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Air pollution and mental health: Evidence from China Health and Nutrition Survey

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ABSTRACT

Using the mental health data of the elderly in China Health and Nutrition Survey and city-level air pollution data, this paper empirically analyzes the influence of air pollution on the mental health of the elderly. Results show that with the aggravation of air pollution, the mental health of the elderly decreases significantly. Specifically, a 10 $\mu g/m^3$ increase in air pollution causes a decrease of 2.43 points in mental health. Air pollution has a greater effect on males, rural residents, and low-income and low-education groups. In addition, this paper tests two mechanisms, namely, health status and individual activity, and finds that air pollution can reduce mental health by increasing the incidence and severity of disease. Moreover, the intensification of air pollution leads the elderly to prefer indoor activities. Based on individual data, this paper estimates the health effects of air pollution, which provides a basis for the formulation of environmental and health policies.

1. Introduction

Over the past 40 years of reform and opening up, China's economic development has made remarkable achievements. However, behind China's rapid economic boom are some urgent problems to be solved. On the one hand, the traditional extensive economy is unsustainable from the perspective of factor consumption and negative externalities. The extensive economy requires large-scale input of labor and energy elements, which are difficult to maintain in the long run. Population aging has become increasingly prominent. The seventh national census showed that the proportion of the population aged 65 and over in China reached 13.50 %. The demographic dividend is gradually disappearing, and labor market problems are more serious. In addition, traditional industries are characterized by high energy consumption and high emissions (Li et al., 2012). If this traditional pattern continues unaltered, we will face energy scarcity as most of these energy sources are non-renewable sources. From the perspective of negative externalities, air pollution problems are becoming more serious due to the energy consumption and emission increase (Brajer et al., 2006; Mayer, 1999; Quah & Boon, 2003; Welsch, 2006). On the other hand, with the continuous improvement of people's requirements for quality of life, environmental health problems brought by development have affected the quality of life of residents (Afoakwah et al., 2020; Chen & Chen, 2020, 2021; Chen et al., 2022b; Filippini et al., 2019; Janke et al., 2009; Liu & Ao, 2021; Palma et al., 2022; Sandujav et al., 2021). The principal contradiction facing Chinese society has evolved, and what we now face is the contradiction between unbalanced, inadequate development and the people's ever-growing needs for a better life. The "Healthy China 2030" also pointed out that "industrialization,

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urbanization, population aging, continuous changes in disease spectra, ecological conditions, and people's lifestyles have also brought a series of new changes to the maintenance and promotion of health." Therefore, speeding up the transformation of the economic development mode and promoting high-quality economic development are necessary. However, under the current situation and background, some important issues still need to be resolved. What kind of efforts should be taken to control the environmental pollution that has already occurred? What effect does the current air pollution have on the growing elderly population? What is the way? How should effective measures be taken to improve the health of the elderly and their quality of life? This paper focuses on these issues and analyzes them.

First, the strength of environmental regulation needs to be weighed. Strict environmental regulations may dampen the production enthusiasm of enterprises and affect economic growth, but environmental deregulation affects the health of residents. Many studies focus on the effects of pollution on physical health (Jones & Goodkind, 2019; Tainio et al., 2021; Yang et al., 2022). However, less research has focused on the effects of environmental pollution on mental health, which may underestimate the health costs of environmental pollution. Based on this, this paper supplements from the mental health perspective. Second, this paper attempts to explore the degree of effect of air pollution on the psychology of the elderly. Medical research has found that air pollution can directly cause inflammation, affect blood clotting, and have a direct negative influence on mental health (Bind et al., 2012; Chen et al., 2018b; Power et al., 2015).[1] Considering endogeneity in the medical analysis, this paper uses temperature inversion as an instrumental variable to deal with this problem. Third, the channels through which air pollution affects mental health are explored and tested. Air pollution can lead to respiratory, cardiovascular, and cerebrovascular diseases, which can extend to individual mental health (Hynninen et al., 2005; Yohannes et al., 2010). Serious diseases limit individual activities and further affect individual health. Air pollution can lead to the reduction of outdoor activities, and a long-term indoor activity can easily lead to psychological problems. Finally, according to the heterogeneous effects and channels of air pollution on the mental health of the elderly, effective measures are proposed in a targeted manner.

In this paper, data from the four waves (2006, 2009, 2011, and 2015) of the China Health and Nutrition Survey (CHNS) are used, matching the mental health data of middle-aged and elderly people with air pollution data at the prefecture-level city level to estimate the effect of air pollution on mental health. Considering the potential endogeneity problem, temperature inversion is used as an instrumental variable of air pollution, and two-stage least squares (2SLS) is used for estimation. The results suggest that air pollution has a significant negative influence on mental health. A 10 $\mu g/m^3$ increase in air pollution causes a decrease of 2.43 points in mental health (each with 15 possible points). In addition, air pollution is more likely to affect middle-aged men, rural residents, low-income people, and people with less education. Finally, two indirect pathways are examined through health status and individual activity for pathogenesis identified in medical research. Overall, these results indicate that air pollution not only reduces the individual's mental health by increasing the incidence and severity of the disease but also increases the individual's preference for indoor sports activities and further reduces the individual's mental health.

This paper contributes to relevant literature in two ways. First, few studies combined the three hot topics of air pollution, population aging, and healthy life for empirical analysis based on data in China. This paper enriches the literature in this area. There are also some related studies in this field (Chen et al., 2018b; Wang & Luo, 2020). This paper has a different focus from those studies. First, we pay more attention to the measurement of mental health. As the main microscopic survey data in the health field, CHNS has more comprehensive and extensive data in measuring individual health. Second, we are more concerned about the long-term impact of air pollution. Previous studies have found that air pollution affects micro-level individual settlement siting (Chen et al., 2021, 2022a; Fu et al., 2021). Individual site selection behavior will lead to estimation bias. To overcome this effect, we employed surveys of earlier CHNS in 1989 by adding fixed effects and retaining a sample of multiple observations. It is beneficial for us to alleviate the bias caused by liquidity.

Second, the pathological effects and the event delivery mechanism of air pollution on mental health are preliminarily analyzed. In the test of the pathological channel influence mechanism pointed out by medical research, a combination of subjective and objective methods is adopted to select indicators, including objective health conditions such as disease incidence, disease type, hospitalization, and subjective health such as self-assessed health and disease severity. Considering individuals can relax their body and mind by doing activities, indicators that reflect physical activity status, such as "walking, Tai Chi," "sports (table tennis, badminton, tennis, football, basketball, and volleyball)," and "fitness" are selected. In addition, indicators that reflect mental activity, such as "watching TV," "playing computer games, game consoles, or surfing the Internet," and "reading" for analysis are used. Finally, the sample is limited due to the problem of resident mobility, and a resident sample that could be observed multiple times is used to slow down the relocation problem effectively. Based on the above, the influence mechanism of air pollution on permanent residents is further analyzed.

The rest of this paper is organized as follows. Section 2 provides a brief medical background on the effects of air pollution on mental health and reviews the existing literature on the topic of environmental health in the field of economics. Section 3 discusses the source and processing of data. Section 4 discusses model specifications and analyzes potential endogeneity issues. Section 5 reports and explains the main results. Section 6 summarizes this study.

[1] Specifically, air pollutants first enter the lungs and then enter the circulatory system through the blood. These fine particles then enter the brain, produce an inflammatory response, and affect blood clotting. Thus, these symptoms are associated with depression and can easily affect mental health.

2. Literature review

The causes and mechanisms of mental illnesses are widely studied in the medical field. Mental health may be influenced by genetic characteristics, substance abuse, and socioeconomic factors. Previous research established that air pollution affects mental health mainly through oxidative stress and neuro-inflammation (Ng et al., 2008; Vogelzangs et al., 2013). The brain is more vulnerable to damage caused by oxidative stress and neuro-inflammation than other organs due to its higher energy demands. To date, several studies have investigated the influence of living environment on mental health. Among environmental factors, air pollution dominated by PM2.5 is more harmful to mental health. After entering the human body, PM2.5 induces oxidative stress and inflammation, which in turn affects mental health (Bind et al., 2012; Power et al., 2015). Traditionally, several lines of evidence suggest that respiratory diseases and cardiovascular and cerebrovascular diseases caused by air pollution further negatively affect mental health (Hynninen et al., 2005; Yohannes et al., 2010). This effect is often reflected in chronic respiratory diseases and cardiovascular and cerebrovascular diseases. It has adverse effects on the patient's psychology due to the persistent disease and long treatment cycle.

Research in the field of economics is also interested in health topics. After Grossman (1972) took health as a human capital input to construct a health production function, the topic of health has received extensive attention from the economics community. (Cropper, 1981) further considered the effect of pollution on the health production function and laid the theoretical foundation for environmental health economics. On this basis, scholars have conducted extensive empirical research. Restricted by medical ethics, human experiments cannot be carried out, and medical research can only rely on epidemiological observational research because of the ineffectiveness of animal experiments. Given that research on this topic is plagued by endogeneity, the results can only illustrate the correlation (Graff Zivin & Neidell, 2013). To overcome the endogeneity problem, the economics community embarked on a long journey to find instrumental variables and quasi-natural experiments. Pope 3rd (1989) was the first to use quasi-natural experiments to identify causal relationships in research on pollution and strikes in steel plants. The study showed that strikes lead to improved air quality and reduce the rate of respiratory hospitalizations and mortality. Likewise, Lavaine and Neidell (2017) concluded that pollution reduction is beneficial for newborn development based on data on changes in pollution levels during the French refinery closures. Following the idea of the event research approach, Jayachandran (2009) found that air quality deteriorated after wildfires in Indonesia, which led to an increase in infant mortality. However, such event studies target a cohort and may affect estimation accuracy (Moulton, 1986). To overcome this disadvantage, Chay and Greenstone (2003) studied the large-scale decline in pollution levels caused by the economic crisis in the United States during the 1980s and found that the decline in total suspended particulate matter concentration effectively reduces neonatal mortality. In recent years, the amount of literature on this topic has been increasing in China. Chen et al. (2013) used the Huai River as the dividing line between north and south, and estimated that the average life expectancy of northern residents is three years lower than that of southern residents due to heating. In a study investigating the effects of air pollution, He et al. (2016) reported that every 10 % reduction in air pollution leads to an 8 % reduction in mortality through the exogenous change in the government's policy to reduce air pollution during the 2008 Beijing Olympics. More scholars seek effective instrumental variables to solve the problem of endogeneity because finding quasi-natural experiments limited by regions and practices is difficult. Moretti and Neidell (2011) used the number of ships entering and leaving the port of Los Angeles as an instrumental variable for ozone concentration and found that the adverse effects of pollution are underestimated when endogeneity is not considered. In an investigation into the effect of pollution on crime rates, considering the different levels of pollution between upwind and downwind, Herrnstadt and Muehlegger (2015) used wind direction as an instrumental variable. When estimating the influence of air pollution on student health and attendance, Chen et al. (2018a) used temperature inversion as an instrumental variable, whereas Liu and Salvo (2018) used wind speed as an instrumental variable. Bondy et al. (2020) used atmospheric inversions and wind direction as exogenous shocks to local pollution, In the study of the link between air pollution and impaired memory, Powdthavee and Oswald (2020) exploited the direction of the prevailing westerly wind and levels of population density as two instrumental variables, and found that human memory is worse in areas where NO2 and PM10 concentrations are high.

With the enrichment of data, the scope of research continues to expand. With the deepening of research, scholars have begun to study the environmental pollution and health of different age groups and different health states. Chen et al. (2018a) used student health monitoring data from the Guangzhou Center for Disease Control and Prevention, and found that air pollution causes students' absenteeism due to respiratory illness. In a further study, Liu and Salvo (2018) focused on the national schools in Northern China adversely affected by pollution and found that high levels of particulate pollution can lead to student absenteeism; these schools then responded defensively to air pollution. Surveys such as that conducted by Zhang et al. (2018) showed that air pollution has a negative effect on cognitive performance, which increases with age. Chen et al. (2018b) also used CFPS data to find that each standard deviation increase in air pollution leads to a 6.67 % increase in the probability of serious mental illness, and mental health among older adults is more vulnerable to air pollution. In medicine, research on the relationship between air pollution and mental health is in the ascendant. Pedersen et al. (2004) based on data on air pollution at birth on 7455 children followed from 1970 to 2001 and noted that air pollution is associated with increased risk of schizophrenia in children. Lundberg et al. (2009) analyzed the link between urbanization and mental illness in Uganda, and found that air pollution is a suspected factor leading to mental illness. Tong et al. (2016) studied the incidence data in Tianjin of China from 2008 to 2011 and found that the increase of PM10, SO2, and NO2 increases the incidence of psychosis. In the same vein, Lim et al. (2012) argued that depression worsens in older adults after short-term exposure to air pollution.

Overall, these studies have the following research trends: 1) In terms of research methods, endogenous treatment has always been a major problem that must be solved in the study of air pollution. With the abundance of climate data in recent years, its exogenous nature is easier to satisfy, which is favored by many researchers. Most researchers investigating pollution have utilized inversion temperature and wind speed as guaranteed exogenous variables. Its mechanism of action is mainly to change the spatial distribution of pollution: Wind speed mainly transfers pollution from one area to another, and temperature inversion affects the degree of diffusion of

pollution. Based on existing research, this paper uses temperature inversion as an instrumental variable. 2) In terms of research content, the scope of research is constantly expanding, such as selecting from initial mortality to morbidity and from physical health to mental health.[2] According to Chen et al. (2018b), older adults are more affected by air pollution's effects on mental health, and the literature on air pollution and public health is further enriched by focusing on the mental health of the elderly as society pays more attention to the health problems brought about by the aging population. In this paper, CHNS data in the field of nutrition and health are used, and then the endogenous problems and mechanisms are analyzed from a microscopic perspective.

3. Data

Mental health data and individual-level control variables are collected from the CHNS, Macro control variables come from the China Stock Market & Accounting Research Database (CSMAR). Air pollution data are obtained from the Columbia University Center for International Geoscience Information Network. Temperature inversion data are sourced from National Aeronautics and Space Administration (NASA).

One of the challenges is how to find accurate indicators to measure mental health. In the medicine field, the measurement of mental health mainly relies on the symptom self-rating scale (SCL-90),[3] which contains 90 items such as feeling, emotion, thinking, consciousness, and behavior. However, the scale data are so complicated that a large amount of manpower and material resources are needed to collect them. Therefore, current micro surveys rarely use this scale to measure mental health. The CHNS is a relatively authoritative survey on China's health and nutrition status survey, which began in 1989 and is jointly conducted by the University of North Carolina and the Chinese Center for Disease Control and Prevention. It involves more than 30,000 people from about 7200 families in 15 provinces (or municipalities), and the selected locations have significant differences in geographic conditions, economic development, public resources, and health indicators. Since 2006, questionnaires in the CHNS database have included questions about mental health among middle-aged and elderly people over the age of 55,[4] which are "I have as much pep as I had in last year," "I am as happy now as I was younger," and "As I get older, things are better than I thought they would be." These three questions contain five grades of options, and 1–5 are used to assign values. The higher the score is, the greater the agreement with the above point of view. The scores are directly added to construct a mental health score because the above three questions are of equal status. Can this newly constructed indicator reflect an individual's mental health relatively accurately? From the content point of view, the first question reflects the individual's health status and is a simplified index of somatization in SCL-90 (mainly reflecting subjective physical discomfort). The second question reflects the individual's psychological state and is a simplified measure of depression, anxiety, hostility, and terror in SCL-90. The third question is the individual's perceptions and attitudes toward the world around them, which is a broader indicator. Therefore, these questions are a great simplification of SCL-90. It incorporates broader indicators, which can reflect the mental health of individuals. Although these indicators are not as accurate as full scales, the use of scales have the potential for sample selection bias. For example, individuals use the scale only if they have psychological problems themselves or have been suspected by a doctor of mental health, especially at the time of employee onboarding. By contrast, the CHNS can avoid this kind of selection bias and has more abundant control variables to solve the problem of omitted variable bias. A description of the selection for the elderly sample is added. Older people are defined differently across time and country. As our survey spans nearly 10 years, this issue needs to be approached with caution. First, the criteria are given when collecting data in the CHNS. As for mental health survey, it is mainly aimed at middle-aged and elderly people: The age of the respondents in the questionnaires are over 45 (2006), over 55 (2019, 2011), and over 50 (2015). Definitions of middle-aged and elderly people have varied in different years in CHNS, which may lead to bias in sample selection (e.g., 2009 and 2011 surveys included younger individuals who may have had higher levels of fitness). To avoid this problem, selecting samples over 55 years old as the research object is more appropriate. Second, this paper considers international and Chinese standards, both of which are 60 years old and above.[5] Is selecting samples over 60 years old as research subjects better? The average life expectancy of the Chinese population and the age and retirement age of the elderly are increasing. Therefore, the elderly 10 years ago may not meet this standard. Furthermore, restricting age to a higher standard leads to a decrease in sample size, affecting the precision of the estimates. Based on the above reasons, individuals over 55 years old are selected as our research sample. Moreover, considering that 60 years old is also an important criterion, the regression results of samples over 60 years are further provided for robustness testing.

The main independent variable is PM2.5, for which data are sourced from the International Geoscience Information Network Center of Columbia University because of the historical lack of PM2.5 concentration data in China. The agency converts the aerosol optical depth measured by Moderate Resolution Imaging Spectroradiometer and Multiangle Imaging Spectro Radiometer into annual global PM2.5 data in the form of raster data (van Donkelaar et al., 2018). ArcGIS software is used to analyze the annual average PM2.5

[2] Three limitations exist when selecting infants as study subjects in early research: 1). Birth data have better availability. 2). Infants are less mobile, which can overcome endogeneity to some extent. 3). Babies are more sensitive to air pollution than adults.

[3] The SCL-90 contains 12 somatization indicators, 10 obsessive–compulsive symptoms indicators, 9 interpersonal sensitivity indicators, 13 depression indicators, 10 anxiety indicators, 6 hostility indicators, 7 terror indicators, 6 paranoia indicators, psychosis, 10 sexual indicators, and 7 other factors.

[4] Taking the 2015 questionnaire as an example, question 1 compares the energy status of the previous year, whereas the actual data are from 2014. The rest of the survey years are followed by analogy.

[5] In international standards, the standard given by the World Health Organization is over 60 years old. In China, Article 2 of the Law of the People's Republic of China on the Protection of the Rights and Interests of the Elderly states that "the elderly refer to citizens over the age of sixty."

Table 1
Descriptions of variables.

Variables	Notation	Description
Mental health	*MH*	The sum of the three sub-indicators
Mental health sub-indicator 1	*MH1*	I have as much pep as I had in last year
Mental health sub-indicator 2	*MH2*	I am as happy now as I was younger
Mental health sub-indicator 3	*MH3*	As I get older, things are better than I thought they would be
$PM_{2.5}$	*PM2.5*	Annual average of PM2.5 concentration at city level (unit: $\mu g/m^3$)
Age	*Age*	Unit: Year
Gender	*Gender*	1 = Female; 0 = Male
Marriage	*Marriage*	1 = Married ; 0 = Others (e.g. unmarried, divorced, widowed, separated)
Education	*Education*	6 = Master's degree or higher; 5 = University or college degree; 4. = Technical or vocational degree; 3 = Upper middle school degree; 2 = Lower middle school degree; 1 = Graduated from primary school; 0 = Illiteracy
Income	*Income*	Household per capita income, unit: CNY
Medical insurance	*Insurance*	1 = People with medical insurance; 0 = Others
Place of residence	*Urban*	1 = Urban; 0 = Rural
Smoking	*Smoke*	1 = Smoke; 0 = Others
Drinking	*Drink*	1 = Drink alcohol; 0 = Others
Level of economic development	*GDP*	GDP; Unit: CNY 100 million
Medical resources	*MR*	# Hospitals and health centers
# Inversion days	*Inversion*	Unit: Day

Data sources: Temperature inversion data are from the NASA. PM2.5 data are from Columbia University International Geoscience Information Network Center. Economic development level and medical resource data are from the CSMAR database. Other variables are from the CHNS.

Table 2
Summary statistics of key variables.

Variables	Mean	SD	Min	Max
MH	9.175	2.295	3	15
PM2.5	49.269	13.561	18.543	86.300
Age	65.816	7.893	55	100
Gender	0.496	0.500	0	1
Marriage	0.835	0.372	0	1
Education	1.385	1.400	0	6
Income (Ln)	9.038	1.470	0	12.965
Insurance	0.874	0.332	0	1
Urban	0.397	0.489	0	1
Smoke	0.329	0.470	0	1
Drink	0.296	0.456	0	1
Inversion	26.074	10.342	0	48
GDP	2322.954	2524.888	234.150	15,717.270
MR	211.476	128.470	66	1568

Note: Sample size is 7514.

concentration of prefecture-level cities in China from 1998 to 2016 into specific values. The missing data are filled, and measurement errors are reduced. In addition, PM2.5 is selected as a proxy variable for air pollution due the following reasons: 1) Compared with other pollutants, PM2.5 is highly active and easily carries toxic, harmful substances (Pandey et al., 2013). It not only penetrates into the gas exchange area of the lungs (Pinkerton et al., 2000) but also further enters the circulatory system through the respiratory barrier and spreads throughout the body (Wang et al., 2013). 2) PM2.5 is more harmful to human health due to its long residence time in the air and long diffusion distance. Considering that satellite data may be affected by climatic factors, Chen et al. (2017) compared the above data with the disclosure by the China Environmental Monitoring Station of the Ministry of Ecology and Environment, and found minimal difference between them, which shows the validity of the data. Finally, due to the short disclosure period of the latter (starting in 2013), the latter data are not used.

As mentioned earlier, air pollution is potentially endogenous, so the number of inversion days is used as an instrumental variable. NASA provides gridded data on global surface temperature every six hours. Each grid data covers a range of 50 km × 60 km, the height starts from 110 m, and the vertical height layers total 42. This paper refers to the method of Arceo et al. (2016) to calculate the number of temperature inversions per day and aggregate by city limits. Four observations are made per day, and the criterion for selecting a temperature inversion day is that more than half of the temperature inversion phenomena occurs in a day. Finally, the data are added by year, and then the yearly data on the number of inversion days for each city are obtained.

Referring to previous studies on air pollution (Yang & Zhang, 2018; Zhang et al., 2018), this paper selects age, marital status, income, and education level as the control variables. Considering that smoking and drinking status may lead to respiratory,

cardiovascular, and cerebrovascular diseases, these two variables are also included. Macroeconomic development level and local medical resource indicators, which affect the mental health of individuals, are included. Finally, the data are matched at the prefecture-level city level.[6] Table 1 shows the metrics used in the regression.

Table 2 Summary statistics for variables used in basic regression. For mental health, the average value is about 60 % of the maximum value, indicating that the overall mental health level of the elderly population in my country is between "neutral" (3 points) and "approval" (4 points). The mean value of the air pollution index PM2.5 is 49.27 μg/m^3, and the standard deviation is 13.56. This result shows that air pollution is more serious, and regional variability is large, which is suitable for a more in-depth study of the sample. The sample age is over 55 years old, the average is around 65 years old, and the ratio of male to female is relatively close. At the education level, the average value of the indicator is 1.385, which corresponds to the sample's education level between "graduated from elementary school" and "graduated from junior high school." This result is consistent with the situation of difficulty in obtaining an education in the early year. Among the survey samples, the coverage rate of medical insurance is over 87 %. Moreover, about 30 % of individuals have the habit of smoking or drinking. The temperature inversion is about 26 times a year, accounting for about 7 % of the year.

4. Empirical strategy

Considering the effect of air pollution on mental health faces potential endogeneity problems, this paper follows the 2SLS method for estimation, and the specific model is set as follows:

$$Health_{it} = \beta_0 + \beta_1 airpollution_{it} + \beta_2 X_{it} + \alpha_i + \rho_t + \varepsilon_{it}, \tag{1}$$

$$airpollution_{it} = \gamma_0 + \gamma_1 IV_{it} + \gamma_2 X_{it} + \alpha_i + \rho_t + \nu_{it}, \tag{2}$$

where $Health_{it}$ is the mental health level of individual i on period t. $airpollution_{it}$ is the air pollution status of individual i in period t, which is represented by PM2.5 concentration. IV_{it} is the number of inversion days in the city where the individual is located. The control variables include age, income, level of economic development, medical resources, and dummy variable for personal characteristics. Vector X_{it} is a set of these controls. α_i and ρ_t are the individual and time fixed effects. $\varepsilon_{it}, \nu_{it}$ are disturbance terms. Standard errors clustered to the individual level.

Endogeneity has three main sources. First, a measurement error exists in air pollution. On the one hand, the mobility of individuals over the life cycle allows for differences between exposure and monitoring levels. On the other hand, a certain distance is observed between the monitoring point and the resident survey point, which also leads to the measurement error of air pollution. Second, the complex, diverse influencing factors of mental health lead to the existence of omitted variable bias. For example, residents may opt to "vote with their feet" to find a more livable place due to the serious pollution of the current living environment. Moreover, in heavily polluted areas, people with poor health may migrate, whereas individuals with better health stay. The health effects of air pollution are probably underestimated. Finally, a simultaneous equation bias exists between air pollution and health effects. In recent years, as the concept of "lucid waters and lush mountains are invaluable assets" has taken root in the hearts of the people, local governments have stepped up efforts to control air pollution. Therefore, a case of reverse causality. Briefly, endogeneity problems are almost unavoidable.

Endogenous problem solving relies on exogenous shocks, which can be overcome by finding instrumental variables and quasi-natural experiments. This paper uses the number of inversion days as an instrumental variable. In general, the higher the altitude is, the lower the temperature. However, due to climatic reasons, within a certain altitude range, an increase in altitude and an increase in temperature may be observed. This phenomenon is called "temperature inversion," which makes spreading difficult for air pollutants. Therefore, a strong correlation is noted between inversion temperature and air pollution. Temperature inversion is caused by random exogenous climate changes, and it has difficulty affecting individual mental health in the short term, so the exogenous nature of temperature inversion can be guaranteed. Based on the above explorations, temperature inversion is selected as an instrumental variable for air pollution.

One issue that needs to be discussed is sample selection bias. This problem mainly comes from the migration of samples caused by air pollution. In the short term, individuals may choose to travel (Chen et al., 2021). In the long term, individuals may choose to relocate (Chen et al., 2022a). Especially those individuals who are sensitive to pollution, they may be more prone to air pollution-related diseases. If they live in areas with severe air pollution for a long time, their health may decline. Therefore, individuals who are vulnerable to air pollution are more likely to stay away from air-polluted areas. In the long run, areas with higher levels of pollution will leave individuals with higher levels of health. Areas with lower levels of pollution have many individuals with respiratory illnesses. This fact may lead to bias in the estimated results. We refer to Fu et al. (2021) for their approach to labor mobility. We added individual fixed effects in the regression to mitigate the influence of individual inherent health factors. In addition, in the robustness test, we further limited the migration samples and retained samples with multiple observations to reduce the impact of sample migration on the estimation results.

This paper also focuses on analyzing the mechanisms by which air pollution affects mental health. Therefore, relevant approaches

[6] In the data matching, the sample only includes these years because the data on the mental health of the elderly in CHNS only appeared in 2006, 2009, 2011, and 2015. In the regional matching, the initial survey of China is obtained. Regional data are for eight provinces, so the sample only includes eight provinces and municipalities.

Table 3
Baseline results.

	(1) OLS MH	(2) OLS MH	(3) 2SLS PM2.5	(4) 2SLS PM2.5	(5) 2SLS MH	(6) 2SLS MH
PM2.5	-0.011*	-0.029***			-0.275***	-0.243***
	(0.006)	(0.008)			(0.101)	(0.059)
Inversion			0.241***	0.477***		
			(0.039)	(0.044)		
Age		0.333**		-0.007		0.348*
		(0.152)		(0.345)		(0.178)
Marriage		0.674***		-0.495		0.566***
		(0.190)		(0.347)		(0.199)
Education		-0.003		-0.228**		-0.054
		(0.057)		(0.101)		(0.060)
Income (Log)		0.001		0.035		0.012
		(0.027)		(0.048)		(0.029)
Insurance		-0.580***		-1.959***		-1.035***
		(0.127)		(0.235)		(0.181)
Smoke		0.100		-0.257		0.040
		(0.120)		(0.227)		(0.128)
Drink		0.087		-0.191		0.050
		(0.108)		(0.199)		(0.116)
GDP		0.000***		0.000		0.000***
		(0.000)		(0.000)		(0.000)
MR		-0.011***		-0.042***		-0.020***
		(0.002)		(0.003)		(0.003)
KPF Statistics			37.941	115.780		
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample Size	10,070	7514	10,070	7514	10,070	7514

Note: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level.

are sorted out, and an analysis framework is built. First, as mentioned above, air pollution can directly produce oxidative stress, which can lead to psychological problems such as depression in individuals. Testing this mechanism is difficult for us. We have no way of knowing whether an individual has developed oxidative stress, which is subject to further medical testing. Second, air pollution can affect the physical health of individuals. Individuals are more prone to irritability after developing or increasing the severity of illness, which affects their mental health. In addition, serious illness may limit individual activities and affect individual health. In the end, air pollution can lead to a reduction in outdoor activities, which can lead to psychological problems. For the potential influence pathways mentioned above, the following three-step regression model is constructed.

$$Health_{it} = \alpha_0 + \beta_1 airpollution_{it} + \beta_5 X_{it} + \alpha_i + \rho_t + \varepsilon_{it} \tag{3}$$

$$M_{it} = \alpha_0 + \beta_2 airpollution_{it} + \beta_5 X_{it} + \alpha_i + \rho_t + \varepsilon_{it} \tag{4}$$

$$Health_{it} = \alpha_0 + \beta_3 airpollution_{it} + \beta_4 M_{it} + \beta_5 X_{it} + \alpha_i + \rho_t + \varepsilon_{it} \tag{5}$$

Eq. (3) is consistent with Eq. (1). M_{it} is the mediating variable reflecting the mechanism. The remaining variables are consistent with the previous ones. Eq. (4) can test whether the mediator variable is affected by air pollution. Eq. (5) includes the mediator variable and air pollution at the same time, and observes how the coefficient of air pollution changes. Preacher and Kelley (2011) elaborated on how the model judges whether a mediating effect exists. First, the mediating effect exists only when β_1 and β_2 are significant, and the economic implication is that air pollution affects mental health and mediating variables. Next, the significance of β_3 and β_4 is determined. When β_4 is not significant, although air pollution has an effect on the mediator variable, the mediator variable has no effect on mental health, which means the mechanism is not complete. A partial mediation effect exists if $\beta_4$and β_3 are both significant. If β_4 is significant but β_3 is not, then it shows a relatively rare complete mediation effect. The size of the mediating effect can be obtained by calculating the difference. In this model, temperature inversion is used as an instrumental variable when the explanatory variable is air pollution.

5. Results

5.1. Effects of air pollution on mental health

Table 3 uses OLS to estimate Eq. (1), and Eqs. (1) and (2) are estimated using the 2SLS method. Column (1) of Table 3 first makes a simple estimate of air pollution and mental health. A negative correlation is observed between air pollution and mental health. Column (2) of Table 3 includes individual control variables, and the air pollution coefficient is more significant. Considering the potential

Table 4
Correlation coefficient.

	MH	*MH1*	*MH2*	*MH3*
MH	1			
MH1	0.816***	1		
MH2	0.868***	0.573***	1	
MH3	0.817***	0.455***	0.599***	1

Note: * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level.

Table 5
Air pollution and mental health subindicators.

	(1) OLS *MH1*	(2) 2SLS *MH1*	(3) OLS *MH2*	(4) 2SLS *MH2*	(5) OLS *MH3*	(6) 2SLS *MH3*
PM2.5	-0.010***	-0.062***	-0.009***	-0.064***	-0.010***	-0.117***
	(0.003)	(0.024)	(0.003)	(0.023)	(0.003)	(0.024)
KPF statistic		115.780		115.780		115.780
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	7514	7514	7514	7514	7514	7514

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3.

endogeneity problem, OLS can only provide their correlation. Endogeneity is further considered, using 2SLS for estimation. Before proceeding with 2SLS estimation, the validity of instrumental variables needs to be discussed. As mentioned above, the exogenous nature of temperature inversion is guaranteed to some extent. For the correlation of instrumental variables, many studies have found that the occurrence of temperature inversion hinders the spread of air pollution, and the correlation between inversion temperature and air pollution can be tested. Columns (3) and (4) of Table 3 report the first-stage regressions under different control variables. Both coefficients are positive and significant at the 1 % significance level, so our conjecture is confirmed. The minimum KPF statistic is 37.941, which is greater than the critical value of 16.38 under the 10 % standard, so too much concern about weak instrumental variables is not needed. Columns (5) and (6) of Table 3 report the second-stage regressions corresponding to Columns (3) and (4). Comparing the estimates of OLS and 2SLS reveals that the coefficients differ by a factor of about 8, and OLS severely underestimates the effect of air pollution on mental health. This finding can be interpreted in two ways: 1) When faced with endogeneity problems, measurement errors of explanatory variables can lead to a biased decay of estimated coefficients. 2) Individual precautionary behavior makes the sample selection bias, which also leads to the underestimation of OLS estimates. Combined with the above, based on considering endogeneity, air pollution has a negative effect on mental health, which is easily underestimated. Each 10 $\mu g/m^3$ increase in air pollution causes a decrease of 2.43 points in mental health (full score 15 points). Currently, the average concentration of air pollution in the sample is 49.267 $\mu g/m^3$, and the average mental health score is 9.175. According to the requirements for PM2.5 concentration in the "Ambient Air Quality Standard" promulgated by China in 2016, the first- and second-level concentration thresholds are 15 and 35 $\mu g/m^3$, respectively. If air quality reaches the threshold of the first-level concentration, pollution drops by 34.267 $\mu g/m^3$ (69.554 %), and mental health level increases by 8.327 (90.757 %) which is close to the full score at this time. The average effect is estimated, and the conclusion is more applicable to small changes at the mean. If air quality reaches the second-level concentration threshold, pollution drops by 14.267 $\mu g/m^3$ (28.959 %), and mental health increases by 3.467 (37.787 %). These results suggest that mental health improves dramatically when air quality is up to standard.

From the perspective of control variables, a positive correlation exists between age and mental health, which is inconsistent with the results of some studies. One possible reason is that as the age of the elderly increases, individuals constantly adjust their state to adapt to life. Another reason is that older people receive more chaperones despite declining individual health. Having a spouse significantly improves the mental health of older adults. Contrary to our experience, a negative relationship exists between individuals' purchase behavior of health insurance or local medical resources and mental health possibly as a result of individual self-selection. Individuals with poor mental health opt to buy medical insurance for themselves and seek better medical resources to settle in areas. Moreover, a positive relationship exists between the level of local economic development and mental health.

The mental health index is constructed by combining three subindicators, and more information needs to rely on the analysis of the three subindicators. Table 4 shows the correlation between the mental health index and the three sub-indicators. A high correlation exists between the mental health index and the subindicators, whose values exceed 0.8 and within the 1 % significance level. It shows that the three subindicators can also reflect the content of each subindicator. The correlation coefficient is also higher than 0.4 among the subindicators, which implies that the three subindicators consistently reflect the individual's mental health status.

Considering the high correlation between the three subindicators, the three subindicators are analyzed separately. The results are summarized in Table 5. Columns (1) and (2) report the results for subindicator 1, Column (1) uses OLS estimation, and Column (2) uses temperature inversion as an instrumental variable for 2SLS estimation. Similarly, Columns (3)–(6) report the OLS estimates and 2SLS

Table 6
Robustness check: using different metrics.

	(1) *MH*	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	-0.243***					
	(0.059)					
$PM_{2.5}\_Max$		-0.209***				
		(0.051)				
$PM_{2.5}\_Min$			-0.255***			
			(0.062)			
$Ln\_PM_{2.5}\_Mean$				-9.200***		
				(2.181)		
$Ln\_PM_{2.5}\_Max$					-11.823***	
					(2.817)	
$Ln\_PM_{2.5}\_Min$						-9.047***
						(2.161)
KPF statistic	115.780	141.833	143.389	188.840	195.248	166.401
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	7514	7514	7514	7514	7514	7514

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3.

Table 7
Robustness check: more than two observations.

	(1) *MH*	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	-0.276***					
	(0.061)					
$PM_{2.5}\_Max$		-0.241***				
		(0.052)				
$PM_{2.5}\_Min$			-0.291***			
			(0.064)			
$Ln\_PM_{2.5}\_Mean$				-10.527***		
				(2.239)		
$Ln\_PM_{2.5}\_Max$					-13.599***	
					(2.904)	
$Ln\_PM_{2.5}\_Min$						-10.285***
						(2.212)
KPF statistic	112.196	136.900	137.941	179.476	190.459	160.031
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	6226	6226	6226	6226	6226	6226

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3.

estimates of subindicators 2 and 3 in turn. OLS does not consider endogeneity and underestimates the effect of air pollution on the three subindicators, which may be caused by measurement errors and omitted variables as analyzed previously.

5.2. Robustness checks

To verify the robustness of the results, three types of robustness tests are mainly conducted. (1) Substitute core explanatory variables. First, the core explanatory variable PM2.5 is replaced. Air quality index is a commonly used indicator, but it has been published since 2013, resulting in a small overlap with our sample, which may affect the accuracy of the estimate. Based on this, the maximum and minimum values of PM2.5 at the prefecture-level city level are use as proxy indicators. The true value of individual exposure to pollution is largely between the annual maximum value and the minimum value of the local city. Second, in addition to using maximum and minimum values, the explanatory variable of the log-transformed is used to examine its sensitivity to the functional form. (2) Test for endogeneity. Instrumental variables are used to address the endogeneity of the health effects of air pollution. However, individuals who are sensitive to air pollution may choose to relocate to areas with better air quality. Instrumental variables have limitations because this problem cannot be necessarily solved effectively. As such, our results underestimate the health effects of air pollution, making our results unreliable. Fortunately, the CHNS conducts reinvestigations every three years on average, and the behavior of “voting with your feet” can be quantified. Specifically, the number of sample observations is limited: If an individual is

Table 8
Robustness check: samples over 60 years old.

	(1) *MH*	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	-0.242***					
	(0.074)					
$PM_{2.5}\_Max$		-0.199***				
		(0.060)				
$PM_{2.5}\_Min$			-0.289***			
			(0.090)			
$Ln\_PM_{2.5}\_Mean$				-8.971***		
				(2.687)		
$Ln\_PM_{2.5}\_Max$					-11.278***	
					(3.389)	
$Ln\_PM_{2.5}\_Min$						-9.677***
						(2.956)
KPF statistic	75.733	101.808	73.153	125.437	136.561	92.015
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	5075	5075	5075	5075	5075	5075

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3.

Table 9
Air pollution and mental health: gender and urban–rural differences.

	(1) *MH*	(2)	(3)	(4)
PM2.5	-0.186**	-0.289***	-0.054	-0.310***
	(0.093)	(0.077)	(0.079)	(0.079)
Subsample:				
Female	Yes	No	No	No
Male	No	Yes	No	No
Urban	No	No	Yes	No
Rural	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
KPF statistic	46.902	69.537	60.772	63.913
Sample size	3786	3728	2984	4530

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3.

observed at every survey during our sample period, it indirectly indicates that the individual is not relocated, that is, a negative correlation exists between the number of observations and the likelihood of relocation. The regression results of samples with more than two observations are further reported. (3) Analysis of sample age selection. China's statutory standards are further used for robustness testing because the definition of the elderly by the CHNS is different from the Law of the People's Republic of China on the Protection of the Rights and Interests of the Elderly.

Table 6 reports the results of the first robustness test. The maximum and minimum values of PM2.5 negatively affect mental health. The logarithm of the mean, maximum, and minimum values are further evaluated. The KPF statistics in the first stage are all above 100, so worrying about weak instrumental variables is not needed. Table 7 reports the results of the second robustness test. The results are consistent with Table 6, indicating that our results are robust. After limiting the sample, the coefficient increases slightly. The reasons can be summed up in two points. First, these small changes may result in different estimates due to reduced sample size. Second, in Table 7, the samples are less mobile, live in one place for a long time, and hardly "vote with their feet," so they are more affected. Some individuals may have been relocated due to air pollution before the survey, and the data obtained are all the results of the relocation. Using data to test this situation is difficult for us. Fortunately, the observations are mainly concentrated before 2013, when individuals were less concerned about air pollution (the detection of air quality in China is mainly after 2013). Therefore, the slight coefficient increase is likely due to residents not relocating. Table 8 reports the results for the samples over 60 years old, and the results are unchanged.

5.3. Heterogeneity analysis

From the perspective of human health, large differences are observed in the status of different groups of people. Therefore,

Table 10
Air pollution and mental health: differences in income and education.

	(1) *MH*	(2)	(3)	(4)
PM2.5	-0.158**	-0.379***	-0.116	-0.343***
	(0.079)	(0.122)	(0.093)	(0.083)
Subsample:				
High income	Yes	No	No	No
Low income	No	Yes	No	No
High education	No	No	Yes	No
Low education	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
KPF statistic	53.603	33.442	38.649	66.533
Sample size	3144	3121	2717	4296

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3. The sum of the subsample sizes is less than the total sample size. When estimated using the "ivreghdfe" command in Stata, drop singleton groups are dropped. See Correia (2015) for details.

heterogeneity analysis is conducted from four aspects of gender, residence, income, and education level.

In general, men are exposed to air pollution by performing more outdoor physical work. Therefore, the sample is divided according to gender. Columns (1) and (2) of Table 9 report the regression results of male samples and female samples, respectively. Air pollution affects males more than females. The sample is divided according to the place of residence due to the possibility of regional heterogeneity. Columns (3) and (4) of Table 9 report the regression of urban samples and rural samples, respectively. Rural populations are more vulnerable to air pollution. It may be related to the behavior of rural individuals. Many agricultural activities are carried out outdoors, making rural residents more vulnerable to air pollution.

From the perspective of residents' health, the improvement of family income and education level is conducive to improving the health of residents (Conti et al., 2010; Gerdtham et al., 1992). Residents with different income levels and education levels respond dissimilarly to air pollution. For example, high-income people may relocate their families when facing high pollution. A close relationship exists between income and education, with higher education levels leading to higher income levels. In addition, more educated individuals work mainly indoors, which also reduces the effect of air pollution on them.

The sample is divided into two groups of high income and low income, using the median income as the cut-off point. Columns (1) and (2) of Table 10 are samples with income greater than or less than the median. The mental health of low-income individuals is more susceptible to pollution, in line with our expectations.

In terms of educational attainment, the elderly population is born earlier, and the access to education is not comparable to that nowadays. The average level is between primary and junior high school levels, and the two groups of samples are divided with the median as the boundary. Columns (3) and (4) of Table 10 are the high- and low-education groups, respectively. The results show that the low education group is more susceptible to air pollution.

5.4. Mechanism analysis

Several lines of evidence from the medical field suggest that air pollution may directly affect the mental health of individuals and can influence the mental health of individuals by suffering from respiratory, cardiovascular, and cerebrovascular diseases. Individual activities can also affect mental health. Air pollution may reduce outdoor activities and affect residents' mental health. Both types of mechanisms are examined.

The indirect mechanism of air pollution is the transmission mechanism of the condition from the body to the mental health through the occurrence of the disease in the individual. This mechanism is consistent with our cognition that when a disease occurs, individuals are prone to irritability and anxiety, which in turn affects their mental health. The CHNS provides some indicators for individual health status, and "During the past 4 weeks, have you been sick or injured? Have you suffered from a chronic or acute disease?" (*Illness*) is used as the indicator of disease.[7] "How severe was the illness or injury?" (*Severity*) is used as an indicator of illness severity.[8] This indicator is aimed at patients with the disease, which seriously reduces the sample size. For this reason, the individual without the disease is assigned a value of 0. "Was it an outpatient or inpatient visit?" (*Hospital*) is used as an objective measure of disease severity.[9] Compared with the former, outpatient or inpatient treatment more objectively reflects the severity of the disease. The indicator "Right now, how would you describe your health compared to that of other people your age?" (*Health*) to is used reflect self-rated health.[10]

[7] Three options are given for the onset of the disease: 0 (no), 1 (yes), and 9 (unknown). Samples with a value of 9 are excluded.
[8] Disease severity has three options: 1 (not severe), 2 (somewhat severe), and 3 (quite severe).
[9] 0 (outpatient), and 1 (inpatient).
[10] Self-assessment of health status has six options: 1–5 (very good–very poor), 9 (unknown). In the sample, this question only appeared in the questionnaires in 2006 and 2009, and the value of 9 is eliminated.

Table 11
Mechanism analysis: health status.

	(1) *MH*	(2) *Illness*	(3) *MH*	(4) *Severity*	(5) *MH*	(6) *Health*	(7) *Hospital*
PM2.5	-0.243***	0.025***	-0.234***	0.039**	-0.223***	0.045	-0.025
	(0.059)	(0.010)	(0.058)	(0.017)	(0.057)	(0.034)	(0.055)
Illness			-0.293***				
			(0.091)				
Severity					-0.162***		
					(0.048)		
Mediation effect			0.009		0.020		
KPF statistic	115.780	115.534	117.625	118.612	119.659	28.183	2.548
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	7514	7489	7489	7353	7353	1122	543

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3.

Table 12
Mechanism analysis: outdoor activities.

	(1) *MH*	(2) *Walking*	(3) *Sports*	(4) *Body building*
PM2.5	-0.243***	0.017	0.015	0.012
	(0.059)	(0.028)	(0.022)	(0.025)
KPF statistic	115.780	114.836	114.836	114.677
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Sample size	7514	7493	7493	7492

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3.

It should be noted that self-rated health serves as the underlying mechanism. There may be two different impacts. First, there is a correlation between self-rated health and physical health. Therefore, self-rated health can be regarded as a proxy variable of physical health. Although some sub-healthy people do not have the disease, they also feel unwell in their daily lives. If disease is used as an indicator of health status, the difference between healthy and sub-healthy groups is not obvious. Self-rated health has certain advantages in this respect. Therefore, the channel through which self-rated health affects mental health is close to that of illness. Second, there are certain particularities in self-rated health. Individuals with better mental health tend to be more positive about life. This can lead to mentally healthy individuals having higher ratings of their own health. Therefore, the result is the combined result of these two effects.

Table 11 reports the estimated results of health status. In the estimation of Eq. (4), the condition and severity of the disease are significant, whereas the self-assessed health and hospitalization are not, and the reason may be the small sample size. The data on self-assessed health only appeared in the questionnaires in 2006 and 2015, and Column (7) is for individuals who are already ill. They were for individuals who were already ill. Unexpectedly, increased severity of pollution-induced illness has a greater effect on mental health than pollution-induced illness on the individual's mind. The mediation effect of the former is 0.009 (3.70 %), that of the latter is 0.020 (8.23 %).

In addition to health status, individual activities can influence mental health. Individual preference for outdoor activities decreases when the air pollution is serious, and they prefer indoor activities. Spending too much time indoors can trigger mental health effects. This channel is analyzed. CHNS contains data on physical activity preferences of individuals, including six aspects: "walking, Tai Chi," "sports (ping pong, badminton, tennis, soccer, basketball, and volleyball)," "body building," "watching TV," "playing computer/video games, surfing the Internet," and "reading."[11] The first three are classified as outdoor activities, and the last three as indoor activities.

Table 12 reports the estimated effect of pollutants on outdoor activities, which use the 2SLS estimation method. The results do not reflect a reduction in the frequency of outdoor activities due to air pollution. The inaccurate measure of outdoor activity may be the reason for the insignificant results. The above outdoor activities can often be performed indoors as well. Tai chi and some fitness activities can also be performed indoors. Therefore, air pollution may cause individuals to move indoors for activities. Limited by data, outdoor activities need more accurate variables to describe.

Table 13 further reports the results of the indoor activities. Air pollution reduces mental health levels by increasing indoor activity,

[11] The six optional physical activity preferences are 1–5 (dislike very much–like very much) and 9 (does not participate). To reflect the preference order and ensure the sample size, the corresponding value of not participating is changed by converting 9–0.

Table 13
Mechanism analysis: indoor activities.

	(1) *MH*	(2) *TV*	(3) *Internet*	(4) *Reading*	(5) *MH*
PM2.5	-0.243***	0.032	0.005	0.076***	-0.229***
	(0.059)	(0.021)	(0.021)	(0.027)	(0.058)
Reading					-0.202***
					(0.040)
mediation effect					0.014
KPF statistic	115.780	115.329	113.873	114.704	120.472
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Sample size	7514	7499	7490	7491	7491

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3.

Table A1
Effects of air pollution on indoor and outdoor workers.

	(1) *MH*	(2) *MH*	(3) *MH*	(4) *MH*
PM2.5	-0.468	-0.280	-0.361	-0.228**
	(0.587)	(0.193)	(0.382)	(0.090)
Subsample:				
Indoor work	Yes	No	No	No
Outdoor work	No	Yes	No	No
Indoor work in 1989	No	No	Yes	No
Outdoor work in 1989	No	No	No	Yes
KPF statistic	1.526	9.777	4.250	48.788
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Sample size	353	1223	1398	3025

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3. Outdoor work includes farmer, fisherman, hunter (B4_05 in CHNS), non-skilled worker (ordinary laborer, logger, B4_07 in CHNS), ordinary soldier, policeman (B4_09 in CHNS), and driver (B4_10 in CHNS).

Table A2
Outdoor work and individual activities.

	(1) *Walking*	(2) *Sports*	(3) *Body building*	(4) *TV*	(5) *Internet*	(6) *Reading*
Outdoor Work	-0.046	0.040	-0.003	0.028	-0.147	-0.238*
	(0.170)	(0.125)	(0.137)	(0.095)	(0.116)	(0.126)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	1735	1735	1735	1738	1735	1734

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3.

which increases preference for reading, but not TV viewing and online gaming. The mediating effect is 0.014, accounting for 5.76 % of the total effect.

There are two issues that need attention in the analysis of indoor and outdoor activities. First, whether indoor and outdoor activities are closely related to the nature of work of the elderly. Experienced long-term working conditions have had a profound impact on the living habits of the elderly. Past or current work will also create inertia for indoor and outdoor activities. We wanted to know whether the mental health of older adults who worked outdoors was more vulnerable to air pollution. Table A1 reports the heterogeneous effect of occupation of older adults. We recoded data on occupation from the CHNS questionnaire. Outdoor work includes farmer, fisherman, hunter (B4_05 in CHNS), non-skilled worker (ordinary laborer, logger, B4_07 in CHNS), ordinary soldier, policeman (B4_09 in CHNS), and driver (B4_10 in CHNS). Columns 1 and 2 in Table A1 report the impact of air pollution on indoor and outdoor workers, respectively. We found no significant difference between the two. This may be because there are not many elderly people who are still working at this stage, and the sample is too low to be significant. To avoid the bias caused by the low sample size, we use the working

Table A3
The role of reading between outdoor workers and indoor workers.

	(1) *Reading (Indoor Work in 1989)*	(2) *Reading (Outdoor Work in 1989)*
PM2.5	0.067*	0.360
	(0.036)	(0.225)
Controls	Yes	Yes
Year FE	Yes	Yes
Individual FE	Yes	Yes
Sample size	1392	3012

Notes: Standard errors are clustered at the individual level and reported in parentheses. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level. Controls include all controls in Table 3.

data of the first wave of CHNS survey in 1989. The results showed that outdoor workers were more vulnerable to air pollution. This shows that job attributes will lead to heterogeneous effects on air pollution, and this effect remains after old age.

Second, why reading has a negative impact on mental health. In the previous analysis, we regarded reading as an indoor activity, and increasing indoor activities will crowd out outdoor activities. But there may be some doubts about this claim. Reading also has the effect of increasing mental health, which can even outweigh the negative effects of reducing outdoor activities. To further analyze the impact mechanism of reading, we compare the benefits of reading in different groups. Indoor workers tend to have more time to read. Consequently, the marginal mental health benefits of increasing their reading tend to be small. Due to long-term outdoor activities, outdoor workers tend to spend less time reading than indoor workers. Therefore, the marginal mental health benefits of increasing their reading tend to be large. Table A2 discusses the differences between indoor and outdoor workers in different activities. We found that the differences were most pronounced in reading. Indoor workers are more inclined to read in old age. Table A3 discusses which groups of people read air pollution exactly. We found that air pollution increases reading for indoor workers. But the benefits of reading for indoor workers are lower in terms of mental health, which may be lower than the benefits of outdoor activities. Therefore, reading reduces mental health, mainly for indoor workers. Their benefits from reading may be lower than those from outdoor activities. Therefore, too much indoor reading and neglect of outdoor activities may reduce their mental health.

Overall, these results indicate that air pollution may reduce mental health of individuals by affecting physical health and increasing indoor activity. The mediating effect of these potential mechanisms account for about 17.69 % of the total effect. Therefore, this paper only initially explores the mechanism, and other potential mechanisms cannot be fully tested.

6. Conclusion

This paper empirically analyzes the influence of air pollution on the mental health of the elderly by matching mental health data from the CHNS and air pollution data. The results show that a 10 $\mu g/m^3$ increase in air pollution causes a decrease of 2.43 points in mental health (out of 15 points). The robustness of the basic conclusion is further demonstrated by changing explanatory variables, functional forms, and restricted samples. Another important finding is that air pollution affects mental health more significantly in men, rural residents, low-income people, and people with less education. For potential mechanisms, both pathways are tentatively examined through individual health status and individual activity. First, air pollution reduces individual mental health by increasing the incidence and severity of disease. Second, air pollution increases individual preference for indoor sports activities and further reduces individual mental health. Our paper enriches the literature on the health effects of air pollution. However, the potential mechanism of air pollution affecting mental health needs to be further investigated due to the lack of more accurate data. Further progress can still be made in investigating the effects of different pollutants on mental health. On the one hand, the correlation between various pollutants is high, which is prone to multicollinearity problems. On the other hand, temperature inversion affects not only PM2.5 but also other pollutants.

These experiments confirm that air pollution negatively affects older adults' mental health. Under the background of population aging, this provides some inspiration for improving the quality of life of the elderly population. First, strengthening the attention to the mental health of the elderly population, establishing a sound monitoring mechanism, and popularizing the knowledge about the prevention of mental diseases and disorders are necessary. At present, the health policy of the elderly mainly focuses on physical health, which only involves the management of chronic diseases, and does not pay enough attention to their mental health. Therefore, regular mental health tests should be carried out for the elderly while paying attention to physical and mental health. Second, monitoring the mental health of key groups in the elderly population according to the conditions of the population is necessary. The group of men, rural residents, low income, and low education are more vulnerable to air pollution. Health departments should focus on the mental health of these groups. Finally, the living environment for the elderly needs to be improved. The possibility of "voting with your feet" is lower, resulting from less mobility of the elderly population. Therefore, the living environment of the elderly population needs to be improved, especially nursing homes in many rural areas. Moreover, the activity facilities for the elderly must be improved to encourage them to engage in outdoor activities.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See Appendix Tables A1–A3.

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