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Analyzing Public Environmental Concerns at the Threshold to Reduce Urban Air Pollution

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Abstract: This work focuses on the extraction and analysis of large-scale data from the Internet, specifically using panel data consisting of 273 prefecture-level cities spanning the period from 2011 to 2021. The data are processed using both the panel fixed-effect model and the panel smooth transformation model (PSTR). This study examines the relationship between public environmental concern and urban air pollution, as well as the impact of various city area divisions on public environmental concern and urban ambient air pollution. The regression analysis reveals several key findings: (1) It is observed that the impact of public participation in environmental pollution control on suppressing air pollution exhibits a lag of approximately three periods. This implies that it takes some time for the power of public participation to manifest its effect in reducing air pollution. (2) The study finds that urban public environmental concern, as measured by the Baidu Index, has a suppressive effect on air pollution once it surpasses a threshold value of 20,455.36. (3) This effect is found to be strengthened as the level of public concern increases. Lastly, it is noted that public environmental concern exhibits regional heterogeneity, which can be attributed to factors such as economic development and scientific and technological advancements. These factors influence the level of public environmental concern in different regions. The findings may be succinctly summarized as follows: geographical variations in public environmental concern can be attributed to the impact of economic growth and advancements in science and technology. Regional variability may arise from several sources, including economic growth, scientific and technical advancements, and other influences, all of which impact public environmental concerns.

Keywords: public environmental concerns; air pollution; PM2.5; Baidu Index; PSTR model

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1. Introduction

Cities serve as catalysts for economic development while also being significant contributors to energy consumption and environmental degradation [1]. The last three decades in China have seen a notable enhancement in the living standards of its populace, owing to the country's rapid economic expansion and urbanization. However, this progress has been marred by a pronounced decline in environmental conditions. The issue of haze pollution has resurfaced, prompting a renewed focus on its research within the field of environmental economics. The topic of air quality has once again garnered significant public attention, with Chai Jing's documentary "Under the Dome" serving as an additional means for the general population to acquire insight into the problem of haze [2]. This text serves as a means of popularizing the haze problem while also making a compelling argument for the implementation of effective haze governance measures. Public involvement in pollution control refers to the active engagement of the public in addressing environmental challenges, particularly via a bottom-up approach to environmental governance. On 22 April 1970, a significant event took place in the United States when about 20 million individuals actively engaged in a march dedicated to environmental preservation [3]. This

event marked a pivotal moment in the nation's history, serving as a catalyst for the subsequent establishment of robust environmental governance in the United States of America. Since that time, various civil organizations dedicated to environmental protection have emerged. Additionally, government agencies focused on environmental protection have been established, and a series of pertinent laws and regulations have been implemented. In the United States, environmental protection has become a government-led initiative, with numerous voluntary organizations and the general public actively engaging in the legal framework pertaining to environmental conservation. The public's concern has the potential to draw the attention of the government toward environmental management, aiding in the enhancement of the efficacy of environmental policy formulation [4]. Hence, the public plays a pivotal role in the regulation of air pollution, deriving its influence from both the objective fact and the interplay among the government, the market, and the public itself.

The acquisition of facts pertaining to public concern is of paramount importance in the examination of this matter. The proliferation of Internet technology and the widespread use of smartphones have led to an increased reliance on the Internet by the general population for information retrieval purposes. Based on the 43rd Statistical Report on Internet Development in China published by the China Internet Network Information Center (CNNIC), the number of Internet users in China as of June 2023 stood at 1.067 billion, encompassing 1.065 billion individuals using mobile phones. Furthermore, the report indicates that the Internet penetration rate in China reached 75.6%. The use of extensive data derived from search engines for the purpose of examining the focus of Internet users on certain subjects presents new avenues of inquiry and conceptual frameworks for social science research [5]. Baidu, the preeminent Chinese search engine, has the distinction of being the biggest of its kind globally, commanding a significant market share in China. Its reach extends to an impressive 97.5% of Chinese Internet users. The Baidu Index is a data-sharing platform that utilizes Baidu's extensive dataset of Internet user behavior. It employs a scientific approach to analyze and compute the weighted sum of search frequencies for specific keywords within Baidu's web searches. This platform offers search indices for personal computers spanning from June 2006 to the present, as well as for mobile searches from January 2011 onward. The index undergoes daily updates, promptly capturing the online community's interest in a certain term and documenting its fluctuations over time. By using the search index, one may promptly examine keyword search patterns, obtain a valuable understanding of shifts in online users' focus, and assess alterations inside certain industrial sectors. In contrast to conventional data and methodologies such as questionnaire surveys and sample surveys, the utilization of the Baidu Index for data monitoring presents distinct advantages in terms of scale, objectivity, and immediacy. Consequently, it has garnered increasing attention from scholars in recent years and has found application in the realm of public opinion analysis [6,7].

Simultaneously, this study used PM2.5 as a metric for evaluating haze pollution, which provides an objective assessment of the environmental conditions inside a city, particularly the state of air environmental pollution [8]. PM2.5, sometimes referred to as fine particulate matter or fine particles, is a term used to describe tiny particles. The term "fine particulate matter" refers to airborne particles found in the environment that have an aerodynamic equivalent diameter of 2.5 microns or less. The duration of suspension in the air may be extended, and the severity of air pollution increases proportionally with the quantity of its constituents in the atmosphere. Nevertheless, it was only toward the conclusion of 2012 that China successfully implemented a comprehensive ground-level monitoring network for PM2.5. The absence of ground-level PM2.5 measurement data before 2013 posed challenges in comprehending the historical patterns of PM2.5 in China, both in terms of regional distribution and temporal variations [9]. Given the prevailing social and institutional context in China, it is pertinent to inquire whether the public's environmental concerns can really have an effect on the issue of urban air pollution. To enhance air quality and mitigate the levels of PM2.5 concentration, it is important to identify the key areas

that need attention. Based on the aforementioned analysis, it is essential to investigate this inquiry.

The primary focus of this study is on its contribution, which can be primarily seen via two key aspects: The present research aims to analyze the level of concern among Internet users in China over environmental pollution, specifically focusing on the search index trend for each city in China using "PM2.5" as the search keywords. The period frame of this research spans from 2011 to 2021, including the weighted combination of the PC search index and the mobile index to form the overall index. This research aims to address the lack of attention given to environmental economics at the city level by conducting a comprehensive analysis on a municipal basis. Furthermore, this study utilizes PM2.5 concentration as an independent variable to examine its impact on government investment in governance, taking into account the influence of public concern. The aim is to determine whether public environmental concern significantly affects PM2.5 levels and to identify the duration and magnitude of this impact. The findings of this research can serve as a foundation for the central government, media outlets, and non-governmental organizations (NGOs) to effectively harness this emerging force, enabling it to contribute more actively and positively to the development of ecological civilization. This will provide a theoretical foundation for the central government, media, and non-governmental organizations (NGOs) to efficiently harness this expanding power in order to assume a more constructive and engaged role in the development of ecological civilization. The subsequent sections of this study are structured as follows: the second section comprises the literature review and research hypotheses; the third section encompasses the data processing and model creation; and the fourth section entails the conclusion and policy suggestions.

1.1. To Effectively Combat Air Pollution, the General Population Must Take the Lead

It is not commonplace for researchers, both domestically and internationally, to do research on connected concerns. In their study, Guo et al. (2010) examined the feasibility of utilizing Google Trends as a proxy variable to measure the attention of Internet users [10]. In their study, Kang et al. (2013) employed Google Trends as a tool to gauge the level of public interest in illness-related material. They then examined the association between Google Trends data and disease surveillance and subsequently applied these findings to the domain of disease surveillance and prevention [11]. According to Cheng and Liu (2018), there is a growing public interest in environmental preservation. They suggest that firms receiving greater public attention tend to adopt environmentally friendly behaviors, particularly when they bear higher pollution costs [12]. Therefore, it is evident that the existing body of study pertaining to the influence of public authority is more comprehensive and holds significant significance within the realm of environmental conservation studies. According to a study conducted by Hu Jianlin et al. (2017), the mortality rate attributed to exposure to PM2.5 was estimated to be 1.3 million. The analysis of sources revealed that industrial and residential emissions accounted for 30.5% and 21.7% of the mortality rate, respectively, making them the primary contributors to this adverse outcome [13]. Hence, addressing the issue of air pollution's impact on human health necessitates a comprehensive approach that encompasses two primary dimensions: industrial emission sources and household emission sources. The involvement of the general population is of utmost importance in the mitigation of air pollution. Based on a scholarly investigation into the governance of air pollution in China, it has been observed that local governments possess commendable executive capacity and adeptness in managing public affairs. Consequently, they assume a pivotal position in the domains of regional ecological management and air pollution mitigation [14]. Nevertheless, the research also revealed that local governments have challenges, such as limited engagement with other governing entities, inadequate policy tools, and insufficient market-driven governance strategies. A further research study discovered that families relying on media controlled by the government exhibit a notable decrease in their responsiveness to periods of high pollution. This suggests that the dissemination of biased information can have an impact on the influx of labor within

a municipality, extending beyond purely economic considerations [15]. In conclusion, it is evident that local governments possess a substantial responsibility in the realm of air pollution control. However, it is equally important for the general population to actively engage in this endeavor by acquiring knowledge and promptly responding to instances of heightened pollution levels.

The importance of public engagement in air pollution reduction is evident. Research has indicated that the dissemination of information to the general population regarding air pollution and its associated impacts has the potential to result in a decrease in levels of air pollution [16,17]. The involvement of the general public can also have an impact on the emission patterns exhibited by both people and corporations [18]. The utilization of the theory of planned behavior has been employed to examine the underlying process by which participation behavior in air pollution control is formed [19,20]. It is possible for governments to engage in collaborative efforts with one another and with the general public in order to effectively manage and regulate air pollution [21,22]. The advancement of the Internet can also play a role in the mitigation of air pollution through enhancements in environmental monitoring and the facilitation of public engagement in environmental oversight [23]. Hence, it is important to engage the general population in endeavors aimed at mitigating air pollution and to enhance their understanding of the underlying factors and consequences associated with air pollution.

In summary, the current and persistent issue of environmental pollution may serve as a foundation for actively encouraging more public engagement in environmental conservation efforts, hence facilitating advancements in urban environmental pollution management. The present study posits a hypothesis that suggests a relationship between public environmental concern and air pollution, whereby it is argued that public environmental concern exerts an inhibitory influence on air pollution. Furthermore, it is hypothesized that this inhibitory impact is subject to a temporal lag.

1.2. Urban Air Pollution and Public Environmental Concerns Have a Nonlinear Connection

Public environmental concerns have a significant impact on air pollution. Public awareness and support are important for environmental policies designed to resolve air pollution issues. Public perception of the environment is both a social and an environmental issue. Governments have the capability to improve air quality through policy change [24]. The COVID-19 pandemic reveals just how seriously governments take their responsibility to ensure the health and well-being of the populations they govern [25], and restricting activity to limit pathogen spread can have other public health repercussions, such as reducing air pollution levels [26]. Social media is a useful tool for collecting data about public opinion and conducting analysis of air pollution. Previous studies have shown that public environmental concerns are the main function that is undertaken with the intention to change the environment [27]. People who are more likely to participate in activities to reduce air pollution are those who have been concerned about and are aware of problems related to air pollution [28,29].

Previous studies have drawn positive conclusions about the relationship between public environmental concerns and government investment in pollution control. It is a bottom-up transmission mechanism, and in the initial stage, the impact between the two is bidirectional. Xin Zhang (2017) studied the impact of air pollution on different types of mental health and well-being indicators. The results of the study showed that air pollution significantly reduces the level of immediate happiness and makes people feel more unhappy unhappiness in the short term [30]. Air pollution has significant effects on people's well-being and health. It is responsible for various health hazards and diseases in humans and other living organisms [31]. This scenario is expected to generate significant public apprehension over air pollution, hence exerting a substantial effect on business environmental practices and government funding for governance [32,33]. The environmental concern expressed by the general population has been shown to have a significant impact on local governments, prompting them to prioritize environmental governance.

This, in turn, leads to improvements in the environmental pollution levels inside cities via increased investment in environmental governance and the enhancement of industrial structure [34–36]. Previous research has shown that the public's heightened environmental concern serves as a catalyst for government engagement with environmental governance issues, leading to enhanced efficacy in policy formulation and implementation. Subsequently, with regard to policy outcomes, the Chinese government has intensified the scrutiny and evaluation of local governments via the implementation of the "energy conservation target responsibility system". Nevertheless, within the context of the top-down pressure transfer system, it is important for the level of public environmental concern to surpass a certain threshold in order to have a substantial influence on regional air quality. Based on the aforementioned study, the second hypothesis posits that there exists a nonlinearity in the impact of public environmental concern on air pollution, which may be described by an inverted U-shaped relationship.

1.3. The Main Methods for Studying Nonlinear Problems

There are various methods for studying nonlinear quantitative relationships. The first category belongs to attribute selection methods. These methods involve selecting a subset of relevant features from a larger set of input variables. Examples of attribute selection methods include principal component analysis (PCA), non-negative matrix factorization (NMF), ReliefF, multiple linear regression (MLR), mutual info, and F-regression [37]. The second category belongs to regression algorithms. These algorithms are used to model the relationship between input variables and output variables. Examples of regression algorithms include linear regression and nonlinear regression algorithms [37]. The PSTR (panel smooth transition regression) model is a specialized regression model and differs from other regression models in that it is specifically designed to analyze nonlinear relationships between variables. Unlike linear regression models, which assume a linear relationship between the dependent and independent variables [38], the PSTR model allows for a threshold effect, where the relationship between variables changes at a certain point. This makes it particularly useful in cases where there is a nonlinear relationship between variables, such as in research related to energy efficiency [39], environmental pollution [40], economic growth [41], and financial development [42]. For example, Yao used the PSTR model to conclude that the impact of environmental regulations on the efficiency of the green economy presents an inverted "U" shape, with a threshold of 0.5128 for environmental regulations [43]. Kong empirically analyzes the nonlinear effect of the exchange rate on the economic growth of countries through the PSTR model and finds that exchange rate appreciation has a certain role in promoting economic growth [44]. Therefore, the PSTR model chosen in this paper to study the nonlinear effect of public environmental concern on air pollution is very applicable. Other regression models, such as multiple linear regression, logistic regression, and Poisson regression, assume a linear relationship between the dependent and independent variables.

2. Materials and Methods

2.1. Indicator Selection and Data Sources

This study establishes the sample period as 2011–2021, taking into account that the most recent data year available in the China Urban Data Yearbook is 2022, while the earliest statistical year available in the Baidu Index is 2011. The present study excluded prefecture-level cities that had significant missing data and those that had been established in recent years. Consequently, a total of 273 prefecture-level cities were determined as the focus of this research. The data on air quality, specifically the concentration of PM2.5 particles, were collected from two sources: the annual World PM2.5 Density Map published by Columbia University. The public's level of concern regarding environmental issues was obtained from the "Baidu Index" website. Baidu, as the largest search engine in China, has the highest market share. Therefore, the Baidu Index is able to reflect a more realistic and comprehensive user behavior. Baidu Index is based on search term data, which are

more intuitive to understanding user needs and feedback, making the data more accurate. Additionally, the daily PM2.5 Baidu Index data for each prefecture-level city were acquired using Python crawler technology. The data pertaining to the total population, GDP per capita, foreign direct investment, share of the secondary sector, research and technology expenditures, total energy consumption, and industrial waste emissions were extracted from the China Urban Statistics Yearbook spanning the years 2012 to 2022. According to the official website of the National Bureau of Statistics of China, the China Urban Statistics Yearbook is highly informative, authoritative, continuous, and informative. The incomplete variables in the dataset of this research article are replaced with full ones using the process of interpolation.

2.2. Description of Variables

2.2.1. Core Variable

The core explanatory variables in this study are urban environmental concerns, which will be abbreviated as BI. This study is centered on using the Python programming language to perform web crawling operations on the PM2.5 Baidu Index data for various cities on a daily basis, spanning the time period from 2011 to 2021. The following is a description of the algorithm used in this study. Utilizing the search volume of Baidu users as the primary data source and employing keywords as the subject of statistical research, this study aims to conduct scientific analysis and calculations to determine the search frequency weight of each keyword inside Baidu's online search. The search index is separated into two categories, namely the PC search index and the mobile search index, depending on the data source.

2.2.2. Explained Variable

PM2.5 is often used as a metric for assessing haze pollution, serving as an objective indicator of a city's environmental circumstances, particularly with regard to air pollution levels. The PM2.5 concentration numbers presented in this article are sourced from the World PM2.5 Density Map by Year, a publication by Columbia University. PM2.5, or fine particulate matter, is often referred to as tiny particles. Fine particulate matter (PM2.5) is characterized as particulate matter present in the surrounding atmosphere with an aerodynamic equivalent diameter that is equal to or less than 2.5 μm. The substance has the ability to remain suspended in the atmosphere for an extended duration, and the severity of air pollution increases proportionally with increased concentrations of the substance in the air.

2.2.3. Conversion Variable

The degree of apprehension regarding the urban environment (BI) and the overall populace of the city at the conclusion of the year (POPU). The objective of this study is to examine the distinct impacts of urban built environment (BI) on air quality, as well as to determine the threshold values of BI that influence the relationship between the two variables. While urban population serves as the foundation for BI, it is also important to explore the characteristics of urban size that contribute to a higher likelihood of BI mitigating the effects of environmental pollution.

2.2.4. Control Variables and Descriptive Statistics

1. Indicator of economic development: gross domestic product per capita (GDPpc). The environmental Kuznets curve (EKC) demonstrates the presence of a U-shaped link between economic development and environmental quality. This study posits that there exists a correlation between the degree of economic growth of a city and the corresponding level of air quality inside such a city.
2. The industrial composition of the urban area: the relative contribution of the secondary sector to the gross domestic product (GDP). Based on the environmental Kuznets curve (EKC) hypothesis, the state of the environment is influenced by the composition

of industries. In this study, the fraction of the secondary industry is used as an indicator to assess the industrial structure of the city.

3. The allocation of funds from local government budgets toward scientific and technical innovation, specifically the portion dedicated to scientific spending within the overall budgetary expenditure of local finance. The advancement of scientific and technological endeavors has the potential to successfully mitigate the degradation of environmental conditions, particularly in relation to enhancing air quality. This study examines the correlation between the level of science and technology and urban air quality. Specifically, it focuses on the allocation of funds for scientific research within the general budget spending of local finance as an indicator of the degree of urban science and technology.
4. The degree of external engagement: the effective exploitation of foreign direct investment (FDI). There exists a noteworthy inverse relationship between the degree of a city's external integration and its environmental performance. Additionally, the study establishes a link between a city's level of external integration with its air quality. This study examines the relationship between urban energy consumption and emission levels, specifically focusing on the overall energy consumption in metropolitan areas and the emissions of industrial waste.

This paper presents an argument regarding the positive correlation between total energy consumption, industrial waste emissions, and air quality. The total energy consumption is determined based on urban data, specifically the total amount of urban gas (both artificial and natural gas), total gas supply, and liquefied petroleum gas supply, which is then converted into the total amount of discounted standard coal. The combined value of industrial three-waste emissions, including industrial wastewater emissions, industrial sulfur dioxide emissions, and industrial soot emissions, is calculated using the entropy weight method. Table 1 presents the significance and descriptive statistics of each variable. Regional heterogeneity in this paper divides China into eastern, central, and western regions based on the level of economic development.

Table 1. Variable definitions and descriptive statistics.

Variable Name		Meaning	N	Mean Value	Variance	Minimum Value	Maximum Value
Explained Variable	PM	Air quality (PM2.5, $\mu g/m^3$)	3003	38.077	16.333	4.676	116
Core Variable and Conversion Variable	BI	Environmental concern	3003	884.071	529.037	1	1810
	POPU	Total population at the end of the year (10,000)	3003	5.268	1.319	−3.219	9.626
Control Variables	PAGDP	GDP per capita (million CNY/person)	3003	1.94	1.307	−2.93	12.707
	FDI	Foreign direct investment (billions of USD)	3003	904.024	533.06	1	1839
	SI	Share of secondary sector (%)	3003	742.94	403.02	1	1477
	SCI	Expenditures on science and technology (USD million)	3003	10.104	1.505	−0.945	15.211
	ECT	Total energy consumption (tons of standard coal)	3003	944.692	547.053	1	1890
	TW	Industrial waste emissions (tons)	3003	8.223	1.072	1.867	12.006

2.3. Model Setting

This research aims to investigate the potential impact of urban environmental concerns on urban air quality using a panel regression model.

$$y_{it} = \mu_i + \alpha BI_{it} + \beta X_{it} + \varepsilon_{it} \tag{1}$$

Let y_{it} represent the explained variable that signifies the carbon emission level of area i during period t. Similarly, BI_{it} represents the explanatory variable that symbolizes the public environmental concern of region i in period t. X_{it} is the control variable, μ_i represents the unknown individual impact, and ε_{it} represents the random error term. The undetermined variables α and β may be determined by selecting suitable samples and using estimate techniques.

Both the grouping regression and the threshold regression are commonly used analytical methods in this field of study. The grouping regression approach has gained considerable popularity because of its straightforwardness and comprehensibility; nonetheless, it still exhibits some limitations. The initial assumption of the model is that the user possesses prior knowledge of the information used for grouping and must externally determine both the number of subgroups and the criteria for division. However, in empirical applications, the availability of grouping information is often limited. Additionally, the grouping regression approach analyzes sub-samples independently, resulting in the loss of shared information between the samples. Furthermore, the model assumes that individuals within each subgroup strictly adhere to a specific linear relationship and that there is no transitional process between the two subgroups, such as a "jump" near the breakpoint. This assumption is clearly unreasonable when dealing with continuous variables that have been grouped. Thirdly, the model makes the assumption that individuals belonging to each subgroup strictly adhere to a particular linear relationship without any transitional process between the two subgroups. This implies the presence of abrupt changes or "jumps" near the breakpoints. However, this assumption is evidently unreasonable when the subgroup variables are continuous in nature.

Similar to the panel smooth transition regression model (PSTR) is the threshold regression. Threshold regression is a type of regression analysis that is used to model and analyze situations where the dependent variable is expected to change once a certain threshold of an independent variable is reached. The PSTR model was first introduced by Gonzalez et al. [45]; the PSTR model is a type of nonlinear regression model that allows for smooth transitions between different regimes. This model is particularly useful when the relationship between the dependent and independent variables is not constant but changes depending on the value of another variable, known as the transition variable. The PSTR model can capture more complex dynamics in the data, such as threshold effects, where the impact of an independent variable on the dependent variable changes at certain levels of the transition variable. Hence, the PSTR model has the capability to internally determine the number of groups and the placement of breakpoints while also achieving a seamless transition between regimes. Based on the aforementioned research, this study formulates the subsequent PSTR model (Equation (2)) and robustness check model (Equation (3)).

$$y_{it} = \mu_i + \left(\alpha_0 \ln BI_{it} + \beta_0' X_{it}\right) + \sum_{j=1}^{r} \left(\alpha_j \ln BI_{it} + \beta_j X_{it}\right) g_j\left(q_{it}^j; \gamma_j, c_j\right) + \varepsilon_{it} \tag{2}$$

$$y_{it} = \mu_i + \left(\alpha_0 \ln BI_{it} + \beta_0' X_{it}\right) + \sum_{j=1}^{r} \left(\alpha_j \ln POPU_{it} + \beta_j X_{it}\right) g_j\left(q_{it}^j; \gamma_j, c_j\right) + \varepsilon_{it} \tag{3}$$

$$g_j\left(q_{it}^j; \gamma_j, c_j\right) = \left[1 + \exp\left(-\gamma_j\left(q_{it}^j - c\right)\right)\right]^{-1} \tag{4}$$

The conversion coefficient, denoted as γ_j, represents the slope function and is responsible for determining the rate of conversion. It is important to note that γ_j is a positive

value. Currently, the alteration of the conversion variable in the two equations is influenced by the modifications made to Equations (5) and (6), correspondingly [46].

$$\alpha_{it} = \frac{\partial y_{it}}{\partial BI_{it}} = \alpha_0 + \sum_{j=1}^{r} \alpha_j g_j(q_{it}^j; \gamma_j, c_j) \tag{5}$$

$$\alpha_{it} = \frac{\partial y_{it}}{\partial POPU_{it}} = \alpha_0 + \sum_{j=1}^{r} \alpha_j g_j(q_{it}^j; \gamma_j, c_j) \tag{6}$$

In other words, the coefficients corresponding to each person for a given time exhibit a continuous relationship with the converted variable q_{it}. Through the examination of the correlation between variables α_{it} and q_{it}, it becomes feasible to assess if there exists a precise threshold at which the public's environmental concern and the total urban population considerably impact urban air quality.

To mitigate the issue of "pseudo-regression" that may arise from directly modeling volatile data, a panel data unit root test is first performed on each variable. The outcomes of the test indicate that the series for each variable exhibits smoothness and does not possess a unit root. Prior to estimating the parameters of the PSTR model, it is essential to perform a nonlinearity test in order to ascertain the significance of the institutional transformation impact and identify the appropriate number of transformation functions. The construction of the auxiliary regression equation often involves doing a first-order Taylor expansion of the conversion function at $\gamma = 0$. In order to enhance the reliability and validity of the findings, it is essential to build the following three statistics concurrently [47]:

$$LM = \frac{TN(SSR_0 - SSR_1)}{SSR_0} \tag{7}$$

$$LM_F = \frac{(SSR_0 - SSR_1)/mk}{SSR_1/(TN - N - mk)} \tag{8}$$

$$LRT = -2\log\frac{SSR_1}{SSR_0} \tag{9}$$

SSR_0 represents the panel residual sum of squares while considering the original hypothesis, whereas SSR_1 represents the panel residual sum of squares when considering the alternative condition. According to the initial hypothesis, the *LM* and *LRT* statistics exhibit an asymptotic $\chi^2(mk)$ distribution, whereas the *LMF* statistic follows an asymptotic $F(mk, TN - N - mk)$ distribution. The sample interval, denoted as t, represents the time duration between consecutive samples. *N*, on the other hand, refers to the total number of samples taken. In the event that the first hypothesis about the "nonlinearity test" is refuted, the subsequent step involves conducting the "residual nonlinearity effect test (H_0*: r = 1*; H_1*: r = 2*)". Until the null hypothesis (H_0) cannot be rejected. Ultimately, the model may be determined to have an optimum number of transformation functions, denoted as *r*.

3. Results

3.1. Panel Regression Model Results

The regression findings of Model I reveal that the public environmental concern of the city has a positive link with urban air quality at the 1% significance level. In the same era, public environmental concern and air quality are associated because the increase in PM2.5 concentration activates people's worry about air quality, and everyone will become more conscious of the value of environmental protection as a result of increased environmental awareness, and people will be more likely to utilize energy-efficient home appliances and transportation options, resulting in decreased energy usage and emissions. At the enterprise level, it will encourage enterprises to take an active role in environmental preservation initiatives and decide to support and buy ecologically friendly goods and services to lessen

reliance on fossil fuels and support and take part in renewable energy initiatives such as solar and wind energy. In addition, under the influence of public environmental concern, the government will take further measures such as environmental tax to improve air quality. Furthermore, this paper estimates the time when urban air quality can be significantly improved through the bottom-up influence mechanism of urban environmental concern through Models II, III, and IV; while ensuring the unidirectional influence relationship of the explanatory variables on the explanatory variables. Before regression, this paper first carried out a multicollinearity test on all the data, and the test results showed that the VIF value of each variable was not greater than 2.5, and the overall VIF value was 1.43, which indicated that the lagged period of variable BI's did not have multicollinearity with other variables. The results of Model II show that the public environmental concern in the city after one period of lagging does not have an inhibitory effect on the air, but the coefficients of the public environmental concern in the city in two and three periods of lagging are significantly negative in Model III and Model IV, which indicates that from the two periods of lagging, with the gradual increase in the public's concern for environmental problems and enthusiasm for participation, the government's environmental governance policies and environmental governance investment measures have begun to bear fruit. The government's environmental governance strategy and investment in environmental governance measures have started to be successful. However, the coefficients of BI for the two periods after Model III are only significant at the 5% level, and the coefficients of the two lagged periods are not significant at all after adding the lagged three variables of BI, indicating that the growing force of public concern has a more obvious impact on urban air quality in the lagged three periods (Table 2).

Table 2. Fixed effects model estimation results.

Variable Name	I	II	III	IV
BI	0.0004213 ***	0.000351 ***	0.0003351 ***	0.0003435 ***
	(6.44×10^{-5})	(6.66×10^{-5})	(6.66×10^{-5})	(6.63×10^{-5})
L1_BI		0.0001868 ***	0.000234 ***	0.000213 ***
		(4.74×10^{-5})	(5.15×10^{-5})	(5.16×10^{-5})
L2_BI			−0.0001174 **	−0.0000531
			(4.76×10^{-5})	(5.18×10^{-5})
L3_BI				−0.0001644 ***
				(5.04×10^{-5})
PAGDP	−0.0000518	−0.0000519	−0.0000456	0.00000283
	(4.55×10^{-5})	(4.54×10^{-5})	(4.53×10^{-5})	(4.75×10^{-5})
FDI	0.0009395 *	0.0009043	0.0009525 *	0.0009289 *
	(5.82×10^{-4})	(5.802×10^{-4})	(5.788×10^{-4})	(5.764×10^{-4})
SI	0.0057841 ***	0.0057825 ***	0.0052941 ***	0.0056478 ***
	(9.01×10^{-4})	(8.999×10^{-4})	(9.044×10^{-4})	(9.022×10^{-4})
SCI	-5.78×10^{-6} ***	−0.00000595 ***	−0.00000603 ***	−0.00000615 ***
	(1.76×10^{-6})	(1.75×10^{-6})	(1.75×10^{-6})	(1.74×10^{-6})
ECT	−0.0004432	−0.0004446	−0.0003921	−0.0002037
	(6.29×10^{-4})	(6.274×10^{-4})	(6.274×10^{-4})	(6.25×10^{-4})
POPU	0.005885 ***	0.0061271 ***	0.0062674 ***	0.0063673 ***
	(7.52×10^{-4})	(7.54×10^{-4})	(7.537×10^{-4})	(7.51×10^{-4})
TW	0.0003874 ***	0.0003934 ***	0.0003918 ***	0.0004062 ***
	(4.77×10^{-5})	(4.77×10^{-5})	(4.76×10^{-5})	(4.75×10^{-5})
Constant term	25.84035 ***	25.20225 ***	25.82714 ***	25.74213 ***
	(1.200576)	(1.207475)	(1.215259)	(1.211406)
F test	34.27 ***	32.27 ***	29.14 ***	28.36 ***
Hausman test	56.79 ***	51.02 ***	52.60 ***	60.09 ***
N	1910	1637	1364	1091

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are included in parenthesis, the same as below.

3.2. PSTR Model Results

When employing BI and POPU as the primary explanatory variables and transformed variables, respectively, the nonlinear test statistics exhibited significance at the 1% level. Consequently, the original hypothesis was rejected, suggesting that the impacts of BI and POPU on air pollution in various regimes possess evident nonlinear characteristics. However, the residual nonlinear test for BI yielded a notably larger *p*-value compared to the nonlinear test, and only the LRT statistic demonstrated significance, while the remaining statistics did not pass the significance test. This suggests that the model does not have sufficient evidence to reject the hypothesis that there is only one conversion function in the residual nonlinear test. As a result, the model concludes that the number of conversion functions, denoted as r, is ultimately decided to be 1. Likewise, the findings from the residual nonlinear test conducted on the POPU model suggest that the number of conversion functions, denoted as r, is similarly equal to 1.

Once the number of transformation functions has been determined, it becomes imperative to ascertain the number of positional parameters associated with the two PSTR models, denoted as m. The Akaike Information Criterion (AIC) and the Bayesian Criterion (BIC) were computed for the models with m = 1 and m = 2, respectively. Based on the decision criteria of the AIC and the BIC, the model with lower values should be chosen. The outcomes are presented in Table 3. Table 3 demonstrates that the AIC and BIC values are lower for m = 1 compared to m = 2. Hence, the ultimate two models have identical values of r = 1 and m = 1, indicating that they are both two-regime PSTR models including a conversion function.

Table 3. Nonlinearity test and a number of positional parameters m determination.

Conversion Variable	Nonlinearity Test H_0:r = 0; H_1:r = 1			Residual Nonlinearity Test H_0:r = 1; H_1:r = 2			Optimal m-Value			
							AIC		*BIC*	
	LM	*LMF*	*LRT*	*LM*	*LMF*	*LRT*	*m* =1	*m* = 2	*m* = 1	*m* = 2
BI	59.677 ** (0.000)	4.641 ** (0.000)	60.809 ** (0.000)	21.808 * (0.126)	1.628 (0.185)	21.956 * (0.025)	4.34	4.34	4.42	4.43
POPU	24.767 * (0.010)	1.884 ** (0.037)	24.960 *** (0.009)	29.042 (0.102)	2.178 (0.113)	29.307 (0.102)	4.37	4.46	4.49	4.58

Note: , *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The parameter estimates for the piecewise linear spline transformation regression (PSTR) model with a single regime (r = 1) and a single knot (m = 1) are shown in Table 4.

As seen in Table 4, when BI is used as the conversion variable, the institution-specific conversion variable is 20,455.36, indicating that the effect of urban public environmental concern on urban air quality is converted when BI reaches 20,455.36. The pace parameter of inter-institutional transformation is 2.571, which indicates that the inter-institutional transformation is gradual rather than a "sudden change" at a certain breakpoint. According to the regression results for the two extreme regimes, the linear component coefficient is 0.8455, which is statistically significant at the 1% level. The coefficient of the nonlinear component is −0.3868, which is also statistically significant at the 1% level. It indicates that the relationship between urban public environmental concern and urban air quality is positive before crossing the value of the location parameter (20,455.36). When public environmental concern exceeds the threshold (20,455.36), it has a significant inhibitory effect on air pollution, which is consistent with the results of the previous panel regression, and the conclusions of the previous section still hold. When POPU is used as the transformed variable, the variable POPU reaches 193.13; the public environmental concern will have a significant inhibitory effect on air pollution, which indicates that the inhibitory effect is closely related to the size of the urban population.

Table 4. PSTR model estimation and results of robustness tests.

	Explanatory Variable	Coefficient	*PM (BI)*	*PM (POPU)*
Linear partial estimation	BI	a0	0.8455 *** (2.8582)	−0.0903 ** (−2.0617)
	L.BI	b1	−1.5968 (−0.0603)	0.5946 ** (1.9805)
	PAGDP	b2	−0.5853 (−1.2978)	0.4486 (0.5252)
	FDI	b3	0.5146 *** (6.4242)	0.7257 ** (2.5259)
	SI	b4	7.9945 (−0.2212)	9.6712 *** (5.4754)
	SCI	b5	−0.9865 (−1.3495)	−2.1251 *** (−4.0596)
	ECT	b6	−0.1846 *** (3.5662)	−0.0214 (−0.0438)
	POPU	b7	2.1777 *** (3.4737)	0.8566 (0.8265)
	TW	b8	1.9978 *** (5.8088)	3.0052 *** (5.7836)
	DB	b9	7.6287 *** (3.5541)	13.7089 *** (5.4611)
	ZB	b10	6.8688 *** (2.7229)	11.638 *** (3.9132)
Nonlinear partial estimation	BI	a1	−0.3868 *** (−4.8708)	−2.3392 *** (3.3197)
	L.BI	b1‘	−0.3107 ** (2.505)	−3.2811 *** (−3.4362)
	DB	b9‘	45.4838 *** (4.1951)	−3.4719 (0.31)
	ZB	b10′	5.6709 ** (1.7215)	−4.693 (0.616)
Influence coefficient	a0 + a1		0.4587	−2.4295
Smoothness parameter	g		2.571	54.7871
Positional parameters	c		9.926	5.2637
	exp(c)		20,455.36	193.19
Goodness of fit	R2		0.7290	0.7274
	F		4803.3112	4766.2151
Regression sum of squares	RSS		120,375.023	121,056.558

Note: **, and *** indicate significance at the 5%, and 1% levels, respectively.

Furthermore, this study categorizes the chosen cities into three distinct groups according to their geographical position, namely east, center, and west. These classifications are then represented as dummy variables and included in the model. Based on the findings presented in Table 4, it can be observed that the utilization of *BI* as the transformed variable yields more impactful regression outcomes for each explanatory variable in both linear and nonlinear components within the eastern region compared to the central and western regions. This implies that, as environmental pollution intensifies, the public's level of environmental concern exhibits the highest magnitude in the eastern region, followed by the central region, and is relatively weaker in the western region. This suggests that the public demands in the eastern area have been met with favorable responses, and measures for environmental governance and ecological environment conservation have been successfully implemented and proven effective. Hence, with regard to spatial and temporal distribution, it can be observed that only two cities, namely Beijing and Shanghai, surpassed the threshold value of 20,455.36 in the year 2013. In the subsequent year, 2014, the number of cities that exceeded this threshold increased to five, including Beijing, Tianjin,

Shanghai, Hangzhou, and Guangzhou. Furthermore, up until the year 2017, the cities that surpassed the threshold encompassed Beijing, Tianjin, Shanghai, Xi'an, Chongqing, Chengdu, Hangzhou, and Zhengzhou. These cities are situated in regions characterized by comprehensive economic prowess. These urban areas exhibit significant levels of robust economic prowess, potential for scientific and technical innovation, proficiency in information communication, and accessibility in terms of transportation infrastructure.

In order to ensure the robustness of the regression results in this paper, the air quality index (AQI) is used to replace PM2.5 as an indicator of the explanatory variables, and the regression results of the pstr model are consistent with the original regression results to further ensure the stability of the results in this paper.

4. Discussion

This study aims to enhance comprehension of the association between concern and total urban population, as well as their respective thresholds. Public concerns about environmental pollution, particularly air pollution, have been increasing globally. The detrimental effects of pollution on human health, such as respiratory and cardiovascular diseases, have been widely recognized [48]. Air pollution is a major environmental concern that has harmful effects on human health. Exposure to fine particulate air pollution, such as PM2.5, can cause respiratory and cardiovascular diseases [49]. Risks posed by air pollution can be more readily perceived by the public than soil and lead contamination [50]. Public environmental concerns play an important role in the process of environmental governance and can affect corporate environmental behavior by increasing external environmental pressure [51]. Public awareness and support are important for environmental policies designed to resolve air pollution issues [52]. Public environmental campaigns to reduce air pollution can take many forms, from government policies to citizen-led initiatives [53]. For example, Environmental tax reform can significantly reduce urban air pollution. Green technology innovation and industrial structure upgrading are vital transmission mechanisms for environmental tax reform to improve air quality [54]. This paper empirically explores that if the public environmental concern is measured by the Baidu Index when the Baidu Index exceeds 20,455.36, the conduction mechanism of public environmental concern to inhibit air pollution can play a significant role. Overall, public awareness and concern about air pollution have grown, prompting the need for action to minimize its harmful effects on both human health and the environment.

Due to a number of variables, including industrial operations, transportation, and meteorological circumstances, air pollution levels differ across cities [55,56]. The middle and western cities in the sample of cities in this article had far lower levels of urban concern than the eastern ones. The degree of economic and technical growth, among other things, might be blamed for this. As a result, there are geographical disparities in the level of public concern about the environment between the central and western areas, and it may be challenging for the opinions of certain marginalized groups to be adequately represented within the network of concern. Thus, one of the main concerns now is how to raise public awareness of environmental issues. An effective strategy for increasing environmental knowledge and promoting responsible behavior is environmental education. According to research, children's environmental awareness, particularly their knowledge and attitudes about the environment, may be effectively increased via narrative-based environmental education. This implies that promoting environmental awareness among the general population via environmental education in schools and communities is a successful tactic [50]. Another tactic to raise public awareness of environmental issues is to support green transportation. As one sustainable development goal (SDG) to combat climate change, Seoul, South Korea, established a bicycle sharing system (BSS) to encourage green transportation practices. The environmental advantages of these activities were brought to light by this campaign [57]. Residents' opinions of environmental health have also improved as a result of education regarding the precise kinds and concentrations of pollution in their homes [58]. By informing the public about the threat of air pollution

and increasing stakeholder engagement, governments can more effectively utilize financial resources and implement more sustainable solutions [59].

5. Conclusions and Recommendations

The results of the empirical analysis show that it takes about three years for public environmental concerns to have a dampening effect on air pollution. According to the analysis, once the urban public environmental concern, as assessed by the Baidu Index, is above the threshold of 20,455.36, it will have a suppressive impact on air pollution. Furthermore, this effect is expected to intensify in proportion to the escalation of public worry. The level of public concern over the environment is influenced by economic and technical advancements, among other variables, resulting in regional variations.

The present study's results lead to the formulation of two recommendations.

Urban environmental concern is a facet of social opinion that pertains to the quality of urban air. It serves as a means of expression for individuals and also gives rise to social conflicts resulting from air quality issues, particularly those related to PM2.5, which is a commonly used indicator for measuring air quality. As a result of public concern, the government has started to address environmental governance matters, with a specific focus on improving urban air quality within a three-year timeframe. The government's ability to enhance air quality will be contingent upon meeting the threshold of public environmental concern. The city's environmental concern is measured by a threshold value of 20,455.36. In order to effectively address this issue, it is imperative for relevant government agencies, media organizations, and other pertinent entities to provide appropriate guidance in terms of timing and magnitude. On one side, it is important to encourage public engagement and mobilize the public to actively participate in environmental conservation efforts. This may be achieved by effectively promoting the notion of "environmental protection starts with me," encouraging a greater number of individuals to join the collective endeavor of promoting sustainable practices.

The variation in public environmental concerns in urban regions may be attributed to many variables, including the degree of economic development, scientific and technology advancements, urban industrial structure, and urban energy usage. This observation indicates that the Internet does not adequately reflect the views of marginalized people residing in certain impoverished regions. This issue needs significant emphasis from policymakers. Based on the findings of the regional dummy variables as presented in the study, it is suggested that the Chinese government needs to prioritize the provision of optimal feedback in response to public requests in the eastern area, followed by the central region, while the western region exhibits comparatively worse performance in this regard. Based on the aforementioned analysis, it is imperative for the government to prioritize the concept of justice in order to develop a robust monitoring system for China's ecological environment and effectively execute measures for ecological environmental preservation.

6. Limitation

In order to correspond to the measure of air pollution (PM2.5), the Baidu Index with PM2.5 as the keyword was used for public environmental concerns in this paper. However, there may be other keywords for air pollution concerns, such as the air quality index, and further refinement of the index is needed in future research.

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