Supply spillovers during the pandemic: Evidence from high-frequency shipping data

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Abstract
World trade contracted dramatically during the global economic crisis induced by the COVID-19 pandemic. Disruptions in international supply chains were widely reported as governments imposed containment measures (lockdowns) to halt the spread of the disease. At the same time, demand declined as households and firms scaled back spending. This paper attempts to disentangle the supply and demand channels in trade by quantifying the causal effect of supply spillovers from lockdowns. We utilise a novel dataset of daily bilateral seaborne trade and design a shift-share identification strategy that leverages geography-induced cargo delivery lags to track the transmission of supply disruptions across space. We find strong but short-lived supply spillovers of lockdowns through international trade. Moreover, the evidence is suggestive of the downstream propagation of countries’ lockdowns through global supply chains. The short-lived nature of the disruptions despite the unprecedented scale of the shock caution against any blunt use of trade and tax policies to create costly redundancies in global supply chains.

Keywords
lockdowns, spillovers, supply chains, trade
1 | INTRODUCTION

One of the distinctive features of the COVID-19 crisis is the confluence of sharp turns in supply and demand conditions as governments imposed strict lockdowns in tandem with households and firms scaling back spending. Quantifying the actual bearing of government containment measures on the evolution of global trade during the pandemic is crucial for debates about the role of supply disruptions during the global crisis, and questions about whether trade and tax policies should be used to try to reshape global production as insurance against shocks are bound to linger long after the pandemic ends. Leveraging a unique dataset of high-frequency estimates of seaborne trade, we propose a shift-share research design to quantify the supply spillovers of government measures aimed at containing the spread of the virus.

A rapidly growing literature has sought to quantify the effect of containment measures on domestic economic activity (see e.g. Chen et al., 2020; Deb et al., 2020; IMF, 2020; Maloney & Taskin, 2020).1 In contrast, and to the best of our knowledge, no paper has tried to gauge the international spillover effects of these measures. Although the effects of the crisis on cross-border transactions were widely reported in the press,2 data availability has constrained most empirical research to understanding domestic effects. We aim to fill this gap by using daily bilateral trade volume information and exploiting geography-induced lags in how disruptions transmit across borders.

A country’s imports during the pandemic are affected by the lockdown measures imposed by the country’s partners that supply these goods. We thus propose and construct a measure of lockdown exposure to trace the effects of these supply-side disruptions. To estimate the effect of these disruptions on import growth, we rely on a unique dataset of daily estimates of bilateral trade volumes based on the radio signals that the world fleet of cargo ships emits for navigational safety purposes (Cerdeiro et al., 2020). The high-frequency nature yields multiple sources of variation that allows identification of the causal effect. In particular, the variation in our data is not just due to different timing of lockdown measures (shift) and different import weights across countries (shares), but also due to the geography-induced lags in the transmission of lockdowns between countries.

Figure 1 illustrates our identification strategy. Because China was among the first countries to impose lockdown restrictions, a visual analysis of its initial effects is less likely to be affected by confounding factors and, therefore, more amenable to a simple illustration. The top two panels in Figure 1 show the distribution of travel times in our bilateral seaborne trade dataset from China to Korea (left panel) and from China to the U.S. West Coast (right panel). With most trips taking between 1 and 3 days, the lockdowns imposed by China on January 23rd (red vertical line in bottom two charts of Figure 1) very soon raised our measure of lockdown exposure for Korea. Korean import growth fell significantly in the wake of this sudden increase in the country’s lockdown exposure. A similar pattern is observed for the U.S. West Coast, where the modal travel time from China is of around 2 weeks. Overall import growth also fell significantly in the United States as the strict containment measures imposed by China on January 23rd kicked in the region’s lockdown exposure. Of course, these are only two countries in our sample, and even

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1For a review of this literature, see Chapter 2 of the 2020 October World Economic Outlook (IMF, 2020) or Brodeur et al. (2020).

2See, for example “World Economy Shudders as Coronavirus Threatens Global Supply Chains’, Wall Street Journal, February 23, 2020; “US supply chains and ports under strain from coronavirus’, Financial Times, March 2, 2020.
in these simple examples there are various possible confounding factors. To claim identification, we develop a rigorous shift-share regression design with appropriate control variables.

Our empirical analysis finds very strong but short-lived trade spillovers from supply disruptions due to lockdowns. Our preferred estimate over the entire sample covering the first half of 2020 implies that in a hypothetical case where all of a country's suppliers went from no lockdown to a full lockdown would lead to more than 20 percentage points drop in the country's seaborne import growth. This estimated spillover effect, however, is especially large and statistically significant in the early stages of the crisis—explaining about 10% contraction of world trade in February–March—and it becomes statistically insignificant later in the sample.

We also explore the possibility that the effects of lockdowns reverberate indirectly through supply chains guided by earlier results from the literature on the transmission of shocks through production networks (Acemoglu et al., 2016). Specifically, a lockdown in country $A$ may indirectly affect a country $C$ if, for example, $A$ supplies inputs that are necessary for a country $B$ to export to $C$. We propose an extension of our specification to evaluate this possibility. Various factors make identification in this case more challenging, and strong assumptions are needed to take the model to the data, including due to possibly heterogeneous processing lags across ports and an intrinsic difficulty in identifying the right weights to construct indirect lockdown exposures. We argue that these assumptions

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**FIGURE 1** Lockdown exposure and import growth: The cases of Korea and the United States. The top-row panels show the distribution of travel times from China to Korea and the U.S. West Coast, respectively. Our lockdown exposure variable captures these geography-induced lags, which affect the timing of import disruptions—as shown in the bottom-row panels.
are likely to bias our estimates towards not finding indirect supply-chain effects from lockdowns. Despite this, we find that during the early stages of the crisis both direct and indirect supply-chain effects are marginally significant and economically sizeable, and we strongly reject the hypothesis of joint non-significance of direct and indirect supply-chain effects. The results are suggestive of the downstream propagation of countries’ lockdowns through global supply chains.

In all, our main finding—that the international transmission of supply disruptions during the crisis had significant but very short-lived effects—should contribute to the debate on whether the use of trade and tax policies is warranted to deliberately reshape global supply chains in response to the COVID-19 crisis. While the COVID-19 shock per se is not expected to lead firms to actively reconfigure their international ties (Antràs, 2020), it would be natural for policymakers to consider the question of whether enhancing the resilience of global supply chains is a pressing macro-critical need (see e.g. Goldberg, 2020, for an early discussion on the topic). Any such decision should carefully weigh any potential benefits from enhanced resilience with its costs—for example the costs that would be involved in ensuring redundancy of suppliers across value chains. Based on our findings, we would caution that the benefits may be small, at least as measured by the short-lived nature of disruptions in the face of an unprecedented, once-in-a-century shock. In that sense, our results add to existing arguments in support of globalised production on the grounds of the benefits from diversification in the face of localised lockdowns (Bonadio et al., 2020).

The rest of the paper is organised as follows. Section 2 lays out the shift-share design underlying our empirical estimates. Section 3 summarises how the high-frequency dataset was constructed, presents other data sources, and discusses the construction of key regressors. Section 4 presents the results from our baseline specification. Section 5 shows the results of an extension of the model that accounts for indirect supply-chain effects. Section 6 concludes.

2 | A SHIFT-SHARE DESIGN ON HIGH-FREQUENCY TRADE DATA

Our empirical specification has an interpretation as a shift-share research design following Bartik (1991). We study the impact of a set of aggregate shocks or ‘shifters’ on units differentially exposed to them, where the exposure is measured by a set of weights or ‘shares’. Our units are countries that are differentially exposed to lockdown measures in other countries due to the heterogeneity in pre-existing trade connections.

2.1 | Specification

Let \(\hat{M}_{it}\) denote year-on-year import growth in country \(i\) on day \(t\). We want to identify the supply spillover effect that foreign governments’ lockdowns may have had on this import growth. Let \(l_{jt}\) be the stringency of lockdown measures in country \(j\) and on day \(t\). Further let \(w_{ij}\) denote the pre-COVID fraction of imports into country \(i\) that come from country \(j\), and define \(d(i,j)\) as the travel time in days from country \(J\) to country \(i\). Then, our empirical model can be written as:

\[
\hat{M}_{it} = \gamma_{t} + \alpha_{i} + \beta LE_{it} + X'_{it} \delta + \varepsilon_{it},
\]

\[
LE_{it} = \sum_{j} w_{ij} l_{jt} - d(i,j),
\]
where $\gamma_{t}$ and $\alpha_{t}$ are time (i.e. days) and country fixed effects, and $X_{it}$ includes control variables that may affect import growth and may be correlated with the lockdown exposures ($LE_{it}$).

It is worth noting that, as in any shift-share design, our aim is to capture aggregate, macro-level disruptions from lockdowns. If a lack of supply from one country is easily substituted with supply from another country, then this would not qualify as a (macro-level) disruption and would, therefore, not be picked up by the left-hand side of Equation 1.

2.2 Fixed effects and controls

To identify the effect of spillovers, the choice of control variables should ensure that the lockdown exposures ($LE_{it}$) are orthogonal to omitted factors ($\epsilon_{it}$). Conceptually, the main concern is that the spread of the virus not only triggers lockdown measures in trading partners but can also impact demand for imports through other channels. Note that the daily frequency and fine geographic disaggregation of our dataset facilitate identification, because many of the confounding factors are expected to work at a slower pace. Nevertheless, it is important to discuss and mitigate potential endogeneity problems.

Travel times are partially determined by the geographical distance between ports and virus outbreaks can also be clustered in space. Hence, proximity to other ports in virus hotspots is likely associated with both high lockdown exposure and a high number of current or expected local infections. Worsening local health conditions can reduce imports through channels that are unrelated to the containment measures of trading partners, such as depressed consumer confidence and voluntary isolation that dent import demand, or locally imposed lockdowns that, for example, disrupt the ability of domestic ports of receiving imports. Similar concerns apply to the exogeneity of the pre-COVID trade links insofar as there may be more trade between nearby ports as the gravity model suggests. These arguments highlight the importance of including indicators of domestic COVID intensity and mandated lockdowns as controls. To address these issues, in practice we include the following variables among the controls: domestic COVID cases, domestic deaths (both in ratio to the domestic population) and the stringency of domestic lockdowns.3

Initial conditions in different regions of the world may also affect the propensity of (foreign) authorities to impose lockdown measures. For example, it is possible for governments in regions experiencing lower growth to be more reluctant to impose lockdowns. To control for these idiosyncratic factors that also affect imports and can be correlated with our foreign lockdown-exposure measure, our specification includes country fixed effects.

\[ \sum_{j} w_{ij} = 1, \quad (3) \]

It is worth noting that some potential endogeneity issues are tackled more directly by using import growth (rather than import levels) as dependent variable. In particular, the empirical gravity model of trade tells us that country $i$’s import levels are determined by distance. Since distance also determines how quickly the virus could spread to country $i$, it also affects how consumers may adapt to news of neighbouring outbreaks. The reasoning here in favour of the use of growth rates instead of levels echoes the arguments brought forward in a more general context by Goldsmith-Pinkham et al. (2020) (see specifically the discussion on p. 2588). As importantly, we also note that, by expressing everything in growth rates, vanishing trade would be reflected as $-100$ percent import growth and not as missing values.
The prevalence of containment measures can also be correlated with other relevant factors over the time dimension. For example, as the virus spreads and more countries go under lockdowns, rising health and economic uncertainty may boost households’ precautionary saving, and revised expectations in financial markets may lead to a tightening of financing conditions. Both developments could dampen demand for imports. While these effects will not necessarily play out at the daily frequency, we include time fixed effects to control for common trends associated with these time-varying global factors.

In all, our preferred specification, therefore, includes the following controls and fixed effects: domestic lockdown stringency, (change in) domestic cases in ratio to population, (change in) domestic deaths in ratio to population, and country and time fixed effects.4

### 2.3 Sources of identification

Before moving on to the overview of the data source and variable construction, it can be instructive at this stage to spell out the sources of variation that enable identification. Identification comes from three separate sources, the first two of which are standard in the shift-share literature.

Time-series variation at the daily frequency:

1. evolution of lockdown policies (l_{jt}): the stringency of containment measures evolves over time, so even countries with identical trade shares and identical travel times will see changes in their lockdown exposure.

Cross-sectional variation across countries:

2. heterogeneity in pre-COVID trade shares (w_{ij}): countries that historically imported more from areas with stricter COVID containment measures will have higher effective lockdown exposure.
3. heterogeneity in travel times (d(i,j)): countries that are closer to areas with stricter COVID containment measures will face higher effective lockdown exposure sooner.

While (1) and (2) are standard sources of identification in shift-share regressions, (3) is unique to our problem and dataset. It is unique to our problem because seaborne trade inherently involves meaningful differences in delivery lags from the same origin to different destinations. It is unique to our dataset because standard sources for bilateral trade data are at best at a monthly frequency that is too low to allow for adequate identification.

### 3 HIGH-FREQUENCY DATA AND VARIABLE CONSTRUCTION

This section describes the data sources and explains how the different variables included in the specification were constructed. All data used are at daily frequency.

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4We also further investigate our results through ancillary specifications that add COVID cases and deaths in trading partners as additional controls. While not very likely, the inclusion of foreign disease variables could aid identification in cases where foreign production is affected by voluntary decisions not to report to work despite the absence of government-mandated lockdowns.
3.1 | High-frequency world seaborne trade dataset: Background

More than 80% of merchandise trade by volume and 70% by value is carried by the world vessel fleet (UNCTAD, 2017). Much like airplanes and their transponders, for navigational safety purposes virtually all cargo ships in the world are required to carry a device commonly known as AIS (Automatic Identification System) that periodically emits a signal. The radio messages emitted by these devices—which include information about position, speed, draught, etc.—are visible to nearby ships so as to avoid collisions and are also collected by terrestrial receivers (if the ship is near a shore) and commercial satellites (if the ship is in the deep oceans).

Cerdeiro et al. (2020; CKLS henceforth) show how different machine-learning techniques can be used to construct port-to-port voyages and estimates of trade volumes based on AIS data. We use their estimates that build on over one billion AIS messages collected between January 1st 2015 and June 30th 2020. To make this paper self-contained, we briefly illustrate here the process of going from the raw AIS messages to port-to-port volume estimates. The reader is referred to CKLS for further details.

First, a spatial clustering algorithm is applied to all low-speed messages reporting navigational status anchored or moored to detect areas on the map that are presumed to be ports and using publicly available information these areas are mapped to ports and to countries. Second, a random forest classifier is trained using official U.S. vessel-level entry records to tell us, for any ship stepping on any of these port areas, whether this visit is related to trade or if the ship was simply passing by. Finally, trade volumes are calculated on the basis of draught information contained in the messages, that is how deep the ship is into the water. The mapping of these volumes to imports, exports or intra-country trade is a function of the country where the previous and next ports are located and the full sequence of draught values of the ship. The process is summarised in Figure 2.

Throughout the paper, the bilateral data are aggregated to the country-pair level except for the United States. Given the very different travel times from/to different U.S. coasts, U.S. ports are grouped into two regions (U.S. West and U.S. East). We also focus only on non-commodity trade (general cargo, container ships and vehicle carriers).

Finally, we take two steps to reduce noise in the data. First, small countries tend to receive ships very infrequently, resulting in large and abrupt jumps in daily import growth rates. All our results are, therefore, based on the top 50 importing countries, which in aggregate account for the overwhelming majority of world trade volumes. Second, even for large countries the daily data are noisy, as 1 day can see many more incoming ships than adjacent days. We, therefore, use a 7-day moving average of the daily trade estimates. To further reduce idiosyncratic volatility in our data, we calculate daily growth rates for 2020, covering the time window from January 1st to June 30th, by taking the average of the same dates in the previous 3 years (2017–2019) as the base period. Defining the base period, this way also mitigates

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5While most ships send AIS messages with a frequency of 2–10 s, the data we use are down-sampled to the hourly frequency. The raw AIS data were collected by MarineTraffic.

6The country-level aggregated trade volume estimates can be visualised at https://comtrade.un.org/data/monitor and downloaded at https://comtrade.un.org/data/ais.

7The moving-average transformation mechanically introduces autocorrelation in our error term—for example any ship arriving unexpectedly at time t will reverberate in our transformed data for six additional days. Econometrically, we address the resulting inference problem by clustering standard errors at the country-level which are robust to autocorrelation.
problems with shifting trade patterns in 2019 because of U.S. tariffs and their retaliatory counterparts.\(^8\)

### 3.2 Overview of high-frequency cargo data

The main interest in CKLS is to nowcast trade volumes at the country level. As a result, CKLS include an in-depth analysis of country-level estimates of trade volumes. In contrast, the spillover analysis of the present paper requires the use of bilateral trade estimates. We, therefore, deem necessary to briefly describe here some features of the bilateral data that are relevant for our purposes.\(^9\)

Table 1 shows the estimated metric tons of imports for the top 50 countries considered in the analysis, estimated using AIS data since April 1st 2015.\(^10\) In aggregate, these countries account for 87% of the estimated global non-commodity imports by weight. The top 3 importers are in Asia, the centre of the world’s largest regional supply chain. Major importing hubs in Europe—the United Kingdom and the Netherlands—are also present in the top 10. The ports of the U.S. East coast rank 5th and receive significantly larger volumes than U.S. West ports, which altogether as a region are ranked 12th. Combined, U.S. East and U.S. West would be ranked at number 2. In all, the top 50 regions cover economies across Africa, America, Asia and Europe.

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\(^8\)Focusing on the largest importers and smoothing daily observations also ensures that we do not have any zero trade flows in levels. This implies that daily import growth rates—the dependent variable our regressions—are well-defined and never missing.

\(^9\)The data that support the findings of this study are available from the corresponding author upon reasonable request.

\(^10\)While the raw-AIS data sample starts on January 1, 2015, the classification of a port call as imports requires knowing that the previous port is in fact located in a different country. To avoid start-point estimation problems, we censor our estimates before April 1, 2015.
| Rank | Region                | Millions of metric tons of imports | Cumulative world share | Rank | Region    | Millions of metric tons of imports | Cumulative world share |
|------|-----------------------|-----------------------------------|------------------------|------|-----------|-----------------------------------|------------------------|
| 1    | China                 | 571.0                             | 8.3                    | 26   | Morocco   | 84.9                             | 69.3                   |
| 2    | Singapore             | 320.6                             | 13.0                   | 27   | France    | 84.8                             | 70.5                   |
| 3    | Korea                 | 287.4                             | 17.2                   | 28   | Greece    | 80.9                             | 71.7                   |
| 4    | United Kingdom        | 287.3                             | 21.4                   | 29   | Thailand  | 78.8                             | 72.8                   |
| 5    | US East               | 255.9                             | 25.1                   | 30   | Australia | 66.0                             | 73.8                   |
| 6    | Japan                 | 249.4                             | 28.7                   | 31   | Sweden    | 59.7                             | 74.7                   |
| 7    | Netherlands           | 213.3                             | 31.8                   | 32   | Israel    | 58.4                             | 75.5                   |
| 8    | Malaysia              | 212.7                             | 34.9                   | 33   | Colombia  | 55.6                             | 76.3                   |
| 9    | Hong Kong SAR         | 194.0                             | 37.7                   | 34   | Denmark   | 51.1                             | 77.1                   |
| 10   | United Arab Emirates  | 189.4                             | 40.5                   | 35   | Bangladesh| 48.6                             | 77.8                   |
| 11   | Taiwan Province of China | 166.5                         | 42.9                   | 36   | Portugal  | 48.4                             | 78.5                   |
| 12   | US West               | 165.5                             | 45.3                   | 37   | Algeria   | 46.9                             | 79.2                   |
| 13   | Germany               | 159.2                             | 47.6                   | 38   | Pakistan  | 46.8                             | 79.9                   |
| 14   | Turkey                | 154.7                             | 49.9                   | 39   | Canada    | 45.5                             | 80.5                   |
| 15   | Spain                 | 143.7                             | 52.0                   | 40   | Egypt     | 44.6                             | 81.2                   |
| 16   | Italy                 | 138.6                             | 54.0                   | 41   | South Africa | 44.2                         | 81.8                   |
| 17   | India                 | 138.5                             | 56.0                   | 42   | Nigeria   | 43.9                             | 82.4                   |
| 18   | Saudi Arabia          | 135.2                             | 58.0                   | 43   | Russia    | 43.2                             | 83.1                   |
| 19   | Belgium               | 115.8                             | 59.7                   | 44   | Malta     | 42.5                             | 83.7                   |
| 20   | Indonesia             | 107.5                             | 61.2                   | 45   | Poland    | 39.9                             | 84.3                   |
| 21   | Brazil                | 103.6                             | 62.8                   | 46   | Oman      | 39.4                             | 84.9                   |
| 22   | Vietnam               | 94.3                              | 64.1                   | 47   | Norway    | 39.4                             | 85.4                   |
## Table 1 (Continued)

| Rank | Region     | Millions of metric tons of imports | Cumulative world share | Rank | Region     | Millions of metric tons of imports | Cumulative world share |
|------|------------|------------------------------------|------------------------|------|------------|------------------------------------|------------------------|
| 23   | Sri Lanka  | 92.1                               | 65.5                   | 48   | Finland    | 38.6                               | 86.0                   |
| 24   | Mexico     | 90.7                               | 66.8                   | 49   | Kenya      | 35.1                               | 86.5                   |
| 25   | Philippines| 86.3                               | 68.0                   | 50   | Peru       | 34.1                               | 87.0                   |

*Notes: The Table shows the top 50 countries ranked by the estimated volume of non-commodity imports over 2015–2019 based on AIS data.*
Table 2 shows the top routes in our dataset, ranked by the metric tons of imported cargo estimated through end 2019. While our dataset for non-commodity trade detects a total of 7580 active routes over this period, the top 50 routes alone (i.e. 0.66% of all routes) account for 30% of non-commodity trade. Of the top 10 routes, eight correspond to intra-Asia trade, only one is fully outside Asia (Netherlands to United Kingdom), and the remaining one is the route from China to the U.S. West Coast.

When laying out the research design in Section 2, we emphasised that a key source of variation that enables identification—the heterogeneity in travel times—is unique both to our problem and our high-frequency dataset. We argue that trying to estimate lockdown spillovers using standard sources of monthly bilateral trade data is likely to be elusive. Figure 3 aims to convey this intuition by showing the distribution of country-to-country travel times. The left panel in Figure 3 shows the empirical density of international travel times. Around 93% of all country-to-country voyages take place within a 30-day window. The right panel in Figure 3 shows, in turn, the volume of trade taking place under each different travel time. As can be readily seen, virtually all world seaborne trade is shipped and delivered within the month. As a result, daily trade data are crucial in order to identify the effects of lockdown policies that can be changed at an equally high frequency.

3.3 Lockdown intensity and disease-spread data

Lockdown stringency and disease-spread data are from Hale et al. (2020). Hale et al.’s lockdown stringency index is constructed as a simple average of nine different ordinal indicators designed to quantify the intensity of governments’ responses aimed at containing the spread of the virus by restricting ‘people’s behaviour’. Of the nine ordinal indicators, eight refer to closures and containment (school closures, workplace closing, cancellation of public events, restrictions on gatherings, closures of public transport, stay-at-home requirements, restrictions on internal movement and international travel controls), and one records a health measure (public information campaigns). All nine indicators take integer values, with a maximum possible value of 4. The resulting stringency index is then normalised such that it takes values from 0 (no restrictions) to 100 (the most stringent lockdown possible).\(^{11}\)

We also rely on the daily series of confirmed COVID cases and confirmed deaths from the dataset by Hale et al. These underlying disease-related series are originally compiled by the European Centre for Disease Control.

3.4 Time-to-delivery and variable construction

In the empirical model above, we assumed that the travel time between two countries is a single number given by \(d(i,j)\) (see Equation 2). In reality, even for identical ships the travel time between two ports may vary (e.g. due to weather conditions). That is, \(d(i,j)\) should not be interpreted as a

\(^{11}\)The data are available at https://covidtracker.bsg.ox.ac.uk/. For China, we use an updated version of the lockdown stringency index presented in Zhang (2022). This paper broadly follows the data sources and methodology of Hale et al. (2020) but derives province-level stringency indices, which are then aggregated to the national level. Since Chinese lockdowns varied substantially across provinces, this bottom-up index better captures the evolution of average lockdown intensity in China.
### TABLE 2 Top routes by 2015–2019 import volume

| Rank | Route Description | Millions of metric tons of cargo | Cumulative world share | Rank | Route Description | Millions of metric tons of cargo | Cumulative world share |
|------|-------------------|----------------------------------|------------------------|------|-------------------|----------------------------------|------------------------|
| 1    | From CN to KR     | 153.5                            | 2.0                    | 26   | From GB to NL     | 36.3                            | 20.9                   |
| 2    | From SG to CN     | 146.7                            | 3.8                    | 27   | From ES to IT     | 35.9                            | 21.3                   |
| 3    | From CN to JP     | 89.6                             | 5.0                    | 28   | From CN to VN     | 34.4                            | 21.8                   |
| 4    | From KR to CN     | 87.3                             | 6.1                    | 29   | From KR to USW    | 34.3                            | 22.2                   |
| 5    | From HK to CN     | 81.4                             | 7.1                    | 30   | From SG to AE     | 34.3                            | 22.7                   |
| 6    | From SG to MY     | 74.6                             | 8.1                    | 31   | From TW to HK     | 33.8                            | 23.1                   |
| 7    | From CN to USW    | 66.1                             | 8.9                    | 32   | From NL to DE     | 32.4                            | 23.5                   |
| 8    | From NL to GB     | 66.0                             | 9.8                    | 33   | From SG to BR     | 32.2                            | 23.9                   |
| 9    | From SG to HK     | 61.7                             | 10.6                   | 34   | From KR to MX     | 31.8                            | 24.3                   |
| 10   | From MY to CN     | 60.7                             | 11.4                   | 35   | From OM to AE     | 31.7                            | 24.7                   |
| 11   | From MY to IN     | 57.9                             | 12.1                   | 36   | From CN to AE     | 30.8                            | 25.1                   |
| 12   | From JP to KR     | 57.7                             | 12.8                   | 37   | From AE to SA     | 30.6                            | 25.5                   |
| 13   | From MY to SG     | 57.6                             | 13.6                   | 38   | From KR to USE    | 30.0                            | 25.9                   |
| 14   | From TW to CN     | 54.7                             | 14.3                   | 39   | From MY to AE     | 29.8                            | 26.3                   |
| 15   | From JP to CN     | 52.5                             | 14.9                   | 40   | From USW to KR    | 28.7                            | 26.6                   |
| 16   | From CN to HK     | 50.3                             | 15.6                   | 41   | From CN to TH     | 27.9                            | 27.0                   |
| 17   | From CN to TW     | 47.2                             | 16.2                   | 42   | From CN to ID     | 27.5                            | 27.4                   |
| 18   | From SA to AE     | 47.1                             | 16.8                   | 43   | From USW to JP    | 27.4                            | 27.7                   |
| 19   | From SG to ID     | 46.4                             | 17.4                   | 44   | From TW to JP     | 26.5                            | 28.0                   |
| 20   | From CN to SG     | 40.9                             | 17.9                   | 45   | From USW to TW    | 26.5                            | 28.4                   |
| 21   | From RU to TR     | 40.4                             | 18.4                   | 46   | From GB to BE     | 26.1                            | 28.7                   |
| 22   | From IN to LK     | 40.1                             | 18.9                   | 47   | From CN to MY     | 26.0                            | 29.1                   |
| 23   | From BE to GB     | 40.1                             | 19.5                   | 48   | From MY to BD     | 25.4                            | 29.4                   |
| 24   | From LK to GB     | 37.8                             | 19.9                   | 49   | From TH to SG     | 25.1                            | 29.7                   |
| 25   | From KR to JP     | 36.5                             | 20.4                   | 50   | From SG to GR     | 23.9                            | 30.0                   |

*Notes:* The Table shows the top 50 routes ranked by the estimated volume of non-commodity imports over 2015–2019 based on AIS data. Economies represented by their respective ISO-2 codes, except: USW (U.S. West Coast), USE (U.S. East Coast).
scalar, but rather as a random variable whose distribution we can estimate from the historical data. Let \( f_{ij}(d) \) denote the estimated probability mass function of the travel time from country \( j \) to country \( i \): 

\[
f_{ij}(d) \equiv \text{Prob}[d(i,j) = d].
\]

Then, from the perspective of country \( i \)'s imports from country \( j \) on day \( t \), the average lockdown stringency can be defined as:

\[
\bar{l}_{ijt} = \sum_{d=0}^{\infty} f_{ij}(d)\bar{l}_{j,t-d},
\]

and the formula for the aggregate lockdown exposure of country \( i \) changes to

\[
LE_{it} = \sum_{j} w_{ij} \bar{l}_{ijt}.
\]

In order to drop extreme values, we truncate the empirical distribution of the \( d(i,j) \) travel times by leaving out, for each country pair, values below the 10th and above the 90th percentile.

To adequately aid identification of the effect of lockdown exposure, control variables also need to account for geography-induced delivery lags. Just as the effects of foreign lockdowns take time to materialise due to distance, controls need to account for potential confounding factors at the time when these incoming ships set sail from the ports of origin. \(^{12}\) With the obvious exception of the fixed effects, all our control variables are, therefore, also measured based on the empirical distribution of \( d(i,j) \) and the import weights of partner countries. That is, if

\(^{12}\) A stark illustration of the type of problem that could arise if these lags were not accounted for is ports in the United States and Europe being flooded with goods in April 2020 due to orders placed before demand conditions significantly deteriorated as the virus started spreading in those regions. See example “European ports and warehouses brace for surge in containers’, *Financial Times*, April 12, 2020.
|                  | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              | (7)              |
|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| Domestic lockdown| −0.105*** (0.0228) |                  |                  |                  |                  |                  |                  |
| Foreign lockdowns|                  | −0.158*** (0.0255) | −0.261** (0.0781) | −0.284** (0.105) | −0.246*** (0.0682) | −0.226** (0.0715) | −0.210** (0.0767) |
| D.Domestic cases |                  | −0.122 (0.414) | −0.0226 (0.471) |                  |                  |                  |                  |
| D.Domestic deaths |                  | −6.406 (4.065) | −7.836 (4.090) |                  |                  |                  |                  |
| D.Foreign cases  |                  | −0.702 (0.755) |                  |                  |                  |                  |                  |
| D.Foreign deaths |                  |                  |                  |                  |                  | 6.082 (9.721) |                  |
| Constant         | 3.588 (2.086) | 5.772* (2.522) | 5.935* (2.538) | 8.112* (3.170) | 8.115* (3.326) | 10.94** (3.237) | 10.94** (3.245) |
| Observations     | 8869            | 8869            | 8869            | 8869            | 8869            | 8771            | 8771            |
| Time FE          | No              | No              | No              | Yes             | Yes             | Yes             | Yes             |
| Country FE       | No              | No              | No              | No              | Yes             | Yes             | Yes             |

* 5%, ** 1% and, *** 0.1% significance. Standard errors are clustered by country.
The sample goes from January 1st to June 30th, 2020.
\( x_{it} \) denotes the observed value of a control variable for country \( i \) at time \( t \), then the regressor we include in practice is:

\[
\bar{x}_{it} = \sum_j W_{ij} \left( \sum_{d=0}^{\infty} f_{ij}(d) x_{i,t-d} \right).
\]

4 | RESULTS

4.1 | Main results

Table 3 presents the estimates of the effect of lockdown measures on import growth. The variable *Domestic lockdown* refers to the restrictions imposed by local authorities, while *Foreign lockdowns* captures the exposure to containment measures in the country's trading partners. To interpret the results, recall that both domestic and foreign lockdowns are measured on a scale from 0 (no restrictions) to 100 (strictest possible lockdown).

The first column of Table 3 shows that going from no restrictions to a full lockdown in the local economy is associated with 10.5 percentage point lower import growth. Such a large association between domestic lockdowns and imports is consistent with the findings of Deb et al. (2020). When only including our foreign lockdown-exposure measure (column (2)), we find that all suppliers of a country simultaneously going from no restrictions to a full lockdown is associated with 15.8 percentage point lower import growth.

When controlling for both domestic and partners’ lockdown stringencies (column (3)), the coefficient on foreign lockdown exposure remains large and negative while the one on domestic lockdown becomes insignificant. This suggests that supply spillovers from trading partners may have a more clear-cut impact on imports than local lockdowns. These results remain remarkably stable as we subsequently include time (column (4)) and country (column [5]) fixed effects.

Our preferred specification is shown in column (6), where we further control for the number of confirmed COVID-19 cases and deaths in ratio to countries’ populations. The coefficient on foreign lockdown exposure in this specification suggests that all partners going from no lockdown to a full lockdown leads to a fall of 22.6 percentage points in import growth. While not statistically significant, the negative coefficients on domestic disease variables may speak to the detrimental demand effects of the pandemic, likely working through fear and falling consumer confidence.

In column (7) we check whether the spillover effect of lockdowns is robust to including the disease intensity of the countries supplying the imported goods. Our question is whether supply disruptions are related to (foreign) government-imposed lockdowns or voluntary behavioural changes such as firms and workers choosing to reduce activity beyond the stringency of official containment measures. We assume that these voluntary behaviours are driven by fear of contracting the disease, and we capture them through changes in confirmed cases and deaths.

The results in column (7) confirm that the supply disruptions are indeed captured by the lockdown-exposure variable, while foreign disease variables do not appear to significantly affect import growth. It is worthwhile to put this result in the context of related research that investigated the relationship between domestic lockdowns and economic activity in the United States and Europe (Chen et al., 2020; Goolsbee & Syverson, 2020). These papers attribute a milder impact to actual lockdown measures and highlight the role of disease intensity and observed mobility as the proximate causes of declining activity. In contrast to these papers, our analysis focuses
on the supply and transportation of exported goods as opposed to overall activity in the domestic economy. Taken together, the evidence suggests that government lockdowns were important determinants for the supply of internationally traded goods, even if more of the local economic contraction can be explained by the fear-driven collapse of demand.

In all, the notably consistent results in Table 3 speak to a sizable supply component in the evolution of trade during the first 6 months of the COVID-19 crisis as the lockdown decisions of suppliers seem to have had significant and economically meaningful spillovers on countries’ import growth. The estimates further suggest that the supply disruptions in trading partners might have been a more important driver of imports than domestic lockdown measures.

4.2 Time-varying spillovers and aggregate effects

The estimated coefficient of $-0.226$ in our preferred specification (6) is not constant through the sample. Figure 4 shows the point estimate and confidence bands for the model in column (6) estimated over 60-day rolling windows. The effect of foreign lockdowns is economically very large, and statistically significant during the early stages of the crisis, hovering around $-0.4$ between mid-February and late March. By April; however, the effect dissipates, both in size and in significance.

What could explain the vanishing lockdown spillovers in our empirical estimates? In any shift-share design there is an assumption that general equilibrium effects are not pervasive in the given time frame, or in other words there are frictions preventing reallocation after the shock. Consequently, in practice shift-share regressions test a joint hypothesis: the presence of frictions and the effect of the shock. The finding of an effect in the earlier part of our

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13In the credit-supply shock literature, where, for example firms are exposed to banks, the underlying assumption is that it is hard to switch banks. If firms can easily switch lenders and banks could easily pick up demand for loans, then a shock to a few banks should have no aggregate effect. In the more trade-related work by Autor et al. (2013), the units are commuting zones and industries, and the assumption is that labor cannot easily move across commuting zones and across industries. If workers could easily switch jobs, then the China shock could not possibly have large aggregate employment effects.
sample means that the frictions are large enough to trump any possible reallocation. Conversely, the absence of a statistically significant effect towards the later part of our sample could be either because general equilibrium forces compensated any possible effects (i.e. supply chains reconfigured) or because the lockdowns imposed during that later period did not have an effect to begin with.

Empirically distinguishing these two explanations is challenging. Anecdotal evidence suggests that the early Asian lockdowns were qualitatively different from subsequent lockdowns in other parts of the world, which is hard to capture quantitatively in a stringency index. There may also be non-linearity at play where supply disruptions only kick in after a tipping point in lockdown stringency is achieved. The initial shock of Chinese lockdowns also triggered many discussions on how to make supply chains more flexible by building in redundancy and buffers. It is conceivable that 2–3 months was sufficient time for many firms to start re-configuring and adapting their supply chains to a more volatile environment. We leave it for future research to disentangle these possible channels.

Given strong evidence for trade spillovers of lockdowns in early 2020, it is natural to ask what these estimates imply for the evolution of world trade in the first stages of the pandemic. Our estimates can be readily used to compare observed import volumes with counterfactual volumes in the absence of foreign government lockdowns. The estimated effect of foreign lockdowns on import growth rates, \( \beta LE_{it} \), readily translates into an estimated effect in differences as \( M_{it-365} - \beta LE_{it} \), where \( M_{it-365} \) is the base-period import volume. Counterfactual import volumes in country \( i \), \( M_{it}^c \) can, therefore, be obtained as:

\[
M_{it}^c = M_{it} - M_{it-365} \beta LE_{it}.
\]

Equipped with a value for \( \beta \) and the country-level, time-varying lockdown-exposure measures, it is then straightforward to obtain a counterfactual series for world import volumes. The same procedure can be used to isolate the effect of one specific country’s lockdowns. Recall from (4) that \( LE_{it} = \sum_j w_{ij} \hat{I}_{jt} \). The counterfactual effect on country \( i \)’s imports due to one specific foreign country \( j \)’s lockdown is obtained by using, in Equation (5), \( w_{ij} \hat{I}_{jt} \) instead of \( LE_{it} \).

Figure 5 shows the resulting ratio of actual to counterfactual world trade through mid-March using a value of \( \beta = -0.4 \). The Figure shows the effect of lockdowns around the world as well as the standalone effect of China’s lockdown. The results imply that supply disruptions due to lockdowns, on average, reduced global seaborne imports in February–March 2020 by 10%, with China’s lockdowns contributing about 4 percentage points.

### 4.3 Robustness check: changes in trade policy and the impact of lockdowns\(^{16}\)

Changes in domestic policies that affect aggregate import growth could bias our estimates of the effects of lockdowns if these changes significantly impacted aggregate imports and

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\(^{14}\)See example “China’s coronavirus lockdown strategy: brutal but effective’, *The Guardian*, March 19, 2020

\(^{15}\)See example “Coronavirus Is a Wake-Up Call for Supply Chain Management’, *Harvard Business Review*, March 27, 2020

\(^{16}\)We are very grateful to an anonymous referee for suggesting this robustness check to our baseline results.
were at the same time correlated with countries’ exposure to foreign lockdowns. Existing evidence points to increased trade policy activism in the early stages of the pandemic (Evenett et al., 2022). Even though trade policy changes appear to have been narrowly targeted to certain products (such as medical goods), as a robustness check this section proposes an alternative specification that is fully robust to any changes in domestic policies—trade-related or otherwise.

While explicitly attempting to measure domestic policies at a daily frequency is a practically impossible task, we can circumvent the need to do so by exploiting the bilateral nature of our daily trade data. In particular, we can measure the impact of foreign lockdowns at the bilateral level while controlling for any time-variant domestic factors. To be sure, this is not a free lunch. As noted above, and as in any shift-share design, our baseline specification is able to capture aggregate, macro-level disruptions from lockdowns, that is where any lack of supply from one country is not sufficiently substituted with supply from another country. In this section we control for domestic factors but look instead at bilateral disruptions.

Specifically, and following the local projection method popularised by Jordà (2005), we estimate the following import equation at the daily frequency to measure the effect of a lockdown imposed by country $j$ on bilateral import growth in country $i$ at horizon $h$, $\hat{M}_{ij,t+h}$:

$$\hat{M}_{ij,t+h} = \gamma_{it} + \alpha_{ij} + \beta LS_{jt} + X'_{jt}\delta + \sum_{k=1}^{7} \hat{M}_{ij,t-k} + \epsilon_{ijt},$$

where bilateral import growth from $j$ to $i$, $\hat{M}_{ijt}$ refers to the 7-day moving average of year-on-year growth rates with respect to 2017–2019 averages, and $LS_{jt}$ denotes the lockdown stringency of the exporter country.\(^{17}\) Crucially, the specification includes the importer-time fixed effect $\gamma_{it}$ to control for any unobserved time-varying factors affecting country $i$’s imports. We also include a bilateral pair fixed effect $\alpha_{ij}$, and the vector of control variables $X'_{jt}$ (including new COVID-19 cases in ratio to the

\(^{17}\)As in our baseline results, lockdown measures are lagged to account for delivery lags in shipping.
population, and an aggregate measure of how much the exporter itself is exposed to foreign lockdowns).

Figure 6 shows the resulting estimated impact of exporters’ lockdowns on countries’ bilateral imports, for the sample restricted to the first quarter of 2020 (left panel) and for the entire sample covering the first half of 2020 (right panel). The results are in line with the conclusions stemming from our baseline specification: lockdowns had a significant impact on imports during the onset of the crisis, but this effect faded later on.

5 | INDIRECT SUPPLY-CHAIN EFFECTS

Our main results show that, in the early stages of the crisis, supply disruptions significantly affected trade volumes. In this section we explore whether these supply shocks may have reverberated through indirect supply-chain linkages. The existing literature provides strong guidance on how these shocks should propagate. In particular, and as shown theoretically and empirically (based on U.S. input–output data) by Acemoglu et al. (2016), supply shocks propagate downstream. In what follows, we, therefore, extend the baseline model to account for indirect supply-chain linkages. We begin with an illustrative example and then show the general formulation and discuss the assumptions that we make to take this formulation to the data.

5.1 | An illustrative example

To fix ideas, consider a world economy where there are only three seaports, denoted China, Korea and the United States. China exports to both Korea and United States, and Korea only exports to the United States. The United States does not export. Further assume the following travel times between ports: China to Korea—3 days, China to the United States—14 days and Korea to the United States—11 days. We want to capture the spillover effects of Chinese and Korean lockdown policies on U.S. imports at daily frequency. With the assumptions made, China’s

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18Regression results are available from the authors upon request.
lockdowns will have a direct impact on U.S. imports (via the direct route that connects China to the United States) and an indirect impact (as China may supply inputs used in the route that connects Korea to the United States).

As before, let \( l_{j,t} \) denote the stringency of lockdown measures at port \( j \) and on day \( t \) and let \( w_{i,j} \) denote the pre-COVID fraction of imports into port \( i \) that come from port \( j \). We can write U.S. import growth \( (\hat{M}_{US,t}) \) as a function of direct lockdown exposure \( (LE_{1US,t}) \), indirect lockdown exposure \( (LE_{2US,t}) \) and other factors \( (\epsilon_{US,t}) \):

\[
\hat{M}_{US,t} = \beta_1 LE_{1US,t} + \beta_2 LE_{2US,t} + \epsilon_{US,t}.
\]

Considering the travel times described above:

\[
LE_{1US,t} = w_{US,KOR}l_{KOR,t-11} + w_{US,CHN}l_{CHN,t-14}.
\]

\( LE_{2US,t} \) is the indirect lockdown exposure, that is the lockdown exposure not of the United States, but of the trading partners of the United States. We define it recursively as

\[
LE_{2US,t} = w_{US,KOR}LE_{1KOR,t-11} + w_{US,CHN}LE_{1CHN,t-14}.
\]

That is, in our example, Korea’s lockdown exposure at time \( t-11 \) is a relevant driver of U.S. imports at time \( t \). The coefficient \( \beta_1 \) measures the direct spillover effect of lockdowns, whereas the coefficient \( \beta_2 \) measures the effects that act through global supply chains.

5.2 Specification, assumptions and results

The empirical model behind the illustrative example can be written as:

\[
\hat{M}_{it} = \gamma_i + \alpha_i t + \sum_{k=1}^{K} \beta_k LE_{it}^{k} + X'_{it} \delta + \epsilon_{it} \tag{6}
\]

\[
LE_{1it} = \sum_{j} w_{ij}l_{j,t-d(i,j)} \tag{7}
\]

\[
LE_{kit} = \sum_{j} w_{kj}LE_{j,t-d(i,j)}^{k-1} \text{ for } k = 2, \ldots, K \tag{8}
\]

\[
\sum_{j} w_{kj} = 1 \tag{9}
\]

Here, \( X_{it} \) includes the necessary control variables. This formulation includes higher-order indirect exposures (e.g. \( LE_{US,t}^{k} \), for \( k = 2, \ldots, K \)) that would capture long supply-chain links.

We make three assumptions to take this model to the data.

First, we take \( K = 2 \). That is, we only go one step further than our baseline results and assume away any effect of lockdowns three and more steps away from the importing country. Given the short-lived nature of direct lockdown effects, especially in relation to global delivery lags involved in seaborne trade, our prior was that attempting to estimate higher-order effects would be unlikely to yield precise estimates. This is confirmed by our results below,
which show that even results for $K = 2$ are only marginally significant at standard confidence levels.

Second, we further assume that $w_{ij}^2 = w_{ij}^1$. In the illustrative example above, the lockdown exposures of the U.S. trading partners affect U.S. imports in proportion to the imports of the United States from these countries (i.e. the equation for $LE_{US,t}^2$ uses the same weights as the equation for $LE_{US,t}^1$). If, however, Korea’s imports from China were all destined to final consumption, then Korea should not feature in $LE_{US,t}^2$. In other words, the weights used to construct $LE_{US,t}^2$ should ideally reflect higher-order input linkages. In the absence of data that could be used to construct such weights, we thus assume that $w_{ij}^2 = w_{ij}^1$.

Finally, an implicit assumption in the illustrative example and the formal model is zero processing time of intermediate inputs. This is clearly not credible. When estimating indirect spillovers below, we impose homogeneous processing lags across countries and use the data to explore plausible lags.

Before moving on to the results, a discussion of how these assumptions could bias our results is warranted. While the assumption that $K = 2$ is reasonable given the time-series dimension of the sample, the assumptions on equal direct and indirect weights ($w_{ij}^2 = w_{ij}^1$) and homogeneous processing times can introduce measurement error in our variables. However, there is no obvious a priori reason to believe that this error is systematically related to the true values. To the extent that this measurement error corresponds to the classical errors-in-variables case, the point estimates and t-statistics discussed below are actually biased downwards.

Panel (a) in Figure 7 shows the point estimate and confidence bands for the two main coefficients of interest, using different lags of indirect foreign lockdown exposure $LE_{it}^2$ and estimating the model over the full sample. Both point estimates have the expected sign for every processing time considered. Furthermore, the coefficient on indirect lockdown exposure exhibits an intuitive U-shaped pattern as we increase the number of days allocated to processing times. Even though we cannot pin down the duration of intermediate production

$19$While input–output matrices could be used to construct higher-order weights, such weights would not necessarily correspond to input linkages embedded in trade that takes place by sea.
steps a priori, the data confirms that it cannot be either too short or too long. While direct foreign lockdown exposure is significant for processing lags greater than around 2 weeks, indirect foreign lockdown exposure is not statistically significant in the full sample under any of the processing lags considered.

We, therefore, explore the estimates when focusing on the initial stages of the crisis, where earlier—in the main result section—we found strong direct spillover effects. The point estimates and confidence bands for the two main coefficients of interest are shown in panel (b) of Figure 7. The U-shape of estimated indirect spillovers is even more pronounced in this sample with the maximum effect at around 2-week processing lags. Despite the smaller sample, at 2-week processing lags both the direct ($p$-value: .061) and indirect ($p$-value: .068) foreign lockdown exposures are marginally statistically significant at standard significance levels. In what follows we, therefore, focus the discussion on the results obtained in this sample.

The first column in Table 4 reproduces our preferred specification estimated over the full sample (column (6) in Table 3 above). Column (2) adds the indirect foreign spillover measure based on a 14-day processing lag, showing the negative but insignificant indirect lockdown effect in the full sample.20 As a benchmark, column (3) presents our preferred baseline specification estimated over the sample that goes through March 31. As shown in the discussion of our baseline results, the coefficient on direct lockdown exposure is both sizeable and statistically significant.21 Column (4) in Table 4 adds the indirect lockdown exposure corresponding to the 14-day processing lag of Figure 6b. As shown already in Figure 6, the point estimates on direct and indirect lockdown exposures are economically sizeable. While the point estimate on indirect lockdown

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20As we include a 14-day lag, we lose the first two weeks of observations. We checked that imputing zero indirect lockdown exposures before January 1, 2020 do not change the results in any meaningful way.

21A noteworthy difference in the estimates of columns (1) and (2) (obtained with the entire January–June sample) and those of columns (3) and (4) (focusing on the January–March period) is the magnitude of the coefficient associated with domestic deaths. This variable aims to capture consumer confidence/fear as demand shifter. The marginal effect of an extra reported death on fear/consumer confidence was higher—by a factor of around 10—at the beginning than in the second quarter of 2020. This, in part, reflects the dramatic increase in global deaths and how consumers may have become more numb to them. In fact, the first difference of global deaths was itself on average around a factor of 10 higher in 2020Q2 compared to 2020Q1 (average daily increase in deaths at the global level: 1683 and 19,955 in Q1 and Q2, respectively).
exposure is larger, an F-test cannot reject the null that direct and indirect foreign lockdown coefficients are equal to each other \( (p\text{-value: .3972}) \). At the same time, the null that both coefficients are equal to zero is strongly rejected \( (p\text{-value: .0011}) \). In all, the results are suggestive to the downstream propagation of countries’ lockdowns through global supply chains.

6 | CONCLUDING REMARKS

This paper implemented a shift-share research design on novel high-frequency bilateral trade data to uncover the origins of the marked trade collapse during the global COVID-19 recession. This period is often referred to as the Great Lockdown, because countries introduced unprecedented measures to reduce the movement and contact of citizens to contain the spread of the novel coronavirus. Lockdown measures led to major disruptions in the production and transportation of goods, which quickly spilled over to other countries through international supply chains. This prompted many observers to attribute most of the observed drop in trade to supply effects and to lockdowns in particular. At the same time, demand also dissipated on the back of increased risk aversion, revised income expectations and fear of the disease. The age-old question in economics resurfaced: Are the observed changes in trade volumes driven mostly by supply or demand effects?

This paper separates the supply and demand channels in trade by constructing a measure of lockdown exposure to trace the effects of these supply-side disruptions. To estimate the spillover from one country’s lockdown to other countries’ import growth, we rely on a unique dataset of daily bilateral trade volumes estimated via tracking virtually all cargo ships in the world. These high-frequency data are key to our analysis, because it allows us to use geography-induced travel times to follow the transmission of lockdown shocks across the globe.

The results in this paper confirm that lockdowns and supply disruptions did play a significant role in the trade collapse—at least at the beginning of the crisis. Countries that historically had stronger trade links with and are closer to countries under heavy lockdowns experienced larger and faster contraction in their imports. We also find some evidence for indirect spillovers from lockdowns through global supply chains, as higher lockdown exposure of a country’s trading partners is also associated with lower import growth. However, these spillover effects were only present during the first 2–3 months of the pandemic. After then, demand effects likely dominated the evolution of global trade. In all, the short-lived nature of the disruptions despite the unprecedented scale of the shock caution against any blunt use of trade and tax policies to create costly redundancies in global supply chains.

Future research should investigate the underlying mechanism that produces the vanishing supply spillovers from lockdowns. We hypothesise two possible explanations. It could be that frictions resolved within the timeframe of the analysis and firms were able to flexibly adapt their supply chains to the pandemic, including by finding new suppliers. Alternatively, it is possible that lockdowns imposed in the West in the later part of the sample were intrinsically different from early lockdowns imposed in Asia and Europe at the beginning of the sample.

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DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon reasonable request.
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