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The Impact of Public Policy Implementation on Air Pollution and Health Levels

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Abstract

Increasing public concern regarding health issues caused by air quality has intensified the search for effective solutions to air pollution. This paper collects annual data from 31 regions in China from 2013 to 2018, applying a First-Difference model, a Difference-in-Differences (DID) model, and a Two-Stage Least Squares (2SLS) model to analyze the impact of air pollutants on health levels. Furthermore, it examines the effects of two new environmental protection laws—the Environmental Protection Law (2015) and the Law on the Prevention and Control of Atmospheric Pollution (2016)—on air quality and health. The research results indicate that the growth of PM2.5 has a significant positive impact on the first difference of Death Total Population (DTP). The implementation of the new laws significantly reduces the concentration of air pollutants; in areas with severe air pollution, the decline in PM2.5 concentration is even more pronounced. However, no significant correlation was found between the two new laws and health levels. This paper provides a theoretical basis for governing air pollution and improving public health.

Keywords

Air pollution; Health indicators; Environmental Protection Law; Law on the Prevention and Control of Atmospheric Pollution

1. Introduction

Rapid economic growth is often accompanied by a booming industrial sector; however, environmental issues have progressively surfaced behind this industrial prosperity. Since the Industrial Revolution, the surge in coal consumption has led to increasing pollutant emissions, leaving cities shrouded in smog. This haze not only damages architectural surfaces but also severely impairs visibility, resulting in frequent traffic accidents. Furthermore, air pollution has led to a rising incidence of cardiopulmonary diseases, such as bronchitis and pneumonia; significant mortality linked to severe pollution has incurred incalculable economic losses [1]. Infants born during periods of high pollution suffer impaired brain and cognitive development due to prolonged exposure, ultimately generating lower labor value by age 30 compared to those born under normal conditions [2].

During the 1960s, the drive for domestic development led to a neglect of environmental protection. The absence of relevant regulatory frameworks allowed factories to prioritize profit at the expense of the environment, causing air pollutants like PM2.5 to exceed safety standards significantly [3]. Consequently, the proportion of cardiopulmonary diseases rose, leading to premature deaths among workers and a surge in pollution-related mortality [4]. Although the Chinese government recognized the importance of environmental protection and trialed its

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first Environmental Protection Law in 1979, the law's impact was minimal due to limited enforcement capabilities at the time. It was not until 2008, in an effort to ensure a clean environment for the Beijing Olympics, that the government implemented temporary control measures to mitigate pollution. However, these measures were not sustained post-Olympics [5], leading to a notable rebound in pollutant concentrations [6]. Similar temporary measures during the 2010 Shanghai Expo yielded equally limited long-term results. Realizing that temporary fixes were unreliable, the government began revising the Environmental Protection Law in 2011, officially implementing the new version in 2015. One year later, on January 1, 2016, the new Law on the Prevention and Control of Atmospheric Pollution took effect, establishing strict emission standards and penalties. These two laws have yielded significant results since their inception.

Kuerban et al. [7] analyzed China’s air pollution from 2015 to 2018, finding that concentrations of pollutants such as PM2.5、PM10、SO2, and CO decreased during this period. Simultaneously, the number of deaths and illnesses related to PM2.5 also declined, suggesting a positive correlation between air pollution levels and health outcomes. While existing literature extensively explores the health impairments and economic losses caused by air pollution, few scholars have conducted analyses from a policy perspective to determine whether these new environmental laws effectively mitigate pollution and improve public health.

Against this backdrop, this paper focuses on the Environmental Protection Law (2015) and the Law on the Prevention and Control of Atmospheric Pollution (2016). Using a Difference-in-Differences (DID) model, we compare the impact of air pollution on health before and after the implementation of these laws, as well as the laws' direct effects on air quality and health levels. This study selects the annual average concentration of PM2.5 as the indicator for air pollution. Building on prior research, we utilize mortality rates, maternal mortality rates, annual Diagnosis and Treatment per capita (DTP), and Hospital Admission Rates (HAR) as indicators to measure public health levels.

2. Literature Review

2.1. Air Pollution and Life Satisfaction

Rehdanz and Maddison [8] selected air quality and noise levels as indicators to evaluate environmental quality, using survey data to analyze the relationship between environmental quality and life satisfaction in Germany. Their results indicated that severe air and noise pollution significantly reduce well-being and life satisfaction; as pollution gradually mitigates, these negative impacts diminish. Orru et al. [9] further explored this correlation, finding a negative relationship between PM10 and life satisfaction, where every 1μg/m3 increase in PM10 led to a 0.017-unit decrease in satisfaction valuation. This suggests that higher pollution levels correspond to lower life satisfaction, even when particulate concentrations are relatively low. Isen [2] analyzed the long-term effects of the U.S. Clean Air Act, using Total Suspended Particulates (TSP) as a proxy for pollution. Applying a DID model, the study found that infants born in areas with higher pollution levels exhibited lower earnings and labor force participation by age 30. However, Rehdanz [8] noted that data regarding emotions—such as life satisfaction and happiness—are inherently subjective and prone to bias compared to objective metrics, potentially lowering the reliability of such findings.

2.2. Air Pollution and Health Indicators

Environmental pollution significantly impacts public health. In 2012, 8.4 million deaths globally were attributed to soil, water, and air pollution, with one in seven deaths linked to environmental degradation[10]. Numerous scholars have found that environmental

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deterioration harms physical and mental health, triggering various diseases. Evans and Jacobs[11] observed that gaseous pollutants such as SO2, NO2, and CO can suppress the immune system and disrupt heart rates, leading to cardiovascular diseases. Furthermore, these pollutants can damage the nervous system and psychological well-being, even impacting cognitive intelligence [12]. Indirectly, air pollution reduces outdoor time, physical exercise, and social activities, further affecting mental and physical health [11]. Additionally, weather conditions influence mood; Owili et al. [13] specifically discussed the link between air pollution and maternal mortality in Africa, finding that high PM2.5 levels increase maternal death rates.

Zhang Minsi et al. [4] analyzed the health impacts of air pollution in urban Beijing from 2000 to 2004, identifying a significant correlation between pollution and cardiovascular and respiratory diseases. Their research demonstrated that any level of air pollution poses health risks, implying that even areas with mild pollution are not exempt—a finding consistent with Orru et al. [9]. Zhao et al. [14] analyzed the economic costs of health risks from 1994 to 2012, proving that health losses caused by air pollution accounted for 0.03% of Beijing's GDP. Yao Ming et al. [15] focused on the cross-regional transmission of emissions and its impact on health in Shanghai, showing that cross-regional PM2.5transport (PM2.5_CTRT) significantly contributed to increases in related deaths, cardiovascular and respiratory cases, and internal medicine and pediatric outpatient visits. Kuerban et al. [7] analyzed the relationship between air pollution and health risks in China from 2015 to 2018, noting a declining trend in pollutants (PM2.5, PM10, SO2, and CO) alongside a decrease in PM2.5 related mortality and morbidity.

2.3. Air Pollution Shock Events

To study the impact of air pollution on health, scholars often utilize "shock events" to explore post-impact differences. In studying the air pollution effects on the Chinese stock market, He and Liu [16] selected four major events likely to alter Public Environmental Awareness (PEA): the 2008 Beijing Olympics, the start of PM2.5 monitoring by the U.S. Embassy in 2009, the inclusion of PM2.5 in the national monitoring system in 2012, and the implementation of the strictest environmental laws in 2015. They argued that higher PEA leads to greater public attention to pollution and a higher likelihood of being affected by it [16]. Regarding sporting events, Traversi et al. [17] found no significant correlation between the 2006 Turin Winter Olympics and air pollution. In contrast, Cruz et al. [18] found that for the Rio Olympics, local emission control measures reduced PM10 concentrations by 17% compared to the pre-Olympic period.

Many researchers analyzed the 2008 Beijing Olympics; Schleicher et al. [6] found that pollutant concentrations during the Games were significantly lower than before or after, though they noted that meteorological conditions like wind also played a role. Wang et al. [5] corroborated that control measures lowered pollution levels but also identified rainfall as a contributing factor.

Beyond sporting events, new regulations are frequently studied as shock events. Isen et al. [2] used the 1970 U.S. Clean Air Act to analyze whether early-life exposure to pollution correlates with labor performance at age 30. By comparing regions substantially affected by the Act with those that were not using a DID model, they proved that the Clean Air Act Amendments (CAAA) reduced TSP concentrations by 10%. They further noted that improved air quality enhances cognitive abilities, while higher birth-year pollution leads to lower adult income.

Similar to the U.S. Clean Air Act, China's 2015 New Environmental Protection Law represents a milestone in environmental awareness and governance. However, few scholars have focused on this specific event. While Kuerban et al. [7] analyzed the post-law period, they did not compare the differences in pollution and health across the periods before and after implementation. While life satisfaction is affected by pollution, subjective measurements can introduce bias. Health indicators, as an objective component of well-being, are also significantly

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impacted by pollution. The 2015 New Environmental Protection Law is regarded as the strictest in history; its implementation serves as a robust shock event for research, for which the DID model is an appropriate analytical framework.

3. Research Design

3.1. Research Sample and Data Sources

We employ various models to analyze the relationship between air pollution and public health levels. Following the methodology of He and Liu [16], who selected a four-year window (two years prior to and two years following a specific event) to analyze the impact of air pollution shocks on the stock market, we have designated 2013–2018 as our research period. The study covers 31 regions in China, including 22 provinces, 5 autonomous regions, and 4 municipalities.

As noted by Yao et al. [15], PM2.5 is more easily absorbed by the human body and poses a greater health risk than PM10. Furthermore, PM2.5 is respirable [17] and significantly correlated with premature mortality. Consequently, this paper selects the annual average concentration of PM2.5 across the 31 regions as the primary explanatory variable. Air pollution data were retrieved from the Air Quality Online Monitoring Analysis Platform (www.aqistudy.cn).In their study, Yao et al. [15] utilized non-accidental mortality, respiratory mortality, hospitalizations, and outpatient visits as health indicators. Additionally, air pollution has been shown to have a substantial impact on maternal mortality [13], with higher PM2.5 levels corresponding to increased maternal death rates. Therefore, we select four metrics to measure public health: Total Mortality Rate, Maternal Mortality Rate, Diagnosis and Treatment per capita (DTP), and Hospital Admission Rate (HAR). The calculation for DTP is as follows:

$$\mathrm{DTP} = \frac{\mathrm{DTN}}{\mathrm{POP}} \tag{1}$$

Where DTN represents the total number of diagnoses and treatments in a specific region, and POP is the total population of that region. The Hospital Admission Rate (HAR) is calculated as:

$$\mathrm{HAR} = \frac{\mathrm{HAN}}{\mathrm{POP}} \tag{2}$$

Where HAN represents the total number of hospital admissions in a specific region. We utilize DTP and HAR to control for the impact of population growth on the results. Health-related data were obtained from the National Bureau of Statistics and the China Health Statistical Yearbook.

3.2. Research Hypotheses

Based on existing literature, we propose the following four hypotheses:

Hypothesis 1 (H1): Following the implementation of the two new laws, PM2.5 concentrations and their growth rates will decrease significantly, particularly in regions with severe air pollution.

Hypothesis 2 (H2): The implementation of the new laws will lead to a reduction in the growth rates of the four health indicators.

Hypothesis 3 (H3): The growth in annual average PM2.5 concentration has a significant positive impact on the growth of health indicators. This implies that higher PM2.5 growth leads to higher growth in mortality rates, maternal mortality rates, DTP, and HAR.

Hypothesis 4 (H4): The Environmental Protection Law (2015) and the Law on the Prevention and Control of Atmospheric Pollution (2016) have different degrees of impact on air pollution and health indicators.

3.3. Model Specification

Following the approach of Isen et al. [2], who employed OLS, 2SLS, and DID models to analyze the relationship between early-life air pollution exposure and adult outcomes, this paper establishes four models to explore the effects of the new laws on air pollution and public health.

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Model 1: OLS First-Difference Model

The first model examines the direct impact of PM2.5 changes on health indicators:

$$\Delta ya,t=\beta 0+\beta 1\Delta PM2.5a,t+\mu a,t \qquad (3)$$

Where ya,t represents the health indicator for a specific region a in year t; PM2.5a,t is the annual average concentration of PM2.5 with coefficient β1, Δya,t=ya,t−ya,t−1 denotes the first-difference value; and μa,t is the error term.

Model 2: OLS General and First-Difference Models

This model evaluates the impact of policy implementation on air pollution levels.

$$PM2.5a,t=\theta 0+\theta 1Heaa+\theta 2Impt+\theta 3(Heaa\times Impt)+i=130\gamma iDi+Va,t \quad (4)$$

$$\Delta PM2.5a,t=\lambda 0+\lambda 1Heaa+\lambda 2Impt+\lambda 3(Heaa\times Impt)+i=130\sigma iDi+\mu a,t \quad (5)$$

According to the Ambient Air Quality Standards released in China in 2012, the Grade II annual average PM2.5 limit is 35μg/m3. Accordingly, we define a dummy variable Heaa: Heaa = 1 if the region's annual average PM2.5 concentration exceeds 35μg/m3, and Heaa= 0 otherwise. Based on 2013–2015 data, 6 regions are classified as low-pollution areas, while the remaining 25 are categorized as high-pollution areas.

The policy dummy variable Impt captures the legal shifts. Given that the Environmental Protection Law and the Law on the Prevention and Control of Atmospheric Pollution were implemented in 2015 and 2016 respectively, Impt is split into Impet and Impat:

□$Impe_t$: 1 after 2015, 0 for 2013 and 2014.

□$Impa_t$: 1 from 2016 onwards, 0 for 2013, 2014, and 2015.

The interaction termHeaaImpt equals 1 for high-pollution regions after the implementation of the new laws. The term ∑γiDi represents regional dummy variables (Di=1 for region i), controlling for time-invariant regional characteristics across the 31 studied areas.

Model 3: OLS First-Difference Model for Health

This model analyzes the impact of the new laws specifically on health indicators:

$$\Delta ya,t=\varphi 0+\varphi 1Heaa+\varphi 2Impt+\varphi 3(Heaa\times Impt)+i=130\rho iDi+\varepsilon a,t \quad (6)$$

In this specification, Δya,t replaces ΔPM2.5a,t from Model 2, while all other variables remain consistent.

Model 4: 2SLS Model

To address potential endogeneity, we use an Instrumental Variable (IV) approach with a Two-Stage Least Squares (2SLS) framework:

Stage 1 (DID Model):

$$\Delta PM2.5a,t=\lambda 0+\lambda 1Heaa+\lambda 2Impt+\lambda 3(Heaa\times Impt)+i=130\sigma iDi+\mu a,t \qquad (7)$$

Stage 2:

$$\Delta ya,t=K0+K1\Delta PM2.5a,t+\zeta a,t \qquad (8)$$

Where ζa,t is the error term. The first stage utilizes the DID structure (identical to Model 2.2) to demonstrate the laws' impact on PM2.5 concentrations, which then serves as the instrument for the second stage.

Table 1: Variable Definitions

Category	Variable	Definition	Unit
Dependent	MOR	Mortality Rate	‰

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Variables	MMR	Maternal Mortality Rate	per 100,000
	DTP	Diagnosis and Treatment per capita	times per person
	HAR	Hospital Admission Rate	%
Explanatory Variable	PM2.5	Annual average concentration of PM2.5	μg/m3
Dummy Variables	Hea	Presence of severe air pollution	Yes = 1, No = 0
	Impe	Implementation of the new Environmental Protection Law	Yes = 1, No = 0
	Impa	Implementation of the new Law on the Prevention and Control of Atmospheric Pollution	

Table 2: Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
MOR	186	6.08	0.78	4.26	7.54
MMR	186	16.78	18.38	1.10	154.50
DTP	186	5.53	1.88	2.97	11.14
HAR	186	0.16	0.03	0.06	0.23
PM2.5	186	46.96	16.64	6.20	91.83

4. Empirical Analysis

4.1. 4.1 T-Test Results

To determine whether substantial differences exist in our variables between regions with severe air pollution and those with cleaner air, we conducted four sets of T-tests for the periods associated with the two new laws.

Table 3 reports the T-test results prior to 2015. There are significant differences between the two groups of regions regarding maternal mortality rate (MMR), Hospital Admission Rate (HAR), PM2.5 levels, and their respective first differences. The data indicate that regions with severe air pollution exhibit lower maternal mortality rates but higher hospital admission rates and annual average PM2.5 concentrations. Furthermore, the growth rate of HAR is higher in heavily polluted regions, while the growth rate of PM2.5 is lower. Table 2 further reveals that maternal mortality rates are declining in both heavily polluted and cleaner regions; however, the decline is more rapid in cleaner areas.

As shown in Table 3, following the implementation of the new Environmental Protection Law, both groups of regions experienced a decrease in maternal mortality rates and PM2.5 concentrations. More importantly, the growth rates of the mortality rate (MOR), DTP, and PM2.5 also declined across both groups. The results show that mortality rates, HAR, and PM2.5 remain significantly higher in heavily polluted regions, while maternal mortality remains lower—a trend consistent with the pre-2015 findings. Additionally, mortality and HAR grew more rapidly in the heavily polluted group, while the decline in maternal mortality was less pronounced. A notable shift occurred after the new Environmental Protection Law took effect: mortality rates in cleaner regions began to trend downward, and PM2.5 levels decreased in both groups. The mean values for PM2.5 suggest that concentrations in heavily polluted regions are decreasing at a faster rate than in cleaner regions.

Table 3: T-Test Results (Pre-2015)

Hea	Obs.	MOR	MMR	DTP	HAR	PM2.5
1	50	6.073	14.582	5.3969	14.3395	59.5437
0	12	5.9383	36.1333	4.9558	12.8597	27.6625
t-value		-0.5676	3.1627***	-0.7786	-1.5613*	-6.8188***
Hea	Obs.	ΔMOR	ΔMMR	ΔDTP	ΔHAR	ΔPM2.5
1	25	0.1516	-0.532	0.1941	0.8439	6.2393
0	6	0.02	-8.4333	0.1803	0.5066	11.925
t-value		-0.9234	-2.0905**	-0.1689	-1.8322**	1.4558*

Note: This table includes data from 2013 and 2014. ***, *, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 4: T-Test Results (Post-2015)

Hea	Obs.	MOR	MMR	DTP	HAR	PM2.5
1	100	6.1499	12.947	5.7059	16.6526	
0	24	5.8396	27.6167	5.3614	14.6402	25.2604
t-value		-1.6854**	4.3781***	-0.777	-2.7348***	-9.1980***
Hea	Obs.	ΔMOR	ΔMMR	ΔDTP	ΔHAR	ΔPM2.5
1	75	0.0893	-0.424	0.0991	0.9417	-4.2356
0	18	-0.0383	-2.4278	0.1505	0.7174	-1.3657
t-value		-2.0543**	-1.4951*	1.1587	-1.4352*	2.7960***

Note: This table includes data from 2015 to 2018.

Subsequently, we analyzed the disparities surrounding the implementation of the Law on the Prevention and Control of Atmospheric Pollution. Prior to 2016, as shown in Table 5, the mean values and first differences for mortality (MOR), maternal mortality (MMR), DTP, HAR, and PM2.5 across both groups mirror the T-test results from the pre-2015 period. However, compared to the pre-2015 data, the growth rates of mortality, DTP, HAR, and PM2.5 were lower. Mortality rates in less-polluted regions and PM2.5 levels in heavily polluted regions began to decline. Importantly, a significant difference was observed in the growth rate of maternal mortality between the two groups.

Post-2016, the T-test results presented in Table 6 are highly consistent with those from the post-2015 period. The combined findings from Tables 5 and 6 suggest that the implementation of the new Environmental Protection Law had a more profound impact on health indicators and air pollution mitigation than the Law on the Prevention and Control of Atmospheric Pollution.

Table 5: T-Test Results (Pre-2016)

Hea	Obs.	MOR	MMR	DTP	HAR	PM2.5
1	75	6.0501	14.2053	5.4421	14.5909	
0	18	5.9144	33.5056	5.0086	13.0783	27.4602

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Hea	Obs.	MOR	MMR	DTP	HAR	PM2.5
t-value		-0.6831	3.7291***	-0.9193	-1.9588**	-8.4639***
Hea	Obs.	ΔMOR	ΔMMR	ΔDTP	ΔHAR	ΔPM2.5
1	50	0.0036	-0.698	0.1163	0.5882	-1.1503
0	12	-0.0308	-6.05	0.1243	0.4546	2.6778
t-value		-0.3255	-2.6261***	0.1425	-0.8213	1.0945

Note: This table includes data from 2013 to 2015. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 6: T-Test Results (Post-2016)

Hea	Obs.	MOR	MMR	DTP	HAR	PM2.5
1	75	6.1984	12.7787	5.7637	17.1721	
0	18	5.8306	27.4056	5.4438	15.0151	24.662
t-value		-1.7259**	3.9249***	-0.6165	-2.5674***	-7.9305***
Hea	Obs.	ΔMOR	ΔMMR	ΔDTP	ΔHAR	ΔPM2.5
1	50	0.079	-0.434	0.0808	0.8325	-4.3767
0	12	-0.0575	-5.2917	0.1473	0.6624	-1.5694
t-value		-1.8698**	-2.7073***	1.1407	-0.7978	2.5242***

Note: This table includes data from 2016 to 2018.

4.2. Regression Results

4.2.1. Impact of PM2.5 Growth on Health Indicators

The regression results for Equation (1) are presented in Table 7, covering the four dependent variables. Tests for heteroscedasticity were conducted, revealing its presence at the 0.01 significance level. Consequently, we employ robust standard errors to ensure the validity of our inferences.

Table 7: Impact of PM2.5 Growth on Health Indicators

	(1)	(2)	(3)	(4)
	ΔMOR	ΔMMR	ΔDTP	ΔHAR
ΔPM2.5	0.0065	-0.0739	0.0039***	0.0085
	(0.0043)	(0.1067)	(0.0014)	(0.0061)
Observations	155	155	155	155

Note: ***, **, and * denote significance at the 0.01, 0.05, and 0.1 levels, respectively. Robust standard errors are in parentheses.

Columns (1) through (4) display the first-difference results for mortality, maternal mortality, Diagnosis and Treatment per capita (DTP), and Hospital Admission Rate (HAR). The results indicate that only the first difference of DTP (ΔDTP) exhibits a significant positive correlation with PM2.5 growth. The coefficient for ΔDTP suggests that a one-unit increase in PM2.5 concentration leads to a 0.0039-unit increase in DTP. This aligns with the fact that air pollution exacerbates cardiovascular and respiratory diseases, forcing individuals to seek more medical diagnosis and treatment as air quality worsens. Specifically, every 300-unit increase in PM2.5 results in nearly one additional diagnosis and treatment session per person. However, no significant relationship was found between PM2.5 growth and the first differences of mortality, maternal mortality, or HAR.

4.2.2. Impact of Legal Implementation on Environmental PM2.5 Exposure

Equations (2) and (3) serve as the first stage of the 2SLS model, examining the impact of the Environmental Protection Law and the Law on the Prevention and Control of Atmospheric Pollution on annual average PM2.5 concentrations. The regression results in Table 8 control for regional fixed effects and utilize two interaction terms: Heaa×Impetand Heaa×Impat. Robust standard errors are applied throughout. Panels A and B report regressions for PM2.5 levels and their first differences, respectively.

Table 8: Impact of Legal Implementation on Environmental PM2.5 Exposure

Variable	（1）	（2）	（3）	（4）
		Panel A PM2.5		
Hea	31.8812***	30.2767***	35.2755***	33.6710***
	(3.9504)	(2.8460)	(2.8526)	(2.8125)
Imp	-2.4021	-2.7981	-2.4021	-2.7981
	(3.4927)	(2.6216)	(2.4827)	(1.7623)
Hea×Imp	-8.9549**	-8.7310**	-8.9549***	-8.7310***
	(4.2643)	(3.3644)	(2.7783)	(2.0599)
		Panel B ΔPM2.5		
Hea	-5.6857*	-3.8281	-5.1659	-3.3083
	(3.0114)	(3.5974)	(4.1689)	(5.5983)
Imp	-14.5917***	-4.0435	-14.5917***	-4.0435
	(2.5813)	(3.2861)	(2.7893)	(3.5951)
Hea×Imp	3.0407	0.9583	3.0407	0.9583
	(3.1795)	(3.6533)	(3.3961)	(3.9888)
Imp	Impe	Impa	Impe	Impa
Regional Fixed Effects			YES	YES

In Panel A, columns (1) and (2) show that both laws had similar effects on air pollution. The coefficient for Heaaconfirms that heavily polluted regions indeed suffer from higher pollution, with PM2.5 concentrations approximately 30 μg/m3 higher than in less-polluted areas. Following the implementation of the two laws, annual average PM2.5 concentrations in heavily polluted regions dropped significantly by nearly 9μg/m3. No significant relationship was found between the laws and overall PM2.5 concentrations across all regions.

In Panel B, the analysis of PM2.5 growth indicates that only the new Environmental Protection Law (Impe) had a significant impact. The negative coefficient for Heaa suggests that PM2.5 growth in heavily polluted regions was 5.7μg/m3 slower than in cleaner regions, likely due to a higher baseline and stricter regulatory limits in those areas. Furthermore, following the implementation of the new law, PM2.5 growth across both groups was 14.6μg/m3 lower than in the pre-implementation period, indicating that the new Environmental Protection Law significantly decelerated the growth of PM2.5.

When controlling for regional fixed effects (Columns 3 and 4), the coefficients remain very close to the previous models. However, the Heaa coefficient in Panel B becomes non-significant.

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Overall, Table 8 demonstrates that the new laws effectively mitigated air pollution, though they exerted varying influences on PM2.5 growth, particularly differing between high-pollution and low-pollution regions.

We subsequently replaced ΔPM2.5 with the first differences of our health indicators and re-ran the regression using Model 3 to analyze the laws' impact on health. The results are presented in Table 9.

Table 9: Impact of Legal Implementation on Health Indicators

	(1)	(2)	(3)	(4)
Panel A: Mortality Rate (MOR)				
Hea	0.1316	0.0344	-0.0168	-0.1139
	(0.0810)	(0.0650)	(0.1060)	(0.0870)
Imp	-0.0692	-0.0075	-0.0692*	-0.0075
	(0.0543)	(0.0539)	(0.0402)	(0.0538)
Hea×Imp	-0.0515	0.0932	-0.0515	0.0932
	(0.0914)	(0.0796)	0.0808)	(0.0813)
Panel B: Maternal Mortality (MMR)				
Hea	7.9013	5.3520	4.3783	1.8289
	(7.0034)	(3.6598)	(4.4575)	(2.8486)
Imp	5.6958	3.6222	5.6958	3.6222
	(7.2164)	(4.3781)	(4.9378)	(3.6265)
Hea×Imp	-5.6978	-3.3482	-5.6978	-3.3482
	(7.2559)	(4.4144)	(4.9973)	(3.6733)
Panel C: DTP				
Hea	0.0138	-0.0079	0.0348	0.0132
	(0.0478)	(0.0399)	(0.0848)	(0.0829)
Imp	-0.0504	0.0262	-0.0504	0.0262
	(0.0420)	(0.0483)	(0.0497)	(0.0513)
Hea×Imp	-0.0597	-0.0435	-0.0597	-0.0435
	(0.0594)	(0.0584)	(0.0604)	(0.0586)
Panel D: HAR				
Hea	0.3373	0.1336	0.7001*	0.4964
	(0.2294)	(0.1952)	(0.3569)	(0.3138)
Imp	0.1321	0.2628	0.1321	0.2628
	(0.2679)	(0.2565)	(0.2859)	(0.2684)
Hea×Imp	-0.1866	0.0908	-0.1866	0.0908
	(0.2833)	(0.2724)	(0.2971)	(0.2815)
Imp	Impe	Impa	Impe	Impa
Regional Fixed Effects			YES	YES

Without fixed effects, the results in columns (1) and (2) suggest that neither law had a significant impact on the growth of health indicators. However, once regional fixed effects are controlled for (columns 3 and 4), the results shift slightly. In Panel A, the implementation of the new Environmental Protection Law (Impe) is associated with a 0.07-unit reduction in mortality growth. This effect appears consistent across both heavily polluted and cleaner regions. In

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Panel D, the Heaa coefficient indicates that hospital admission rate (HAR) growth in heavily polluted areas is 0.7% higher than in cleaner areas. This positive correlation between PM2.5 levels and HAR growth is expected due to the higher pollution concentrations in these regions. Regression (4) indicates that the Law on the Prevention and Control of Atmospheric Pollution (Impa) had no significant impact on health indicator growth.

Table 10: 2SLS Regression: Impact of PM2.5 Exposure on Health

	(1)	(2)	(3)	(4)
	Panel A: Mortality Rate			
ΔPM2.5	0.0065	-0.0225*	0.0058	-0.0137
	(0.0044)	(0.0123)	(0.0043)	(0.0089)
	Panel B: Maternal Mortality			
ΔPM2.5	-0.1676	-0.5975	-0.1888	-0.5094**
	(0.1621)	(0.3620)	(0.1644)	(0.2915)
	Panel C: DT			
ΔPM2.5	0.0080***	0.0053	0.0056**	-0.0031
	(0.0028)	(0.0055)	(0.0026)	(0.0057)
	Panel D: HAR			
ΔPM2.5	-0.0029	-0.0837**	-0.0032	-0.0526*
	(0.0078)	(0.0405)	(0.0077)	(0.0247)
Imp	Impe	Impa	Impe	Impa
Regional Fixed Effects			YES	YES

Table 10 presents the results of the 2SLS model. Since the interaction term (Heaa×Impt) serves as an instrumental variable (IV) for the average PM2.5 levels, and Impt is bifurcated into Impet and Impat, we conduct four separate regressions. Regional fixed effects are controlled in the first stage, with adjustments made for robust standard errors.

Columns (1) and (2) report results without regional fixed effects. In column (1), PM2.5 shows a significant positive impact only on ΔDTP, with a coefficient larger than that observed in the OLS results (Table 7). In column (2), the coefficients surprisingly suggest a negative correlation between ΔPM2.5 and both ΔMortality and ΔHAR, implying that larger increases in PM2.5 correspond to smaller growth rates in mortality and hospital admissions for the following year.

When regional fixed effects are included (column 3), the coefficient for ΔDTP remains significantly positive, though slightly smaller than in column (1), yet still larger than the OLS estimates in Table 7. No significant relationship is found between PM2.5 growth and other health indicators in this specification. In column (4), the first differences of maternal mortality and HAR exhibit a negative correlation with ΔPM2.5. The disparities between columns (1)/(3) and (2)/(4) underscore that the two laws exerted distinct influences on health outcomes.

In summary, growth in annual average PM2.5 positively impacts the growth of diagnoses and treatments per capita (DTP). Crucially, the implementation of both laws significantly reduced the annual average PM2.5 in heavily polluted regions by approximately 9μg/m3. Furthermore, the new Environmental Protection Law markedly decelerated PM2.5 growth across all regions by 14.6μg/m. Following the 2015 law's enactment, mortality growth across both groups also saw a significant reduction of approximately 0.07%. Overall, the findings indicate that the two

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laws have differential impacts on air pollution and health variables, with the Environmental Protection Law demonstrating a more substantial influence than the Law on the Prevention and Control of Atmospheric Pollution.

5. Robustness Check and Discussion

5.1. Controlling for Meteorological Factors

To further validate our findings, we incorporated weather factors as control variables and re-ran the regressions to examine consistency with the results in Section 4. Following the methodology of Isen [2], we used temperature and precipitation data to control for meteorological influences on air pollution. Other researchers, such as Chen et al., Kuerban et al., and Wang et al., have also noted that temperature and precipitation significantly affect the concentration of air pollutants [19][5][7]. Additionally, Howarth and Hoffman [20] found that humidity and sunshine duration significantly influence mood.

Consequently, we selected annual average temperature, annual average precipitation, annual average humidity, and annual average sunshine duration as weather controls. The raw meteorological data were monthly and limited to provincial capitals; therefore, we used the capital city's data as a proxy for the entire region. All meteorological data were obtained from the CSMAR database. The regressions in this section were conducted using regional fixed effects and robust standard errors.

Table 11: Variable Definitions

Variable	Definition	Unit
Tem	Annual average temperature	℃
Pre	Annual average precipitation	mm
Hum	Annual average relative humidity	%
Sun	Annual average sunshine duration	hours

Table 12: Descriptive Statistics for Meteorological Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Tem	186	14.5289	5.0790	4.2833	25.3333
Pre	186	83.0094	46.7484	15.9167	244.975
Hum	186	65.5729	12.0585	34.3333	83.75
Sun	186	171.3932	45.8182	54.4	259.3667

We re-estimated the model from Table 7 with these new controls, and the results are presented in Table 13. As shown, the findings are highly consistent with our previous results. PM2.5 growth continues to exert a significant positive impact on the growth of DTP. The coefficient for DTP remains identical to that in Table 7 and maintains the same significance level. These results suggest that meteorological factors do not significantly alter the impact of air pollution on health outcomes.

Table 13: Impact of PM2.5 Growth on Health Indicators

	（1）	（2）	（3）	（4）
	ΔMOR	ΔMMR	ΔDTP	ΔHAR
	0.0065	-0.0724	0.0039***	0.0087

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ΔPM2.5	-0.0043	-0.0999	-0.0015	-0.0064
Weather Controls	Yes	Yes	Yes	Yes

Regarding the laws' impact on PM2.5 concentrations, we re-ran Models 2.1 and 2.2. The results in Table 14 show no significant correlation between PM2.5 and Heaa, which differs from the previous regressions. In column (1), after the implementation of the Environmental Protection Law, PM2.5 concentrations in heavily polluted regions alone decreased by approximately 8μg/m3. In column (2), PM2.5 concentrations decreased in both heavily and mildly polluted areas. Furthermore, PM2.5 levels in heavily polluted regions were reduced by 8μg/m3 more than in cleaner regions, which also deviates from the prior findings.

Overall, the PM2.5 results remain largely consistent with those in Table 8 (Panel B). These findings further indicate that the new Environmental Protection Law primarily restricted PM2.5 growth, whereas the Law on the Prevention and Control of Atmospheric Pollution had a greater impact on absolute PM2.5 levels. As previously noted, weather conditions can influence the dispersion of PM2.5. These results suggest that meteorological factors do influence air pollution and may interfere with the analyses in regressions that do not account for them.

Table 14: Impact of Legal Implementation on Environmental PM2.5 Exposure

	(1)	(2)	(3)	(4)
	PM2. 5		ΔPM2.5	
Hea	-29.9796	18.0519	-21.8781	37.4272
	(22.4708)	(23.250)	(38.8147)	(41.9047)
Imp	-4.4468	-3.2277*	-14.8763***	-3.9282
	(2.7453)	(1.8696)	(3.1542)	(3.7563)
Hea×Imp	-7.8016***	-7.9657***	3.3833	2.2690
	(2.8481)	(2.1272)	(4.0056)	(4.4525)
Imp	Impe	Impa	Impe	Impa
Regional Fixed Effects	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes

Model 3 was re-estimated incorporating weather controls, with the results presented in Table 15. The data indicate that only Heaa has a significant correlation with the growth of mortality rates. Specifically, mortality growth is higher in regions with severe air pollution compared to cleaner regions. Given the higher PM2.5 concentrations in heavily polluted areas, this provides indirect evidence of a positive correlation between PM2.5 and mortality growth.

Table 15: Impact of Legal Implementation on Health

Variable	（1）	（2）
	Panel A: Mortality Rate (MOR)	
Hea	1.7346*	2.0333**
	(1.0400)	(0.9223)
	-0.0105	0.0026
Imp	(0.0519)	(0.0646)
	-0.1336	0.1031

Hea×Imp	(0.0866)	(0.1035)
	Panel B: Maternal Mortality (MMR)	
Hea	33.0829	22.0215
	(23.8075)	(20.3877)
Imp	5.9079	3.6971
	(5.1642)	(3.6744)
Hea×Imp	-5.3412	-3.1090
	(5.2115)	(3.8497)
	Panel C: DTP	
Hea	-0.1534	0.3539
	(0.6583)	(0.6787)
Imp	-0.0443	0.0343
	(0.0544)	(0.0525)
Hea×Imp	-0.0961	-0.0604
	(0.0649)	(0.0637)
	Panel D: HAR	
Hea	0.7345	0.7068
	(2.1962)	(2.4165)
Imp	0.1665	0.2519
	(0.2952)	(0.2748)
Hea×Imp	-0.2982	0.1414
	(0.3111)	(0.3099)
Imp	Impe	Impe
Regional Fixed Effects	Yes	Yes
Weather Controls	Yes	Yes

Note: This table reports coefficients from eight independent regressions (two for each panel). Robust standard errors are in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.1 levels, respectively.

Upon re-estimating Model 4, the results shown in Table 16 are nearly identical to those in Table 10. The findings confirm that DTP growth is significantly and positively correlated with PM2.5, with the DTP coefficient remaining almost unchanged from our baseline 2SLS results. In column (2), the first difference of HAR remains negatively correlated with PM2.5 growth, although the absolute value of the coefficient is smaller.

Table 16: 2SLS Results: Impact of PM2.5 Exposure on Health

Variable	(1)	(2)
	Panel A: Mortality Rate	
PM2.5	0.0045	-0.0054
	(0.0045)	-0.0072
	Panel B: Maternal Mortality	
PM2.5	-0.1679	-0.2280
	(0.1580)	(0.1781)
	Panel C: DTP	

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PM2.5	0.0054**	-0.0013
	(0.0025)	(0.0041)
	Panel D: HAR	
PM2.5	-0.0020	-0.0251*
	(0.0072)	(0.0146)
Imp	Impe	Impa
Regional Fixed Effects	Yes	Yes
Weather Controls	Yes	Yes

In conclusion, the robustness checks in this section confirm that the correlations between air pollution and health indicators, as well as the relationship between the implementation of new environmental regulations and PM2.5 concentrations, are statistically robust.

5.2. Discussion

Based on the empirical analysis in Section 4, a significant positive correlation exists between the growth of PM2.5 and the growth of Diagnosis and Treatment per capita (DTP). However, no significant correlation was found between air pollution and mortality rates, Hospital Admission Rates (HAR), or maternal mortality rates.

We utilized the first differences of PM2.5 and health variables to analyze their relationships rather than using raw level data. This choice was motivated by the observation that mortality, DTP, and HAR did not exhibit a synchronized downward trend when PM2.5 concentrations declined. As illustrated in Figure 1, the annual average concentration of PM2.5 increased from 2013 to 2014, followed by a continuous downward trend starting in 2015.

With the exception of maternal mortality, which trended downward from 2013 to 2018, the trends for mortality, DTP, and HAR diverged from that of PM2.5. The results in Section 4 indicate that the primary effect of the new laws was the deceleration of growth in these health indicators, rather than a reduction in their absolute values. It is plausible that mortality, maternal mortality, DTP, and HAR are influenced by a multitude of other factors, such as public health awareness, advancements in medical technology, and other environmental stressors, including water pollution and noise pollution.

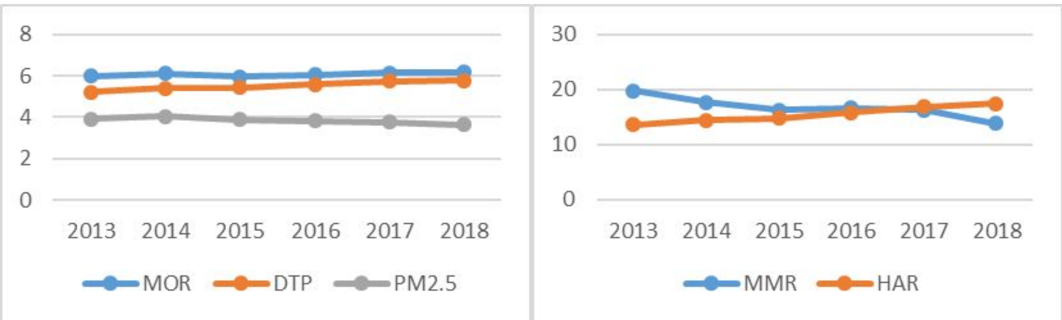

Figure 1: Trends of Dependent and Independent Variables (2013–2018)

Regarding mortality rates, two conflicting channels may influence this variable. The first channel suggests that air pollution increases mortality by inducing cardiovascular and respiratory diseases and exacerbating negative emotions. Thus, higher pollution levels should lead to higher mortality. However, a secondary channel—as noted by Evans and Jacobs [11]—suggests that severe air pollution may reduce outdoor activities, thereby lowering the incidence of accidents such as traffic fatalities. These two channels exert opposing effects. Since our

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analysis primarily focuses on the first channel, its statistical significance may be attenuated by the counteracting influence of the second.

For maternal mortality rate (MMR), T-test results indicated higher rates in cleaner regions. As explained by Liang et al. [21], MMR is heavily influenced by economic development, healthcare services, and education. Regions with rapid economic growth and superior medical infrastructure typically exhibit lower MMR. Consequently, maternal deaths are more prevalent in rural and remote areas due to a lack of prenatal knowledge and limited access to healthcare. Some regions identified as having "mild air pollution" are geographically underdeveloped with less advanced medical facilities, resulting in higher MMR. Furthermore, the sustained decline in China's MMR is primarily driven by the expansion of national medical insurance, which may overshadow the impact of reduced air pollution.

Figure 1 reveals a visible upward trend in the Hospital Admission Rate (HAR) as PM2.5 declines, which may be attributed to an increase in outdoor accidents. The lack of statistical significance for HAR suggests that air pollution only accounts for a very limited portion of its variance.

When incorporating weather conditions as control variables, the disparity in PM2.5 concentrations between heavily polluted and cleaner regions becomes less pronounced, indicating that meteorological conditions play a vital role in pollution mitigation. Table 17 presents the T-test results for weather variables, showing that heavily polluted regions have significantly lower temperature, precipitation, and humidity, but higher sunshine duration compared to cleaner regions. Rainfall is a known scavenger of air pollutants; thus, higher precipitation likely explains the lower pollution levels in the latter group. This implies that anthropogenic (human-caused) pollution levels might actually be comparable across both groups.

Table 17: T-Test Results for Meteorological Variables

Hea	Obs.	Temperature	Precipitation	Humidity	Sunshine
1	150	13.7018	74.0361	64.3715	173.7492
0	36	17.9752	120.3980	70.5787	161.5766
t-value		4.7955***	5.7951***	2.8255***	-1.4356*

Furthermore, we found no significant correlation between the implementation of new laws and the growth of health indicators. This may be because health outcomes are governed by numerous factors, with environmental legislation exerting only a marginal influence. Additionally, the impact of these laws is indirect; due to their relatively lower status in the legal hierarchy and limited public engagement, their binding force is insufficient to yield immediate, large-scale improvements in public health.

The analysis reveals that the Environmental Protection Law (EPL) and the Law on the Prevention and Control of Atmospheric Pollution (LPCAP) had differential impacts. The LPCAP is a supplementary law specifically targeting air quality. However, following the 2015 EPL—which mandated production restrictions and the closure of high-pollution factories—pollution across air, water, and electromagnetic radiation had already been significantly curtailed. Consequently, the 2016 LPCAP had less "regulatory room" to effect further improvements. Our analysis confirms that the 2016 LPCAP had a smaller impact on air pollution and health indicators compared to the 2015 EPL.

6. Conclusion

In this study, we employed four distinct econometric frameworks—the Ordinary Least Squares (OLS) model, Difference-in-Differences (DID) models for both air pollution and health

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indicators, and a Two-Stage Least Squares (2SLS) model using first-difference regressions—to analyze the nexus between air pollution and health, as well as the impact of two new environmental laws.

Prior to the regression analysis, T-tests were conducted to examine the disparities between heavily polluted regions and cleaner regions. The results indicate substantial differences between these two groups prior to the legal implementation, which persisted even after the laws took effect. Following the implementation of the legislation, we observed a downward trend in PM2.5 concentrations, PM2.5 growth rates, and the growth rates of certain health indicators, such as mortality and Diagnosis and Treatment per capita (DTP). Furthermore, the Environmental Protection Law (EPL) exerted a more pronounced impact on PM2.5 levels and public health compared to the Law on the Prevention and Control of Atmospheric Pollution (LPCAP).

The results from Model 1 and Model 4 demonstrate that the first difference of PM2.5 has a significant positive effect on the growth of DTP. Results from Model 2 and Model 3 suggest that the implementation of both laws significantly reduced PM2.5 concentrations in heavily polluted areas. Specifically, the new EPL substantially decelerated the growth rate of PM2.5 in both regional groups. However, no significant evidence was found to link the implementation of these two laws directly to the growth rates of health indicators.

To ensure the robustness of our findings, meteorological variables were incorporated into the models. When controlling for weather effects, the correlation between PM2.5 growth and the growth of health indicators remained consistent with the baseline results. While the correlation between legal implementation and air pollution remained largely robust, we found no evidence of higher PM2.5 concentrations specifically in heavily polluted regions under these controlled conditions, nor was there a significant correlation between the laws and the growth of health indicators.

In summary, this study confirms that the correlations between air pollution and health indicators, as well as the impact of legal implementation on PM2.5, are statistically robust. Moreover, the new EPL yielded a greater influence on health and air quality than the LPCAP. While a positive correlation may exist between air pollution and mortality or HAR, further research is required to substantiate these relationships.

This analysis is subject to several limitations. First, due to data availability, our health indicators were restricted to total mortality, maternal mortality, DTP, and HAR. While some scholars have found more significant results by focusing specifically on PM2.5-related mortality or cardiovascular and respiratory diseases, such granular data is not available across all Chinese provinces. Second, PM2.5 impacts health through two competing pathways: a direct biological pathway (inducing respiratory or mental illness) and a behavioral pathway (reducing outdoor activities and associated accident risks). Due to the difficulty in quantifying behavioral changes, we could not isolate this effect, which may have confounded the regression results. Finally, weather conditions, such as precipitation, play a significant role in mitigating air pollution. If shifts in meteorological patterns after 2015 significantly influenced PM2.5 concentrations, the estimated impact of the two new laws on air pollution and health may be slightly overestimated.

References

[1] Calderón-Garcidueñas, L., Maronpot, R.R., Torres-Jardon, R., Henríquez-Roldán, C., Schoonhoven, R., Acuñaayala, H. and Swenberg, J.A. (2003). 'DNA damage in nasal and brain tissues of canines exposed to air pollutants is associated with evidence of chronic brain inflammation and neurodegeneration', Toxicologic Pathology, 31 (5), pp. 524-538.

[2] Isen, A., Rossin-Slater, M. and Walker, W.R. (2017) 'Every Breath You Take—Every Dollar You'll Make: The Long-Term Consequences of the Clean

ISSN: 3008-1769

[3] Zhang, B., Cao, C., Gu, J. and Liu, T. (2016) 'A New Environmental Protection Law, Many Old Problems? Challenges to Environmental Governance in China', Journal of Environmental Law, 28 (2), pp. 325–335, doi:10.1093/jel/eqw014.

[4] Zhang, M., Song, Y. and Cai, X. (2007) 'A health-based assessment of particulate air pollution in urban areas of Beijing in 2000–2004', Science of The Total Environment, 376 (1–3), pp. 100-108.

[5] Wang, X., Wang, T., Pathak, R.K., Hallquist, M., Gao, X., Nie, W., Xue, L., Gao, J., Gao, R., Zhang, Q., Wang, W., Wang, S., Chai, F. and Chen, Y. (2013) 'Size distributions of aerosol sulfates and nitrates in Beijing during the 2008 Olympic Games: Impacts of pollution control measures and regional transport', Advances in Atmospheric Sciences, 30 (2), pp. 341–353. doi:10.1007/s00376-012-2053-4.

[6] Schleicher, N., Norra, S., Chen, Y., Chai, F. and Wang, S. (2012) 'Efficiency of mitigation measures to reduce particulate air pollution—A case study during the Olympic Summer Games 2008 in Beijing, China', Science of The Total Environment, 427–428, pp. 146-158.

[7] Kuerban, M., Waili, Y., Fan, F., Liu, Y., Qin, W., Dore, A.J., Peng, J., Xu, W. and Zhang, F. (2020) 'Spatio-temporal patterns of air pollution in China from 2015 to 2018 and implications for health risks', Environmental Pollution,258, pp. 113659.

[8] Rehdanz, K. and Maddison, D. (2008) 'Local environmental quality and life-satisfaction in Germany', Ecological Economics, 64 (4), pp. 787-797.

[9] Orru, K., Orru, H., Maasikmets, M., Hendrikson, R. and Ainsaar, M. (2016) 'Well-being and environmental quality: Does pollution affect life satisfaction?', Quality of Life Research, 25 (3), pp. 699-705.

[10] Landrigan, P.J. and Fuller, R., (2014) 'Environmental Pollution and Occupational Health in a Changing World', Annals of Global Health, 80(4), pp. 245–246.

[11] Evans, G. W. and Jacobs, S. V. (1981) 'Air pollution and human behavior', Journal of Social Issues, 37, pp. 95-125.

[12] Weiss, B. (1988) 'Behavior as an early indicator of pesticide toxicity', Toxicology and Environmental Health, 4, pp. 351–360.

[13] Owili, P.O., Lien, WH., Muga, M.A. and Lin, TH. (2017) 'The Associations between Types of Ambient PM2.5 and Under-Five and Maternal Mortality in Africa', International Journal of Environmental Research and Public Health, 14 (4), pp. 359.

[14] Zhao, X., Yu, X., Wang, Y. and Fan, C. (2016) 'Economic evaluation of health losses from air pollution in Beijing, China', Environ Sci Pollut Res, 23, pp. 11716–11728, doi:10.1007/s11356-016-6270-8.

[15] Yao, L., Zhan, B., Xian, A., Sun, W., Li, Q. and Chen, J. (2019) 'Contribution of transregional transport to particle pollution and health effects in Shanghai during 2013–2017', Science of The Total Environment, 677,pp. 564-570.

[16] He, X., Liu, Y. (2018) 'The public environmental awareness and the air pollution effect in Chinese stock market', Journal of Cleaner Production,185, pp. 446-454.

[17] Traversi, D., Degan, R., Marco, R.D., Gilli, G., Pignata, C., Ponzio, M., Rava, M., Sessarego, F., Villani, S. and Bono, R. (2008) 'Mutagenic properties of PM2.5 air pollution in the Padana Plain (Italy) before and in the course of XX Winter Olympic Games of "Torino 2006"', Environment International, 34 (7), pp. 966-970.

[18] Cruz, A.R.H.D.L., Calderon, E.R.D., França, B.B., Réquia, W.J. and Gioda, A. (2019) 'Evaluation of the impact of the Rio 2016 Olympic Games on air quality in the city of Rio de Janeiro, Brazil', Atmospheric Environment, 203, pp. 206-215.

[19] Chen, Y., Ebenstein, A., Greenstone, M. and Li, H. (2013) 'Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy', PNAS, 110 (32), pp. 12936-12941.

[20] Howarth, E. and Hoffman, M.S. (1984) 'A Multidimensional Approach to the Relationship between Mood and Weather' , British Journal of Psychology, 75 (15-23).

[21] Liang, J., Zhu, J., Dai, L., Li, X., Li, M. and Wang, Y. (2010) 'Maternal mortality in China, 1996–2005', International Journal of Gynecology & Obstetrics, 110 (93-96), doi:10.1016/j.ijgo.2010.03.013

ISSN: 3008-1769

[22] Airila, A., Hakanen, J.J., Luukkonen, R., Lusa, S. and Punakallio, A. (2013) 'Positive and Negative Mood Trajectories and Their Relationship With Work Ability, Self-Rated Health, and Life Satisfaction: A 13-Year Follow-Up Study', Journal of Occupational and Environmental Medicine, 55 (7) , pp. 779-785, doi: 10.1097/JOM.0b013e3182988925.

[23] Landrigan, P.J. and Fuller, R., (2014) 'Environmental Pollution and Occupational Health in a Changing World', Annals of Global Health, 80(4), pp. 245–246.