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Quantifying the impact of pandemic lockdown policies on global port calls

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ABSTRACT

The recent experience of lockdowns during COVID-19 highlights the prolonged impact a pandemic could have on ports and the shipping industry. This paper uses port call data derived from the Automatic Identification System (AIS) reports from the world's 30 largest container ports to quantify both the immediate and longer-term impact of national COVID-19 lockdown policies on global shipping flows. The analysis uses the Difference-in-Difference (DID) and combined regression discontinuity design (RDD)-DID models to represent the effects of lockdown policies. The combination of RDD and DID models is particularly effective because it can mitigate time trends in the data, e.g., the Chinese New Year effect on Chinese ports. This study further examines the potential shock propagation effects, namely, how lockdown policy in one country (i.e., China) can affect the number of port calls in other countries. We categorize ports in other countries into a high-connectivity (with Chinese ports) group and a low-connectivity group, using a proposed connectivity index with China derived from individual vessel trajectories obtained from the AIS data. The results provide a clearly measurable picture of the kinds of trade shocks and consequent pattern changes in port calls over time caused by responses to lockdown policies of varying levels of stringency. We further document the existence of significant shock propagation effects. As the risk of pandemics rises in the twenty-first century, these results can be used by policy makers to assess the potential impact of different levels of lockdown policy on the maritime industry and trade flows more broadly. Maritime players can also use findings such as these to manage their capacity during lockdowns more effectively and to respond more flexibly to changing demand in seaborne transportation.

1. Introduction

The spread of the COVID-19 virus has brought severe effects on global society and the world economy due to the policy responses of national leaders. Governments have implemented unprecedented national lockdown policies (dubbed the Great Lockdown by the IMF) to contain the spread of the virus since early 2020. While effective in slowing down the spread of the virus, these containment measures have negatively affected economies around the world and, particularly, the global supply chain which relies on freight transportation Disruptions caused by the pandemic on supply chains are often characterized by the existence of disruption with unpredictable scaling

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effects and few warning signs, the existence of the ripple effect (i.e., disruption propagations) accompanying the spread of the virus; wide geographical coverage; and, disruptions in demand, supply and logistics infrastructures simultaneously (Ivanov, 2020; Notteboom et al., 2021). Needless to say, ensuring the functioning of supply chain and transportation networks is critical for economic development, as much of it is enabled and powered by freight transportation (Loske, 2020). Among all the categories of freight transport, maritime freight alone moves over 80 % of the volume of world trade (UNCTAD, 2019), which further underscores the importance of maritime transport in trade and development.

The impact of the COVID-19 outbreak and associated national lockdown policies on the maritime transport industry is seen as unprecedented in that lockdowns deal multiple blows to the industry on two fronts simultaneously (Heiland and Ulltveit-Moe, 2020). On the one hand, the industry faces a contraction in demand for seaborne transportation due to the Great Lockdown. A massive number of production facilities have been shut down across countries and sectors, leading to collapsing demand for transport services and subsequently cancelled voyages. On the other hand, shipping companies also face novel regulations as countries have implemented direct restrictions on port access and sea transport. For instance, some countries have banned marine vessels from sailing into certain ports, which has forced such vessels to change their original destinations. Sometimes, the entry of vessels has been prohibited because their last ports of call happened to be located in a country with a high risk of epidemic spread. Countries have also implemented rules concerning crew changes and seafarers' mobility on incoming ships. It should further be noted that these restrictions affect not only the imposing countries and shipping companies, but also all of their trading partners (Heiland and Ulltveit-Moe, 2020).

In order to mitigate these effects going forward, it is crucial to define the exact effects of lockdown measures for policymakers. The objective of this research is thus to examine the effect of national lockdown policies on maritime transportation by analyzing the port call data of the world's largest 30 container ports. After the initial spread of COVID-19, there have been two waves of large-scale national lockdowns around the world in the first half of 2020. The first lockdown was announced in China on 23 January 2020 (i.e., Week 4 in 2020), and the second one was announced on 18 March 2020 (i.e., Week 12 in 2020), mainly in Asia, Europe and North America.[1] With this in mind, we aim to tackle two specific research questions: 1) What is the impact of national lockdown policies on local port calls, both in the short term (i.e., one or two weeks) and long term (i.e., four to six weeks)? 2) Is there evidence of disruption propagation effects on ports across different regions? Heiland and Ulltveit-Moe (2020) have pointed out that the propagation effect of local disruptions through the liner shipping network can be detrimental and long-lasting. Little is known, however, about how the shock propagates, and to what extent. In order to address these questions, a Difference-in-Difference (DID) model is proposed to measure the impact of national lockdowns on the number of port calls in the medium to long term. The DID model is widely used for analyzing average medium to long term effects of social policies, making it a well-adapted tool for our analysis. For the first question, we quantify the immediate effect of national lockdowns on port calls through a combined regression discontinuity design (RDD)-DID model of the data collected from a few weeks pre- and post- lockdown. The combination of RDD and DID models can thus mitigate the time trend in the data, especially as it relates to the effect of the Chinese New Year on ports. In order to answer the second question, specifically how lockdown policy in China might affect port calls in other countries, we first categorize ports in other countries into a high-connectivity (with Chinese ports) group and a low-connectivity group; we do this by using a proposed connectivity index. Then, we separately examine the impact of Chinese lockdown on each of the different port groups.

Recent studies have evaluated the impact of COVID-19 on transportation by comparing indicators of 2020 with those of the same period in previous years with (quasi-) experimental research methods, such as DID and RDD (Vandoros, 2021; Barnes et al., 2020). We aim to extend the analysis to ports and address the potential problems when applying the (quasi-)experimental method to our research objective, e.g., separating the effect of Chinese New Year from that of COVID-19 on ports. Concretely, our contribution is threefold: First, by applying the quasi-experimental research methods, e.g., DID and RDD models, we provide a method to isolate the impact of COVID-19 lockdown policy on port call changes clearly from those associated with the Chinese New Year. The method can exclude the noise and give more reliable results compared to comparative analysis or time series analysis that have been commonly used in existing literature. Second, we propose a new port connectivity measurement method based on dynamic ship data extracted from the Automatic Identification System (AIS) data. The data is particularly useful, as it can provide near real-time information on maritime transport and trade. Third, by taking port connectivity into consideration, we also identify the propagation effects of one country's lockdown policy on the shipping activities of other countries, which has not been addressed before. Our results provide significant guidance for policy makers when drafting national lockdown policies, and help diverse groups of stakeholders to understand and estimate the impact of lockdown policies, both at local and global levels.

The remainder of the paper is structured as follows: Section 2 reviews the related research literature. Section 3 introduces data and methodology. Section 4 reports the direct lockdown effects on ports in certain countries, while Section 5 takes shock propagation into consideration and examines the indirect lockdown effects. Section 6 provides policy suggestions based on these empirical results, and Section 7 concludes the paper.

2. Literature review

This section briefly reviews two strands of literature that are related to our study, namely, COVID-19 and maritime transport; and, RDD and RDD-DID application in COVID-19 and transportation studies.

[1] https://en.wikipedia.org/wiki/COVID-19_lockdowns.

2.1. COVID-19 and maritime transport

COVID-19 has significantly affected global supply chains and maritime transportation in 2020. Researchers have mainly used the comparative analysis method to examine the economic indicators of 2020 against those from the same period in previous years in order to assess the impact of COVID-19 on maritime transport (see, for example, UNCTAD, 2020; Millefiori et al., 2020; EMSA, 2020; Depellegrin et al., 2020). The indicators used mainly include port calls, volume of cargo carried, deployed capacity, cumulative navigated miles, and time in ports.

UNCTAD (2020) used the AIS data from the first 24 weeks of 2020 to estimate how COVID-19 affects port calls and the container liner shipping connectivity index. This study found that during the first half of 2020, global ship calls contracted by 8.7 % compared with the number of ship calls in the first half of 2019. In another study, Cumulative Navigated Miles (CNM) and the number of active and idle ships were derived from AIS in order to measure the global maritime mobility change between 2016 and 2020 (Millefiori et al., 2020). The dataset contained more than 50,000 commercial ships across the globe, and the analysis of this data revealed that CNM declined significantly across all categories of commercial shipping from March to June of 2020. These results suggest that the number of idle ships increased significantly across all types of ships globally in the first six months of 2020. EMSA (2020) issued a report evaluating the impact of COVID-19 on shipping traffic using data mainly from the Union Maritime Information and Exchange System. This study found that the number of vessel calls at EU ports declined by 12.3 % in the first 52 weeks of 2020 compared to the same period in the previous year. Depellegrin et al. (2020) estimated the impact of one national lockdown on maritime traffic in the Veneto Region of Italy. The AIS data culled for this study covered fishing vessels, passenger ships, tanker and cargo vessels and compared shipping traffic from March to April in 2017 and 2020. The results showed that vessel activity decreased by 69 % during the lockdown. Zhu et al. (2020) used monthly container port calls and berthing time data derived from the AIS from January to April 2020, and selected Shanghai, Ningbo-Zhoushan and Tianjin as sample ports. When they compared the data from 2020 with that from the previous year, they found that the number of ships arriving at Chinese ports was not significantly affected; but, the average berthing time of ships at port decreased significantly from January to April 2020.

Using global port call as a proxy of demand, Michail and Melas (2020) estimated how freight rates (dry bulk, clean, and dirty tankers) have been affected by rapid changes in the macro-economic environment. They adopted both GARCH and Vector Autoregression (VAR) specifications for the purposes of their analysis. The independent variables were global calls, China calls, the world total confirmed cases, Shanghai Composite Index, and the S&P 500. Dependent variables were the Baltic Clean Tanker Index (BCT), Baltic Dry Index (BDI), and Baltic Dirty Tanker Index (BDTI). The daily data covered the period from January 3, 2019 to June 1, 2020. They found that that freight rates were negatively related to the number of coronavirus cases, while global port calls were significantly, positively related with freight rates. In summary, the comparative data analysis method and related econometric methods (GARCH, VAR) have been popularly adopted in evaluating the impact of COVID-19 on maritime transport. Since the initial COVID-19 lockdown coincided with the Chinese New Year, however, comparative analysis and time series analysis (e.g., GARCH, VAR) techniques cannot isolate the impact of COVID-19 lockdown policy on port call changes from those associated with Chinese New Year. Therefore, quasi-experimental research design methods including DID and RDD models may more accurately allow researchers to examine the real impact of COVID-19 lockdown policy on maritime activities.

2.2. DID and RDD application in COVID-19 and transportation studies

The DID model is a quasi-experimental research design that researchers frequently use to study causal relationships in transportation. It measures not only the differences of outcome between a treatment group and the control group, but also the differences between the pre-treatment period and the post-treatment period. Fang et al. (2020) applied DID to study the impact of the lockdown on human mobility in Wuhan. They collected city-pair population migration data and the intra-city population movement data from Baidu Migration. The data covers 22 days before and 38 days after the city lockdown on January 23, 2020. In order to eliminate the Spring Festival effect, the data from the same lunar calendar period in 2019 was included in the analysis as the control group. They found that the lockdown reduced inflows to Wuhan by 76.98 %, outflows from Wuhan by 56.31 %, and movement within Wuhan by 55.91 %. DID has also been used to estimate the impact of COVID-19 lockdowns on the decline in motor traffic collision (Vandoros, 2021) and in road traffic-related deaths and injuries (Oguzoglu, 2020).

In the maritime domain, Baldwin and Evenett (2020) used a DID model and AIS data to investigate the impact of the COVID-19 pandemic and the subsequent policy response on shipping activity in Norway. As March 12, 2020 was the day when Norwegian government implemented restrictions on movement and activity, the authors selected five weeks prior to and five weeks after March 12th across the years 2020, 2019, 2018 in the DID model. In general, in 2020 the number of ships dropped by 6 % compared to the change observed in previous years. The authors' contention was that national restrictions on sea transportation were responsible for the decline in shipping activity during the pandemic. The authors combined information from vessels departing from Norway with cross-country information on crew change restrictions to further assess the hypothesis. They found that voyages to destinations where crew changes were prohibited were down by almost 20 % for container ships, as compared to a decline of 6 % to destinations which imposed milder restrictions, such as screening rules.

An RDD model is also a quasi-experimental design to study the causal effects of interventions. When an intervention happens, it is regarded as a cutoff, or threshold. RDD estimates the average treatment effect by comparing the observations that lie closely on either side of the threshold. RDD has been adopted to examine the effect of the COVID-19 lockdown and reopening on the daily movement of individuals (Ding et al., 2021). The authors recorded the number of daily steps of 815 Chinese adults living in Shanghai before, during and after the lockdown as a measure of movement during each of these periods. At the beginning of the lockdown, it was observed that the average daily step count dropped sharply by 3,796 steps. Subsequently, the daily step count increased by an average of 34 steps/day until the end of the lockdown. On the other side of the globe, Barnes et al. (2020) used the RDD method to estimate the lockdown's effect on mobility and traffic accidents in the state of Louisiana. They collected data from Google Community Mobility reports and Uniform Traffic Crash Reports from the Louisiana Department of Transportation and Development (LaDOTD). They also adopted the RDD-DID method to control for changes over the same period in 2019. They found that the stay-at-home order caused a significant decrease in mobility, as measured through road traffic.

To summarize, previous studies mainly used the DID or RDD methods to estimate the impact of lockdowns on human mobility, using either step-monitoring or traffic accidents as a proxy for individual movement. The impact of lockdowns on maritime transport, on the other hand, has most often been investigated using the comparative analysis methods described above, and less frequently through more rigorous statistical methods like RDD or DID models that can give a more precise account of this causal relationship.

3. Data and methodology

This section first presents the analytical framework, our construction of weekly port call data drawn from the AIS. Then the DID and RDD-DID models are introduced.

The analytical framework is provided in Fig. 1. To begin with, we gauge the direct effect of the first lockdown on Chinese top seven container ports and the direct effect of the second lockdown on the top ten ports in other countries. Next, we separately examine the indirect effects of Chinese lockdown on high-connectivity Asian ports, high-connectivity European ports, and low-connectivity ports.

3.1. Data

We selected for analysis the world's 30 largest container ports (measured in terms of throughput) located in countries that implemented lockdown policies during the period from January 2020 to March 2020. Among them, as shown in Table 1, seven Chinese ports were affected by the lockdown policy implemented in China in January 2020, including Shanghai, Shenzhen, Ningbo-Zhoushan, Guangzhou, Qingdao, Tianjin, and Xiamen. Ten other ports worldwide were affected by lockdown policies in their respective countries in March 2020, including Rotterdam, Port Klang, Antwerp, Los Angeles, Tanjung Pelepas, Hamburg, New York, Colombo, Bremerhaven, and Piraeus.[2] We use port call as the indicator, because it is broadly treated as demand and port traffic proxy of port in previous studies (UNCTAD, 2020; Michail and Melas, 2020; Baldwin and Evenett, 2020). The necessary time windows from before and after the lockdown announcements were selected based on trends in the number of port calls and the results of a parallel trend test, which will be discussed in subsequent sections.

The AIS data can track individual ship movements and provide specific information, including a ship's identity, location, speed, and draft, among other details (Yang et al., 2019). Combined with vessel information from Lloyd's List Intelligence, including IMO number and vessel type, we can derive dynamic movement records for any given container ship.

The following criteria are, moreover, used to identify port calls: every time a ship stays within 30 km of any port for more than 1 h with speed less than 1 knot will be considered as one port call for that port. If the ship is mooring at the overlapping region of several ports, then the nearest port will be chosen.

Notably, the first wave of lockdowns in China was implemented on January 23, 2020, just before the Chinese New Year, which is often characterized by a reduced numbers of port calls at Chinese ports during this time period. Due to the coincidence of the lockdown policy and the Chinese New Year holiday, we need to first identify the reason for the decrease in port calls. Fig. 2 plots the weekly port calls in the selected seven Chinese ports during the 2019 and 2020 Chinese New Year periods, respectively. It can be observed that port calls went down significantly during the Chinese New Year period in both years. In order to remove the Chinese New Year effect on port calls data and to obtain the pure lockdown effect, we selected the same period of port calls data for both 2019 and 2020 (i.e., six weeks before and after the Chinese New Year) for the DID model.

We propose a connectivity index between each port in other countries and Chinese ports in order to measure their connectivity. Specifically, for every ship, we obtain the time series of sequential port calls through AIS data based on the method described before. Then, for each port under investigation, we use the following equation to calculate a port c's connectivity index with Chinese ports.

$$Connectivity_c = \sum_{i=1}^{n} Y_i \cdot \left(\sum\nolimits_{j=i}^{m} C_j \right) \tag{1}$$

where n is the total number of global ships' port call time series in 2019. Y_i equals 1 if this time series of port calls contains port c and 0 otherwise. In this equation, m is the number of port calls in one ship's time series, and C_j is a dummy variable which takes a value of 1 if the port call is a Chinese port and takes a value of 0 otherwise.

3.2. Difference-in-difference model

The DID model has been broadly applied to quantify the effect of an experimental treatment by comparing the average change in the outcome variable over time in control and treatment groups, respectively, thus eliminating the effects of extraneous factors and

[2] World Shipping Council: https://www.worldshipping.org/about-the-industry/global-trade/top-50-world-container-ports.

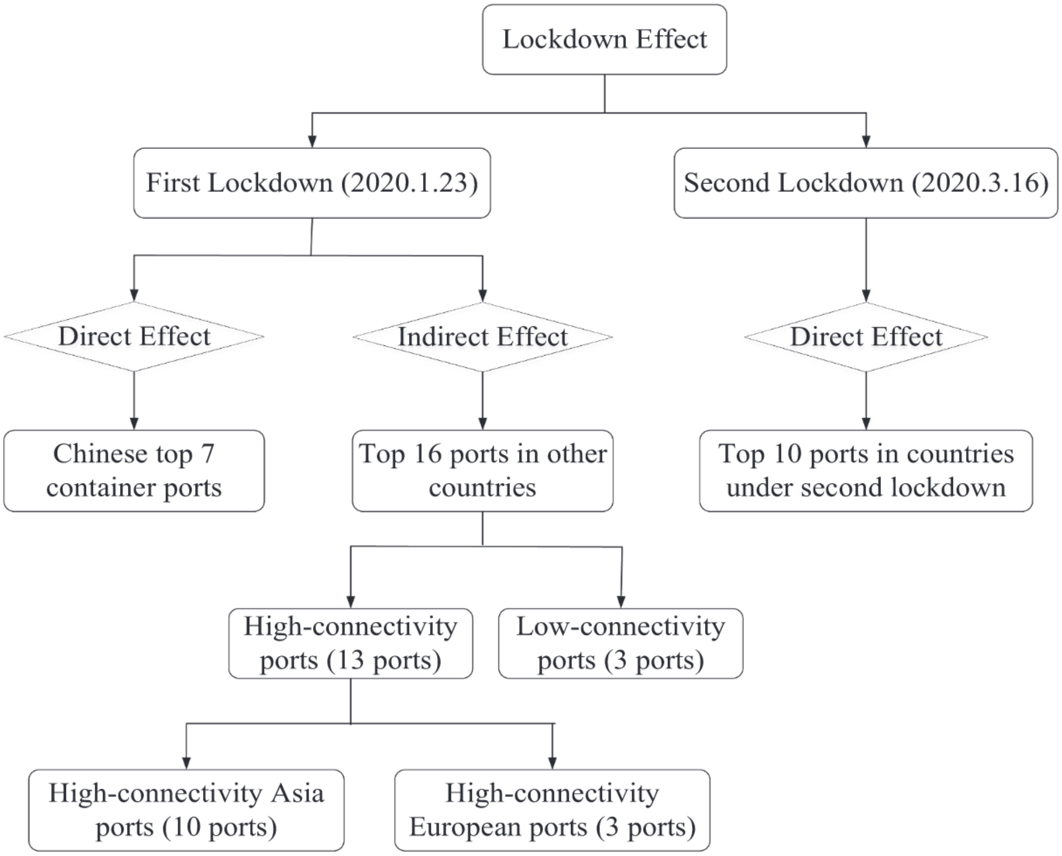

Fig. 1. Analytical framework.

Table 1
Ports affected by two waves of lockdown policy

	Time	Scope	Ports affected
First wave of lockdown	January 2020	China	Shanghai, Shenzhen, Ningbo-Zhoushan, Guangzhou, Qingdao, Tianjin, Xiamen
Second wave of lockdown	March 2020	Europe, Asia, and America	Rotterdam, Port Klang, Antwerp, Los Angeles, Tanjung Pelepas, Hamburg, New York, Colombo, Bremerhaven, Piraeus

selection bias (Meng et al., 2018; Alemi et al., 2018). In our study, the ports in the control group and treatment group are the same. We distinguish the treatment and control group in terms of the occurrence time (year of 2019 and 2020). The port call in 2019 is used as control group and the port call in 2020 is selected as the treatment group. The following DID model is constructed:

$$W_{i,c} = \beta_0 + \beta_1 Year_i + \beta_2 T_i + \beta_3 T_i \cdot Year_i + \mu_i + \rho_c + \epsilon_{i,c} \tag{2}$$

$\mathbf{T_i}$ is a dummy variable that takes the value of 1 after the intervention (lockdown) date and 0 before the intervention. For Chinese ports, it is 1 after the 4th week and 0 before the 4th week of 2020; it is 1 after the 6th week and 0 before the 6th week of 2019. For ports in other countries, the dummy variable takes the value of 1 after the 12th week of the years of 2019 and 2020, and 0 before the 12th week. Table 2 shows the value of $\mathbf{T_i}$ on different dates. $\mathbf{Year_i}$ is a dummy variable that takes the value of 1 in 2020, and 0 in 2019. The model includes port fixed effect ρ_c as well as week fixed effect $\boldsymbol{\mu_i}$ to control the port and time variance. β_0 reflects the baseline average. β_1 reflects the difference of port calls between the years of 2019 and 2020 before the lockdown implementation (it is the week 4 for 2020 and the week 6 for 2019). β_2 represents the time trend in control group (port calls of 2019). β_3 indicates the average effect of lockdown on affected ports.

For the DID model, our key assumption is that without the lockdown policy, the port calls data would have changed in the same way as the previous year, i.e., a parallel trend assumption. In order to ensure the validity of this assumption, we also perform a parallel trend test through an event study model, which is detailed in Section 3.4.

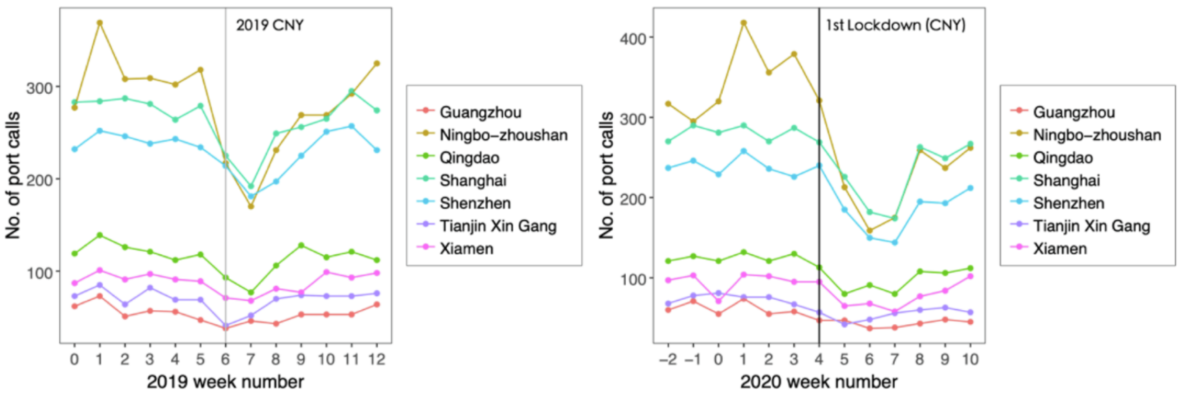

Fig. 2. Port calls data of seven Chinese ports during 2019 and 2020 Chinese New Year Period Notes: The 2019 week number represents the actual week number in 2019; Week 0 (starting 24 December 2018) represents Week 52 of 2018, that is, the last week in 2018. In 2019, the Chinese New Year began in Week 6 (starting 04 February 2019). For 2020, the week number represents the actual week number in 2020, and Week 0 (starting 23 December 2019), Week −1 (starting 16 December 2019), Week −2 (starting 09 December 2019) represent Week 52, Week 51 and Week 50 in 2019, respectively; that is, the last three weeks in 2019. In 2020, the Chinese New Year celebration took place in Week 4 (starting 20 January 2020).

Table 2
Value of T_i on different dates.

T_i	2019		2020	
Chinese ports	Pre-week 6 0	Post-week 6 1	Pre-week 4 0	Post week 4 1
Other ports	Pre-week 12 0	Post-week 12 1	Pre-week 12 0	Post-week 12 1

3.3. Regression-Discontinuity-Design (RDD)-DID model

In order to further quantify the immediate effect caused by lockdown policies, we propose an RDD-DID model. The proposed model builds on the RDD model, which can estimate potential breaks in a relatively short time period around the policy intervention date (Brodeur et al., 2021). We assume the lockdown announcement date as the cutoff, then week i can be considered in the treatment group if week i is after the date; otherwise, week i is in the control group. The equation is given by:

$$W_{i,c} = \beta_0 + \beta_1 T_i + \mu_i + \rho_c \tag{3}$$

where $W_{i,c}$ is the number of port calls in affected port c in week i. We define $T_i = 1$ if week i is after the lockdown announcement, 0 otherwise; and the week fixed effect is represented by μ_i. β_1 is the immediate change measurement that we are interested in.

Applying nonparametric estimation on Eq. (3), a running variable D is defined as the absolute distance in weeks from the lockdown policy implementation date; the value is negative for the weeks before and positive for the weeks after the lockdown, while the week of the lockdown implementation is set at 0. The lockdown implementation dummy T_i is defined in a similar way as in the DID model. The RDD regression equation is written as:

$$W_{i,c} = \beta_0 + \beta_1 T_i + \beta_2 f(D_i) + \beta_3 T_i \cdot f(D_i) + \beta_4 W_{i-1,c} + \mu_i + \rho_c \tag{4}$$

where $f(D_i)$ is a polynomial function of D_i, which interacts with T_i, and can be used to allow for different effects on either side of the cutoff date, and $f(0) = 0$. $W_{i-1,c}$ is the port calls data the week before, which eliminates any self regression effects. Our regression model uses polynomials of order one. As for the other independent variables, we include the same controls as in the DID model. β_1 indicates the immediate effect of the lockdown announcement on port calls data in the lockdown announcement week aside from self-regression.

In order to eliminate the time trend in the data from Chinese ports for each of the two years selected, we propose the RDD-DID model. This allows us to remove the effects of Chinese New Year and accurately estimate the true effects of the lockdown on maritime freight. In the RDD-DID model, we first calculate data breaks in 2019 and 2020, respectively; the port call break in 2019 can be related to the Chinese New Year. We then take the difference between the 2020 break and the 2019 break to obtain the port calls break caused purely by COVID-19 lockdown policy.

The RDD-DID model can be written as follows:

$$W_{i,c} = \beta_0 + \beta_1 T_i \cdot Year_i + \beta_2 f(D_i) \cdot T_i \cdot Year_i + \beta_4 f(D_i) \cdot T_i + \beta_5 T_i + + \beta_6 W_{i-1,c} + \mu_i + \rho_c + \epsilon_{i,c} \tag{5}$$

where we include the same control variables as in the RDD model. β_5 indicates the immediate break of port calls data in 2019, and $(\beta_1 + \beta_5)$ indicates the break in 2020. The immediate effect of the lockdown policy on port calls is measured by β_1.

3.4. Event study and parallel trend tests

To choose appropriate analysis time window and verify the validation of DID models, we perform an event study to test the parallel trends in the data used in the DID models and RDD-DID models; we also test for adaptation effects to the lockdown, namely, how trends in port calls changed after the lockdown announcement. The event study model can be written as follows:

$$W_{i,c} = \sum_k \alpha_k E_{k,c} \cdot Year_i + \sum_k \beta_k E_{k,c} + \mu_i + \rho_c + \epsilon_{i,c} \tag{6}$$

where $E_{k,c}$ are a group of k dummy variables that represent weeks in the DID and RDD-DID models, which take a value of 1 for week k and 0 for the other weeks. The week before the lockdown announcement (treatment) is the reference period. The estimated coefficients of the $E_{k,c}$ dummies (α_k) should therefore be interpreted as being in week k, the effect difference between two years.

For an ideal dataset used in both the DID and RDD-DID models, the effect difference of the weeks before the lockdown treatment should not be significant, which would indicate that the port calls trend in 2019 and 2020 would have stayed the same without the lockdown announcement.

4. Empirical results of direct lockdown effects

4.1. Descriptive analysis

We begin our analysis by examining port call data within the six week period before and after the beginning of lockdowns in 2020 in seven critical Chinese ports (the lockdown policy was announced in the Chinese New Year week, that is, Week 4). At first glance, port calls at these harbors experienced a relatively sharp decrease after the lockdown date, and kept decreasing for about three weeks before beginning to recover.

Fig. 3 plots the trends around the Chinese New Year date for both 2019 and 2020. In both years, there were a sharp decrease in port call data around the Chinese New Year, but in 2020, the declining trend lasted for a longer time, which may have been caused by the lockdown policy.

As for the top container ports in other countries that announced a lockdown policy in Week 12 of 2020 (refer to Table 1 for affected ports and lockdown policy), Fig. 4 shows the port call changes in these ports from Week 7 to Week 16 in 2019 and 2020. The decrease in port calls around the lockdown announcement in 2020 can thus be observed against the trends of the prior year.

4.2. Results of direct lockdown effects on Chinese ports

The direct lockdown effects on Chinese ports calculated using the DID model and RDD-DID models are presented in Table 3. To gauge the average effect of lockdown on Chinese ports, we apply the DID estimator. We select data from four weeks before and after the Chinese New Year in 2019 and 2020 as our estimation time window, based on the parallel trend tests outlined in Section 4.4. The DID

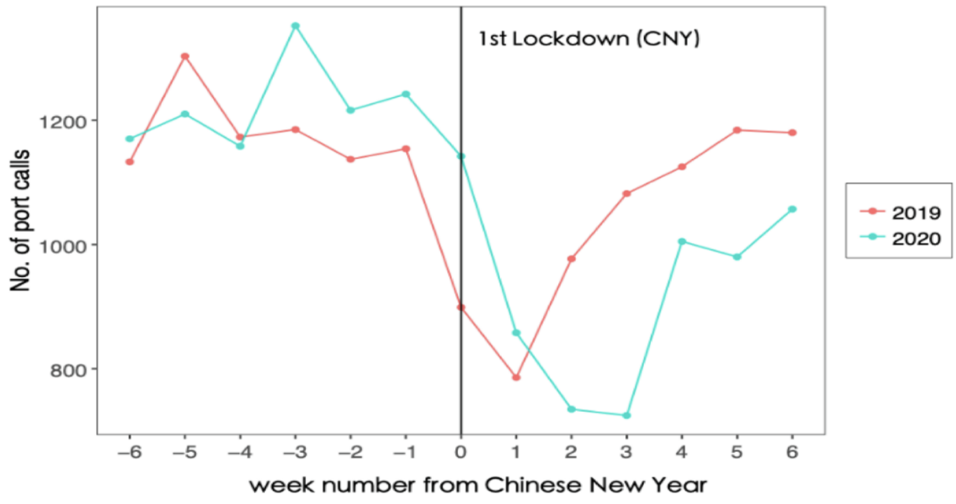

Fig. 3. Total port calls at seven Chinese ports around the 2019 and 2020 Chinese New Year Notes: The week number in the figure above shows the relative weeks between the actual week and the Chinese New Year week. Week 0 represents the Chinese New Year week, that is actual Week 6 in 2019 (starting February 4, 2019) and actual Week 4 in 2020 (starting January 20, 2020).

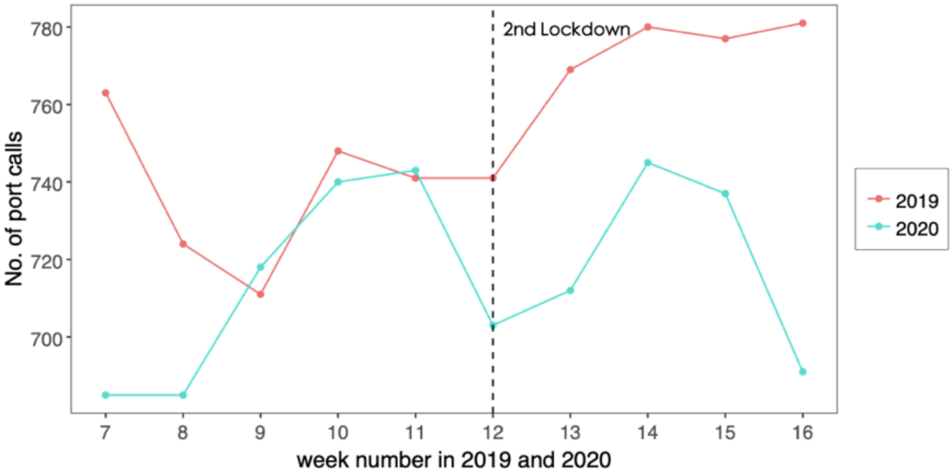

Fig. 4. Total port calls at other countries' ports during the sampling period (Week 7-Week 16 in 2019 and 2020) Notes: The week number here represents the actual week number in 2019 and 2020. For these countries, the lockdown policy was implemented in Week 12 in 2020 (starting 16 March 2020).

estimator is significantly negative at the 10 % significance level, indicating that the lockdown policy in China had a significant impact on port calls at Chinese ports. The results show that the number of port calls in the top seven Chinese ports decreased by 21.5 per week, or 13.0 % on average (in 2019, the average number of weekly port calls at these Chinese ports is 165). On the other hand, using the same study period, the RDD-DID estimator is not significant, indicating that after taking Chinese New Year effect into account, Chinese lockdown policy did not cause an immediate port call break near the lockdown date; this suggests rather, that the effect of lockdowns was gradual in magnitude.

4.3. Results of direct lockdown effects on other ports

In order to test the direct lockdown effect on ports in other countries during the second wave of national lockdowns, we apply the same DID and RDD-DID models. We select the time span from four weeks before the lockdown announcement to four weeks after that date. As verified in the parallel trend tests in Section 4.4, during this time period port call data at these ports in 2020 was not affected by the mid-January Chinese lockdown, illustrating the same trend as 2019 before lockdown. Estimators of the DID and RDD-DID models indicate that there was an immediate and significant decrease in port call data at these ports at the start of lockdowns, although the magnitude of the effect was moderate at best, as presented in Table 4. Within four weeks of the announcement of lockdown policies, the average port call levels of these harbors decreased by 3.3 per week (or 4.5 %) compared to before (in 2019, the average weekly port calls at these ports is 73.75).

Table 3
The direct effects of lockdown on Chinese ports.

Time period	DID model week −4 – week 3	RDD-DID model week −4 – week 3
$T_i \cdot Year_i$	−21.536*	16.437
	(10.90)	(9.77)
Port FE	Yes	Yes
Year and week FE	Yes	Yes
Autoregressive Effect	No	Yes
N	112	112
adj. R^2	0.959	0.977

Notes: The results in the above table are estimated based on Eqs. (1) and (4) for the DID model and RDD DID model, respectively. Coefficient estimates for $T_i \cdot Year_i$ are presented. Standard errors are reported in parenthesis. The symbol *, ** and *** indicate significance at 10%, 5% and 1% levels respectively. The treatment group for the DID model and RDD-DID model is four weeks before and after 2020 Chinese New Year, while the control group is four weeks before and after 2019 Chinese New Year, respectively.

Table 4
The direct effects of lockdown on other ports.

Time period	DID model week −4 – week 3	RDD-DID model week −4 – week 3
$T_i \cdot Year_i$	-3.300^{**}	-4.225^{**}
	(1.59)	(1.83)
Port FE	Yes	Yes
Year and week FE	Yes	Yes
Autoregressive Effect	No	Yes
N	160	160
adj. R^2	0.979	0.980

Notes: The results in the above table are estimated based on Eqs. (1) and (4) for the DID model and RDD-DID model, respectively. Coefficient estimates for $T_i \cdot Year_i$ are presented. Standard errors are reported in parenthesis. The symbol *, ** and *** indicate significance at 10%, 5% and 1% levels respectively. The treatment group for the DID model and RDD-DID model is four weeks before and after 2020 Chinese New Year, while the control group is four weeks before and after 2019 Chinese New Year, respectively.

4.4. Event study and parallel trend tests for direct lockdown effects

In order to confirm the validity our DID and RDD-DID models presented above, we perform an event study based on Eq. (6). The purpose of this is to test the common trend assumption, namely, that the same port call trends existed in 2020 before the announcement of lockdowns as in 2019.

Specifically, for Chinese ports, we perform an event study on port calls in 2019 and 2020 from five weeks before and after the Chinese New Year. The corresponding results are shown in Fig. 5. As modeled below, the 95 % confidence intervals for coefficients before the Chinese New Year all include zero, indicating that the trends in 2019 and 2020 from before the Chinese New Year can be considered identical.

The results of the event study model for ports affected by the second lockdown wave in March 2021 are shown in Fig. 6. The time range is from five weeks before the lockdown date to five weeks after the date. As can be seen in the graph, in Week 7 (the fifth week before the lockdown date), there is a significant difference in port call data between 2019 and 2020, which violates the common trend assumption between the treatment and control group before the policy intervention. Thus, we only use a four-week time span for our direct effect DID and RDD-DID models across all ports examined in order to retain consistency. As depicted in Figs. 5 and 6, the four-week time span satisfies the common trend assumption and confirms the validity of the DID and RDD-DID models.

5. Empirical results of indirect lockdown effects

In order to further examine port call changes in ports affected by the second wave of lockdowns, Fig. 7 plots port calls for these ports from Week 1 to Week 16 of 2020. As seen, there seems to be an unexpected break in most of these port calls around Week 7 in 2020 (i.e., about three weeks after the start of the Chinese lockdown policy). Considering that it takes about two to three weeks for

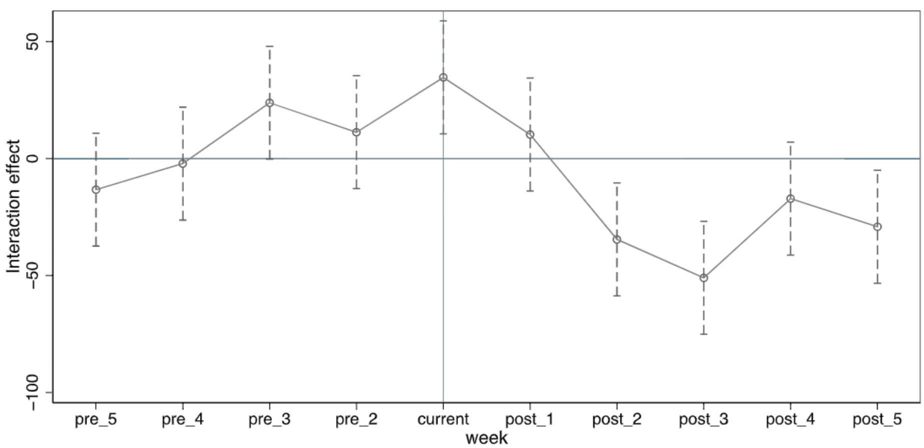

Fig. 5. Coefficient plots for DID and RDD-DID models analyzing the direct lockdown effects on Chinese ports during the first wave of lockdown Notes: Based on Eq. (6). Current week refers to the cutoff week (lockdown announcement week). The last week before the treatment (pre_1) is the reference week.

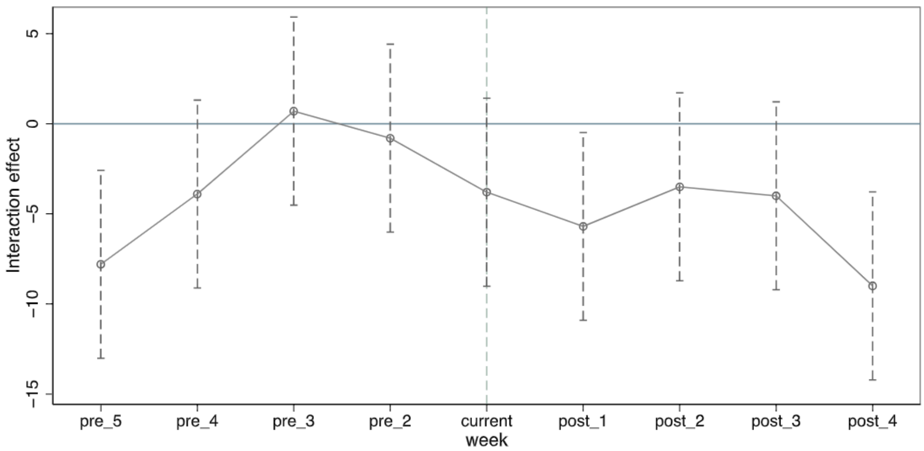

Fig. 6. Coefficient plots for DID and RDD-DID models analyzing the direct lockdown effects on internationl ports affected by the second wave of lockdowns Notes: Based on Eq. (6). Current week refers to the cutoff week (lockdown announcement week). The last week before the treatment (pre_1) is the reference week.

international container ships to travel across continents, the Chinese lockdown policy may also have affected these ports indirectly through the container shipping network.

Next, we examine this potential indirect lockdown effect, namely, how lockdown policy in one country can affect port calls in other countries through the container shipping network. In order to formally examine this shock propagation effect, we first classify ports based on their connectivity to Chinese ports. Then, we run the DID and RDD-DID models separately on high-connectivity and low-connectivity groups, using the date when the effects of the Chinese lockdown propagated to each group as the policy intervention date.

5.1. *Connectivity with China*

Based on the trends in port calls shown in Fig. 7, we hypothesize that the impact of lockdown policy in China on port calls in other countries varied across ports due to different connectivity levels with Chinese ports. To verify this point, we categorize ports in other countries into a high-connectivity (with Chinese ports) group and a low-connectivity group by using a proposed connectivity index introduced in Section 3. Based on each port's connectivity index and the port location, we grouped these ports into three categories for further analysis, as shown in Table 5. The standard for being a high connectivity port is that the number of ship visits between this port and Chinese ports in 2019 is more than 2,000.

5.2. *Empirical analysis of high connectivity ports*

Fig. 8 plots the total port calls in high-connectivity ports in 2019 and 2020 around the Chinese New Year week, respectively. Two

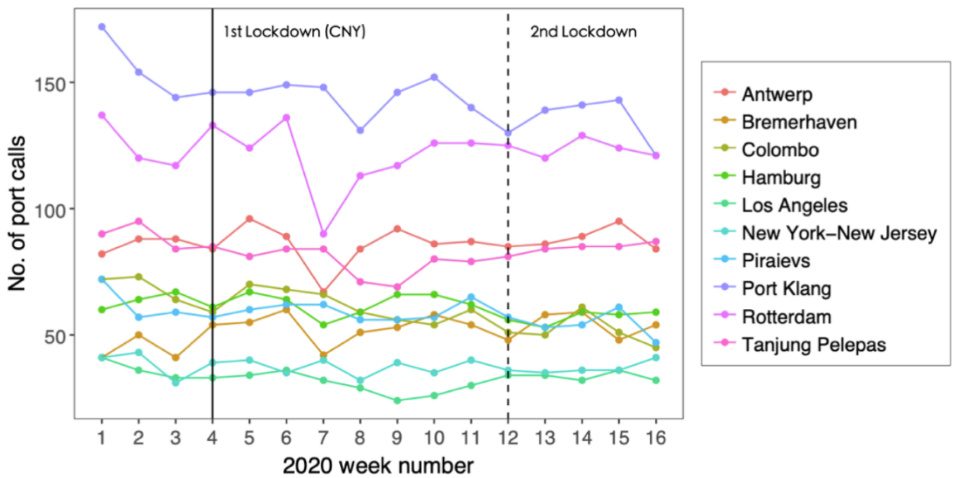

Fig. 7. Port calls at ports affected by the second wave of lockdown from Week 1 to Week 16 of 2020 Notes: The week number represents the actual week number in 2020. For these countries, the lockdown policy was implemented in Week 12 (starting from March 16, 2020).

Table 5
Classification of ports in other countries with connectivity index and location.

High-Connectivity Ports		Low-Connectivity Ports
Asian Ports	European Ports	
Pusan (16130), Hong Kong (14313), Singapore (13952), Port Klang (7852), Tanjung Pelepas (5605), Ho Chi Minh (4916), Manila (4156), Colombo (3835), Mina Jabal Ali (3459), Jakarta (2688)	Rotterdam (3275), Hamburg (2166), Antwerp (2161),	New York (1602), Bremerhaven (1095), Piraeus (1798),

Notes: Connectivity is in parentheses.

weeks after the Chinese New Year, the trends in port calls in 2019 and 2020 varied significantly: while the number of port calls in 2019 recovered quickly to the same level as before the Chinese New Year, port calls in 2020 remained at a low level for about three more weeks before showing signs of recovery. This indicates that the effect of Chinese lockdown policy almost certainly propagated to other ports with high connectivity to Chinese ports. Considering the different propagation times along the global shipping network (i.e., the amount of time necessary for propagation would be longer for crosss-regional routes and shorter for intra-regional routes), we separately investigate the propagation effects on high-connectivity ports in Asia and Europe.

5.2.1. Empirical analysis of high-connectivity Asian ports

The total number of port calls at Asian high-connectivity ports in 2019 and 2020 are plotted in Fig. 9. As seen from the chart, there exists a significant difference between 2019 and 2020 port calls. In 2019, from two weeks after the Chinese New Year, the port calls gradually increased to the same level as before the New Year. Alternatively, in 2020, the number of port calls at these Asian ports continued to decline, due to the propagation effects of China's lockdown. Therefore, it is reasonable to use two weeks as the shock propagation time from China to other high-connectivity ports in Asia after the lockdown announcement in China. In the subsequent model set up for Asian ports, we use two weeks after the Chinese implementation of lockdown as the cutoff point.

Table 6 shows the DID and RDD-DID model estimation results for Asian high-connectivity ports. Different time spans are considered. Specifically, we consider port calls that are four, three, and two weeks before and after the cutoff point so as to examine the impact duration of the shock propagation effect. In the DID models, the coefficient of the models with a four-week span is significant at the 1 % level, indicating that the propagation effect of Chinese lockdown policy led to a relatively prolonged decrease in port calls at high-connectivity Asian ports. Using the four-week span, the average number of port calls in high-connectivity Asian ports decreased by 8.23. The coefficients of all RDD-DID models examined and DID models with a shorter span are not significant, suggesting that this effect is neither short-term nor immediate.

5.2.2. Empirical analysis of high-connectivity European ports

We further examine the propagation effects of Chinese lockdown policy on European ports. Fig. 10 shows the port call data in these ports around the Chinese New Year in both 2019 and 2020. As seen below, these ports experienced a sharp decline in port calls three

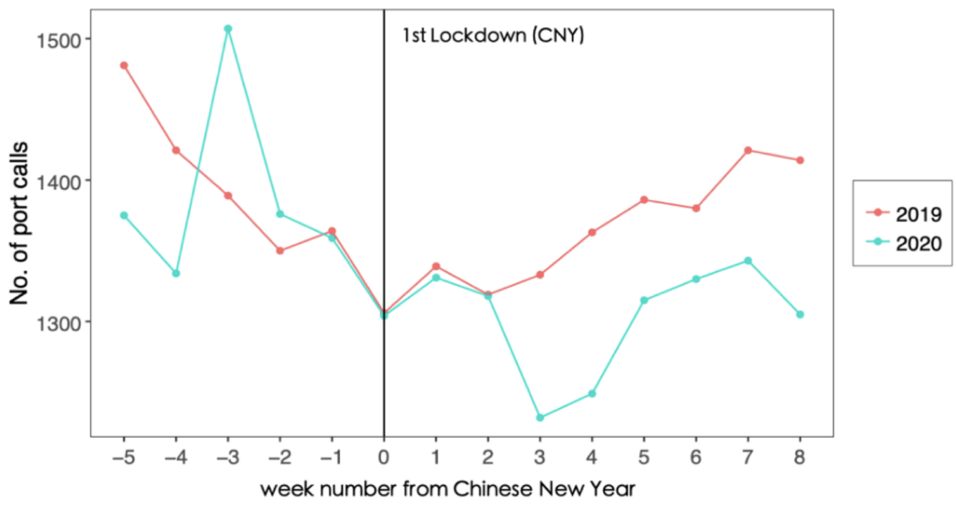

Fig. 8. Total port calls in high-connectivity ports in 2019 and 2020 around Chinese New Year Notes: The week number in this figure represents the relative weeks between the actual week and the Chinese New Year week. Week 0 represents the week of Chinese New Year, that is Week 6 in 2019 (starting February 4, 2019) and Week 4 in 2020 (starting January 20, 2020).

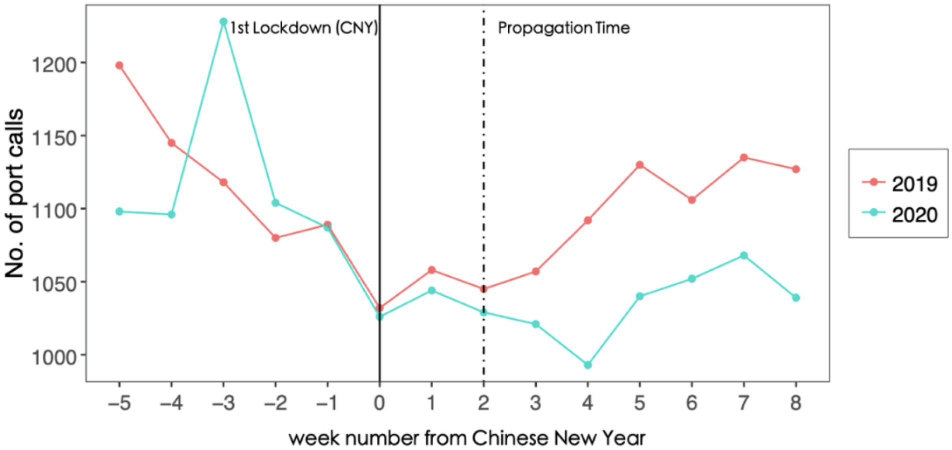

Fig. 9. Total port calls in high-connectivity ports in Asia in 2019 and 2020 around Chinese New Year Notes: Refer to the notes for Fig. 8. The black line in week 2 indicates that Chinese lockdown effects propagated to high-connectivity ports in Asia two weeks after the policy's announcement.

Table 6
DID and RDD-DID estimation results for high-connectivity Asian ports.

	DID model			RDD-DID model		
Time period	week 0 – week 3	week −1 – week 4	week −2 – week 5	week 0 – week 3	week −1 – week 4	week −2 – week 5
$T_i \cdot Year_i$	−3.900	−6.200	−8.225***	5.935	7.673	3.017
	(27.54)	(3.49)	(2.89)	(15.31)	(9.19)	(6.50)
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Autoregressive Effect	No	No	No	Yes	Yes	Yes
N	80	120	160	80	120	160
adj. R^2	0.371	0.985	0.987	0.985	0.986	0.988

Notes: Results are estimated based on Eqs. (1) and (4) for the DID model and RDD-DID model respectively. The symbol *, ** and *** indicate significance at 10%, 5% and 1% levels respectively. The week number in the table represents the relative weeks between the actual week and the week of Chinese New Year. Week 0 represents the Chinese New Year week, that is Week 6 in 2019 and Week 4 in 2020. The policy intervention (cutoff) time is Week 2 (two weeks after the Chinese New Year considering the propagation time) in 2019 and 2020. The treatment group for the DID model and RDD-DID model is four, three, and two weeks before and after the policy intervention in 2020; the control group is the same period in 2019.

weeks following the Chinese lockdown, but recovered quickly. At first glance, the impact seems to be rather severe and short-lived. Based on the graph below, as well as the voyage durations between China and Europe, we identify Week 3 after China's implementation of lockdowns as the cutoff point for the subsequent statistical analysis using DID and RDD-DID models.

The DID and RDD-DID estimation results for high-connectivity European ports (with a cutoff week of three weeks after the announcement of lockdowns in China), are presented in Table 7. Models with different time spans are also examined. The coefficients of the RDD-DID models under different bandwidths and DID models with shorter bandwidth are all significant, indicating that at three weeks after the Chinese lockdown, port calls in high-connectivity European ports experienced a sharp and immediate drop. As for the DID model, however, when using a four-week and a three-week span, the coefficient is not significant, suggesting that the drop in port calls recovered quickly and that the propagation effect only lasted for two to three weeks in high-connectivity European ports. The coefficient of the two-week span DID model indicates that the Chinese lockdown policy led to the reduction of port calls by 16.83 on average in high-connectivity European ports.

5.3. *Empirical analysis of low-connectivity ports*

As for low-connectivity ports, after the implementation of lockdowns in China, port calls at these ports did not exhibit any obvious decreasing trend, as evidenced by Fig. 11.

In order to empirically test the effect of China's lockdowns on these ports, we run the DID and RDD-DID models on port calls in low-connectivity ports using two weeks after the implementation of Chinese lockdown policy as the cutoff, considering the average voyage duration of container ships. The results are presented in Table 8. As seen below, none of the coefficients in the DID and RDD-DID models are significant at the 10 % level. Therefore, we conclude that there exists no significant propagation impact on these low-connectivity ports.

As a short summary, we find the coefficient of DID model is significant with four-week span for high-connectivity Asian ports and

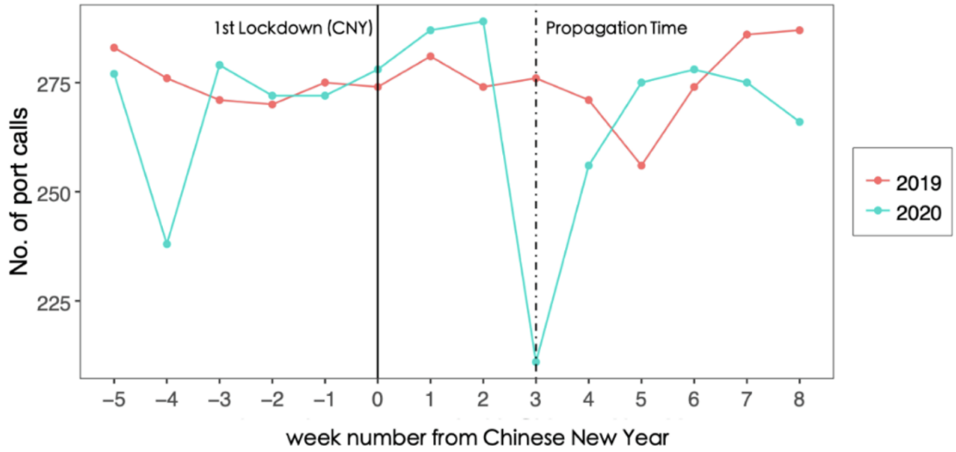

Fig. 10. Total port calls in high-connectivity ports in Europe in 2019 and 2020 around Chinese New Year **Notes: Refer to the notes in** Fig. 8**. The line in Week 3 indicates that the effects of the Chinese lockdown propagated to high-connectivity ports in Europe three weeks later.**

Table 7
DID and RDD-DID estimation results for high-connectivity European ports.

	DID model			RDD-DID model		
Time period	week 1 – week 4	week 0 – week 5	week −1 – week 6	week 1 – week 4	week 0 – week 5	week −1 – week 6
$T_i \cdot Year_i$	−16.8[illegible]***	−9.556*	6.553	−57.222	−61.333***	−43.497***
	(5.75)	(5.03)	(3.93)	(33.46)	(14.38)	(9.82)
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Autoregressive Effect	No	No	No	Yes	Yes	Yes
N	24	36	48	24	36	48
adj. R^2	0.926	0.916	0.928	0.940	0.946	0.949

Notes: Refer to the notes for Table 5. The symbol *, ** and *** indicate significance at 10%, 5% and 1% levels respectively. The policy intervention (cutoff) time is Week 3 (three weeks after the Chinese New Year considering the propagation time) in 2019 and 2020. The treatment group for the DID model and RDD-DID model is four, three, and two weeks before and after the policy intervention date in 2020; the control group is the same period in 2019.

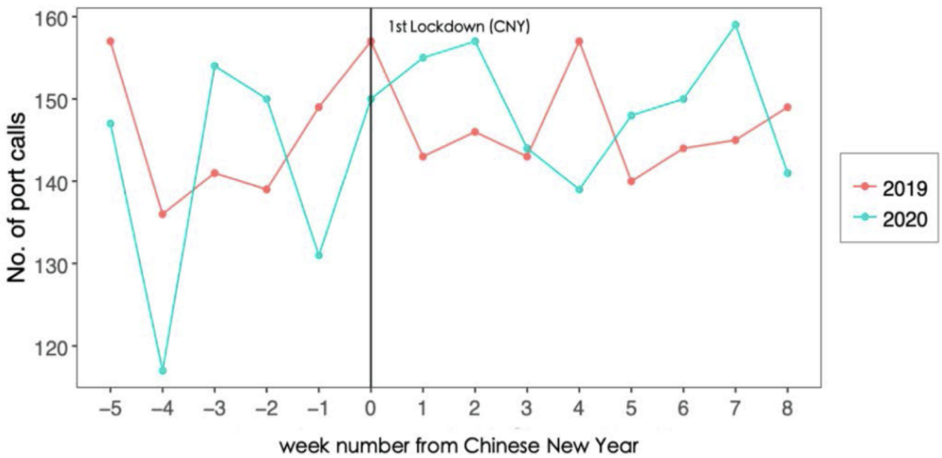

Fig. 11. Total port calls in low-connectivity ports in 2019 and 2020 around Chinese New Year Notes: The week number in this figure represents the relative weeks between the actual week and the week of Chinese New Year week. Week 0 represents the Chinese New Year week, that is Week 6 in 2019 and Week 4 in 2020.

the results of the three RDD-DID models are not significant for these ports. It means that the Chinese lockdown policy leads to a relatively prolonged reduction in port calls in high-connectivity Asian ports. Meanwhile, the coefficients of DID models with two-week span and three-week span and RDD-DID models with three-week span and four-week span are all significant for high-connectivity European port. It indicates that port calls in high-connectivity European ports experienced a sharp and relatively prolonged drop. We find that the coefficients of all DID models are not significant for the low-connectivity ports. It means that there exists no significant propagation effect on these low-connectivity ports.

5.4. Event study and parallel trend tests for indirect lockdown effects

Similar to Section 4.4, we perform a further event study based on Eq. (6) on port calls for all three groups of ports to confirm the validity of the proposed models. The corresponding coefficient plots are presented in Figs. 12-14. As shown in the graphs, from four weeks before each model's cutoff point to the cutoff point, the 95 % confidence intervals for coefficients all include 0, thus indicating that there is no significant difference between the control group (2019 data) and the treatment group (2020 data) before the indirect effect of Chinese lockdown policy kicks in. Therefore, the application for DID and RDD-DID models using a four-week span can be justified.

We acknowledge the estimation bias may exist without controlling some external effects, such as the international trade. However, we believe the effect is minor as the results of event study demonstrate that the port calls in 2019 and 2020 have the same trends without the lockdown announcement.

6. Implications

The results above clearly show that the direct impact of national COVID-19 lockdowns on local port calls varied across regions. The impact on Chinese ports tended, on average, to be strong with no immediate break, the effects on the other ports under investigation seem to have been less severe in magnitude, with an immediate break after the lockdown announcement. The reason for the non-existence of an immediate break in the data for Chinese ports is that, after the sudden outbreak of COVID-19 in China in January 2021, it took time for container lines to realize the severity of the COVID-19 pandemic and adjust their capacity accordingly. On the other hand, container lines appear to have been more responsive during the second wave of national lockdowns, given the experience of the first lockdown wave.

The difference in impact magnitude is mainly because the level of stringency of the lockdown policies varied between China and the rest of the world, and, consequently, the nature of disruptions brought about by those policies is different. As Notteboom et al. (2021) pointed out, the response to COVID-19 has been characterized by several sequential phases from a supply chain perspective. The first phase started from mid-January 2020, with hard lockdown measures announced in China (mandatory stay-at-home orders with few exceptions), causing a major supply shock. Most of the workforce and major industrial production facilities were suddenly affected, resulting in a sharp drop in Chinese port throughput due to the combined effects of reduced export volume and limited workforce in ports.

The second phase started in mid-March 2020 as different lockdown policies were implemented globally, leading to dampened global demand for transoceanic shipping due to lower industrial and consumer confidence. Thus, the disruption in the second phase for the countries studied in this paper was mainly considered as the result of a demand shock. On the one hand, the lockdown policies implemented in the Asian and European countries under investigation were often more moderate, compared to those in China. Thus, production of those regions was not as heavily influenced. On the other hand, demand for most consumer products witnessed a drastic decline except for certain essential goods (e.g., food and medicines). Compared to a supply shock, a demand shock generally happens gradually, as it takes time for individual consumer behaviours to become observable in the aggregate. Considering the differences between lockdown policies and the nature of the shock, container lines adopted slightly different capacity adjustment strategies, which

Table 8
DID and RDD-DID estimation results for low-connectivity ports.

	DID model			RDD-DID model		
Time period	week 0 – week 3	week −1 – week 4	week −2 – week 5	week 0 – week 3	week −1 – week 4	week −2 – week 5
$T_i \cdot Year_i$	1.167	0.778	0.333	11.290	15.016	4.196
	(3.57)	(3.03)	(2.56)	(12.95)	(7.90)	(6.25)
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Autoregressive Effect	No	No	No	Yes	Yes	Yes
N	24	36	48	24	36	48
adj. R^2	0.802	0.805	0.799	0.801	0.824	0.796

Notes: Refer to the notes for Table 5. The symbol *, ** and *** indicate significance at 10%, 5% and 1% levels respectively. The policy intervention (cutoff) time is Week 2 (two weeks after the Chinese New Year considering the propagation time) in 2019 and 2020. The treatment group for the DID model and RDD-DID model is four, three, and two weeks before and after the policy intervention date in 2020; the control group is the same period in 2019.

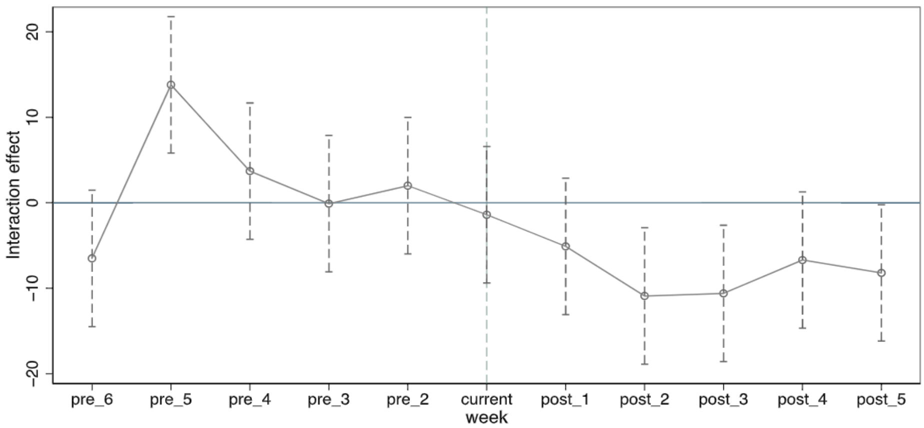

Fig. 12. Coefficient plots for DID and RDD-DID models analyzing the indirect lockdown effect in high-connectivity Asian ports Notes: Based on Eq. (6). Current week refers to the cutoff week, i.e., two weeks after the Chinese lockdown. The last week before the current week (pre_1) is the reference week.

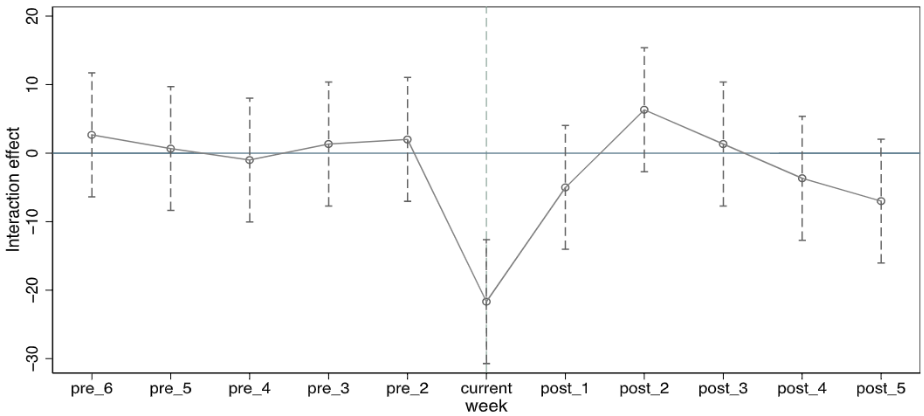

Fig. 13. Coefficient plots for DID and RDD-DID models analyzing the indirect lockdown effect in high-connectivity European ports Notes: Based on Eq. (6). Current week refers to the cutoff week, i.e., three weeks after the Chinese lockdown. The last week ˙ efore the current week (pre_1) is the reference week.

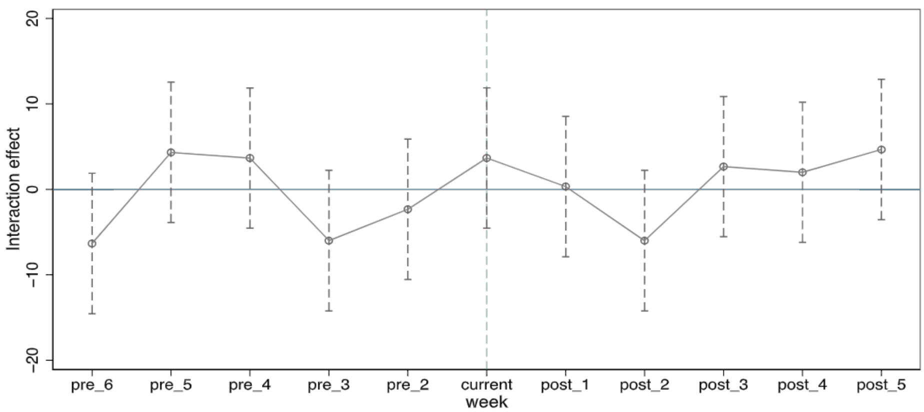

Fig. 14. Coefficient plots for DID and RDD-DID models analyzing the indirect lockdown effects in low-connectivity ports Notes: Refer to the notes for Fig. 12.

was then reflected in changes in the number of port calls. In response to the first wave of lockdowns in China characterized by hard lockdown measures and an induced production shock, container lines reacted (after a slight delay) by significantly reducing the number of vessels calling at Chinese ports. On the other hand, during the second wave of lockdowns characterized by moderate lockdown measures and an induced demand shock, container lines took more prompt yet moderate port call reduction measures due to the reduction in demand. Therefore, we observe a significant drop in port calls with no immediate break at Chinese ports during the first wave of lockdowns in China, while the decrease in port calls at ports affected by the second wave of lockdown is less severe in maginitude, with an immediate break after the lockdown announcement.

The second major implication is that through the interconnected global shipping network, a local shock in one country can propagate to other regions and becomes a global shock. The results presented here show that, in February 2020, port calls at those ports with high levels of connectivity to Chinese ports were significantly affected by Chinese lockdown policies, with a time lag of two to three weeks, depending on the voyage duration of a container ship. The indirect shock of China's lockdown on close neighbours varied slightly from that on highly connected ports in distant regions. There was no significant immediate break in the number of port calls to Asian countries with high connectivity to Chinese ports, while a significant break did exist in European ports with high connectivity to Chinese ports, as evidenced by the RDD-DID model results.

These effects can largely be attributed to the capacity adjustment strategies implemented by container lines, which led to shock propagations throughout the global network. Container lines nowadays are better at capacity management, compared to decades past. In order to cope with declining demand for seaborne transportation amid the COVID-19 outbreak, container lines implemented blank sailings, a term used to describe the situation in which a vessel skips a port call along its route or an entire journey is cancelled. By doing so, container lines could reduce the fleet supply available in the market, thus maintaining a reasonable level of freight rate and vessel utilization. After the lockdown announcement in China at the end of January 2020, container lines reacted by implementing the first wave of blank sailings in February 2020. Specifically, around 36 % of Asia-to-Europe and 28 % of transpacific shipping capacity was withdrawn during that period. Considering the sailing time between China and Europe, these effects were only realized in European ports by the end of Feburary 2020. From April to May 2020, around 11 % of the world's container fleets were idle (Notteboom et al., 2021). The impact of blank sailing was more visible in ports located in the major long-haul trading routes (e.g., from Asia to Europe). The empirical results also confirm that blank sailings due to Chinese lockdown policies had a significant and immediate effect on European ports at the end of Feburary 2020. The immediate impact of blank sailings on Asian ports, however, were not significant due to the substitution phenomenon between Chinese ports and adjacent Asian ports. When port operations were significantly disrupted due to a limited workforce, certain container volumes originally destinated for China were diverted to adjacent ports like Pusan Port which, in a way, compensated for the port call losses due to blank sailings at these adjacent ports. Nonetheless, on average, port calls declined in Asian ports with high connectivity to Chinese ports in Feburary 2020.

The results carry significant implications for policy makers, port operators, and container lines. During a pandemic outbreak, any sudden changes in demand and supply can be quickly reflected in shipping and port activities. Thus, weekly port call statistics can serve as a timely and high-frequency economic indicator that reflects a country's trade flow changes in real time. The impact of various lockdown measures demonstrated here on changes in both local and global port call numbers can provide an additional source of information for policy makers when crafting lockdown policies. Policy makers can make more informed decisions, weighing the different levels of supply and demand shocks brought by lockdown policies with different levels of stringency and their associated immediate and longer-term impacts on trade volume changes. For port operators, understanding the potential impact of local lockdowns on local port call changes help them adjust port operations in a more timely manner. In addition, the lockdown policies in other regions may also affect the port calls of local ports due to the propagation effect, thus port operators need to prepare in advance for the possible port call changes, such as increasing connectivity to regions without shock. From the perspective of container lines, the results presented here can help them understand the effects of blank sailing on the broader global liner network. Furthermore, the findings on the impact of national lockdown policies on local port call numbers provide decision support for container lines to better manage their capacity and adjust their network service arrangement, by considering various lockdown policies in different ports across the globe. To better manage capacity, container lines can adopt parallel service to maintain connectivity through the alliance network and allocate idle vessels to longer routes to maintain higher ship utilization rates.

7. Conclusions

The recent COVID-19 pandemic response highlights the prolonged impact that a similar pandemic outbreak could have on ports and shipping. This paper quantifies both the immediate and longer-term impact of COVID-19 national lockdown policies on port calls in major international container ports using DID and RDD-DID models. The results show that lockdown policies with different levels of stringency can lead to different types of trade shocks and, consequently, different patterns in changes in the numbers of port calls. We further document the existence of significant shock propagation effects. Specifically, we find that the initial lockdown in China induced container lines to take up capacity adjustment strategies so as to cope with a decline in seaborne transport demand. This response in turn created propagation effects from Chinese ports through the global container shipping network to harbors in the rest of the world with a high degree of connectivity to Chinese ports.

The existing studies compare port call data for the same period in 2019 and 2020 to quantify overall changes in port calls caused by COVID-19. Alternatively, we account for the impact from Chinese New Year in our model, so our results eliminate the seasonal changes in port calls around Chinese New Year and can capture the pure changes in port calls in short term due to pandemic lockdowns. Unlike the existing studies that gauge the impact of COVID-19 on certain regions, we also measure the propagation effect of container shipping from China to Europe and the United States referring to their connectivity to Chinese ports.

This research contributes to the literature on the impact of pandemic outbreaks on the transportation sector. First, an analytical framework is proposed to evaluate the impact of national lockdown policies on both local port calls and global port calls through propagation effects. The framework is based on DID and RDD-DID models that can evaluate both the immediate break and the longer-term impact of a policy. Results can be used by policy makers to assess the potential impact of different levels of lockdown policies during pandemic outbreaks on the maritime industry and trade flows in the longer term and on a broader scale. Maritime players can also use the findings to better manage their capacity and cope with changing demand for seaborne transportation. Second, our study also constructs weekly, high-frequency port call data for global ports, which provides a timely picture of changes in shipping activity, as well as trade flow changes. The exact shock progagation mechanism can be further investigated in future research.

This study can be further improved with more available company (shipping line) level data. For example, the shipping cancellation data combined with the change of port call can help to reveal more details of strategies adopted by the shipping line during the lockdown, such as, the preference of shipping lines to ports, the network effect and etc., which have important implications on managing shipping capacity. Integrating our findings from this study with port performance data such as congestion, berthing time, and etc., researchers can also investigate port's resilience ability during shock with appropriate methods, such as dynamical system model and network theory.

Ethical approval

This article contains no study that was performed by any of the authors on human participants.

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CRediT authorship contribution statement

Xiwen Bai: Conceptualization, Writing – original draft, Methodology, Supervision. **Ming Xu:** Investigation, Methodology. **Tingting Han:** Methodology. **Dong Yang:** Conceptualization, Methodology, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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