industry i, counterfactual exports in month t are

$$X_{it}^{T,CF1} = X_{i,t-12}^{T} \frac{2 + G_{it}^{T,CF1}}{2 - G_{it}^{T,CF1}}, \qquad t \in 2020. \tag{14}$$

I add these counterfactual exports to other exporters' observed exports to obtain $X_{t}^{CF1} = \sum_{i} X_{it}^{T,CF1} + X_{t}^{O}$. The counterfactual export values determine the new industry weights $w_{it}^{T,CF1}$ and the new aggregate share λ_{t}^{CF1}.[14] Other exporters' exports and industry weights remain unchanged. Applying the accounting identity in Equation (12) gives

$$G_{t}^{CF1} = \lambda_{t}^{CF1} \sum_{i} w_{it}^{T,CF1} G_{it}^{T,CF1} + (1 - \lambda_{t}^{CF1}) \sum_{i} w_{it}^{O} G_{it}^{O}. \tag{15}$$

3.5.2 Counterfactual 2

I give top exporters other exporters' pre-COVID industrial composition while keeping top exporters' total exports at $t - 12$ unchanged. Their counterfactual baseline exports in industry i are

$$X_{i,t-12}^{T,CF2} = s_{i,t-12}^{O} X_{t-12}^{T}. \tag{16}$$

[13] In industries where one exporter type accounts for almost all industry exports, the growth rate of the other type is undefined in some months or based on very few exporters. For these industries, I use the industry-level growth rate, $G_{it} = 2(X_{it} - X_{i,t-12})/(X_{it} + X_{i,t-12})$, in place of the type-specific growth rate: in place of G_{it}^{O} for Petroleum and Natural Gas (B06), where top exporters account for 99.9% of industry exports in 2019, and in place of G_{it}^{T} for Fishing and Aquaculture (A03) and Coal and Lignite Mining (B05), where top exporters account for almost none.

[14] Counterfactual midpoint weights are calculated as follows: $w_{it}^{T,CF1} = (X_{it}^{T,CF1} + X_{i,t-12}^{T})/(X_{t}^{T,CF1} + X_{t-12}^{T})$, and $\lambda_{t}^{CF1} = (X_{t}^{T,CF1} + X_{t-12}^{T})/(X_{t}^{CF1} + X_{t-12})$ where $X_{t}^{T,CF1} = \sum_{i} X_{it}^{T,CF1}$.

I then apply top exporters' observed growth rate in each industry:

$$X_{it}^{T,CF2} = X_{i,t-12}^{T,CF2} \frac{2 + G_{it}^{T}}{2 - G_{it}^{T}}. \tag{17}$$

Other exporters' exports remain unchanged. These export values determine the counterfactual aggregate export at t, $X_t^{CF2} = \sum_i X_{it}^{T,CF2} + X_t^O$, counterfactual midpoint industry weights $w_{it}^{T,CF2}$ and aggregate share λ_t^{CF2}.[15] Applying the accounting identity in Equation (12) gives

$$G_t^{CF2} = \lambda_t^{CF2} \sum_i w_{it}^{T,CF2} G_{it}^{T} + (1 - \lambda_t^{CF2}) \sum_i w_{it}^{O} G_{it}^{O}. \tag{18}$$

Figure 5 shows a sharp contrast between the two counterfactuals. In Panel A, assigning top exporters the pre-COVID-adjusted growth rates of other exporters within each industry leaves the COVID-19 collapse largely unchanged. At the May trough, aggregate midpoint growth changes from -78.1 percent in the data to -75.3 percent in the counterfactual, a difference of 2.8 percentage points. In Panel B, giving top exporters the industrial composition of other exporters raises counterfactual midpoint growth to -57.0 percent, reducing the decline by 21.1 percentage points.

This contrast extends beyond May. I measure the cumulative shortfall in 2020Q2 as the change in total exports relative to the same quarter in 2019:[16]

$$\text{Q2 shortfall} = \frac{\sum_{t=\text{Apr}}^{\text{Jun}} X_t}{\sum_{t=\text{Apr}}^{\text{Jun}} X_{t-12}} - 1. \tag{19}$$

Table 6 shows that exports fell by 37.2 percent in 2020Q2. The equal-response counterfactual yields a shortfall of 36.6 percent, close to the observed decline. This small aggregate effect does not mask large offsetting changes across industries. In nearly every industry, the counterfactual contribution to the Q2 shortfall is close to the observed one (Appendix D.6). The equal-composition counterfactual reduces the shortfall to 28.6 percent, eliminating 8.6 percentage points, or about 23.2 percent, of the observed decline. This reduction comes mainly from moving top exporters' exports away from Motor Vehicles and Petroleum

[15] Counterfactual midpoint weights are calculated as follows: $w_{it}^{T,CF2} = (X_{it}^{T,CF2} + X_{i,t-12}^{T,CF2})/(X_t^{T,CF2} + X_{t-12}^{T})$, and $\lambda_t^{CF2} = (X_t^{T,CF2} + X_{t-12}^{T})/(X_t^{CF2} + X_{t-12})$ where $X_t^{T,CF2} = \sum_i X_{it}^{T,CF2}$.

[16] Unlike the midpoint growth rates used elsewhere in the paper, I measure the cumulative shortfall in 2020Q2 as the percent change in export levels relative to the same quarter in 2019.

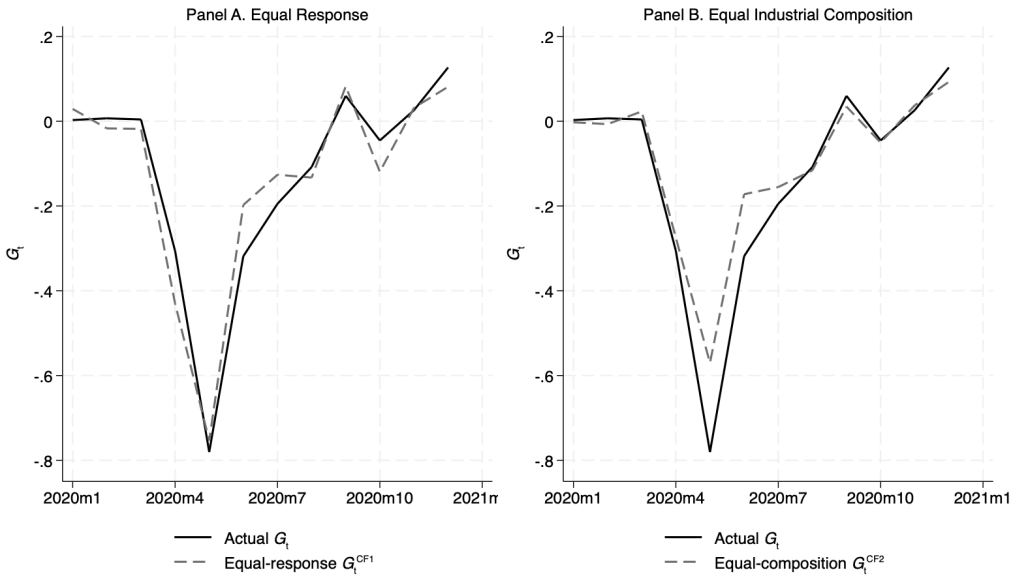


Figure 5: Counterfactuals at the May 2020 Trough

Notes: Panel A compares actual aggregate export growth with a counterfactual that equalizes the within-industry responses of top and other exporters. Panel B compares actual growth with a counterfactual that assigns top exporters the industrial composition of other exporters. At the May 2020 trough, the equal response counterfactual attenuates the decline by 2.8 percentage points, whereas the equal composition counterfactual attenuates it by 21.1 percentage points.

Table 6: Counterfactuals for the 2020Q2 Export Shortfall

	Actual	Equal response	Equal industrial composition
Q2 cumulative shortfall (%)	−37.23	−36.63	−28.61
Difference from actual (pp)	—	0.60	8.62
Share of Q2 shortfall eliminated (%)	—	1.61	23.15

Notes: This table reports the cumulative export shortfall in 2020Q2 under the observed economy and two counterfactuals. The equal response counterfactual assigns top exporters the industry-specific pre-COVID-adjusted growth rates of other exporters, while the equal industry composition counterfactual assigns top exporters the pre-COVID industrial composition of other exporters.

and Natural Gas, industries in which top exporters' exports were concentrated and which contracted sharply (Appendix D.6).

Taken together, industrial composition matters more for the Q2 collapse than differences in response between top and other exporters within the same industry. Top exporters contributed more to the trade collapse because they initially accounted for a large share of exports and a substantial share of their exports came from industries that contracted sharply.

4 U.S. Demand

4.1 Measuring U.S. Industry-Level Demand Conditions

This section explores why some industries that account for a large share of top exporters' exports were hit harder than others. Durable manufacturing accounts for the largest share of top exporters' exports among sectors, and purchases of durable goods tend to be large, infrequent and can often be postponed during economic downturns (Caballero (1993), Bils and Klenow (1998), Leahy and Zeira (2005)). For this reason, durable goods have been identified as a major contributor to the trade collapse during the GFC (Eaton et al. (2016), Engel and Wang (2011), Levchenko et al. (2010), Behrens et al. (2013)). Moreover, Figure 4 suggests that even within durable manufacturing, industries experienced substantially different degrees of contraction. Given that approximately 80 percent of Mexican exports go to the United States, I examine whether U.S. demand conditions for durable goods are associated with the sharp decline in Mexican exports and the variation in contractions across Mexican industries.

To isolate the U.S. demand component of industry output, I follow Celasun et al. (2022) and estimate a bivariate sign-restricted structural vector autoregression (SVAR) using monthly industrial production index and real finished-goods inventories.[17] While they use industrial production and producer price indices, I use inventories in place of prices because industry-level producer prices move little.[18] The identification assumption is that a positive demand shock raises output while drawing down inventories, whereas an adverse supply shock lowers both.

[17] Kemp et al. (2023) also use the same methodology.

[18] Finished-goods inventories are not available for Motor Vehicles and Other Transportation. I used retail inventories from U.S. Census Bureau (retrieved from FRED) for Motor Vehicles and unfilled orders from U.S. Census Bureau M3 survey for Other Transportation.

$$\begin{pmatrix} IP_{it} \\ INV_{it} \end{pmatrix} = \begin{pmatrix} + & - \\ - & - \end{pmatrix} \times \begin{pmatrix} demand\ shock_{it} \\ supply\ shock_{it} \end{pmatrix} \tag{20}$$

All variables are in real terms, seasonally adjusted and enter in log levels, quadratically detrended with the trend estimated over 2004–2019. The VAR is estimated over the same period, and the 2020 shocks and historical decomposition are computed from these pre-pandemic estimates. Among the many impact matrices satisfying the sign restrictions, I select the admissible matrix whose implied impulse responses of output and inventories are closest to the pointwise median responses across all admissible draws (Fry and Pagan (2011)). Using this matrix, I decompose each durable manufacturing industry's output into demand- and supply-driven components. I denote the demand-driven component by D_{jt}^{USA}, which captures the extent to which U.S. industrial production deviates from its normal level due to demand conditions.[19] In subsection 4.2, I use this deviation as a proxy for the proportional change in U.S. final demand for that industry. Figure E.1 in Appendix reports the historical decomposition of industrial production into demand and supply components for each industry, and Figure E.2 reports each industry's contraction attributable to demand in 2020. In motor vehicles, the demand component of output reached a midpoint deviation from trend of -37.6 percent in April 2020 and moved above trend in the second half of the year. In computers and electronics, it remained close to trend throughout 2020.

4.2 Mapping U.S. Demand Conditions to Mexican Industries

To measure the U.S. demand conditions facing each Mexican industry, I use a shift-share-style measure (Autor et al. (2013)). It combines U.S. industry-level demand conditions with predetermined weights that capture each Mexican industry's exposure to those industries. I construct the exposure weight π_{ij} using previous year's OECD ICIO table. The weight measures how much Mexican industry i is exposed to U.S. industry j. Holding the previous year's input-output structure fixed, I raise U.S. final demand for industry j by one unit in proportional terms and calculate the implied change in Mexican industry i's

[19] The demand component is not the demand shock realized in a given month. It is the cumulative effect of all demand shocks since the start of the sample, measuring how much these shocks have raised or lowered current output relative to its quadratic trend.

exports, Δe_{ij}^{MEX}.[20] This change includes both exports to U.S. final users and intermediate exports that reach them through the global production network. I divide it by Mexican industry i's average monthly exports in previous year to express the implied change as a proportion of baseline exports:

$$\pi_{ij} = \frac{\Delta e_{ij}^{MEX}}{e_{i,year-1}^{MEX}/12}, \tag{21}$$

where $e_{i,year-1}^{MEX}$ denotes annual exports of Mexican industry i in previous year. Thus, π_{ij} captures the proportional change in Mexican industry i's exports implied by a unit proportional increase in U.S. final demand for industry j. π_{ij} is based entirely on the pre-COVID input-output structure. This approach builds on the global input-output accounting in Johnson and Noguera (2012) and Koopman et al. (2014), which use the Leontief inverse to trace the production associated with final demand through direct and indirect input linkages. Appendix F details its construction.

I interpret the demand-driven deviation of U.S. industrial production from trend as a proxy for the proportional deviation in U.S. final demand for that industry. Under this interpretation, multiplying D_{jt}^{USA} by π_{ij} gives the predicted proportional export movement associated with U.S. demand conditions.

$$D_{it}^{MEX} = \sum_{j} \pi_{ij} D_{jt}^{USA}. \tag{22}$$

I refer to D_{it}^{MEX} as the U.S. demand condition transmitted to Mexican industry i. [21]

Figure 6 plots the measure of U.S. demand conditions transmitted to each Mexican industry during 2020. This is broadly consistent with the cross-industry heterogeneity documented in Figure 4. Motor Vehicles, which experienced one of the largest export declines, also faced the sharpest deterioration in the transmitted demand measure. In contrast, computer and electronics experienced relatively modest declines in both exports and the transmitted demand measure.[22] These comparisons suggest that U.S. demand

[20] The unit proportional increase normalizes π_{ij}, so that it measures the proportional change in Mexican industry i's exports per unit proportional change in U.S. final demand for industry j.

[21] Because ICIO tables are in values, D_{jt}^{USA} is expressed as a proportional change. After multiplication, I convert a proportional change D_{it}^{MEX} into a midpoint growth rate since export growth throughout the paper is measured using midpoint growth rates.

[22] Petroleum is an important exception. Despite its severe export contraction, the measure shows little variation for Petroleum because U.S. demand conditions are estimated only for durable manufacturing industries.

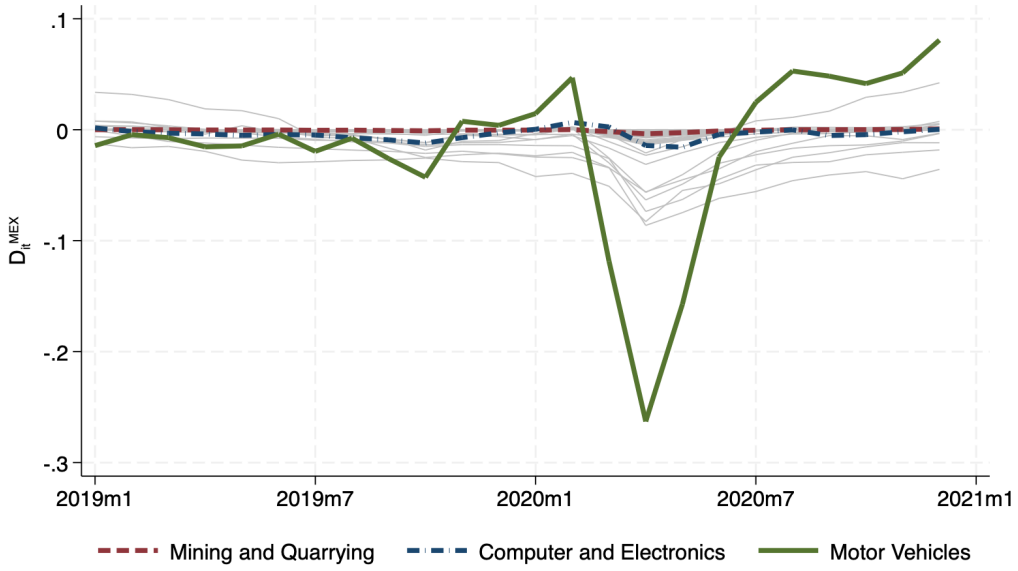


Figure 6: U.S. Demand Conditions Transmitted to Mexican Industries

Notes: This figure plots U.S. demand conditions transmitted to Mexican industries, D_{it}^{MEX}, during 2020. U.S. industry-level demand conditions are mapped to each Mexican industry through predetermined global input-output linkages constructed from the previous year's OECD ICIO table. The exposure measure captures both direct and indirect export exposure to U.S. final demand.

conditions may have played an important role in the variation in export declines across durable manufacturing industries.

4.3 Aggregate Exposure to U.S. Demand Conditions

I next quantify how the industrial composition of large exporters amplified Mexico's aggregate exposure to the U.S. demand contraction. I construct a baseline aggregate growth component by assigning both top and other exporters the transmitted U.S. demand condition as their industry-level growth rate. Following Acemoglu et al. (2015), I use the one-month lag $D_{i,t-1}^{MEX}$ to limit concerns about contemporaneous joint determination of measured U.S. demand conditions and Mexican exports.

$$X_{it}^{T}(D) = X_{i,t-12}^{T}\frac{2 + D_{i,t-1}^{MEX}}{2 - D_{i,t-1}^{MEX}}, \quad X_{it}^{O}(D) = X_{i,t-12}^{O}\frac{2 + D_{i,t-1}^{MEX}}{2 - D_{i,t-1}^{MEX}} \tag{23}$$

The resulting midpoint weights are denoted by $\lambda_t(D)$, $w_{it}^T(D)$, and $w_{it}^O(D)$ from Equations (7) and (9). The aggregate growth component associated with U.S. demand conditions under the observed industry composition is then

$$G_t^D = \lambda_t(D) \sum_i w_{it}^T(D) D_{i,t-1}^{MEX} + (1 - \lambda_t(D)) \sum_i w_{it}^O(D) D_{i,t-1}^{MEX}. \tag{24}$$

I construct the counterfactual aggregate growth component using the same $D_{i,t-1}^{MEX}$, but assign top exporters the pre-COVID industrial composition of other exporters,

$$X_{it}^T(D, CF) = s_{i,t-12}^O X_{t-12}^T \frac{2 + D_{i,t-1}^{MEX}}{2 - D_{i,t-1}^{MEX}}, \tag{25}$$

where $s_{i,t-12}^O$ denotes the industrial composition of other exporters pre-COVID and X_{t-12}^T denotes total export values of top exporters at $t-12$ in Equation (6). The resulting midpoint weights are denoted by $\lambda_t(D, CF)$, $w_{it}^T(D, CF)$, and $w_{it}^O(D, CF)$. The counterfactual aggregate growth component is then

$$G_t^{D,CF} = \lambda_t(D, CF) \sum_i w_{it}^T(D, CF) D_{i,t-1}^{MEX} + (1 - \lambda_t(D, CF)) \sum_i w_{it}^O(D, CF) D_{i,t-1}^{MEX} \tag{26}$$

The difference between the two growth components, G_t^D and $G_t^{D,CF}$, measures how much the industrial tilt of top exporters amplifies aggregate exposure to U.S. demand conditions. Because $D_{i,t-1}^{MEX}$ is held fixed across the two cases, the difference captures how the assumed industrial composition changes the aggregate growth component associated with measured U.S. demand conditions.

Figure 7 plots the aggregate growth component associated with $D_{i,t-1}^{MEX}$ under the observed industrial distribution, G_t^D, and the equal-industrial-composition counterfactual, $G_t^{D,CF}$. Both decline during the initial COVID contraction, reaching midpoint growth rates of -9.3 and -5.7 percent, respectively, in May. Equalizing the industrial composition of top and other exporters attenuates the peak decline associated with U.S. demand conditions by about 3.6 percentage points. The gap between the two series shows that the aggregate effect of U.S. demand conditions depended importantly on the industrial composition of top exporters.

The difference remains substantial over the entire second quarter. Table 7 reports a cu-

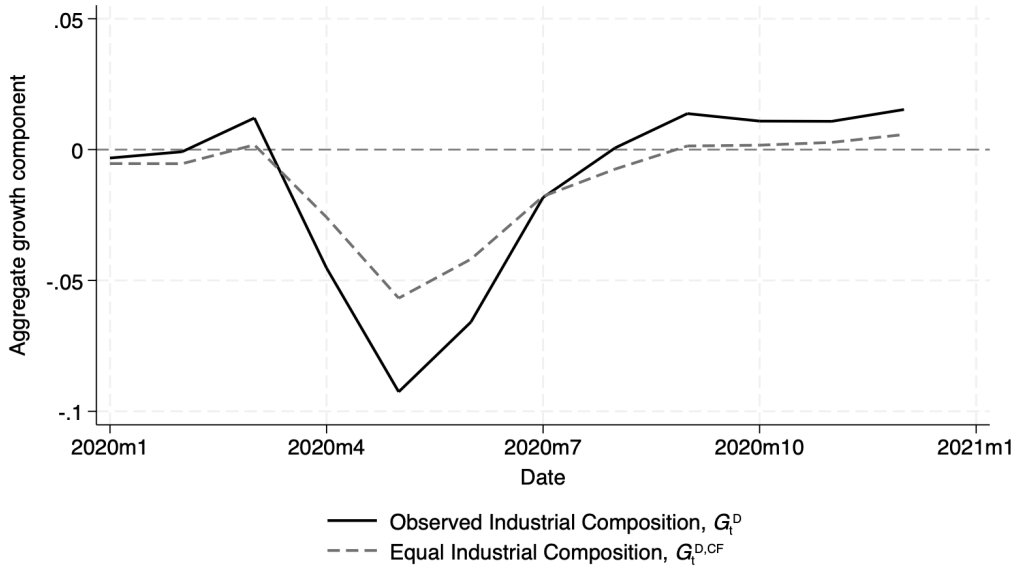


Figure 7: Industrial Allocation and Aggregate Exposure to U.S. Demand Conditions

Notes: This figure plots the aggregate export growth component associated with transmitted U.S. demand conditions under the observed industrial composition and the equal-industrial-composition counterfactual. The counterfactual assigns top exporters the pre-COVID industrial composition of other exporters while holding transmitted U.S. demand conditions fixed.

mulative Q2 shortfall of 6.6 percent under the observed industrial composition, compared with 4.1 percent under the equal-industrial-composition counterfactual. Equalizing industrial composition therefore eliminates approximately 38.1 percent of the Q2 shortfall in the aggregate growth component associated with U.S. demand conditions. Compared with the 23.2 percent reduction in the realized export shortfall in Table 6, the larger reduction in the U.S.-demand-associated component suggests that the composition effect is particularly pronounced for this component. Large exporters' industrial composition amplified the aggregate export decline associated with adverse transmitted U.S. demand conditions.

Table 7: Aggregate Exposure to U.S. Demand Conditions

	Observed	Equal Industrial Composition
Q2 cumulative shortfall (%)	-6.60	-4.09
Difference from observed (pp)	—	2.51
Share of Q2 shortfall eliminated (%)	—	38.08

Notes: This table reports the cumulative 2020Q2 decline in the aggregate export growth component associated with transmitted U.S. demand conditions. The equal-industrial-composition counterfactual assigns top exporters the pre-COVID industrial composition of other exporters while holding transmitted U.S. demand conditions fixed.

5 Conclusion

This paper examines why large exporters declined more and accounted for a disproportionate share of aggregate export fluctuations. Using monthly Mexican firm-level export data from 2012 to 2020, I first show that top 1 percent of exporters accounted for 70 percent of aggregate exports in 2019 but account for 99 percent of net decline in exports from 2019 to 2020. This is partly because large exporters contracted substantially more than smaller exporters. While this is contradictory to conventional beliefs that large firms are less cyclically sensitive, Bricongne et al. (2025) find that this is because large exporters are inherently more responsive to common aggregate fluctuations. I examine whether this difference persists when the common fluctuation is measured separately within each industry. I find no systematic evidence that larger exporters have higher loadings on these industry-level fluctuations. This result suggests that their stronger aggregate response partly reflects differences in industrial composition and exposure to industry-level contractions.

I then quantify the aggregate importance of industrial composition of large exporters. The top 1 percent exporters are disproportionately represented in motor vehicles, computer and electronics, and petroleum, while the remaining 99 percent exporters are more broadly distributed across industries. Some of the industries that accounted for large shares of large exporters' exports, such as motor vehicles and petroleum, contracted sharply during the COVID collapse. A counterfactual in which top exporters follow the industry-specific responses of other exporters produces little change in the cumulative export decline in 2020Q2. By comparison, replacing their pre-COVID industrial composition with that of other exporters lowers the shortfall in 2020Q2 from 37.2 percent to 28.6 percent, explaining approximately 23.2 percent of the observed shortfall. I then examine a potential source of

the heterogeneous industry contractions underlying this aggregate effect. U.S. demand conditions are aligned with the cross-industry variation in Mexican export growth during 2020. Under the observed industrial allocation, the U.S.-demand-induced component implies a Q2 shortfall of 6.6 percent, compared with 4.1 percent under the equal-composition counterfactual. This result shows that foreign demand conditions were amplified into aggregate trade fluctuations through the industrial composition of the largest exporters.

The findings also speak to the relationship between firm size and sensitivity to aggregate fluctuations. Previous studies of domestic firms often find that larger firms are less sensitive to business cycles, while recent evidence on exporters finds that larger exporters are more sensitive to aggregate trade fluctuations. I show that these patterns need not imply different responses associated with firm size. In Mexico, the greater sensitivity of large exporters in aggregate does not persist systematically when exporters are compared within the same industry. Their industrial composition helps explain why large exporters appear more sensitive in aggregate. When large exporters' exports are unevenly represented in industries that contract sharply, they can appear to decline more at the firm level even without a systematically stronger response to fluctuations within the same industry.

These findings provide a link between firm granularity and sectoral concentration as sources of aggregate volatility. Firm concentration determines the aggregate importance of large firms, while sectoral composition determines exposure to heterogeneous industry-level fluctuations. The two cannot be fully understood separately when large firms are unevenly allocated across industries. The aggregate consequences of large firms and sectoral shocks depend jointly on how large firms are allocated across industries. In the case of Mexican exports during COVID-19, this interaction amplified the transmission of foreign demand conditions to aggregate exports.

This paper does not explain how large exporters came to be disproportionately represented in industries such as motor vehicles and computer and electronics. Figure D.1 in Appendix shows that motor vehicles account for an increasing share of top exporters' exports, while the share of computer and electronics remains relatively stable and that of petroleum declines substantially over the sample period. One possible explanation for these changes is that the industrial composition of large exporters evolved alongside Mexico's integration into global production networks. Participation in global value chains may shape not only export levels but also the industries in which large exporters emerge. Whether this process contributed to the observed changes is a question for future research.

A separate question concerns the benefits and risks of an export structure in which large

firms are disproportionately represented in a few industries. Such a structure may reflect gains from specialization, scale, and productivity. The results in this paper show that it can also amplify the aggregate export decline associated with adverse foreign demand conditions. Future research could quantify the productivity gains and examine how they compare with the resulting exposure to external shocks.

Appendix

A Firm Size

Figure A.1 and Figure A.2 plot export values and estimated loadings by exporters' 2019 size percentile. Export values begin to rise noticeably above the 90th percentile, with the top 1 percent standing apart from the rest of the distribution. The loadings also show an upward pattern above the 90th percentile. Based on these patterns, I divide exporters into the bottom 90 percent, the 90th–99th percentiles, and the top 1 percent.

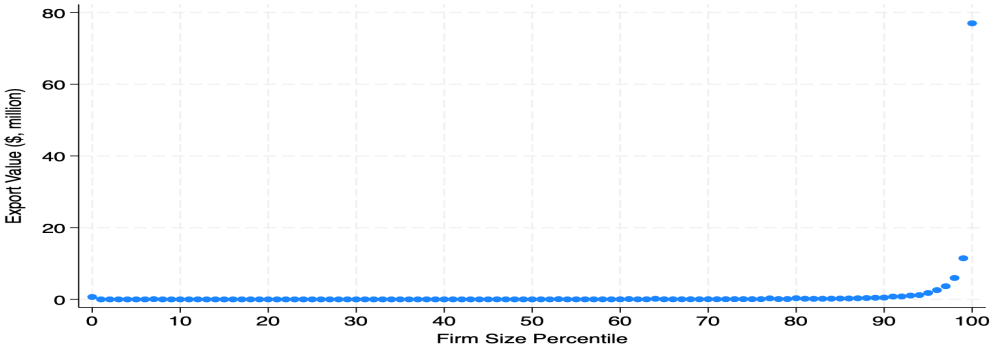


Figure A.1: Export Value by Percentile, 2019

Notes: This figure plots export values by firm size percentile in 2019. Firms are ranked based on their total export value in 2019.

B Matching HS codes to ISIC Industries

Panjiva reports products using HS codes, whereas the OECD ICIO tables classify economic activity using ISIC Revision 4 industries. I construct a concordance between the two classifications in two steps. First, I map six-digit HS codes to CPC (Central Product Classification) Version 2.1 product categories. I then map the CPC categories to ISIC Revision 4 industries and aggregate them to the industries used in the ICIO tables.

I use six-digit HS codes because the first six digits are standardized across countries, while more detailed codes are country-specific. The sample covers two HS revisions. I use the HS 2012-to-CPC 2.1 concordance for 2012–2016 and the HS 2017-to-CPC 2.1 concordance for 2017–2020. Both are then mapped from CPC 2.1 to ISIC Revision 4 using the same CPC-to-ISIC concordance. All concordance tables are obtained from the United Nations Statistics Division.

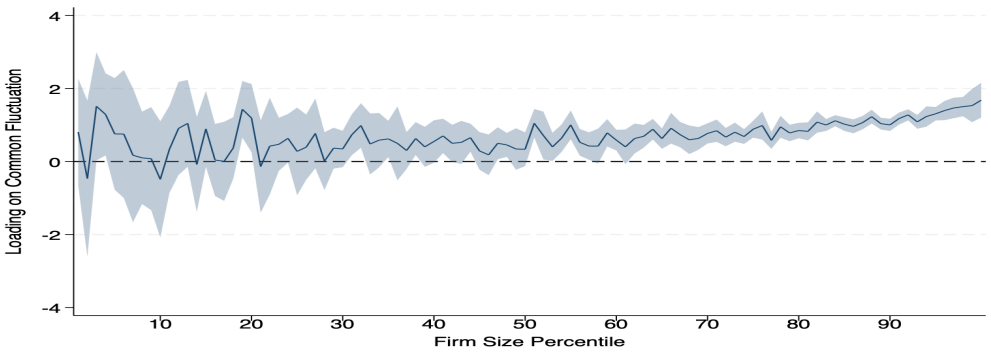


Figure A.2: Loadings by Percentile

Notes: This figure plots the estimated loading on the leave-one-out common movement by firm size percentile. The estimates are unweighted and use observations from 2013 to 2020. The shaded area shows pointwise 95% confidence intervals.

Some HS codes map to more than one ICIO industry. For these codes, I use the annual ICIO tables to construct destination-specific allocation weights. Let $\mathcal{J}(h)$ be the set of industries matched to HS code h, and let X_{jdy}^{ICIO} denote ICIO exports from Mexico in industry j to destination d in year y. The weight assigned to industry j is

$$w_{hjdy} = \frac{X_{jdy}^{ICIO}}{\sum_{k \in \mathcal{J}(h)} X_{kdy}^{ICIO}}. \tag{B.1}$$

I then allocate the observed export value of HS code h across its matched industries using these weights. If X_{hdt} is the export value reported by Panjiva, the value assigned to industry j is

$$X_{hjdt} = w_{hjdy} X_{hdt} \text{ where } t \in y. \tag{B.2}$$

For example, suppose an HS code maps to industries $A01$ and $A02$. If ICIO exports from Mexico to destination d are X_1 in $A01$ and X_2 in $A02$, the product's export value is divided between the two industries using the shares $X_1/(X_1 + X_2)$ and $X_2/(X_1 + X_2)$. Thus, the allocation can vary by destination and year. If an HS code maps to only one industry, its entire export value is assigned to that industry.

C Intensive vs Extensive Margins

This section examines whether fluctuations in aggregate exports are driven by changes in the exports of continuing firms or by exporter entry and exit. This approach largely follows the comparison of the intensive and extensive margins in di Giovanni et al. (2014). I use the firm-level growth rate g_{ft} defined in Equation (1) and aggregate midpoint weight $w_{ft} = (x_{ft} + x_{f,t-12})/(X_t + X_{t-12})$. G_t^{agg} denotes aggregate growth rate of all firms.

Let $\mathcal{C}_t$ denote the set of continuing firms, defined as firms with positive exports in both t and $t-12$. The intensive-margin contribution to aggregate export growth is

$$G_t^{\text{int}} = \sum_{f \in \mathcal{C}_t} w_{ft} g_{ft}. \tag{C.1}$$

The extensive-margin contribution is defined as

$$G_t^{\text{ext}} = G_t^{\text{agg}} - G_t^{\text{int}}. \tag{C.2}$$

Table C.1: Intensive and Extensive Margins

	2013-2019		2020	
	St. Dev.	Relative SD	St. Dev.	Relative SD
	(1)	(2)	(3)	(4)
Actual	0.0786	1.0000	0.2430	1.0000
Intensive	0.0793	1.0087	0.2340	0.9629
Extensive	0.0105	0.1333	0.0142	0.0585

Notes: This table presents the standard deviations, in absolute and relative terms with respect to the actual, for the two components of aggregate export growth—intensive and extensive margins—over 2013-2020.

Table C.1 reports the standard deviations of aggregate export growth and its intensive- and extensive-margin components. The table presents both their absolute standard deviations and their standard deviations relative to that of actual aggregate export growth. During 2013–2019, the standard deviation of the intensive margin is 0.0793, approximately equal to the standard deviation of actual aggregate growth, 0.0786. The same pattern holds during the COVID-19 crisis. In 2020, the standard deviation of aggregate export growth increases sharply to 0.2430, and the standard deviation of the intensive component rises correspondingly to 0.2340. The intensive margin therefore remains 96.3 percent as volatile

as aggregate export growth. By comparison, the extensive-margin standard deviation is only 0.0142, or 5.9 percent of aggregate volatility. These results show that aggregate export fluctuations are driven overwhelmingly by changes in the exports of continuing firms, both before the pandemic and during the exceptionally large fluctuations of 2020.

D Robustness Checks

D.1 All-Firms Estimates

As a robustness check, I re-estimate equation (3) including entering and exiting firms. The leave-one-out common movement is defined as

$$\bar{g}_t^{-f} = \begin{cases} \dfrac{1}{N_t - 1} \displaystyle\sum_{\substack{j \in \mathcal{C}_t \\ j \neq f}} g_{jt}, & f \in \mathcal{C}_t, \\ \dfrac{1}{N_t} \displaystyle\sum_{j \in \mathcal{C}_t} g_{jt}, & f \notin \mathcal{C}_t. \end{cases} \tag{D.1}$$

For continuing firms, the common movement is calculated as the average growth rate of all other continuing firms, excluding firm f as in Equation (2). For entering or exiting firms, which are not included in the continuing-firm set $\mathcal{C}_t$, the common movement is simply the average growth rate of all continuing firms. Table D.1 reports the results. The top 1 percent of exporters exhibit a larger loading on the common movement than the bottom 90 percent, but the difference is not significant. This implies the size gradient is more pronounced in the sample of continuing exporters.

D.2 Structural Breaks

I examine whether the size gradient in firms' exposure to the common movement changed in 2020. To do so, I estimate

$$g_{ft} = \sum_b \left[(\alpha_b + \gamma_b \text{COVID}_t) + (\beta_b + \delta_b \text{COVID}_t)\, \bar{g}_t^{-f} \right] \mathbf{1}\{f \in I_t^{(b)}\} + \varepsilon_{ft} \tag{D.2}$$

where COVID_t equals one in 2020. The coefficient β_b measures the loading of size group b on the common movement during 2013–2019, while $\beta_b + \delta_b$ measures its loading in 2020. The change in the size gradient between the top 1 percent and bottom 90 percent exporters is

Table D.1: Exporter Size and Aggregate Export Fluctuations, Full Sample

	(1)
	g_{ft}
$\bar{g}_t^{-f}$	1.258***
	(0.224)
$[90, 99] \times \bar{g}_t^{-f}$	-0.125
	(0.243)
$[99, 100] \times \bar{g}_t^{-f}$	0.523
	(0.357)
Adjusted R^2	0.040
Observations	1,721,606
Clustering	firm, date
Number of Cluster	96

Notes: Weighted OLS estimations of Equation (3) with all firms. The dependent variable is the year-on-year midpoint growth rate at the firm-by-month level, g_{ft}. $\bar{g}_t^{-f}$ is the unweighted average of growth rate of firms at date t. Base group is exporters at bottom 90%, and coefficient for interaction term represents the estimated difference in response from the base group. Standard errors are two-way clustered at the firm and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$$\underbrace{[(\beta_3 + \delta_3) - (\beta_1 + \delta_1)]}_{\text{Difference in 2020}} - \underbrace{(\beta_3 - \beta_1)}_{\text{Difference in 2013-2019}} = \delta_3 - \delta_1. \tag{D.3}$$

Thus, the null hypothesis of no structural break in the size gradient is $H_0 : \delta_3 - \delta_1 = 0$. Because the bottom 90 percent is the omitted size group, this difference is identified directly by the coefficient on $\text{COVID}_t \times [99, 100] \times \bar{g}_t^{-f}$.

Table D.2 reports the estimated changes in the size gradient. Column (1) estimates equation (D.2) at the firm level. Columns (2) and (3) estimate its industry-level counterpart, replacing the dependent variable g_{ft} with firm–industry growth g_{fit} and the aggregate leave-one-out common movement $\bar{g}_t^{-f}$ with the corresponding industry-level measure $\bar{g}_{it}^{-f}$. Across all three specifications, the triple-interaction coefficient for the top 1 percent is not statistically significant. Thus, there is no evidence that the loading differential between the top 1 percent and bottom 90 percent exporters changed in 2020, either at the firm level or within industries.

Table D.2: Structural Breaks in Responses

	(1) g_{ft}	(2) g_{fit}	(3) g_{fit}
		All Sectors	Manufacturing
COVID $\times$ $[90, 99] \times \bar{g}_t^{-f}$	-0.366		
	(0.583)		
COVID $\times$ $[99, 100] \times \bar{g}_t^{-f}$	-0.0384		
	(0.797)		
COVID $\times$ $[90, 99] \times \bar{g}_{it}^{-f}$		0.381	0.304
		(0.407)	(0.570)
COVID $\times$ $[99, 100] \times \bar{g}_{it}^{-f}$		0.744	0.251
		(0.501)	(0.664)
Adjusted R^2	0.050	0.042	0.048
Observations	981,536	2,192,317	2,003,066
Industry FE		✓	✓
Clustering	firm, date	firm, date	firm, date
Number of Clusters	96	96	96

Notes: This table reports weighted OLS estimates of equation (D.2). Only the triple-interaction coefficients are reported. All regressions include the corresponding main effects and lower-order interaction terms. The bottom 90% of exporters is the omitted size group. Therefore, the coefficient on $\text{COVID}_t \times [99, 100] \times \bar{g}_t^{-f}$ measures the change in the loading differential between the top 1% and bottom 90% exporters from 2013–2019 to 2020. Standard errors are two-way clustered by firm and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D.3 Alternative Industry Classification

Table D.3 examines Equation (4), differential responsiveness to industry-level common fluctuations, using HS two-digit and three-digit industries over 2013–2020. Column (1) defines industries at the HS two-digit level. The point estimate for the top 1 percent is positive, indicating greater responsiveness than the bottom 90 percent, although it is not statistically significant. Column (2) uses the more disaggregated HS three-digit classification, under which the differential loading of the top 1 percent becomes negative and remains statistically insignificant. The disappearance of the positive size gradient under the finer industry classification is consistent with the view that the greater responsiveness of large exporters reflects differences in industry composition rather than firm size itself.

Table D.3: Alternative Industry

	(1) g_{fit}	(2) g_{fit}
$\bar{g}_{it}^{-f}$	0.696***	0.674***
	(0.139)	(0.103)
$[90, 99] \times \bar{g}_{it}^{-f}$	0.088	-0.052
	(0.137)	(0.120)
$[99, 100] \times \bar{g}_{it}^{-f}$	0.270	-0.183
	(0.215)	(0.240)
Industry	HS2	HS3
Adjusted R^2	0.049	0.033
Observations	2,446,843	3,081,639
Industry FE	✓	✓
Cluster	firm, date	firm, date
Number of Clusters	96	96

Notes: This table reports weighted OLS estimates of Equation (4) using alternative industry classifications over 2013–2020. Industries are defined at the HS two-digit level in column (1) and at the HS three-digit level in column (2). The dependent variable is the year-on-year midpoint growth rate of firm–industry exports, g_{fit}, and $\bar{g}_{it}^{-f}$ is the leave-one-out average growth rate within industry i. The bottom 90% of exporters is the omitted size group, so the interaction coefficients measure differential responsiveness relative to this group. Standard errors are two-way clustered by firm and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.4 Alternative SE Clustering

The baseline regressions use standard errors two-way clustered by firm and date. Table D.4 reports alternative inference of Equation (4) based on one-way clustering by industry and two-way clustering by industry and date. I also report industry-clustered bootstrap p-values and confidence intervals. The results are consistent across the alternative methods. For all sectors, the top 1 percent of exporters have a significantly lower loading than the bottom 90 percent. Within manufacturing, the differential loading of the top 1 percent is not statistically significant. The bootstrap and conventional clustered standard errors lead to the same conclusions.

Table D.4: Alternative Clustering and Bootstrap Inference

	(1) g_{fit}	(2) g_{fit}	(3) g_{fit}	(4) g_{fit}
	All Sectors		Manufacturing	
$\bar{g}_{it}^{-f}$	0.886***	0.886***	0.941***	0.941***
	(0.173)	(0.167)	(0.217)	(0.218)
$[90, 99] \times \bar{g}_{it}^{-f}$	0.116**	0.116	0.146	0.146
	(0.055)	(0.096)	(0.129)	(0.157)
$[99, 100] \times \bar{g}_{it}^{-f}$	-0.765***	-0.765***	0.198	0.198
	(0.158)	(0.163)	(0.208)	(0.213)
Cluster	Industry, Date	Industry	Industry, Date	Industry
Number of Clusters	24	24	17	17
Adjusted R^2	0.022	0.022	0.048	0.048
Observations	2,192,317	2,192,317	2,003,066	2,003,066
Industry FE	✓	✓	✓	✓
WB p-value 1	0.004	0.003	0.004	0.004
WB p-value 2	0.069	0.238	0.207	0.459
WB p-value 3	0.005	0.008	0.354	0.335
WB CI1	[.4429, 1.281]	[.4527, 1.298]	[.3967, 1.39]	[.3867, 1.419]
WB CI2	[-.02857, .2015]	[-.06535, .3809]	[-.09528, .5048]	[-.1992, .5475]
WB CI3	[-1.104, -.3708]	[-1.114, -.297]	[-.2728, .7021]	[-.2423, .7472]

Notes: This table reports weighted OLS estimates of Equation (4) using alternative clustering methods over sample periods 2013-2020. Columns (1) and (3) use standard errors two-way clustered by industry and date, while columns (2) and (4) use standard errors clustered by industry. All regressions include industry fixed effects. Bootstrap p-values and 95% confidence intervals are computed using industry-level clustering. Bootstrap results 1, 2, and 3 correspond to the coefficients on $\bar{g}_{it}^{-f}$, $[90, 99] \times \bar{g}_{it}^{-f}$, and $[99, 100] \times \bar{g}_{it}^{-f}$, respectively. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.5 Alternative Weights

Table D.5 reports unweighted estimates of the firm-level and within-industry specifications in Equations (3) and (4). Each firm–month observation receives equal weight in column (1), and each firm–industry–month observation receives equal weight in columns (2) and (3), regardless of the firm's export value or the industry's share of aggregate exports. The estimates show a positive size gradient at the firm level. Within industries, the top exporters' interaction coefficient is positive but statistically insignificant in the full sample and positive and significant in manufacturing. These results indicate that the response of a typical firm–industry observation can differ from the response measured by

Table D.5: Exporter Responsiveness, No Weights

	(1)	(2)	(3)
	g_{ft}	g_{fit}	g_{fit}
	All	All	Manufacturing
$\bar{g}_t^{-f}$	0.814***		
	(0.048)		
$[90, 99] \times \bar{g}_t^{-f}$	0.520***		
	(0.145)		
$[99, 100] \times \bar{g}_t^{-f}$	0.856***		
	(0.287)		
$\bar{g}_{it}^{-f}$		0.716***	0.708***
		(0.025)	(0.025)
$[90, 99] \times \bar{g}_{it}^{-f}$		0.213**	0.240***
		(0.087)	(0.088)
$[99, 100] \times \bar{g}_{it}^{-f}$		0.260	0.348**
		(0.165)	(0.146)
Adjusted R^2	0.007	0.005	0.005
Observations	981,536	2,192,317	2,003,066
Industry FE		✓	✓
Cluster	Firm, Date	Firm, Date	Firm, Date
Number of Clusters	96	96	96

Notes: OLS estimations of Equation (3) and (4) over 2013-2020 sample periods without weights. The dependent variable is the year-on-year midpoint growth rate at the firm-by-month level for rows 1-3 and midpoint growth rate at the firm-by-industry-by-month level for rows 4-6. $\bar{g}_t^{-f}$ and $\bar{g}_{it}^{-f}$ are leave-one-out midpoint growth rates defined in Equations (2) and (5). Base group is exporters at bottom 90%, and coefficients for interaction term represent the estimated difference in response from the base group. Standard errors are two-way clustered at the firm and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the export-weighted estimates in the main text. Nevertheless, the smaller size gradient in columns (2) and (3) is consistent with a role for industrial composition even in the unweighted estimates.

D.6 Industry Contribution of Counterfactuals

Table D.6 reports each industry's contribution to the 2020Q2 shortfall under the observed economy and the two counterfactuals.

Table D.6: Industry Contributions to the 2020Q2 Shortfall

			Counterfactual		Difference from actual	
ICIO	Description	Actual	CF1	CF2	CF1	CF2
A01	Agriculture and Hunting	-0.15	-0.12	-0.23	0.04	-0.08
A02	Forestry and Logging	0.00	0.00	0.00	0.00	0.00
A03	Fishing and Aquaculture	-0.02	-0.02	-0.07	0.00	-0.05
B05	Coal and Lignite Mining	0.00	0.00	0.00	0.00	0.00
B06	Crude Petroleum and Natural Gas	-3.45	-3.45	-0.02	0.00	3.43
B07	Metal Ores Mining	-0.09	0.56	0.02	0.66	0.12
B08	Other Mining and Quarrying	-0.03	-0.03	-0.03	-0.01	-0.01
C10T12	Food, Beverages and Tobacco	-0.17	-0.33	-1.15	-0.16	-0.98
C13T15	Textiles and Apparel	-0.68	-0.73	-1.38	-0.04	-0.69
C16	Wood Products	-0.02	-0.01	-0.10	0.01	-0.09
C17T18	Paper, Printing, and Publishing	-0.04	-0.03	-0.46	0.01	-0.42
C19	Coke and Refined Petroleum	-0.21	-0.33	-0.04	-0.12	0.16
C20	Chemicals	-0.38	-0.28	-0.87	0.10	-0.49
C21	Pharmaceuticals	0.17	0.15	0.43	-0.02	0.26
C22	Rubber and Plastics	-0.66	-0.61	-2.09	0.04	-1.44
C23	Non-Metallic Minerals	-0.27	-0.26	-0.85	0.01	-0.58
C24	Primary Metals	-0.35	-0.60	-0.43	-0.25	-0.08
C25	Fabricated Metals	-0.54	-0.55	-1.19	-0.01	-0.66
C26	Computer and Electronics	-3.38	-4.33	-1.67	-0.96	1.71
C27	Electrical Equipment	-2.59	-3.02	-3.54	-0.43	-0.95
C28	Machinery	-2.12	-2.22	-2.98	-0.10	-0.86
C29	Motor Vehicles	-18.67	-16.27	-7.42	2.40	11.25
C30	Other Transportation	-2.08	-2.30	-2.29	-0.22	-0.21
C31T33	Other Manufacturing	-1.50	-1.83	-2.26	-0.33	-0.76
	Total	-37.23	-36.63	-28.61	0.60	8.62

Notes: Each entry is industry i's contribution to the 2020Q2 shortfall, $\sum_{t=\text{Apr}}^{\text{Jun}}(X_{it} - X_{i,t-12}) / \sum_{t=\text{Apr}}^{\text{Jun}} X_{t-12}$, in percentage points. Columns sum to the aggregate Q2 shortfall reported in Table 6.

D.7 Industry Shares of Top Exporters

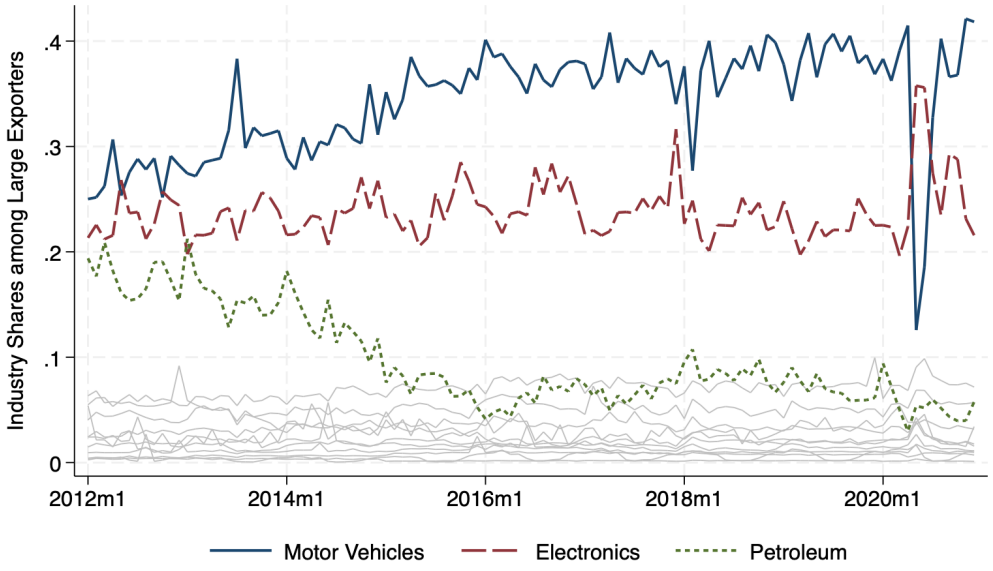


Figure D.1: Industry Shares of Top Exporters' Exports, 2012-2020

Notes: The figure shows each industry's share of the total export value of top 1% exporters by month, s_{it}^{T}, defined in Equation (6). Motor vehicles, computer and electronics, and petroleum are highlighted. All other industries are shown in gray.

E Identification of U.S. Demand Conditions

E.1 Data

For each U.S. durable manufacturing industry, I estimate a VAR with two monthly variables: industrial production (IP) from the Federal Reserve G.17 release and inventories (INV). I use finished goods inventories from the Census M3 survey for most industries and dealer inventories for motor vehicles. For other transport equipment, I use unfilled orders with a negative sign. Table E.1 lists the variables and sources. All variables are in real terms, enter in log levels, and are quadratically detrended.[23]

[23]Nominal values are deflated by the industry-level producer price index (PPI). For motor vehicles and other transportation equipment, PPIs are not available at this level of aggregation, so I construct a weighted average of the PPI growth rates of the constituent four-digit NAICS industries. The weights are the industrial production relative importance weights published by the Board of Governors of the Federal Reserve System.

Table E.1: Variables in the Industry VARs

Industry	NAICS	ICIO	Inventory variable
Wood products	321	C16	Finished goods inventories
Nonmetallic minerals	327	C23	Finished goods inventories
Primary metals	331	C24	Finished goods inventories
Fabricated metals	332	C25	Finished goods inventories
Computers and electronics	334	C26	Finished goods inventories
Electrical equipment	335	C27	Finished goods inventories
Machinery	333	C28	Finished goods inventories
Motor vehicles	3361–3363	C29	Dealer inventories
Other transport equipment	3364–3369	C30	Unfilled orders (−)
Furniture and other manufacturing	337, 339	C31T33	Finished goods inventories

Notes: Industrial production is from the Federal Reserve G.17 release. Finished goods inventories and unfilled orders are from the Census M3 survey. Dealer inventories are retail inventories of motor vehicle and parts dealers from the Census Monthly Retail Trade Survey (FRED series MRTSIM441USS). All nominal series are deflated by the corresponding industry PPI from the BLS.

E.2 Sign Restrictions

For each industry j, let $Y_{jt} = (IP_{jt}, INV_{jt})'$. I estimate

$$Y_{jt} = c_j + \sum_{\ell=1}^{p} B_{j\ell}\, Y_{j,t-\ell} + u_{jt}, \tag{E.1}$$

by OLS over 2004m1–2019m12. The lag length $p = 2$ is common across industries and minimizes the sum of industry-level BIC values. Estimating the VAR only through 2019 keeps the extreme observations of 2020 from affecting the coefficients. The 2020 residuals are computed from these pre-pandemic estimates, and $u_{jt} = (u_{jt}^{IP}, u_{jt}^{INV})'$ denotes the residual.

Let ε_{jt}^{d} and ε_{jt}^{s} denote the structural demand and adverse supply shocks. The reduced-form residuals are linear combinations of these shocks,

$$u_{jt} = A_j \varepsilon_{jt}, \tag{E.2}$$

where $\varepsilon_{jt} = (\varepsilon_{jt}^{d}, \varepsilon_{jt}^{s})'$ and $E[\varepsilon_{jt}\varepsilon_{jt}'] = I$. The residual covariance matrix is then $\Sigma_j = A_j A_j'$, so the data identify Σ_j but not A_j. Let P_j be the Cholesky factor of Σ_j. For any orthogonal matrix Q, $A_j = P_j Q$ also satisfies $\Sigma_j = A_j A_j'$, and every such A_j can be written in this

form.

$$\begin{bmatrix} u_{jt}^{IP} \\ u_{jt}^{INV} \end{bmatrix} = \begin{bmatrix} + & - \\ - & - \end{bmatrix} \begin{bmatrix} \varepsilon_{jt}^{d} \\ \varepsilon_{jt}^{s} \end{bmatrix}. \tag{E.3}$$

I draw many orthogonal matrices Q and keep the impact matrices $P_j Q$ that satisfy the sign restrictions in Equation (E.3). Many matrices satisfy these restrictions. Following Fry and Pagan (2011), I select the admissible matrix whose implied impulse responses of output and inventories over the following 15 months are closest to the pointwise median responses across all admissible matrices. With this matrix, I decompose each industry's output into demand- and supply-driven components. The demand-driven component measures the cumulative effect of past demand shocks on current output relative to trend. I convert it to a proportional deviation from trend and use it as D_{jt}^{USA}.[24] Figure E.1 shows the decomposition for each industry and Figure E.2 shows the demand component of decomposition in 2019-2020.

E.3 Robustness: supplier delivery times

As a robustness check, I add the supplier deliveries index from the Institute for Supply Management (ISM) as a third variable, common across industries following Celasun et al. (2022). The index is a component of the monthly ISM Manufacturing Report on Business, which surveys 300 supply management professionals of U.S. manufacturing firms. Respondents report whether their suppliers' delivery times are faster, slower, or unchanged relative to the previous month. A reading above 50 indicates that delivery times are lengthening. Slower deliveries can reflect either supply bottlenecks or strong demand that strains suppliers, so I assume that both a positive demand shock and an adverse supply shock lengthen delivery times. The impact restrictions are

$$\begin{bmatrix} IP_{jt} \\ INV_{jt} \\ DT_t \end{bmatrix} = \begin{bmatrix} + & - & \\ - & - & \\ + & + & \end{bmatrix} \begin{bmatrix} \varepsilon_{jt}^{d} \\ \varepsilon_{jt}^{s} \\ \varepsilon_{jt}^{o} \end{bmatrix}, \tag{E.4}$$

where DT_t denotes suppliers' delivery time at month t and ε_{jt}^{o} denotes a shock other than the demand and supply shocks. The third shock is left unrestricted.

[24] NAICS 337 and 339 are combined into ICIO sector C31T33 using previous-year Relative Importance Weights.

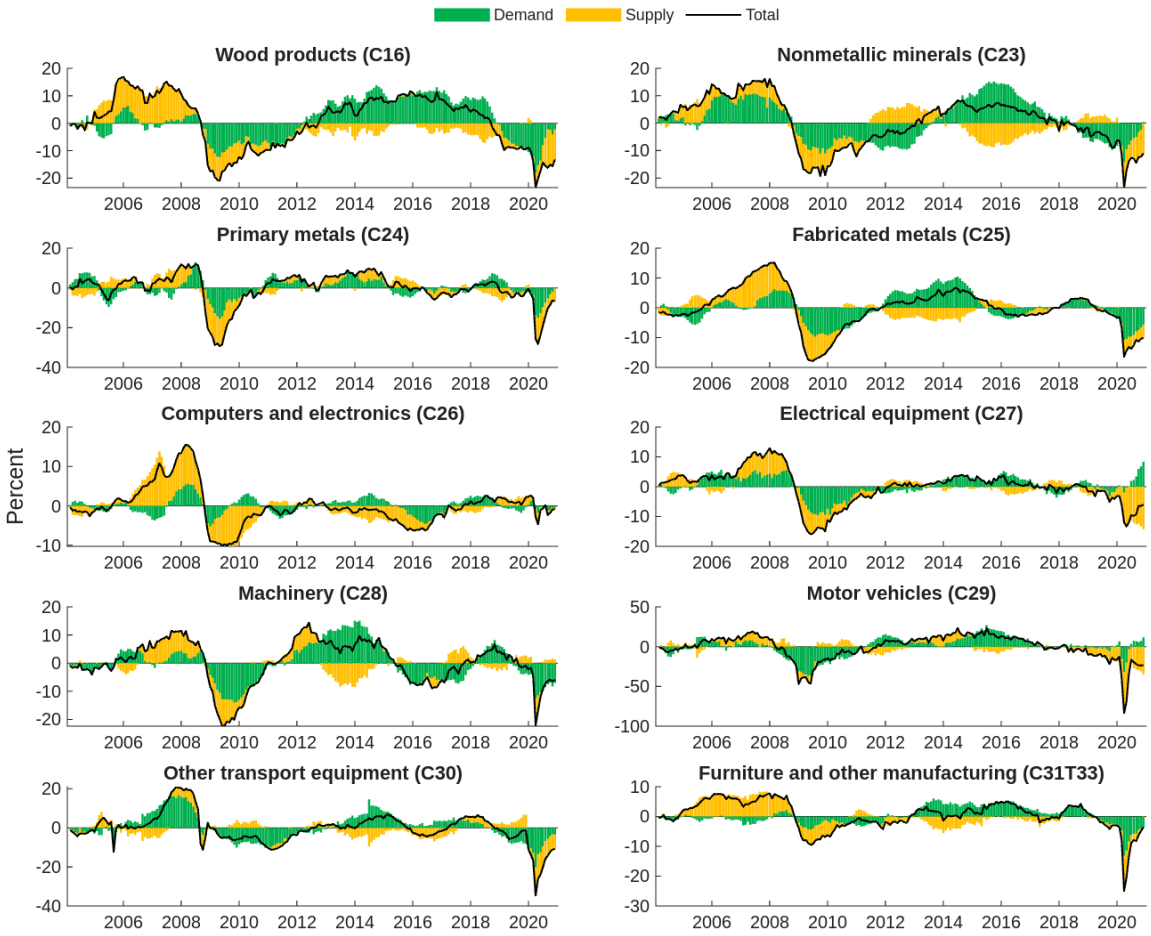


Figure E.1: Supply-Demand Decomposition of Industrial Production, 2004-2020

Notes: Historical decomposition from the bivariate sign-restricted VAR, estimated over 2004–2019. Bars show contributions of demand and adverse supply shocks. The line shows their sum. Percent deviation from a quadratic trend. Vertical scales differ across panels.

Compared with the bivariate SVAR, the three-variable model attributes a larger share of the decline in the second quarter of 2020 to supply shocks, in line with the sharp lengthening of delivery times during the initial lockdowns. For example, the midpoint deviation of demand-driven output from trend in the motor vehicles industry was −37.6 percent in April 2020 in the bivariate model and −26.5 percent in the three-variable model. However, the industry composition effect remains at the aggregate level. The aggregate growth component in which the industry growth rate is replaced with D_{it}^{MEX} in Equations (24) and (26) reaches midpoint growth of −6.4 percent in May under the observed industry

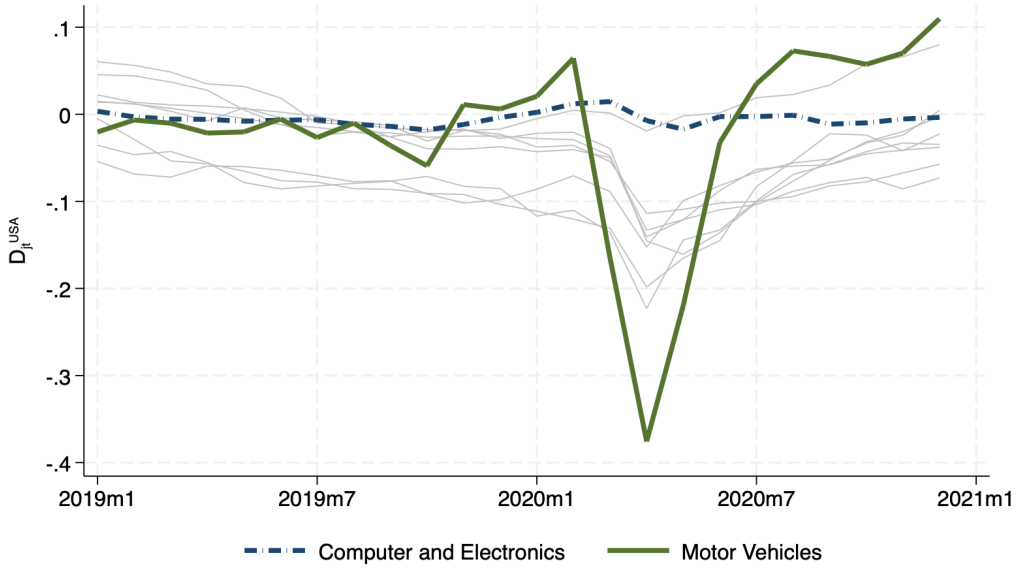


Figure E.2: U.S. Demand Conditions, by Industry

Notes: Demand-driven component of U.S. industrial production by industry, relative to trend. For comparability with Mexican export growth, values are converted to midpoint growth rates. Gray lines show the other industries.

composition and −3.9 percent in May under the counterfactual equal-industry composition. The quarterly cumulative shortfall is 4.1 percent under the observed industry composition and 2.6 percent under the counterfactual equal-industry composition, a reduction of 37.6 percent that is almost identical to the 38.1 percent in the bivariate SVAR.[25] Although the estimated demand collapse is smaller, the industry composition effect is preserved.

F Construction of U.S. Demand Exposure through the Global Input-Output Network

F.1 Global Input-Output Framework

The OECD ICIO system consists of annual symmetric industry-by-industry global input-output tables (Yamano et al. (2023)). Let C denote the number of countries and K the number of industries. Throughout this appendix, (c, i) indexes a producing country-industry pair, while (d, j) indexes a purchasing country-industry pair. Stacking country-

[25]The Q2 shortfall is expressed as a percent change in export levels.

industry pairs yields CK production nodes in the global input-output system. I use the following objects.

- $\mathbf{Z}$ is the $CK \times CK$ intermediate-use matrix, where z_{ij}^{cd} denotes the flow of intermediate inputs from industry i in country c to industry j in country d.
- $\mathbf{q}$ is the $CK \times 1$ gross-output vector, where q_i^c denotes gross output of industry i in country c.[26]
- $\mathbf{Y}$ is the $CK \times C$ final-demand matrix, after aggregating across final-use categories.[27] Its d-th column, $\mathbf{y}^d$, is the $CK \times 1$ vector of final demand in country d for output produced by each country-industry. Thus,

$$\mathbf{Y} = \begin{bmatrix} \mathbf{y}^1 & \cdots & \mathbf{y}^C \end{bmatrix}.$$

  I denote global final demand, summed across destination countries, by

$$\mathbf{y} \equiv \sum_{d=1}^{C} \mathbf{y}^d.$$

  In particular, $\mathbf{y}^{USA}$ denotes the $CK \times 1$ vector of U.S. final demand.

- $\mathbf{A}$ is the $CK \times CK$ input-coefficient matrix, with elements

$$a_{ij}^{cd} = \frac{z_{ij}^{cd}}{q_j^d}.$$

  Thus, a_{ij}^{cd} denotes the amount of input from industry i in country c required to produce one unit of gross output in industry j in country d. The global input-output system satisfies

$$\mathbf{q} = \mathbf{A}\mathbf{q} + \mathbf{y}.$$

[26] The OECD ICIO documentation conventionally denotes gross output by $\mathbf{X}$. I use $\mathbf{q}$ because X denotes export value elsewhere in the paper.

[27] It includes HFCE (Final consumption expenditure of households), NPISH (Final consumption expenditure of non-profit institutions serving households), GGFC (Final consumption expenditure of general government), GFCF (Gross fixed capital formation).

- $\mathbf{L}$ is the $CK \times CK$ Leontief inverse,

$$\mathbf{L} \equiv (\mathbf{I} - \mathbf{A})^{-1},$$

so that

$$\mathbf{q} = \mathbf{L}\mathbf{y}.$$

F.2 Construction of π_{ij}

To construct π_{ij}, I consider a unit proportional increase in U.S. final demand for each industry $j \in \{1, \ldots, K\}$. The unit proportional increase is a normalization used to calculate π_{ij}, and the observed U.S. demand conditions enter later through D_{jt}^{USA}. Let $\Delta\mathbf{y}^{USA,j}$ denote the $CK \times 1$ vector of changes in final demand across source country-industries (c, i) induced by a unit proportional increase in U.S. final demand for industry j. I apply the same proportional increase to industry $i = j$ output from every source country c, with changes for all other industries set to zero. Thus,

$$\left[\Delta\mathbf{y}^{USA,j}\right]_{(c,i)} = \frac{y_{i,year-1}^{c,USA}}{12}\mathbf{1}\{i = j\}, \tag{F.1}$$

where $y_{i,year-1}^{c,USA}$ denotes U.S. final demand for output produced by industry i in country c, taken from the previous year's ICIO table. The division by twelve converts annual ICIO flows into monthly values.

The U.S. final-demand change affects Mexican exports through two channels. First, it directly changes U.S. final demand for goods and services produced in Mexico. Second, it changes production throughout the global input-output network, which in turn changes demand for intermediate inputs produced in Mexico. I therefore decompose the export response of Mexican industry i into a final-export response and an intermediate-export response.

The final-export response is given directly by the Mexico-origin elements of $\Delta\mathbf{y}^{USA,j}$. Let

$$\Delta\mathbf{e}^{MEX,final} = [\Delta\mathbf{y}^{USA,j}]_{MEX}, \tag{F.2}$$

where $[\Delta\mathbf{y}^{USA,j}]_{MEX}$ denotes the $K \times 1$ block corresponding to output produced in Mexico.

To obtain the intermediate-export response, I use the global output response

$$\Delta \mathbf{q}_j = \mathbf{L}_{year-1} \Delta \mathbf{y}^{USA,j} \tag{F.3}$$

where $\mathbf{A}_{year-1}$ is the previous year's global input-coefficient matrix and $\mathbf{L}_{year-1} \equiv (\mathbf{I} - \mathbf{A}_{year-1})^{-1}$. Let $[\mathbf{A}_{year-1}]_{MEX}$ denote the Mexico-origin rows of the previous year's input-coefficient matrix, with columns corresponding to Mexican purchasing industries set to zero. This excludes domestic intermediate sales within Mexico. The resulting change in Mexican intermediate exports is

$$\Delta \mathbf{e}^{MEX,int} = [\mathbf{A}_{year-1}]_{MEX} \Delta \mathbf{q}_j. \tag{F.4}$$

The total export response is therefore

$$\Delta \mathbf{e}^{MEX} = \Delta \mathbf{e}^{MEX,final} + \Delta \mathbf{e}^{MEX,int}. \tag{F.5}$$

Let Δe_{ij}^{MEX} denote the i-th element of $\Delta \mathbf{e}^{MEX}$. It measures the change in exports of Mexican industry i induced by a unit proportional increase in U.S. final demand for industry j.

I define the exposure of Mexican industry i to U.S. industry j as

$$\pi_{ij} = \frac{\Delta e_{ij}^{MEX}}{e_{i,year-1}^{MEX}/12},$$

where $e_{i,year-1}^{MEX}$ denotes the annual export value of Mexican industry i in the previous year. Thus, π_{ij} measures the proportional change in Mexican industry i's monthly exports induced by a unit increase in U.S. final demand for industry j. Because π_{ij} is constructed from the previous year's ICIO structure and final-demand levels, it is predetermined with respect to the demand conditions it is combined with. For example, the transmitted demand conditions for 2020 use π_{ij} from the 2019 ICIO table, which predates the 2020 demand shocks.

The demand condition transmitted to Mexican industry i is then

$$D_{it}^{MEX} = \sum_j \pi_{ij} D_{jt}^{USA}.$$

Table G.1: Exporter Size and Transmitted U.S. Demand Conditions

	(1)	(2)	(3)	(4)
	g_{fit}	g_{fit}	g_{fit}	g_{fit}
	All Sectors		Manufacturing	
$D^{MEX}_{i,t-1}$	3.628***		3.429***	
	(1.306)		(1.304)	
$[90,99] \times D^{MEX}_{i,t-1}$	-2.356	-2.206	-2.172	-2.005
	(1.438)	(1.420)	(1.421)	(1.402)
$[99,100] \times D^{MEX}_{i,t-1}$	-2.062	-1.934	-1.850	-1.704
	(1.476)	(1.495)	(1.451)	(1.469)
Adjusted R^2	0.024	0.149	0.020	0.127
Observations	2,192,361	2,192,317	2,003,066	2,003,066
Industry FE	✓		✓	
Industry × Date FE		✓		✓
Cluster	Firm, Date	Firm, Date	Firm, Date	Firm, Date
Number of Clusters	96	96	96	96

Notes: Weighted OLS estimations of Equation (G.1) with weights given by w_{fit} over 2013-2020. The dependent variable is the year-on-year midpoint growth rate at the firm-by-industry-by-month level. Standard errors are clustered at the firm and date level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G Exporter Size and Response to the U.S. Demand

$$g_{fit} = \sum_b (\alpha_b + \beta_b D^{MEX}_{i,t-1}) \mathbf{1}\{f \in I^{(b)}_t\} + \varepsilon_{fit} \tag{G.1}$$

Equation (G.1) measures heterogeneous firms' response to transmitted U.S. demand conditions, $D^{MEX}_{i,t-1}$ analogously to Equation (4). Table G.1 reports the weighted OLS estimates with weights w_{fit}. Columns (1)-(2) are for all sectors and columns (3)-(4) are for manufacturing sectors only. Column (1) and column (3) include industry fixed effects, column (2) and (4) include industry × date fixed effects. In the industry × date specifications, the response of the base group is absorbed by the fixed effects, and identification comes entirely from heterogeneous responses to the industrial fluctuation associated with U.S. demand conditions across firms within a given industry and date. Comparing firms within the same industry and date also absorbs supply disruptions and other shocks com-

mon to firms in that industry at that point in time. Column (4) therefore provides the most restrictive specification for examining heterogeneity in firms' responses to common industry-level fluctuation across firm size.

The interaction terms measure differences in responsiveness to U.S. demand-related industry fluctuations relative to the bottom 90 percent of exporters: $\beta_{[99,100]} - \beta_{[0,90]}$ and $\beta_{[90,99]} - \beta_{[0,90]}$. The coefficient on $D_{i,t-1}^{MEX}$ for the base group is positive and significant in columns (1) and (3), indicating that transmitted U.S. demand conditions explain firm-industry export growth. The interaction coefficients are negative in all columns but statistically insignificant. Thus, there is no evidence that larger exporters respond more strongly to U.S. demand conditions, consistent with the earlier finding that large exporters are not more sensitive to common industry fluctuations.

References

Acemoglu, D., Akcigit, U., and Kerr, W. (2015). Networks and the macroeconomy: An empirical exploration. Working Paper 21344, National Bureau of Economic Research.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China Syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, 103(6):2121–68.

Behrens, K., Corcos, G., and Mion, G. (2013). Trade crisis? What trade crisis? *The Review of Economics and Statistics*, 95(2):702–709.

Bils, M. and Klenow, P. J. (1998). Using consumer theory to test competing business cycles models. *Journal of Political Economy*, 106(2):233–261.

Bricongne, J.-C., Carluccio, J., Fontagné, L., Gaulier, G., and Stumpner, S. (2025). From macro to micro: Large exporters coping with global crises. *Journal of International Economics*, 153:104037.

Caballero, R. J. (1993). Durable goods: An explanation for their slow adjustment. *Journal of Political Economy*, 101(2):351–384.

Carvalho, V. M., Nirei, M., Saito, Y. U., and Tahbaz-Salehi, A. (2021). Supply chain disruptions: Evidence from the Great East Japan Earthquake. *The Quarterly Journal of Economics*, 136(2):1255–1321.

Casal, L. and Guntin, R. (2025). The business cycle volatility puzzle: Emerging vs developed economies. *Journal of International Economics*, 158:104182.

Celasun, O., Hansen, N.-J., Mineshima, A., Spector, M., and Zhou, J. (2022). Supply Bottlenecks: Where, Why, How Much, and What Next? *IMF Working Papers*, 2022(031):1.

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

di Giovanni, J. and Levchenko, A. A. (2012). Country size, international trade, and aggregate fluctuations in granular economies. *Journal of Political Economy*, 120(6):1083–1132.

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 Mejean, I. (2024). Foreign shocks as granular fluctuations. *Journal of Political Economy*, 132(2):391–433.

di Giovanni, J. d. and Levchenko, A. A. (2009). Trade openness and volatility. *The Review of Economics and Statistics*, 91(3):558–585.

Eaton, J., Kortum, S., Neiman, B., and Romalis, J. (2016). Trade and the global recession. *American Economic Review*, 106(11):3401–38.

Engel, C. and Wang, J. (2011). International trade in durable goods: Understanding volatility, cyclicality, and elasticities. *Journal of International Economics*, 83(1):37–52.

Foster, L., Haltiwanger, J. C., and Krizan, C. J. (2001). *Aggregate Productivity Growth: Lessons from Microeconomic Evidence*, pages 303–372. University of Chicago Press.

Fry, R. and Pagan, A. (2011). Sign restrictions in structural vector autoregressions: A critical review. *Journal of Economic Literature*, 49(4):938–60.

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

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

Huo, Z., Levchenko, A. A., and Pandalai-Nayar, N. (2019). International comovement in the global production network. Working Paper 25978, National Bureau of Economic Research.

Johnson, R. C. and Noguera, G. (2012). Accounting for intermediates: Production sharing and trade in value added. *Journal of International Economics*, 86(2):224–236.

Kemp, H., Portillo, R., and Santoro, M. (2023). Assessing the Impact of Supply Disruptions on the Global Pandemic Recovery. *IMF Working Papers*, 2023(042):1.

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–42.

Koopman, R., Wang, Z., and Wei, S.-J. (2014). Tracing value-added and double counting in gross exports. *American Economic Review*, 104(2):459–94.

Koren, M. and Tenreyro, S. (2007). Volatility and development. *The Quarterly Journal of Economics*, 122(1):243–287.

Leahy, J. V. and Zeira, J. (2005). The timing of purchases and aggregate fluctuations. *The Review of Economic Studies*, 72(4):1127–1151.

Levchenko, A. A., Lewis, L. T., and Tesar, L. L. (2010). The collapse of international trade during the 2008–09 crisis: In search of the smoking gun. *IMF Economic Review*, 58(2):214–253.

Yamano, N., Alsamawi, A., Webb, C., Cimper, A., Zürcher, C., and Chiapin Pechansky, R. (2023). Development of the OECD inter country input-output database 2023. Technical Report 2023/08, OECD Publishing, Paris.