

参赛学生姓名：张沐和

中学：北京师范大学附属实验中学

省份：北京

国家/地区：中华人民共和国

指导老师姓名：曹静、郁露

指导老师单位：清华大学经济管理学院经

济系、北京师范大学附属实验中学

论文题目：**Environmental Policy and
Psychological Well-being: Evidence from
China's Clean Air Action Plan**

Environmental Policy and Psychological Well-being: Evidence from China's Clean Air Action Plan

Muhe Zhang

The Experimental High School

Attached to Beijing Normal University

Abstract

This paper examines how environmental regulation policies exert influence through both direct and indirect channels, focusing on the impact of China's so far most stringent air pollution control policy, the 2013 Air Pollution Prevention and Control Action Plan (APPCAP). Exploiting variations in stringencies of the implementation of the policy, the study finds that the APPCAP significantly reduced the emission levels of major targeted pollutants while simultaneously generating synergistic pollution control effects. These effects remain robust across sub-regional analysis. We further investigate how the APPCAP can improve individuals' psychological well-being. Our findings indicate that for every 1% increase in the policy's target stringency, the corresponding public anxiety indicator decreases by 1.66%, reaffirming significant mental health benefits from the environmental regulation. This effect is particularly significant in areas with lower levels of urbanization.

Keywords: Air pollution, Psychological Wellness, Environmental regulation, Air Pollution Prevention and Control Action Plan

Contents

1 Introduction	1
2. Background	3
3 Data and empirical strategy	6
3.1 Variables.....	6
3.2 Control variables	13
3.3 Summary statistics.....	14
3.4 Empirical strategy.....	15
4 Main results: The impacts of APPCAP on pollution.....	16
4.1 Baseline results.....	16
4.2 Sectoral Analysis	18
4.3 Parallel Trend Test	20
4.4 Placebo Test	23
4.5 Heterogeneous Analysis	25
5 Main results: The Impact of policy on psychological wellness.....	27
5.1 Baseline results.....	27
5.2 Parallel trend test.....	29
5.3 Placebo test.....	31
5.4 Heterogeneous Analysis	32
6 Conclusion.....	34

1 Introduction

Air pollution is one of the most pressing environmental issues posing a shared global challenge. The European Environment Agency identified air pollution as the largest environmental risk in EU (EEA, 2025). Given that the ecological environment is a public good, the negative externalities of pollution cause market failures, which necessitates regulatory government intervention a common practice globally. Therefore, governments worldwide primarily employ regulatory intervention to mitigate environmental degradation. Among various governance mechanisms, environmental regulation policies are the most widely adopted administrative instruments (e.g., the U.S. Clean Air Act, the UK Clean Air Act, and Japan's Air Pollution Control Act).

The war against air pollution is widely recognized as a long-term, complex, and challenging endeavor (Ministry of Ecology and Environment, March 2023). The "Air Pollution Prevention and Control Action Plan" (hereinafter referred to as "China's Clean Air Action Plan" or APPCAP) is regarded as the most pivotal policy driving the remarkable improvement of air quality in China.

The Air Pollution Prevention and Control Action Plan (APPCAP) is one of the most extensively studied subjects in China's environmental governance research. Existing literature has yielded substantial findings, which can be broadly categorized into the following aspects:

First, regarding emission reduction effectiveness. A large body of literature has evaluated the air quality improvements achieved under the APPCAP, demonstrating significant reductions in PM_{2.5}, PM₁₀, and SO₂ concentrations at both the national and key regional levels, along with an increase in the proportion of days with good air quality and a decrease in heavily polluted days, using data from ground-level monitors (e.g. Huang et al., 2018), emission-based model predictions (e.g. Zheng et al., 2017), and satellite-based reanalysis products (e.g. Yue et al., 2020).

Second, in terms of industrial restructuring. Some studies have found that the APPCAP contributed to a decline in carbon emission intensity and energy consumption intensity by phasing out outdated production capacities, rectifying scattered and polluting enterprises, and promoting optimization of the energy structure (e.g., reduced coal consumption and increased share of clean energy). It also enhanced the total-factor energy productivity in the industrial sector (e.g., Cheng et al., 2023). Some literature has examined its impact on employment and capital allocation, suggesting that the

policy reduced industrial labor and capital inputs, constrained the scale of industrial production and new capacity expansions, and facilitated a shift toward technology-intensive, cleaner, and more efficient economic development models.

Third, regarding socioeconomic impacts. Several studies have quantitatively estimated the social effects of the APPCAP through cost-benefit analyses. For example, Gao et al., 2016 reported a total benefit of 748.15 billion Yuan and a total cost of 118.39 billion Yuan, with a cost-benefit ratio of 6.32.

Fourth, in terms of individual well-being. Many studies have assessed the policy's effects on mortality, incidence of cardiovascular and cerebrovascular diseases, and life expectancy, revealing significant positive impacts on human health (e.g., Lu et al., 2021).

However, certain limitations and challenges remain, which inspire the research objectives of this paper.

First, in the evaluation of pollutant emission reduction effects. Due to limited publicly available data in earlier stages, most studies focused on the reduction of major pollutants such as PM_{2.5} and PM₁₀, while more detailed analyses of specific pollutants are relatively scarce. With growing attention to the synergistic effects of reducing multiple air pollutants, non-target pollutants should also be considered in research.

Second, in the assessment of health effects. Most studies have concentrated on physical health, with insufficient evaluation of the emotional and mental health impacts of the APPCAP. Particularly in the context of shifting from a pollution control perspective to an ecological civilization perspective, a more comprehensive understanding of the mechanisms through which environmental policies affect public psychological well-being is needed.

This paper examines the intended and unintended effects of China's Air Pollution Prevention and Control Action Plan employing a continuous Difference-in-Differences (DID) approach. The main findings are as follows: First, APPCAP significantly reduced atmospheric pollutants, with observed effects not only on the targeted pollutants but also on non-targeted pollutants. With 1% increase in the PM₁₀ emission target is associated with an average reduction of 1.04% in CO, 0.88% in PM₁₀, 0.82% in NO_x, 0.80% in PM_{2.5}, 0.74% in SO₂, 0.61% in BC, 0.46% in OC, and 0.39% in NH₃ emissions, respectively. For 1% increase in the PM₁₀ reduction target, a corresponding decrease of specific pollutant emissions is associated with as follows: in

the industrial sector: CO decreases by 1.93%, OC decreases by 1.27%, SO₂ decreases by 1.14%, both PM₁₀ and PM_{2.5} decrease by 1.23%, NO_x decreases by 0.57%. In the residential sector: BC decreases by 0.55%, and PM₁₀ decreases by 0.42%. In the transportation sector: NH₃ increases by 1%. In the power sector: NO_x decreases by 2.05%. In the agricultural sector: NH₃ decreases by 0.42%.

Second, the policy positively influenced public mental well-being. We find a consistent pattern for both the anxiety and confidence indices. This effect is particularly pronounced in the Yangtze River Delta and Pearl River Delta regions. For instance, 1% increase in the policy target is associated with 1.66% decrease in the anxiety index across all cities, 1.47% in the Yangtze River Delta, and 1.88% in the Pearl River Delta, on average. The contributions of this study are twofold. First, it provides supplement to the existing literature by analyzing the emission reduction effects of APPCAP across specific sectors and pollutants, in the meanwhile offering supporting evidence for the importance of synergistic pollution control. Second, it addresses a gap in the current research by shedding light on the psychological impact mechanisms of environmental policies.

2. Background

During the 2012-2013 period, China experienced severe haze events notable for their extensive spatial extent, prolonged duration, and elevated levels of pollutants, which drew significant public and scholarly attention due to its substantial health and environmental risks. In response, September 2013 marked a pivotal turn in Chinese environmental policy, as the government enacted a comprehensive package of air pollution control measures widely deemed the most rigorous in the nation's history.. These measures encompassed several key initiatives, such as the inaugural inclusion of PM_{2.5} into the national ambient air quality standards, and the launch of China's Clean Air Action Plan.

APPCAP (Air Pollution Prevention and Control Action Plan) is a top-down policy formulated by the central government, who established pollution control targets, and was implemented hierarchically across all administrative levels. In accordance with the policy requirements, after the implement of the APPCAP, provincial governments signed their respective Air Pollution Prevention and Control Target Responsibility Agreements, and further decomposed the emission reduction targets down to the prefectural city level.

The specific targets committed to by local governments varied. On the one hand, this reflected the central government's differentiated management requirements for various regions. The national APPCAP policy document, released in September 2013, set the following specific objectives: by 2017, inhalable particulate matter (PM₁₀) concentrations in cities at the prefectural level and above should decrease by at least 10% compared to 2012 levels. For pilot regions such as the Beijing-Tianjin-Hebei area, the Yangtze River Delta, and the Pearl River Delta, the target pollutant was set more stringently as fine particulate matter (PM_{2.5}), with greater reduction requirements: the heavily polluted Beijing-Tianjin-Hebei region was required to reduce PM_{2.5} concentrations by at least 25% by 2017; the Yangtze River Delta region (covering three provinces and one municipality) was required to achieve a 20% reduction; the Pearl River Delta was tasked with a 15% reduction; while other regions outside these three key areas were required to reduce PM₁₀ by over 10%. On the other hand, the emission reduction targets reflected local governments' trade-offs between external pressures (such as political mandates from higher authorities and public opinion) and internal motivations (such as path dependence in economic development, concerns over economic slowdown, and unemployment).

Much of existing studies have reached a consistent conclusion that the Air Pollution Prevention and Control Action Plan has achieved significant emission reduction effects across multiple pollutants. For instance, Yu et al. (2022) employ matching and Difference-in-Differences (DID) estimation in a panel of 271 cities to estimate APPCAP's effect on PM_{2.5} levels in 47 target cities. They estimate PM_{2.5} reductions between 18-26% in PM_{2.5} levels on average, slightly smaller than the before-and-after comparison in Ma et al. (2019). Synthetic Control methods produce similar estimates of the effects in targeted regions compared to other regions in China (Peng et al., 2020; Zhang et al., 2022). Similar conclusion has been drawn with respect to air quality index, sulfur dioxide, and ozone).

On the effects of environmental policy on psychological well-being. As mentioned in the previous section, there is a substantial body of research on the impact of environmental policies on public health. However, most of these studies focus on physical health, while literature examining the effect of environmental governance on mental health remains limited, with inconsistent findings.

Stringent environmental policies can raise public awareness and perception of

pollution. On one hand, increased attention may evoke anxiety about environmental pollution. This is particularly true for APPCAP, which was China's first action plan aimed specifically at improving ambient air quality. Its unprecedented scope and intensity meant that many members of the public were introduced for the first time to concepts such as inhalable particulate matter and the health hazards of haze. Therefore, the "awareness-anxiety mechanism" was likely stronger for APPCAP compared to subsequent policies like the Three-Year Action Plan for Winning the Blue Sky War and the Air Quality Continuous Improvement Action Plan.

On the other hand, as environmental policies are implemented and emission reductions take effect, people—through daily life and media reports—perceive the determination behind governance efforts and improvements in environmental quality (air pollution is more readily perceptible to residents than other types of pollution). This leads to a reduction in anxiety about environmental pollution.

Meanwhile, some studies have found that air pollutants can directly affect mood through physiological mechanisms. Air pollutants such as fine particulate matter (PM_{2.5}) have been verified to affect the central nervous system (CNS) through neuroimmune or neuroinflammatory responses, and to alter the neural structure and function of key regions in the frontolimbic system (such as the prefrontal cortex, amygdala, and hippocampus), thereby increasing an individual's susceptibility to disorders such as depression and anxiety (Genc et al., 2012; Calderón-Garcidueñas et al., 2015; Zundel et al., 2022). That is, even in the absence of subjective perception, if policy implementation leads to emission reductions, it may biologically reduce the occurrence of negative emotions.

This paper argues that the psychological impact of environmental governance policies on the public results from multiple mechanisms. In summary, the Air Pollution Prevention and Control Action Plan represents a comprehensive environmental regulation policy with multifaceted channels of impact. Building on relevant literature discussed earlier, we illustrate its transmission mechanism in Figure.2-1. The blue sections in the figure denote the direct effects of the policy, while the orange sections represent its indirect effects (on the household sector). Among the direct effects, the pollution reduction outcomes stem from emission mitigation contributions across various private sectors, which constitute the first primary research focus of this paper. Among the indirect effects, the positive impact on public health through emission reduction channels is intended, whereas the mixed effects on household well-being

through micro-level cognitive, behavioral, and emotional channels are unintended. The latter constitutes the second primary research focus of this study.

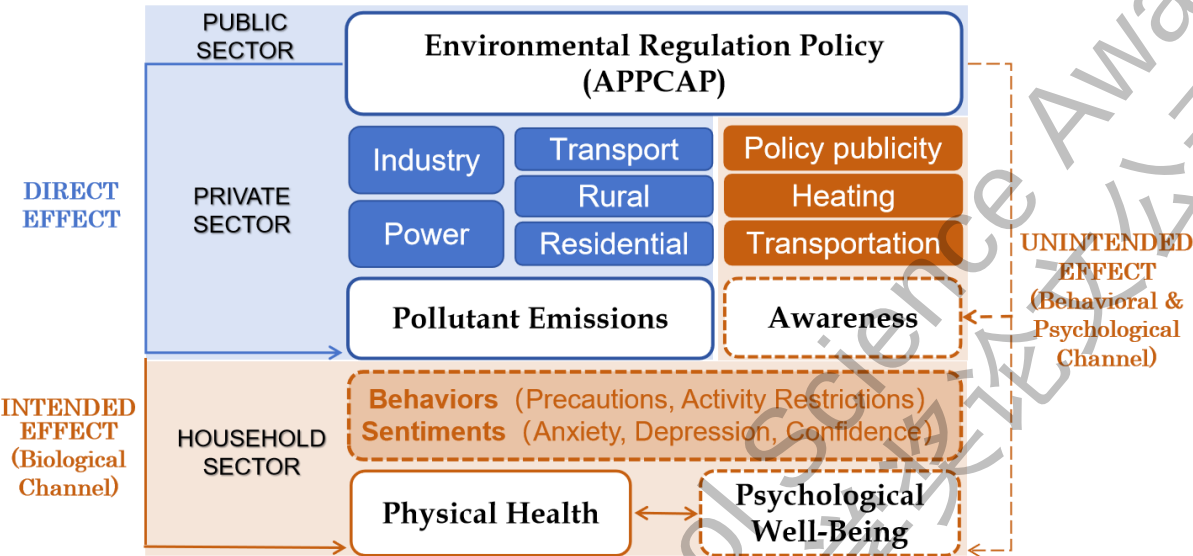


Figure.2-1 Comprehensive Impact of the Air Pollution Prevention and Control Action Plan

3 Data and empirical strategy

3.1 Variables

3.1.1 Policy variables

This paper utilizes the quantitative targets of APPCAP at the prefecture-level as a measure of the stringency of environmental regulation. This approach has also been adopted in previous studies evaluating environmental policies during China's 11th Five-Year Plan (Shi and Xu, 2018). We manually collect all provincial- and prefecture-level policy documents nationwide and compile the air pollutant reduction targets at the prefecture-level city level.

Among the 337 prefecture-level cities, 265 established reduction targets for inhalable particulate matter (PM₁₀), while the remaining 72 cities—primarily located in pilot regions—set targets for fine particulate matter (PM_{2.5}). Figure 3-1 plots the realized percentage reductions in PM_{2.5} against those in PM₁₀ from 2012 to 2020 across prefecture-level cities, revealing a strong positive correlation between the reduction levels of the two air pollutants. Accordingly, following Equation (3-1), we convert all PM_{2.5}-based reduction targets into PM₁₀-equivalent targets to facilitate subsequent analysis. Thereby we obtain standardized measure of policy intensity across all prefectural-level cities based on the target for PM₁₀ reductions.

$$PM10_target_{it} = \frac{\Delta PM10_{c,2012-2020}}{\Delta PM2.5_{c,2012-2020}} \times PM2.5_target_{it} \quad (3-1)$$

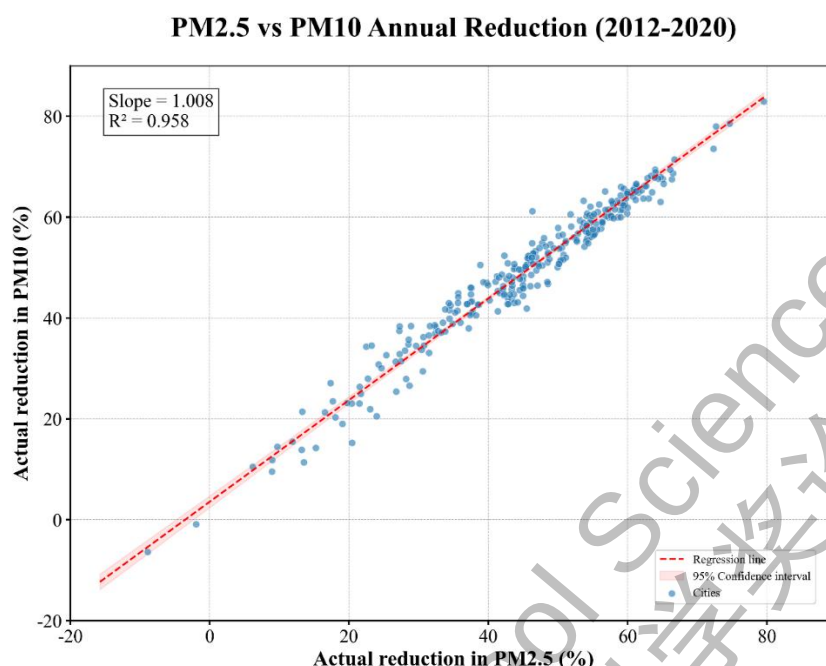


Figure.3-1 Linear relationship between actual reduction of PM10 and PM2.5

Figure.3-2 illustrates the spatial distribution of regulation targets. It can be observed that average reduction target was 10.8%, with a median of 10.0%. Most regions set their PM_{10} concentration reduction targets at around 10%. The standard deviation of 7.4% is close to the mean value, indicating a high dispersion of targets. Spatially, North China, the Fenwei Plain, the Yangtze River Delta, and the Pearl River Delta set relatively higher targets, whereas most areas in western China established lower targets, falling below 10% or even 5%.

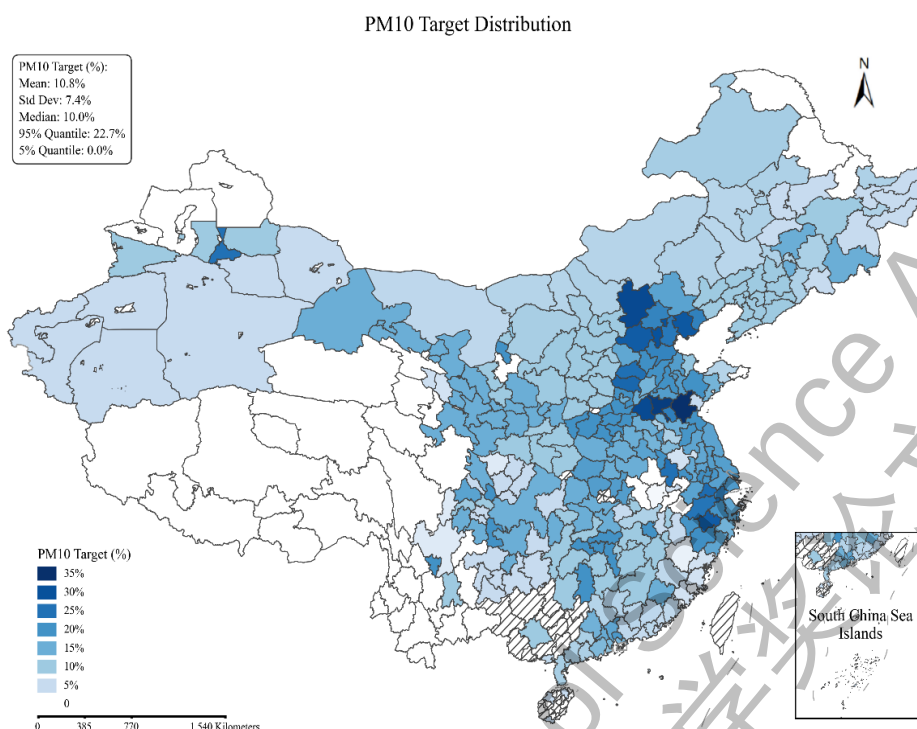


Figure.3-2 Heat Map of PM10 reduction targets Spatial distribution

3.1.2 Pollution data

We obtain pollutant emission data from the Multi-resolution Emission Inventory for China (MEIC, <http://meicmodel.org.cn>). Developed with support from the National Natural Science Foundation of China (NSFC), MEIC data is directly utilized in the top-level design of national policies, implementation tracking, and effectiveness assessment. It is recognized as one of the most comprehensive and detailed atmospheric pollutant source emission inventory datasets for China available, featuring refined quantification and accurate characterization of emissions (Ministry of Science and Technology, 2020).

The MEIC inventory covers over 700 types of anthropogenic emission sources, categorizes into five sectors (power generation, industry, civilian sources, transportation, and agriculture). It provides high-resolution gridded emission data for ten primary atmospheric pollutants: sulfur dioxide (SO_2), nitrogen oxides (NO_x), carbon monoxide (CO), non-methane volatile organic compounds (VOC), ammonia (NH_3), particulate matter with aerodynamic diameter less than 2.5 micrometers ($\text{PM}_{2.5}$), particulate matter with aerodynamic diameter less than 10 micrometers (PM_{10}), black carbon (BC), organic carbon (OC), and carbon dioxide (CO_2).

We process and convert the atmospheric pollutant emission inventory into panel data. Specifically, we utilize ArcGIS software to spatially match the MEIC emission raster data with Chinese cities by acquiring their administrative boundary coordinates from the National Platform for Common GeoSpatial Information Services. For each city, the MEIC emission values are aggregated across all raster cells within its boundaries, resulting in city-level emission estimates. Figure.3-3 illustrates the data aggregation process, using PM_{2.5} emissions in Tangshan in October 2014 as a representative example.

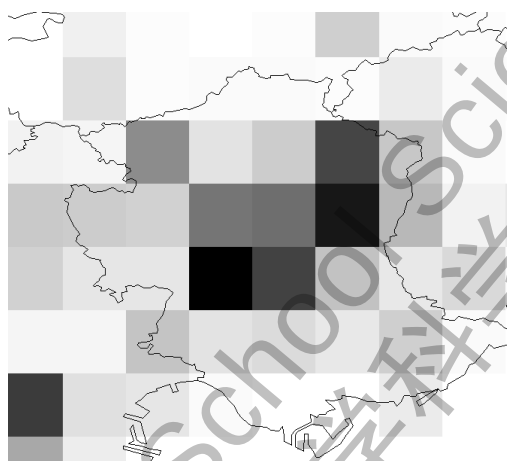
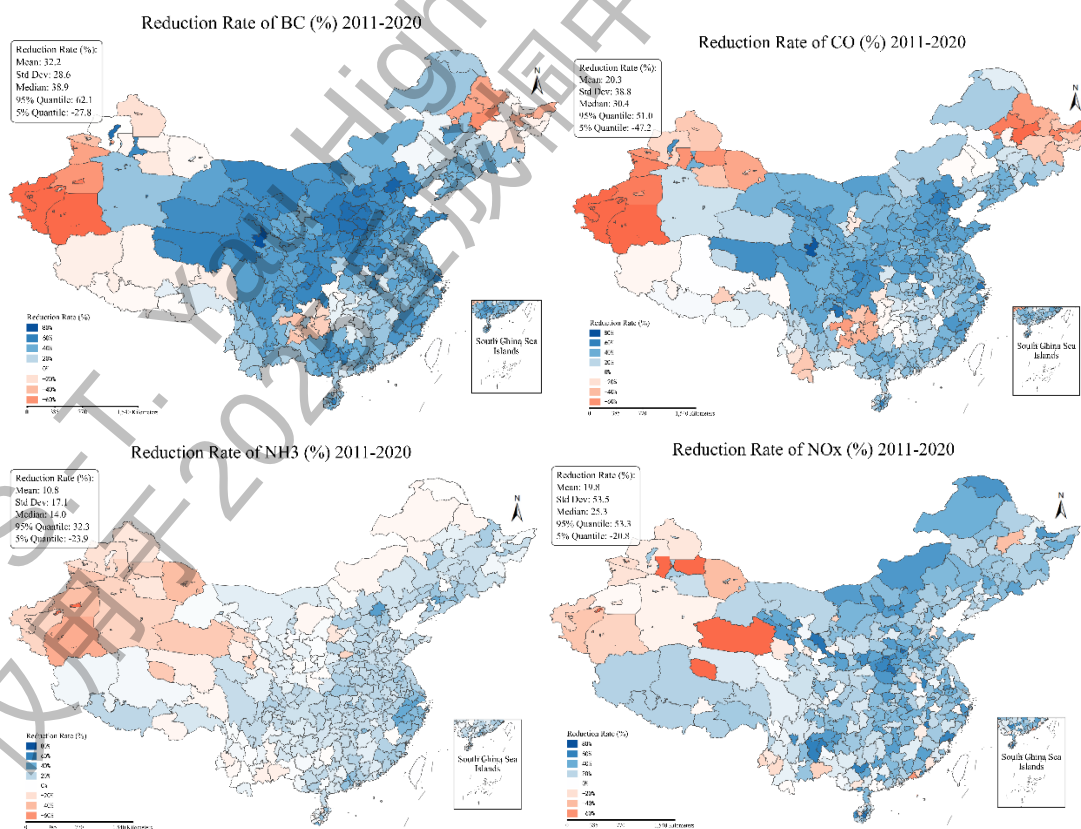


Figure.3-3 Raster map of PM_{2.5} emissions in Tangshan 2014.11



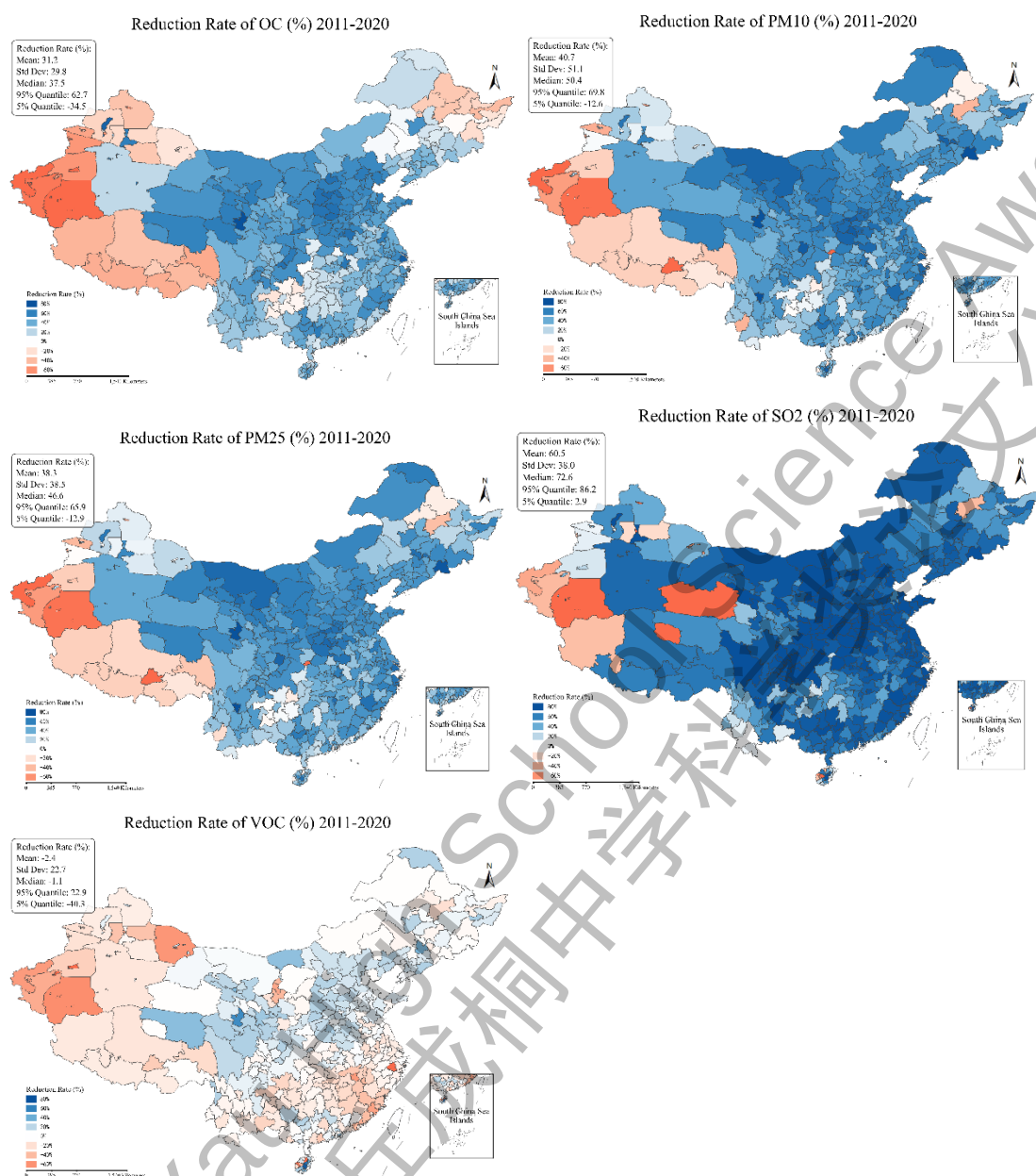


Figure.3-4 Heat Map of Pollutant Emission Reduction Percentage

The generated MEIC gridded emission data are expressed in “tons per grid cell.” Therefore, the converted pollutant emission data are measured in tons. Unlike studies that utilize pollutant concentration as a variable, this paper employs emission data, which provides a more direct measure of policy effectiveness by minimizing potential confounding effects inherent in concentration measurements.

Figure.3-4 shows a comparison of the pollutant emissions before and after the implementation of APPCAP. It can be observed that, except for VOC, the total emissions of most pollutants decreased significantly after the policy implementation.

3.1.3 Proxy for psychological wellness: Baidu search index

Existing literature commonly employs psychological scales and survey data (e.g., Zhang et al., 2017; Chen et al., 2018) as indicators of psychological states. This study adopts behavioral microdata as a measure of psychological well-being.

Baidu Search Index. According to CNNIC's 2013 report, Baidu held an 86.7% overall first-choice share, firmly leading China's search engine market (China Search Engine Market Research Report, 2013). Compared to traditional survey data, Baidu search data offers a more casual and spontaneous data source. Individuals perceive it as safer and less intrusive to privacy, while all search activities are automatically recorded by frequency. This makes search data particularly valuable for capturing and measuring naturally occurring emotional states. Baidu categorizes its search data into PC and mobile endpoints. This study uses PC-end data, due to the absence of mobile-end data before 2013. PC was Baidu's main platform during this period, so the data selection does not affect the findings.

Anxiety Indicator. To construct city-level anxiety index, we crawl and collect Baidu search volumes for anxiety-related keywords. We select 25 Chinese words for constituting the anxiety indicator with reference to (Bae et al., 2020). These keywords include stress, sadness, fear, depression, palpitation, frustration, etc. (see Table.3-1 for details). To eliminate comparability issues arising from differences in population sizes across cities, the indicator is adjusted into a per capita basis.

Table.3-1 Construction for Anxiety Indicator

Selected Words (in Chinese) for Anxiety Indicator
压力、悲伤、害怕、郁闷、心悸、沮丧、抱怨、自杀、抑郁、 酗酒、失眠、孤独、恐惧、紧张、绝望、压抑、烦躁、胸闷、 担心、精神障碍、安定、安眠药、三唑仑、阿米替林、帕罗西汀

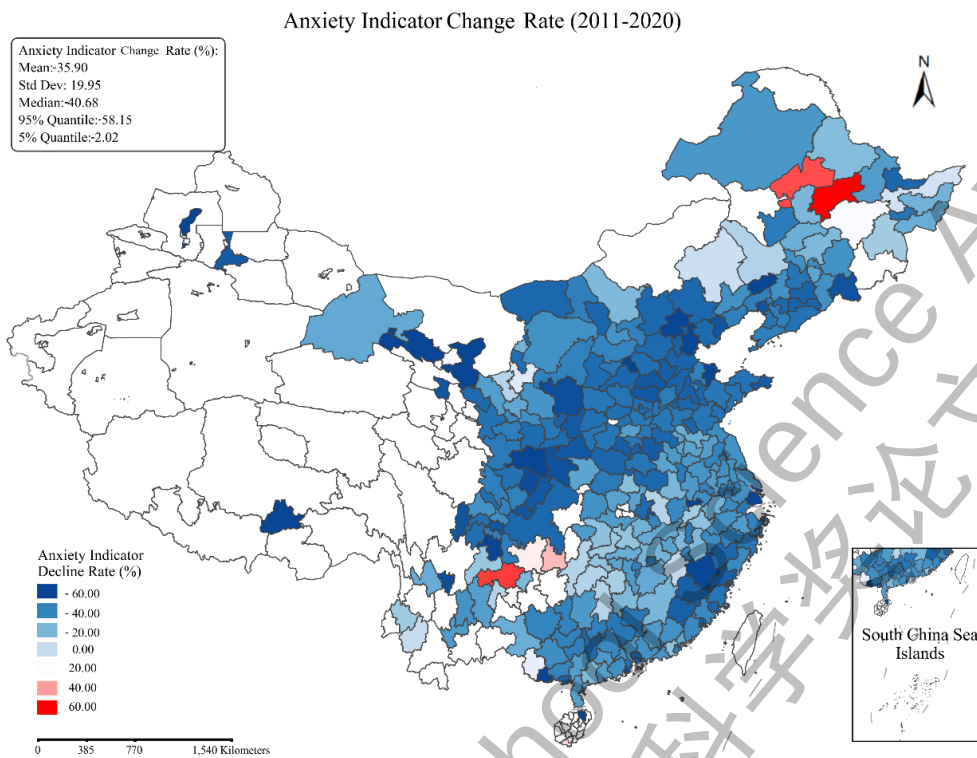


Figure.3-5 Heat map of anxiety indicator change rate in 2011 to 2020

Figure. 3-5 illustrates the changes in anxiety index during the sample period of this study. It can be observed that there are significant variations in the index across cities, while the vast majority of regions nationwide experienced a decline in anxiety, with an average reduction of 35.9%.

Confidence Indicator. The theoretical foundation of the confidence indicator stems from Preis et al. (2012), who proposed that the degree of future orientation in a region can be measured by comparing the ratio of search volumes for the next year to those for the previous year. Specifically in this paper, confidence indicator for a given period equals the search volume for the next year divided by the search volume for the previous year during that period, as shown in Equ (3-2). For example, the Confidence Indicator for 2018 would be the search volume for "2019" divided by the search volume for "2017" during 2018.

Following a computational and processing methodology analogous to that used for the Anxiety Index, we construct Confidence Index indicators for 290 prefecture-level cities in China from 2011 to 2020.

$$ConfidenceIndicator_{i,T} = \frac{Baidu\ Index\ for\ "Year(T)+1"\ during T}{Baidu\ Index\ for\ "Year(T)-1"\ during T} \dots\dots (3-2)$$

Figure.3-6 illustrates the changes in anxiety index during the sample period of this study. First, the variation among cities is more pronounced in the change of confidence index, with a S.D. close to mean. Second, with its standard deviation being close to the mean value. Second, most cities experienced an increase in confidence during the sample period, particularly in the Yangtze River Delta and southern coastal regions of China.

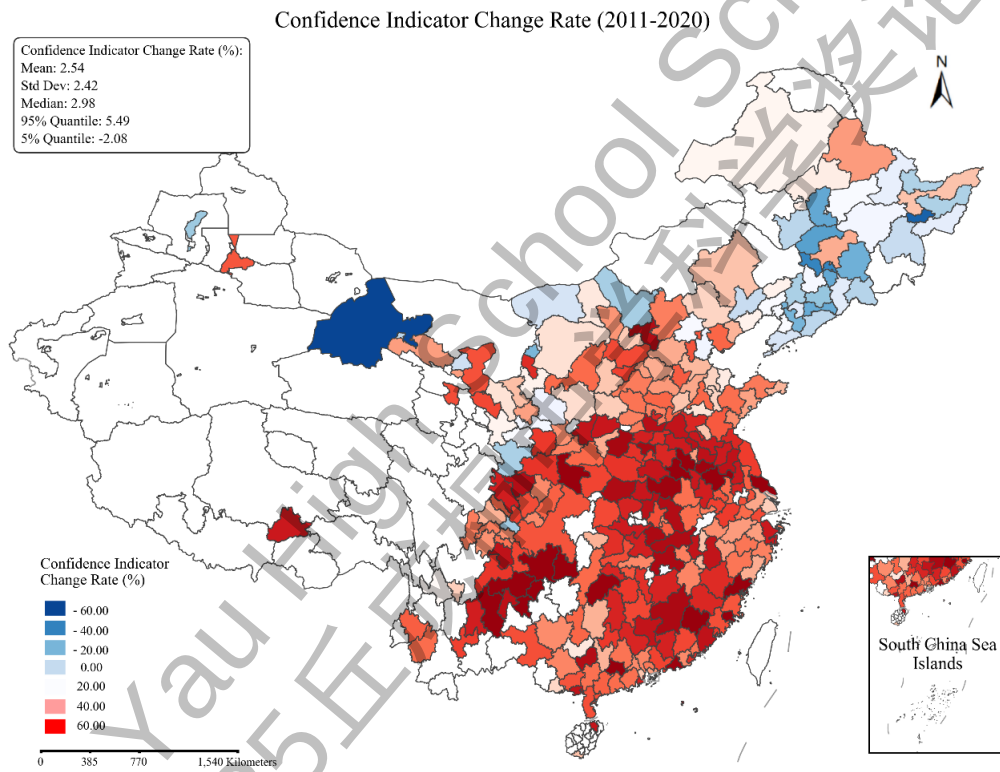


Figure.3-6 Heat map of confidence indicator change rate in 2011 to 2020

3.2 Control variables

3.2.1 Regional socioeconomic variables

We collect city-level socioeconomic variables, such as GDP, population, urbanization rate, share of secondary and tertiary Industry, from various statistical yearbooks and China Macro-Economy Database (CMED) within the EPS Global Statistical Data Analysis Platform.

Housing prices are a significant factor influencing psychological wellness, and exhibit significant variations across cities. We collect annual average housing price data from Anjuke website. The 2015 stock market crash had a substantial impact on collective psychological states. Consider stock price is a uniform shock across cities, it is not incorporated as a control variable in this study.

3.2.2 Weather variables

Weather conditions are found to affect individuals’ moods, social behavior, and health (Berry et al., 2010; Cunningham, 1979). We include various weather covariates. Controlling for these weather conditions helps to isolate the impact of air pollution on mental health from weather-related factors,. These variables include temperature, precipitation, and wind speed. We obtain weather data from the China Meteorological Data Service Center.

3.3 Summary statistics

We merge various datasets according to the county geocode and month. **Table.3-2** reports the summary statistics. All sample values lie within a plausible range.

Table.3-2
Variables and summary statistics.

Variables		Obs	Mean	S.D.	Min	Max
Pollutant Emissions	PM _{2.5} (t)	34800	2238.98	2023.04	17.80	40114.39
	PM ₁₀ (t)	34800	3082.83	2799.54	18.78	50604.68
	SO ₂ (t)	34800	4447.43	6371.03	27.24	153307.2
	CO (t)	34800	38541.91	37160.66	463.36	651881.1
	BC (t)	34800	340.86	325.97	5.05	6879.15
	NH ₃ (t)	34800	2530.03	2124.56	19.97	28757.85
	NOx (t)	34800	6211.07	5729.73	62.12	46874.68
	OC (t)	34800	605.01	652.81	5.34	18244.86
	VOC (t)	34800	7378.35	6981.36	357.12	60087.16
Mental health Indicator	Anxiety Indicator	34800	44.64	35.91	2.99	597.38
	Confidence Indicator	34800	1.26	2.19	0.00	30.63
Policy Indicator	PM10 Reduction Target(%)	34800	9.01	8.07	0	35
Control Variables		Obs	Mean	S.D.	Min	Max
GDP (log)		34800	17.07	17.41	14.10	19.77

Regional Socioeconomic Conditions	GDP per capita (log)	34800	10.88	10.43	8.77	13.05
	GDP growth rate	34800	0.09	0.09	-0.47	0.61
	Urbanization rate	34800	0.55	0.15	0.18	1.00
	Tertiary industry ratio	34800	0.42	0.10	0.10	0.84
	Secondary and tertiary industry ratio	34800	0.88	0.08	0.50	0.89
	Population (log)	34800	5.89	0.70	2.97	8.14
	Housing price (yuan/m ²)	34800	6774.14	5501.98	1746.00	59695.50
	Temperature (°C)	34800	13.99	10.96	-27.91	39.21
Weather Conditions	Precipitation (mm)	34800	87.47	92.90	0.00	1386.27
	Wind speed (10m/s)	34800	3.40	0.91	0.97	8.09

Notes: This table presents summary statistics for the main variables in the empirical analyses. With regards to socioeconomic control variables, we follow the methodology suggested by Huang et al. (2022), by constructing relative trends using a baseline period (2012) to further address potential endogeneity issues.

The standardized Anxiety Indicator represents the monthly search volume of anxiety-related keywords per 100 persons. The data exhibits a substantial range, with a minimum value of 2.99 per hundred people (Lhasa, January 2020) and a maximum value of 597.38 per hundred people (Beijing, May 2020). The numerical values of the Confidence Index are generally lower overall. This suggests an asymmetry in search behavior regarding psychological states: people are more inclined to search for relevant keywords when experiencing anxiety or depression than when they are in positive moods.

The Housing price shows a minimum value of 1746.00 yuan (Hegang, 2018) and a maximum value of 59,695.50 yuan (Beijing, 2019).

For Temperature (°C), the minimum recorded value is -27.91 (Heihe, January 2013), while the maximum is 39.21 (Turpan, July 2017). The maximum Precipitation (mm) value in our sample of 1386.27 was recorded in Sanya City in October 2020. During that month, five tropical cyclones affected Hainan Province, making it the second-highest number of occurrences for the same period in historical records.

3.4 Empirical strategy

The Difference-in-Differences (DID) design has been widely used to evaluate the impact of environmental regulations and air pollution (Deschenes et al., 2017; Xie et al., 2023). In this paper, a continuous difference-in-differences (DID) model is

employed to study the impact of environmental regulation on outcome variables of interest, by exploiting the variations in the implementation stringencies of the APPCAP.

To evaluate the emission reduction effects of the APPCAP, the regression is specified as in EQ (3-3).

$$Emission_{i,t} = \alpha + \beta PM10Tar_i \bullet Airten_{i,t} + \phi X_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \quad (3-3)$$

where, $Emission_{i,t}$ represents the emissions of pollutant in city i at time t . $PM10Tar_i$ represents the emission reduction target specified for city i . $Airten_{i,t}$ is a dummy variable indicates whether the policy has been implemented in city i at time t . The coefficient β is of primary interest, as it captures the causal effect of the policy on pollutant emissions. $X_{i,t}$ represents a set of control variables for city i at time t . The model also incorporates regional fixed effects μ_i , and time fixed effects η_t (including year, month, month-by-year fixed effects).

To evaluate the emission reduction effects of the APPCAP, the regression is specified as in EQ (3-4) and (3-5).

$$AnxietyIndicator_{i,t} = \alpha + \theta PM10Tar_i \bullet Airten_{i,t} + \phi X_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \quad (3-4)$$

$$ConfidenceIndicator_{i,t} = \alpha + \gamma PM10Tar_i \bullet Airten_{i,t} + \phi X_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \quad (3-5)$$

where $AnxietyIndicator_{i,t}$ and $ConfidenceIndicator_{i,t}$ represent the indicator for individuals' psychological state in city i at time t . Housing price is included as a control variable in this regression. The remaining specifications are analogous to the preceding model. θ and γ are the coefficients of interest.

4 Main results: The impacts of APPCAP on pollution

4.1 Baseline results

Table.4-1 reports the estimation results of Eq. (3-3).

Several findings are noteworthy. First, the estimate of β shows that the implementation of the APPCAP has resulted in statistically significant decrease in the emissions of PM2.5, PM10, SO₂, NH₃ and NO_x, which were the main targets of environmental regulations.

Second, emissions of CO, BC, and OC were also significantly reduced by the policy. As these were not primary target pollutants of the 2013 Air Pollution Prevention and Control Action Plan, this outcome demonstrates the co-benefit effect of pollutant emission reduction.

Third, VOC emissions increased between 2011 and 2020. This observation aligns with the complexity and recurrent challenges in VOC reduction highlighted by some scholars.

Fourth, consider the quantitative implications of the estimate of β . It represents the change in emissions of the corresponding pollutant induced by a 1% increase in the PM10 emission target on average. Using the year 2012 as the base year, we divide the coefficients of each pollutant by their respective emissions in the base year to obtain the policy's average emission reduction elasticity for each pollutant. 1% increase in the PM10 emission target is associated with an average reduction of 1.04% in CO, 0.88% in PM₁₀, 0.82% in NO_x, 0.80% in PM_{2.5}, 0.74% in SO₂, 0.61% in BC, 0.46% in OC, and 0.39% in NH₃ emissions, respectively.

Table 4-1

Effects of APPCAP on total emissions

Emission	PM25	PM10	SO2	CO
$\beta(PM10Tar \cdot Airten)$	-20.592*** (6.223)	-31.591*** (9.089)	-47.31** (15.122)	-396.421*** (105.525)
Controls	YES	YES	YES	YES
Constant	8710.37*** (682.954)	13168.599*** (1001.011)	34028.572*** (4997.194)	127698.309*** (11498.433)
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Year_Month FE	YES	YES	YES	YES
F-statistic	12.86	14.60	10.18	10.75
R-squared	0.885	0.898	0.822	0.886
Observations	34,800	34,800	34,800	34,800

Table 4-1 (continued)

Effects of APPCAP on total emissions

Emission	BC	NH3	NO _x	OC	VOC
$\beta(PM_{10}Tar \cdot Airten)$	-2.227** (1.009)	-9.218*** (2.310)	-51.677*** (15.084)	-2.893* (1.496)	5.784 (10.353)
Controls	YES	YES	YES	YES	YES
Constant	1189.6*** (116.260)	3573.8*** (216.337)	15691.3** (1263.947)	1892.0*** (196.341)	5359.6*** (944.053)
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Month FE	Yes	Yes	Yes	Yes	Yes
Year_Month FE	YES	YES	YES	YES	YES
F-statistic	11.15	16.41	15.05	10.29	5.501
R-squared	0.843	0.944	0.966	0.765	0.971
Observations	34,800	34,800	34,800	34,800	34,800

Notes: *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses.

4.2 Sectoral Analysis

We further explore the effects by sector. MEIC emission data categorizes emission sources into different sectors (agriculture, industry, power, residential and transport), which facilitates the sector-by-sector analysis in this study. We conduct 45 continuous DID regressions based on Eq(3-3) across 5 sectors for all 9 pollutants. Table.4-2 reports the estimation results by sector.

Table.4-2

Effects of APPCAP on sectoral emissions

Emission	PM25	PM10	SO2	CO	BC	NH3	NO _x	OC	VOC
Sector: INDUSTRY									
$\beta(PM_{10}Tar \cdot Airten)$	-16.488*** (5.351)	-26.064*** (7.920)	-33.81*** (12.195)	-309.835** (95.737)	-1.234 (0.749)	-0.125 (0.309)	-13.011** (5.136)	-1.701* (0.987)	9.395 (10.254)
Observations	34800	34800	34800	34800	34800	34800	34800	34800	34800
R-squared	0.931	0.929	0.821	0.94	0.899	0.937	0.96	0.865	0.96
Sector: RESIDENTIAL									
$\beta(PM_{10}Tar \cdot Airten)$	-3.142 (1.992)	-4.164* (2.474)	0.126 (5.383)	-72.248 (44.066)	-0.908* (0.510)	0.039 (0.139)	-0.819 (0.663)	-1.161 (1.022)	-0.215 (1.972)
Observations	34800	34800	34800	34800	34800	34800	34800	34800	34800

R-squared	0.723	0.719	0.634	0.714	0.708	0.794	0.719	0.729	0.765
Sector: TRANSPORT									
$\beta(PM_{10}Tar \cdot Airten)$	-0.113 (0.134)	-0.107 (0.136)	-0.126 (0.077)	-13.424 (14.653)	-0.083 (0.078)	0.07*** (0.016)	1.086 (2.251)	-0.026 (0.025)	-3.373 (2.597)
Observations	34800	34800	34800	34800	34800	34800	34800	34800	34800
R-squared	0.987	0.987	0.973	0.975	0.986	0.978	0.976	0.988	0.98
Sector: POWER									
$\beta(PM_{10}Tar \cdot Airten)$	-0.85 (1.457)	-1.256 (2.307)	-13.472 (12.914)	-0.914 (4.223)	-0.002 (0.003)	- (2.298)	-38.865** (13.965)	0 (0.000)	-0.024 (0.055)
Observations	34800	34800	34800	34800	34800	34800	34800	34800	34800
R-squared	0.754	0.749	0.744	0.933	0.755	-	0.849	0.608	0.92
Sector: AGRICULTURE									
$\beta(PM_{10}Tar \cdot Airten)$	- (2.298)	- (2.298)	- (2.298)	- (2.298)	- (2.298)	-9.20*** (2.298)	- (2.298)	- (2.298)	- (2.298)
Observations	34800	34800	34800	34800	34800	34800	34800	34800	34800
R-squared	-	-	-	-	-	0.936	-	-	-

Notes: Only NH₃ emissions are non-zero in agriculture sector. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses.

Following the aforementioned method, we calculate the sector-specific policy-induced emission reduction elasticities. For 1% increase in the PM₁₀ reduction target, a corresponding decrease of specific pollutant emissions is associated with as follows: in the industrial sector: CO decreases by 1.93%, OC decreases by 1.27%, SO₂ decreases by 1.14%, both PM₁₀ and PM_{2.5} decrease by 1.23%, NO_x decreases by 0.57%. In the residential sector: BC decreases by 0.55%, and PM₁₀ decreases by 0.42%. In the transportation sector: NH₃ increases by 1%. In the power sector: NO_x decreases by 2.05%. In the agricultural sector: NH₃ decreases by 0.42%.

The industrial sector demonstrates the most pronounced emission reduction effects. This is consistent with intuition and, as noted in the literature, stems from the fact that the industrial sector acts as a direct conduit for policy implementation. By adopting clean raw materials and energy sources, as well as advanced process technologies and equipment, it effectively reduces pollutant emissions. This may be attributed to the widespread adoption of measures such as industrial restructuring and stricter environmental regulations for enterprises during policy implementation. Most

notably, PM_{10} , $PM_{2.5}$, and CO showed significant reductions under the policy—pollutants widely recognized as major threats to public health.

It is noteworthy that the energy sector plays a significant role in reducing nitrogen oxide (NO_x) emissions. The first of the Ten Measures for Air Pollution Prevention and Control explicitly required "accelerating the retrofitting of desulfurization, denitrification, and dust removal in key industries." By the end of 2013, nearly 200 million kilowatts of power generation units had completed flue gas denitrification retrofits, with the national capacity of denitrification-equipped units reaching approximately 430 million kilowatts. The denitrification ratio of coal-fired power units approached 55%, and the operation of these denitrification facilities significantly enhanced the removal efficiency of nitrogen oxides. According to publicly available information from the MEIC data team, the calculation for the power sector incorporates unit-specific hourly generation data. The estimated policy elasticity results reflect the well-targeted and highly effective nature of the Ten Measures.

The transportation sector is a major source of ammonia (NH_3) emissions. During the implementation period of the APPCAP, emissions from this sector increased rather than decreased. This indicates that the binding effect of the Ten Measures on the transportation sector was relatively weak, which supports findings reported in the existing literature.

In the residential sector, significant emission reductions were observed for PM_{10} and BC. Residential emissions primarily originate from household heating and crop residue burning, which are major sources of both PM_{10} and BC. These results suggest a discernible policy effect on the residential sector.

4.3 Parallel Trend Test

As we employ DID model in this study, it is essential to conduct parallel trend test for Eq. (3-3) The parallel trends test regression is specified as follows:

$$Emission_{i,t} = \alpha + \sum_{year=2011}^{2012} \beta_{year} PM10Tar_i \cdot Airten_{i,year} + \sum_{year=2014}^{2020} \beta_{year} PM10Tar_i \cdot Airten_{i,year} + \phi X_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \quad (4-1)$$

where $Airten_{i,year}$ is a dummy variable indicating whether the policy has been implemented in city i in a given year. β_{2011} and β_{2012} represent the regression coefficients for the two years preceding the policy implementation, respectively. $\beta_{2014} \cdots \beta_{2020}$ represent those seven years following policy implementation, respectively.

Taking PM_{2.5}, PM₁₀, and NO_x as examples, the results for parallel trend test are shown in Table.4-3.

Table.4-3

Parallel trend tests for total emissions (3 main pollutants)

	PM2.5	PM10	NOx
target_year_2011	-6.0422 (4.1642)	-10.8607* (5.8746)	-1.1687 (9.1040)
target_year_2012	2.0080 (3.0244)	1.7661 (4.1854)	13.5106** (6.5289)
target_year_2014	-6.2070 (3.8617)	-11.1771** (5.5953)	-31.9289*** (8.0603)
target_year_2015	-17.6098*** (5.9252)	-29.1866*** (8.4205)	-51.4401*** (11.8052)
target_year_2016	-26.7888*** (6.7152)	-44.4456*** (9.6076)	-56.5352*** (13.3914)
target_year_2017	-28.3628*** (7.5173)	-45.8430*** (10.8202)	-62.7182*** (14.6568)
target_year_2018	-28.8257*** (8.0675)	-46.2360*** (11.5161)	-56.7539*** (15.4438)
target_year_2019	-30.7486*** (8.9196)	-47.6055*** (12.6820)	-52.8808*** (16.1285)
target_year_2020	-32.9981*** (9.5471)	-49.2489*** (14.3681)	-64.8928*** (17.8966)
Observations	31,320	31,320	31,320
R-squared	0.947	0.898	0.966

Notes: Taking the policy implementation period as the reference year (2013) and omitting it from the regression. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses.

The parallel trends test results for these three pollutants are similar. For the years preceding the policy implementation (2011 and 2012), most of the regression coefficients are statistically insignificant and close to zero, indicating no significant differences in PM_{2.5}, PM₁₀, or NO_x emissions between cities with varying intensity levels of the policy implementation prior to its enactment. After 2013, emissions of all three pollutants decreased significantly, with negative regression coefficients, confirming that the parallel trends assumption holds on an annual basis for these pollutants.

This study presents event-study graphs illustrating the year-by-year dynamics of the parallel trends test of pollutant emissions relative to policy intensity. As shown in Figure.4-1's first figure, using PM_{2.5} as an example, the estimated coefficients relative to policy intensity are insignificant and show no clear trend before the policy intervention but become significantly negative in the years following implementation, providing further validation of the parallel trends assumption.

For total emissions, parallel trend tests were conducted for all pollutants included in the analysis. The results are summarized in Figure 4.1

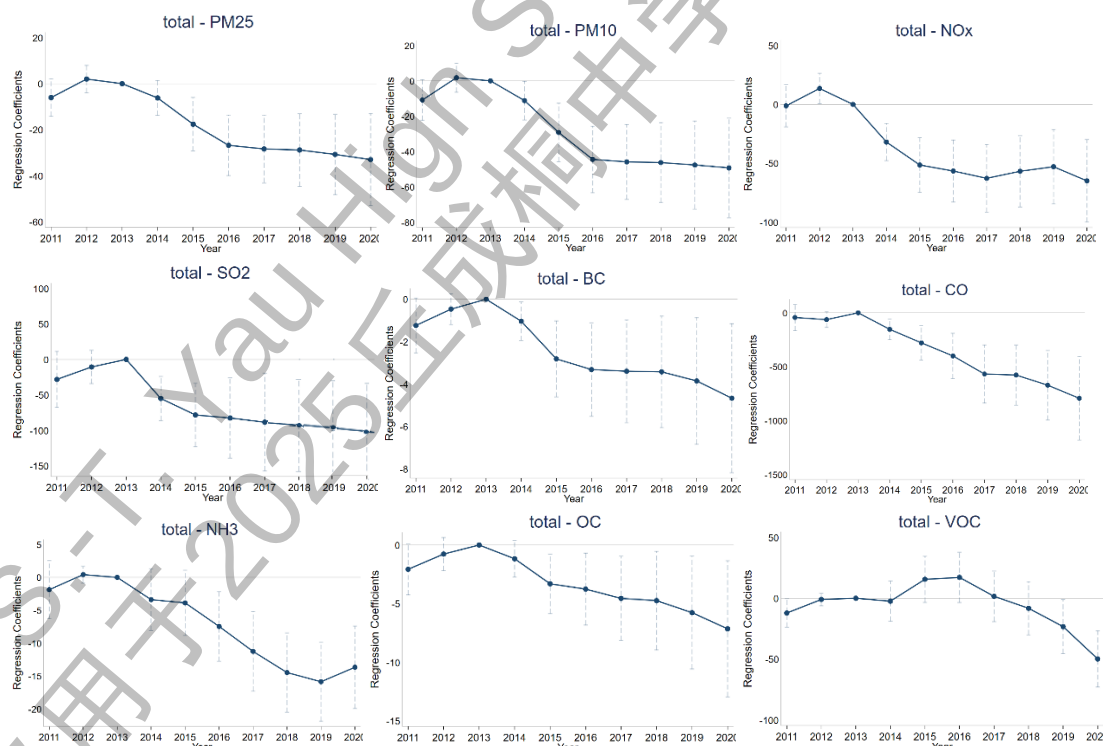


Figure.4-1 Parallel trend tests for total emissions (by pollutants)

Notes: The figure depicts coefficients and the 90% confidence intervals for an parallel trend test, The regression model is specified as model (4.4)

The results of the parallel trends tests for the nine pollutants are consistent with the regression outcomes of Eq. (4-1). Seven pollutants—PM₁₀, CO, NO_x, NH₃, SO₂, BC, and OC—exhibit patterns similar to those of PM_{2.5}: their associations with policy implementation and intensity are statistically significant. Following the policy intervention, cities with greater policy enforcement intensity showed significant reductions in emissions of these pollutants, while no clear pre-policy trends were observed, satisfying the parallel trends assumption.

In contrast, the regression coefficients for VOC did not show a notable decline until after 2018, the emission changes of VOC in the later stage cannot be readily attributed to the policy implemented in 2013.

Furthermore, the parallel trend test for the 10 regression equations with significant regression coefficients in Table.4-2 is discussed using Eq. (4-1). The results are presented in Table.4-4, which shows except for the performance of the NH₃ in the transportation sector, all other tests pass the parallel trend test.

Table.4-4

Parallel trend test results for emissions (by sectors and pollutants)

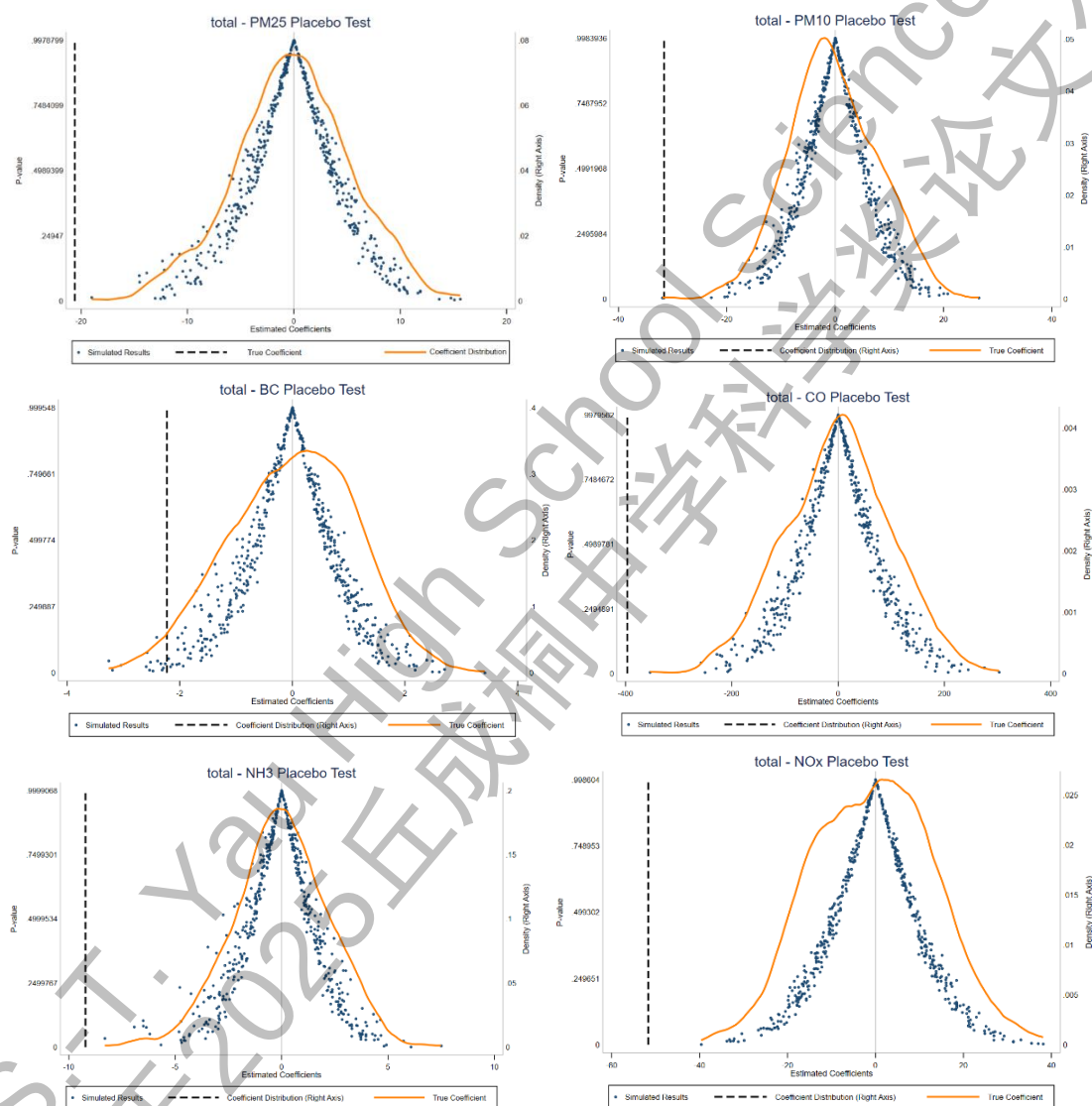
SECTOR	Pollutant								
	PM25	PM10	SO2	CO	BC	NH3	NOx	OC	VOC
INDUSTRY	Yes	Yes	Yes	Yes	-	-	Yes	Yes	-
RESIDENTIAL	-	Yes	-	-	Yes	-	-	-	-
TRANSPORT	-	-	-	-	-	No	-	-	-
POWER	-	-	-	-	-	-	Yes	-	-
AGRICULTURE	-	-	-	-	-	Yes	-	-	-

Notes: This table displays the results of the parallel trend tests pertaining to the regression models that yield statistically significant coefficients. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses.

4.4 Placebo Test

We perform the placebo tests by randomly selecting the policy implementation strength PM10target in cities (see Fig.4-2). In Fig.4-2 the estimated policy effects from 500 random sampling of regressions for 9 kinds of pollutants are plotted. Results show that for the 6 pollutions (PM2.5, PM10, CO, SO₂, NH₃, NO_x), the estimated policy effects are small and most are close to 0, also most of the corresponding P-values are greater than 0.1. For pollution OC and BC the distance between the true regression

coefficient and the center of the simulation is not as large as that in the previous experiment, but most are close to 0 and most P-values are greater than 0.1. For the pollutant VOC, the distance between the true coefficient and the simulated value is not large enough, and its placebo test fails to pass. The results of the placebo test are consistent with the significance of the base regression Equ(3-1) which lending further support that the reduction in pollution is indeed the result of the APPCAP policy.



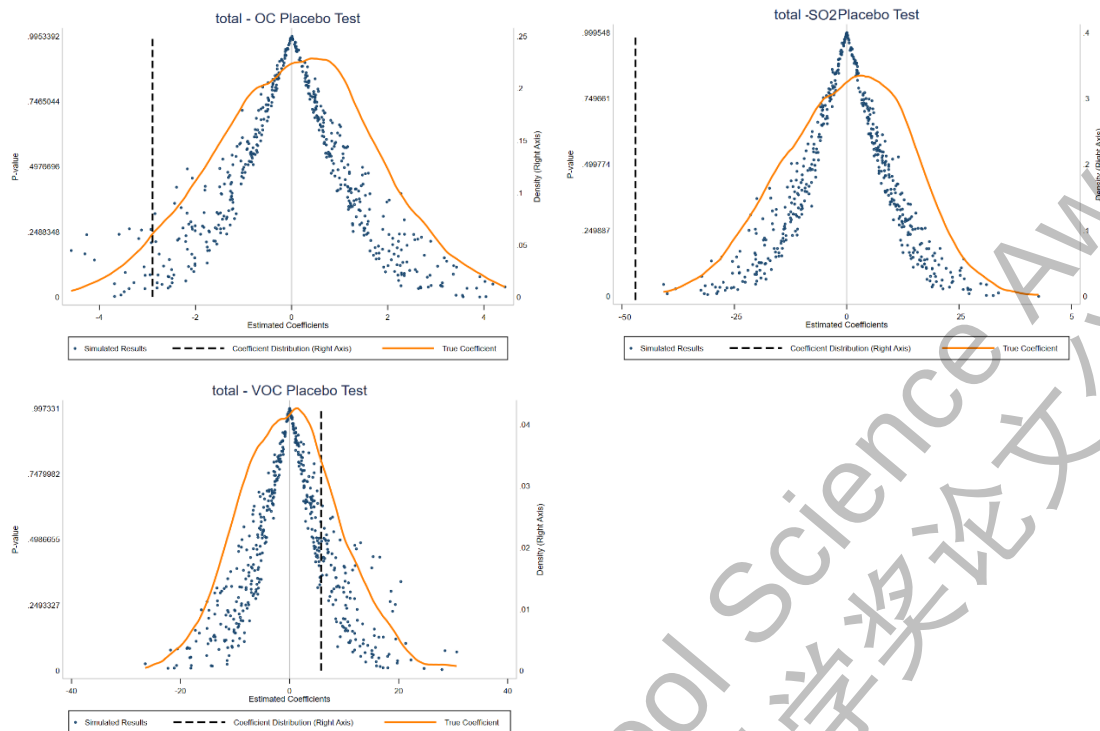


Figure.4-2 Placebo tests for total emissions (by pollutants)

4.5 Heterogeneous Analysis: Sub-region

To further investigate the effects, we divide samples into three primary urban clusters: the Beijing-Tianjin-Hebei region, the Yangtze River Delta urban agglomeration, and the Pearl River Delta urban agglomeration. Results are shown in Table 4-5.

Cities clustered by region

City Name	
Beijing-Tianjin-Hebei Region (N=13)	Beijing, Tianjin, Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, Hengshui
Yangtze River Delta (N=41)	Shanghai, Nanjing, Wuxi, Xuzhou, Changzhou, Suzhou, Nantong, Lianyungang, Huai'an, Yancheng, Yangzhou, Zhenjiang, Taizhou, Suqian, Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Quzhou, Zhoushan, Taizhou, Lishui, Hefei, Wuhu, Bengbu, Huainan, Ma'anshan, Huaibei, Tongling, Anqing, Huangshan, Chuzhou, Fuyang, Suzhou, Lu'an, Bozhou, Chizhou, Xuancheng

Pearl River Delta (N=9)	Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, Dongguan, Zhongshan, Huizhou, Zhaoqing
-----------------------------------	--

Table 4-6

Effects for APPCAP on pollutant emissions (sub-regions)

Emission	PM _{2.5}	PM ₁₀	SO ₂	CO	BC	NH ₃	NO _x	OC	VOC
Beijing-Tianjin-Hebei Region									
$\beta(PM_{10}Tar \cdot Airten)$	-43.967* (20.047)	-54.751* (21.320)	-133.202* (53.281)	-262.32 (280.87)	-6.019 (4.594)	8.971 (7.880)	62.923 (60.10)	-10.051* (5.669)	7.150 (51.96)
Observations	1560	1560	1560	1560	1560	1560	1560	1560	1560
R-squared	0.959	0.919	0.97	0.963	0.931	0.956	0.979	0.914	0.987
Yangtze River Delta									
$\beta(PM_{10}Tar \cdot Airten)$	4.596 (5.86)	-5.379* (3.38)	11.502 (20.71)	147.39* (86.18)	-1.392* (0.726)	-8.640** (3.59)	-26.135 (20.46)	2.304 (1.63)	1.749 (17.99)
Observations	4920	4920	4920	4920	4920	4920	4920	4920	4920
R-squared	0.935	0.948	0.949	0.959	0.937	0.935	0.975	0.839	0.975
Pearl River Delta									
$\beta(PM_{10}Tar \cdot Airten)$	-10.008 (6.407)	-17.222 (14.765)	-151.01* (85.522)	33.094 (92.251)	-1.262** (0.339)	6.006 (6.31)	-176.86 (117.7)	-0.804 (1.098)	-53.02 (104.2)
Observations	1080	1080	1080	1080	1080	1080	1080	1080	1080
R-squared	0.97	0.962	0.966	0.988	0.981	0.947	0.977	0.984	0.971

Notes: *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses.

Within the Beijing-Tianjin-Hebei (BTH) region, the emission reduction efforts targeting OC, PM₁₀, PM_{2.5}, and SO₂ have yielded significant results. This region implemented the Air Pollution Prevention and Control Action Plan with the greatest intensity, and the societal attention regarding the reduction of PM_{2.5} and PM₁₀ was particularly high. Given that the PM₁₀ reduction targets within this region were generally ambitious and exhibited limited variation, the observed significant results carry even greater explanatory power. Quantitatively, a 1% increase in the PM₁₀ emission reduction target in the BTH region is associated with a 0.82% decrease in PM₁₀, a 0.81% decrease in SO₂, a 0.72% decrease in PM_{2.5}, and a 0.63% decrease in OC.

In the Yangtze River Delta (YRD) region, significant emission reductions were observed for PM₁₀, BC, CO, and NH₃. A 1% increase in the PM₁₀ emission reduction

target in the YRD corresponds to a 0.38% decrease in BC, a 0.35% decrease in NH_3 , a 0.32% decrease in CO, and a 0.13% decrease in PM_{10} .

The Pearl River Delta (PRD) region showed statistically significant reductions only in BC and SO_2 emissions. The baseline pollution level in this region was relatively low compared to others, and the emission reduction targets were also set lower, resulting in the least pronounced policy effectiveness in terms of emission reduction. Quantitatively, a 1% increase in the PM_{10} emission reduction target in the PRD is linked to a 2.61% decrease in SO_2 and a 0.38% decrease in BC.

5 Main results: Impact of policy on psychological wellness

5.1 Baseline results

Table.5-1 reports the full-sample and sub-regional estimation results of Eq. (3-4) and Eq. (3-5).

The regression results reveal a consistent pattern for both the anxiety and confidence indices: key coefficients indicate that environmental policies significantly reduce anxiety and promote confidence. This effect is particularly pronounced in the Yangtze River Delta and Pearl River Delta regions. For instance, 1% increase in the policy target is associated with 1.66% decrease in the anxiety index across all cities, 1.47% in the Yangtze River Delta, and 1.88% in the Pearl River Delta, on average.

However, the coefficient lacks statistical significance in city group 2. We root this primarily in the limited variation in the policy target variable within the Beijing-Tianjin-Hebei region. With a standard deviation of only 2.53% against a mean value of 24.15%, it indicates that the PM_{10} reduction targets were set uniformly high across cities in this region. The resulting lack of dispersion in the explanatory variable makes it difficult to identify corresponding policy-induced psychological effects, given that the effect is less evident compared to the emission reduction effects of the policy.

Table 5-1

Effects for APPCAP on emotion (sub- city groups)

Variable	(1) All City	(2) Beijing-Tianjin- Hebei Region	(3) Yangtze River Delta	(4) Pearl River Delta
A. Anxiety Indicator				
$\theta(PM10Tar \cdot Airten)$	-0.363*** (0.106)	-0.175 (0.167)	-0.386** (0.076)	-0.887** (0.214)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year_Month FE	Yes	Yes	Yes	Yes
Observations	31,900	1430	4510	990
R-squared	0.893	0.863	0.916	0.879
B. Confidence Indicator				
$\gamma(PM10Tar \cdot Airten)$	0.0037** (0.0017)	0.0087 (0.0084)	0.0049** (0.0024)	0.01232** (0.0062)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year_Month FE	Yes	Yes	Yes	Yes
Observations	31,900	1430	4510	990
R-squared	0.9415	0.963	0.956	0.979

Notes: Observations in June are dropped from each year's dataset to eliminate potential confounding effects caused by the National College Entrance Examination (Gaokao) on public sentiments. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses

Table5-2

summary statistics of reduction targets in the Beijing-Tianjin-Hebei region

PM10_Target(%)	Mean	SD	Min	P25	P50	P75	Max
Beijing-Tianjin-Hebei Region	24.148	2.533	19.289	22.039	23.882	28.289	31.136
YangtzeRiverDelta	15.146	7.55	0	14	17	19.609	28.297
Pearl River Delta	13.592	3.907	6.079	13.118	13.42	15.459	18.867
Total	11.858	7.134	0	6.261	10	16.676	35

5.2 Parallel trend test

We employ 2 event study model to test for parallel trends test for Equ(3-4) and (3-5) by estimating (4-5) and (4-6)

$$\begin{aligned} AnxietyIndicator_{i,t} = & \alpha + \sum_{year=2011}^{2012} \theta_{year} PM10Tar_i \cdot Airten_{i,year} \\ & + \sum_{year=2014}^{2020} \theta_{year} PM10Tar_i \cdot Airten_{i,year} + \phi X_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \end{aligned} \quad (5-1)$$

$$\begin{aligned} ConfidenceIndicator_{i,t} = & \alpha + \sum_{year=2011}^{2012} \gamma_{year} PM10Tar_i \cdot Airten_{i,year} \\ & + \sum_{year=2014}^{2020} \gamma_{year} PM10Tar_i \cdot Airten_{i,year} + \phi X_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \end{aligned} \quad (5-2)$$

where $Airten_{i,year}$ ($Year \in (2011, 2012, 2014, 2015, 2016, 2017, 2018, 2019, 2020)$) is a set of year dummies, indicating whether the data is before the policy implementation or after the policy. The coefficient of θ_{year} indicates differences in mental well-being outcomes between the treatment and control groups in the years before or after the implementation of the APPCAP. This study takes the policy implementation year as the reference year (2013) and standardizes the coefficients for each year.

Fig.5-1 shows that the anxiety indicator and the confidence indicator yield similar conclusions: in the models for all cities, the Yangtze River Delta, and the Pearl River Delta, there is no significant difference in mental well-being trends between the treatment and control groups prior to the implementation of the APPCAP. Consequently, we fail to reject the parallel trend assumption which shows that mental well-being trends of the treatment and control groups were parallel before the APPCAP was implemented—for these models.

Furthermore, the coefficient for the anxiety indicator turns out to be significantly negative after the implementation of the APPCAP, which confirms the negative effect of this regulation on mental well-being. Meanwhile, a similar conclusion holds for the confidence index, which is significantly positive.

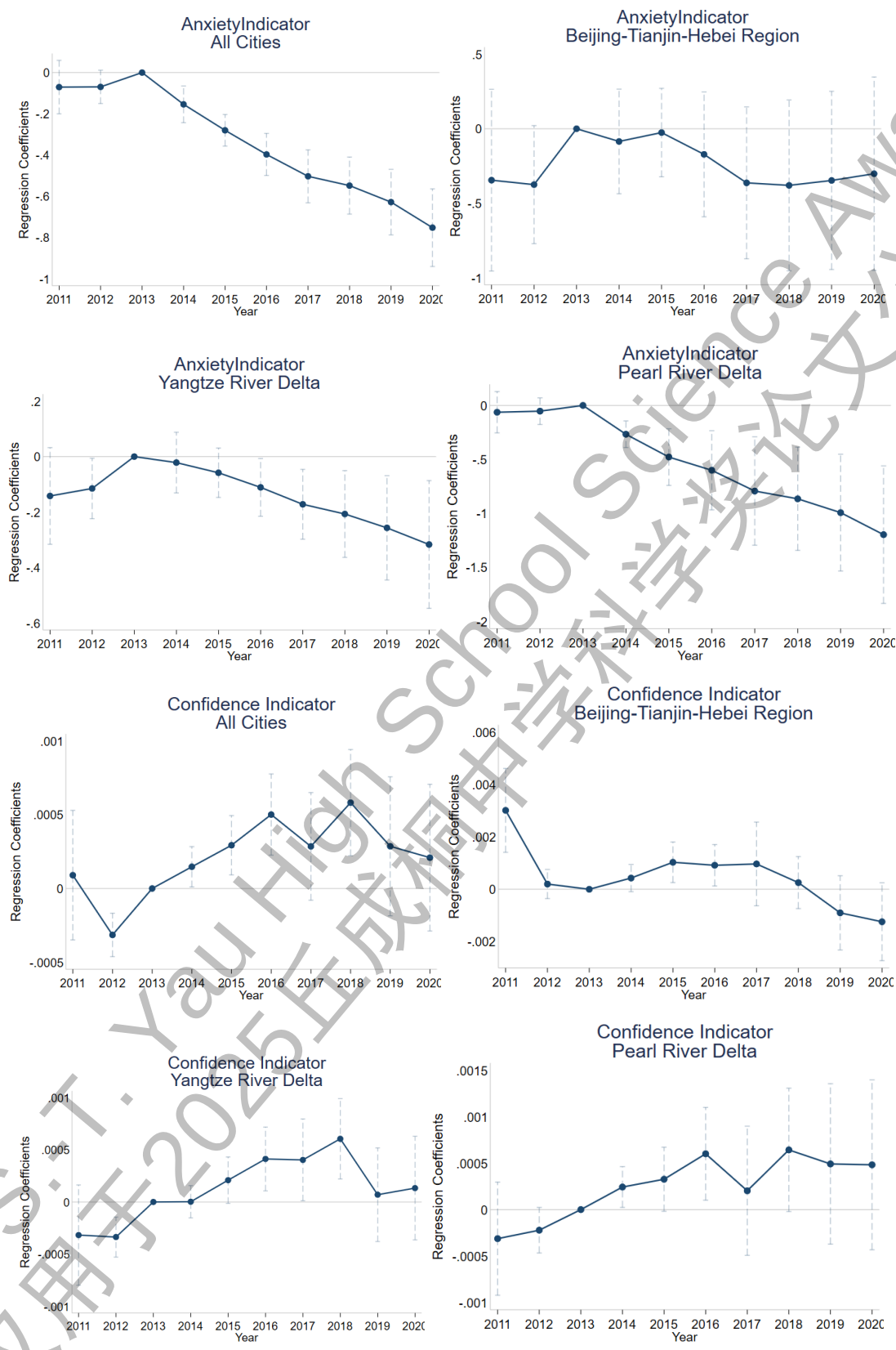
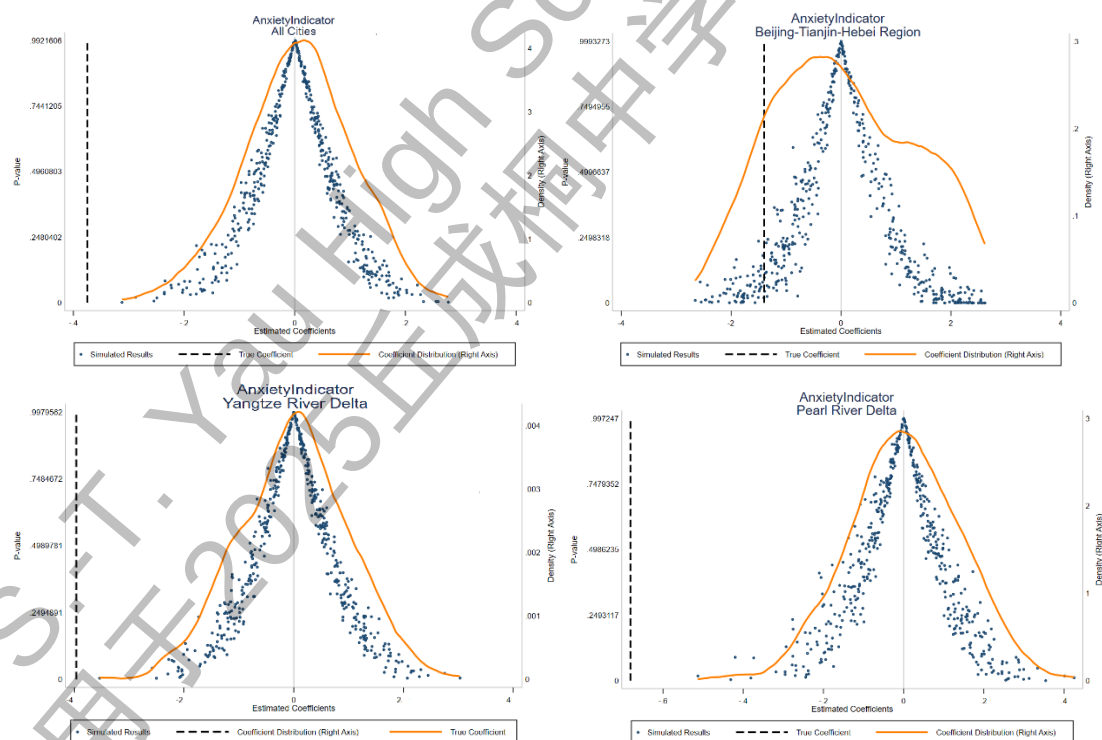


Figure.5-1 Parallel trend tests for emotions (by cities groups)

5.3 Placebo test

Similar to Chapter 4.1.4, we perform the placebo tests by randomly selecting the policy implementation strength PM10 target in cities (see Figure.5-2). In Figure.5-2, The estimated policy effects from 500 random sampling regressions for the anxiety indicator and confidence indicator across 4 city groups are plotted. Results show that the findings for the anxiety indicator and confidence indicator are similar: the estimated policy effects are small in the all sample regression, the Yangtze River Delta, and the Pearl River Delta, with most values close to 0, and most of the corresponding p-values are greater than 0.1. However, the placebo test fails to pass in the Beijing-Tianjin-Hebei region. The results of the placebo test are consistent with the significance of Eq(3-4) and Eq(3-5) which lending further support that the decrease in the anxiety indicator and the increase in the confidence indicator are indeed the result of the APPCAP policy.



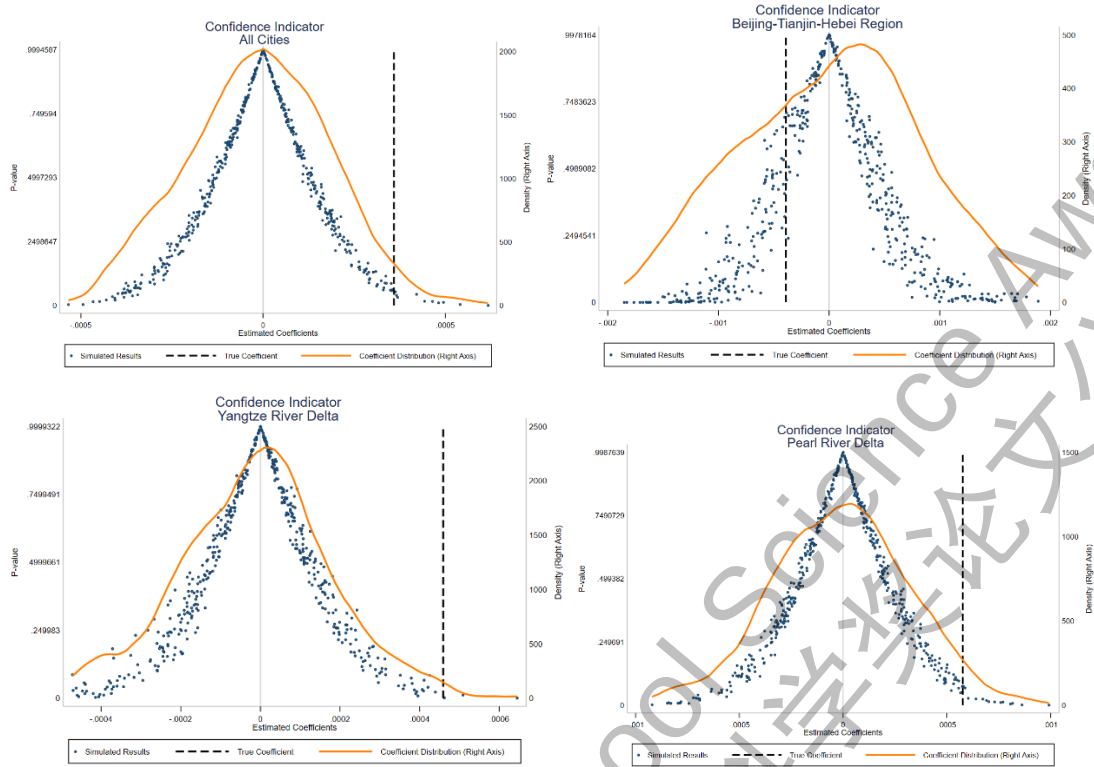


Figure.5-2 Placebo tests for emotions (by cities groups)

5.4 Heterogeneous Analysis: Urbanization

Urbanization may influence residents' physical and mental health through disparities in availability with respect to medical resource, social security and infrastructure(Di G, et al.,2024). In 2011, China's urbanization rate exceeded 50% for the first time (reaching 51.27%). By 2012, the national urbanization rate rose to 52.6%, and further increased to 60.6% in 2019. According to the Chinese Academy of Social Sciences (CASS), an urbanization rate above 50% signifies an initial urbanized society; 61%–75% indicates an intermediate urbanized society; 76%–90% represents an advanced urbanized society; and above 90% reflects a fully urbanized society.

We divide samples into high/low urbanization groups based on the 50% unbarnization rate threshold by 2012 (128 cities with high urbanization rates and 162 low high urbanization rates). Results show that, both in alleviating anxiety and fostering positive sentiments, the psychological health benefits of environmental regulations are significant in low-urbanized and rural areas. 1% increase in the policy target is associated with 0.81% decrease in the anxiety index and 0.41% increase in the confidence index in low urbanized areas.

This finding aligns with discussions in existing literature, suggesting that urban populations possess more resources and strategies to mitigate exposure to environmental pollution and associated negative emotions, while rural populations tend to be relatively more vulnerable to similar stressors.

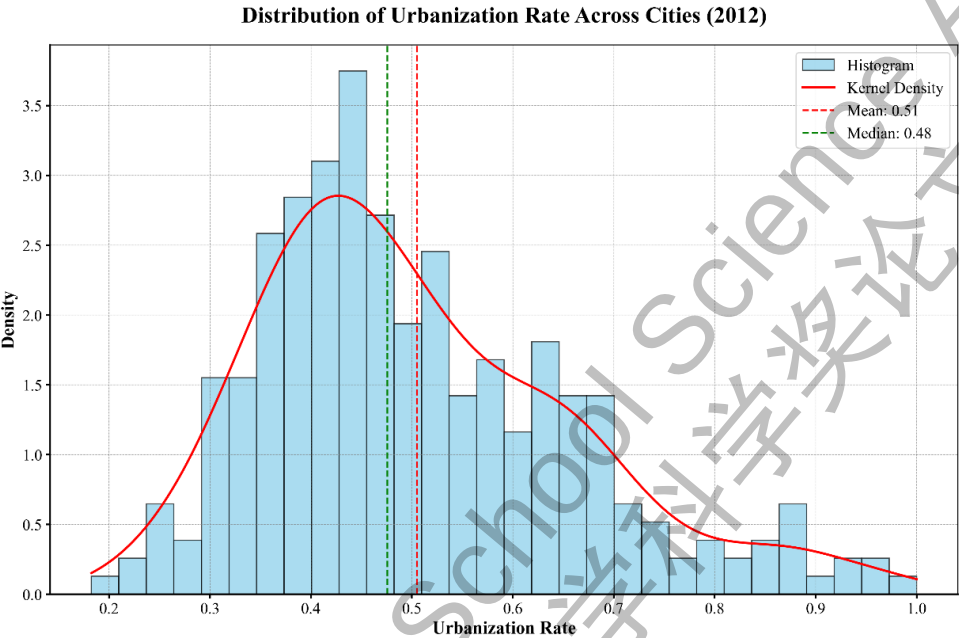


Figure.5-3 Placebo tests for emotions (by cities groups)

Table5-3
Effects for APPCAP on emotion (High&Low Urbanization)

	(1) Low Urbanization	(2) High Urbanization
A. Anxiety Indicator		
$\theta(PM10Tar \cdot Airten)$	-0.4414*** (0.0972)	-0.2162 (0.2198)
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes
Year_Month FE	Yes	Yes
Observations	16480	13530
R-squared	0.8723	0.9077
B. Confidence Indicator		
$\gamma(PM10Tar \cdot Airten)$	0.004* (0.002)	0.003 (0.003)
Controls	Yes	Yes

City FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes
Year_Month FE	Yes	Yes
Observations	16480	13530
R-squared	0.9032	0.957

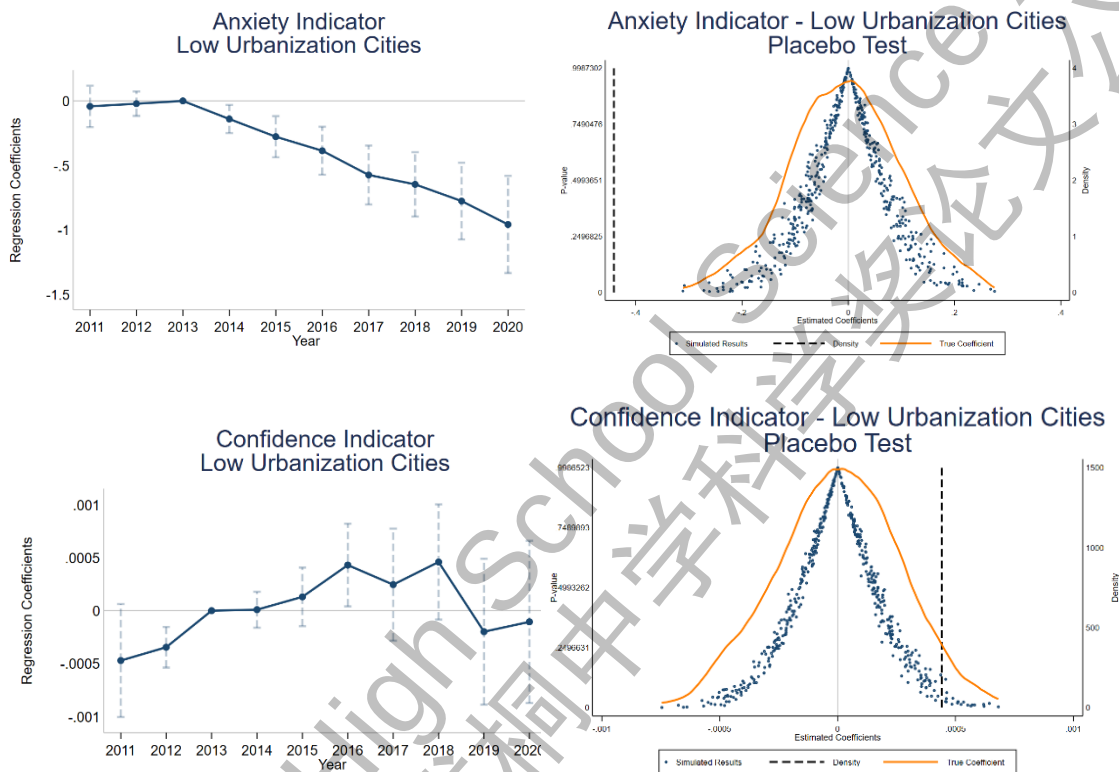


Figure.5-4 Placebo tests and Parallel trend test for emotion (High&Low Urbanization)

6 Conclusion

To conclude, in this paper, we explore the intended and unintended impacts of the Air Pollution Prevention and Control Action Plan (APPCAP). We find that the APPCAP achieved substantial emission reduction effects, both in the full sample and in analyses disaggregated by sector and region. Employing causal inference methods, we further uncover the policy's unanticipated psychological dividends, namely a reduction in public anxiety and a rise in confidence. This unintended psychological effect of environmental policy was found to be more pronounced in areas with lower urbanization levels.

This paper offers insightful implications for future environmental policy design. The impacts of environmental regulations are multifaceted and far-reaching, as reflected in the broad spectrum of affected stakeholders and the diversity of resultant outcomes. In an era increasingly oriented toward public well-being, this study underscores the necessity for policymakers to incorporate a more integrated and forward-thinking approach in environmental policy design.

Our study indicates that it is imperative to capitalize on the pivotal role of the industrial sector in emission abatement, while adopting a policy mix encompassing both administrative mandates and market-oriented mechanisms to foster engagement from agricultural, transportation, and residential sectors. Such coordinated initiatives are essential to generate synergistic effects in pursuing collective emission reduction goals. Concurrently, increased emphasis should be placed on strategic science communication, improving psychological well-being and public motivation, as well as galvanizing broader societal endorsement and implementation of environmental policies.

REFERENCE

Bae M, et al. Role of emissions and meteorology in the recent PM_{2.5} changes in China and South Korea from 2015 to 2018[J]. *Environmental Pollution*, Volume 270, 2021, 116233, ISSN 0269-7491, DOI:10.1016/j.envpol.2020.116233.

Calderón-Garcidueñas L, et al. Long-term air pollution exposure is associated with neuroinflammation, an altered innate immune response,[J]. *Toxicol Pathol.* 2008 Feb;36(2):289-310. doi: 10.1177/0192623307313011.

Cheng, et al.,. Stringent environmental regulation and inconsistent green innovation behavior: Evidence from air pollution prevention and control action plan in China[J], *Energy Economics*, Volume 120, 2023, 106571, ISSN 0140-9883, DOI:10.1016/j.eneco.2023.106571.

Deschênes, Olivier, Michael Greenstone, Joseph S. Shapiro. 2017. Defensive Investments and the Demand for Air Quality: Evidence from the NO_x Budget Program[J]. *American Economic Review*. 107 (10): 2958–89. DOI: 10.1257/aer.20131002.

Di G, et al.,Environmental regulation: An enhancing or burden for social welfare and public health[J].*Journal of Cleaner Production*,Volume 441, 2024, 140985, ISSN 0959-6526, DOI:10.1016/j.jclepro.2024.140985.

Gao et al.,Improving air pollution control policy in China: A perspective based on cost–benefit analysis[J], *Science of The Total Environment*, Volume 543, Part A, 2016, Pages 307-314, ISSN 0048-9697, DOI:10.1016/j.scitotenv.2015.11.037.

Genc S, et al.,. The adverse effects of air pollution on the nervous system[J]. *J Toxicol.* 2012;2012:782462. doi: 10.1155/2012/782462.

Geng, et al. Efficacy of China's clean air actions to tackle PM_{2.5} pollution between 2013 and 2020[J]. *Nat. Geosci.* 17, 987–994 (2024). DOI:10.1038/s41561-024-01540-z.

Huang et al.,Health impact of China's Air Pollution Prevention and Control Action Plan: an analysis of national air quality monitoring and mortality data, *The Lancet Planetary Health*, Volume 2, Issue 7, 2018, Pages e313-e323, ISSN 2542-5196, DOI: 10.1016/S2542-5196(18)30141-4.

Huang W, Zhang Z, Liu A. From Difference-in-Differences to Event Study Methodology[J]. Reprinted Journal Materials: Statistics and Actuarial Science, 2022(5):17.

Li, et al. Anthropogenic emission inventories in China: a review[J]. National Science Review, 2017.DOI:10.1093/nsr/nwx150.

Shi X , Xu Z .Environmental regulation and firm exports: Evidence from the eleventh Five-Year Plan in China[J].Journal of Environmental Economics and Management, 2018, 89(MAY):187-200.DOI:10.1016/j.jeem.2018.03.003.

Xie et al. Information, awareness, and mental health: Evidence from air pollution disclosure in China[J].Journal of Environmental Economics and Management, Volume 120, 2023, 102827, ISSN 0095-0696, DOI:10.1016/j.jeem.2023.102827.

Yu Y, et al. Air pollution prevention and control action plan substantially reduced PM2.5 concentration in China [J].Energy Economics, Volume 113, 2022, ISSN 0140-9883, DOI:10.1016/j.eneco.2022.106206.

Yue, H., He, C., Huang, Q. et al. Stronger policy required to substantially reduce deaths from PM2.5 pollution in China[J]. Nat Commun 11, 1462 (2020). <https://doi.org/10.1038/s41467-020-15319-4>.

Zheng, et al.Air quality improvements and health benefits from China's clean air action since 2013[J], Environmental Research Letters, Volume 12. DOI 10.1088/1748-9326/aa8a32.

Zundel et al. Air pollution, depressive and anxiety disorders, and brain effects: A systematic review[J]. Neurotoxicology. 2022 Dec;93:272-300. doi: 10.1016/j.neuro.2022.10.011.

Acknowledgment

Accomplishing this research paper is a marvelous journey that has helped me attain valuable skills in dissecting a question, taught me persistence and devotion, and given me the chance to be a better version of myself. Most importantly, this journey could not have been completed without the help from many great people. I want to express my sincerest gratitude to all of them.

With an anticipation of taking a profound look into the questions that I find great interest in, I talked to Ms. Yu about them. While encouraging me to develop my interest, Ms. Yu laid out the basic principles in economics modeling and explained to me the prospect of each of my ideas. With her help, I was able to narrow down my thoughts and get more specific. I then decided to do a research on an analysis on a environmental policy. However, I thought about the impact the environment has on human and society, and had no realization that this inclination may impact my future research. Ms. Yu also advised me to contact with a professor in the university, and actively reach for further advise on data collecting, modeling and analysis. Thanks to her help, the journey had a wonderful start.

I contact with Ms. Cao and was grateful that she was willing to help without pay. She taught me some modeling strategy and gave me learning resources in econometrics. After finishing the learning, I was introduced to the methods of cleaning data. Then Ms. Cao gave me literature regarding the policy. After reading 8 articles on it, I gained a much more comprehensive view on the impact of the policy not only on the physical health of human, but also the overlooked impact on psychological well being which deserves more close investigation. I exchanged my view with professor Cao and find it an honor to work on the impact of air policy on emotional behaviors such as depression and anxiety. She frequently discussed with me about the research papers and I wrote a literature review. This process was essential as I drew connections between environmental policy and psychological conditions. I often reflect on reality to target the most interesting parts in the study.

Cleaning the empirical data was not easy for me, since the identification strategy was beyond the stuff I learned in school. And when the diagrams went wrong, she was always there to help me figure it out. Ms. Cao gave useful suggestions and went along with me on this journey to analysis and drawing conclusions. My gratitude may not

only flowed on the surface of technical help she has given me, for the lessons she taught me in being an ambitious and patient person can't be valued by words. I have met her many times in person and have learned a lot from her in doing researches and in being a curious person.

I have lived in a polluted Beijing before and I am amazed by how fast time flies and we are now returned to the clear blue sky. But as a matter of fact, a policy may have an unintended effect as well as the more intelligible and intended one. I'm a big fan of the novel Dune and I'm enthralled by how the ecosystem can shape human society, or even the universe. People change the environment, and the environment changes them in turn. The fatal interconnection gave me the natural fascination toward nature. However, my grandpa suffered from lung cancer and my grandma once stayed in house for 2 months due to the worry of getting ill because of the haze. Emotional well being has been widely discussed nowadays, and I want to find the connection.

This journey has seemingly reached an end but I know that it's just a celebration of a little hill that has been overcome. I want to thank my school SDSZ to have provided the chance for high school students to do research and learn along the way. And let me express deep gratitude to all the friends and families that have answered my question and supported me.