Cities 148 (2024) 104871

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Impact of China's ECA policies on air pollution in coastal cities: Empirical analysis based on synthetic-DID model

Jia Shi [a,b], Wenjie Han [b,c], Jihong Chen [a,b,c,d,*], Tao Yan [e], Xizhi Chen [b,d], Hao Chen [a,b], Jianghao Xu [b,d], Xiutao Huang [b,d]

[a] *College of Management, Shenzhen University, Shenzhen 518071, China*
[b] *Shenzhen International Maritime Institute, Shenzhen 518083, China*
[c] *College of Transport and Communications, Shanghai Maritime University, Shanghai 201306, China*
[d] *College of Civil and Transportation Engineering, Shenzhen University, Shenzhen 518060, China*
[e] *Shenzhen Pilot Station, Shenzhen 518081, China*

ARTICLE INFO

Keywords:
Ship emission control area
Sulfur dioxide
Particulate matter
Synthetic DID model
Policy effect

ABSTRACT

Emissions from ships stand as one of the principal contributors to air pollution in coastal areas. China has implemented the Domestic Ship Emission Control Area (DECA) policy progressively since 2016 to alleviate sulfur oxide and particulate matter pollution in coastal cities by limiting the sulfur content in marine fuel oil. This study utilizes Synthetic Difference-in-Differences model to construct a counterfactual framework for evaluating the DECA policy effect on air quality of cities in the Yangtze River Delta, the Pearl River Delta, and the Bohai Rim region. Results revealed that DECA policy significantly reduced the urban sulfur dioxide (SO_2) concentrations of YRD, BR, and PRD regions by 9.93 %, 8.64 %, and 7.09 %, respectively. However, the policy's efficacy in restraining fine particulate matter ($PM_{2.5}$) concentrations was found to be non-significant. This study further estimated the dynamic changes in SO_2 concentration in coastal cities of different regions in the DECA coverage. The results showed that the DECA policy generally began to significantly reduce SO_2 concentration levels in the second year after implementation, and with the tightening of the DECA policy, the reduction effect followed a growing-and-then-falling trend. Finally, the paper offers policy recommendations to further reduce ship emissions, aligned with recent emission reduction advancements.

1. Introduction

The widespread use of high-sulfur heavy diesel oil has led to extensive sulfur oxides (SOx) emissions into the air from ship operations in coastal areas, accounting for 4 % to 9 % of the global total anthropogenic sulfur oxides emissions (Anastasopolos et al., 2021; Chen et al., 2019, b; Eyring et al., 2010; Tao et al., 2013; Watson, 2020). In addition, the study by Saraga et al. (2019) showed that ships and ports, as the principal sources of local primary and secondary particulate matter emissions, contributed in excess of 10 % to the regional $PM_{2.5}$ concentration on average. Prolonged exposure to air pollution from ship emissions increases the risk of respiratory and cardiovascular diseases, leading to premature deaths. It is estimated that the global number of premature deaths attributable to ship pollution has increased from 60,000 in 2002 to about 265,000 in 2020, accounting for −0.5 % of the global mortality rate, with the East Asian region being the most severely affected. (Corbett et al., 2007; Liu et al., 2019; Mueller et al., 2023). Experiencing a rapid pace of growth in import and export trade, China has emerged as one of the most dynamic economies in recent years. The shipping industry handles the transportation of >85 % of China's cross-border trade, while the Yangtze River Delta (YRD), Pearl River Delta (PRD), and Bohai Rim (BR) regions serve as the epicenters of these bustling shipping activities. Home to seven of the top 10 ports in terms of global throughput in 2021, these regions represent the most economically developed urban clusters in China and act as critical nodes in the global shipping network (Tan et al., 2021; UNCTAD, 2021). However, coupled with this trend is the latent hazard of escalating ship emission pollution in China. According to statistics, ship pollution has increased the concentration of air pollutants in China's inland cities and coastal cities by about $0.2\mu g/m^3$ and $1.3\mu g/m^3$, respectively (Li et al., 2018; Lv et al., 2018).

Approximately 97 % of the sulfur present in ship fuel undergoes

* Corresponding author at: College of Management, Shenzhen University, Shenzhen 518071, China.
E-mail address: cxjh2004@163.com (J. Chen).

https://doi.org/10.1016/j.cities.2024.104871
Received 10 August 2023; Received in revised form 24 January 2024; Accepted 5 February 2024
Available online 16 February 2024

oxidation to sulfur oxides (SO_X) following high-temperature combustion, subsequently inducing atmospheric chemical reactions that generate inhalable particulate matter (PM) (Gan et al., 2022; Li et al., 2022, b). To effectively control air pollutants such as SO_2 and $PM_{2.5}$ emitted by ships, the International Maritime Organization (IMO) has consecutively approved the establishment of four emission control areas (ECAs), including the Baltic Sea region, the North Sea region, North America, and the United States Caribbean region (IMO, 2016). Furthermore, the latest 78th session of the Marine Environment Protection Committee (MEPC 78) recently ratified the designation of the Mediterranean Sea as an emission control area for SOx and PM. Starting from May 1, 2025, in these waters that connect Europe and Africa, the sulfur limit for ship fuel will be set at 0.10 % m/m. The increasing measures demonstrate a heightened attention to ship emissions, with authorities endeavoring to mitigate air pollution in coastal cities by reducing the sulfur content in ship fuel (Ye et al., 2024). In light of this international initiative, China has subsequently begun to expedite the establishment of its ship emission control areas. The Ministry of Transport of China released in December 2015 the *Implementation Plan in Ship Emission Control Areas of Pearl River Delta, Yangtze River Delta and Bohai Rim Waters (Beijing, Tianjin and Hebei)*, designating the Pearl River Delta (PRD), Yangtze River Delta (YRD), and Bohai Rim (BR) regions as a Domestic Ship Emission Control Area (DECA) aimed at controlling control ship exhaust emissions by enforcing a sulfur content ceiling in ship fuel oil (MOT, 2015). The progressive steps in the implementation of China's emission control areas are outlined in Table 1.

Following the implementation of ECAs over a defined period, the necessity of post-evaluation for air environmental protection policies becomes apparent. These evaluations are pivotal, not only in precisely measuring the efficacy of policies in enhancing air quality and reducing emissions but also in optimizing the allocation of resources (Wan et al., 2021). Additionally, these evaluations are instrumental in enabling the necessary modifications and enhancements of policies, keeping them aligned with the ever-evolving environmental and socio-economic landscapes. Grounded in empirical scientific data, such evaluations are crucial in shaping future policy development and in informing the decision-making process, thereby playing a central role in the strategic planning of environmental governance (Yang et al., 2024; Zhang et al., 2020).

Consequently, this study is dedicated to systematically assessing the impact of China's DECA policy on air pollution control in coastal cities. The Yangtze River Delta (YRD), China's economic powerhouse, is home to some of the world's busiest ports such as Ningbo-Zhoushan and Shanghai. In contrast, the industrialized Bohai Rim (BR) region accommodates approximately 8 % of the Chinese population, while the fast-growing Pearl River Delta (PRD) region is prominent in container and tanker shipping. (Cheng et al., 2007; Li et al., 2022, b). Owing to the diverse transportation structures and geographical environments in the aforementioned regions, independent studies were conducted for each, covering the period from 2005 to 2019. Using the Synthetic DID model, this paper constructed a counterfactual framework for China's ECA policy to examine the following three key issues. (1) whether there was a significant reduction in SO_2 and $PM_{2.5}$ concentration indicators in coastal cities following the implementation of China's DECA policy in 2016, and what contribution the DECA policy made to this; (2) whether there were any regional differences in the effects of the DECA policy, and the reasons behind any variance in the policy's efficacy across different regions; (3) the reasons for the policy's effectiveness or ineffectiveness, as well as recommendations for improving future controls on ship-originating pollution in China.

Table 1
Implementation process of China's DECA policy.

Time	Scope
2016.4.1–2017.1.1	Core ports in Yangtze River Delta
2017.1.1–2018.1.1	All core ports in the control areas
2018.1.1–2018.10.1	All ports in the control areas
2018.10.1–2019.1.1	Including the non-berthing ships in the core ports of the Yangtze River Delta
2019.1.1 and later	All ships in the control areas

A parallel trend test was performed on the sample data to demonstrate the limitations of using traditional DID models for studying these issues, thereby addressing the aforementioned concerns. This study further established a Synthetic DID model, with the annual average concentrations of SO_2 and $PM_{2.5}$ in coastal cities and other provincial capitals in China as dependent variables and socio-economic data and urban meteorological data as control variables, to evaluate the impact of China's ECA policy on reducing urban air pollution. Finally, different testing methods are utilized to verify the reliability of the results. This study makes significant contributions in three areas. Firstly, it provides a quantitative evaluation of China's DECA policy in reducing SO_2 and $PM_{2.5}$ concentrations in coastal cities, supplying scientific backing for policymakers. Secondly, it highlights the regional disparities in the policy's impact and the reasons behind them, offering valuable suggestions for enhancing regional environmental policies. Lastly, the application of the Synthetic DID model introduces a new approach for assessing policy effectiveness in complex environmental contexts, thereby improving research applicability and result reliability. This methodological advancement offers a novel perspective and framework for environmental policy effect assessment.

The remaining part of this article is organized as follows. Section 2 analyzes the mechanism of the effects on air pollutants. Section 3 introduces sample selection, data sources, and model construction. Section 4 interprets the model results and conducts analysis. Section 5 tests the robustness of the empirical results, and Section 6 discusses key issues and puts forward suggestions for future policy improvements and research directions. Section 7 presents a summary of this study.

2. Literature review

Following the establishment of ECAs in North America and Europe, their impact on coastal air quality received extensive scholarly attention. Researchers primarily employed Automatic Identification System (AIS) data to calculate ship emissions and used air quality forecasting and health assessment models to compare the influence of ECAs on coastal air quality and human health burden (Aulinger et al., 2016; Feng et al., 2019; Monteiro et al., 2018; Moore et al., 2018; Panagakos et al., 2014; Tran & Mölders, 2012). Tichavska et al. (2019) utilized the Ship Traffic Emission Assessment Model (STEAM) to demonstrate that sulfur oxide concentrations in non-ECA ports exceeded those in ECA ports by over 16 times. Gong et al. (2018) employed the Global Environmental Multiscale-Air Quality and Air Quality Model to simulate the implementation of ECA policies and assess the atmospheric deposition and dispersion of shipping emissions in the Canadian Arctic and northern regions. Russo et al. (2023) used the WRF-CHIMERE modeling system to quantify the current and future contributions of European shipping to total pollutant concentrations, evidencing the effectiveness of ECAs in controlling the worsening of ship emission pollution. Other researchers utilized monitoring station data, commonly identifying vanadium (V) and nickel (Ni) as tracers of heavy fuel oil emissions from ships, and assessed policy impacts indirectly through changes in atmospheric tracer concentrations (Wang et al., 2021; Anastasopolos et al., 2023; Spada et al., 2018). Kotchenruther (2015) investigated long-term pollutant concentration data from monitoring stations near North American ports using methods like Positive Matrix Factorization (PMF), with most stations indicating significant reductions in $PM_{2.5}$ and SO_2 as ocean-going vessels switched from high to low sulfur fuels. Anastasopolos et al. (2021) found that after implementing the 0.1 % sulfur content regulation, average hourly variations in residual fuel oil (RFO) markers V and Ni in $PM_{2.5}$ at major Canadian port cities ranged from −7 % to −37 %.

As China gradually implemented its DECA, both aforementioned methodologies were similarly employed to evaluate the effect of DECA on mitigating coastal air pollution (Jing et al., 2021; Yu et al., 2021; Wan et al., 2023; Feng et al., 2023; Li et al., 2023). Cheng et al. (2022) observed a significant decrease (16–22 %, $p < 0.01$) in vanadium concentrations in the coastal region of the Yangtze River Delta following the comprehensive implementation of low-sulfur fuel replacement for marine vessels. Chen, Saikawa, et al. (2019) estimated the impact of ship emissions on air quality and human health in China's Pearl River Delta (PRD) region for 2015 and predicted future ship emissions and related impacts both with and without ECA, based on two potential land-based scenarios. However, challenges in accessing complete AIS data and corresponding maritime technical specification data hindered long-term analyses (Jalkanen et al., 2012; Wang et al., 2019). Additionally, calculations of emissions using AIS data typically assumed strict compliance by all vessels with regulations, but in reality, some commercial ships did not switch to low-sulfur fuels before entering ECAs to save costs, potentially leading to overestimations of the policy's effectiveness (Mou, 2019; Peng et al.,). Monitoring station data, on the other hand, could be influenced by surrounding land-based emission sources and location constraints. Recent developments in econometrics have provided new perspectives for evaluating the effectiveness of environmental policies. Zhang et al. (2020) and Wan et al. (2021) utilized Regression Discontinuity (RD) and Difference-in-Differences (DID) models, respectively, to compare air quality changes before and after DECA policy implementation in coastal cities of the Yangtze River Delta and non-pilot cities.

It is noteworthy that RD models can only focus on a single subject for study and fail to quantify some missing variables that might affect the results. While the DID model, an efficient and widely-used method, faces potential obstacles in DECA policy assessment studies, particularly concerning endogeneity issues and satisfying parallel trends assumptions. This is especially relevant considering the pre-existing systematic differences between implementation and control areas, potentially making it challenging to find control subjects most similar to the treatment group in characteristics (Abadie et al., 2015). In contrast, the Synthetic DID model, combining the synthetic control method with traditional DID, offers a more robust approach to assess the impact of China's DECA policy on air quality in coastal cities. This model's advantage lies in eliminating reliance on parallel trends assumptions and allows for the application of individual and temporal weights, better comparing control and treatment groups' dynamic differences after policy implementation.

3. Influencing mechanism analysis

As illustrated in Fig. 1, the principal determinants of urban air pollution can be divided into three key dimensions. Socio-economic factors constitute one dimension, encompassing activities like industrial production, power consumption, and transportation. These activities, entailing the utilization of coal, oil, and other energy sources, result in the release of atmospheric contaminants, including sulfur oxides and particulates. Concurrently, meteorological factors indirectly modulate the mean concentration of pollutants by influencing their dispersion, transmission, and chemical transformation in the atmosphere. Additionally, environmental protection strategies ameliorate air pollution by exerting influence on socio-economic activities. They achieve this through the implementation of stricter emission norms, decommissioning of highly polluting industries, and the promotion of alternative energy sources.

Specifically, in terms of anthropogenic emission factors, previous studies have shown that with the continuous development of industry, the consumption of coal and other energy sources can increase the concentration of pollutants in urban air (Jin & Wu, 2017). Urban electricity generally comes from the conversion of coal, oil, and natural gas, among other energy sources, and the consumption of these energy sources directly impacts the concentration of pollutants such as SO_2 and $PM_{2.5}$ in the urban air (Dinda, 2004). The amount of car ownership and road freight volume can represent how busy the urban traffic is, while vehicle exhaust emissions is also one of the important factors causing urban air pollution (Kassomenos et al., 2009; Mensink et al., 2000). On the other hand, urban greening can effectively reduce the concentration of inhalable particulate matter such as $PM_{2.5}$ and PM_{10} and other pollutants in the air and alleviate urban air pollution. Therefore, the government's annual investment in environmental protection is also an important reference indicator (Brännlund et al., 2007).

Moreover, meteorological factors can affect the dispersion and transport of pollutants through factors such as wind speed, wind direction and atmospheric stability. It can also affect the chemical reaction rate and generation process of pollutants through factors such as temperature and humidity. (Calkins et al., 2016). For instance, rising temperatures may increase the oxidation of SO_2 in the air and the vertical movement activity of the atmosphere, hindering SO_2 accumulation (Ding et al., 2015). Rainfall assists in diluting SO_2 and $PM_{2.5}$ (He et al., 2017). Wind can accelerate the diffusion of pollutants and reduce the concentration of pollutants (Zhang et al., 2015). Atmospheric pressure, by influencing temperature and humidity changes, indirectly impacts pollutant activities such as diffusion and dilution (Chen et al., 2009; Crippa et al., 2013; Gao et al., 2011).

Fig. 1 demonstrates the impact mechanism of socio-economic and meteorological factors on air pollution in coastal cities.

4. Research design and methodology

4.1. Sample selection and data sources

By the end of 2021, Chinese ports were leading globally in terms of cargo throughput, with ports in the Yangtze River Delta (YRD), Pearl

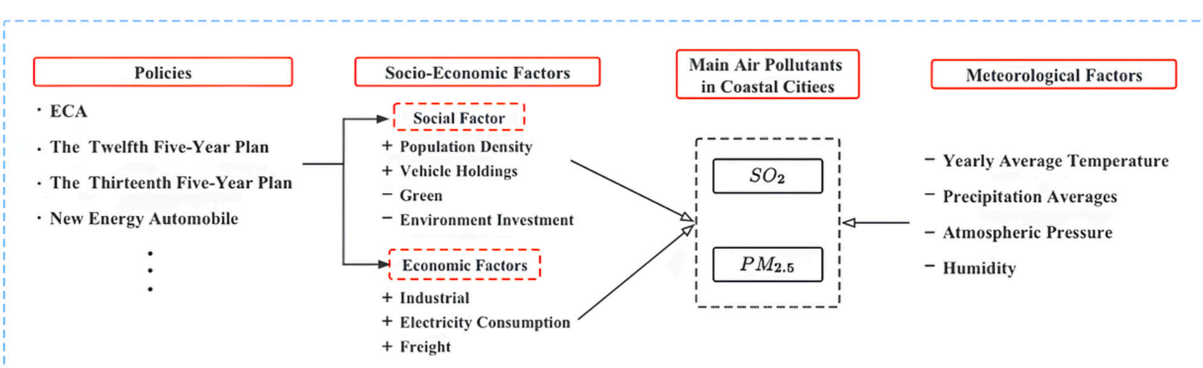


Fig. 1. Mechanisms of factors affecting major air pollutants in coastal cities.

River Delta (PRD), and Bohai Rim (BR) regions contributing to approximately 70 % of the national total. Due to the severe air pollution from ship emissions in these areas, major port cities within the DECA - including Shanghai, Tianjin, Guangzhou, Shenzhen, Zhuhai, Tangshan, and Ningbo - were selected as the treatment group. In light of the economic significance of these coastal cities, 22 Chinese provincial capital cities, unaffected by the DECA policy and with comparably strong socio-economic development, were identified as the control group. Fig. 2 illustrates the geographic distribution of the treatment and control group cities.

Dependent variable: In this study, the annual average concentration of SO_2 and the annual average concentration of $PM_{2.5}$ were selected as the explained variables. Given the challenge of accurately quantifying the impact of the COVID-19 pandemic on ship pollution emissions in 2020 and beyond, the period for data collection was set from 2005 to 2019 (Shi et al., 2023). The annual average concentration data for SO_2 and $PM_{2.5}$ were sourced from the China Statistical Yearbook and the China Environmental Statistical Yearbook. To address outliers and missing values, cross-checks were conducted using the statistical yearbooks of relevant provinces and cities, along with the China Meteorological Data Network (https://data.cma.cn/).

Control variables: Social, economic, and meteorological factors were added to the model as control variables in this study, namely per capita industrial output value (Industrial), per capita environmental governance investment (Investment), road freight volume (Freight), per capita green area (Green), energy consumption per unit of GDP (Energy), population density (DPOP), electricity consumption per 10,000 Renminbi of social output (PEC), car ownership per 10,000 people (PCO), annual average temperature (Temperature), annual average rainfall (Rain), annual average air pressure (hPa), and annual average humidity (HUM). Specifically, the data of socio-economic variables came from the *China City Statistical Yearbook* and *China Environmental Statistical Yearbook* issued by China's National Bureau of Statistics. The data of meteorological variables came from the *China Meteorological Yearbook*, and the missing data was based on the *City Statistical Yearbook* compiled by the China Meteorological Administration.

Both dependent and control variables were logarithmically processed to eliminate the impact of heteroscedasticity. Table S1 (Supporting Information, SI) shows the descriptive statistics of dependent and control variables for YRD, BR, and PRD regions.

4.2. Empirical model

In order to effectively examine the impact of a specific policy, a reliable evaluation model is crucial. The Difference-in-Differences (DID) method is a commonly employed tool. DID eradicates time-invariant unobservable factors by analyzing the changes in the gap between the experimental and control groups, thereby employing a two-way fixed-effect model to circumvent endogeneity. It's important to note, however, that applying the DID model requires an assumption of no systematic differences in SO_2 and $PM_{2.5}$ concentration trends between treatment and control groups in the absence of policy effects. The study opted for the more advanced policy evaluation model, Synthetic Difference-in-Differences (SDID), to mitigate reliance on the parallel trend hypothesis. The econometric regulations of both traditional DID and Synthetic DID models are presented below.

4.2.1. Difference in Differences (DID)

The traditional DID regards the researched public policy as a natural experiment and divides the researched samples into an affected treatment group for policy intervention and an unaffected control group. The main idea is to select an indicator to characterize the policy

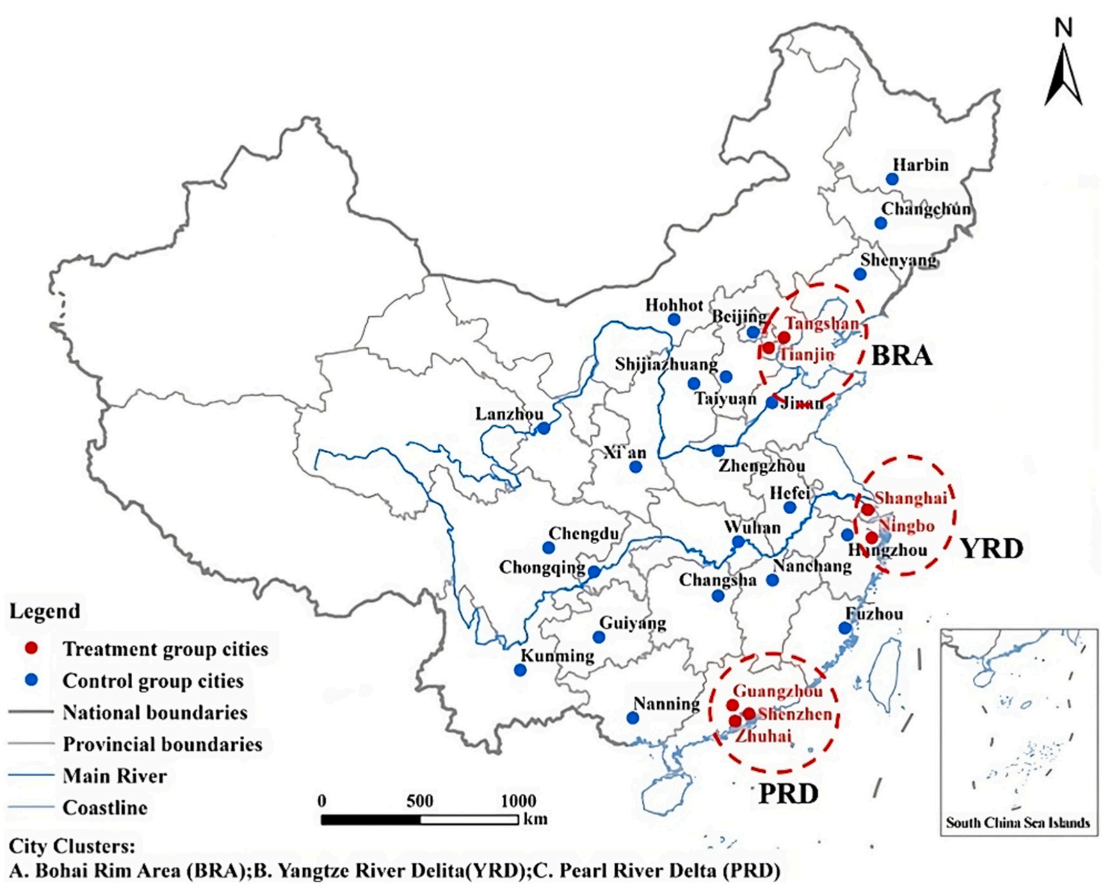


Fig. 2. Geographical distribution of cities in the treatment and control groups.

implementation goal, and perform the first difference on the treatment group and the control group before and after the policy start time point, so as to obtain two groups of variables. Then the second difference calculation is performed between the two groups of variables to eliminate the time increments and finally obtain the net effect of the policy implementation. If the traditional regression equation is used, the sample self-selection and variable endogeneity will arise, and the DID method can address such problems well.

The general expression of the traditional DID model is as follows.

$$Y_{it} = \alpha_0 + \alpha_1 du_{it} + \alpha_2 dt_{it} + \alpha_3 du_{it}dt_{it} + \alpha_4 Z_{it} + \varepsilon_{it} \tag{1}$$

Specifically, the subscript i and t represent the city and the year, respectively; Z represents the array of control variables; ε represents the random error item; Y represents the explained variable, namely the annual average concentrations of SO_2 and $PM_{2.5}$ in the city; du is a dummy variable (for the treatment group city, $du = 1$); dt is a time dummy variable (after the policy takes effect, $dt = 1$); $du*dt$ is a DID interaction item, and its coefficient reflects the degree of change in the net impact of the policy; α_0, α_1, α_2, α_3, and α_4 represent various coefficients, respectively.

Logarithmic processing is performed on the variable data based on the original panel data to eliminate the influence of heteroscedasticity. Therefore, the benchmark model adopted in this study is as follows.

$$lnPM_{2.5it}^{a,b,c} = \alpha_0 + \alpha_1 du_{it}^{a,b,c} + \alpha_2 du_{it}^{a,b,c} + \alpha_3 du_{it}^{a,b,c} dt_{it}^{a,b,c} + \alpha_4 lnZ_{it}^{a,b,c} + \varepsilon_{it}^{a,b,c} \tag{2}$$

$$lnSO_{2it}^{a,b,c} = \alpha_0 + \alpha_1 du_{it}^{a,b,c} + \alpha_2 du_{it}^{a,b,c} + \alpha_3 du_{it}^{a,b,c} dt_{it}^{a,b,c} + \alpha_4 lnZ_{it}^{a,b,c} + \varepsilon_{it}^{a,b,c} \tag{3}$$

Specifically, the superscripts $a, b,$ and c represent three different regions of YRD, PRD, and BR, respectively.

4.2.2. Synthetic Difference-in-Differences

Synthetic DID can apply individual and time weights to the control group objects, and compare the differences between the control and treatment groups before the policy takes effect. As a result, consistency and asymptotic normality can be established even when the estimator or weight is not selected correctly (Arkhangelsky et al., 2021). Most importantly, the unique advantage of Synthetic DID lies in that it can eliminate the reliance on the parallel trend hypothesis. When the experimental data does not meet the hypothesis, a "false" sample that meets the requirements of the parallel trend is fitted based on the original control group for subsequent differential processing, so as to accurately estimate the policy effect.

In line with the DID method, the study involves calculating the SDID estimator $\hat{\tau}^{sdid}$ by employing the SDID method through weighted DID regression. The specific model is as follows.

$$\left(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{argmin} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_i - W_{it}\tau\right)^2 \hat{\omega}^{sdid} \hat{\lambda}_t^{sdid} \right\} \tag{4}$$

To find the unit weight $\hat{\omega}^{sdid}$, it is necessary to solve the optimization problem $\left(\hat{\omega}_0, \hat{\omega}^{sdid}\right) = \underset{\omega_0 \in R, \omega \in \Omega}{argmin} l_{unit}(\omega_0, \omega)$, where

$$l_{unit}(\omega_0, \omega) = \sum_{t=1}^{T_{pre}} \left(\omega_0 + \sum_{i=1}^{N_{co}} \omega_i Y_{it} - \frac{1}{N_{tr}} \sum_{i=N_{co}}^{N} Y_{it}\right)^2 + \zeta^2 T_{pre} \|\omega\|_2^2 \tag{5}$$

$$\Omega = \left\{ \omega \in R_+^N : \sum_{i=1}^{N_{co}} \omega_i = 1, \omega_i = N_{tr}^{-1} \text{ for all } i = N_{co} + 1, \ldots, N \right\} \tag{6}$$

During the time weight calculation $\hat{\lambda}_t^{sdid}$, $\left(\hat{\lambda}_0, \hat{\lambda}^{sdid}\right) = \underset{\lambda_0 \in R, \lambda \in \Delta}{argmin} l_{time}(\lambda_0, \lambda)$ must be solved, where, $l_{time}(\lambda_0, \lambda) = \sum_{i=1}^{N_{co}} \left(\lambda_0 + \sum_{t=1}^{T_{pre}} \lambda_t Y_{it} - \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{it}\right)^2$;

$$\Delta = \left\{ \lambda \in R_+^T : \sum_{t=1}^{T_{pre}} \lambda_t = 1, \lambda_t = T_{post}^{-1} \text{ for all } t = T_{pre} + 1, \ldots, T \right\} \tag{7}$$

In the above equation, $\hat{\tau}^{sdid}$ represents the SO_2 and $PM_{2.5}$ point estimator calculated using SDID; N represents the target city object, T represents the time period, and the result of the unit period is denoted by Y_{it}. $\hat{\omega}^{sdid}$ indicates the unit weight to make the trend of the control group unit before the policy implementation consistent with the trend of the experimental group unit before the policy implementation; $\hat{\lambda}_t^{sdid}$ indicates the time weight to balance the time period before and after the policy implementation. The settings of both groups of weights are based on the data.

4.2.3. Parallel trend test

This article refers to the parallel trend hypothesis testing method (Long & Wan, 2017) and uses the following model for parallel trend testing.

$$lnPM_{2.5it}^{a,b,c} = \sum_{\tau \in (1,2,\ldots,11)} \beta_\tau (pre_\tau * treat_i) + \beta' Z_{i\tau} + \mu_i + \sigma_\tau + \varepsilon_{i\tau} \tag{8}$$

$$lnSO_{2it}^{a,b,c} = \sum_{\tau \in (1,2,\ldots,11)} \beta_\tau (pre_\tau * treat_i) + \beta' Z_{i\tau} + \mu_i + \sigma_\tau + \varepsilon_{i\tau} \tag{9}$$

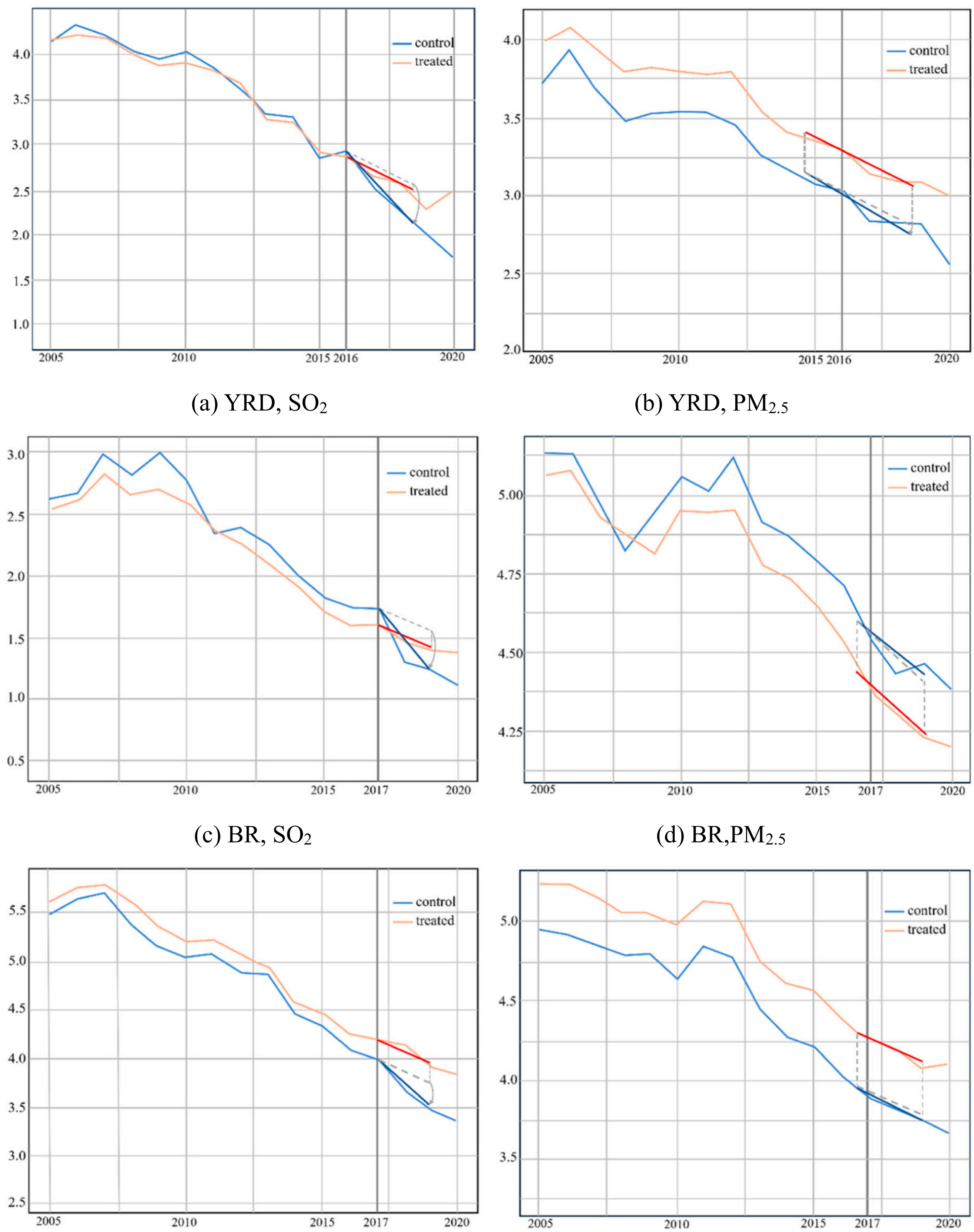
Specifically, $a, b,$ and c represent Yangtze River Delta (YRD), Bohai Rim (BR), and Pearl River Delta (PRD), respectively, and i represents the city. pre_1, pre_2, …, and pre_{11} represent the 1st year to the 11th year before the policy implementation, respectively. If the sample observation value is the data from the 1st year to the 11th year before the DECA policy implementation, then pre_1, pre_2, …, $pre_{11} = 1$, otherwise, the value is 0. It is important to note that the DECA policy was implemented in the YRD region in 2016 and in the BR and PRD regions in 2017. Consequently, the year 2005 was used as the base period for parallel trend testing. $treat_i$ is a dummy variable. If city i is within China's DECA policy implementation scope, then $treat_i = 1$. The coefficients β_1, β_2, β_3 are used here to evaluate whether the treatment group and the control group meet the parallel trend requirements before the policy implementation. When the coefficient is not significant, it indicates that there is no significant difference in the trend between the two groups before the policy intervention.

5. Empirical results and discussions

5.1. Policy effects in different regions

Fig. S1 (in the supplementary information) illustrates parallel trend test results of SO_2 and $PM_{2.5}$ in the YRD, BR, and PRD regions. The interaction coefficients between the treatment and control groups showed significant deviation from 0 in certain years prior to DECA policy enforcement, suggesting non-parallel trends. Consequently, it's unfeasible to accurately assess the policy's effectiveness post-implementation using this approach. Additionally, analyzing samples from the three regions collectively to estimate an average effect could potentially lead to an oversight of regional variations in policy impact, which may arise from factors such as port transportation structures and pollution control measures. Therefore, this study employed the Synthetic DID model to individually estimate the DECA policy effects within the YRD, BR, and PRD regions. The estimation results of the Synthetic DID model are displayed in Fig. 3 and Table 2.

In Fig. 3, the graphs (a), (c), and (e) show the impact on SO_2 levels in the YRD, BR, and PRD regions respectively, and graphs (b), (d), and (f) illustrate the impact on $PM_{2.5}$ levels in these regions. The blue and orange solid lines represent the actual pollutant concentration, while the



(a) YRD, SO_2 (b) YRD, $PM_{2.5}$

(c) BR, SO_2 (d) BR, $PM_{2.5}$

(e) PRD, SO_2 (f) PRD, $PM_{2.5}$

Fig. 3. Estimation results of the Synthetic DID model for DECA policy effects.

dotted line depicts the pollutant level under a counterfactual scenario not influenced by the DECA. The difference between the two represents the average policy effect.

Table 2 and Fig. 3 present the specific results of Synthetic DID policy effects $\hat{\tau}^{sdid}$ in each region. In terms of the annual average concentration of SO_2, China's DECA policy had an inhibitory effect on the SO_2 concentration of coastal cities in the YRD, BR, and PRD regions, with median treatment effects in the three regions of −0.3536, −0.3025, and − 0.2192, respectively. Specifically, the policy led to reductions of about 9.93 %, 8.64 %, and 7.09 % in SO_2 concentration in the YRD, BR, and PRD regions respectively, at the 10 % significance level. In terms of $PM_{2.5}$ concentration, DECA had no statistically significant effect in any of the three regions. The control effect of the DECA policy in the PRD region was slightly lower than that in the other two regions. The possible

Table 2
Estimation results of treatment effects using the Synthetic DID model.

Percentiles					Mean	S.D	Min	Max
10 %	25 %	50 %	75 %	90 %				
(a) YRD: SO_2								
−0.6619***	−0.4637**	−0.3536*	−0.3149	−0.2456	−0.4252**	0.2565	−0.7942	−0.1994
(b) YRD: $PM_{2.5}$								
−0.1414**	−0.0814	−0.0254	−0.0024	−0.0016	−0.0583	0.0849	−0.1814	−0.0010
(c) BR: SO_2								
−0.3977***	−0.3620***	−0.3025***	−0.2979***	−0.2952***	−0.3391***	0.0715	−0.4215	−0.2933
(d) BR: $PM_{2.5}$								
−0.0228	−0.0062	0.0216	0.0483	0.0643	0.0209	0.0544	−0.0339	0.0749
(e) PRD: SO_2								
−0.2609***	−0.2453***	−0.2192***	−0.2174***	−0.2163***	−0.2354***	0.0313	−0.2715	−0.2156
(f) PRD: $PM_{2.5}$								
−0.0751*	−0.0575	−0.0282	−0.0015	0.0146	−0.0299	0.0561	−0.0868	0.0252

Note: The values in parentheses denote the standard errors. ***, **, and * denote that the coefficient is statistically significant at the 1 %, 5 %, and 10 % levels, respectively.

reason is that the PRD region had taken several measures to reduce ship emissions before the DECA policy implementation, such as promoting LNG fuel and shore power (Wan et al., 2019).

Most current studies use the DID, SC, or RD models to estimate a policy's average treatment effect for a certain period after its implementation. To validate the accuracy of the Synthetic DID results, the mean policy effect $\hat{\tau}^{sdid}$ in each region was calculated and then compared with the aforementioned results (Table 2). The results showed that the average SO_2 treatment effects in the YRD, BR, and PRD regions were -0.4252, -0.3391, and -0.2354, respectively, which were almost consistent with the median treatment effect of Synthetic DID. The average $PM_{2.5}$ treatment effects in the three regions were -0.0583, 0.0209, and -0.0299, respectively, confirming again that DECA is ineffective in alleviating $PM_{2.5}$ pollution.

Furthermore, the study investigated the dynamic effects of DECA on SO_2 concentrations in coastal cities within the YRD, BR, and PRD regions (refer to Table 3). Note that core ports in the YRD region began to implement DECA in 2016, and those in BR and PRD regions began to implement DECA in 2017. The percentage refers to the year-on-year change in the annual average concentration of SO_2 after the DECA implementation. It can be observed that the SO_X concentrations in the YRD, BR, and PRD regions all began to drop significantly in the second year of DECA implementation. Within three years after the implementation, the average annual drop was 4.02 %, 14.05 %, and 10.99 %, respectively, in the three regions, indicating an inverted "V" shaped trend.

5.2. Discussions

The effectiveness of China's DECA policy in reducing SO_2 concentrations varies across different port cities, influenced by regional differences in industrial structure and shipping intensity. The Yangtze River Delta, home to some of the world's busiest ports with intense shipping activities, has been identified as a primary source of SO_2 pollution from ship emissions (Feng et al., 2019; Wan et al., 2020). Consequently, the DECA policy effectively reduces sulfur oxide emissions from ships, significantly improving air quality in these port cities. For the Bohai Bay region, despite the rapid growth of industrial production and natural resource extraction, port development has been driven, the predominance of heavy industry in urban areas means that industrial emissions play a more significant role in air pollution, rendering the control of ship emissions less impactful in comparison (Yang et al., 2023). For the Pearl River Delta region, its hot and rainy climate conditions are more conducive to the dispersion and dilution of SO_2 (Krotkov et al., 2016). Early-stage government policies promoting shore power and LNG might also mitigate the effects of DECA. However, research has found that while SO_2 pollution is not severe in the coastal areas of the Pearl River Delta, it is one of the regions in China with the highest concentrations of nitrogen oxides (Chen, Saikawa, et al., 2019; Wang et al., 2023). This indicates the need for differentiated governance strategies tailored to the environmental characteristics, industrial structure, and transportation patterns of each area, thus enhancing the specificity and feasibility of policies.

Table 3
Estimation results of regional SO_2 dynamic changes.

Year	YRD	BR	PRD
	Percentage	Percentage	Percentage
2016	−1.91 %	–	–
2017	−10.59 %	−6.63 %	−3.53 %
2018	−12.68 %	−24.87 %	−6.68 %
2019	−18.24 %	−14.12 %	−6.17 %

Empirical studies have demonstrated that China's DECA policy has significantly lowered SO_2 concentrations in coastal cities. However, the changes in $PM_{2.5}$ concentration in the three regions did not show statistical significance, according to the SDID model results. The contributions of ship emissions to the overall atmospheric $PM_{2.5}$ levels are only a fraction, with the majority of $PM_{2.5}$ pollution originating from other sources like industrial emissions, vehicle exhaust, and agricultural combustion. Unless these emission sources are effectively controlled, the total amount of $PM_{2.5}$ may not significantly change. Furthermore, the generation of particulate matter (PM) emitted by ships isn't solely related to the sulfur content of marine fuels. Carbon in the fuel, as well as other impurities such as metals and other organics, may also generate some solid particles during combustion. Moreover, different types of engines (such as two-stroke or four-stroke engines) and operating conditions (such as low or high load) also impact PM generation. It is suggested that China's domestic ship emission control area (DECA) policy should be based on the existing successful experience in reducing SO_2 pollutant emissions from ships. Future efforts should focus on setting regulatory standards for PM pollutant emissions, promoting the application of ship exhaust gas treatment technologies, and optimizing ship operation modes. These efforts would aim to achieve a systematic and coordinated management and treatment of pollutants discharged from ships (Corbett et al., 2007; Gilbert et al., 2017; Nikopoulou, 2017; Winnes & Fridell, 2010).

Regarding the observed initial increase followed by a decrease in the effectiveness of the DECA policy in curbing SO_2 pollution in port cities, there are likely two contributing factors. Firstly, at the onset of DECA's implementation, the switch to low-sulfur fuel was limited to vessels berthed at core ports, resulting in a lower emission reduction from coastal shipping. This could also be due to the lack of a comprehensive regulatory system initially, where some vessels engaged in opportunistic behavior by using high-sulfur fuel in violation of regulations, thus limiting the effectiveness of DECA in controlling sulfur oxide pollution in its early stages (Peng et al., 2022). Secondly, as DECA's coverage gradually expanded from vessels berthed at core ports to all operating vessels within 12 nautical miles of the coast, there was a significant reduction in SO_X emissions from coastal vessels, leading to a noticeable increase in policy effectiveness. Subsequently, as DECA did not continue to expand its coverage or further tighten sulfur content limits, there was a slight decline in its pollution control effectiveness, which then stabilized.

6. Robustness test

6.1. Comparison of existing research

Currently, the empirical studies on China's emission control areas using econometrics are few in number. In the studies of Wan et al. (2019) and Wan et al. (2021), the authors used the traditional difference-in-differences model to estimate the effect of China's DECA policy, believing that China's DECA policy had an obvious inhibitory effect on SO_2 concentration in the YRD and BR regions, but the effect in the PRD region was not satisfactory. In terms of regional $PM_{2.5}$ concentration, the author believed that the policy had an inhibitory effect in the YRD region, and no effect in the BR and PRD regions. Zhang et al. (2020) used a regression discontinuity model to estimate the effect of China's ECA policy in Shanghai, and the results showed that there was a discontinuity near the cut-off point of the ECA policy, indicating that the DECA policy had a significant positive effect on reducing the SO_2 concentration in the air.

The main reason for the difference between some of the aforementioned results and the findings of this study is believed to lie in the choice of model. The above studies used the traditional DID model and RD model. The former required to find the control object that is the most similar to the relevant characteristics of the treatment group from the control group. However, it is clear that the endogeneity of China's DECA policy and the systematic differences between implementing regions and non-implementing regions before the DECA implementation are the biggest obstacles to using the DID model. The RD model selected a single object as the treatment target and couldn't quantify some missing variables that might affect the results. Besides, the RD model measured the local average effect near the critical value, rather than the overall average effect. As mentioned in the model description section and compared with DID and RD models, Synthetic DID was more advantageous in accurately estimating the effect of China's DECA policy.

6.2. Placebo test

A potential limitation on the Synthetic DID model results is that the effects of all time-invariant urban characteristics on air pollution can be controlled by fixed effects, but some unobservable characteristics may produce different impacts on policy effects over time, and these impacts are beyond the control of the model in this study. Therefore, the placebo test was used to verify the reliability of the results, a robustness test method widely used in related research. (Chetty et al., 2009; Liu et al., 2022). This study first randomly selected all sample cities and re-estimated the effect coefficient, and then randomly selected and re-estimated the implementation year of DECA in the same way. The above steps were repeated 500 times in each region. If most of the effect coefficients of all unobservable features were around 0, it indicated that the placebo test was passed. Fig. 4 showed the placebo test results in the YRD region (results in the BR and PRD regions are shown in Fig. S2 (SI)). The points in Fig. 4 represent the significance of the policy dummy variable and the curve represents the density curve of the coefficients. The placebo test results showed that the SO_2 effect coefficients in a random environment were concentrated around 0, and most of the coefficients were not statistically significant. The results of multiple repetitions of the experiment confirm that the reduction effect of DECA on urban SO_2 concentration is not coincidental, and other unobservable characteristics of the cities do not affect the SO_2 metrics, thus validating the reliability of the Synthetic DID estimation results.

6.3. Variable substitution test

In this section, data robustness was tested by substituting variables. The dependent variables SO_2 and $PM_{2.5}$ in the original panel data were replaced with the 90th percentile concentration ($\mu g/m^3$) of ozone (O3), which was not affected by the DECA policy, to re-evaluate the effect and verify whether the DECA effect was influenced by other factors or air pollutants. The test results are shown in Table 4. The Synthetic DID treatment effect and the average treatment effect of O_3 in all regions didn't show statistical significance, proving that the effect of China's DECA policy on the SO_X emission reduction of YRD, BR, and PRD regions wasn't accidental.

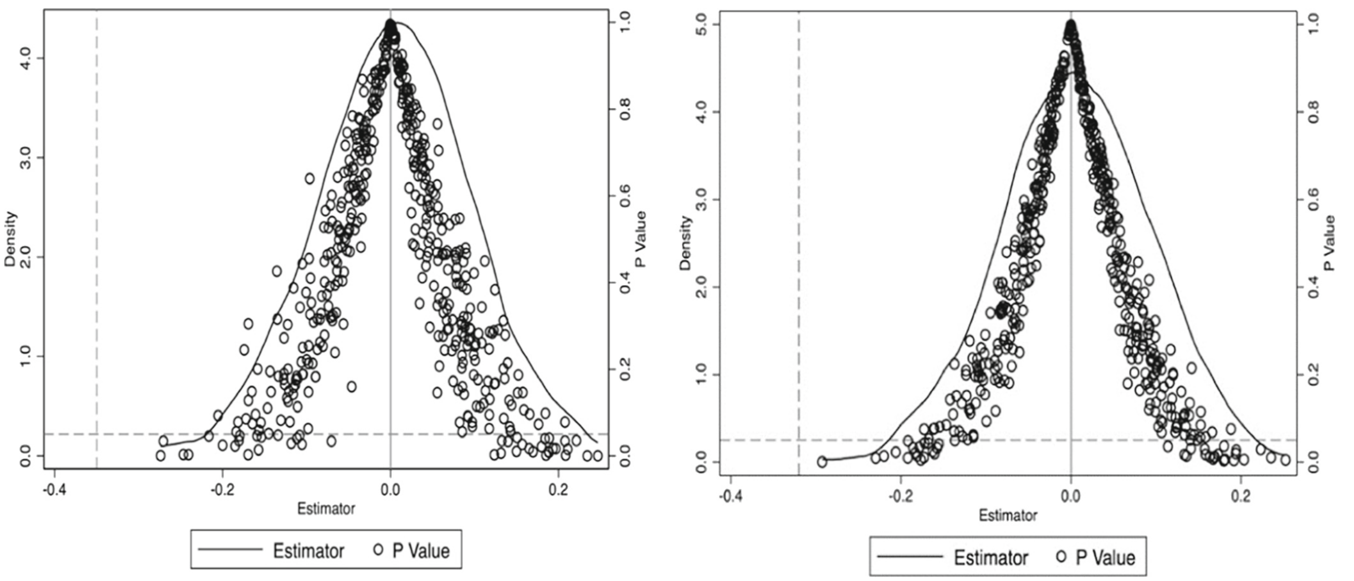
7. Conclusions

This study critically assesses China's Domestic Emission Control Area (DECA) policy, focusing on its impact on reducing SO_2 and $PM_{2.5}$ concentrations. Through a sophisticated Synthetic Difference-in-Differences (DID) model, we have discerned that the DECA policy has led to a substantial reduction in SO_2 levels in the air of coastal cities, with a 9.93 % decrease in the Yangtze River Delta (YRD) at a 10 % significance level, and reductions of 8.64 % and 7.09 % in the Bohai Rim (BR) and Pearl River Delta (PRD) regions, respectively, at a 1 % significance level. These findings underscore the policy's notable success in these regions, particularly in the YRD.

Further, the article delves into the dynamics of SO_2 concentration changes under DECA's influence in different regions. The study reveals that SOX concentrations in the YRD, BR, and PRD regions began to significantly decline in the second year following the policy's implementation, with an average annual drop of 4.02 %, 14.05 %, and 10.99 % respectively, over three years, exhibiting an inverted "V" shaped trend. This pattern is likely linked to the characteristics of China's DECA policy, initially implemented on a trial basis and then expanded gradually.

Despite these successes, the DECA policy showed no statistically significant impact on $PM_{2.5}$ concentrations in the coastal cities of these regions. This variation is attributed to the diversity of PM emission sources, with the majority originating from industrial emissions, vehicle exhaust, and agricultural combustion. Furthermore, the generation of particulate matter from ships is not solely dependent on the sulfur content of marine fuels, but also influenced by factors like the carbon content, metal impurities, engine types, and operating conditions.

Based on our findings, this study proposes three recommendations. Firstly, tighten the sulfur content limits in fuel used by ships within China's coastal Emission Control Areas (ECAs). Post-2020 global sulfur cap, China's DECA policy aligns with international maritime fuel standards, losing its unique impact. Our analysis suggests a decline in DECA's effectiveness in mitigating SO_2 pollution in coastal cities. We recommend lowering the sulfur limit in marine fuel from 0.5 % m/m to



(a) (b)

Fig. 4. Placebo tests (a) and (b) are the results of 500 repetitions of SO_2 based on randomly selected cities and years in the YRD region, respectively.

Table 4
Variable substitution test.

	Percentiles					Mean	S·D
	10 %	25 %	50 %	75 %	90 %		
(a) YRD: O_3 $\hat{\tau}^{sdid}$	−0.1033	−0.0879	0.0049	0.0945	0.1039	0.0016	0.1144
(b) BR: O_3 $\hat{\tau}^{sdid}$	−0.0457*	−0.0333	−0.0127	−0.0019	0.0044	−0.0193	0.0319
(c) PRD: O_3 $\hat{\tau}^{sdid}$	−0.0125	−0.0019	0.0157	0.0425	0.0585	0.0218	0.0447

Note: The values in parentheses denote the standard errors. ***, **, and * denote that the coefficient is statistically significant at the 1 %, 5 %, and 10 % levels, respectively.

0.1 % m/m, aligning with North American and European ECA standards, to enhance coastal air quality protection. Secondly, refine policies controlling shipborne particulate matter (PM) emissions. $PM_{2.5}$, a major health hazard, was not significantly reduced by DECA. Considering sulfur content is only one factor in ship PM emissions, additional measures like mandating shore power for berthed ships and reducing ship speeds in ports should be implemented to curb PM emissions. Finally, tailor environmental policies regionally. Our research indicates limited DECA effectiveness in reducing SO_2 in the Pearl River Delta, but significant nitrogen oxide (NOx) pollution from ships. For regions with controlled SO_2, prioritizing the establishment of Nitrogen Emission Control Areas (NECAs) and mandating exhaust treatment systems to reduce NOx emissions is recommended.

Due to the differences between cities, the factors affecting air pollution in coastal port cities are diverse. Apart from the impact of pollutants discharged by ships, emissions from highly polluting industries and other local socio-economic factors will all affect the final emission reduction performance. Therefore, for fine particulate matter, nitrogen oxides, and other air pollutants that may be affected by the policy, follow-up studies can consider the combined effect of regional policies and use different quantitative methods to detect the possible heterogeneity of the DECA policy for in-depth research. Due to limitations in data availability, this study selected only the largest ports from each of the three major port clusters for analysis. Another future direction could be expanding the scope of research to comprehensively evaluate the effect of the DECA policy on mitigating air pollution in China's coastal cities.

CRediT authorship contribution statement

Jia Shi: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Wenjie Han:** Data curation, Formal analysis, Software, Visualization, Writing – original draft. **Jihong Chen:** Funding acquisition, Project administration, Supervision, Resources. **Tao Yan:** Project administration, Supervision, Validation. **Xizhi Chen:** Investigation, Software. **Hao Chen:** Conceptualization, Data curation, Visualization. **Jianghao Xu:** Data curation, Methodology, Validation. **Xiutao Huang:** Methodology, Resources, Software.

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.

Data availability

The authors do not have permission to share data.

Acknowledgements

This research is supported by the National Social Science Fund of China (20VHQ006).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2024.104871.

References

Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science, 59*(2), 495–510.

Anastasopolos, A. T., Hopke, P. K., Sofowote, U. M., Mooibroek, D., Zhang, J. J., Rouleau, M., & Sundar, N. (2023). Evaluating the effectiveness of low-sulphur marine fuel regulations at improving urban ambient PM2. 5 air quality: Source apportionment of PM2. 5 at Canadian Atlantic and Pacific coast cities with implementation of the North American Emissions Control Area. *Science of the Total Environment, 904*, Article 166965.

Anastasopolos, A. T., Sofowote, U. M., Hopke, P. K., Rouleau, M., Shin, T., Dheri, A., … Sundar, N. (2021). Air quality in Canadian port cities after regulation of low-sulphur marine fuel in the North American Emissions Control Area. *Science of the Total Environment, 791*, Article 147949.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., & Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review, 111*(12), 4088–4118.

Aulinger, A., Matthias, V., Zeretzke, M., Bieser, J., Quante, M., & Backes, A. (2016). The impact of shipping emissions on air pollution in the greater North Sea region–part 1: Current emissions and concentrations. *Atmospheric Chemistry and Physics, 16*(2), 739–758.

Brännlund, R., Ghalwash, T., & Nordström, J. (2007). Increased energy efficiency and the rebound effect: Effects on consumption and emissions. *Energy Economics, 29*(1), 1–17.

Calkins, C., Ge, C., Wang, J., Anderson, M., & Yang, K. (2016). Effects of meteorological conditions on sulfur dioxide air pollution in the North China plain during winters of 2006–2015. *Atmospheric Environment, 147*, 296–309.

Chen, C., Saikawa, E., Comer, B., Mao, X., & Rutherford, D. (2019). Ship emission impacts on air quality and human health in the Pearl River Delta (PRD) region, China, in 2015, with projections to 2030. *GeoHealth, 3*(9), 284–306.

Chen, J., Zheng, T., Garg, A., Xu, L., Li, S., & Fei, Y. (2019). Alternative maritime power application as a green port strategy: Barriers in China. *Journal of Cleaner Production, 213*, 825–837.

Chen, Y., Zhao, C., Zhang, Q., Deng, Z., Huang, M., & Ma, X. (2009). Aircraft study of mountain chimney effect of Beijing, China. *Journal of Geophysical Research: Atmospheres, 114*(D8).

Cheng, K., Chang, Y., Kuang, Y., Ling, Q., Zou, Z., & Huang, R. J. (2022). Multiple-year changes (2014–2018) in particulate vanadium linked to shipping regulations in the world's largest port region. *ACS Earth and Space Chemistry, 6*(2), 415–420.

Cheng, Y. L., Bai, Y. H., Li, J. L., & Liu, Z. R. (2007). Modeling of air quality with a modified two-dimensional Eulerian model: A case study in the Pearl River Delta (PRD) region of China. *Journal of Environmental Sciences, 19*(5), 572–577.

Chetty, R., Looney, A., & Kroft, K. (2009). Salience and taxation: Theory and evidence. *American Economic Review, 99*(4), 1145–1177.

Corbett, J. J., Winebrake, J. J., Green, E. H., Kasibhatla, P., Eyring, V., & Lauer, A. (2007). Mortality from ship emissions: A global assessment. *Environmental Science & Technology, 41*(24), 8512–8518.

Crippa, M., Canonaco, F., Slowik, J. G., El Haddad, I., DeCarlo, P. F., Mohr, C., … Prévôt, A. S. (2013). Primary and secondary organic aerosol origin by combined gas-particle phase source apportionment. *Atmospheric Chemistry and Physics, 13*(16), 8411–8426.

Dinda, S. (2004). Environmental Kuznets curve hypothesis: A survey. *Ecological Economics, 49*(4), 431–455.

Ding, J., van der A, R. J., Mijling, B., Levelt, P. F., & Hao, N. (2015). NO x emission estimates during the 2014 youth Olympic games in Nanjing. *Atmospheric Chemistry and Physics, 15*(16), 9399–9412.

Eyring, V., Isaksen, I. S., Berntsen, T., Collins, W. J., Corbett, J. J., Endresen, O., … Stevenson, D. S. (2010). Transport impacts on atmosphere and climate: Shipping. *Atmospheric Environment, 44*(37), 4735–4771.

Feng, J., Zhang, Y., Li, S., Mao, J., Patton, A. P., Zhou, Y., … Walker, K. (2019). The influence of spatiality on shipping emissions, air quality and potential human exposure in the Yangtze River Delta/Shanghai, China. *Atmospheric Chemistry and Physics, 19*(9), 6167–6183.

Feng, X., Ma, Y., Lin, H., Fu, T. M., Zhang, Y., Wang, X., … Yang, X. (2023). Impacts of ship emissions on air quality in Southern China: Opportunistic insights from the abrupt emission changes in early 2020. *Environmental Science & Technology, 57*(44), 16999–17010.

Gan, L., Che, W., Zhou, M., Zhou, C., Zheng, Y., Zhang, L., … Song, L. (2022). Ship exhaust emission estimation and analysis using automatic identification system data: The west area of Shenzhen port, China, as a case study. *Ocean & Coastal Management, 226*, Article 106245.

Gao, Y., Liu, X., Zhao, C., & Zhang, M. (2011). Emission controls versus meteorological conditions in determining aerosol concentrations in Beijing during the 2008 Olympic Games. *Atmospheric Chemistry and Physics, 11*(23), 12437–12451.

Gilbert, P., Wilson, P., Walsh, C., & Hodgson, P. (2017). The role of material efficiency to reduce CO2 emissions during ship manufacture: A life cycle approach. *Marine Policy, 75*, 227–237.

Gong, W., Beagley, S. R., Cousineau, S., Sassi, M., Munoz-Alpizar, R., Ménard, S., … Holt, R. (2018). Assessing the impact of shipping emissions on air pollution in the Canadian Arctic and northern regions: Current and future modelled scenarios. *Atmospheric Chemistry and Physics, 18*(22), 16653–16687.

He, J., Gong, S., Yu, Y., Yu, L., Wu, L., Mao, H., … Li, R. (2017). Air pollution characteristics and their relation to meteorological conditions during 2014–2015 in major Chinese cities. *Environmental Pollution, 223*, 484–496.

IMO. (2016). International Convention for the Prevention of Pollution from Ships (MARPOL) Accessed July 10, 2023. http://www.imo.org/en/About/Conventions/ListOfConventions/Pages/International-Convention-for-the-Prevention-of-Pollution-from-Ships-(MARPOL).aspx

Jalkanen, J. P., Johansson, L., Kukkonen, J., Brink, A., Kalli, J., & Stipa, T. (2012). Extension of an assessment model of ship traffic exhaust emissions for particulate matter and carbon monoxide. *Atmospheric Chemistry and Physics, 12*(5), 2641–2659.

Jin, C. Y., & Wu, A. B. (2017). An empirical study on the nonlinear effects of industrial economic structure and economic growth on environmental pollution. *China Population, Resources and Environment, 27*, 64–73.

Jing, D., Dai, L., Hu, H., Ding, W., Wang, Y., & Zhou, X. (2021). CO2 emission projection for Arctic shipping: A system dynamics approach. *Ocean & Coastal Management, 205*, Article 105531.

Kassomenos, P., Karakitsios, S., & Pilidis, G. (2009). Daily variation of traffic emissions in Athens, Greece. *International Journal of Environment and Pollution, 36*(1–3), 324–335.

Kotchenruther, R. A. (2015). The effects of marine vessel fuel sulfur regulations on ambient PM2. 5 along the west coast of the US. *Atmospheric Environment, 103*, 121–128.

Krotkov, N. A., McLinden, C. A., Li, C., Lamsal, L. N., Celarier, E. A., Marchenko, S. V., … Streets, D. G. (2016). Aura OMI observations of regional SO 2 and NO 2 pollution changes from 2005 to 2015. *Atmospheric Chemistry and Physics, 16*(7), 4605–4629.

Li, C., Borken-Kleefeld, J., Zheng, J., Yuan, Z., Ou, J., Li, Y., … Xu, Y. (2018). Decadal evolution of ship emissions in China from 2004 to 2013 by using an integrated AIS-based approach and projection to 2040. *Atmospheric Chemistry and Physics, 18*(8), 6075–6093.

Li, C., Zhang, Y., Chen, Z., Wang, X., Yue, M., Liu, J., … Cai, G. (2023). Systematic and dynamic impacts of the COVID-19 pandemic on marine economic development, air pollution and energy consumption: A case study of China's coastal regions. *Ocean & Coastal Management, 244*, Article 106774.

Li, L., Pan, Y., Gao, S., & Yang, W. (2022). An innovative model to design extreme emission control areas (ECAs) by considering ship's evasion strategy. *Ocean & Coastal Management, 227*, Article 106289.

Li, Z., Zhu, Y., Wang, S., Xing, J., Zhao, B., Long, S., … Chen, Y. (2022). Source contribution analysis of PM2. 5 using response surface model and particulate source apportionment technology over the PRD region, China. *Science of the Total Environment, 818*, Article 151757.

Liu, H., Meng, Z. H., Lv, Z. F., Wang, X. T., Deng, F. Y., Liu, Y., … He, K. B. (2019). Emissions and health impacts from global shipping embodied in US–China bilateral trade. *Nature Sustainability, 2*(11), 1027–1033.

Liu, X., Li, Y., Chen, X., & Liu, J. (2022). Evaluation of low carbon city pilot policy effect on carbon abatement in China: An empirical evidence based on time-varying DID model. *Cities, 123*, Article 103582.

Long, X., & Wan, W. (2017). Environmental regulation, corporate profit margins and compliance cost heterogeneity of different scale enterprises. *China Ind. Econ, 6*, 155–174.

Lv, Z., Liu, H., Ying, Q., Fu, M., Meng, Z., Wang, Y., … He, K. (2018). Impacts of shipping emissions on PM 2.5 pollution in China. *Atmospheric Chemistry and Physics, 18*(21), 15811–15824.

Mensink, C., De Vlieger, I., & Nys, J. (2000). An urban transport emission model for the Antwerp area. *Atmospheric Environment, 34*(27), 4595–4602.

Ministry of Transport. (2015). *Implementation plan of ship emission control zones in the PRD, the YRD, and the Bohai Sea Rim (Beijing, Tianjin, and Hebei)*.

Monteiro, A., Russo, M., Gama, C., & Borrego, C. (2018). How important are maritime emissions for the air quality: At European and national scale. *Environmental Pollution, 242*, 565–575.

Moore, T. J., Redfern, J. V., Carver, M., Hastings, S., Adams, J. D., & Silber, G. K. (2018). Exploring ship traffic variability off California. *Ocean & Coastal Management, 163*, 515–527.

Mou, P. (2019). *Annual report on port state control, 2012*.

Mueller, N., Westerby, M., & Nieuwenhuijsen, M. (2023). Health impact assessments of shipping and port-sourced air pollution on a global scale: A scoping literature review. *Environmental Research, 216*, Article 114460.

Nikopoulou, Z. (2017). Incremental costs for reduction of air pollution from ships: A case study on North European emission control area. *Maritime Policy & Management, 44*(8), 1056–1077.

Panagakos, G. P., Stamatopoulou, E. V., & Psaraftis, H. N. (2014). The possible designation of the Mediterranean Sea as a SECA: A case study. *Transportation Research Part D: Transport and Environment, 28*, 74–90.

Peng, X., Li, T., Wu, L., Huang, L., Wen, Y., Zhou, C., … Li, J. (2022). Optimal site selection for the remote-monitoring sulfur content of ship fuels in ports. *Ocean & Coastal Management, 225*, Article 106211.

Russo, M., Carvalho, D., Jalkanen, J. P., & Monteiro, A. (2023). The future impact of shipping emissions on air quality in Europe under climate change. *Atmosphere, 14*(7), 1126.

Saraga, D. E., Tolis, E. I., Maggos, T., Vasilakos, C., & Bartzis, J. G. (2019). PM2. 5 source apportionment for the port city of Thessaloniki, Greece. *Science of the Total Environment, 650*, 2337–2354.

Shi, J., Jiao, Y., Chen, J., & Zhou, S. (2023). Construction of resilience mechanisms in response to container shipping market volatility during the pandemic period: From the perspective of market supervision. *Ocean & Coastal Management, 240*, Article 106642.

Spada, N. J., Cheng, X., White, W. H., & Hyslop, N. P. (2018). Decreasing vanadium footprint of bunker fuel emissions. *Environmental Science & Technology, 52*(20), 11528–11534.

Tan, Z., Liu, H., Shao, S., Liu, J., & Chen, J. (2021). Efficiency of Chinese ECA policy on the coastal emission with evasion behavior of ships. *Ocean & Coastal Management, 208*, Article 105635.

Tao, L., Fairley, D., Kleeman, M. J., & Harley, R. A. (2013). Effects of switching to lower sulfur marine fuel oil on air quality in the San Francisco Bay area. *Environmental Science & Technology, 47*(18), 10171–10178.

Tichavska, M., Tovar, B., Gritsenko, D., Johansson, L., & Jalkanen, J. P. (2019). Air emissions from ships in port: Does regulation make a difference? *Transport Policy, 75*, 128–140.

Tran, T. T., & Mölders, N. (2012). Potential impacts of an emission control area on air quality in Alaska coastal regions. *Atmospheric Environment, 50*, 192–202.

UNCTAD. (2021). Review of maritime transport. https://unctad.org/system/files/official-document/rmt2021_en_0.pdf.

Wan, Z., Cai, Z., Zhao, R., Zhang, Q., Chen, J., & Wang, Z. (2023). Quantifying the air quality impact of ship emissions in China's Bohai Bay. *Marine Pollution Bulletin, 193*, Article 115169.

Wan, Z., Ji, S., Liu, Y., Zhang, Q., Chen, J., & Wang, Q. (2020). Shipping emission inventories in China's Bohai Bay, Yangtze River delta, and Pearl River delta in 2018. *Marine Pollution Bulletin, 151*, Article 110882.

Wan, Z., Zhou, X., Zhang, Q., & Chen, J. (2021). Influence of sulfur emission control areas on particulate matter emission: A difference-in-differences analysis. *Marine Policy, 130*, Article 104584.

Wang, G., Deng, X. J., Wang, C. L., Zhang, X. Y., Yan, H. H., Chen, D. H., & Guo, T. (2019). A new and detailed assessment of the spatiotemporal characteristics of the SO2 distribution in the pearl river delta region of China and the effect of SO2 emission reduction. *Aerosol and Air Quality Research, 19*(8), 1900–1910.

Wang, R., Wang, L., Sun, J., Zhang, L., Li, Y., Li, K., … Wang, Y. (2023). Maximizing ozone control by spatial sensitivity-oriented mitigation strategy in the Pearl River Delta Region, China. *Science of The Total Environment, 905*, Article 166987.

Wang, X., Yi, W., Lv, Z., Deng, F., Zheng, S., Xu, H., & He, K. (2021). Ship emissions around China under gradually promoted control policies from 2016 to 2019. *Atmospheric Chemistry and Physics, 21*(18), 13835–13853.

Watson, S. M. (2020). Greenhouse gas emissions from offshore oil and gas activities—Relevance of the Paris Agreement, Law of the Sea, and Regional Seas Programmes. *Ocean & Coastal Management, 185*, Article 104942.

Winnes, H., & Fridell, E. (2010). Emissions of NOX and particles from manoeuvring ships. *Transportation Research Part D: Transport and Environment, 15*, 204–211.

Yang, X., Gao, Y., Li, Q., He, J., Liu, Y., Duan, K., & Ji, D. (2023). Maritime and coastal observations of ambient PM2. 5 and its elemental compositions in the Bohai Bay of China during spring and summer: Levels, spatial distribution and source apportionment. *Atmospheric Research, 106897*.

Yang, Z., Lau, Y. Y., & Lei, Z. (2024). Analysis of pollution prevention performance of vessels in Southeast Asia: Implications towards vessel emission control and reduction. *Ocean & Coastal Management, 248*, Article 106942.

Ye, J., Chen, J., Shi, J., Jiang, X., & Zhou, S. (2024). Novel synergy mechanism for carbon emissions abatement in shipping decarbonization. *Transportation Research Part D: Transport and Environment, 127*, Article 104059.

Yu, G., Zhang, Y., Yang, F., He, B., Zhang, C., Zou, Z., … Chen, J. (2021). Dynamic Ni/V ratio in the ship-emitted particles driven by multiphase fuel oil regulations in coastal China. *Environmental Science & Technology, 55*(22), 15031–15039.

Zhang, H., Wang, Y., Hu, J., Ying, Q., & Hu, X. M. (2015). Relationships between meteorological parameters and criteria air pollutants in three megacities in China. *Environmental Research, 140*, 242–254.

Zhang, Q., Zheng, Z., Wan, Z., & Zheng, S. (2020). Does emission control area policy reduce sulfur dioxides concentration in Shanghai? *Transportation Research Part D: Transport and Environment, 81*, 74–102289.