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Lockdowns and export growth: the role of domestic production networks

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Abstract

This study investigates the role of domestic production networks in transmitting lockdown shocks originating in upstream and downstream provinces and shaping export performance in the focal province. Using a firm-to-firm transaction-based interprovincial input–output table to construct exposure measures, we find that a one-standard-deviation increase in downstream lockdown exposure reduces export growth by 13.6 log points, whereas upstream lockdown exposure has negligible effects. The impact is short-lived and concentrated in ordinary trade, differentiated products, and durable goods. These findings indicate complementarity between domestic sales and exports. Our evidence supports the economies of scale channel over liquidity constraints.

Keywords: **international trade; lockdown; domestic production network; input–output.**

JEL classifications: **F14, I18, R11, R15.**

1. Introduction

Production networks matter. In the spirit of Long and Plosser (1983), industries are connected through input–output linkages, whereby each sector uses the outputs of other sectors as intermediate inputs in production. As a result, sectoral and regional shocks can propagate through production networks, with important implications for both firm-level and aggregate outcomes. In particular, a growing strand of the literature documents that supply-side disruptions—arising from natural disasters (Barrot and Sauvagnat 2016) or pandemic-triggered lockdowns (Khanna et al., 2022)—propagate through domestic production networks and adversely affect firm-level outcomes, such as inputs and sales. Much less is known,

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however, about the role of domestic production networks in amplifying downstream demand shocks for export performance.[1]

In this study, we provide evidence that downstream demand shocks, as proxied by exposure to lockdowns in customer provinces, are amplified by domestic production networks and exert a large negative effect on export growth, while upstream supply shocks play a limited role.[2] Quantitatively, a one-standard-deviation increase in downstream lockdown exposure reduces 12-month product-level export growth by 13.6 log points, whereas upstream exposure has no economically meaningful effect. To construct these exposure measures, we follow a Bartik-style shift-share design and define them at the province-sector level as weighted sums of lockdown stringency in other provinces, where the weights are given by predetermined interprovincial intermediate input and output shares from the interprovincial input–output (IPIO) table for China. These measures capture the exposure of export products in the focal province to lockdown stringency in upstream supplier provinces and downstream customer provinces, with upstream exposure (backward linkage) reflecting supply-side disruptions and downstream exposure (forward linkage) capturing demand-side contractions. A unique feature of the IPIO table is that its intermediate input–output matrix is constructed using firm-to-firm transaction data derived from value-added tax (VAT) invoices, which enhances the measurement of interprovincial production linkages.[3] Our outcome variable, export growth, is measured at the province-partner-product (HS6) level, where partner denotes a foreign destination country and product is defined at the HS 6-digit level. We use monthly customs data from January 2018 to December 2020 obtained from the Chinese Customs Statistics.

We employ a generalized difference-in-differences design to estimate the causal effects of upstream and downstream lockdown exposure on export growth. Specifically, we compare changes in export growth in 2020 relative to the pre-pandemic period across products with varying degrees of lockdown exposure. Two features of the Chinese context provide a favorable setting for identification. First, lockdown policies in China exhibited considerable geographic heterogeneity across provinces during the pandemic (Fang et al., 2020; Chen et al., 2025), creating notable variation in local demand conditions. Importantly, even a single detected case could trigger rapid and localized containment measures, often implemented within hours. This swift and targeted approach significantly reduces potential endogeneity in policy responses (Chen et al., 2025). Second, interprovincial trade in intermediate inputs and outputs plays a central role in China's domestic production networks (Chen et al., 2022). This suggests that lockdown-induced supply and demand shocks in upstream and downstream provinces can propagate through domestic production networks and plausibly affect export performance in the focal province. Note that although our primary interest lies in downstream exposure, we account for upstream exposure to isolate demand-side network effects from supply-side disruptions.

We find an economically large but short-lived effect, with the decline in export growth concentrated in the first two quarters of 2020. This timing is consistent with the short-lived nature of stringent lockdown policies. The result also points to complementarity between domestic sales and exports, whereby contractions in domestic demand translate into weaker export performance. Our results remain robust across a battery of checks, including alternative exposure measures, the exclusion of outliers, and additional

1. By contrast, the role of global value chains in transmitting COVID-19 supply and demand shocks for international trade has been extensively examined in the literature (e.g. Baldwin and Tomiura 2020; Bonadio et al., 2021; Kejžar et al., 2022; Lafrogne-Joussier et al., 2023; Bricongne et al., 2025).
2. One closely related paper is Chen et al. (2025), who study the effects of lockdowns in China using city-to-city truck flow data and quantify spillover effects through intercity trade linkages within a gravity framework. Relatedly, Fang et al. (2023) rely on the same dataset to proxy for interregional economic linkages. In contrast, our study examines the spillover effects of lockdowns on export growth through interregional input–output linkages, which are theoretically grounded in the production-network perspective (Long and Plosser 1983; Acemoglu et al., 2012; Caliendo et al., 2018).
3. A growing body of literature uses firm-to-firm data to study the propagation of supply chain shocks and their effects on various economic outcomes (Barrot and Sauvagnat 2016; Carvalho et al., 2021; Khanna et al., 2022). Due to confidentiality concerns, we have access only to aggregate data at the province-sector level, rather than firm-level data.

controls. Heterogeneity analyses further show that the effects are more pronounced for ordinary trade, differentiated goods, and durable goods.

To establish a causal relationship between upstream and downstream lockdown exposure and export growth, we address potential endogeneity concerns along several dimensions. First, the institutional features of China's lockdown policies mitigate significant endogeneity concerns (Chen et al., 2025). Second, our exposure measures are constructed by aggregating lockdown stringency in upstream and downstream provinces—rather than in the focal province—using predetermined input–output shares at the province-sector level. This construction permits the inclusion of province-by-time fixed effects to absorb province-specific shocks, such as the local evolution of the pandemic and contemporaneous policy responses (Berthou and Stumpner 2024; Chen et al., 2025). In addition, we include province-by-sector fixed effects to account for time-invariant sectoral heterogeneity, as well as partner-by-HS6-product-by-time fixed effects to control for supply and demand shocks in foreign markets and sectoral shocks common across provinces.

Nevertheless, we cannot fully rule out the possibility that unobserved shocks at the province-sector-time level may be correlated with both lockdown exposure and export performance. To further address potential endogeneity concerns, we conduct a series of robustness exercises. One particular concern is that neighboring provinces may experience correlated supply and demand shocks and are often tightly connected through trade and input–output linkages (Barrot and Sauvagnat 2016; Carvalho et al., 2021). Another concern is that sectors critical to national or global supply chains may have been prioritized for reopening, potentially influencing lockdown intensity in their upstream and downstream provinces. A third concern is that lockdowns at major international ports may affect export performance through alternative channels, such as higher trade costs arising from port congestion and freight delays. To address these endogeneity concerns, we reconstruct the exposure measures by excluding trade flows between focal provinces and (1) neighboring provinces and (2) provinces hosting major international ports from the IPIO table. We also exclude sectors deemed critical to national or global value chains. The main results remain qualitatively unchanged.

To explore the mechanisms behind the effect of downstream demand shocks on export performance, we analyze how sectoral characteristics influence the transmission of lockdown exposure. Following Berman et al. (2015), we interact upstream and downstream lockdown exposure with sector-level measures of economies of scale and liquidity constraints. Our results show that the negative effect of downstream lockdown exposure on export growth is more pronounced in sectors characterized by increasing returns to scale (IRS), a higher Herfindahl–Hirschman Index (HHI), and a larger four-firm concentration ratio (CR4). By contrast, we find little evidence that liquidity-constrained sectors are more sensitive to demand shocks originating from downstream provinces. These findings point to the economies-of-scale channel as the primary mechanism driving our results.

This study contributes to several strands of literature. First, it adds to the literature on shock transmission through production networks. A large body of theoretical work shows that disaggregated shocks propagate through sectoral and interregional input–output linkages, generating spillovers along production networks (Long and Plosser 1983; Acemoglu et al., 2012; Caliendo et al., 2018; Baqaee and Farhi 2022). Empirical work has largely focused on upstream (backward) propagation through input linkages (e.g. Barrot and Sauvagnat 2016; Boehm et al., 2019; Khanna et al., 2022), while comparatively less attention has been devoted to downstream (forward) propagation (Acemoglu et al., 2016; Carvalho et al., 2021). In particular, Acemoglu et al. (2016) show that supply- and demand-side shocks propagate asymmetrically along production networks: supply shocks exert stronger downstream than upstream effects, whereas demand shocks propagate upstream. We build on this literature by jointly examining upstream supply disruptions and downstream demand contractions within China's interprovincial production network and comparing their effects on product-level export growth. We find that downstream demand shocks exert substantially stronger effects on exports, suggesting that domestic production networks act as amplifiers of downstream demand shocks.[4]

Second, our study relates to the growing literature examining how COVID-19 shocks transmit through global supply chains and shape international trade outcomes. Conceptually, lockdowns may affect trade performance through multiple channels, including domestic supply disruptions, global supply chain contagion effects, and global demand contractions (Baldwin and Tomiura 2020). However, the relative importance of these channels remains debated. Some studies emphasize the role of supply-side disruptions (e.g. Bonadio et al., 2021; Lafrogne-Joussier et al., 2023; Meier and Pinto 2024), while others highlight the importance of demand shocks at either the country level (Kejžar et al., 2022) or the firm level (Bricongne et al., 2025). We contribute by shifting the focus to domestic production networks.[5] Specifically, we exploit variation in province-level lockdown stringency to construct upstream and downstream lockdown exposure measures based on the IPIO table and evaluate their differential effects on export growth.

Finally, our findings speak to the literature on the relationship between domestic sales and exports. The empirical evidence is mixed. One strand documents complementarity between domestic sales and foreign exports (Berman et al., 2015; Bardaji et al., 2019; Erbahar 2020; Barrows and Ollivier, 2021, while another finds substitution effects (Vannoorenberghe 2012; Blum et al., 2013; Almunia et al., 2021). Bugamelli et al. (2015) show that the sign of this relationship may vary over the business cycle depending on liquidity, credit, and capacity constraints. Identifying this relationship requires adequately separating domestic supply shocks from domestic demand shocks. By isolating upstream supply disruptions from downstream demand contractions within domestic production networks, we provide evidence that downstream demand shocks are associated with lower export growth, consistent with complementarity between domestic sales and exports.

The remainder of the study proceeds as follows. Section 2 provides the policy background; Section 3 describes the data and empirical strategy; Section 4 presents the main results; Section 5 examines the underlying mechanisms; and the final section concludes.

2. Policy background

The outbreak of COVID-19 was unexpected and exogenous. To curb the spread of SARS-CoV-2, China implemented a broad set of containment policies, including stringent lockdowns and social distancing measures. Under the coordination of the National Health Commission (NHC), the State Council established the Joint Prevention and Control Mechanism (*lianfanglianKong*) to facilitate coordination across government departments and enhance the effectiveness of containment efforts. Similar coordination mechanisms were subsequently established at lower jurisdiction levels. More importantly, containment measures were not uniform across the country. Supplementary Figure A1 shows that local governments adjusted the stringency of their policies according to local epidemiological conditions. On 29 January 2020—9 days after the NHC confirmed human-to-human transmission—all 31 provinces in China activated a first-level public health emergency response. By February 29, eight provinces, including Guangdong, had lowered their response level to Level II, while nine provinces, including Liaoning, had reduced theirs to Level III. By March 31, 22 provinces, including Zhejiang, had transitioned to Level III. In contrast, Hubei province did not downgrade its response to Level II until May 2. Finally, the

4. Stumpner (2019) analyzes the regional propagation of housing-driven demand shocks through interregional trade linkages within the United States. While he emphasizes downstream demand channels, our framework distinguishes between upstream supply and downstream demand shocks and examines their transmission through interregional input–output networks.
5. See Ding et al. (2022) for evidence from China and Laeven (2022) for evidence from the United States that downstream lockdown exposure within domestic production networks affects financial outcomes. Notably, Ding et al. (2022) construct a sector-level, time-invariant measure centered on exposure to Hubei province. By contrast, we define exposure at the province–sector level and allow it to vary over time with lockdown stringency, capturing shocks from upstream and downstream provinces other than the focal province.

Beijing-Tianjin-Hebei region lowered its response level to Level III on June 6, with Hubei following one week later.[6]

To capture cross-province variation in the stringency of containment policies, we draw on eight containment indicators from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2021) to construct a monthly measure of lockdown stringency, following Ding et al. (2021). The eight indicators cover school closures (C1), workplace closures (C2), cancellation of public events (C3), restrictions on gatherings (C4), public transport closures (C5), stay-at-home orders (C6), restrictions on internal movement (C7), and international travel controls (C8). The original provincial containment indicators are recorded at the daily frequency, whereas our trade data are available monthly. To harmonize the two datasets, we first compute monthly averages for each indicator and normalize them to range between 0 and 1. We then aggregate the eight normalized indicators and rescale the resulting province-month composite index to range from 0 to 1. As shown in Fig. 1, lockdown stringency rose sharply during the first 2 months of the pandemic and declined rapidly thereafter. Cross-province variation in lockdown stringency closely mirrors differences in public health responses across provinces.

Wuhan, the capital city of Hubei province, lifted its lockdown on April 8. Three weeks later, on 29 April 2020, the State Council announced that China had entered a phase of regular pandemic prevention and

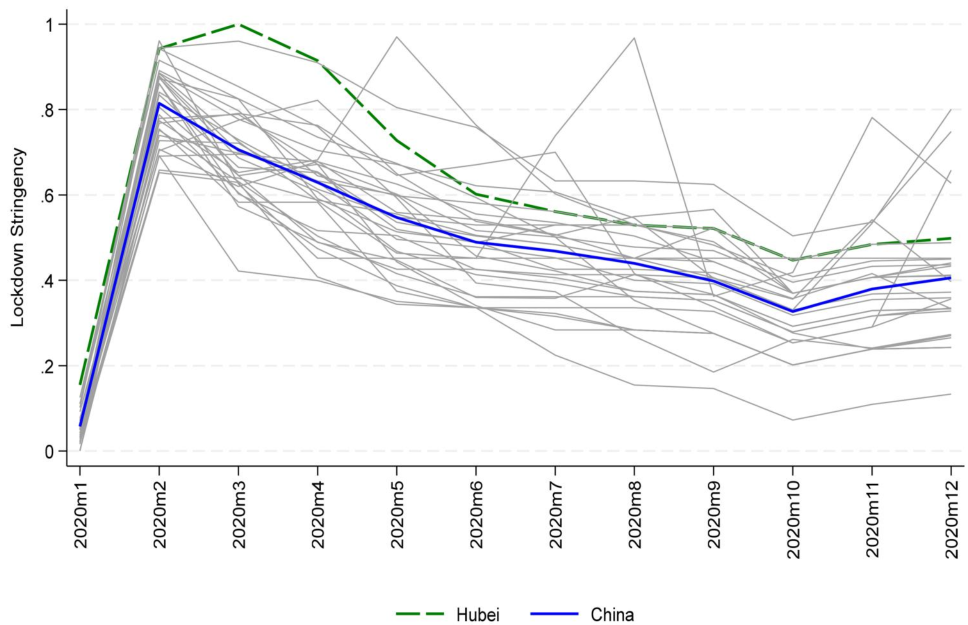

Figure 1. Lockdown stringency by province in 2020. This figure illustrates the evolution of lockdown stringency across Chinese provinces in 2020, measured by a composite index constructed from eight sub-indicators from the OxCGRT. The eight sub-indicators include school closures (C1), workplace closures (C2), cancellation of public events (C3), restrictions on gatherings (C4), public transport closures (C5), stay-at-home orders (C6), restrictions on internal movement (C7), and international travel controls (C8). For each indicator, we first compute monthly averages at the province level and normalize them to range between zero and one. We then sum the eight normalized indicators and rescale the resulting province-month composite index to range from 0 to 1. The dashed green line corresponds to Hubei Province, the solid blue line represents the national average, and the gray lines denote all other provinces.

6. In response to newly confirmed cases linked to the Xinfadi market on June 11, Beijing raised its emergency response level to Level II on June 16 and subsequently lowered it to Level III on July 20.

control, as the domestic spread of COVID-19 had largely been contained. Subsequent outbreaks were sporadic and effectively managed. As a result, restarting economic activity and resuming work became top policy priorities, with containment efforts shifting toward "preventing imported cases and domestic resurgences." This timeline suggests that the most stringent lockdown measures were concentrated in the early months of 2020. Accordingly, and in line with the literature, we end the sample in December 2020 to focus on the immediate export responses to these short-lived disruptions.

A key question during the COVID-19 lockdowns is whether firms were primarily constrained by supply disruptions or demand shortfalls. Survey evidence from Xinhuanet and the State Administration for Market Regulation indicates that by February 2020, 63% of firms identified declining market orders as their main challenge, compared with 51% citing labor shortages and 22% reporting shortages of raw materials. A similar survey conducted by the United Nations Development Program in March 2020 echoed these results.[7] By October 2020, surveys from the China Enterprise Reform and Development Society show that more than half of firms continued to report weak demand as their primary difficulty, while only about 25% and 20% pointed to labor supply and raw material shortages, respectively.[8]

This survey evidence is consistent with a growing literature documenting that demand shocks were firms' dominant challenge during the pandemic (Bartik et al., 2020; Dai et al., 2021; Alekseev et al., 2023). Theoretically, Guerrieri et al. (2022) characterize pandemic-induced disturbances as Keynesian supply shocks that, through sectoral complementarities and market incompleteness, can result in amplified contractions in aggregate demand. Consistent with this framework, our results show that demand shocks originating from downstream provinces have a larger impact on export growth than upstream supply shocks.

Stringent lockdowns in China are found to be cost-effective (Fang et al., 2020; Pei et al., 2022; Chen et al., 2025). The transmission of the virus was largely confined to Hubei Province, which accounted for more than 80% of confirmed cases nationwide. By March 2020, daily confirmed cases in China had fallen to single digits, with only occasional resurgences. In stark contrast, many other countries continued to report daily infections in the tens of thousands. By the end of 2020, cumulative infections totaled 87,000 in China, compared with more than 20 million in the United States and over 10 million in India. On the other hand, stringent containment measures substantially restricted the movement of goods and people, disrupting domestic production networks. Using city-to-city truck flow data, Chen et al. (2025) find that truck flows connected to locked cities decreased by up to 54%, resulting in significant real income losses in affected cities. Fang et al. (2020) and Pei et al. (2022) document large reductions in both inter-city and intra-city mobility following lockdowns. However, existing studies have yet to examine how lockdown-induced disruptions originating in other provinces transmit through domestic production networks and affect export performance in the focal province. This study aims to fill that gap.

3. Data and empirical strategy

3.1 Data

The first dataset we use is the China Customs trade statistics at the provincial level, which represent the most disaggregated data available. The dataset provides detailed information on exporters' registration locations, products classified under the harmonized system (HS) at the 8-digit level, destination country, trade regimes, and transaction values denominated in US dollars. In this study, we use monthly trade data at the province-partner-product level from January 2018 to December 2020 and conduct the

7. Assessment Report on the Impact of the COVID-19 Pandemic on Chinese Enterprises, United Nations Development Programme. Available at: https://www.undp.org/china/publications/assessment-report-impact-covid-19-pandemic-chinese-enterprises (accessed April 10, 2020).

8. Reports on the impact of COVID-19 on enterprise operations: a series of tracking surveys (issues 1–4) (in Chinese). Available at: https://www.cerds.cn (accessed November 10, 2020).

analysis at the HS 6-digit level to ensure cross-country comparability. To align the trade data with our province-sector-level explanatory variables, we use the concordance provided by the National Bureau of Statistics (NBS) and Chen et al. (2022) to map HS 2017 product codes to IPIO sectors.[9]

The second dataset is the OxCGRT, maintained by the Blavatnik School of Government at the University of Oxford (Hale et al., 2021). It provides a comprehensive set of containment indicators for approximately 190 economies, as well as sub-national units for selected countries. As described in Section 2, we construct a provincial lockdown stringency measure using eight specific indicators following Ding et al. (2021). The resulting composite index is first rescaled to range from 0 to 1. To facilitate the interpretation of the estimated coefficients, we further standardize this index to have a mean of zero and a standard deviation of one before estimation. In robustness checks, we also employ the composite stringency index (SI) and its legacy version provided by OxCGRT, with both original 0–100 indexes rescaled by dividing them by 100.

The third dataset is the 2012 IPIO table for China, which covers 31 provinces and 39 sectors (Chen et al., 2022). The table is constructed using VAT invoice data from the State Administration of Taxation (SAT), which record firm-to-firm transactions and therefore provide an accurate measure of interprovincial trade flows. A typical VAT invoice records the locations and sectors of both sellers and buyers, as well as transaction dates, transaction values, and taxes paid. It should be noted, however, that the VAT records available to Chen et al. (2022) identify only the primary sectors of buyers and sellers rather than the specific goods traded, so interprovincial trade flows are measured based on firms' main sector classifications.[10]

In addition to the advantages of the VAT-based data, two features of the 2012 IPIO table, relative to more recent IPIO tables, are important for our identification. This reflects a trade-off between data recency and data reliability, as well as the table's suitability for our empirical setting. First, the export vector is held fixed during the balancing procedure used to construct the table, ensuring that the resulting input–output coefficients are independent of export variation. This feature is particularly relevant in our context because the outcome variable in our analysis is export growth. Second, the balancing procedure focuses on reconciling the interprovincial intermediate transaction matrix, with VAT records used as initial estimates, rather than treating intermediate flows and final uses symmetrically. Because our baseline exposure measures are constructed from these intermediate production linkages, this feature further strengthens the suitability of the 2012 IPIO table for our empirical design.

We leverage the IPIO table to construct Bartik-style measures of exposure to lockdown stringency in upstream and downstream provinces.[11] Specifically, our sectoral upstream and downstream lockdowns are defined as:

$$Upstream\ \ Lockdown_{pst} = \sum_{r \neq p} u_{psr} Lockdown_{rt}, \tag{1}$$

$$Downstream\ \ Lockdown_{pst} = \sum_{r \neq p} d_{psr} Lockdown_{rt}. \tag{2}$$

Here, p and r denote provinces, and s denotes sectors. $Lockdown_{rt}$ is the lockdown stringency in province r at month t. The weight u_{psr} is the share of intermediate inputs that sector s in province p sources from province r, while d_{psr} is the share of outputs that sector s in province p sells to province r.

9. We first link HS 2017 product codes to the 2017 national input–output table using the concordance table provided by the NBS, and then aggregate them into the 39 IPIO sectors using the crosswalk developed by Chen et al. (2022). The resulting HS-IPIO concordance table is available upon request. Supplementary Table A1 summarizes the distribution of HS 6-digit products across IPIO sectors, illustrating the breadth of products mapped to each sector.
10. The original VAT invoice database compiled by the SAT aggregates transactions into a 31-region, 58-industry matrix. Chen et al. (2022) further aggregate these industries to obtain the 31×39 province–sector matrix in the 2012 IPIO table.
11. Our measure is akin to the gravity-based instrument in Almunia et al. (2021) in that both construct exposure as a weighted sum of shocks in other locations.

Table 1. Summary statistics.

Variables	Obs.	Mean	SD	Min.	Max.
Export (thousand USD)	10,036,075	437.883	6,571.684	0.001	4,606,411.049
ΔlogExport	10,036,075	0.030	2.031	−16.017	17.443
ΔlogQuantity	9,921,584	0.007	2.166	−19.265	17.034
ΔlogUnitValue	9,921,584	0.024	1.280	−16.114	16.278
logOutput	10,036,075	17.509	1.233	5.709	19.762
UpShare	10,036,075	0.278	0.169	0	0.927
DownShare	10,036,075	0.268	0.233	0	1
Lockdown	10,036,075	0.223	0.262	0	1
Upstream Lockdown	10,036,075	0.062	0.091	0	0.718
Downstream Lockdown	10,036,075	0.059	0.105	0	0.818
log(1 + Confirmed cases)	10,036,075	1.389	1.936	0.000	11.011
log(1 + Confirmed deaths)	10,036,075	0.064	0.397	0.000	7.834

Notes: Exports are defined at the province-partner-HS6 level, measured in thousands of US dollars. ΔlogExport is defined as the 12-month log difference in export values between month m and month m–12. Analogously, Δlog*Quantity* and Δlog*UnitValue* are defined as the 12-month log differences in export quantities and export unit values, respectively. lo*gOutput* is the natural logarithm of total output at the province-sector level. *UpShare* and *DownShare* denote, respectively, the total share of intermediate inputs sourced from and outputs sold to other provinces at the province-sector level. *Lockdown* is a composite index constructed as the sum of eight indicators capturing government containment and closure policies at the provincial level and is standardized to range from 0 to 1. *Upstream Lockdown* is the input-share-weighted exposure to lockdown stringency in upstream provinces other than the focal province; *Downstream Lockdown* is defined analogously using output shares. *Confirmed cases* and *deaths* refer to newly confirmed cases and deaths in each month; one is added prior to taking logarithms to include zero values.

Upstream Lockdown$_{pst}$ is an input share-weighted sum of lockdown stringency in upstream provinces, capturing exposure to upstream supply disruptions. *Downstream Lockdown*$_{pst}$ is defined analogously as an output-share-weighted sum of lockdown stringency in downstream provinces, capturing exposure to downstream demand contractions.[12] We exclude the focal province when constructing both measures; as a result, the input and output shares need not sum to one. Finally, we extract industry-level output data from the 2017 provincial input–output tables for all 31 provinces and map the sector classifications to those in the IPIO table used in our analysis.

Table 1 reports the summary statistics. On average, the export value of an HS 6-digit product is approximately US$438,000, with substantial dispersion across observations. The 12-month log difference in product-level exports has a mean of 0.030. The sample means of *UpShare* and *DownShare*, which measure the total share of intermediate inputs sourced from and outputs sold to provinces outside the focal province, are 0.278 and 0.268, respectively. This implies that interprovincial input–output linkages are economically meaningful. The means of the two explanatory variables of interest, *Upstream Lockdown* and *Downstream Lockdown*, are 0.062 and 0.059, respectively. Finally, the sample also exhibits considerable variation in log(1 + confirmed cases) and log(1 + confirmed deaths), with mean values of 1.389 and 0.064, respectively.

3.2 Empirical strategy

Lockdown policies are short-lived, and it is therefore plausible that their effects are concentrated in the short term. Accordingly, we use granular monthly trade data to examine how lockdown-induced shocks propagate through domestic production networks and affect product-level export growth (Pei et al., 2022; Bricongne et al., 2025). To alleviate concerns about seasonality, we take a 12-month log difference

12. We use only the intermediate transaction matrix when constructing the above measures. This choice reflects our focus on domestic production networks, as measures that incorporate imported inputs or foreign final demand may confound identification. Laeven (2022) adopts a similar approach to study the supply chain effects of lockdowns in the United States.

of exports, yielding a final sample period from January 2019 to December 2020. We then implement a generalized difference-in-differences design to assess whether products with greater upstream and downstream lockdown exposure experienced differential changes in export growth in 2020 relative to 2019. Our estimation specification is as follows:

$$\begin{aligned}\Delta \log Export_{pckt} &= \beta_1 Upstream\ Lockdown_{pst} + \beta_2 Downstream\ Lockdown_{pst} \\ &+ \textstyle\sum_{\tau \in T} \theta_\tau \mathbf{X}_{ps,t_0} \times \mathbf{1}\{t = \tau\} + \eta_{pt} + \delta_{ps} + \varphi_{ckt} + \varepsilon_{pckt},\end{aligned} \tag{3}$$

where p, c, k, and t represent province, foreign destination country, HS 6-digit product, and time (year-month), respectively. s denotes sectors in the IPIO table. The dependent variable, $\Delta \log Export_{pckt}$, is defined as the 12-month log difference in export values between calendar month m of year t and the same calendar month in the previous year. The explanatory variables of interest are $Upstream\ Lockdown_{pst}$ and $Downstream\ Lockdown_{pst}$, which capture the exposure of sector s in province p to lockdown stringency in upstream and downstream provinces, respectively. Both variables are normalized to zero in 2019. T denotes the set of year-month time periods in the sample spanning January 2019 to December 2020. $\mathbf{1}\{t = \tau\}$ is an indicator function that equals one if t corresponds to year-month τ, and zero otherwise. The vector $\mathbf{X}_{ps,\ t0}$ includes pre-pandemic control variables measured at the province-sector level, namely the logarithm of sectoral output ($\log Output_{ps}$), the total share of intermediate inputs purchased from other provinces (*UpShare*) and the total share of intermediate outputs sold to other provinces (*DownShare*). We interact these variables with time dummies to allow for differential trends across sectors with different initial sizes and degrees of interprovincial supply-chain dependence. As *UpShare* and *DownShare* do not necessarily sum to one, their interactions with time dummies can also address concerns related to incomplete shares, following Borusyak et al. (2022).

We include several sets of fixed effects to control for confounding factors at various levels. Province-time fixed effects (η_{pt}) absorb time-varying province-specific shocks, such as local lockdown stringency and the evolution of the pandemic (Berthou and Stumpner 2024; Chen et al., 2025). Province-sector fixed effects (δ_{ps}) control for time-invariant heterogeneity at the province-sector level. Partner-HS6-time fixed effects (ψ_{ckt}) absorb any unobserved time-varying supply and demand shocks at the destination-country and product level, including importer lockdowns, changes in foreign demand, tariff adjustments, as well as sector-specific domestic policies that are common across provinces. These fixed effects are crucial for isolating the effects of domestic production-network shocks from global value-chain linkages (Kejžar et al., 2022). Standard errors are clustered at the province-sector level to account for heteroskedasticity and serial correlation within province-sector cells.

In our generalized difference-in-differences framework, identification comes from within province-sector variation over time in upstream and downstream lockdown exposure, after accounting for the controls and fixed effects described above. The two exposure variables are akin to Bartik-style (*shift-share*) exposure measures, combining time-varying lockdown stringency in upstream and downstream provinces with pre-determined input–output shares from the IPIO table. Thus, a clarification regarding the exogeneity of either the shifts or the shares is essential (Borusyak et al., 2025). In our case, the *shift* component, namely changes in lockdown stringency, is plausibly exogenous to export performance. For one thing, existing studies document that China's lockdown measures were largely driven by local pandemic conditions rather than contemporaneous socio-economic outcomes (Fang et al., 2023; Chen et al., 2025). This evidence suggests that variation in lockdown stringency is plausibly exogenous conditional on local pandemic severity. Furthermore, our exposure measure relies on lockdown stringency in upstream and downstream provinces, while lockdown stringency in the focal province is absorbed by province-time fixed effects. Because policies in upstream and downstream provinces are determined by local conditions in those provinces, they are unlikely to respond to short-run export fluctuations in the focal province-sector. Consistent with this interpretation, our estimates remain stable when we additionally control for shift-share aggregates of upstream and downstream pandemic severity constructed using the same input–output shares as in the baseline exposure measures.

4. Empirical results

4.1 Baseline estimates

Table 2 presents the baseline estimates from regressions based on Equation (3). We focus primarily on manufacturing exports, as agricultural and mining products are less reliant on interprovincial production networks. Columns (1)–(3) report estimates for HS 6-digit products mapped to manufacturing sectors in the IPIO table, while Column (4) reports estimates for all HS 6-digit-matched sectors ("All sectors").[13] To facilitate interpretation, we normalize the two key explanatory variables to have mean zero and standard deviation one.

Column (1) reports estimates from a specification that includes only upstream lockdown exposure, along with the full set of fixed effects and control variables. The estimated coefficient on *Upstream Lockdown* is small in magnitude and statistically insignificant.[14] By contrast, Column (2) includes only downstream lockdown exposure (*Downstream Lockdown*), yielding a coefficient of −0.1339 that is statistically significant at the 1% level. Column (3) further includes both upstream and downstream lockdown exposure. The estimated coefficient on *Downstream Lockdown* remains negative and statistically significant, whereas the coefficient on *Upstream Lockdown* remains statistically indistinguishable from zero.

Using the estimates in Column (3) as a benchmark, a one-standard-deviation increase in downstream lockdown exposure is associated with a 13.6 log-point reduction in 12-month export growth. To gauge

Table 2. Baseline estimates.

	(1) Manufacturing	(2) Manufacturing	(3) Manufacturing	(4) All sectors
Upstream lockdown	−0.0132		0.0161	0.0143
	(0.0342)		(0.0354)	(0.0346)
Downstream lockdown		−0.1339***	−0.1357***	−0.1320***
		(0.0503)	(0.0517)	(0.0499)
logOutput × Time dummies	Yes	Yes	Yes	Yes
UpShare × Time dummies	Yes		Yes	Yes
DownShare × Time dummies		Yes	Yes	Yes
Province-Time FE	Yes	Yes	Yes	Yes
Province-Sector FE	Yes	Yes	Yes	Yes
Partner-HS6-Time FE	Yes	Yes	Yes	Yes
Observations	10,036,075	10,036,075	10,036,075	10,122,188
R^2	0.2635	0.2635	0.2635	0.2639

Notes: "All Sectors" includes all IPIO sectors matched to HS 6-digit products (mainly agriculture, mining, and manufacturing). "Manufacturing" restricts the sample to IPIO manufacturing sectors. The dependent variable is Δlog*Export*, defined as the 12-month log difference in export values between month m and month m − 12. *Upstream Lockdown* is the input-share-weighted exposure to lockdown stringency in upstream provinces other than the focal province; *Downstream Lockdown* is defined analogously using output shares. The control variables include log*Output*, *UpShare*, and *DownShare*. See Table 1 for descriptions of the control variables. Robust standard errors in parentheses are clustered at the province-sector level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

13. All sectors' refers to all IPIO sectors matched to HS 6-digit products in the customs data, which in practice are overwhelmingly concentrated in agriculture, mining, and manufacturing, with only a negligible number of observations in service sectors.
14. This finding does not rule out the possibility that upstream supply shocks may also affect export performance. As argued by Barrot and Sauvagnat (2016), the propagation of supply shocks depends on the presence of relationship-specific rather than nonspecific inputs. Investigating this channel, however, lies beyond the scope of this paper.

the economic magnitude, we consider a representative product with an average export value of US$438,000. A back-of-the-envelope calculation implies that products with higher downstream lockdown exposure export approximately US$60,000 less than otherwise similar products with lower exposure.

To facilitate comparison with the literature on the relationship between domestic sales and exports, a simple back-of-the-envelope calculation implies a positive elasticity of exports with respect to domestic sales of approximately 0.4–0.6. In other words, a 10% decline in domestic sales is associated with a 4%–6% decline in exports. This magnitude is consistent with the complementarity documented by Berman et al. (2015), who find that a 10% increase in exports raises domestic sales by 1%–3%.[15]

Finally, Column (4) re-estimates the specification using the full sample and yields similar results, indicating that the findings from the manufacturing sample are robust. Taken together, the results suggest that downstream demand shocks transmitted through domestic production networks were an important determinant of export growth, whereas we find little evidence that upstream supply disruptions played a comparable role.

4.2 Changing effects over time

As illustrated in Section 2, lockdown stringency in China declined steadily over the course of 2020, with occasional adjustments across provinces. In this section, we explore whether the effects of lockdown exposure on export growth varied over time. To do so, we re-estimate our baseline specification by interacting upstream and downstream lockdown exposure with indicators for each calendar month in 2020. The regression equation is as follows:

$$\begin{aligned} \Delta \log Export_{pckt} = & \textstyle\sum_{\tau \in \mathcal{T}_{2020}} \beta_\tau^U Upstream\ Lockdown_{pst} \times \mathbf{1}\{t = \tau\} \\ & + \textstyle\sum_{\tau \in \mathcal{T}_{2020}} \beta_\tau^D Downstream\ Lockdown_{pst} \times \mathbf{1}\{t = \tau\} \\ & + \textstyle\sum_{\tau \in \mathcal{T}} \theta_\tau \mathbf{X}_{ps,t_0} \times \mathbf{1}\{t = \tau\} + \eta_{pt} + \delta_{ps} + \varphi_{ckt} + \varepsilon_{pckt}, \end{aligned} \tag{4}$$

where $\mathcal{T}_{2020}$ denotes the subset of year-month periods in 2020. The coefficients β_τ^U and β_τ^D capture the month-specific effects of upstream and downstream lockdown exposure, respectively, relative to the corresponding calendar month in 2019. All other terms are defined as in Equation (3).

Figure 2 plots the estimated monthly coefficients on upstream and downstream lockdown exposure from Equation (4). Consistent with our baseline findings, downstream lockdown exposure—capturing demand-side shocks—exhibits large and statistically significant negative effects in the early months of 2020. These effects are most pronounced between January and April and attenuate gradually thereafter. In contrast, the estimated coefficients on upstream lockdown exposure—capturing supply-side disruptions—are small in magnitude and statistically insignificant throughout the year. These results suggest that, at least in the short run, downstream demand shocks played a more prominent role in shaping export performance during the early stages of the pandemic. Additionally, the subsequent attenuation of these effects coincides with the relaxation of stringent containment measures following the lifting of the Wuhan lockdown in April and the transition toward regular pandemic prevention and control. A similar temporal pattern is documented by Berthou and Stumpner (2024), who find that the adverse effects of lockdowns on export performance across countries were strongest in the spring of 2020 and diminished thereafter as firms and households adapted to pandemic-related disruptions.

In Supplementary Table A2, we further investigate how the effects of upstream and downstream lockdown exposure on export growth vary across different time horizons by aggregating the data to 1-, 3-, 5-,

15. This elasticity is inferred by combining our estimated effect of downstream lockdown stringency on export growth with existing evidence on lockdown-induced domestic sales declines. Using VAT invoice data, Chen et al. (2024) document sales declines of 23%–35% across firm sizes following the Wuhan lockdown. This calculation serves as an interpretive benchmark rather than a structural estimate, as the underlying estimates differ in their levels of aggregation and time horizons. The implied elasticity should therefore be interpreted with caution.

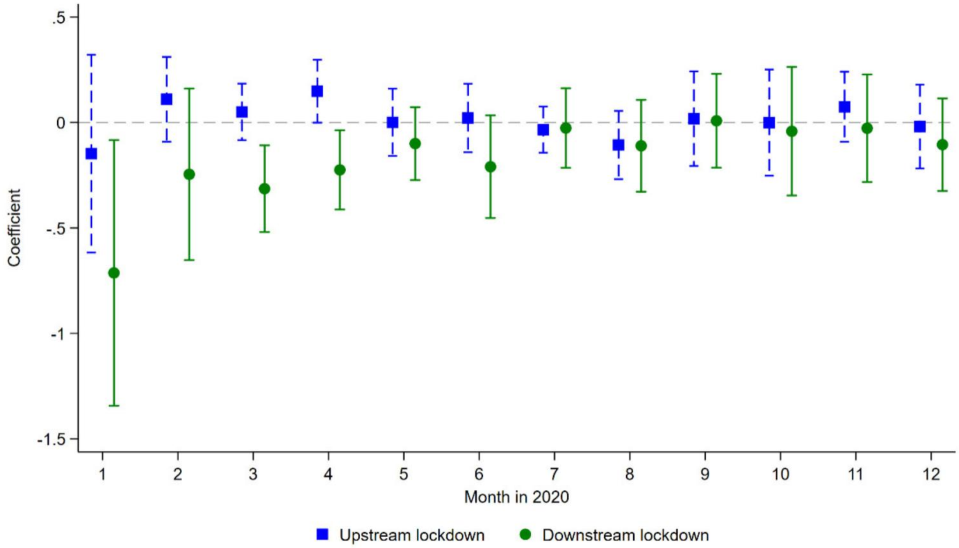

Figure 2. Effect of lockdowns on export growth over time. This figure plots the coefficients on upstream and downstream lockdowns estimated from Equation (4), by calendar month in 2020. Coefficients for upstream lockdowns are shown with blue square markers, while those for downstream lockdowns are shown with green circle markers. Bars represent 95% confidence intervals. The dependent variable is Δlog*Export*, defined as the 12-month log difference in export values between month m and month m–12. *Upstream Lockdown* is the input-share-weighted exposure to lockdown stringency in upstream provinces other than the focal province; *Downstream Lockdown* is defined analogously using output shares. We control for log*Output*, *UpShare* and *DownShare*, interacted with time dummies. We control for province-time, province-sector, and partner-HS6-time fixed effects. See Table 1 for descriptions of the control variables. Standard errors are clustered at the province-sector level.

and 12-month intervals, and then re-estimating our baseline specifications. For ease of comparison, the first column reproduces the baseline 1-month estimates from Table 2 before presenting the estimates based on longer aggregation windows. The estimates show that the effect of downstream lockdown exposure on export growth is a short-term phenomenon, with statistically significant effects concentrated within horizons of up to 6 months. When the data are aggregated to an annual frequency, the estimated downstream effect becomes much smaller and statistically insignificant. This pattern suggests that lockdown-induced demand shocks are largely short-lived and may be obscured when using coarser time aggregation. For upstream lockdown exposure, the estimated coefficient remains statistically insignificant at shorter horizons but becomes negative at the twelve-month frequency. While this pattern may reflect delayed adjustment to upstream disruptions, for example through inventory buffering, short-run effects remain imprecisely estimated. Overall, the dynamic responses indicate that downstream lockdown exposure exhibits more robust and immediate effects in our setting.

4.3 Robustness checks

In this section, we conduct a battery of robustness checks. We re-estimate Equation (3) with additional controls, alternative measures of lockdown exposure, potential outliers excluded, panel fixed effects, and alternative clustering levels. The first set of results is reported in Table 3, with additional checks presented in Supplementary Tables A3–A6.

Table 3. Robustness check: Additional controls.

	(1) COVID-19 deaths	(2) Differentiated local lockdown	(3) Other province lockdown	(4) Imported supply shocks	(5) Foreign demand shocks
Upstream lockdown	0.0166	0.0145	0.0173	0.0137	0.0162
	(0.0353)	(0.0356)	(0.0353)	(0.0362)	(0.0356)
Downstream lockdown	−0.1368***	−0.1364***	−0.1319**	−0.1377***	−0.1356**
	(0.0519)	(0.0515)	(0.0518)	(0.0519)	(0.0528)
Upstream COVID deaths	0.0025				
	(0.0064)				
Downstream COVID deaths	−0.0054				
	(0.0085)				
Within-province share × Local lockdown		0.0644			
		(0.0840)			
Other province lockdown			−0.1216		
			(0.0979)		
Upstream imported lockdown				−0.0066	
				(0.0074)	
Downstream foreign demand shock					0.0034
					(0.2334)
Controls × Time dummies	Yes	Yes	Yes	Yes	Yes
Province-time FE	Yes	Yes	Yes	Yes	Yes
Province-sector FE	Yes	Yes	Yes	Yes	Yes
Partner-HS6-time FE	Yes	Yes	Yes	Yes	Yes
Observations	10,036,075	10,036,075	10,036,075	9,968,538	10,036,075
R^2	0.2635	0.2635	0.2635	0.2640	0.2635

Notes: The dependent variable is Δlog*Export*, defined as the 12-month log difference in export values between month m and month m – 12. *Upstream Lockdown* is the input-share-weighted exposure to lockdown stringency in upstream provinces other than the focal province; *Downstream Lockdown* is defined analogously using output shares. Column (1) controls for upstream and downstream COVID-19 severity using input- and output-share-weighted log(1+*deaths*) in upstream and downstream provinces, excluding the focal province. Column (2) adds an interaction between provincial lockdown stringency and within-province supply-chain dependence, measured as the average share of inputs sourced from and outputs sold within the same province. Column (3) accounts for trade diversion by including lockdown stringency in other provinces weighted by pre-pandemic export shares (2019 HS4). Column (4) controls for imported supply shocks using import-share-weighted lockdown stringency in source countries (2019 HS4). Column (5) further controls for downstream foreign demand shocks, constructed as destination-weighted lockdown stringency based on pre-pandemic export shares (2019) and aggregated using interprovincial input–output coefficients. The control variables include log*Output*, *UpShare*, and *DownShare*. See Table 1 for descriptions of the control variables. Robust standard errors in parentheses are clustered at the province-sector level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.3.1 Additional controls

First, a key concern is the potential endogeneity of upstream and downstream lockdown stringency with respect to the pandemic severity (Berthou and Stumpner 2024). If COVID-19 cases and deaths are disproportionately concentrated in provinces that serve as major suppliers or customers of a given province-sector, observed declines in export growth may reflect the severity of the pandemic itself rather than the effects of lockdown measures. More specifically, heightened infection risk and fear may propagate through inter-provincial production networks, thereby depressing export performance in affected sectors. To address this concern, we follow Berthou and Stumpner (2024) and control for pandemic severity by including the log of one plus the number of deaths in upstream and downstream provinces, constructed using the same inter-provincial input and output weights as in the baseline specification. Column (1) of Table 3 shows that the coefficient on the proxy of pandemic severity is tiny and statistically insignificant, suggesting that pandemic severity in downstream provinces is unlikely to be the primary driver of our baseline estimates.

Second, another potential concern relates to the differentiated lockdown measures that local governments imposed on different sectors. Firms with fully integrated within-province supply chains, as well as those producing essential goods or medical supplies, were often prioritized for reopening. However, such differentiated containment policies are unlikely to drive our main findings. On the one hand, any time-varying unobserved confounders at the product level are absorbed by partner-HS6-time fixed effects. On the other hand, interactions between time dummies and two measures of interprovincial supply chain dependence, the total shares of inputs sourced from and outputs sold to other provinces, help address differential sectoral trends. That said, in Column (2), we additionally include an interaction between local lockdown stringency and within-province supply-chain dependence, defined as the average of the within-province input and demand coefficients, where the input coefficient measures the share of inputs sourced from sectors within the same province and the demand coefficient measures the share of outputs sold to sectors within the same province.[16] We expect sectors relying heavily on within-province supply chains to exhibit greater resilience in export growth. We find that the coefficient on this interaction term is positive, although statistically insignificant at conventional levels. Importantly, our baseline estimates are unaffected, suggesting that sector-specific lockdown measures do not materially bias our results.

Third, we control for the "trade diversion" effect (Espitia et al., 2022; Liu et al., 2022). A related concern is that provinces facing less stringent lockdown measures retained greater export capacity and were therefore better positioned to serve foreign markets, potentially displacing exports from the focal province in the same product-destination market. To address this concern, we construct a weighted sum of lockdown stringency across all other provinces, denoted as *Other Province Lockdown*, where the weights are given by each province's pre-pandemic export share of the product at the HS 4-digit level in 2019. We use this measure to account for pandemic-control conditions in competing provinces and the associated potential for trade diversion. Column (3) shows that the estimated coefficient on this variable is indistinguishable from zero, suggesting that the trade diversion effect does not drive our baseline results.

Fourth, in our baseline specification, we account for supply shocks from foreign trading partners by including partner-HS6-time fixed effects that are common to all provinces. Here, we further control for imported supply shocks specific to the focal province, as such shocks may be an alternative channel through which exports decline. Moreover, if imported products are not entirely used for production within the focal province but are instead redistributed to other provinces, imported supply shocks may propagate across provinces and thus be correlated with our explanatory variables. To capture this channel, we construct an import-share-weighted sum of lockdown exposure to all source countries from which the focal province imports, which we refer to as *Imported Lockdown*. Following Handley et al. (2020), we approximate supply-chain linkages by matching HS6 export products to imported products within the same HS4 heading. The weights are constructed using each province's 2019 import shares by country at the HS4 level. Column (4) shows that our estimates are robust to the inclusion of this additional control.

Finally, one might also be concerned that foreign demand shocks faced by downstream provinces are correlated with downstream lockdown exposure. Specifically, when firms in a downstream province disproportionately serve foreign markets, a contraction in its foreign demand can reduce production independently of local lockdown policies. At the same time, if governments in downstream provinces tighten containment measures when the opportunity cost of restrictions is lower, weaker foreign demand may be mechanically associated with more stringent downstream lockdowns. In this case, the estimated downstream lockdown coefficient would partly capture foreign demand shocks transmitted through downstream provinces rather than domestic demand disruptions.

16. It is worth noting that estimating the model with separate shares of inputs sourced from and outputs destined for the same province produces comparable results.

To address this concern, we explicitly control for foreign demand shocks transmitted through domestic production linkages. We first measure the foreign demand shock faced by each downstream province as an export-share-weighted sum of lockdown stringency in its destination countries, using pre-pandemic (2019) export shares as weights, akin to Bricongne et al. (2025). We then aggregate these shocks to the province-sector level using the shares of outputs sold to downstream provinces, d_{psr}. The resulting measure captures foreign demand contractions faced by downstream provinces that may reduce their production and, in turn, their demand for intermediate inputs from upstream regions. Reassuringly, Column (5) shows that including this control leaves the estimated downstream lockdown coefficient essentially unchanged.

4.3.2 Alternative measures

We recompute upstream and downstream lockdown exposure using alternative measures of lockdown stringency while keeping the input–output weights unchanged. The results are reported in Supplementary Table A3. In Column (1), we employ the composite SI directly provided by OxCGRT, which differs from our baseline measure by additionally incorporating the public information campaign indicator (H1). Column (2) uses the legacy version of the composite stringency index (LSI), which is based on a subset of the original indicators with alternative definitions. Column (3) replaces the monthly average of daily stringency with the monthly median. Finally, in Column (4), we redefine input–output shares using conventional denominators: total input net of imports for intermediate inputs sourced from other provinces, and total output net of exports for intermediate outputs sold to other provinces. Across all four specifications, the estimated coefficient on *Downstream Lockdown* remains negative and statistically significant at the 5% level.

4.3.3 Other robustness checks

We assess robustness by excluding potentially influential observations, with the results reported in Supplementary Table A4. First, the surge in demand for masks and medical equipment during the pandemic may have induced local governments to adopt differentiated export policies for sectors producing these goods. Accordingly, Column (1) excludes 53 COVID-19-related medical products at the HS 6-digit codes, jointly defined by the World Customs Organization (WCO) and the World Health Organization (WHO).[17] Using an alternative classification of COVID-19-related goods provided by China's Customs also yields similar results.[18] Second, local governments may have implemented differentiated containment measures for food and beverage products, which are essential daily necessities. Column (2) therefore excludes all agricultural products classified under HS chapters 01–24. Third, to alleviate concerns that our findings are driven by large export declines in Hubei province, Column (3) excludes all observations associated with Hubei. Overall, our main results remain qualitatively unchanged, indicating that our findings are not driven by these potentially influential sectors or provinces.

We address concerns about pre-existing trends by including province-partner-HS6 fixed effects, which absorb time-invariant export patterns specific to each province-partner-product combination. Column (1) of Supplementary Table A5 presents the results. We also extend the sample to include 2017 to examine the sensitivity of our estimates to longer-run pre-trends. Columns (2) and (3) report the results without and with panel fixed effects, respectively. The estimates remain essentially unchanged, suggesting that pre-existing trends are unlikely to drive our findings.

17. HS Classification reference for COVID-19 medical supplies, 2.1 Edition. Available at: https://www.wcoomd.org/-/media/wco/public/global/pdf/topics/nomenclature/covid_19/hs-classification-reference_2_1-24_4_20_en.pdf?la=en (accessed April 30, 2020).
18. Guidelines for the customs clearance of export epidemic prevention materials (in Chinese). Available at: http://www.customs.gov.cn/customs/302249/302270/302272/3044873/index.html (accessed May 10, 2020).

Finally, our results are robust to alternative clustering of standard errors at the province, province-HS 2-digit product, and province-partner levels (Supplementary Table A6). Two-way clustering by province-sector and province-partner yields similar conclusions.

4.4. Heterogeneous treatment effects

4.4.1 Processing trade versus ordinary trade

Processing trade in China is characterized by its reliance on both intermediate inputs and final demand from abroad. By contrast, exporters involved in ordinary trade sell a substantial share of their products domestically. As a result, exports under processing trade are less likely to be affected by disruptions in domestic production networks. Following the literature, we define processing trade as including both processing with imported materials and processing with supplied materials. We then divide the sample into two groups: ordinary trade and processing trade. Table 4 presents the results. As expected, the estimated coefficient on downstream lockdown exposure is statistically significant only for ordinary trade. This difference, however, should be interpreted with caution. Our analysis relies on aggregate export data at the product level rather than at the firm level, which precludes us from distinguishing firms that are simultaneously engaged in both ordinary and processing trade.

4.4.2 Differentiated versus homogeneous products

Differentiated products rely on relationship-specific investments, making it difficult for firms to find alternative suppliers and customers. Barrot and Sauvagnat (2016) show that input specificity plays a key role in propagating supply shocks to downstream customers. It is therefore plausible that exports of differentiated products experience larger declines when facing downstream demand shocks. We classify products as differentiated or homogeneous following Rauch (1999), who distinguishes products based on whether they are traded on an organized exchange. The results, shown in Columns (3) and (4), align with this intuition: the coefficient on downstream lockdown exposure is large and statistically significant for differentiated products, but statistically insignificant for homogeneous products.

Table 4. Heterogeneous effects by trade regime and product characteristics.

	(1) Ordinary trade	(2) Processing trade	(3) Differentiated goods	(4) Homogeneous goods	(5) Durables	(6) Non-durables
Upstream lockdown	0.0015	0.0479	0.0113	0.0260	0.0375	0.0176
	(0.0345)	(0.1280)	(0.0414)	(0.0555)	(0.0630)	(0.0335)
Downstream lockdown	−0.1233**	−0.0834	−0.1488***	−0.0442	−0.2528**	−0.0898*
	(0.0520)	(0.1302)	(0.0569)	(0.0937)	(0.1082)	(0.0521)
Controls × Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Province-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Partner-HS6-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,060,898	806,950	8,473,307	1,562,656	2,048,451	7,971,907
R^2	0.2319	0.3476	0.2616	0.2768	0.2846	0.2589

Notes: The dependent variable is Δlog*Export*, defined as the 12-month log difference in export values between month m and month m – 12. *Upstream Lockdown* is the input-share-weighted exposure to lockdown stringency in upstream provinces other than the focal province; *Downstream Lockdown* is defined analogously using output shares. Columns (1) and (2) split exports into ordinary trade and processing trade. Columns (3) and (4) distinguish between differentiated and homogeneous products based on the Rauch (1999) classification. Columns (5) and (6) split products into durable and nondurable goods, where durable goods are defined following Espitia et al. (2022). The control variables include log*Output*, *UpShare*, and *DownShare*. See Table 1 for descriptions of the control variables. Robust standard errors in parentheses are clustered at the province-sector level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.4.3 Durable versus nondurable goods

The third dimension we consider is the differential impact of downstream lockdowns on durable and nondurable goods. Lockdown measures restrict households primarily to purchasing daily necessities, while income losses due to business shutdowns further depress consumption of durable goods. As a result, demand contractions are more pronounced for durable goods, which in turn lead to larger declines in their exports. We classify durable goods following Espitia et al. (2022), based on the Broad Economic Category (BEC) classification, which includes durable goods (61), semi-durable goods (62), passenger cars (51), and non-industrial vehicles (522). Columns (5) and (6) show that the estimated coefficient on downstream lockdown exposure is significantly larger for durable goods than for nondurable goods. This pattern reveals that demand contractions in domestic markets induced by downstream lockdowns translate into disproportionately larger export declines for durable goods.

4.5 Endogeneity concerns

In this section, we discuss potential endogeneity concerns and our approach to addressing them.

4.5.1 Anticipation and reverse-causality concerns

One potential concern is that our exposure measures may partly capture policy responses to trade-related activity rather than exogenous lockdown shocks. During the pandemic, local customs authorities implemented quarantine and inspection measures for international travelers and imported goods, and containment efforts gradually shifted toward imported infections once domestic transmission was largely under control. This concern is particularly relevant for provinces with major seaports, airports, or other international transportation hubs, which faced both more intensive cross-border flows of goods and people and a higher risk of imported infections. If trade activity in a focal province contributed to infections or containment responses in upstream or downstream provinces through cross-provincial movements of goods and people, export performance in the focal province could influence subsequent lockdown exposure in connected provinces. This would give rise to a potential reverse-causality concern.

To assess concerns about reverse causality and anticipatory responses, we augment our baseline specification by including both leading and lagged terms of upstream and downstream lockdown exposure, following the logic of strict exogeneity test in Wooldridge (2010). If current export activity affects subsequent lockdown exposure, or if exporters anticipate future lockdowns, the leading terms are expected to differ from zero. We use a 2-month window in the baseline specification because our data are monthly and COVID-19 containment policies evolved rapidly over short horizons. This short window provides a parsimonious diagnostic check of whether future lockdown exposure is systematically correlated with current export growth. The specification is as follows:

$$\begin{aligned}\Delta \log Export_{pckt} = &\sum_{l=-2}^{l=2} \beta_l^U Upstream\ Lockdown_{ps,t-l} \\ &+ \sum_{l=-2}^{l=2} \beta_l^D Downstream\ Lockdown_{ps,t-l} \\ &+ \textstyle\sum_{\tau\in\mathcal{T}} \theta_\tau \mathbf{X}_{ps,t_0} \times \mathbf{1}\{t=\tau\} + \eta_{pt} + \delta_{ps} + \varphi_{ckt} + \varepsilon_{pckt},\end{aligned} \tag{5}$$

where β_l^U and β_l^D represent the coefficients on the l-month leads and lags of upstream and downstream lockdown exposure, respectively. The index l denotes the number of months relative to export growth in month m. When $l<0$, the term refers to future lockdown exposure relative to export growth in month m; when $l>0$, it refers to lagged lockdown exposure; and $l=0$ denotes contemporaneous lockdown exposure. All other terms are defined as in Equation (3).

Figure 3 reports the estimated coefficients from Equation (5). The coefficients on the leading terms of both upstream and downstream lockdown exposure are small in magnitude and statistically

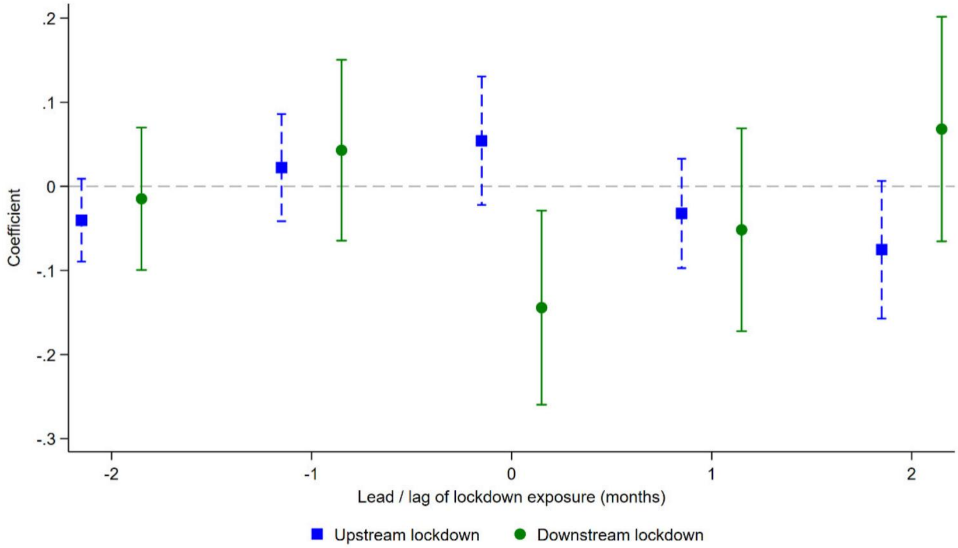

Figure 3. Testing for anticipation effects and reverse causality. This figure plots the coefficients on the lead and lag terms of upstream and downstream lockdown exposure estimated from Equation (5). The horizontal axis reports the lead or lag of lockdown exposure relative to export growth in month *m*. Coefficients for upstream exposure are shown with square markers, while those for downstream exposure are shown with circle markers. Bars represent 95% confidence intervals. The dependent variable is $\Delta \log Export$, defined as the 12-month log difference in export values between month m and month m – 12. *Upstream Lockdown* is the input-share-weighted exposure to lockdown stringency in upstream provinces other than the focal province; *Downstream Lockdown* is defined analogously using output shares. We control for log*Output*, *UpShare* and *DownShare*, interacted with time dummies. We control for province-time, province-sector, and partner-HS6-time fixed effects. See Table 1 for descriptions of the control variables. Standard errors are clustered at the province-sector level.

insignificant, providing no evidence that future lockdown exposure systematically predicts current export growth. This alleviates concerns about anticipation effects or reverse causality. Additionally, the estimated effect of downstream lockdown exposure is concentrated in the contemporaneous term, suggesting that the impact of downstream demand shocks is short-lived. Extending the lead-lag window to ±4 or ±6 months yields similar results.[19]

4.5.2 Omitted variable concerns

The omission of unobserved confounders would threaten our causal inference if such factors are correlated with both upstream and downstream lockdown exposure and export growth. Given that the key explanatory variables are measured at the province-sector-month (year-month) level, it is impractical to directly control for all potential confounders at the same level. Instead, we mitigate concerns about omitted variable bias by incorporating more saturated fixed effects, refining the construction of the explanatory variables, and excluding potential outliers.

19. When extending the window to ±4 and ±6 months, joint tests of the leading terms fail to reject the null that all leads are equal to zero. For the ±4-month window, the *P*-values are 0.3603 for upstream exposure and 0.4423 for downstream exposure; for the ± 6-month window, the corresponding *P*-values are 0.2947 and 0.6649.

4.5.2.1 More stringent fixed effects

We begin by addressing potential concerns about time-varying confounders at the province-sector level. Supplementary Table A7 reports the results. Specifically, we augment Equation (3) by including province-sector-calendar-month fixed effects.[20] This approach restricts the identifying variation to comparisons within the same province-sector and calendar month, exploiting differences in upstream and downstream lockdown exposure across provinces. Given the short period under consideration, these fixed effects absorb a wide range of unobserved sector-specific supply or demand shocks—such as technological changes or demand conditions—that could otherwise confound the estimates. Column (1) shows that the estimated coefficient on downstream lockdown exposure remains robust and is slightly larger in magnitude.

Another possible concern is that export declines may reflect time-varying factors specific to province-partner pairs, such as disruptions to export routes or increases in freight costs. First, given the heterogeneous severity of the pandemic across trading partners, governments imposed differential restrictions on travelers and shipments based on country of origin. Second, exporters—particularly those located in inland provinces—must ship goods to coastal seaports for international trade and typically follow the "shortest path" (Fan et al., 2023). If the provinces along these routes also maintain close trade or IO linkages with the focal province, unobserved shocks may simultaneously affect trade flows and lockdown stringency in those provinces, raising additional endogeneity concerns. While province-by-time fixed effects can account for common shocks across destinations, they may not fully capture such route-specific disruptions. We therefore estimate a variant of Equation (3) that includes province-partner-time fixed effects. Column (2) shows that the estimated coefficient on downstream lockdown exposure is −0.1123, slightly smaller than the baseline estimate but still statistically significant at the 5% level. This suggests that province-partner-specific confounders are unlikely to be the primary driver of our main findings. In Column (3), we further re-estimate Equation (3) with both sets of additional fixed effects and obtain similar results.

4.5.2.2 Refining the construction of the explanatory variables

We refine the construction of the exposure measures by excluding trade flows between the focal province and potentially influential provinces, thereby assessing whether our baseline results are driven by omitted variable bias. Table 5 reports the results. First, neighboring provinces are typically exposed to similar supply and demand shocks (Barrot and Sauvagnat 2016; Carvalho et al., 2021), and tend to exhibit stronger inter-regional IO linkages. As a result, unobserved time-varying shocks at the province-sector level may simultaneously affect lockdown policies in both the focal province and its neighbors. To address this concern, we exclude trade flows involving directly adjacent provinces from the IPIO table and reconstruct our key explanatory variables accordingly. Column (1) shows that the estimated coefficient on downstream lockdown exposure remains statistically significant at the 5% level, albeit slightly smaller in magnitude.

Second, lockdown measures in major international port cities like Shanghai may affect export growth not only through interprovincial production networks but also by disrupting maritime shipping. These disruptions, including port congestion and delays in cargo handling, can impede the timely delivery of exports. To isolate this channel, we exclude trade flows between the focal province and the four provinces hosting China's five largest international trading ports and reconstruct the lockdown exposure measures.[21] Column (2) shows that our baseline results remain robust, suggesting that downstream demand shocks are the primary driver.

20. Here, month refers to the calendar month (January–December), rather than a specific year–month combination (e.g. January 2019)
21. The five largest international trading ports, defined by cargo-handling capacity, are Shanghai Port (Shanghai), Tianjin Port (Tianjin), Qingdao Port (Shandong), and the ports of Shenzhen and Guangzhou (Guangdong).

Table 5. Address concerns of omitted variable bias: Exclusion of outliers.

	(1) Exclude neighboring provinces	(2) Exclude international ports	(3) Exclude sectors ≥30% of national output	(4) Exclude sectors ≥30% of national export
Upstream lockdown	0.0093	0.0329	0.0153	0.0097
	(0.0278)	(0.0323)	(0.0358)	(0.0362)
Downstream lockdown	−0.0907**	−0.1424***	−0.1311**	−0.1433***
	(0.0438)	(0.0432)	(0.0525)	(0.0527)
Controls × time dummies	Yes	Yes	Yes	Yes
Province-time FE	Yes	Yes	Yes	Yes
Province-sector FE	Yes	Yes	Yes	Yes
Partner-HS6-time FE	Yes	Yes	Yes	Yes
Observations	10,036,075	10,036,075	9,866,403	8,111,543
R^2	0.2635	0.2635	0.2639	0.2618

Notes: The dependent variable is Δlog*Export*, defined as the 12-month log difference in export values between month m and month m − 12. *Upstream Lockdown* is the input-share-weighted exposure to lockdown stringency in upstream provinces other than the focal province; *Downstream Lockdown* is defined analogously using output shares. Column (1) excludes trade flows involving neighboring provinces from the IPIO table and reconstructs the key explanatory variables. Column (2) excludes trade flows between focal provinces and the four provinces hosting the largest international trading ports (Fang et al., 2020), and reconstructs the key explanatory variables. Columns (3) and (4) exclude sectors accounting for more than 30% of national output and HS6 products accounting for more than 30% of national exports, respectively. The control variables include log*Output*, *UpShare*, and *DownShare*. See Table 1 for descriptions of the control variables. Robust standard errors in parentheses are clustered at the province-sector level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.5.2.3 Excluding potential outliers

In addition to daily necessities and medical products, the State Council encouraged local governments to prioritize the reopening of industries deemed critical to national or global supply chains. Given their central position in domestic production networks, the resumption of these sectors may involve differentiated containment and reopening policies across provinces. Importantly, sector-specific policy adjustments in the focal province may induce coordinated responses in upstream and downstream regions, thereby affecting our lockdown exposure measures. If such targeted policies also directly influence export performance, failing to account for them would raise an omitted-variable concern. One might also be concerned that, because our exposure measures are constructed using the 2012 IPIO table, structural reallocation and agglomeration driven by comparative advantage between 2012 and 2020 may introduce measurement error. Such structural change is most likely to occur in nationally dominant sectors and products.[22]

To address these concerns, we exclude province-sector pairs whose sectoral output exceeds 30% of national output and province-product pairs whose HS 6-digit exports account for more than 30% of national exports. Sectoral output shares are computed using the 2017 provincial input–output tables, and export shares are calculated as the average HS 6-digit export shares over 2017–2019. As shown in Columns (3) and (4), this exclusion has a minimal effect on the estimated coefficients of interest.

5. Mechanisms

Thus far, our results indicate that negative domestic demand shocks lead to declines in export growth, suggesting that domestic sales and exports are complementary. This finding stands in contrast to the

22. To the extent that changes in interprovincial input–output linkages between 2012 and 2020 are not systematically correlated with the true lockdown exposure, the resulting measurement error in the constructed exposure variable would attenuate the estimated coefficients toward zero, thereby rendering our estimates conservative.

prediction of the capacity constraints channel, which predicts a reallocation of sales across domestic and foreign markets when firms face binding short-run capacity constraints (e.g. Vannoorenberghe 2012). Although we cannot entirely rule out the relevance of capacity constraints, our estimates suggest that this mechanism is unlikely to be the primary driver of the observed export responses. We therefore, in this section, focus on two alternative and theoretically plausible channels: economies of scale and liquidity constraints.

In the short run, under economies of scale characterized by a downward-sloping marginal cost curve, a negative domestic demand shock, such as that induced by downstream lockdowns, can force firms to reduce their production scale, thereby raising marginal costs. As a result, profit margins in export markets shrink, which in turn lead firms to cut back on exports (Kim 2021). Moreover, in the presence of financial frictions, declines in domestic sales may reduce cash flows and collateral values, making it more difficult for firms to obtain external financing for export activities and further depressing exports (Berman et al., 2015). Table 6 reports the results. Panel A presents the economies-of-scale channel, while Panel B examines the liquidity-constraint channel. Overall, our suggestive evidence is consistent with the economies-of-scale channel.

5.1 Economies of scale

To examine this channel, we use industry-level estimates of returns to scale at the two-digit standard industrial classification (SIC) level from Diewert and Fox (2008) to construct a dummy equal to one for sectors exhibiting IRS. Using US manufacturing data, they document that 9 out of 18 sectors satisfy this criterion. We map HS 6-digit products to SIC industries using the concordance provided by the World Integrated Trade Solution (WITS). Since industries characterized by IRS are more sensitive to contractions in production, we expect the negative impact of downstream lockdowns to be more pronounced in these scale-intensive sectors. This prediction is borne out in Column (1), where the coefficient on the interaction between downstream lockdown exposure and the indicator for IRS is negative and statistically significant.

We further employ the HHI and CR4 as alternative measures of industry-level economies of scale (Harrigan 1994; Ding and Niu 2019). In doing so, we note that HHI and CR4 measure market concentration rather than economies of scale directly. Their interpretation as proxies for economies of scale relies on the assumption that scale economies foster industry consolidation, resulting in fewer and larger firms within an industry. The HHI is defined as the sum of the squared employment shares across firms within an industry, while CR4 captures the combined employment share of the four largest firms in that industry. We construct the two measures using firm-level employment data from administrative enterprise income tax records provided by the SAT for the years 2016–2019. Firms are first classified into four-digit Chinese Industrial Classification (CIC) industries, which we manually concord to IPIO sectors. For each province and year, we compute the HHI and CR4 at the province-sector level and then take 4-year averages. Notably, we construct these measures at the provincial level, reflecting the fragmented nature of China's interprovincial markets (Poncet 2005; Fan 2019; Tombe and Zhu 2019). Columns (2)–(3) yield results that are consistent with Column (1), providing further support for the economies-of-scale channel.[23]

23. An implication of the economies-of-scale channel is that a negative downstream demand shock may raise marginal costs and thereby increase export unit values. To assess this implication, we decompose export values into quantities and unit values and re-estimate our benchmark specification (Supplementary Table S8). The estimated effect on unit values is positive but statistically insignificant (0.0346, SE = 0.0331), while the effect on export quantities is −0.1708 (SE = 0.0521) and statistically significant at the 1% level. This pattern is consistent with evidence that cost pass-through is often incomplete (see Amiti et al., 2019).

Table 6. Economies of scale versus liquidity constraints.

Panel A: The economies of scale channel

	IRS	HHI	CR4
Upstream lockdown	0.0176	0.0160	0.0189
	(0.0377)	(0.0358)	(0.0369)
Downstream lockdown	−0.0951*	−0.1250**	−0.1226**
	(0.0533)	(0.0518)	(0.0514)
Upstream lockdown × Industry measure	0.0110	−0.0143	0.0010
	(0.0123)	(0.0273)	(0.0216)
Downstream lockdown × Industry measure	−0.0235**	−0.0597*	−0.0427**
	(0.0098)	(0.0323)	(0.0214)
Observations	9,803,172	10,032,525	10,032,525
R^2	0.2633	0.2635	0.2635

Panel B: The liquidity constraints channel

	WCR	SFR	SDR	Leverage
Upstream lockdown	0.0252	0.0278	0.0328	0.0140
	(0.0400)	(0.0377)	(0.0372)	(0.0387)
Downstream lockdown	−0.1669***	−0.1346**	−0.1621***	−0.1263**
	(0.0564)	(0.0524)	(0.0571)	(0.0520)
Upstream lockdown × Industry measure	−0.0174	−0.0179	−0.1199	0.0118
	(0.0501)	(0.0251)	(0.0795)	(0.0749)
Downstream lockdown × Industry measure	0.0716	−0.0067	0.1533*	−0.0660
	(0.0458)	(0.0208)	(0.0861)	(0.0670)
Observations	9,988,645	9,988,645	9,988,645	9,988,645
R^2	0.2634	0.2634	0.2634	0.2634

Notes: The dependent variable is Δlog*Export*, defined as the 12-month log difference in export values between month m and month m – 12. *Upstream Lockdown* is the input-share-weighted exposure to lockdown stringency in upstream provinces other than the focal province; *Downstream Lockdown* is defined analogously using output shares. Panel A examines the economies-of-scale channel: Column (1) interacts upstream and downstream lockdown exposure with an indicator for industries exhibiting increasing returns to scale (IRS) at the two-digit SIC level (Diewert and Fox 2008). Columns (2) and (3) alternatively use 4-year average HHI and CR4 constructed at the province-sector level. Panel B examines the liquidity-dependence channel. Following Berman et al. (2015), Columns (1)–(4) interact upstream and downstream lockdown exposure with four industry-level (two-digit SIC) measures of short-term liquidity dependence: working capital requirement ratio (WCR), self-financing ratio (SFR), short-term debt ratio (SDR), and leverage, respectively. All specifications control for log*Output*, *UpShare*, and *DownShare*, interacted with time dummies, and include province-time, province-sector, and partner-HS6-time fixed effects. See Table 1 for descriptions of the control variables. Robust standard errors in parentheses are clustered at the province-sector level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

5.2 Liquidity constraints

To explore the potential role of liquidity constraints in explaining our findings, we closely follow Berman et al. (2015) in constructing industry-level measures of short-term liquidity dependence and assess whether the negative effects of domestic demand shocks are more pronounced in liquidity-dependent sectors. Specifically, we consider four measures: the working capital requirement ratio (WCR), the self-financing ratio (SFR), the short-term debt ratio (SDR), and leverage. The WCR is defined as the ratio of working capital (*wcap*) to the sum of common equity (*ceq*) and long-term debt (*dltt*). The SFR is defined as the ratio of retained earnings (*re*) to the sum of common equity (*ceq*) and long-term debt (*dltt*). The SDR is measured as short-term debt (*dlc*) divided by total debt (*dlc* + *dltt*), while financial leverage is defined as total debt divided by the book value of assets (*at*). We follow Rajan and Zingales (1998) and compute these measures using data on US public firms from Compustat over the period 2010–2019, and then calculate industry medians at the two-digit SIC level. We subsequently re-estimate our baseline specification, adding interactions of upstream and downstream lockdown exposure with these sectoral liquidity measures.

Panel B of Table 6 displays the results. Across Columns (1)–(4), the estimated coefficients on the interaction terms are largely statistically insignificant, suggesting that liquidity constraints are unlikely to be a primary channel driving our results.

Overall, we find no evidence that liquidity constraints play a meaningful role in shaping the effect of downstream demand shocks on export growth. This suggests that, in our setting, the economies-of-scale channel is more consistent with the data.

6. Concluding remarks

This study shows that domestic production networks can amplify the effects of downstream demand shocks on export performance. A one-standard-deviation increase in downstream lockdown exposure reduces 12-month product-level export growth by 13.6 log points, while upstream exposure has no statistically or economically meaningful effect. These findings suggest that the impact of geographically uneven lockdowns operates primarily through downstream demand channels that are transmitted and magnified through domestic production linkages.

Interestingly, the negative impact of downstream domestic shocks on export growth suggests that domestic and foreign sales are complementary rather than substitutes. Sectors characterized by stronger economies of scale exhibit greater sensitivity to downstream exposure, whereas liquidity constraints appear to play a more limited role. Taken together, this evidence points to scale economies as the primary mechanism through which demand shocks transmit to export performance.

Our findings have implications for trade policy during geographically uneven disruptions. Export losses may arise not only from constraints on exporters' own production or upstream supply, but also from downstream demand shocks transmitted through domestic production networks. This suggests that policymakers should adopt a production-network perspective when designing policies to stabilize trade, paying attention not only to upstream supply shortages and downstream demand conditions, but also to the linkages through which local shocks propagate. In particular, consistent with recent evidence that digital technologies enhanced firm resilience during the COVID-19 pandemic (Bai et al., 2021; Cong et al., 2024), a practical implication is to promote the digital transformation of supply chains, thereby improving information sharing and joint decision-making across regions, sectors, and firms.

A limitation of our analysis is that it relies on province-level product export data. More granular firm-level information would allow for a sharper assessment of heterogeneity and potential aggregation bias. Future work incorporating such data could further refine our understanding of how supply- and demand-side shocks propagate through production networks. Nevertheless, our results reveal that spatially uneven containment policies can generate substantial spillovers through domestic production linkages. Accounting for such network-based spillovers is therefore crucial for a comprehensive evaluation of the economic consequences of geographically targeted policy interventions.

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Supplementary material

Supplementary material is available at *Journal of Economic Geography* online.

Conflicts of interest

None declared.

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Ethics statement

This article does not include any studies involving human participants or animals conducted by the authors. This manuscript has not been published or submitted for publication elsewhere.

Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

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