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Research article

China's Coal Ban policy: Clearing skies, challenging growth

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ABSTRACT

China's Coal Ban policy is one of the world's most extensive and ambitious programs designed to mitigate air pollution. However, the effects of this policy on the environment and the economy remain unknown. This study examines the impacts of the Coal Ban policy, which has been implemented in 28 cities in Beijing and its adjacent provinces, on air quality and economic growth. Based on a panel dataset spanning 138 cities between 2010 and 2019, the policy was found to have reduced atmospheric particulate matter with a diameter less than or equal to 2.5 μm ($PM_{2.5}$) by 4.74 $\mu g/m^3$ in the 28 cities, but have also reduced per capita gross domestic product (GDP) by 5.8%. Further, the policy has also produced spatial spillover effects. In cities near the 28 cities, the policy has reduced $PM_{2.5}$ by 4.40 $\mu g/m^3$ and per capita GDP by 0.9%. Robustness tests corroborated the reliability of the conclusions. These findings underscore the importance of fostering a harmonious relationship between efforts to mitigate air pollution and the pursuit of economic growth objectives.

1. Introduction

The excessive burning of fossil fuels is a major contributor to air pollution (Shi et al., 2020; Thurston, 2022), which has resulted in serious socioeconomic consequences such as mortality and poverty (Cohen et al., 2017; World Bank, 2016). Clean air policies have been implemented to mitigate air pollution across the world (World Health Organization, 2018). Extensive studies have been conducted to evaluate the impacts of these policies. While some studies have detected the effectiveness of clean air policies in reducing air pollution such as particulate matter with a diameter less than or equal to 2.5 μm ($PM_{2.5}$), sulfur dioxide (SO_2) and nitrogen oxides (Harrington et al., 2012; Zhao et al., 2020; Zheng et al., 2018), others have found that the policies failed to improve air quality (Begum and Hopke, 2018; Gould et al., 2018; Peng et al., 2020). Therefore, the effectiveness of these policies is still an open question. In addition, past studies have predominantly focused on assessing the effect of clean air policies within the targeted regions, the spatial spillover effects of the policies on the surrounding areas have often been neglected.

Clean air policies that intend to reduce pollution emissions can pose socioeconomic challenges (Becker, 2005). However, only a few studies have explored the economic effects of the policies. For example, Greenstone et al. (2012) and Zhu and Xu (2022) found that clean air policies reduced the production efficiency of polluting enterprises. Li et al. (2019) showed that air pollution abatement policies led to a 1.4%–2.3% loss in the annual gross domestic product (GDP). However, studies often do not integrate economic and environmental effects to comprehensively assess the impacts of clean air policies.

Previous research has traditionally assessed policy effectiveness by comparing alterations in air pollutant concentrations before and after the policy implementation (Wang et al., 2020; Zhang et al., 2019; Zhao et al., 2020; Zheng et al., 2018). However, this approach is susceptible to several methodological challenges, including omitted variable bias, selection bias, endogeneity, and counterfactual problem, which can compromise the reliability of findings. Moreover, the approach in previous studies cannot detect potential spillover effects. Compared to the previous approach, the Propensity Score Matching and Difference-in-Differences (PSM-DID) model treats policy as a quasi-natural experiment that compares changes between the treatment group and the control group both before and after the policy implementation. This method can provide more accurate estimation of policy effects (Yu et al., 2021). In addition, the spatial lag model and Difference-in-Differences model (SLM-DID) can capture potential spillover effects of policy implementation.

The air pollution in the Beijing-Tianjin-Hebei region of China is among the most severe of major metropolitan regions in the world

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(IQAir, 2018), which has resulted in the implementation of several clean air policies. Between 2010 and 2016, the government released a few regulations to encourage residents and businesses to transition from coal to cleaner energy sources such as natural gas or electricity (Beijing Municipal Ecology and Environment Bureau, 2015; Ministry of Ecology and Environment, 2016; State Council, 2013). However, no apparent effects of these policies have been detected (Yu et al., 2021). In order to improve the effectiveness of the effort in mitigating air pollution, the government has released another set of regulations to strengthen the enforcement of replacing coal with cleaner energy sources strictly (Ministry of Ecology and Environment, 2017a, b; Ministry of Finance, 2017). In this paper, the set of regulations that have been implemented since 2017 are referred to as the "Coal Ban policy" hereafter.

The region where the Coal Ban policy has been implemented contains a total of 28 cities. In addition to Beijing and Tianjin, these cities are located in Hebei, Shandong, Shanxi and Henan provinces. An annual investment of 15.8 billion yuan (presently, 1 USD = 6.9 yuan) has been invested by the central government for actions such as adopting clean heating project, eliminating all of the small coal-fired boilers, and reducing coal consumption. Studies on the Coal Ban policy have found significant reduction in the $PM_{2.5}$ concentrations since the implementation of the policy (Meng et al., 2019; Wang and Zheng, 2019). However, these studies do not concurrently evaluate the environmental and economic impacts of the policy. In addition, no study has tested the spatial spillover effects of the policy on the surrounding areas.

The goal of this paper is to accurately estimate the magnitude of effects of the Coal Ban policy on air quality and economic growth both within and beyond the area where the policy is implemented. Based on a dataset encompassing 138 prefecture-level cities in China from 2010 to 2019, this study used the PSM-DID and SLM-DID models to evaluate the policy's effects. This assessment promises a deeper understanding of the Coal Ban policy's multifaceted consequences and provides policymakers with a more precise foundation for decision-making.

2. Materials and methods

2.1. Data

The data used in this study encompassed information from 138 cities over ten years spanning from 2010 to 2019. Specifically, the average annual concentrations of $PM_{2.5}$ were sourced from global satellite observations, which were made available through the Socioeconomic Data and Applications Center at Columbia University (Hammer et al., 2022). These observations provided comprehensive data on annual global surface of $PM_{2.5}$ concentrations, measured in micrograms per cubic meter, covering the period from 1998 to 2019. In order to enhance the reliability of the analysis, $PM_{2.5}$ concentrations that were collected by the ground sensors between 2014 and 2019 were also obtained from the China National Environmental Monitoring Centre (2022) . The per capita GDP and other indicators were collected from China's National Bureau of Statistics (2022) . Furthermore, the spatial distribution of 138 cities included in the study was derived from China's Resource and Environment Science and Data Center (Xu, 2023).

2.2. Variables

2.2.1. Dependent variables

In this study, two dependent variables were considered, each representing a critical aspect of analysis: air pollution and economic growth. $PM_{2.5}$ concentrations, a key component of air pollution known to significantly contribute to health issues and disease burden, were employed as an indicator of air pollution (Qu et al., 2020; Wang et al., 2020). And per capita GDP, a fundamental indicator of the economic wealth and development of a country or region, was chosen as a proxy for economic growth (Ding et al., 2019a; Jia et al., 2017). The study employed $PM_{2.5}$ concentrations and per capita GDP to analyze the effects of the Coal Ban policy on both air quality and economic growth.

2.2.2. Independent variables

The independent variable is the Coal Ban policy, which is operationalized by creating an interaction term denoted as *treated* × *time*. This interaction term is constructed by the city dummy variable and time dummy variable. The treatment group that has implemented the policy consists of 28 specific cities, namely Beijing, Tianjin, Shijiazhuang, Tangshan, Baoding, Langfang, Cangzhou, Hengshui, Handan, Xingtai, Zhengzhou, Xinxiang, Hebi, Anyang, Jiaozuo, Puyang, Kaifeng, Jinan, Zibo, Liaocheng, Dezhou, Binzhou, Jining, Heze, Taiyuan, Yangquan, Changzhi and Jincheng. The control group that has not implemented the policy comprises the 110 cities located in Hebei, Henan, Shanxi, Shandong, Shaanxi, Inner Mongolia, Jilin, Liaoning, Anhui, Hubei, and Jiangsu provinces. The treatment and control groups' spatial distribution was shown in Fig. 1.

2.2.3. Control variables

Based upon previous studies (Ding et al., 2019a, 2019b; Yu et al., 2021), the control variables selected are urbanization level, population density, the share of industrial production in the GDP, the green coverage rate, the logarithm of educational investment, and the logarithm of foreign direct investment.

Table 1 shows the definitions and statistics of these variables in detail, including measures of mean and standard deviation. The mean value of per capital GDP is 51,710 yuan with a standard deviation of 29.78. The mean value of $PM_{2.5}$ is 53.76 μg/m^3 with a standard deviation of 17.73. In comparison, the mean value of $PM_{2.5}$_station is 55.33 μg/m^3 with a standard deviation of 16.93, suggesting that the $PM_{2.5}$ concentrations from the two data sources are similar.

2.3. Difference-in-differences (DID)

DID model, initially proposed by Ashenfelter and Card (1985), is a widely adopted approach for assessing the effect of policies. The fundamental concept behind DID is to calculate the treatment effect of a policy by comparing the difference in outcomes between the treatment group (i.e., cities that the policy affected) and the control group (i.e., cities that the policy did not affect) both before and after the policy's implementation. The method is as follows:

$$Y_{it} = \beta_0 + \beta_1 treated_i \times time_t + \beta \sum X_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{1}$$

in which i and t are the i-th city and the t-th year, respectively. Y_{it} is a dependent variable that represents $PM_{2.5}$ concentrations or the logarithm of per capita GDP (lnPGDP), *treated* = 1 for the treatment group, *treated* = 0 for the control group, *time* = 0 denotes before 2017, and *time* = 1 denotes after 2017. X_{it} is a set of control variables. β_1 is the Coal Ban policy's net effect on $PM_{2.5}$ or per capita GDP, μ_i is the individual fixed effect, θ_t is the time fixed effect, and ε is the random disturbance term.

2.4. Propensity Score Matching and Difference-in-differences (PSM-DID)

An important premise of DID methodology is the absence of a systematic difference in the trend of dependent variables between the treatment and control groups before the implementation of the Coal Ban policy. To rigorously satisfy this premise, this study employed the PSM-DID method proposed and developed by Heckman et al. (1997, 1998). Its basic concept is to identify and select cities within the control group that exhibit similar characteristics to those in the treatment group. This process ensures a more precise and balanced comparison between the treatment and control groups.

The specific steps of PSM-DID are as follows. First, logit regression is used to estimate propensity scores based upon the "*treated*" and covariables, and second, matching based upon propensity scores. For the data from one year before the policy implementation, this paper used the

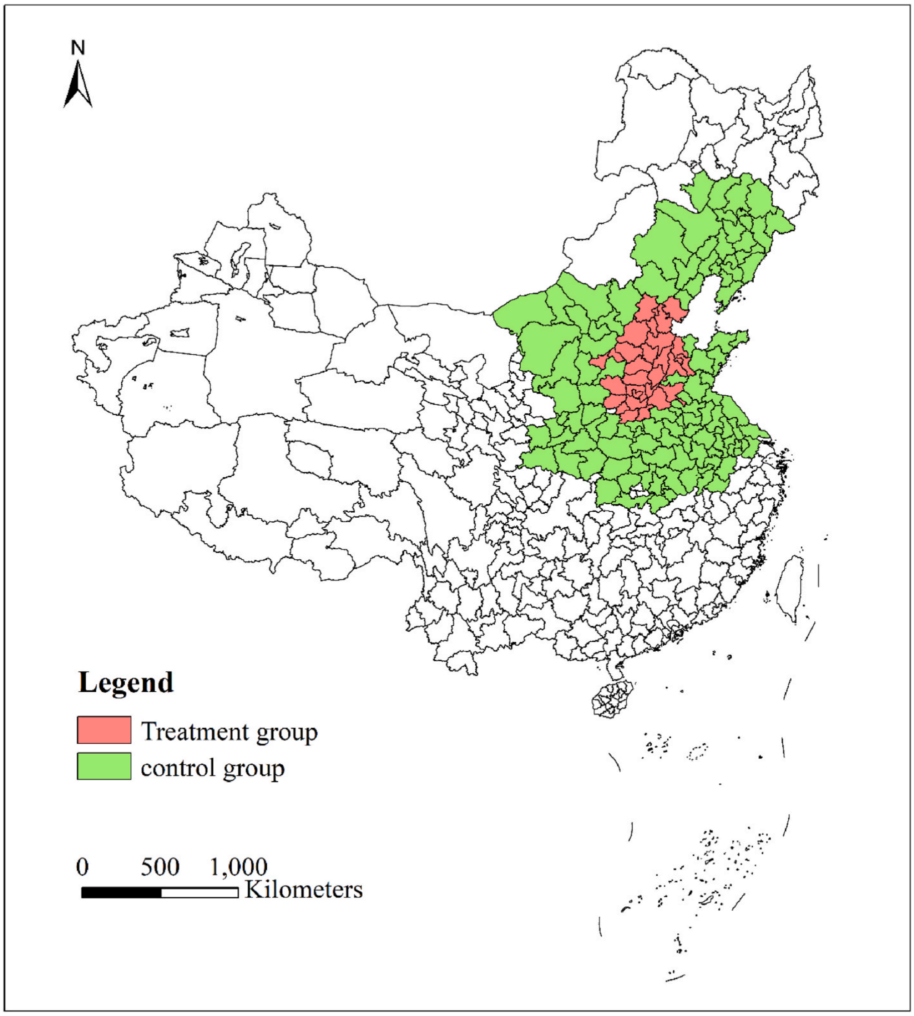

Fig. 1. Location distribution of study area.

nearest neighbor matching method with a matching radius of 0.05 and a ratio of 1:1 (matching a control group sample with each treatment group sample). Finally, after achieving matched datasets, the DID model is used to estimate the average effect of the policy.

2.5. Spatial lag model and difference-in-differences (SLM-DID)

Spatial DID is the combination of the spatial econometric model and the DID model (Dubé et al., 2014). It assumes that changes in one region not only impact the outcome variables within that region but also spill over to nearby regions, thereby acknowledging both direct and spatial spillover effects of the policy. The three most common spatial econometric models are the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM) (Abbreviations can also be seen in Table 6). The SEM is typically chosen when the local interactions are realized through the model's error term. The SLM is used when the independent variable effects on other regions through spatial conduction. The SDM is preferred when the variation of the independent variable affects the dependent variable in both local and adjacent areas.

Based on Xu et al. (2021) and Wang et al. (2022), the process for selecting the suitable spatial econometric model involves the following steps. First, the Moran's I test assesses spatial autocorrelation in variables of interest, such as $PM_{2.5}$ or per capita GDP. If both variables have significant Moran's I values, they exhibit spatially autocorrelation. Second, the Lagrange Multiplier test is used to assess whether the spatial econometric model is necessary. If the Lagrange Multiplier test rejects the null hypothesis that the spatial error term and lag term are not spatially dependent, then the spatial econometric model is warranted. Finally, the Likelihood Ratio (LR) and the Wald tests are used to decide which specific spatial econometric model to employ. The idea behind the two tests is to assume that the paper adopts SDM and then determine whether SDM is transformed into SEM or SLM. If the results support the null hypothesis that the SDM can be transformed into either the SEM or SLM, then the transformed model is used. In this study, it was found that the SLM-DID model was most appropriate for the analysis (described in the results section). Building upon Lin et al. (2020) and Yu et al. (2021), the SLM-DID model takes the following form:

$$Y_{it} = \alpha_0 + \rho W_{ij} Y_{jt} + \alpha_1 treated_i \times time_t + \alpha \sum X_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{2}$$

$$W_{ij} = \begin{cases} \dfrac{1}{d_{ij}} & i \neq j \\ 0 & i = j \end{cases} \tag{3}$$

in which i and j are the i-th city and the j-th city, respectively. d_{ij} is the geographic distance between city i and city j calculated using their latitude and longitude. The reciprocal of the distance between two cities is used as the spatial weight matrix in this paper, denoted as W_{ij}. ρ is the coefficient of spatial lag.

Because of spatial autocorrelation, using traditional ordinary least squares (OLS) to estimate the SLM will lead to biased and inconsistent results (Anselin, 1988). To overcome this problem, Elhorst (2010) used

Table 1
Descriptive statistics for all variables.

Variables	Variable description	Mean	SD
Dependent variables			
$PM_{2.5}$	Annual average $PM_{2.5}$ concentration ($\mu g/m^3$) from the Socioeconomic Data and Applications Center	53.76	17.73
$PM_{2.5}$_station	Annual average $PM_{2.5}$ concentration ($\mu g/m^3$) from the China National Environmental Monitoring Centre	55.33	16.93
Per capital GDP	per capita gross regional product (1000 yuan)	51.71	29.78
GDP	Gross regional product (billion yuan)	261.35	314.88
SO_2	Total industrial sulfur dioxide emissions (1000 tons)	49.51	50.20
Independent variables			
Time	Time dummy variable	0.30	0.46
Treated	City dummy variable	0.20	0.40
Control variables			
Urbanization level	Urban Resident Population/ Resident Population (%)	55.44	12.81
the share of industrial production in the GDP	The industrial production value/ GDP (%)	48.31	9.40
Population density	Permanent Population/Urban land area (100 people/km^2)	4.77	3.17
Green coverage rate	Urban Built-up Area green Space/ Urban built-up area*100 (%)	39.59	5.08
Educational investment	Government expenditure on education (billion yuan)	6.86	8.43
Foreign direct investment	Foreign direct investment (billion yuan)	6.70	13.69

Table 2
PSM-DID results of policy effect on $PM_{2.5}$ and per capita GDP.

Variables	$PM_{2.5}$	lnPGDP
Treated*time	−4.74***	−0.06***
	(1.02)	(0.02)
Urbanization level	−0.24**	0.02***
	(0.12)	(0.003)
Share of industrial production in the GDP	0.20**	0.01***
	(0.09)	(0.001)
Population density	−1.08	–
	(0.81)	
lnPGDP	2.44	–
	(2.65)	
Green coverage rate	−0.11	–
	(0.08)	
Educational investment	–	0.17***
		(0.05)
Foreign direct investment	–	0.02*
		(0.01)
Constant	58.72**	8.14***
	(25.34)	(0.23)
Time fixed effect	Yes	Yes
Individual fixed effect	Yes	Yes
R^2	0.85	0.86
N	370	470

Note: Data in parentheses are robust standard errors. *, **, and *** are significant at the level of 10%, 5%, and 1%, respectively.

Table 3
Moran's I test for $PM_{2.5}$ and per capita GDP.

$PM_{2.5}$			lnPGDP		
Year	Moran's I	Z score	Year	Moran's I	Z score
2015	0.33***	11.08	2015	0.07***	2.47
2016	0.33***	11.05	2016	0.07***	2.70
2017	0.33***	11.36	2017	0.07***	2.60
2018	0.30***	10.21	2018	0.06**	2.20
2019	0.34***	11.48	2019	0.05**	1.80

Note: ** and *** are significant at the level of 5% and 1%, respectively.

Table 4
SLM-DID results of policy effect on $PM_{2.5}$ and per capita GDP.

Variable	$PM_{2.5}$	lnPGDP
Treated*time	−6.26***	−0.03**
	(0.61)	(0.01)
ρ	0.43***	0.23***
	(0.03)	(0.03)
Control variables	Yes	Yes
Individual effect	Yes	Yes
Time effect	Yes	Yes
Direct effect	−6.47***	−0.03**
	(0.64)	(0.01)
Indirect effect	−4.40***	−0.01**
	(0.66)	(0.004)
Total effect	−10.87***	−0.04**
	(1.14)	(0.02)
LM (lag)	358.36***	260.77***
Robust LM (lag)	29.05***	0.38
LM (error)	511.24***	719.25***
Robust LM (error)	181.93***	458.87***
Observations	1380	1380

Note: Data in parentheses are robust standard errors. ** and *** are significant at the level of 5% and 1%, respectively. The positive spatial autocorrelation coefficient (ρ) ($p < 0.01$) confirmed that both $PM_{2.5}$ and per capita GDP exhibited spatial effects.

Table 5
Spatial econometric model diagnosis.

	$PM_{2.5}$			lnPGDP		
	SEM-DID	SDM-DID	SLM-DID	SEM-DID	SDM-DID	SLM-DID
Wald test	Wald Chi 2 = 12.72**			Wald Chi 2 = 20.57***		
		W Wald Chi 2 = 6.69			Wald Chi 2 = 5.43	
LR test	LR Chi 2 = 12.67**			LR Chi 2 = 20.67***		
		LR Chi 2 = 6.65			LR Chi 2 = 5.41	

Note: ** and *** are significant at the level of 5% and 1%, respectively.

Table 6
Interpretation of acronyms.

Abbreviation	Meaning
DID	Difference-in-Differences
GDP	Gross domestic product
lnPGDP	The logarithm of per capita GDP
LR	Likelihood Ratio
$PM_{2.5}$	Particulate matter with a diameter less than or equal to 2.5 μm
PSM	Propensity Score Matching
SDM	Spatial Durbin model
SEM	Spatial error model
SLM	Spatial lag model
SO_2	Sulfur dioxide

the maximum likelihood estimation method to conduct partial differential decomposition of the SLM-DID's spatial effect. The direct effects represent the policy's effect on the targeted region's $PM_{2.5}$ and per capita GDP. The indirect effects are spatial spillover effects, which represent the policy's effect on the surrounding cities' $PM_{2.5}$ and per capita GDP. The total effects are the sum of the direct and indirect effects.

3. Results

3.1. Balancing variables after PSM

Most of the samples fall within the shared range of propensity scores with $PM_{2.5}$ and per capita GDP as outcome variables between the treatment and control groups (Figs. 2 and 3), which suggests a successful

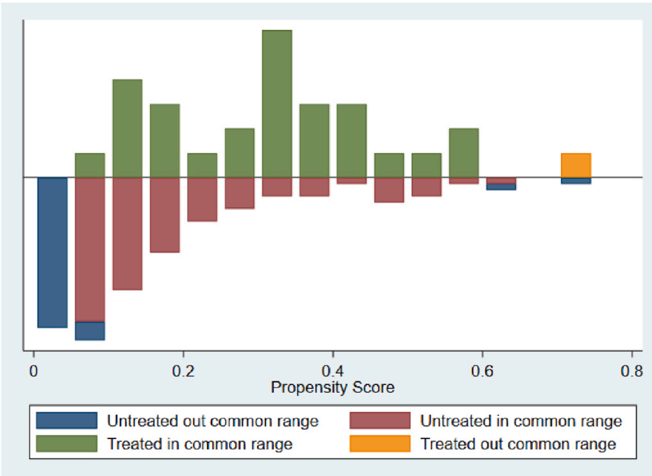

Fig. 2. The distribution of propensity score between the two groups ($PM_{2.5}$). Notes: the treated is the treatment group; the untreated is the control group.

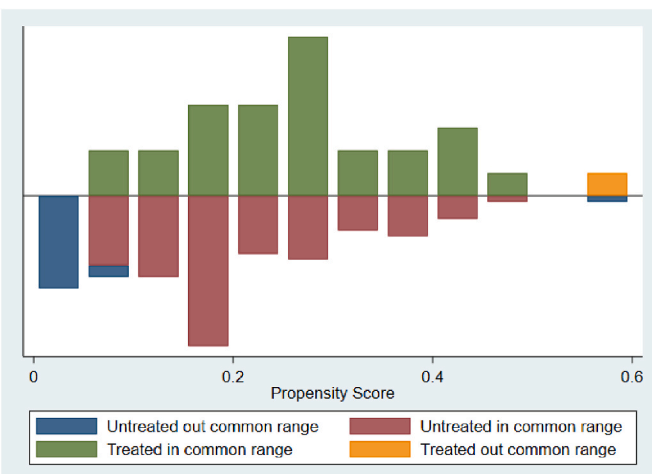

Fig. 3. The distribution of propensity score between the two groups (lnPGDP) Notes: the treated is the treatment group; the untreated is the control group.

matching between the treatment and control groups. In addition, the notable differences in the distribution of propensity scores between the treatment and control groups before the matching procedure have been substantially reduced after the matching (Figs. 4 and 5). Therefore, the PSM has successfully enhanced the comparability between the treatment and control groups, whether the analysis was based on $PM_{2.5}$ concentrations or per capita GDP as the outcome variable.

3.2. The Coal Ban Policy's effect on air pollution and economic growth

The Coal Ban policy has significantly reduced both the $PM_{2.5}$ concentrations and the per capita GDP in the 28 cities ($p < 0.01$). On average, the policy has reduced the $PM_{2.5}$ concentration by 4.74 μg/m^3 (Table 2), which is about 6.7% of the average $PM_{2.5}$ concentration (70.01 μg/m^3) within these cities in 2016. In addition, the policy has also reduced the per capita GDP by 5.8% on average. These findings suggest that while the policy has improved air quality, it has also exerted a discernible inhibitory effect on the economic growth of these cities. Moreover, $PM_{2.5}$ concentrations were negatively correlated to urbanization level and positively correlated to the share of industrial production in the GDP, while the per capita GDP was positively correlated to urbanization level, the share of industrial production in the GDP,

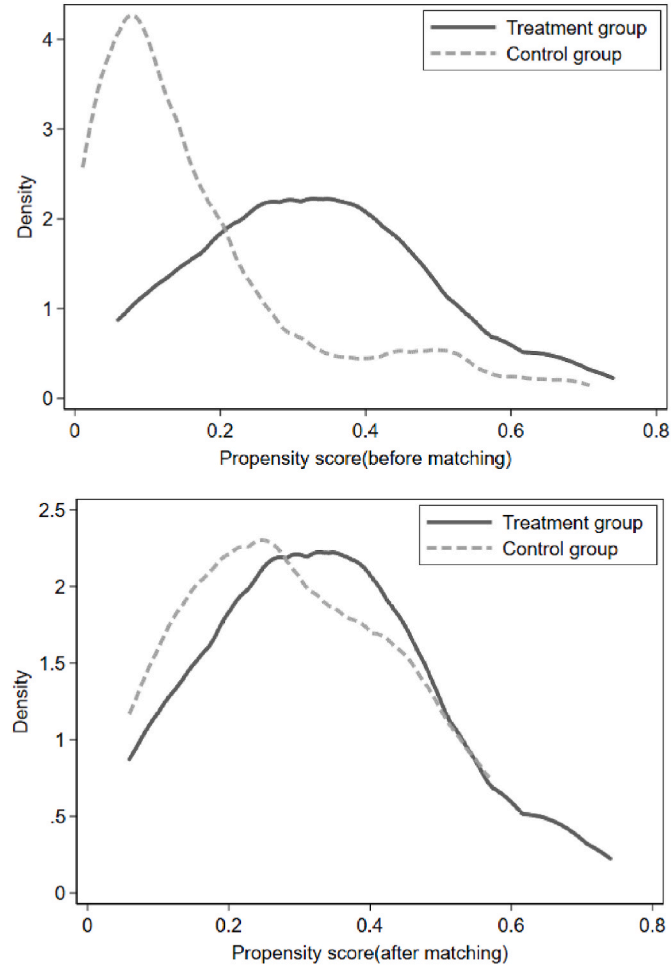

Fig. 4. Comparing the distribution of propensity score between the treatment and control groups before and after matching ($PM_{2.5}$).

educational investment, and foreign direct investment.

3.3. The Policy's spillover effects on air pollution and economic growth

Moran's I values for $PM_{2.5}$ and per capita GDP were significantly positive ($p < 0.05$) in both the two years before and after the policy implementation (Table 3), revealing a positive spatial autocorrelation for both air pollution and economic growth. The Lagrange Multiplier test with $PM_{2.5}$ and per capita GDP as dependent variables indicated that both spatial error term and spatial lag term exhibited spatial dependence (Table 4). As a result, it is necessary to incorporate a spatial econometric model into the analysis. Both the LR test and the Wald test suggested that the SDM could be transformed into SLM, but not SEM in regressions with $PM_{2.5}$ and per capita GDP as dependent variables, as shown in Table 5. Therefore, the SLM-DID model was selected in this paper.

The policy has significantly reduced both the $PM_{2.5}$ concentrations ($p < 0.01$) and the per capita GDP ($p < 0.05$) in the 28 cities (Table 4), which is consistent with the results from the PSM-DID model that were presented above. In addition, the policy has produced significant spatial spillover effects on both $PM_{2.5}$ ($p < 0.01$) and per capita GDP ($p < 0.05$) in the adjacent regions of the 28 cities. Specifically, the policy has reduced the $PM_{2.5}$ concentration and the per capita GDP in the adjacent regions by 4.40 μg/m^3 and 3.1%, respectively. While the spillover effect of the policy on the $PM_{2.5}$ concentration is similar to the direct effect that the policy has exhibited in the 28 cities, the spillover effect of the policy on the per capita GDP is much smaller than the direct effect in the 28 cities. Therefore, the adjacent regions have borne relatively smaller

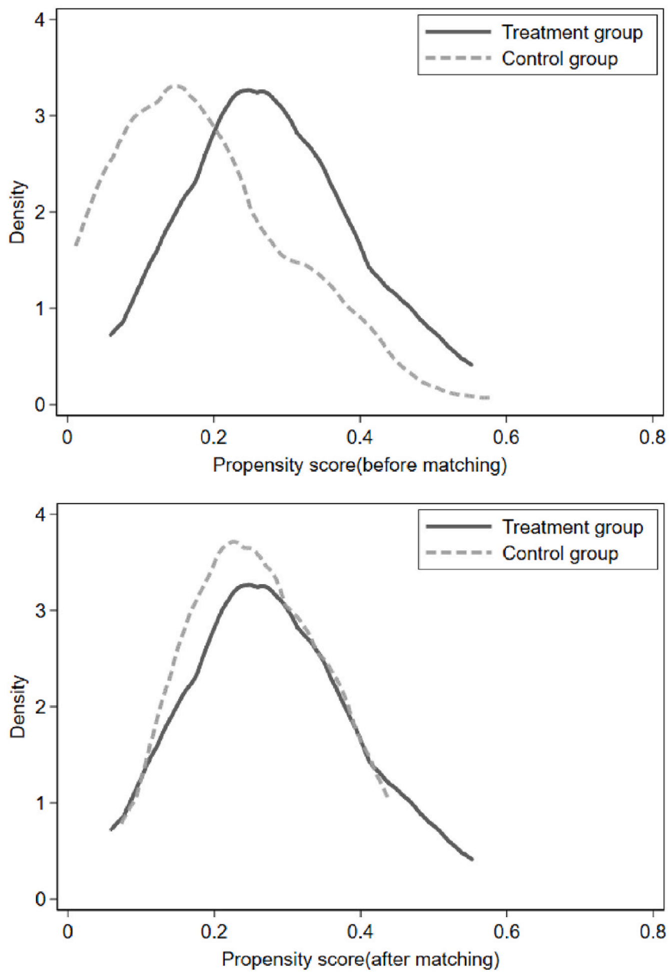

Fig. 5. Comparing the distribution of propensity score between the treatment and control groups before and after matching (lnPGDP).

economic loss in exchange for an improvement in air quality that is similar to the 28 cities.

4. Discussion

This study has produced a few important contributions. In contrast to the existing studies that have focused on the evaluation of the environmental effect of China's Coal Ban policy, this study has filled the knowledge gap by estimating the effects of the policy on both the air quality and the economic growth. Further, the study has uniquely estimated the spatial spillover effects that the policy has produced in the adjacent regions of the areas where the policy has been implemented, which have often been neglected in the studies that assess clean air policies. The methods that the study employed are also novel in the studies of clean air policies. The PSM-DID model can provide more accurate estimation of policy effects than the traditional approach that compare air pollutant concentrations before and after the policy implementation. In addition, the SLM-DID model allowed the detection of potential spillover effects of the policy.

China's Coal Ban policy has improved air quality in the 28 cities where the policy has been implemented. On average, the policy has reduced the $PM_{2.5}$ concentration by 4.74 μg/m^3, which is consistent with levels of reduction in the $PM_{2.5}$ concentration between 3.4 and 5.91 μg/m^3 that were reported in the literature (Wang and Zheng, 2019; Weng et al., 2021). The policy has reduced the per capita GDP by 5.8% on average in the 28 cities. The spillover effect of the policy on the $PM_{2.5}$ concentration in the adjacent regions of the 28 cities is similar to the direct effect that the policy has exhibited in the 28 cities, while the spillover effect on the per capita GDP is much smaller than the direct effect in the 28 cities.

To meet the emission reduction targets, local governments imposed stringent emission standards on key industries, which substantially increased the cost of production and reduced industrial production growth (Zhang and Peng, 2022). The clean heating project of the Coal Ban policy also imposed a significant financial burden on the 28 cities, with an investment of $3.3 billion in 2017 alone (Weng et al., 2021). In addition, the shift of energy for residential heating from coal to natural gas or electricity in a short period of time has led to a shortage in the supplies of these clean energy sources, which has caused the prices of natural gas and electricity to increase rapidly (Liu, 2017). Consequently, the Coal Ban policy might have triggered negative consequences in industrial production, government investment, and residential consumption.

$PM_{2.5}$ particles, which are very small in diameter, exhibit poor settling characteristics, and have strong dispersal capabilities, can be transferred from one area to an adjacent area by the wind (Chen and Ye, 2018). The policy's reduction of $PM_{2.5}$ emissions in the 28 cities can reduce their dispersion into neighboring cities. As a result, $PM_{2.5}$ levels in neighboring cities where the policy has not been implemented also decreased.

The spillover effect of the policy on the economic growth may be attributed to the transmission of supply chain, demand chain, and market relationships between regions. The industrial downsizing in the 28 cities caused by the policy may reduce the production and sales of suppliers in the neighboring cities. Furthermore, downstream processing and logistics companies in the surrounding cities also could experience challenges such as reduced production efficiency, layoffs, and decreased profitability. Additionally, the policy-induced increase in clean energy prices might have also imposed an economic burden on the residents and businesses in the surrounding cities, which could weaken their ability to consume or invest.

The spillover effects indicate an interdependence among cities in which they experience a "win-win" situation in the improvement of air quality, and a "lose-lose" situation in the economic growth. Intriguingly, the adjacent regions have borne relatively a small economic loss in exchange for an improvement in air quality that is similar with the 28 cities. This may create a motivation for the vicinity of areas where the policy has not been implemented to rely on the efforts of policy-implementing cities for air quality improvement without proactive measures (Zhang and Cao, 2022). Regional cooperation, as opposed to individual efforts within separate regions, can be more effective in air pollution control, preventing "free-riding" and promoting coordination of industrial chains among cities.

5. Conclusions

This study estimated the effects of China's Coal Ban policy on both $PM_{2.5}$ concentrations and per capita GDP in the 28 cities where the policy has been implemented as well as the cities that are adjacent to the 28 cities. While the policy has improved air quality in the 28 cities, it has also reduced the per capita GDP. Further, the spillover effect of the policy on the $PM_{2.5}$ concentrations in the adjacent regions is similar to the direct effect that the policy has exhibited in the 28 cities, while the spillover effect on the per capita GDP is much smaller than the direct effect in the 28 cities.

The study has filled the knowledge gap by estimating the effects of the Coal Ban policy on both the air quality and the economic growth, and the spillover effects that the policy has produced in the surrounding areas. The econometric models that the study employed are also novel. The PSM-DID model allowed for accurate and robust estimation of the effects of the Coal Ban policy, while the SLM-DID model made it feasible to detect the spillover effects of the policy.

The findings of the study provide important policy implications.

First, although clean air policies can produce important health benefits, abrupt transition from polluting energy to clean energy can restrict industrial production, impose financial burden on the government, and shock the market of clean energy sources. Second, while the neighboring cities often benefit from the spillover of the effects of clean air policies on the air quality, they may also bear socioeconomic consequences of the policies due to the interconnectedness among adjacent regions. Therefore, regional cooperation in both air pollution control and economic growth can promote gains in air quality and mitigate consequences in economic growth.

As one of the world's largest clean air policies, China's Coal Ban policy deserves careful further studies. Because the Coal Ban policy has been implemented for a relatively short period of time, this study has focuses on its short-term effects. As the policy continue to be implemented, evaluation on the long-term impact of the policy is needed. In addition, the impact of the Coal Ban policy likely differs among different areas. Studies that identify the spatial heterogeneities in the environmental and economic impacts can be used to target specific regions for potential adjustment in policy implementations. Further, future studies may also try to explore the underlying mechanisms that drive the demonstrated policy effects to inform effective policy design and implementation.

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Credit author statement

Jiamei Niu: designed research, performed research, analyzed data, wrote the paper.Xiaodong Chen: designed research, performed research, wrote the paper.Shuwei Sun: performed research, analyzed data.

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

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.119420.

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