Social Science & Medicine 365 (2025) 117584

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Environmental regulation and mental well-being: Evidence from China's air pollution prevention and control action plan

Yuze Wang [a], Zidi Zhang [b,c], Zhuang Hao [a,*], Tor Eriksson [d]

[a] College of Economics and Management, Huazhong Agricultural University, Wuhan, 430070, China
[b] Department of Earth Science & Engineering, Imperial College London, London, SW7 2AZ, UK
[c] School of Statistics and Mathematics, Zhongnan University of Economics and Law, Wuhan, 430073, China
[d] Department of Economics and Business Economics, Aarhus University, Aarhus, 8000, Denmark

ARTICLE INFO

Handling editor: Richard Smith

JEL classification:
I12
I18
Q53
Q58

Keywords:
Mental well-being
Environmental regulation
Public awareness
Air pollution
$PM_{2.5}$

ABSTRACT

This study investigates how enhanced environmental regulation can improve individuals' mental well-being, 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 timing and regions of the implementation of the policy, we find that the APPCAP has significantly improved people's mental well-being. We test several potential socio-economic channels including reduced air pollution, enhanced environmental awareness, improved physical health, and decreased physical activities during periods of heavy pollution, through which environmental regulation may affect mental well-being. Our findings highlight that increased public awareness concerning air pollution plays an important role in the health effects of environmental regulations. The positive effects of environmental regulation on mental well-being are particularly pronounced among individuals aged 45–59 and for those with higher-than-average income or education. We do not find that the positive effects of environmental regulation differ by gender. We further show that the 4-week prevalence of mental/neurological disease dropped significantly, by about 0.38 percentage points, after the implementation of the APPCAP, reaffirming significant mental health benefits from the environmental regulation.

1. Introduction

Air pollution is widely recognized as a major environmental threat to human health. Numerous studies have linked air pollution to the increased risk of developing lung cancer, respiratory diseases, and cardiovascular disease (for example, see Schlenker and Walker, 2016; Brunekreef and Hoffmann, 2016; Balasooriya et al., 2022), substantial reduction in life expectancy (Chen et al., 2013; Ebenstein et al., 2017), and elevated mortality rates over the life-course (Chay and Greenstone, 2003; Deryugina et al., 2019; He et al., 2020; Palma et al., 2022). According to the World Health Organization (WHO), in 2019, 99% of the global population resided in areas where the air quality did not meet the recommended levels and that annually 6.7 million premature deaths worldwide were related to air pollution.[1]

In addition to physical health and mortality, research findings in different fields have also confirmed that air pollution is associated with worsening mental health and well-being worldwide including a growing prevalence of depressive and anxiety disorders, a higher likelihood of developing dementia, and reduced cognitive performance (Bharadwaj et al., 2017; Ailshire et al., 2017; Bishop et al., 2023; Chen et al., 2024). Medical and environmental studies show that air pollutants, especially $PM_{2.5}$, can induce changes in the neural structure and the neurological function (Zhang et al., 2018), resulting in damage to the frontal lobe of the brain, which controls stress and emotions, and stores memory (Herting et al., 2019; Zundel et al., 2022). Zhang et al. (2018) demonstrate that air pollution may reduce the white matter density and decrease the volume of gray matter in the brain, resulting in impaired cognitive performance on verbal and mathematical performance. Zundel et al. (2022) show that exposure to air pollution may affect regions and pathways in the frontal brain that are associated with stress and emotion regulation, thereby increasing vulnerability to mental disorders such as depression and anxiety. Additionally, air pollution influences

* Corresponding author.
E-mail addresses: wangyz@mail.hzau.edu.cn (Y. Wang), zidi.zhang24@imperial.ac.uk (Z. Zhang), zhuang.hao@mail.hzau.edu.cn (Z. Hao), tor@econ.au.dk (T. Eriksson).

[1] See https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health.

https://doi.org/10.1016/j.socscimed.2024.117584
Received 19 July 2024; Received in revised form 6 October 2024; Accepted 29 November 2024
Available online 5 December 2024
0277-9536/

social behaviors. Neidell (2009) finds that people tend to reduce exposure to air pollution by developing avoidance behaviors such as staying indoors, resulting in less outdoor exercise and other physical activities. These behavioral changes may further impact mental health and well-being as well (Takeda et al., 2017).

With the advancement of understanding how air pollution affects human health at even lower concentrations than previously believed, in 2021, WHO lowered its recommended annual average concentration of particulate matter (PM) with aerodynamic diameters of less than or equal to 2.5 μm ($PM_{2.5}$) to 5 μg/m^3 from 10 μg/m^3 set in 2005.[2] The guideline was intended for use in areas where pollution has been generally heavy and worsening due to industrialization, urbanization, and economic development. Like other developing countries, China has faced severe air pollution issues in the past decades. China's annual average $PM_{2.5}$ concentrations have ranged from 26 μg/m^3 to 36 μg/m^3 between 2002 and 2016, well above WHO's recommended levels. Graph (a) and Graph (b) in Fig. 1 depict the correlations between annual $PM_{2.5}$ concentrations and mortality rates of heart disease, respiratory diseases, and mental disease in China. Besides heart and respiratory diseases, the mortality rate of mental disease appears to be highly correlated with $PM_{2.5}$ concentration, both peaking in 2007, falling in later years, and rising again in 2013. The figure supports previous research findings of the detrimental health impact of air pollution in China.

In response to severe air pollution, Chinese government has enacted and implemented a series of environmental regulations and laws. The initial version of the Air Pollution Control Law was enacted in 1987; however, it was considered ineffective as it did not address the pollutant emissions from the energy power sector. In 1995, the law underwent its first revision regarding the regulation of coal burning, particularly restricting the use of high sulfur coal in power plants (Hao et al., 2007). The second amendment to the Air Pollution Control Law came in 2000 with a focus on regulating SO_2 emissions and implementing dust removal measures. In 2007, environmental regulations and outputs, specifically the emission reduction of major air pollutants, were regarded as an important part of evaluating and promoting all local government officials.[3] In 2013, the State Council signed the most stringent air pollution regulation policy so far, the Air Pollution Prevention and Control Action Plan (APPCAP), which has proved to be highly effective in lowering the level of fine particulate matter $PM_{2.5}$ (Yu et al., 2022). The APPCAP and its impact will be discussed in detail in Section 2.

A large body of economic and policy literature has examined the effects of various environmental regulations on physical health and mortality. Studies have shown that environmental regulation has been associated with a reduction in the prevalence of air pollution-related diseases, in particular respiratory illnesses, as well as a decline in infant mortality and premature mortality (Currie et al., 2015; Tanaka, 2015; Zheng et al., 2017; Wang et al., 2023). Huang et al. (2018) find that China's APPCAP brought significant improvements in air quality, resulting in 47,240 fewer deaths and 710,020 fewer years of life lost (YLL) in 74 major cities in 2017 compared to 2013. Maji et al. (2020) show that APPCAP led to a 5.6% decrease in mortality attributable to $PM_{2.5}$ in Beijing in 2018 compared to 2014.

Despite the growing importance of mental health and well-being, few studies have examined the impact of environmental regulation on this aspect of human health. Understanding how mental well-being responds to environmental regulation is crucial, particularly in exploring channels beyond direct pollution reduction. Our study examines the impact of environmental regulation on human health, with a focus on mental well-being. We examine the impact of environmental regulation on mental well-being by exploiting the exogenous timing and regional variations in the implementation of APPCAP. Furthermore, the large variation in specific prefectures' targets for pollution reduction is utilized to increase the robustness of our empirical results. Using the data from the China Health and Nutrition Survey, our difference-in-differences results suggest that the implementation of APPCAP has led to a 4.04% improvement in the *Mental Well-being Score*, an index reflecting the level of individuals' overall mental well-being constructed as the weighted average of numerical answers to three available mental health status questions in the survey.

Three potential channels are studied: the biological channel, the pollution reduction channel, and the environmental awareness channel. Our estimation results suggest that the APPCAP contributed to improved mental well-being via reduced $PM_{2.5}$ concentration, improved public awareness of air pollution, decreased physical activities during periods of heavy pollution, and improved physical health. In addition, we analyze the impact of APPCAP on the 4-week prevalence of mental/neurological diseases, and find that the regulation reduced the prevalence by about 0.38 percentage points, providing suggestive evidence for the biological channel (brain structure and neurological function). Furthermore, we demonstrate significant heterogeneity in the effects of the environmental regulation. The APPCAP has particularly promoted the mental well-being of individuals aged 45–59, as well as those with higher income and higher education. At the same time, the positive effects of APPCAP do not show a significant gender difference.

This study makes three distinct contributions. Firstly, it adds to literature on the impact of environmental regulation on a topic that is becoming increasingly important: mental well-being. While several studies have examined the effects of environmental regulations on physical health outcomes, there is considerably less research on mental well-being. To the best of our knowledge, the only study that has explored the impact of environmental regulation (more precisely, the disclosure of pollution information) on mental well-being is Xie et al. (2023). The focus of their study is on the effects of a pollution information disclosure policy, while the policy in our study is a pollution reduction policy. We test whether government efforts to reduce pollution would also affect individuals' environmental awareness and mental well-being, even in the absence of real-time monitoring and disclosure of pollution information.

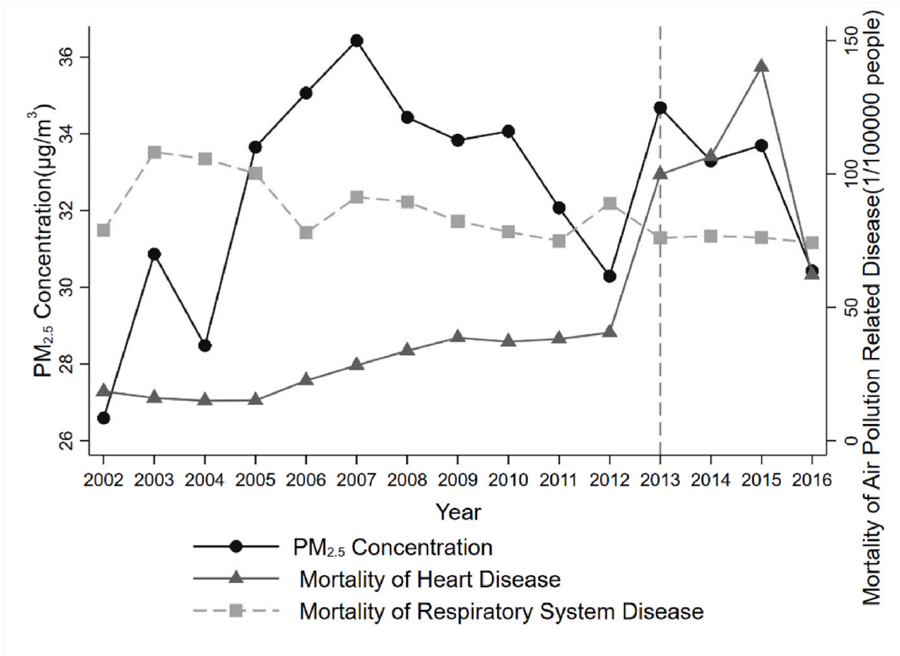
Secondly, this paper highlights the important role of environmental awareness in mediating the impact of environmental regulation on mental health. Existing research presents mixed findings on the health implications of environmental awareness, noting that it can be beneficial due to the increased avoidance behaviors or detrimental due to heightened stress levels (Xie et al., 2023). We demonstrate that the APPCAP has significantly increased public awareness of air pollution. Unlike previous research, we provide empirical evidence of a positive relationship between awareness and various health outcomes. This finding further confirms environmental awareness as a potential mechanism through which environmental regulations can impact mental well-being.

Thirdly, this study provides evidence that helps in better understanding the unintended health impacts of environmental policies. Given the insufficient resources for mental health care in developing countries, relying solely on after-the-fact treatment to improve mental health and well-being is unrealistic. Thus, a better understanding of what other resources can promote mental well-being is essential.

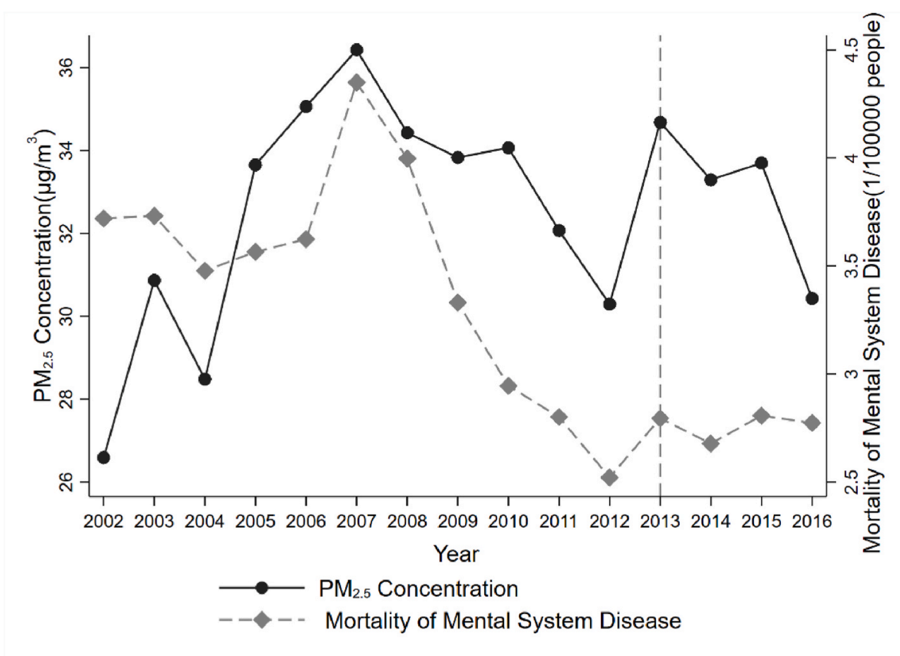
The subsequent sections of this paper are organized as follows: Section 2 provides a brief description of the environmental regulation, APPCAP and its impact. Section 3 discusses the potential channels of environmental regulation influence on mental well-being. Section 4 describes the data and empirical model utilized in our analyses. Section 5 presents the main results, examines the potential channels, and discusses heterogenous effects. Section 6 concludes the paper and offers policy implications derived from our study.

[2] The updated target is specified on page 18 in the guideline "WHO global air quality guidelines: particulate matter ($PM_{2.5}$ and PM_{10}), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide", and the guideline can be accessed through https://www.who.int/publications/i/item/9789240034228.

[3] As shown in Fig. 1, $PM_{2.5}$ concentrations began to decline after 2007.



(a) Temporal Trends in $PM_{2.5}$ Concentration and Physiological Disease



(b) Temporal Trends in $PM_{2.5}$ Concentration and Mental System Disease

Fig. 1. Temporal trends in $PM_{2.5}$ concentration and mortality of air pollution-related diseases.
Notes: The $PM_{2.5}$ data in this study is from the global $PM_{2.5}$ gridded map provided by the National Aeronautics and Space Administration (NASA) of the United States, and authors extracted and visualized this data using ArcGIS software. The mortality rates associated with different illnesses in Fig. 1-(a) and 1-(b) are sourced from the China Health Statistics Yearbook.

2. Background

2.1. The 2013 air pollution prevention and control action plan

Under China's coal-based energy structure, air pollution has for a long time been primarily composed of soot, SO_2, and NO_x. However, there was relatively limited awareness regarding $PM_{2.5}$, fine particulate matter usually found in smoke that has a diameter of 2.5 μm or smaller. Prior to 2012, China's Ambient Air Quality Standards did not include provisions for $PM_{2.5}$, and air quality monitoring stations did not track its levels. With the rapid growth of China's economy, the source of ambient air pollution has changed from mainly coal burning to a mix of sources (Barwick et al., 2024). Simultaneously, regional concentrations of fine particulate matter ($PM_{2.5}$) and ozone (O_3) pollution have been on the rise, leading to prolonged hazy weather in many major cities. Consequently, $PM_{2.5}$, a significant component of haze, has received increased attention. Economic development is not only about quantity, but also about quality. In response to these concerns, in 2013, the Chinese State Council issued the Action Plan for the Prevention and Control of Air Pollution (APPCAP).

The APPCAP stands as China's inaugural initiative reducing the air pollution caused by particulate matter. APPCAP's pollution reduction targets are twofold: First, by 2017, the concentration of respirable particulate matter (PM_{10}) in the prefectures nationwide will be reduced by more than 10% compared with 2012. Second, the concentration of fine particulate matter ($PM_{2.5}$) in the regions of Beijing-Tianjin-Hebei, the Yangtze River Delta (including Shanghai, Jiangsu, Zhejiang, Anhui Province) and the Pearl River Delta (Some cities in south central Guangdong province) will be reduced by about 25%, 20%, and 15%, respectively. The annual average concentration of $PM_{2.5}$ in Beijing is targeted at approximately 60 μg/m^3.[4] This paper focuses on the impact of the $PM_{2.5}$ reduction target in APPCAP on mental well-being for two reasons. First, research has shown that air pollutants that cause neurostructural and neurofunctional changes are mainly $PM_{2.5}$ rather than PM_{10} (Zhang et al., 2018; Zundel et al., 2022).[5] Second, all prefectures in China have uniform PM_{10} reduction targets, while $PM_{2.5}$ reduction targets exist in prefectures in three regions. The variation in the implementation of APPCAP and $PM_{2.5}$ reduction targets across prefectures provides us with a possibility to identify the impact of the regulation on the outcomes of our interest.

The APPCAP is a top-down policy. To ensure the reduction of pollutants, the Ministry of Ecological and Environmental Protection and provincial governments have signed pollution reduction responsibilities, and provinces have developed their own pollution reduction plans based on the reduction responsibilities. Table 1 lists the $PM_{2.5}$ pollution reduction targets collected from official documents published by provincial governments. Acknowledging $PM_{2.5}$ as the primary pollutant with a significant impact on mental health and well-being (Calderón-Garcidueñas et al., 2015), this paper designates regions with $PM_{2.5}$ reduction targets mentioned in Table 1 as the treatment group.[6] These regions' geographical locations are depicted in Fig. 2. Since the pollution reduction target in Shandong Province is set in two phases (see Note under Table 1), which is different from other provinces, we remove the Shandong Province from the sample as a robustness check, and the results are shown in Appendix Table A1.

Table 1
Provincial $PM_{2.5}$ reduction targets under APPCAP.

Province	Target	Province	Target
Anhui	No	Jilin	No
Beijing	25%	Jiangsu	20%
Chongqing	No	Jiangxi	No
Fujian	No	Liaoning	No
Gansu	No	Ningxia	No
Guangdong (Non-Pearl River Delta cities)	No	Qinghai	No
Guangdong (Pearl River Delta cities)	15%	Shaanxi	No
Guangxi	No	Shandong	No
Guizhou	No	Shanghai	20%
Hainan	No	Shanxi	20%
Hebei	25%	Sichuan	No
Heilongjiang	No	Tianjin	25%
Henan	No	Tibet	No
Hubei	No	Xinjiang	No
Hunan	No	Yunnan	No
Inner Mongolia	10%	Zhejiang	20%

Notes: (1) The Pearl River Delta refers to a group of cities in Guangdong Province, including Guangzhou, Foshan, Zhaoqing, Shenzhen, Dongguan, Huizhou, Zhuhai, Zhongshan, and Jiangmen. (2) Shandong Province's pollution reduction plan is divided into two phases. Phase I (2013–2015) does not specify the $PM_{2.5}$ reduction target, and Phase II (2016–2017) specifies the $PM_{2.5}$ reduction target for each prefecture-level city. Since our study period is 2006–2015, the provisions in Phase I are employed. (3) The targets in the table are the reduction percentage of pollutant concentration in 2017 compared with that of 2012. However, the target of Shandong Province is the reduction percentage of pollutant concentration in 2015 compared with that of 2010.

The APPCAP, recognized as the most stringent environmental regulation in China, achieves this "stringency" through several distinct approaches. Primarily, APPCAP stands as the first action plan dedicated to enhancing ambient air quality. Different from prior strategies that embraced Total Control measures, APPCAP focuses on air quality enhancement. This is evidenced by its core focus on air quality improvement targets, contributing to pollutants reduction. The policy outlines ten types of provisions to ensure the achievement of pollution reduction targets, which are detailed in Appendix Table A4. Additionally, a distinctive attribute of APPCAP is its leadership by the State Council. Unlike previous environmental protection documents that primarily originated under the purview of a single ministry and gained approval for publication from the General Office of the State Council, APPCAP's development, mid-term assessment, and final inspection are spearheaded by the State Council itself. This groundbreaking approach underscores a "national action" stance towards addressing air pollution challenges.

2.2. The impact of APPCAP

The APPCAP has demonstrated its efficacy in curtailing pollution emissions, particularly those of $PM_{2.5}$ in designated regions including the Beijing-Tianjin-Hebei, the Yangtze River Delta and the Pearl River Delta. According to the 2017 China Ecological Environment Situation

[4] The $PM_{2.5}$ concentration target of 60 μg/m^3 represents a significant reduction for Beijing (given that the annual average $PM_{2.5}$ concentration was 89.5 μg/m^3 in 2013). However, this concentration level still signifies a relatively considerable degree of pollution when evaluated against both domestic and international standards (In accordance with China's Ambient Air Quality Standard GB 3095-2012, the secondary limit value for the annual average $PM_{2.5}$ concentration is set at 35 μg/m^3. Notably, this value aligns with the WHO Transitional Phase 1 target.).

[5] $PM_{2.5}$ has a much smaller particle size than PM_{10}, so $PM_{2.5}$ could carry toxins through small passages and directly into the brain, causing neurostructural and neurofunctional changes.

[6] Experimental research has shown that air pollutants, especially fine and ultrafine particles ($PM_{2.5}$ and $PM_{0.1}$), exhibit the ability to access the brain. This phenomenon is thought to occur via potential channels such as traversing the blood-brain barrier or translocating along the olfactory nerve. Once within the brain, these pollutants have the potential to impact pathways related to stress response and emotional regulation.

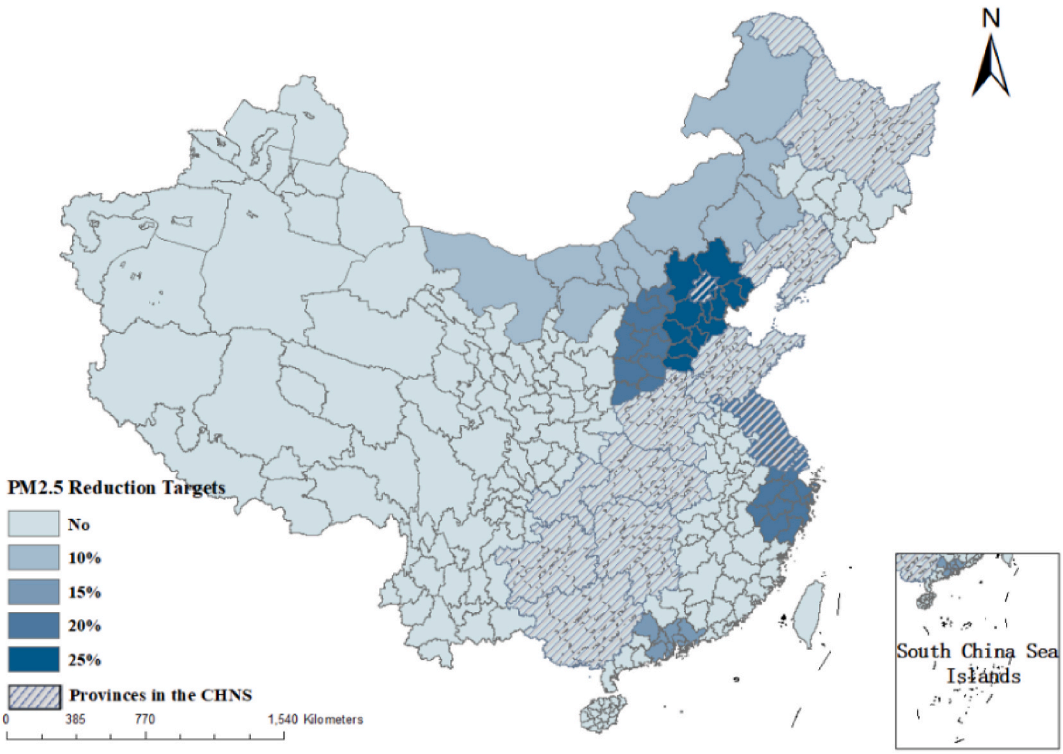


Fig. 2. Provincial distribution of $PM_{2.5}$ reduction targets under APPCAP.
Notes: In this study, CHNS respondents living in prefectures with specific PM2.5 reduction targets are referred to as the treatment group. This includes samples from Beijing, Shanghai and Jiangsu Province. Conversely, respondents from prefectures without PM2.5 reduction targets, namely Henan, Liaoning, Guizhou, Hunan, Guangxi, Heilongjiang, Hubei, Shandong and Chongqing, are referred to as the control group. The figure is created using a standard map sourced from the China National Catalogue Service for Geographic Information (Drawing Review No. GS(2016)2556). The base map remains unaltered.

Bulletin, a marked decline in the average concentration of respirable particulate matter (PM_{10}) was observed in 338 cities at the prefecture level, exhibiting a 22.7% decrease from 2013. Moreover, the average concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta regions was reduced by 39.6%, 34.3%, and 27.7% respectively from 2013 to 2017. Notably, Beijing's average $PM_{2.5}$ concentration decreased from 89.5 $\mu g/m^3$ to 58 $\mu g/m^3$.[7] Thus, the APPCAP successfully achieved its air quality enhancement targets. This effectiveness is highlighted through significant and substantial decreases in $PM_{2.5}$ concentrations (Yu et al., 2022) and also has synergistic reduction effects on PM_{10}, NO_x, CO_2 and other pollutants (Huang et al., 2023), ultimately leading to better air quality.

3. Potential channels

Two direct consequences of APPCAP that may be associated with mental health and well-being are the significant reduction of $PM_{2.5}$ and the heightened public awareness about the health threats from air pollution. In this section, we briefly discuss the potential channels through which the immediate changes as a result of environmental regulation may affect people's mental well-being, as depicted in Fig. 3.

Firstly, environmental regulation like APPCAP can effectively reduce air pollution, consequently mitigating the adverse impact of $PM_{2.5}$ on brain structure and function. This direct action leads to an improvement in mental health and well-being through biological channels. Air pollution such as $PM_{2.5}$ has been shown to affect the central nervous system (CNS) through a neuroimmune or neuroinflammatory response, contributing to the risk of internalizing psychopathology, such as depression, anxiety, and phobias (Genc et al., 2012; Costa et al., 2020). $PM_{2.5}$ is also associated with neurostructural and neurofunctional changes in key frontolimbic regions of the brain, such as the prefrontal cortex, amygdala, and hippocampus. These changes manifest as increased inflammation, oxidative stress, and changes to neurite structure. As a result, $PM_{2.5}$ potentially disrupts pathways related to stress and emotional regulation within the frontolimbic brain, increasing susceptibility to conditions such as depression and anxiety (Calderón-Garcidueñas et al., 2015; Zundel et al., 2022). Studies have also shown that there are gender differences in the effects of air pollution on the frontolimbic brain. Some have found that females are more vulnerable than males to the effects of air pollution on frontolimbic brain regions (Peterson et al., 2015), while others have found that males are more vulnerable than females (Cho et al., 2020). Furthermore, a substantial body of research shows that air pollution is associated with a reduction in gray matter volume and white matter density in the brain (Herting et al., 2019). Gray matter primarily supports mathematical abilities, while white matter plays a central role in language skills (Zhang et al., 2018). Thus, exposure to air pollution has detrimental effects on cognitive performance, particularly on mathematical and language cognition. As the primary role of APPCAP is to reduce $PM_{2.5}$, it directly contributes to improving mental health and well-being through these underlying biological channels.

Secondly, the impact can be mediated through physical health and physical exercise. Air pollutants, particularly $PM_{2.5}$, have the potential to trigger respiratory disorders including asthma, bronchiolitis, chronic obstructive pulmonary disease, and lung cancer (Manisalidis et al., 2020). Moreover, they are linked to cardiovascular diseases, cerebrovascular diseases, and ischaemic heart conditions (Cohen et al., 2017). These health issues can cause discomfort, stress, and anxiety and have cumulative implications for mental well-being. There is medical

[7] The 2017 China Ecological Environment Situation Bulletin can be accessed through https://www.mee.gov.cn/xxgk2018/xxgk/xxgk15/201912/t20191231_754132.html (in Chinese).

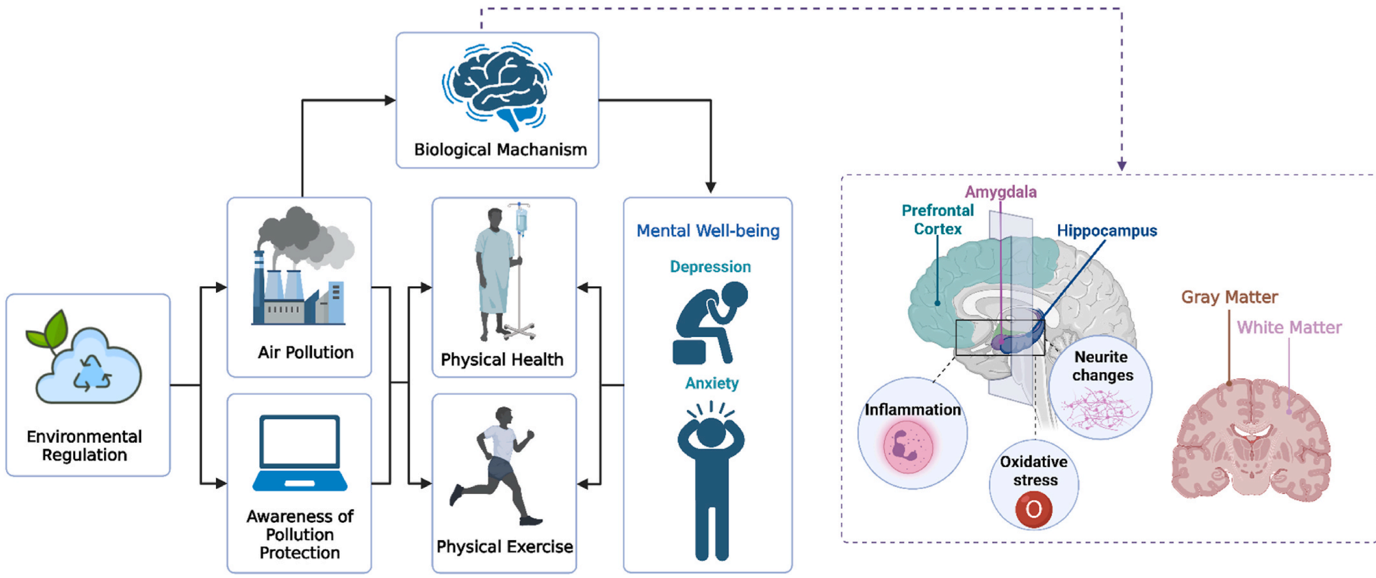


Fig. 3. Potential channels for the impact of environmental regulation on mental well-being.
Notes: Authors create this figure.

evidence showing that mental well-being is associated with chronic physical ailments such as angina, asthma, and chronic obstructive pulmonary disease (Moussavi et al., 2007). Therefore, if APPCAP successfully reduces air pollution and alleviates pollution-related illnesses, it will yield positive effects on mental well-being. Furthermore, individuals often reduce their outdoor social interactions and physical exercise to avoid exposure to air pollution. If APPCAP leads to an improvement in air quality, it can motivate people to engage in more outdoor social activities and physical exercise (Li and Jin, 2024), which can exert a favorable impact on cognitive function and mental well-being (Takeda et al., 2017).

Thirdly, the impact of air pollution on mental health and well-being can also be mediated by heightened awareness of air pollution and pollution protection. Environmental regulations are shown to be related to heightened public consciousness regarding ecological and health concerns (Barwick et al., 2024). The APPCAP received substantial attention through extensive coverage in newspapers, television, and other social media. This widespread coverage is supposed to elevate public awareness concerning the adverse consequences of air pollution, thereby promoting a heightened sense of responsibility toward pollution protection. The improved awareness of air pollution can translate into modified behavior during heavily polluted periods, such as avoiding exposure to pollution by staying indoors or mitigating the exposure by using air purifiers. This behavioral shift can potentially lead to a decreased prevalence of air pollution-related illnesses, consequently contributing to an enhancement in mental health and well-being. The increased awareness has the potential to affect both physical and mental well-being positively.

4. Data and empirical strategy

4.1. Data sources

This study primarily utilizes individual data collected from the China Nutrition and Health Survey (CHNS). The CHNS is a collaborative initiative between the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute of Nutrition and Health of the China Center for Disease Control and Prevention. The overarching aim of the survey is to investigate how China's societal and economic dynamics influence public health and nutrition, thereby enabling assessments of the effects of government-implemented health and nutrition policies at both national and local levels. Initiated in 1989, the CHNS has published data of ten surveys, spanning the years 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015. This extensive 26-year-long follow-up survey period provides an ample timeframe for examining changes in the health status of the population preceding and following the enactment of environmental regulation. Geographically, the CHNS initially covered nine provinces (Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, Guizhou) during its first eight survey waves. In 2011, the survey added three municipalities directly under the central government, Beijing, Shanghai, and Chongqing. Subsequently, in 2015, three additional provinces, Yunnan, Zhejiang, and Shaanxi, were integrated into the survey.

Given that the questions about mental health and well-being status in the CHNS started in 2006 and the APPCAP was implemented in 2013, this study uses the survey waves between 2006 and 2015. The sample is from 12 provinces or municipalities including Beijing, Shanghai, Chongqing, Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, and Guizhou.[8] These provinces span a diverse range of regions across China, characterized by different levels of economic development, environmental pollution, health resources, and variations in the treatment status for the APPCAP. Their geographical locations are illustrated by shaded regions in Fig. 2.

The key measure for air pollution, the annual average $PM_{2.5}$ concentration, is collected from the NASA Socioeconomic Data and Applications Center (SEDAC) Global Annual $PM_{2.5}$ Grids dataset. These gridded datasets are at a resolution of 0.01°, corresponding to approximately 1 km, and are extracted and computed through ArcGIS software. The data for economic variables at the prefecture level are acquired from the China Urban Statistical Yearbook and the China Health Statistical Yearbook.

4.2. Variables

4.2.1. Mental well-being variables

According to WHO, mental health is defined as a state of mental well-being that enables people to cope with the stresses of life, realize their

[8] Yunnan, Zhejiang and Shaanxi only have post-policy data and are therefore excluded from the sample.

abilities, learn and work well, and contribute to their community.[9] There is no consensus about the measurement of mental well-being. In early epidemiology studies, a commonly used measurement is the Center for Epidemiological Studies Depression Scale (CES-D) proposed by Radloff (1977), which contains 20 items such as depressed mood, guilt and worthlessness, feelings of helplessness and hopelessness, psychomotor retardation, loss of appetite, and sleep disturbance.[10] More recent studies start use a shorter form of the CES-D, either K10 (10 items) or K6 (6 items) scale developed by Kessler et al. (2002) (for example, see Zhang et al., 2017). K10 and K6 scales measure behavioral, cognitive, emotional, and physiological aspects of nonspecific psychological distress based on the diagnostic criteria for major depressive episode and generalized anxiety disorder.

In this paper, we use another similar scale to measure one's mental well-being, the *Mental Well-being Score* (*MWS*). *MWS* is constructed using self-rated scores from the designated Section of Mental Health Status in the CHNS. Between 2006 and 2015, the CHNS asked individuals aged 45 and above to rate their mental well-being from three dimensions: (1) pep: I have as much pep as I had last year; (2) happiness: I am as happy as when I was younger; (3) hope: as I get older, things are better than I thought they would be. And respondents' answers, categorized as "strongly disagree", "disagree", "neutral", "agree", and "strongly agree", are assigned numerical values of 1, 2, 3, 4, and 5, respectively. In terms of the scope of these dimensions, the first refers to energy, which can be seen as a simplified indicator of appetite and sleep in CES-D. The second dimension reflects the psychological state, which can be seen as a simplified indicator of depression, nervousness, and restlessness in CES-D, K10, or K6. The third dimension reflects an individual's positive or negative attitudes, which can be seen as a simplified indicator of hopelessness and worthlessness in CES-D, K10, or K6. Overall, these indicators available in the CHNS can be considered to serve as a good simplification of the CES-D, K10 and K6 and reflect individuals' subjective mental well-being. Previous studies based on the CHNS (e.g., Zhang et al., 2017; Bakkeli, 2020) have used these three scores, or the sum of them, to measure an individual's mental health and well-being.

We use the Entropy Weight Method (EWM), introduced by Shannon (1948), to calculate the comprehensive *MWS* as the weighted average of three scores based on the answers to CHNS questions. The EWM has been widely used in research related to environment, health, and other areas (Zhu et al., 2020). Compared to the simple summation of three scores, the EWM assigns a proper weight for each score based on its provided information, instead of assuming that all scores are equally important. The calculated *MWS* ranges from 0 to 1. Appendix A3 gives a detailed description of the calculation of *MWS*. The calculated EWM weights, the distribution of the constructed *MWS*, and the temporal trends of $PM_{2.5}$ concentration and *MWS* are shown in Appendix Table A5, Fig. A2, and Fig. A3, respectively.

In addition to subjective mental well-being, we also use the prevalence of *Mental/Neurological Diseases* to evaluate objective mental well-being. This indicator is generated based on three CHNS questions about mental/neurological disease: "Have you been diagnosed with mental disorder in the past four weeks?", "Have you been diagnosed with mental retardation in the past four weeks?", and "Have you been diagnosed with neurological disorder in the past four weeks?". If any of the three questions is answered yes, the *Mental/Neurological Disease* indicator takes the value of 1, otherwise 0.

In Appendix Fig. A4 (a), we show the 4-week prevalence of *Mental/Neurological Diseases* in our sample, along with the 6-month and the 2-week prevalence of *Mental/Neurological Diseases* from the China Health Statistical Yearbook for comparison.

4.2.2. Channel variables

(1) **Annual average $PM_{2.5}$ concentration.** The reduction of $PM_{2.5}$ is a key target of APPCAP, and we use $PM_{2.5}$ as the main indicator of air pollution. $PM_{2.5}$ concentration is from the annual average raster data, which has been made available by the Socioeconomic Data and Applications Center (SEDAC) affiliated with the U.S. National Aeronautics and Space Administration (NASA). Using ArcGIS, we extract the annual $PM_{2.5}$ concentration from the $0.01^\circ \times 0.01^\circ$ $PM_{2.5}$ raster map and calculate the prefecture-level average annual $PM_{2.5}$ concentration, spanning the years from 2006 to 2015. Moreover, to understand whether the APPCAP has a synergistic effect on other air pollutants, we also collected data of annual average PM_{10} concentration from the National Earth System Science Data Center of China and the industrial SO_2 emission data from China City Statistical Yearbook, and statistical yearbooks of various provinces and municipalities.

(2) **Baidu Index.** In addition to air pollution reduction, heightened public awareness of air pollution is another important channel to be investigated. We use a series of Baidu Index to measure the environmental awareness. ***Baidu Index*** corresponds to the search volume of specific keywords on Baidu, the largest Chinese search engine. This index mirrors the online search habits and topics of Chinese residents. Given that individuals' use of online search engines to investigate specific topics or phenomena is a valuable indicator of their curiosity and concern, we follow the approach of Yu and Jin (2022), Xie et al. (2023) by using the *Baidu Index* to measure environmental awareness and behavior. Specifically, we focus on two broad categories of top-searched pollution-related keywords to capture the complexity of this awareness: (1) keywords related to air pollution and its primary pollutants (e.g., "haze," "$PM_{2.5}$," and "air pollutant"); and (2) keywords related to defensive measures against air pollution (e.g., "particle filtering facemasks" and "air purifiers"). The collated Baidu Index encompasses data collected from both computer and mobile users and spans the years from 2011 to 2016. Taking the *Baidu Index for Haze* as an example, the time trends in environmental awareness and air pollution are shown in Appendix Fig. A4 (b).

(3) **Physical Health.** The evaluation of physical health involves a comprehensive analysis of air pollution-related illnesses, encompassing the diagnosis of four specific conditions associated with air pollution: respiratory diseases, heart diseases, mental/neurological diseases, and tumors (Schlenker and Walker, 2016; Wang et al., 2023). In cases where respondents received a diagnosis of air pollution-related ailments within the four weeks preceding the interview, the corresponding disease indicator is assigned to 1, and otherwise, 0. The corresponding 4-week prevalence of respiratory diseases, heart disease, tumors, and mental/neurological diseases at the national level are shown in Fig. 4. Moreover, a composite indicator, air pollution-related disease, is constructed to gauge physical health status. It is assigned to 1 if a respondent is diagnosed with any of the aforementioned air pollution-related diseases within the last four weeks. Fig. 5 shows the temporal trends in 4-week prevalence of air pollution-related diseases alongside the $PM_{2.5}$ concentration.

(4) **Physical Exercise.** Due to a low response rate (below 1%) to the CHNS question regarding the number of hours dedicated to physical activity, which inadequately represents individuals' actual engagement in physical exercise, we use an indicator of individuals' attitudes toward physical exercise to assess one's willingness to participate in physical exercise. Specifically, respondents were asked to rate their perceived importance of

[9] See https://www.who.int/news-room/fact-sheets/detail/mental-health-strengthening-our-response.

[10] The CES-D contains 8 depressed mood indicators, 2 guilt and worthlessness indicators, 5 feelings of helplessness and hopelessness indicators, 3 psychomotor retardation indicators, 1 loss of appetite indicator, and 1 sleep disturbance indicator.

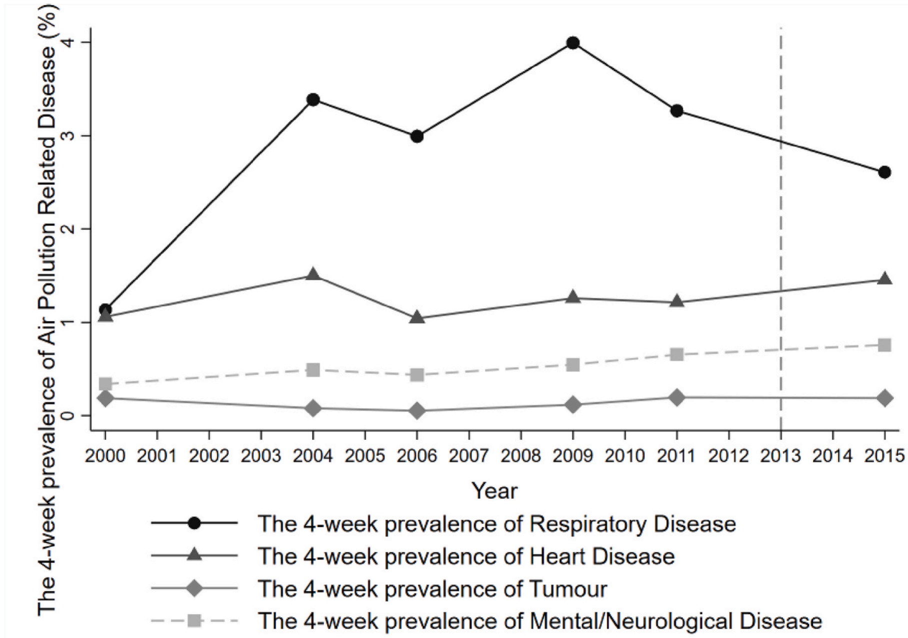


Fig. 4. Prevalence of air pollution-related diseases.
Notes: Authors' compilation of data from the CHNS.

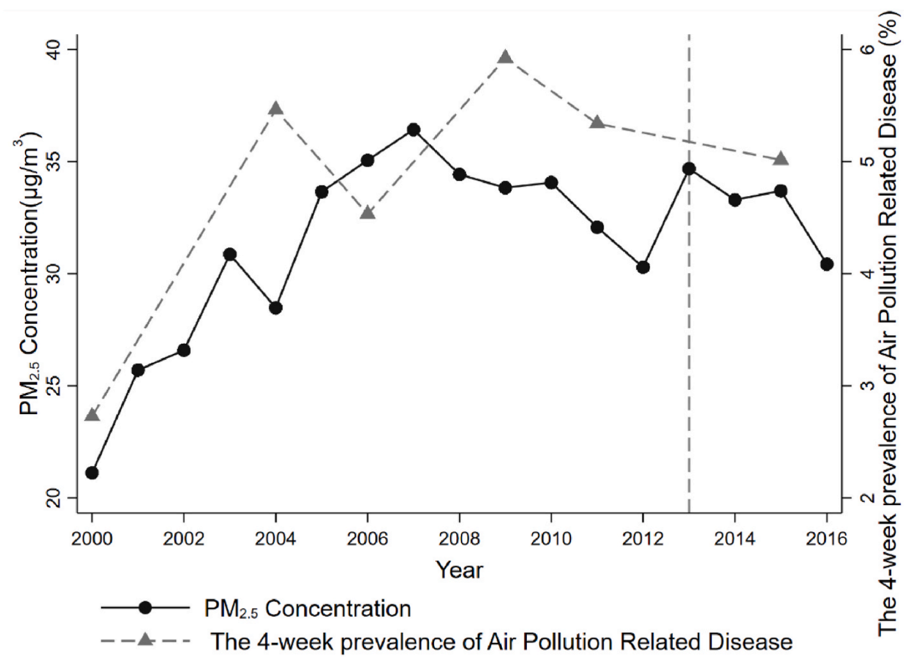


Fig. 5. $PM_{2.5}$ concentration and prevalence of air pollution-related diseases.
Notes: Authors' compilation of data from NASA and the CHNS.

participation in physical exercise under five categories, "not important", "somewhat unimportant", "important", "very important", and "most important" and these responses are assigned values of 1, 2, 3, 4, and 5, correspondingly.

4.2.3. *Control variables*

Control variables include individual demographics, socio-economic status, lifestyle choices, health status, community environment, and regional economic circumstances are shown in Table 2. The number of observations and dropout rates in treatment groups and control groups are shown in Appendix Table A6.

4.3. *Empirical strategy*

The Difference-in-Differences (DID) design has been widely used to evaluate the impact of environmental regulations and air pollution (Clay et al., 2016; Deschenes et al., 2017; Barreca et al., 2021; Du et al., 2022; Huang et al., 2023; Xie et al., 2023). In this paper, a difference-in-differences (DID) model is employed to study the impact of environmental regulation on outcome variables of interest by exploiting the exogenous variations in the implementation timing and cities of the APPCAP. Individuals living in the prefectures with specific $PM_{2.5}$ reduction targets are designated as the treatment group. This

Table 2
Variables and summary statistics.

	Variables	Definition	Mean	SD	Min	Max
Mental Well-being Variables	Mental Well-being Score	A comprehensive scale to measure one's mental well-being	0.543	0.184	0	1
	Pep	Have as much pep as last year (strongly disagree = 1, disagree = 2, neutrality = 3, agree = 4, strongly agree = 5)	3.105	0.905	1	5
	Happiness	Happy as when younger (strongly disagree = 1, disagree = 2, neutrality = 3, agree = 4, strongly agree = 5)	3.144	0.881	1	5
	Hope	Things are better as age grows (strongly disagree = 1, disagree = 2, neutrality = 3, agree = 4, strongly agree = 5)	3.281	0.851	1	5
	Mental/neurological diseases	Diagnosed with mental disorder, mental retardation, or neurological disorder in the past 4 weeks. (yes = 1, no = 0)	0.006	0.079	0	1
Individual Controls	Age	Age of the respondent	59.130	9.601	45	99
	Education	Years of education	7.613	4.358	0	18
	Smoke	Ever smoke = 1, otherwise = 0	0.339	0.474	0	1
	Time in bed	Daily time in bed (hours)	7.755	1.296	0	24
	Marriage	Married = 1, otherwise = 0	0.903	0.297	0	1
	Alcohol	Drink alcohol in last year = 1, otherwise = 0	0.344	0.475	0	1
	Headache	Any headaches in the past four weeks = 1, otherwise = 0	0.060	0.237	0	1
	Heart/chest pain	Any heart/chest pain in the past four weeks = 1, otherwise = 0	0.028	0.165	0	1
	Log income	Logarithm of individual real annual net income	9.360	1.605	0	14.088
	Medical insurance	Have medical insurance = 1, otherwise = 0	0.904	0.295	0	1
	Household registration	Urban = 1, Rural = 0	0.504	0.500	0	1
Community Controls	Sanitation	Sanitation score calculated by CHNS	7.194	2.756	0	10
	Transportation	Traffic score calculated by CHNS	5.670	2.242	0	10
Prefecture Controls	Doctor density	Doctors per ten thousand residents	21.776	12.641	5.837	71.696
	log GDP per capita	Log of real GDP per capita (Ten thousand yuan)	1.614	0.737	0.058	3.168
	Secondary industry	Share of value-added of secondary industry in GDP (%)	44.988	10.765	19.74	70.74
	Primary industry	Share of value-added of primary industry in GDP (%)	12.943	9.420	0.44	39.77
Channel Variables	Log $PM_{2.5}$	Log of annual average $PM_{2.5}$ concentration (μg/m^3)	3.543	0.504	1.048	4.509
	Log PM_{10}	Log of annual average PM_{10} concentration (μg/m^3)	4.492	0.323	3.566	5.275
	Log SO_2	Log of annual industrial SO_2 emission (tons/km^2)	1.310	1.257	−6.866	4.219
	Baidu Index for Haze	Log of the daily "haze" Baidu Index in a prefecture	3.548	1.180	−1.860	8.099
	Baidu Index for $PM_{2.5}$	Log of the daily "$PM_{2.5}$" Baidu Index in a prefecture	3.572	1.157	0	8.100
	Baidu Index for Air Pollution	Log of the daily "air pollution" Baidu Index in a prefecture	1.862	1.054	0	5.344
	Baidu Index for Particle Filtering Facemasks	Log of the daily "particle filtering facemasks" Baidu Index in a prefecture	3.414	3.468	0	10.856
	Baidu Index for Air Purifiers	Log of the daily "air purifiers" Baidu Index in a prefecture	9.318	1.248	0	12.585
	Diseases	Diagnosed with air pollution-related diseases in the past 4 weeks (yes = 1, no = 0)	0.052	0.222	0	1
	Respiratory disease	Diagnosed with respiratory diseases in the past 4 weeks (yes = 1 no = 0)	0.032	0.175	0	1
	Heart disease	Diagnosed with heart diseases in the past 4 weeks (yes = 1 no = 0)	0.013	0.112	0	1
	Tumor	Diagnosed with tumor in the past 4 weeks (yes = 1 no = 0)	0.002	0.039	0	1
	Attitude towards physical exercise	Attitude towards the importance of physical exercise (not important = 1, not very important = 2, important = 3, very important = 4, most important = 5)	3.170	0.687	1	5

encompasses samples from Beijing, Shanghai, and cities of Jiangsu province. Conversely, individuals from prefectures without $PM_{2.5}$ reduction target, specifically in Henan, Liaoning, Guizhou, Hunan, Guangxi, Heilongjiang, Hubei, Shandong, and Chongqing, are designated as the control group. The main model specification is as follows,

$$y_{it} = \beta_1 post_t \times treated_i + \boldsymbol{\beta_2 X_{it}} + \gamma_i + \eta_t + \varepsilon_{it} \quad (1)$$

where, y_{it} denotes the outcome variable of individual i in year t. $post_t$ is an indicator variable, taking the value 1 for years after 2013. $treated_i$ is an indicator variable, taking the value 1 if individual i lives in a prefecture with specific $PM_{2.5}$ reduction target. β_1 is the parameter of our main interest, representing the comparison between the change in individuals' *MWS* induced by the implementation of the environmental regulation in the regulation targeted regions to the change in other regions over time. $\boldsymbol{X_{it}}$ is a vector of control variables including individual, community, and prefecture characteristics. γ_i is the individual fixed effect, η_t is the year fixed effect, and ε_{it} denotes the error term. We cluster robust standard errors at the prefecture level to account for arbitrary correlation of the error term across individuals and over time within the same prefecture. Additionally, in robustness checks, we also cluster robust standard errors at the individual level.

To further study the effect of $PM_{2.5}$ reduction targets on mental well-being, we use a continuous measure of the intensity of treatment, i.e., the specific reduction target of $PM_{2.5}$ in the following model:

Table 3
Effects of APPCAP on mental well-being.

Variables	(1)	(2)	(3)	(4)
	MWS	Pep	Happiness	Hope
Panel A. difference-in-differences model specified in model (1)				
post × treated	0.0219**	0.0862	0.0866*	0.104*
	(0.0108)	(0.0567)	(0.0515)	(0.0586)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,135	13,507	13,464	13,339
R^2	0.4999	0.4729	0.4687	0.5043
Mean of y	0.5426	3.1054	3.1439	3.2813
Panel B. difference-in-differences model specified in model (2)				
post × target	0.0011**	0.0043	0.0040	0.0051*
	(0.0005)	(0.0026)	(0.0024)	(0.0027)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,135	13,507	13,464	13,339
R^2	0.4999	0.4729	0.4687	0.5043
Mean of y	0.5426	3.1054	3.1439	3.2813

Notes: Control variables in this table include individual, community, and prefecture-level variables in Table 2. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses.

$$y_{it} = a_1 post_t \times target_i + \boldsymbol{a_2 X_{it}} + \gamma_i + \eta_t + \varepsilon_{it} \quad (2)$$

where $target_i$ is the prefecture's $PM_{2.5}$ reduction target, and it is calculated as the reduction percentage of $PM_{2.5}$ (%) aimed at, as shown in Table 1.

5. Results

5.1. Baseline results

Columns (1) to (4) in Table 3 list the main effects of environmental regulation on *Mental Well-being Score* (*MWS*) and its three dimensions including pep, happiness, and hope. Each column in Table 3 controls for individual, community, and prefecture-level characteristics, addressing the concern that changes in mental well-being may be explained by changes in observable characteristics of the samples that vary over time and are correlated with $PM_{2.5}$ reduction targets.

Panel A of Table 3 shows that the APPCAP improves the *MWS* by 0.0219 units, indicating a significant improvement in overall mental well-being due to environmental regulation. This policy effect corresponds to an increase in the magnitude of *MWS* by approximately 4.04%.[11] Columns (2) to (4) in Panel A show the impacts of the APPCAP on various aspects of *MWS*. Specifically, happiness and hope show significant positive effects at the 10% level, while the effect on pep is not significant.

Panel B of Table 3 indicates that each additional percentage point of the $PM_{2.5}$ reduction target is associated with an average increase in *MWS* of 0.0011 units. The reduction targets for the treatment group range from 20% to 25%, that is, compared with the control group, the APPCAP improved the *MWS* in the treatment group by 0.0220–0.0275 units,[12] comparable to the estimated policy effect of 0.0219 units of *MWS* estimated in Panel A.

To ensure that the improvement in mental well-being in the treatment group is solely due to the implementation of APPCAP, we test the robustness of the estimated policy effects to different model specifications. In particular, we re-estimate the policy effects based on the model (1) and (2) by: (1) dropping observations from Shandong province that had a $PM_{2.5}$ reduction target in later years (2016–2017); (2) Examining the determinants of the implement of APPCAP; (3) Including interactions between predetermined prefecture-level variables and the linear year trend; (4) using the entropy-balanced data to mitigate the impact of systemic differences between treated and control cities[13]; (5) isolating the influence from other policies; (6) controlling the potential effects of other pollutants, i.e., SO_2 and PM_{10}; (7) taking climatic factors into consideration; (8) adding more detailed Year-Month fixed effects; (9) eliminating outliers of *MWS*; (10) Clustering robust standard errors at the individual level; (11) performing placebo tests. We describe how we conduct robustness checks in detail in Appendix A1 and present the corresponding results in Tables A1, A2, A3, and Fig. A1. The main policy effects remain robust to specifications (1)–(10). In specification (11), we conduct a placebo test that randomly selects the treatment group and constructs a pseudo policy implementation time, and the results become insignificant, ruling out any anticipation effect of the environmental regulation on mental well-being.

5.2. Parallel trend test

The validity of our identification strategy relies on the assumption that the time trends of *MWS* in the control and treatment groups would have been similar if there had been no APPCAP. Although we cannot test the trend over the entire study period, we can test the temporal trends of treated and control groups prior to 2013 when the policy was implemented. We employ an event study model to test for parallel trends test by estimating:

$$\begin{aligned} y_{it} = \theta_1 treated_i \times T_t^{-7} + \theta_2 treated_i \times T_t^{-4} + \theta_3 treated_i \\ \times T_t^{+2} + \boldsymbol{\theta_4 X_{it}} + \gamma_i + \eta_t + \varepsilon_{it} \end{aligned} \quad (3)$$

where, $T_t^{\pm m}$ is a set of year dummies, indicating whether the data is m years before the policy implementation (T_t^{-m}) or m years after the policy implementation (T_t^{+m}). The coefficient of $treated_i \times T_t^{\pm m}$ indicates differences in mental well-being outcomes between the treatment and control groups in the m years before or after the implementation of the APPCAP. This study takes the pre-policy implementation period as the reference year (2011) and standardizes the coefficients for each year. Fig. 6 shows that 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 that before the APPCAP, that is, there is no statistically significant difference in *MWS* between individuals in the pollution reduction targeted cities and other cities. The coefficient turns out to be significantly positive after the implementation of the APPCAP, which confirms the positive effect of the regulation on mental well-being.

5.3. Channels estimates

As discussed in Section 3, the channels through which environmental regulation could impact mental well-being include both biological channels (brain function), as well as socio-economic channels (air pollution, awareness of air pollution, physical health, physical exercise). Since evaluating the significance of biological channels remains beyond our scope due to data limitations, we focus on the role of socio-economic channels.

Columns (1)–(3) in Table 4 demonstrate that the APPCAP significantly reduces average concentration levels of air pollutants. Specifically, column (1) shows that the APPCAP is associated with a 2.04% reduction in $PM_{2.5}$ concentration. The magnitude is smaller compared to the targets in Table 1 for three reasons. First, these two proportions have different meanings. The 2.04% represents the change in $PM_{2.5}$ concentration between the treatment group before and after the 2013 APPCAP minus the change in $PM_{2.5}$ concentration in the control group. However, the APPCAP targets represent the percentage reduction in $PM_{2.5}$ from 2012 to 2017. Second, the calculations are based on different periods. Table 4 uses $PM_{2.5}$ data from 2006 to 2015 to align with the study's baseline, while the APPCAP targets are specific to the 2012–2017 period. Third, both treatment and control groups experienced $PM_{2.5}$ declines due to synergistic emission reductions. Recall that the APPCAP has dual objectives: a reduction of PM_{10} concentration in all prefectures and a decrease of $PM_{2.5}$ concentration in specific areas (that constitute the treatment group in this paper). While the control group does not have a specific $PM_{2.5}$ emission reduction target, addressing PM_{10} likely results in a concurrent reduction in $PM_{2.5}$. Likewise, addressing $PM_{2.5}$ also results in a concurrent reduction in PM_{10}. As a result of this synergistic effect, the $PM_{2.5}$ reduction effect we calculated for the treatment group appears relatively modest.

Column (2) and Column (3) in Table 4 provide further evidence of synergistic emission reductions effects, and results show that the APPCAP has a synergistic effect on PM_{10} but not on SO_2. The possible reason is that $PM_{2.5}$ and PM_{10} are both particulate matter, and when dust control equipment removes $PM_{2.5}$, it also captures the larger PM_{10} particles. As SO_2, on the other hand, is not a target of the APPCAP, the policy is not expected to have a significant impact on industrial SO_2 emissions. Furthermore, studies have shown that $PM_{2.5}$ is the air pollutant directly related to mental well-being (Zhang et al., 2018; Chen et al., 2024). To reduce the confounding effect of synergistic reductions in PM_{10} or

[11] The mean value of the *Mental Health Score* of the respondents is 0.5426. 0.0219/0.5426 = 4.04%.

[12] 0.0011 × 20 = 0.0220; 0.0011 × 25 = 0.0275.

[13] The balancing test performed on the entropy balanced data is shown in Appendix Table A3.

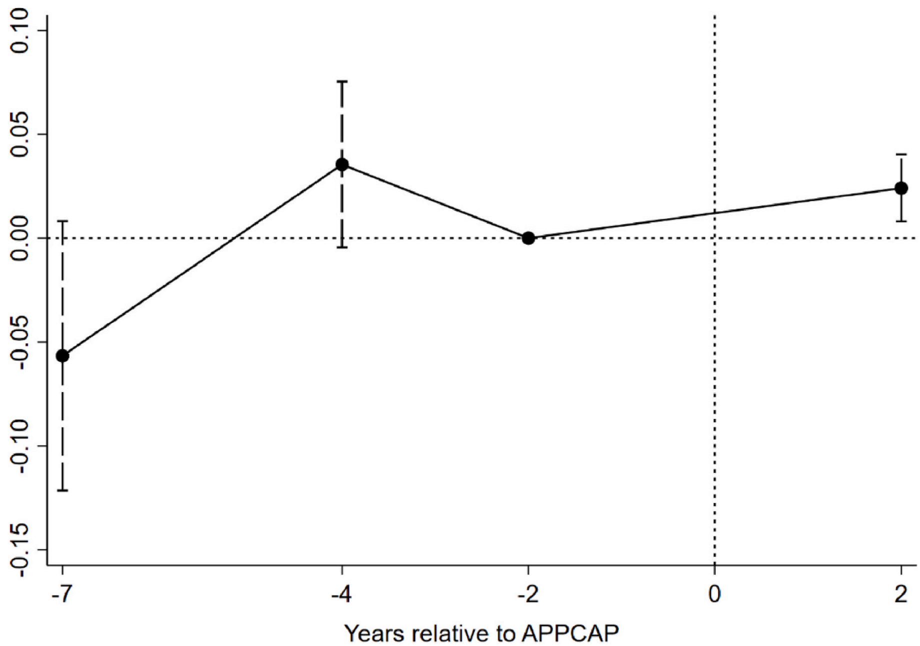


Fig. 6. Event study for the effects of APPCAP on mental well-being score.
Notes: The figure depicts coefficients and the 90% confidence intervals for an event study analysis. On the x-axis, −2 is the omitted group and indicates two years before the APPCAP. The regression model is specified as model (3).

Table 4
Effects of APPCAP on air pollution and Baidu index.

Variables	Log $PM_{2.5}$	Log PM_{10}	Log SO_2	Log Baidu Index for Haze	Log Baidu Index for $PM_{2.5}$	Log Baidu Index for Air pollution	Log Baidu Index for particle filtering facemasks	Log Baidu Index for Air purifier
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
post × treated	−0.0204*	−0.0089**	−0.0133	0.1327***	0.1914***	0.2660***	1.6413***	0.0504
	(0.0124)	(0.0053)	(0.0507)	(0.0281)	(0.0345)	(0.0441)	(0.1554)	(0.0346)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2528	2528	2511	1259	1259	1259	1259	1259
R^2	0.9664	0.9866	0.9250	0.9817	0.9780	0.9561	0.8734	0.9559

Notes: The estimates are based on model (1). The samples are at prefecture level. Study periods are 2006–2015 in Columns (1)–(3) and 2011–2015 in Column (4)–(8), because Baidu index based on search engine user data from both PC and mobile started in 2011. Control variables include Log of real GDP per capita, share of value-added of secondary industry in GDP (%), Log of road freight volume, Log of Scientific expenditure. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses.

changes in other air pollutants on the results, we add PM_{10} and SO_2 as controls into the main specification (see Appendix Table A1). The results show that the health effect of APPCAP is comparable to the baseline estimates (0.0219 vs 0.0213) after controlling for other air pollutants, further suggesting that the effect of the APPCAP on mental well-being is mainly due to the reduction in $PM_{2.5}$ concentration rather than changes in other pollutants.

Column (4) in Table 4 shows that the APPCAP increases the *Baidu Index for Haze* by 13.27%, indicating a heightened public awareness towards air pollution. Columns (5) and (6) show similar trends, with

Table 5
Effects of $PM_{2.5}$ on physical health and physical exercise.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Diseases	Respiratory disease	Mental/Neurological diseases	Heart disease	Tumor	Physical exercise
Log $PM_{2.5}$	0.0778*	0.0485*	0.0294**	−0.0009	0.0008	−0.4970**
	(0.0400)	(0.0278)	(0.0145)	(0.0156)	(0.0036)	(0.1950)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4212	4212	4212	4212	4212	4151
R^2	0.4600	0.4760	0.4420	0.4380	0.3900	0.4730
Mean of *y*	0.0522	0.0316	0.0063	0.0128	0.0015	3.1701

Notes: The estimates are based on model (1). Control variables include age, years of education, marriage, health insurance, smoking, alcohol, time in bed, time spent online, Log of per capita household income, transportation score, sanitation score, Log of doctor density, share of value-added of secondary industry in GDP (%), humidity. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses.

increases of 19.14% in the *Baidu Index for $PM_{2.5}$* and 26.60% for *Air Pollution*. These results suggest a significant increase in environmental awareness following the implementation of the policy. Columns (7) and (8) present the effects of environmental regulation on environmental awareness and behavior. The empirical results indicate that APPCAP increases the *Baidu Index for Particle Filtering Facemasks* by 164%, which is significant at the 1% level. Additionally, while the *Baidu Index for Air Purifiers* rises by 5%, this increase is not statistically significant at the 10% level. These results suggest that the implementation of APPCAP increases public attention to pollution protection products, leading to greater awareness and protective behavior. The more substantial increase in interest for particle-filtering facemasks compared to air purifiers may be attributed to the lower cost and greater accessibility of facemasks. It is important to note that public awareness and behavior regarding air pollution can be influenced by various sources, including not only online search engines but also newspapers, television, and other media. Therefore, the impact of environmental regulation on environmental awareness and behavior may be even greater than what is indicated by the results in columns (4)–(8) of Table 4.

Next, we examine how air pollution affects different kinds of diseases and physical exercise. Columns (1) to (5) of Table 5 present the effects of $PM_{2.5}$ on diseases. Column (1) shows that an increase in the annual average $PM_{2.5}$ concentration is associated with a rise in the 4-week prevalence of air pollution-related diseases. Columns (2) and (3) further demonstrate that higher $PM_{2.5}$ levels correspond to a marked increase in the prevalence of respiratory diseases and mental/neurological disorders. Together with the finding from column (1) of Table 4, our results indicate one potential channel through which the environmental regulation reduces $PM_{2.5}$ concentration and in turn reduces the prevalence of respiratory diseases, ultimately improving the mental well-being. Although it is not possible to directly test the biological channel (brain function) in this paper, the results in column (3) of Table 5 show that $PM_{2.5}$ concentration is strongly associated with mental or neurological disorders, providing suggestive evidence for the potential biological channel which has been extensively studied in the medical research.

From column (6) of Table 5 we may note that a higher concentration of $PM_{2.5}$ significantly lowers people's willingness to get involved in physical exercise, and potentially leads to diminished levels of both the duration and intensity of physical activity. Physical exercise may increase the uptake and deposition of air pollutants in the lungs, respiratory tract and circulation through increased breathing rate and ventilation per minute, which may increase the risk of cardiovascular disease. As a result, people may reduce their physical exercise during periods of high pollution in order to avoid exposure to air pollution and reduce these health risks (Hahad et al., 2021). The findings imply that environmental regulation which effectively reduces $PM_{2.5}$ concentrations holds the potential to improve individuals' motivation for participating in physical exercise. As this translates into increased physical activity, a positive contribution to mental well-being can be anticipated.

Table 6 explores the influences of awareness regarding air pollution on both diseases and physical exercise, using *the Baidu Index for "Haze"* as an example. Columns (1) to (5) suggest that awareness regarding air pollution, measured by the *Log Baidu Index for Haze*, is negatively associated with the 4-week prevalence of air pollution-related diseases, particularly respiratory diseases. Column (6) suggests that *the Baidu Index for "Haze"* is negatively correlated with individuals' willingness to engage in physical exercise. This underscores the potentially significant effect of awareness about air pollution on people's willingness to participate in physical activities. Column (7) further shows that this negative impact on physical exercise is pronounced in highly polluted areas or during periods of heavy pollution. It is reasonable to expect that as the public becomes more informed and knowledgeable about air pollution, they are more likely to reduce their physical exercise during periods of heavy pollution to mitigate the potential harm of the pollution, thereby minimizing the adverse effects of $PM_{2.5}$ on both physical and mental well-being.

In summary, the APPCAP is effective in reducing air pollution and has contributed to an enhanced public awareness of impacts of air pollution. Consequently, the policy has improved physical health and influenced individuals' behavioral decisions. For instance, individuals tend to decrease physical exercise during heavily polluted periods and increase exercise during good air quality conditions. These behavioral adaptations are likely to have a favorable influence on mental well-being.

5.4. Heterogeneous effects

In addition to reporting average treatment effects of environmental regulation on mental well-being, we explore heterogeneous effects that vary according to individuals' demographic characteristics and socioeconomic status, including gender, age, income, and years of education. We introduce interaction terms for *post* × *treated* and *group dummies*, then estimate the following regression specification (4):

$$y_{it} = \lambda_1 post_t \times treated_i + \lambda_2 post_t \times treated_i \times group_{it} + \lambda_3 group_{it} + \lambda_4 \boldsymbol{X_{it}} + \gamma_i + \eta_t + \varepsilon_{it} \tag{4}$$

where, $group_{it}$ denotes the dummy variables for groups: dummy for male,

Table 6
Effects of awareness of air pollution on physical health and physical exercise.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Diseases	Respiratory disease	Mental/Neurological diseases	Heart disease	Tumor	Physical exercise	Physical exercise
Log Baidu Index for Haze	−0.0846***	−0.0686***	0.0046	−0.0087	−0.0119*	−0.4140**	−0.3498**
	(0.0296)	(0.0204)	(0.0143)	(0.0108)	(0.0059)	(0.1540)	(0.1617)
Log Baidu Index for Haze × *High $PM_{2.5}$*	–	–	–	–	–	–	−0.0567*
							(0.0337)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2170	2170	2170	2170	2170	2118	1425
R^2	0.5090	0.5140	0.5050	0.5810	0.5100	0.5360	0.5920
Mean of y	0.0522	0.0316	0.0063	0.0128	0.0015	3.1701	3.1701

Notes: The estimates are based on model (1). Baidu index based on search engine user data from both PC and mobile started in 2011, so the study period in the table above is 2011–2015. Control variables include age, years of education, marriage, commercial health insurance, smoking, alcohol, time in bed, time spent online, Log of per capita household income, transportation score, sanitation score, Log of doctor density, share of value-added of secondary industry in GDP (%), humidity. Control variables in Column (7) also include $HighPM_{2.5}$, an indicator that takes the value 1 if the $PM_{2.5}$ concentration of the prefecture is higher than the mean value and 0 otherwise. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses.

Table 7
Heterogeneous effects by gender, age, income and education.

Variables	By gender	By age	By income	By years of education
	(1)	(2)	(3)	(4)
post × treated	0.0222*	0.0578***	0.0025	−0.0156
	(0.0115)	(0.0157)	(0.0150)	(0.0154)
post × treated × dummy for male	−0.0007			
	(0.0069)			
post × treated × dummy for older age		−0.0526***		
		(0.0144)		
post × treated × dummy for higher income			0.0259*	
			(0.0133)	
post × treated × dummy for higher education				0.0541**
				(0.0194)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13135	13135	18929	13161
R^2	0.4999	0.5007	0.4694	0.5002

Notes: The estimates are based on model (4). Control variables include individual controls, community controls, and prefecture controls in Table 2. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses.

dummy for older age, dummy for higher income, and dummy for higher education. We are primarily interested in the interaction between *post × treated* and *group dummies*, which represent heterogeneous effects across groups.

By gender. Existing studies have mixed conclusions on gender differences in the health effects of air pollution. Some studies suggest females are more vulnerable to the effects of air pollution on frontolimbic brain regions (Peterson et al., 2015), resulting in a greater health effects of air pollution on females compared to males (Tanaka, 2015; Kim et al., 2019). On the other hand, some studies have found that air pollution has a more detrimental effect on males (Abbey et al., 1998; Cho et al., 2020; Li et al., 2024). Columns (1) of Table 7 suggest that the APPCAP improves mental health and well-being, while at the same time this health effect does not show a significant gender difference, suggesting that the health effect of air pollution not show a significant gender difference either.

By age. Given that only respondents aged 45 and above were asked about their mental well-being in the CHNS, we divide the sample into two age brackets: 45–59 (*dummy for older age* = 0), and 60 and above (*dummy for older age* = 1). Columns (2) shows that the impact of environmental regulation varies across age groups. The APPCAP's positive effect on mental well-being is most pronounced among individuals aged 45–59, while the health benefits are substantially diminished for those aged 60 and older. It is possible that those aged 45–59 are more frequently exposed to air pollution as they are more likely to work and therefore benefit more from air quality improvements (Shin et al., 2018).

By socioeconomic status. In Columns (3)–(4), we examine the heterogeneous effects based on individuals' socio-economic status, including income and years of education. The findings suggest that for those with above-average income or above-average years of education, the APPCAP has a significantly positive effect on their mental well-being. However, for the lower-income and less educated groups, no significant health effect is observed. There are two possible reasons for this difference. First, individuals with higher socio-economic status are more likely to have access to internet devices, such as computers and smartphones, making them more exposed to information about environmental policies and, consequently, more likely to increase their environmental awareness (Xie et al., 2023). Second, those with higher levels of income and education are better able to engage in defensive spending to mitigate the health damage caused by air pollution as their environmental awareness improves, and thus benefit more from environmental regulation (Barwick et al., 2024).

Table 8
Effects of APPCAP on mental/neurological diseases.

Variables	Mental/neurological diseases	
	Model (1)	Model (2)
post × treated	−0.0038*	–
	(0.0021)	
post × target	–	−0.0002*
		(0.0001)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year FE	Yes	Yes
Observation	15470	15470
R^2	0.4212	0.4212

Notes: The estimates are based on model (1). Control variables include individual controls, community controls, and prefecture controls in Table 2. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the prefecture level are reported in parentheses.

5.5. Effects of APPCAP on mental/neurological diseases

In this section, we further investigate the impact of the APPCAP on mental/neurological diseases with three objectives. First, our results have shown that the APPCAP has a positive effect on the *Mental Well-being Score*, particularly enhancing people's happiness and hope. The question of whether the regulation also reduced the prevalence of mental illnesses deserves further exploration. Second, we have shown that the $PM_{2.5}$ concentration level is related with the 4-week prevalence of mental/neurological diseases, but whether the policy directly reduced the prevalence of mental/neurological diseases remains to be tested. Third, to supplement the analysis using a subjective measure of mental well-being, we use an objective indicator to measure one's mental health based on the survey question: "have you been diagnosed with any mental disorder, mental retardation, or neurological disorder in the past four weeks?".

Results from model (1) in Table 8 show that the APPCAP significantly reduced the 4-week prevalence of mental/neurological diseases by 0.38 percentage points. We compare our estimates with the literature focusing on the effects of air pollution on mental illness. According to Chen et al. (2024), a 1 μg/m³ increase in $PM_{2.5}$ concentrations is associated with a 0.42 percentage point increase in the probability of severe mental illness. Our study finds that the APPCAP has reduced $PM_{2.5}$ concentrations by 2.04% (as shown in Table 4), which translates to a reduction of approximately 0.71 μg/m³ (given a sample mean of 34.57 μg/m³). Using the estimate from Chen et al. (2024), this reduction would correspond to a decrease in the probability of severe mental illness by approximately 0.30 percentage points. Notably, our results indicate that APPCAP has significantly reduced the 4-week prevalence of mental/neurological diseases by 0.38 percentage points, which is closely aligned with the findings of Chen et al. (2024).

6. Conclusion

This paper examines the effects of APPCAP, the most stringent environmental regulation so far in China, on mental well-being. To measure an individual's overall mental well-being, we construct the *Mental Well-being Score* using data from the designated section of the Mental Health Status in the CHNS. Our main results show that the APPCAP improved the *Mental Well-being Score* by 4.04% and the result is robust to various specifications. We provide empirical evidence that environmental regulation affects mental well-being outcomes through several socio-economic channels, including air pollution, awareness of air pollution, physical health, and physical exercise. Among these channels, awareness of air pollution is innovatively identified using a series of *Baidu Index*. Investigating whether there are spillovers from air pollution to environmental awareness, and quantifying them is the next step on the research agenda. Additionally, our results show that the APPCAP significantly lowers the 4-week prevalence of mental/neurological diseases by 0.38 percentage points, indicating the importance of the biological channel.

The study provides two valuable insights. Firstly, it underlines the pivotal role of environmental regulation, alongside socio-economic considerations, in shaping individuals' mental well-being. The pronounced benefits of environmental regulation highlight the potential of environmental regulation as a public health tool. Secondly, the research demonstrates the importance of public awareness of air pollution impacts in enhancing mental well-being. Thus, efforts to raise environmental awareness and health literacy can empower individuals to mitigate the negative health effects of air pollution. With a more environment-conscious culture, the entire society benefits from a positive feedback loop, where improved air quality and increased awareness work together to improve public health.

A limitation of this study is that the sample was drawn from specific regions of China, where the environmental, economic and social contexts may differ significantly from those in other countries. Future research would benefit from validating our findings in other settings to explore whether similar effects can be observed in different contexts. Nevertheless, our study provides valuable insights into the mechanisms - such as air pollution, environmental awareness, physical health and physical exercise - through which environmental regulations may affect mental well-being. These findings can serve as a useful reference for policy makers and researchers seeking to improve mental health and well-being in different national and regional contexts. Then, the positive health effects are observed for both males and females; however, they are only significant for individuals aged 45–59, as well as those with above-average income or education. Thus, the benefits are not equally distributed. An important topic for future research is what the sources of this heterogeneity in impacts are. Is it for instance because of lack of resources (income, education) and/or differences in awareness? Clearly, the answers would have important implications for the development of future policies. We have also found that environmental policies not only improved subjective mental well-being, but also affected the prevalence of objective mental diseases. Due to the lack of data on mental illness-related health expenditures in the dataset, we are not able to estimate the welfare gains from environmental regulation at large. Future research should explore other datasets to address this issue.

CRediT authorship contribution statement

Yuze Wang: Writing – original draft, Software, Data curation, Conceptualization. **Zidi Zhang:** Writing – original draft, Visualization, Software. **Zhuang Hao:** Writing – review & editing, Validation, Methodology. **Tor Eriksson:** Writing – review & editing, Methodology.

Data availability statement

The authors do not have permission to share the data.

Funding sources

This work was supported by the National Natural Science Foundation of China (Grant numbers 72203066, 72403094, and 72303076), the Philosophy and Social Science Foundation of Ministry of Education of China (Grant number 24JHQ073), and the Fundamental Research Funds for the Central Universities (Grant number 2662021JGQD005).

Declaration of competing interest

The authors declare no conflicts of interest.

Acknowledgments

The authors thank the UNC Carolina Population Center and CCDC National Institute for Nutrition and Health for providing the data. We also thank the editor, anonymous reviewers, and the seminar participants at University of Göttingen for their helpful comments. All remaining errors are our own.

Appendix

A1. Robustness checks

(1) Drop observations from Shandong province

As Table 1 shows, unlike other provinces, Shandong's pollution reduction targets are implemented in two phases. Since the study period in this study is 2006–2015, the provisions in the Phase I (2013–2015) are employed in the baseline estimates. To avoid the influence of different target settings on the results, Shandong Province is removed from the sample for the robustness check in row (1) of Table A1.

(2) Examine the determinants of the implement of APPCAP

A potential threat to the identification is that the prefectures implementing APPCAP were not randomly selected. It is important to highlight that our baseline models account for individual fixed effects, ensuring that constant differences in individual-level and, of course, prefecture-level characteristics do not undermine our identification strategy. Motivated by Barwick et al. (2024), in Table A2 we further test whether the implementation of APPCAP is correlated with time-varying prefecture-level characteristics after controlling for the prefecture fixed effects. We analyze a comprehensive set of factors, including economic development (the log of real GDP per capita), industrial structure (the share of value-added of primary industries in GDP, and the share of value-added of secondary industries in GDP), and medical resource (doctors per ten thousand residents). After controlling for prefecture fixed effects, the implementation of APPCAP shows no significant correlation with these prefecture-level characteristics. These "balancing tests" indicate that prefecture-level confounding variables are less likely to be driving the timing and location of the policy.

(3) Include interactions between predetermined prefecture-level variables and the linear year trend

The prefectures selected for APPCAP implementation may not have been randomly chosen, which could result in systematic differences between the treatment and control groups prior to the implementation of APPCAP. To further address this issue, in row (2) of Table A1, we include interactions between predetermined prefecture-level variables and the linear year trend, allowing the trend to vary according to key observable determinants of the treatment group. These predetermined variables include economic development (log of real GDP per capita), industrial structure (the share of value-added of primary industries in GDP, and the share of value-added of secondary industries in GDP), and medical resources (the number of doctors per ten thousand residents). The year 2011 data—one wave before the implementation of APPCAP[14]—is used to define these predetermined prefecture-level characteristics.

(4) Mitigate the impact of systemic differences between treatment and control cities

To further mitigate the impact of those systemic differences between the treatment and control groups on main results, the impact of APPCAP on individuals' health are re-estimated based on the entropy-balanced data created by the method proposed by Hainmueller (2012). Entropy balancing is a data preprocessing method to achieve covariate balance in observational studies. The balancing tests performed on the entropy balanced data are found in Table A3, and the analysis based on entropy-balanced data is shown in row (3) of Table A1.

(5) Exclude the influence from other policies

To confirm that the treatment effect is not driven by other policies, we conduct two robustness checks in rows (4)–(5). First, from 2007 to 2011, 11 pilot cities implemented the pollutant emissions trading system (PETS) policy, so we exclude the pilot cities from our sample. Second, we restrict the sample to 2011–2015, which corresponds to the period of the China's 12th Five-Year Plan of national economic development. The fact that the time periods (2011–2015) are shorter and fall within one policy regime helps reduce a set of potential confounders in the health environment other than pollution.

A real-time pollution information program was launched in China from 2012 and gradually rolled out across the country in 2014. This has been studied by Barwick et al. (2024) and Xie et al. (2023). The information program should not affect the conclusions of this study for the following main reasons: First, the data we use from the CHNS cover the years 2006, 2009, 2011 and 2015. In 2011, no prefectures had implemented the information program, but by 2015, all prefectures had done so. Therefore, the impact of the information program on mental well-being should be largely explained by year-fixed effects. Second, Xie et al. (2023) show that the information program has no effect on air pollution, whereas in this study the main channel through which the APPCAP affects mental well-being is the reduction of air pollution. Therefore, we believe that the effect of the information program on the conclusions of this paper should be limited. Note, however, that Xie et al. (2023) did not account for the influence of the APPCAP.

(6) Control for other pollutants (SO_2 and PM_{10})

The treatment group in this paper is the one with a $PM_{2.5}$ reduction target. In order to ensure that the improvement in mental well-being is indeed an effect of the APPCAP policy, we have further controlled other pollutants including SO_2 and PM_{10}. Results in row (6) suggest that changes in other pollutants have a limited effect on *Mental Well-being Score*, and that the improvement in mental well-being is primarily driven by the decline in $PM_{2.5}$ from the APPCAP.

(7) Control for climatic factors

Climatic conditions may also affect the state of mind. For example, rainy weather tends to make people feel negative and depressed. To exclude the impact of the climatic impact on our results, we control for the annual average precipitation levels of the prefectures in row (7).

(8) Employ Year-Month FE (to replace the Year FE)

In order to control for the effects of unobservable seasonal factors, we replace the year fixed effects with year-month fixed effects in row (8).

(9) Eliminate outliers

In row (9), we drop individuals whose *Mental Well-being Score* are above 99th percentile or below 1st percentile from the study sample to mitigate the impact of outliers on the main results.

(10) Cluster robust standard errors at the individual level

In the baseline regression, we use robust standard errors clustered at the prefecture level, and as a robustness test in row (10), we complement the empirical results with robust standard error clustering at the individual level to further account for heteroskedasticity and within-individual serial correlation. In the above robustness tests, rows (1)–(10), the coefficients of $post \times treated$ remain significantly positive.

(11) Placebo tests

We perform the placebo tests by randomly selecting the treatment group (see Fig. A1) and constructing a pseudo policy implementation time (the year 2011, one wave prior to the APPCAP, as shown in Table A1). In Fig. A1, the estimated policy effects from 500 random sampling of regressions are plotted. Results show that the estimated policy effects are small and most are close to 0. Also, most of the corresponding P-values are greater than 0.1. Then, the results from a pseudo policy implementation time are reported in rows (11)–(12), Table A1. Row (11) are the results based on the full sample and row (12) are the results based on the pre-reform data (2006, 2009 and 2011 data). The coefficient estimates of $post \times treated$ in rows (11)–(12) are statistically insignificant, lending further support that the improvement in mental well-being is indeed the result of the APPCAP policy.

[14] The APPCAP was implemented in 2013, and the data we use from the CHNS cover the years 2006, 2009, 2011 and 2015, so one wave prior to the APPCAP was 2011.

A2. The specific provisions in the APPCAP

The specific provisions in the APPCAP are shown in Table A4.

A3. Entropy weight method (EWM)

(1) Principle

The weighting method used in this paper is based on information theory, more specifically Shannon's entropy (1948). Entropy weighting assigns weights to different variables in a data set based on their relative information content or uncertainty. The term "entropy" here refers to a concept from information theory that measures the uncertainty or disorder in a data set. The greater the degree of differentiation of index i and the more information can be derived. Therefore, more weight should be given to the index. By using the entropy weight method, the study aims to derive a *MWS* that ranges from 0 to 1, taking into account the different levels of importance and uncertainty associated with different responses to the questions. This can provide a more nuanced and accurate representation of respondents' mental well-being.

(2) Steps

Step 1. Raw data normalization.

Suppose m indicators (in this paper, $m = 3$) and n samples (in this paper, $n = 24930$) are given: $\{X_1, X_2, \cdots X_i, \cdots, X_m\}$, where $X_i = \{x_1, x_2, \cdots x_j, \cdots, x_n\}$. i and j indicate the ith indicator and the jth sample, respectively. It is assumed that the values after standardization of the data for each indicator are $\{Y_1, Y_2, \cdots Y_I, \cdots, Y_m\}$, then:

$$Y_{ij} = \frac{X_{ij} - min(X_i)}{max(X_i) - min(X_i)}, \text{When } X_{ij} \text{ is a positive indicator} \tag{A.1}$$

$$Y_{ij} = \frac{max(X_i) - X_{ij}}{max(X_i) - min(X_i)}, \text{When } X_{ij} \text{ is a negative indicator} \tag{A.2}$$

Step 2. Find out the total amount of contributions of all samples to the index Y_i.

$$p_{ij} = \frac{Y_{ij}}{\sum_{j=1}^{n} Y_{ij}}, i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n. \tag{A.3}$$

Step 3. The entropy value E_i of the ith index is defined.

$$E_i = -\frac{\sum_{j=1}^{n} p_{ij}\, ln\, p_{ij}}{ln\, n} \tag{A.4}$$

The range of the E_i is [0, 1], and $E_i = 0$ (that is $p_{ij} \bullet \ln p_{ij} = 0$) is set when $p_{ij} = 0$ to simplify the computation. The smaller the E_i, the greater differentiation of the index i and the more information that can be derived. Therefore, more weight should be given to the index.

Step 4. Calculate the weight of each index w_i.

$$w_i = \frac{1 - E_i}{\sum_{i=1}^{m} 1 - E_i} \tag{A.5}$$

Step 5. Calculate the comprehensive health index MWS_j of the jth respondent.

$$MHS_i = \sum_{i=1}^{m} \left(w_i x_{ij}\right) \tag{A.6}$$

(3) Results

The indexes and weights of *MWS* calculated based on EWM are shown in Table A5, and the frequency diagram of *MWS* are shown in Fig. A2. Fig. A3 further illustrates the evolution of respondents' *MWS* from 2006 to 2015. Notably, these scores exhibit a marked resemblance to $PM_{2.5}$ concentration trends, although shifts in mental well-being appear to lag behind changes in air pollution levels. This suggests that the impact of air pollution on mental well-being might exhibit a delayed effect, requiring a certain amount of time to manifest.

A4. Temporal trends of some indicators in this study

(1) Temporal trends in the prevalence of mental/neurological diseases

As can be seen from Graph (a) in Fig. A4, the *4-week prevalence of mental/neurological diseases* (from CHNS) has similar trend as the *2-week prevalence of mental/neurological diseases* and *the* 6-month *prevalence of mental/neurological diseases* (from the Chinese Health Statistical Yearbook), and the values are between the *2-week prevalence of mental/neurological diseases* and *the* 6-month *prevalence of mental/neurological diseases*, which suggests that the *4-week prevalence of mental/neurological diseases* data in the CHNS is accurate and reliable.

(2) Temporal trends in air pollution and the *Baidu Index for Haze*

Graph (b) in Fig. A4 shows a discernible pattern: the implementation of the policy in 2013 corresponds with a rapid surge in the Baidu index, and this growth trajectory persists at elevated levels thereafter. As a highly rigorous environmental regulation initiative in China, the APPCAP has garnered substantial attention through comprehensive media coverage encompassing newspapers, television, websites, and other social media platforms. This heightened visibility has triggered public contemplation, prompting questions such as, “What exactly is Haze or $PM_{2.5}$?” and “What are the health risks associated with Haze?” Consequently, individuals engage in online searches to procure relevant information.

A5. Dropout rate

As can be seen from data in Table A6, the dropout rate in the treatment and the control groups are very similar across years.

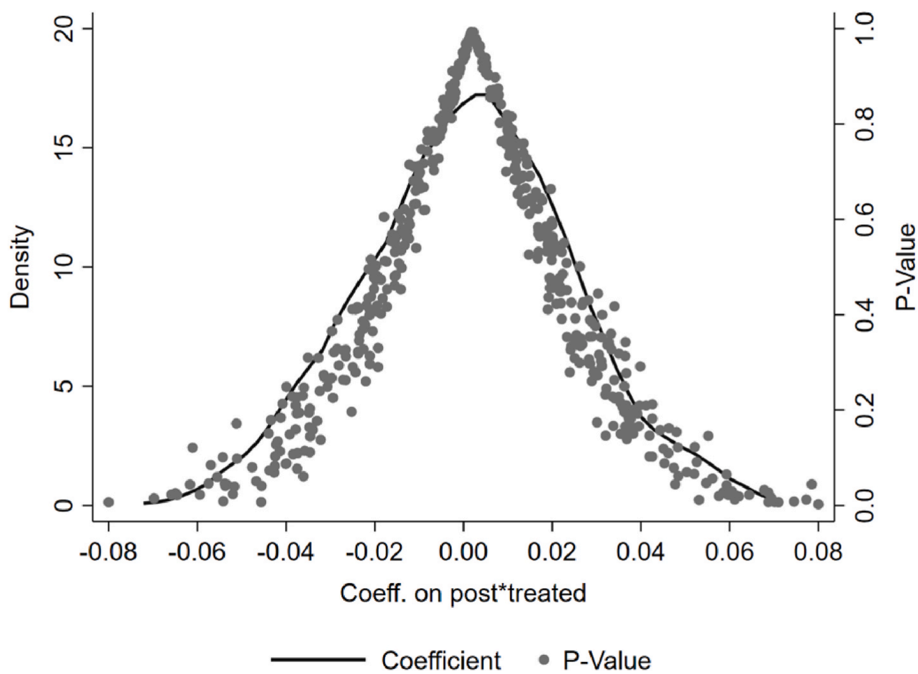


Fig. A1. Kernel density of coefficient estimates of 500 random samples.

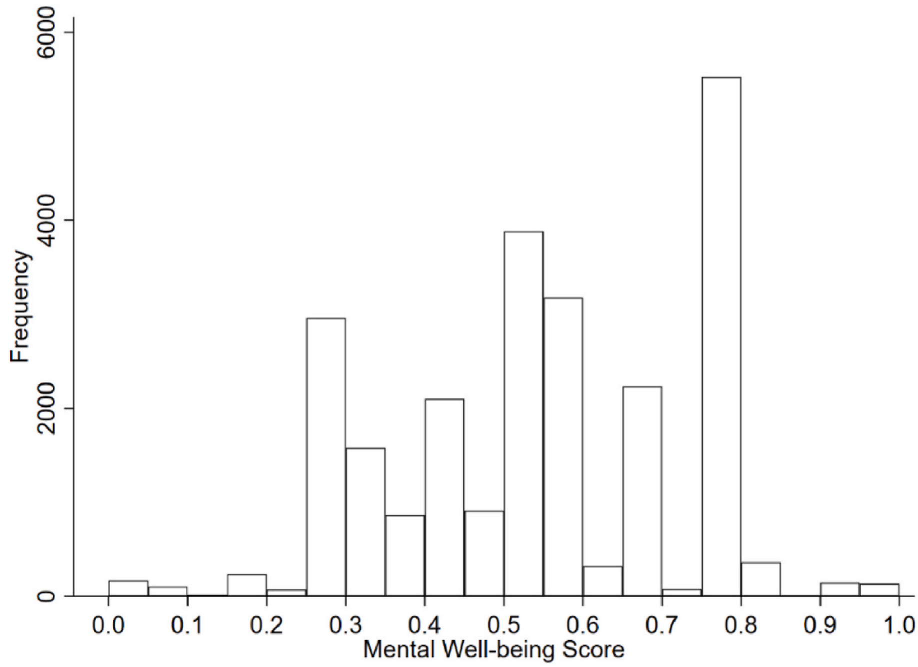


Fig. A2. Frequency diagram of mental well-being score.
Notes: The *Mental Well-being Score* is calculated by the authors.

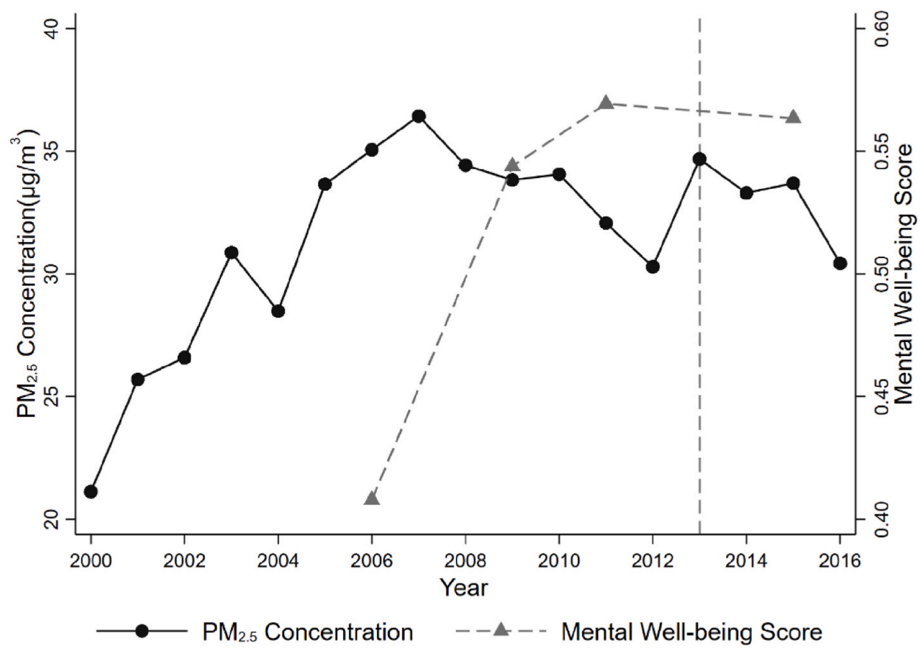
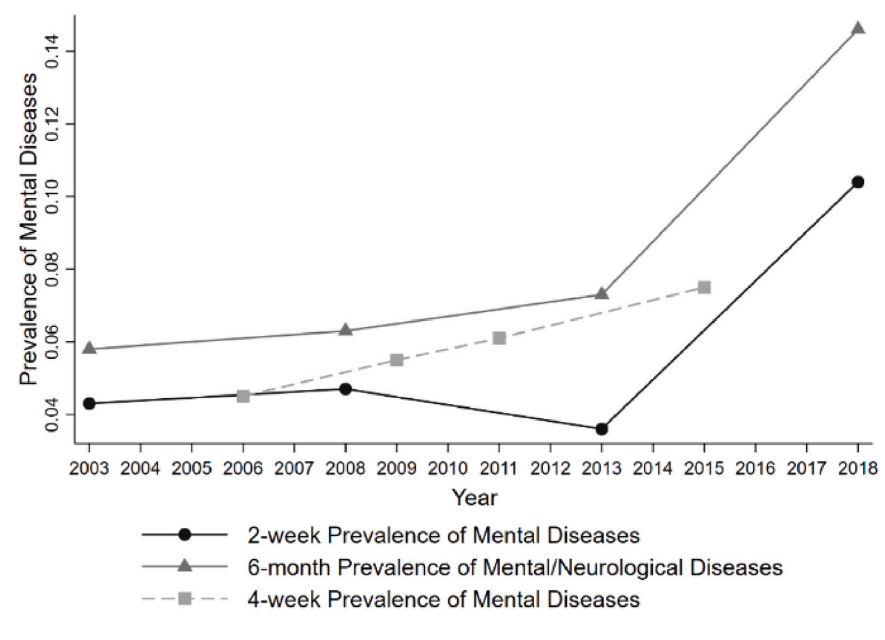
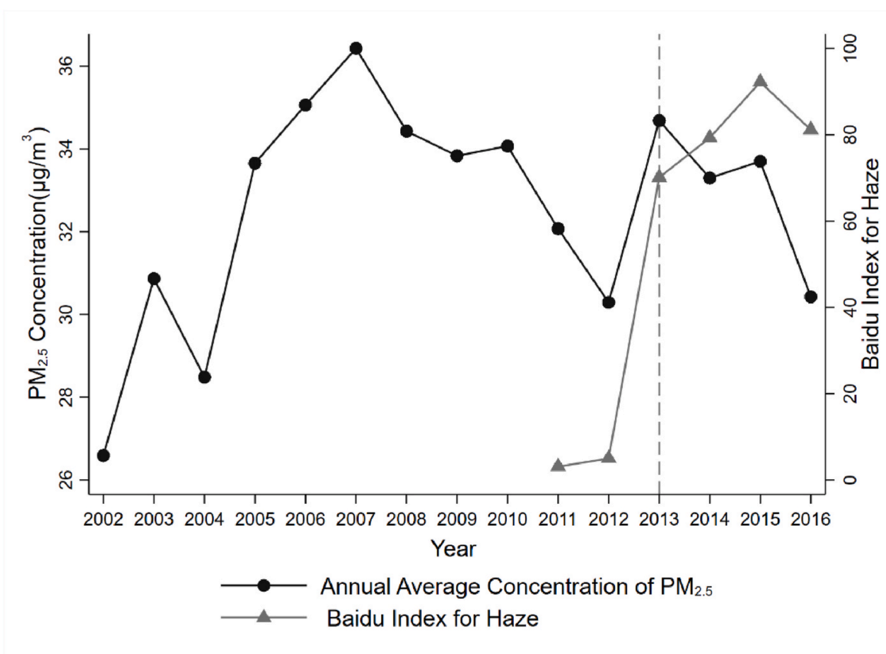


Fig. A3. Temporal trends in $PM_{2.5}$ concentration and mental well-being score.
Notes: The PM2.5 concentration is extracted from the raster map of NASA. The Mental Well-being Score is calculated by the authors.



(a) Temporal Trends in the Prevalence of Mental/Neurological Diseases



(b) Temporal Trends in Air Pollution and the Baidu Index for Haze

Fig. A4Temporal trends in the prevalence of mental/neurological disease, air pollution, and the Baidu index for haze.
Notes: The 4-week prevalence of mental/neurological diseases is calculated based on CHNS. The 6-month prevalence of mental/neurological diseases and the 2-week prevalence of mental/neurological diseases are from China Health Statistical Yearbook. Baidu Index 1.0 was officially launched in 2007, and recorded data only for PC. Baidu Index for mobile was published in 2011. Baidu index employed in this study includes both PC and mobile data, so we use the index data that were published in and after 2011.

Table A1
Robustness checks.

Alternative specifications and analyses	Coefficient estimates	
	Model (1)	Model (2)
(1) Drop observations from Shandong Province	0.0234***	0.0019***
	(0.0099)	(0.0006)
(2) Include interactions between predetermined prefecture-level variables and the linear year trend	0.0240**	0.0011**
	(0.0108)	(0.0005)
(3) Analysis based on entropy-balanced data	0.0353**	0.0014*
	(0.0175)	(0.0008)
(4) Exclude the influence from other environmental policies	0.0427***	0.0016**
	(0.0109)	(0.0007)
(5) Exclude the influence from other national policies	0.0250***	0.0012***
	(0.0079)	(0.0004)
(6) Control for other pollutants (SO_2 and PM_{10})	0.0213*	0.0010*
	(0.0126)	(0.0006)
(7) Control for climatic factors (precipitation)	0.0186*	0.0009*
	(0.0106)	(0.0005)
(8) Employ Year-Month FE (to replace the Year FE)	0.0243*	0.0012**
	(0.0129)	(0.0006)
(9) Eliminate outliers	0.0201*	0.0012**
	(0.0106)	(0.0005)
(10) Cluster robust standard errors at the individual level	0.0203***	0.0010***
	(0.0066)	(0.0003)
(11) Placebo test: a pseudo policy implementation time (based on the full sample)	−0.0025	−0.0001
	(0.0226)	−0.0001
(12) Placebo test: a pseudo policy implementation time (based on the pre-reform data)	−0.0330	−0.0016
	(0.0292)	(0.0015)

Notes: *, **, and *** denote 10%, 5%, and 1% significance levels respectively. Except for row (10), robust standard errors clustered at the prefecture level are reported in parentheses.

Table A2
Determinants of the implement of APPCAP.

Variables	*post × treated*				
	(1)	(2)	(3)	(4)	(5)
log GDP per capita	0.1598				0.2814
	(0.2528)				(0.3850)
Secondary industry		−0.0056			−0.0105
		(0.0055)			(0.0095)
Primary Industry			−0.0050		−0.0130
			(0.0081)		(0.0116)
Doctor density				0.0051	0.0040
				(0.0048)	(0.0045)
Controls	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	194	194	194	194	194
R^2	0.3941	0.3996	0.3922	0.3973	0.4252

Notes: The samples are limited to prefectures included in the CHNS database for the years 2006, 2009, 2011, and 2015. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. Robust standard errors clustered at the provincial level are reported in parentheses.

Table A3
The balancing test performed on the entropy-balanced data.

Variables	Treatment group			Control group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
log GDP per capita	2.4530	0.3202	−0.8230	2.4530	0.3198	−1.1280
Secondary industry	36.5500	134.2000	−0.2254	36.5500	144.6000	0.1928
Primary Industry	3.6600	17.3600	0.9737	3.6600	20.0800	2.1340
Doctor density	37.6700	394.5000	0.8416	37.6700	213.6000	0.0438

Table A4
The specific provisions in the APPCAP.

Category	Provisions
1. Strengthen comprehensive governance to reduce multipollutant emissions.	(1) **Strengthen the comprehensive control of air pollution in industrial enterprises.** Accelerate the desulphurization, denitrification and dust removal projects in key industries; advance the control of volatile organic compound pollution; complete the construction and upgrading of pollution control equipment for coal-fired power plants, coal-fired boilers and industrial furnaces in regions such as the regions of Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta by the end of 2015; complete the comprehensive management of organic waste gas in petrochemical enterprises. (2) **Strengthen non-point source pollution control.** This includes comprehensive management of urban dust; implementation of kitchen fume control in restaurants, etc. (3) **Strengthen the prevention and control of mobile source pollution.** Improve urban traffic management; improve fuel quality; accelerate the phase-out of vehicles that do not meet emission standards and older vehicles; strengthen the environmental management of motor vehicles; accelerate the modernization and replacement of low-speed vehicles; vigorously promote new energy vehicles.
2. Optimize industrial structure and facilitate industrial transformation.	(4) **Strictly control the expansion of "high-energy-consuming, high-polluting" industrial capacity.** (5) **Accelerate the elimination of obsolete production capacity.** (6) **Reduce excess production capacity.** (7) **Resolutely halt the construction of projects with serious overcapacity violations.**
3. Accelerate technological upgrading of enterprises and enhance technological innovation capability.	(8) **Strengthen technological research and development.** (9) **Fully implement clean production.** (10) **Develop the circular economy.** (11) **Develop the energy-saving and environmental protection industries.**
4. Accelerate the adjustment of energy structure and increase the supply of clean energy.	(12) **Control coal consumption.** Prohibit the construction of stand-alone coal-fired power plants in regions such as the Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta regions for new projects. (13) **Accelerate the substitution and utilization of clean energy.** This includes increasing the supply of natural gas, coal-to-gas and coal-bed methane; actively and orderly developing hydropower; developing and using geothermal energy, wind energy, solar energy and biomass energy; and developing nuclear power safely and efficiently. (14) **Promote the clean utilization of coal.** (15) **Improve the efficiency of energy use.**
5. Strictly regulate energy conservation and environmental protection, and optimize industrial layout.	(16) **Adjust industrial layout.** Implement differentiated industrial policies in the eastern, central and western regions, and impose higher energy conservation and environmental protection requirements on regions such as the regions of Beijing-Tianjin-Hebei, the Yangtze River Delta and the Pearl River Delta. (17) **Strengthen energy conservation and environmental protection indicators.** Raise entry thresholds; strictly implement total pollutant emission control. (18) **Optimize spatial planning.** Formulate urban planning scientifically; orderly relocate and transform heavily polluting enterprises, such as steel, petrochemical, chemical, non-ferrous metal smelting, cement, flat glass, located in the main urban areas.
6. Utilize market mechanisms and improve environmental economic policies.	(19) **Use market mechanisms for regulation.** Provide incentives for advanced enterprises with higher energy efficiency and emission intensity; strictly restrict loans and IPO financing for environmentally illegal enterprises; promote pilot use and trading of emission rights. (20) **Improve pricing and tax policies.** Adjust electricity prices on the basis of denitrification costs; promote the reform of the natural gas pricing mechanism; reasonably determine refined oil prices on the basis of fair compensation costs, quality and pollution-based pricing principles; strengthen the collection of pollution charges. (21) **Expand investment and financing channels.** Centrally coordinate major emission reduction projects, establish special funds for air pollution prevention; local governments must provide policy support for "coal-to-gas" projects related to people's livelihoods, elimination of vehicles that do not meet emission standards, and replacement of low-speed freight vehicles.
7. Strengthen legal and regulatory systems, and strictly supervise and manage according to the law.	(22) **Improve legal standards.** Accelerate the revision of the Air Pollution Prevention and Control Law; study the draft of the Environmental Taxation Law; and accelerate the revision of the Environmental Protection Law. (23) **Strengthen environmental monitoring capacity.** Establish a unified layout of national air quality monitoring networks including urban, background and regional stations; establish a national, provincial and municipal three-tier platform for vehicle emission monitoring. (24) **Strengthen environmental law enforcement.** Promote joint enforcement, regional enforcement and cross-sectoral enforcement; close down environmental offenders in accordance with the law; and prosecute those suspected of environmental crimes in accordance with the law. (25) **Implement environmental information disclosure.** Publish monthly lists of the ten cities with the best and worst air quality nationwide; provinces must publish rankings of air quality in their administrative areas; cities at and above the prefectural level must promptly publish air quality monitoring information in local major media.
8. Establish regional cooperation mechanisms and coordinate regional environmental governance.	(26) **Establish regional cooperation mechanisms.** The Beijing-Tianjin-Hebei, Yangtze River Delta Regional Atmospheric Pollution Prevention and Control Cooperation Mechanism to jointly solve regional prominent environmental issues.

(*continued on next page*)

Table A4 (*continued*)

Category	Provisions
	(27) **Decomposition of target tasks.** The State Council and provincial governments shall sign agreements on the responsibility for air pollution prevention and control. At the beginning of each year, the State Council will establish evaluation methods to assess the completion of the previous year's tasks. In 2015, a mid-term evaluation will be conducted and, based on the evaluation, adjustments will be made to the governance tasks. A final evaluation of the Action Plan will be carried out by 2017.
	(28) **Enforce strict accountability.** In case of failure to pass the annual assessment, the Environmental Protection Department, in cooperation with organizational departments, regulatory authorities and other relevant departments, will convene meetings with responsible personnel of the provincial government. They will make recommendations for corrective actions and ensure their implementation.
9. Establish a monitoring, warning and emergency response system to properly cope with heavy pollution weather.	(29) **Establish a monitoring and warning system.** By 2014, the Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta regions should complete the establishment of provincial severe pollution weather monitoring and warning systems. Other provinces, sub-provincial cities and provincial capitals should complete this by the end of 2015.
	(30) **Develop and improve contingency plans.** The Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta regions must establish and perfect a provincial coordinated emergency response system for severe pollution weather. Provincial contingency plans within the region should be submitted to the Ministry of the Environment for submission by the end of 2013.
	(31) **Take prompt emergency measures.** Integrate severe pollution weather response into local government emergency response systems; quickly activate emergency plans based on the severe pollution weather warning level to guide the public in ensuring hygiene protection.
10. Clarify the responsibilities of government, enterprises and society, and mobilize people to participate in environmental protection.	(32) **Clearly define the leadership responsibilities of local government.**
	(33) **Strengthen inter-ministerial coordination and cooperation.**
	(34) **Strengthen corporate governance.**
	(35) **Broadly mobilize community involvement and participation in environmental protection efforts.**

Table A5
Indicator weights of *MWS*.

Indicator (X_i)	Characteristic	Weight
pep	positive	0.3682
happiness	positive	0.3365
hope	positive	0.2953

Table A6
The number of observations and dropout rate in the treatment group and control group.

Wave	Treatment group			Control group		
	Observations	Observations dropped out	dropout rate	Observations	Observations dropped out	Dropout rate
2006	1344	–	–	11274	–	–
2009	1317	372	27.68%	11727	2910	25.81%
2011	2737	282	21.41%	13015	2337	19.93%
2015	3199	631	23.05%	13383	4121	31.66%

Data availability

Data will be made available on request.

References

Abbey, D.E., Burchette, R.J., Knutsen, S.F., Mcdonnell, W.F., Lebowitz, M.D., Enright, L. P., 1998. Long-term particulate and other air pollutants and lung function in nonsmokers. Am. J. Respir. Crit. Care Med. 158 (1), 289–298. https://doi.org/10.1164/ajrccm.158.1.9710101.

Ailshire, J., Karraker, A., Clarke, P., 2017. Neighborhood social stressors, fine particulate matter air pollution, and cognitive function among older U.S. adults. Soc. Sci. Med. 172, 56–63. https://doi.org/10.1016/j.socscimed.2016.11.019.

Bakkeli, N.Z., 2020. Older adults' mental health in China: examining the relationship between income inequality and subjective wellbeing using panel data analysis. J. Happiness Stud. 21 (4), 1349–1383. https://doi.org/10.1007/s10902-019-00130-w.

Balasooriya, N.N., Bandara, J.S., Rohde, N., 2022. Air pollution and health outcomes: evidence from Black Saturday bushfires in Australia. Soc. Sci. Med. 306. https://doi.org/10.1016/j.socscimed.2022.115165, 115165-115165.

Barwick, P.J., Li, S., Lin, L., Zou, E., 2024. From fog to smog: the value of pollution information. Am. Econ. Rev. 114 (5), 1338–1381. https://doi.org/10.1257/aer.20200956.

Barreca, A.I., Neidell, M., Sanders, N.J., 2021. Long-run pollution exposure and mortality: evidence from the acid rain program. J. Publ. Econ. 200, 104440. https://doi.org/10.1016/j.jpubeco.2021.104440.

Bharadwaj, P., Gibson, M., Zivin, J.G., Neilson, C., 2017. Gray matters: fetal pollution exposure and human capital formation. J. Assoc. Environ. Resour. Econom. 4 (2), 505–542. https://doi.org/10.1086/691591.

Bishop, K.C., Ketcham, J.D., Kuminoff, N.V., 2023. Hazed and confused: the effect of air pollution on dementia. Rev. Econ. Stud. 90 (5), 2188–2214. https://doi.org/10.1093/restud/rdac078.

Brunekreef, B., Hoffmann, B., 2016. Air pollution and heart disease. Lancet 388 (10045), 640–642. https://doi.org/10.1016/S0140-6736(16)30375-0.

Calderón-Garcidueñas, L., Calderón-Garcidueñas, A., Torres-Jardón, R., Avila-Ramírez, J., Kulesza, R.J., Angiulli, A.D., 2015. Air pollution and your brain: what do you need to know right now. Prim. Health Care Res. Dev. 16 (4), 329–345. https://doi.org/10.1017/S146342361400036X.

Chay, K.Y., Greenstone, M., 2003. Air quality, infant mortality, and the clean air act of 1970. NBER Working Papers. https://doi.org/10.3386/w10053, 10053.

Chen, S., Oliva, P., Zhang, P., 2024. Air pollution and mental health: evidence from China. In: American Economic Review, Papers and Proceedings, vol. 114, pp. 423–428. https://doi.org/10.1257/pandp.20241062.

Chen, Y.Y., Ebenstein, A., Greenstone, M., Li, H.B., 2013. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. In: Proceedings of the National Academy of Sciences of the United States of America, vol. 32, pp. 12936–12941. https://doi.org/10.1073/pnas.1300018110.

Cho, J., Noh, Y., Kim, S.Y., Sohn, J., Noh, J., Kim, W., et al., 2020. Long-term ambient air pollution exposures and brain imaging markers in Korean adults: the Environmental Pollution-Induced Neurological EFfects (EPINEF) study. Environ. Health Perspect. 128 (11), 117006. https://doi.org/10.1289/EHP7133.

Clay, K., Lewis, J., Severnini, E., 2016. Canary in a coal mine: impact of mid-20th century air pollution on infant mortality and property values. In: NBER Working Paper, 22155.

Cohen, A.J., Brauer, M., Burnett, R., et al., 2017. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. Lancet 389 (10082), 1907–1918. https://doi.org/10.1016/S0140-6736(17)30505-6.

Costa, L.G., Cole, T.B., Dao, K., Chang, Y.C., Coburn, J., Garrick, J.M., 2020. Effects of air pollution on the nervous system and its possible role in neurodevelopmental and neurodegenerative disorders. Pharmacol. Therapeut. 210, 107523. https://doi.org/10.1016/j.pharmthera.2020.107523.

Currie, J., Davis, L., Greenstone, M., Walker, R., 2015. Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings. Am. Econ. Rev. 105 (2), 678–709. https://doi.org/10.1257/aer.20121656.

Deryugina, T., Heutel, G., Miller, N.H., Molitor, D., Reif, J., 2019. The mortality and medical costs of air pollution: evidence from changes in wind direction. Am. Econ. Rev. 109 (12), 4178–4219. https://doi.org/10.1257/aer.20180279.

Deschenes, O., Greenstone, M., Shapiro, J.S., 2017. Defensive investments and the demand for air quality: evidence from the NOx budget program. Am. Econ. Rev. 107 (10), 2958–2989. https://doi.org/10.1257/aer.20131002.

Du, L.Z., Lin, W.F., Du, J.H., Jin, M.L., Fan, M.T., 2022. Can vertical environmental regulation induce enterprise green innovation? A new perspective from automatic air quality monitoring station in China. J. Environ. Manag. 317, 115349. https://doi.org/10.1016/j.jenvman.2022.115349.

Ebenstein, A., Fan, M., Greenstone, M., He, G., Zhou, M., 2017. New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. In: Proceedings of the National Academy of Sciences of the United States of America, vol. 114, pp. 10384–10389. https://doi.org/10.1073/pnas.1616784114, 39.

Genc, S., Zadeoglulari, Z., Fuss, S.H., Genc, K., 2012. The adverse effects of air pollution on the nervous system. J. Toxicol. 2012 (1), 782462. https://doi.org/10.1155/2012/782462.

Hahad, O., Kuntic, M., Frenis, K., Chowdhury, S., Lelieveld, J., Lieb, K., Daiber, A., Muenzel, T., 2021. Physical activity in polluted air—net benefit or harm to cardiovascular health? A comprehensive review. Antioxidants 10 (11), 1787. https://doi.org/10.3390/antiox10111787.

Hainmueller, J., 2012. Entropy balancing for causal effects: a multivariate reweighting method to produce balanced samples in observational studies. Polit. Anal. 20, 25–26. https://doi/10.1093/pan/mpr025.

Hao, J., He, K., Duan, L., Li, J., Wang, L., 2007. Air pollution and its control in China. Front. Environ. Sci. Eng. China 1, 129–142. https://doi.org/10.1007/s11783-007-0024-2.

He, G., Liu, T., Zhou, M., 2020. Straw burning, PM_{25}, and death: evidence from China. J. Dev. Econ. 145, 102468. https://doi.org/10.1016/j.jdeveco.2020.102468.

Herting, M.M., Diana, Y., Campbell, C.E., Chen, J.C., 2019. Outdoor air pollution and brain structure and function from across childhood to young adulthood: a methodological review of brain MRI studies. Front. Public Health 7, 332. https://doi.org/10.3389/fpubh.2019.00332.

Huang, J., Pan, X., Guo, X., Li, G., 2018. Health impact of China's Air Pollution Prevention and Control Action Plan: an analysis of national air quality monitoring and mortality data. Lancet Planet. Health 2 (7), e313–e323. https://doi.org/10.1016/S2542-5196(18)30141-4.

Huang, Z.N., Jia, H.H., Shi, X.H., Xie, Z.Y., Cheng, J.P., 2023. Revealing the impact of China's clean air policies on synergetic control of CO_2 and air pollutant emissions: evidence from Chinese cities. J. Environ. Manag. 344, 118373. https://doi.org/10.1016/j.jenvman.2023.118373.

Kessler, R.C., Andrews, G., Colpe, L.J., Hiripi, E., Mroczek, D.K., Normand, S.L., Walters, E.E., Zaslavsky, A.M., 2002. Short screening scales to monitor population prevalences and trends in non-specific psychological distress. Psychol. Med. 32 (6), 959–976. https://doi.org/10.1017/S0033291702006074.

Kim, H., Noh, J., Noh, Y., Oh, S.S., Koh, S.B., Kim, C., 2019. Gender difference in the effects of outdoor air pollution on cognitive function among elderly in Korea. Front. Public Health 7, 375. https://doi.org/10.3389/fpubh.2019.00375.

Li, F., Lu, C., Li, T., 2024. Air pollution, physical exercise, and physical health: an analysis based on data from the China general social survey. Sustainability 16 (11), 4480. https://doi.org/10.3390/su16114480.

Li, Z., Jin, B., 2024. A breath of fresh air: coal power plant closures and health in China. Energy Econ. 129, 107235. https://doi.org/10.1016/j.eneco.2023.107235.

Maji, K.J., Li, V.O., Lam, J.C., 2020. Effects of China's current Air Pollution Prevention and Control Action Plan on air pollution patterns, health risks and mortalities in Beijing 2014–2018. Chemosphere 260, 127572. https://doi.org/10.1016/j.chemosphere.

Manisalidis, I., Stavropoulou, E., Stavropoulos, A., Bezirtzoglou, E., 2020. Environmental and health impacts of air pollution: a review. Front. Public Health 8, 14. https://doi.org/10.3389/fpubh.2020.00014.

Moussavi, S., Chatterji, S., Verdes, E., Tandon, A., Patel, V., Ustun, B., 2007. Depression, chronic diseases, and decrements in health: results from the World health surveys. Lancet 370 (9590), 851–858. https://doi.org/10.1016/S0140-6736(07)61415-9.

Neidell, M., 2009. Information, avoidance behavior, and health the effect of ozone on asthma hospitalizations. J. Hum. Resour. 44 (2), 450–478. https://doi.org/10.3368/jhr.44.2.450.

Palma, A., Petrunyk, I., Vuri, D., 2022. Prenatal air pollution exposure and neonatal health. Health Econ. 31 (5), 729–759. https://doi.org/10.1002/hec.4474.

Peterson, B.S., Rauh, V.A., Bansal, R., Hao, X., Toth, Z., Nati, G., Perera, F., 2015. Effects of prenatal exposure to air pollutants (polycyclic aromatic hydrocarbons) on the development of brain white matter, cognition, and behavior in later childhood. JAMA Psychiatr. 72 (6), 531–540. https://doi.org/10.1001/jamapsychiatry.2015.57.

Radloff, L.S., 1977. The CES-D Scale: a self-report depression scale for research in the general population. Appl. Psychol. Meas. 1, 385–401. https://doi.org/10.1177/014662167700100306.

Schlenker, W., Walker, W.R., 2016. Airports, air pollution, and contemporaneous health. Rev. Econ. Stud. 283 (2), 768–809. https://doi.org/10.1093/restud/rdv043, 295.

Shannon, C.E., 1948. A mathematical theory of communication. ACM SIGMOB - Mob. Comput. Commun. Rev. 27 (3), 379–423, 10.1002/j.1538-7305.1948. tb01338.x.

Shin, J., Park, J.Y., Choi, J., 2018. Long-term exposure to ambient air pollutants and mental health status: a nationwide population-based cross-sectional study. PLoS One 13 (4), e0195607. https://doi.org/10.1371/journal.pone.0195607.

Takeda, F., Noguchi, H., Monma, T., Tamiya, N., 2017. How possibly do leisure and social activities impact mental health of middle-aged adults in Japan: an evidence from a national longitudinal survey. PLoS One 10 (10), e0139777. https://doi.org/10.1371/journal.pone.0139777.

Tanaka, S., 2015. Environmental regulations on air pollution in China and their impact on infant mortality. J. Health Econ. 104 (10), 90–103. https://doi.org/10.1016/j.jhealeco.2015.02.004.

Wang, Y.Z., Eriksson, T., Luo, N.S., 2023. The health impacts of two policies regulating SO_2 air pollution: evidence from China. China Econ. Rev. 78, 101937. https://doi.org/10.1016/j.chieco.2023.101937.

Xie, T., Yuan, Y., Zhang, H., 2023. Information, awareness, and mental health: evidence from air pollution disclosure in China. J. Environ. Econ. Manag., 102827 https://doi.org/10.1016/j.jeem.2023.102827.

Yu, W.H., Jin, X., 2022. Does environmental information disclosure promote the awakening of public environmental awareness? Insights from Baidu keyword analysis. J. Clean. Prod., 375 https://doi.org/10.1016/j.jclepro.2022.134072.

Yu, Y.J., Dai, C., Wei, Y.G., Ren, H.M., Zhou, J.W., 2022. Air pollution prevention and control action plan substantially reduced $PM_{2.5}$ concentration in China. Energy Econ. 113, 106206. https://doi.org/10.1016/j.eneco.2022.106206.

Zhang, X., Chen, X., Zhang, X.B., 2018. The impact of exposure to air pollution on cognitive performance. Proc. Natl. Acad. Sci. U. S. A 115 (37). https://doi.org/10.1073/pnas.1809474115.

Zhang, X., Zhang, X., Chen, X., 2017. Happiness in the air: how does a dirty sky affect mental health and subjective well-being? J. Environ. Econ. Manag. 85, 81–94. https://doi.org/10.1016/j.jeem.2017.04.001.

Zheng, Y., Xue, T., Zhang, Q., Geng, G., Tong, D., Li, X., He, K., 2017. Air quality improvements and health benefits from China's Clean Air Action since 2013. Environ. Res. Lett. 12 (11), 114020. https://doi.org/10.1088/1748-9326/aa8a32.

Zhu, Y., Tian, D., Yan, F., 2020. Effectiveness of entropy weight method in decision-making. Math. Probl Eng. 2020, 1–5. https://doi.org/10.1155/2020/3564835.

Zundel, C.G., Ryan, P., Brokamp, C., Heeter, A., Huang, Y.X., Strawn, J.R., Marusak, H. A., 2022. Air pollution, depressive and anxiety disorders, and brain effects: a systematic review. Neurotoxicology 93, 272–300. https://doi.org/10.1016/j.neuro.2022.10.011.