Traffic Public Policy Tracking and Evaluation by the Difference in Differences Method and the Linear Regression Model

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Abstract. Energy efficiency and environmental preservation must have substantial support if sustainable growth is to be achieved. Asia has the worst urban air pollution of any region in the world, making air pollution reduction essential. Government policies have an impact on the control of air pollution, as is widely known. This study seeks to ascertain if the city's air quality has been positively impacted by the government's public policies, which include the mist reduction policy of 2017 and the traffic restriction policy of 2013. In order to evaluate the success of the traffic plan using the DID technique and a linear regression model, Chengdu was selected as the intervention group and Chongqing as the control group. The results showed that the city's air quality index dropped significantly after implementing the policy. These findings demonstrate the beneficial impact traffic public policy has on reducing air pollution. China is going through a period of economic growth and transformation, but there are yet no institutions in place to support the implementation of environmental regulation. China's research into and practise of sustainable development will be influenced by examining the efficacy of public policies on air governance.

Keywords: Traffic public policy · Air quality · Linear regression · Modelling & Evaluation · Sustainability

1 Introduction

For socially sustainable growth to be achieved, reasonable environmental policy is essential. Understanding how public policy can impact the environment both intuitively and statistically is crucial. This study tackles this issue by demonstrating how China's city traffic constraint policy have impacted the air quality and overall environment by conducting thorough statistical approach. The empirical study attempts to evaluate how Chengdu's air quality is affected by government policies aimed at lowering air pollution. The factors atmospheric visibility, relative humidity, and AQI are used to create our queries (air quality index). The two events examined in this study are referred to as Event 1: the 2013 traffic restriction regulation. 10. Mist reduction regulations in 2017. 6. To create the control group and intervention group, monthly data from Chengdu's AQI from 2012 to 2015 is extracted, along with a Chinese air and weather database to collect data on atmospheric visibility, relative humidity, and air quality index.

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2 Review of Literature

Governments create and put into practise a variety of environmental policy tools to address air quality issues, but the impact of public policies on air quality improvement has emerged as a key concern that requires immediate attention. At this time, the examination of policy affects focuses mostly on how environmental regulations affect overall social production, technical advancement, global trade, and industrial structure. Regression analysis is the primary tool used by researchers when examining the relationship between environmental policy and other variables. Governments create and put into practise a variety of environmental policy tools to address air quality issues, but the impact of public policies on air quality improvement has emerged as a key concern that requires immediate attention. At this time, the examination of policy affects focuses mostly on how environmental regulations affect overall social production, technical advancement, global trade, and industrial structure. Regression analysis is the primary tool used by researchers when examining the relationship between environmental policy and other variables [6, 7, 9]. The degree of tightness of the environmental policy described, resulting in the estimated results are not stable. The direct and robust assessment of environmental policy effects in cross-region in China has not been adopted in this part of the study. This study aims to conduct an empirical analysis using Chengdu and Chongqing's data with different linear regression setup.

The study of public policy and air quality has been extensively studied by many academics. Shi [10] believes that the "political blue sky; policy" is just a publicity stunt to temporarily enhance air quality. When Chen et al. [3] utilised the DID technique to analyse the changes in Beijing's air quality before, during, and after the Olympic Games, they came to the conclusion that while the improvement in Beijing's air quality is true, it is only transient. Kathuria [5] used policy assessment econometrics to study the impact of New Delhi's ban on gasoline and commercial vehicles on air pollution and found that New Delhi's air quality did not improve with traffic controls. In order to determine the effect of traffic controls on air quality, Davis [4] used hourly air pollution data for all cities in Mexico from 1986 to 2005. By limiting the sample to a relatively short time window during which traffic controls were in effect and using breakpoint regression to control for potential confounders, the results are consistent with Kathuria, who found that the policy did not improve air quality. Ruggieri [8] used the data on the concentration of air pollution in 76 Chinese cities and the regression approach to assess the environmental effects of winter heating in the Huaihe River. Bao et al.'s construction of a natural experiment and application of the DID approach in conjunction with the matching score method allowed them to investigate whether environmental legislation contributed to the suppression of pollution emissions [11]. According to studies, local pollutant emissions cannot be greatly reduced by a straightforward environmental protection legislation.

Contrary to the above research, Liang and Xi [12] found that in provinces with strict environmental protection law enforcement or relatively serious local pollution, environmental protection legislation can achieve obvious environmental improvement effects. As a result of varied selections of different reference groups, the effect is still strong and stable, according to their findings. By comparing the changes in pollutant emissions before and after the implementation of environmental policies, Li and Shen [13, 14] used China's cross-provincial industrial pollution data to get the conclusion that the quality of the environment had greatly improved. Shi et al. evaluated the concept of the local government interviewing policy's impact on reducing air pollution using the linear regression method and discovered an improvement in the air quality following the interview.

3 Methodology

3.1 Linear Regression

The purpose of this study is to determine whether increased public policy input about air pollution can be an explanation for air pollution decrease. It is intended to first examine any potential links between AQI and air quality factors (air quality index). The regression framework is specifically incorporated with air pollution as AQI for demonstrating the test significance.

$$\mathrm{AQI} = \alpha + \beta(\text{atmospheric visibility}) + \gamma(\text{relative humidity}) + \varepsilon_t \tag{1}$$

The linear model's coefficients are calculated for the formulation of a typical regression framework. To obtain the coefficients, one sufficient way is to perform ordinary least square estimation (OLS). Consider a regression setup as,

$$y_i = X_i\beta + \varepsilon_i \tag{2}$$

where X_i is the i-th observation of explanatory variables, β is the coefficients to be estimated, while ε is the error term. The objective of OLS is to minimize the function S:

$$S(\beta) = \sum_{i=1}^{n} \left| y_i - \sum_{j=1}^{p} X_{ij}\beta_j \right|^2 = \|y - X\beta\|^2 \tag{3}$$

and obtain the corresponding estimation for β as,

$$\hat{\beta} = \arg\min_{\beta} S(\beta) = \left(X^\top X\right)^{-1} X^\top y \tag{4}$$

The reason for the choice of ordinary least square estimation is that, OLS estimation is the most optimal linear unbiased estimator for regression analysis when the error terms ε is heteroskedastic, independent of regressors and serially uncorrelated. OLS can offer minimum-variance mean-unbiased estimation for coefficients under the aforementioned circumstance. In order to support and enhance our subsequent investigation of how traffic regulation may affect the air quality, regression analysis is being used to look at the makeup of the AQI index.

3.2 DID Method: Linear Regression with Intervention Group

Another linear regression setup which separates the samples into intervention group and control group is also performed additionally. This is also known as DID method, or difference in difference method. DID method is basically linear regression with additional variable of treatment and intervention group. Two groups are formulated as followed:

Cities in Chengdu that could be impacted by prospective traffic restriction policies and mist reduction policies have created the intervention group.

Cities in Chongqing close to Chengdu that won't be impacted by future traffic restriction policies and mist reduction policies have formed the intervention group. The model of our case study is as follows:

$$\begin{aligned} AQI &= \beta_0 + \beta_1 * \mathrm{Treatment_i} * \mathrm{Post_t} + \beta_2 * \mathrm{visibility} \\ &+ \beta_3 * \mathrm{air\,humidity} + \gamma_i + \alpha_t + \varepsilon_{i,t} \end{aligned} \tag{5}$$

It is necessary to estimate the β_1, β_2 and β_3 for the investigation of variables affecting the overall AQI. Particularly, β_1 is the most important indicator for DID formulation.

Inference about policy impact has seen extensive application of the DID linear regression method. Its ability to perform a better evaluation of the direct and nett impact of a policy or event of interest is the reason it is employed so broadly and sufficiently. The fundamental idea behind the DID method is to view the execution of a public policy as a form of natural experimentation, where all experimental participants are chosen arbitrarily. The samples are then split into two groups: the intervention group, which is influenced by the policy, and the control group, which is not. First, the variation between the comparable indicators in the treatment group prior to and following the implementation of the policy is assessed. Second, the variation in the control group's indicators between the start and end of the policy is measured. The multiple difference, or the nett effect of policy influence, is then obtained by subtracting the two differences. The specific form of the DID method expressed in regression setup is as follows:

$$y_{it} = \beta_0 + \beta_1 \mathrm{Treated_i} + \beta_2 T_t + \beta_3 \mathrm{Treated_i} \times T_t + \mu_{it} \tag{6}$$

In the above formula, y_{it} is the explained variable, representing the observed value of individual i at period t. $\mathrm{Treated_i}$ is a dummy variable policy treatment. If the sample belongs to the control group, $\mathrm{Treated_i}$ is 0, and if it belongs to the intervention group, $\mathrm{Treated_i}$ is 1; T_t is the time dummy variable, if before the policy is implemented, T_t is 0, and vice versa. T_t is 0, and vice versa. At this time, the coefficient β_3 in front of the cross-interaction term $\mathrm{Treated_i} \times T_t$ is the difference estimator, which measures the net effect of the policy, and β_3 can be obtained from two differences. Thus, β_3 is the key coefficient indicating the significant of impact of event. The table below illustrates the coefficients indicators for DID model. β_3 is crucial for difference in difference effect estimation. Our regression problem setup is illustrated as follows:

3.3 Data Collection

We used two datasets for our research. The air quality datasets from Chengdu and Chongqing come first. It was retrieved from https://aqicn.org/here/cn/, the official government air quality monitor website. The Sichuan government measured various indices of NO2, Particle, PM10, PM2.5, CO, and O3 to assess the quality of the air there. The Sichuan government policy dataset [2] is the other dataset. The Traffic Management Bureau of Public Security has decided to implement the management measures of "restricted traffic with tail numbers" for vehicles in the area between the Second and Third

Table 1. The explanation of variables of DID model [self-painted]

Standard model:	$y_{i,t} = \beta 0 + \beta 1 * treat_i * post_t + \beta 3 * X_{i,t} + \gamma_i + \alpha_t + \varepsilon_{i,t}$	
Dependent variable	$y_{i,t}$	AQI index
Independent variable	$treat_i * post_t$	treat dummy * post dummy (whether it belongs to the control group) times (whether the policy has already in effect)
	$X_{i,t}$	a series of control variables that indicate characteristics, including atmosphere visibility, air humidity
Control variable	γ_i	the individual heterogeneity that does not change over time, including regions
	α_t	the time fixed effect of the quarter.

Table 2. Expression of coefficients indicators before and after the policy in Chengdu and Chongqing [self-painted]

	CD	CQ	TD
Before event	$\beta_0 + \beta_1$	β_0	β_1
After event	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	$\beta_0 + \beta_2$	$\beta_1 + \beta_3$
Time difference	$\beta_2 + \beta_3$	β_2	β_3

CD: Chengdu city CQ: Chongqing city TD: time difference

Ring Roads as of July 1, 2013, as a result of a major event in 2013, which this study selected major traffic control policies from 2010 to 2020.

According to Table 2, all that is necessary to determine if policy affects air quality is to concentrate on the regression coefficients β 1 + β 3 as indicated. It can conclude that the policy may influence the environment if the regression coefficients are significant.

4 Result Analysis

4.1 Linear Regression

The outcomes of the AQI model's regression estimations are shown in Table 3. With a p-value of 0, the AQI's reaction to atmospheric visibility is significant at −1.33. It says that the AQI might change by −1.33 units, or between −1.25 and −1.41, for every unit change in the atmosphere's visibility. For air humidity, a change in GDP trend of 1 unit might result in an increase in AQI of 0.15. With a 10 percent p-value of 0.06, the intercept value is similarly significant. The findings show that while air humidity may cause air pollution, resulting in worse air quality and a higher AQI index, atmospheric visibility indicates a better air quality with a lower AQI index.

Table 3. Analysis of Linear Regression [self-painted]

AQI	Coef.	St.Err.	t-value	p-value	[95% Conf Interval]		Sig
Atmosphere Visibility	−1.335	0.042	−7.860	<0.001	−1.251	1.419	***
Air humidity	3.128	0.072	1.760	0.079	−0.015	0.272	*
Constant	−0.043	0.239	−1.810	0.071	−0.904	0.038	*
Mean dependent var	0.942		SD dependent var		1.687		
Number of obs	152		F-test		27.149		

*** $p < .01$, ** $p < .05$, * $p < .1$

Table 4. Analysis of DID linear regression [self-painted]

Variables	AQI	
	(1)	(2)
time1 × treat	−13.671*	
	(0.375)	
time2 × treat		−15.152**
		(0.355)
Atmosphere visibility	0.232***	0.199***
	(0.010)	(0.010)
Air humidity	−0.098***	−0.062***
	(0.006)	(0.006)
Constant	2.872**	3.621**
	(1.672)	(1.671)
Observations	182	182
R-squared	0.212	0.209
Region FE	YES	YES
Year FE	YES	YES

4.2 Results of DID Linear Regression

Table 4 shows how the two policies can effect the AQI in Chengdu. The first column of Table 1 displays the effects of the traffic limitation in 2013 on Chengdu's AQI intensity. The regression coefficient of the treatment interaction term is −13.671 after adjusting for person fixed effects and year fixed effects, which is significant at the 10% level. It suggests that Chengdu's AQI has greatly lowered as a result of the occurrence of this public traffic regulation issue. According to statistics, the AQI in the Chengdu region dropped by around 14 points less than in other unaffected areas.

The regression findings also demonstrate the effect of Chengdu's 2017 Mist Reduction policy on the AQI intensity of Chengdu, which is displayed in the second column of Table 3. Similarly, after accounting for person fixed effects and year fixed effects, the regression coefficient for the treatment interaction term is -15.152, which is significant at the 5% level and indicates that this event may drastically lower the AQI of corresponding cities by a factor of 16.

5 Conclusions

This paper explores the connection between Chengdu's air quality index (AQI) and public policy initiatives to reduce air pollution. The DID model specifically establishes the detrimental consequences of the public health events on Chengdu's AQI, taking into account non-relevant cities of Chongqing for comparison. According to the data, Chengdu's AQI intensity decreased by 14 and 16 points on average when two specific public policies were implemented in 2013 and 2017.

5.1 Discussion and Limitation

Public policies aimed at lowering air pollution have had an impact on Chengdu in terms of their AQI index. The AQI score could decline by 13 points when the traffic limitation legislation is implemented. Similar to this, the AQI in the Chengdu area considerably decreased by 16 points as the Mist Reduction Policy was implemented. There are some restrictions on this paper. The absence of data is the biggest drawback. The reason behind this is that most research reports of the air quality and public policy are conducted in recent years, with short study periods. Most of the data are only available from 2013, which leads to a small-time span for this research, and some variables only have month or annual data. In addition, when compared to other level 1 cities like Shanghai or Beijing, Chengdu's data on air quality and related factors is comparatively lacking.

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