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Air pollution, residents' concern and commercial health insurance's sustainable development

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As Chinese residents are increasingly concerned about environmental and health issues, the importance of commercial health insurance has come to the fore. Therefore, it is necessary to study the relationship and mechanism between air pollution and commercial health insurance. This paper empirically analyzes the impact and mechanism of air pollution on the sustainable development of Chinese commercial health insurance. The analysis is conducted using the IV-probit and IV-tobit models with thermal inversion as the instrumental variable for air pollution, with Chinese households as the study population and 2018 as the study period. The results show that $PM_{2.5}$ concentration has a positive and significant effect on both household participation in commercial health insurance and the level of participation, and that residents' concern is an important channel linking air pollution and commercial health insurance, where pollution reporting plays a negative transmission role, protective behaviors play a positive transmission role, and healthy depreciation plays a positive transmission role. The results of this study contribute to the comprehensive development of China's social security system and the sustainable development of the commercial health insurance market.

KEYWORDS

air pollution, commercial health insurance, sustainable development, thermal inversions, pollution reporting, protective behaviors, healthy depreciation

1 Introduction

Since the occurrence of several severe haze events in China in 2013, the issue of air pollution has become an issue of great concern for Chinese residents, second only to corruption (Wike and Parker, 2015). In 2014, China treated haze as a natural calamity that endangers public health. Haze pollution consists mainly of $PM_{2.5}$ pollution, and the Chinese government believes that the first step in combating air pollution is to control $PM_{2.5}$ concentration. China has also clearly stated in its 14th Five-Year Plan that it will continue to improve environmental quality, enhance awareness of the ecological and environmental protection of society as a whole, and comprehensively fight the battle against pollution. With China's increased efforts to combat environmental pollution, the country's air pollution problem has been gradually addressed and the concentration of air pollutants is gradually decreasing every year; however, there are still many areas where air pollution remains a serious problem. According to the 2019 national air quality figures released by China's

Ministry of Ecology and Environment, 46.6% of the 337 prefecture-level cities met ambient air quality standards, compared to 24.85% in 2016, a considerable improvement but still less than half. Air pollution is not only a matter of national image and economic growth, but also a constant threat to public health.

The impact of air pollution on the physical and mental health of the population cannot be underestimated, as it can directly or indirectly cause short-term and even long-term damage to the human body, increasing the risk of human health issues (Archsmith et al., 2018), such as a shortening life expectancy *per capita* (Chen et al., 2013; He et al., 2016), inducing respiratory diseases (Chay and Greenstone, 1999; Moretti and Neidell, 2009) and increasing the chance of lung cancer (Brunekreef and Holgate, 2002). The effects of air pollution on human health are not only physiological, but also psychological, as residents may experience negative emotions, such as anxiety and depression, as a result of air pollution (Tian et al., 2015; Kim et al., 2020; Pun et al., 2017). In addition to the physical and psychological harm, air pollution also increases the burden of medical costs on residents (Jerrett et al., 2003; Narayan and Narayan, 2008; Zhang et al., 2008; Hou et al., 2012) and reduces family wellbeing (Levinson, 2009; Luechinger and Raschky, 2009; Ferreira et al., 2013). In order to address these issues, commercial health insurance is an effective way to protect the health interests of residents, in addition to combating environmental pollution (Graff Zivin and Neidell, 2013). Commercial health insurance helps to alleviate the pressure on residents' associated medical costs (Fisher, 2003), is an important way to reduce the financial burden of the medical treatments associated with air pollution, and assists in improving family wellbeing (Hadley and Waidmann, 2006). There are numerous studies on environmental pollution and residents' health, but in the research system of the impact of air pollution on commercial health insurance, there is little discussion on the mechanism of air pollution on commercial health insurance. We refer to the relevant literature (Zhang et al., 2018; Ito and Zhang, 2020; Sun et al., 2021a) and then investigate the mechanism of residents' concern as a potential channel for air pollution to affect commercial health insurance.

It is therefore important to study the relationship and mechanism between $PM_{2.5}$ and commercial health insurance participation, not only to help residents understand the negative effects of air pollution so that countermeasure policies can be formulated to improve household welfare, but also to provide a reference for the sustainable development of commercial health insurance for insurance companies.

The main contributions of this paper are as follows: First, in this paper, in order to investigate the relationship between air pollution and household participation behaviors in commercial health insurance, we have used China Household Finance Survey (CHFS) data from a micro perspective to investigate whether air pollution leads households to increase the likelihood and extent of spending on commercial health insurance. Second, we explored the mechanisms of air pollution, residents' concern and commercial health insurance by using residents' concern as a potential channel, providing new perspectives and experiences for mechanism research in this direction. At the same time, the above findings help the comprehensive development of China's medical system and social security system to provide benefits to residents, and moreover, help insurance companies to understand the influencing factors and mechanisms of commercial health insurance products, which are conducive to the sustainable development in commercial health insurance.

2 Literature

With the rapid economic and technological development of modern society, the consumption of environmental resources has become costly and the physical and mental health of the residents has been affected, while highlighting the importance of commercial health insurance (Gong et al., 2019). The role played by commercial health insurance in reducing the cost of healthcare for residents has also contributed to its rapid growth. However, the rapid growth of China's commercial health insurance market has been accompanied by the unhealthy development of commercial health insurance, such as the problem of unbalanced distribution of insurance resources and regions, and the problem of commercial health insurance becoming a luxury that is difficult for low-income residents to consume (Li, 2022). In order to solve the above problems, it is particularly important to identify the factors influencing commercial health insurance, which can contribute to the healthy development of the commercial health insurance market and make an important contribution to improving the social healthcare system (Wu et al., 2020). In order to find out what factors influence commercial health insurance, scholars have conducted a large number of empirical and theoretical studies. The collection and accumulation of the above literature on the factors influencing commercial health insurance will help us to examine the body of empirical research on commercial health insurance and to refine the missing variables.

Early scholars provided detailed summaries of the influences on health insurance, broadly grouped into three main categories: economic, social and legal-political. In addition, a number of scholars have explored new influencing factors (Zietz, 2003; Hussels et al., 2005; Outreville, 2013). In the following, we present some studies on the factors influencing the purchase of commercial health insurance. Using data from individual community micro-surveys to examine the impact of residents' risk attitudes and self-assessed health (SAH) on the purchase of voluntary private health insurance (VPHI), it was found that SAH has a negative impact on VPHI (Tavares, 2020). An empirical study based on data from the Chinese General Social Survey (CGSS) and a Probit model found that household internet use significantly increased the likelihood of purchasing commercial health insurance (Xu et al., 2022). In addition to these results, other studies in the literature have found that educational level, marital status and social health insurance also have an impact on commercial health insurance (Cofie et al., 2013; Xiao, 2018; Li et al., 2021). By combining our research on the factors influencing commercial health insurance, we have added influencing factors such as internet use, risk attitude, educational level, marital status and social health insurance. This completes our empirical study and effectively addresses the problem of omitted variables.

Few studies have examined the impact of air pollution on commercial health insurance, and we have only collected the following six papers. Chang et al. (2018) examined insurance policy data from insurance companies and found that severe air pollution led residents to purchase insurance, but when air pollution decreased, residents dropped their insurance. Pi et al. (2019) used data from the China Health and Retirement Longitudinal Study (CHARLS) to examine the relationship between air pollution and household insurance coverage for each type of insurance. Zhao (2020) used CHFS data to examine the relationship between air pollution and household insurance coverage; Chen and He (2021) used CHARLS data to examine the effect of air pollution on health insurance coverage, again using individual health status as a potential channel; Wang et al. (2021) used CHFS data to examine the relationship between air pollution and commercial health insurance; Jia and Yan (2022) used CHFS data to examine the effect of haze pollution on commercial health insurance. Most of the above literature studies on air pollution and commercial health insurance use CHFS data, which indicates that CHFS is a good help for studying the relationship between air pollution and commercial health insurance. Commercial health insurance in China includes four types of insurance, of which long-term care insurance is a non-health insurance. Most of the above studies do not exclude long-term care insurance from commercial health insurance, which may affect the accuracy of the estimation results. There is also little and incomplete discussion of the mechanisms by which air pollution affects commercial health insurance. Our study has two important innovations over previous studies: First, we exclude long-term care insurance from commercial health insurance to make the estimation results more accurate; second, we classify the potential channels into pollution reporting (before the risk occurs), protective behaviour (when the risk occurs) and health depreciation (after the risk occurs) based on risk management theory, and conduct a more comprehensive mechanism analysis.

3 Hypothesis

Environmental pollution includes a range of issues such as air pollution, soil pollution, water pollution, noise pollution and light pollution (LoPalo and Spears, 2022). Compared to other pollution issues, the high mobility of air makes it more likely that residents will be exposed to air pollution, and residents will suffer greater impacts and harm from air pollution (Manisalidis et al., 2020), which may even lead to respiratory diseases and lung cancer (Turner et al., 2020), and may also increase residents' anxiety or mental illness caused by excessive psychological stress, etc (Bruyneel et al., 2022; Balakrishnan and Tsaneva, 2023). We know that air pollution affects the physical and mental health of residents, and that risk management is needed when households are exposed to air pollution risks. Risk management theory divides risk into before, during and after the risk occurs. Before the risk occurs, households may invest in healthcare to improve their health to resist the hazards of air pollution, or move to areas with better air quality, etc.; when the risk occurs, households may make protective investments such as buying air purifiers, green plants and masks, *etc.*,; after the risk occurs, households are already affected by air pollution and incur certain medical expenses. In addition to the basic protective function of social health insurance, the next best thing is to invest in commercial health insurance. The long-term or short-term effects of air pollution on household members will increase the likelihood that households will purchase commercial health insurance, while the effect of commercial health insurance will increase as the cost of medical care rises. Therefore, we propose the following hypotheses.

Hypothesis 1a: Air pollution will have a positive effect on the likelihood of household participation in commercial health insurance.

Hypothesis 1b: Air pollution will have a positive effect on the level of household participation in commercial health insurance.

Residents' perceptions of the risks posed by air pollution are complex and vary to some extent (Cori et al., 2020; Li et al., 2022). When residents receive information about air pollution and deal with it according to their own perceptions, they are influenced by a number of factors, which are ultimately reflected in their risk management actions (Sereenonchai et al., 2020). Based on risk management theory, we divide air pollution risks into before, during and after (Généreux et al., 2019). Residents perceive the risk at different stages of its occurrence, are concerned about it and will react differently. First, before air pollution risks occur. Residents choose to report pollution in order to improve their living environment and to protect their health capital from the harmful effects of air pollution (Xu et al., 2021). Residents expend energy and costs to report pollution in their area *via* phone, We Chat, the Internet and other means to achieve risk mitigation. This approach can reduce protective investments, medical costs and insurance costs caused by air pollution. Second, when the risk of air pollution occurs. At this point, residents feel that their physical and mental health is being affected by air pollution. In order to protect themselves and their families from the dangers of air pollution, residents may choose to increase their protective investments against air pollution, such as buying air purifiers, masks, greenery, new air systems, etc (Zhang and Mu, 2017). Since residents are already feeling the effects of air pollution, they may choose to purchase commercial health insurance to reduce subsequent medical costs. Third, after the risk of air pollution has occurred. Air pollution has already damaged residents' physical and mental health, causing them to fall ill and incur medical costs. When faced with high medical costs, residents may choose to purchase commercial health insurance to reduce high medical costs in similar situations in the future (Lee and Lee, 2019). The above three potential channels all indicate that residents observe the phenomenon and hazards of air pollution, pay different levels of attention to it, and take different risk management measures, but all with the ultimate aim of preventing and reducing the risks of air pollution. Based on the above analysis, the following hypotheses are proposed in this section.

Hypothesis 2a: Pollution reporting plays an inverse role in the impact of air pollution on commercial health insurance.

Hypothesis 2b: Protective behaviors plays a positive role in the impact of air pollution on commercial health insurance.

Hypothesis 2c: Health depreciation plays a positive role in the impact of air pollution on commercial health insurance.

4 Data and methods

4.1 Data sources and variable selection

4.1.1 Data sources

This paper focuses on the impact of air pollution on household commercial health insurance purchasing behaviour. The data on household commercial health insurance purchasing behaviour are obtained from the 2019 China Household Finance Survey (CHFS). The 2019 CHFS household survey sample uses data from 2018 and covers a sample of 107,008 individuals in 34,643 households from 29 provinces and 343 counties in China, except Xinjiang, Tibet, Taiwan, Hong Kong and Macau. The 2019 CHFS micro data on household finance is very comprehensive, containing a large number of individual and household characteristics, such as total income, total assets, total expenditure, age, gender, place of residence, education level, etc. This provides a rich selection and support for the empirical research in this paper.

The 2019 CHFS data was selected for two reasons: 1) the 2019 CHFS data were up-to-date and current; and 2) the 2019 CHFS data has a breakdown of the types of commercial health insurance, with four types of commercial medical insurance, critical illness insurance, income protection insurance, and long-term care insurance. This facilitates the exclusion of non-illness-related insurance, allowing for more accurate estimates of the impact of air pollution on household commercial health insurance participation behavior, as well as obtaining a clearer mechanism.

Air pollution and thermal inversion data were obtained from NASA's MERRA-2 product. The 2018 p.m.$_{2.5}$ data and thermal inversion data obtained were matched with the 2019 CHFS data based on the prefecture-level cities, and processed to obtain a valid sample size of 32,645.

4.1.2 Variable selection

(1) Air pollution (*pollution*)

Air pollution data is very complex and difficult to obtain, with five common classifications of air pollutants: $PM_{2.5}$, PM_{10}, SO_2, NO_2 and CO. Due to the wide range of air pollutants, China set up an Air Quality Index (AQI) to measure the level of air pollution. These air pollution data are basically obtained from ground-based monitoring stations, and may be subject to manipulation (Ghanem and Zhang, 2014; Sullivan et al., 2017) and may also cause bias problems when conducting empirical studies. To address this issue, some scholars have used satellite remote sensing monitoring data, which has a long time span, covers a wide range of areas and is not subject to manipulation, thus avoiding the problem of bias (Li and Zhang, 2019). Whereas ground-based monitoring stations have limited access to data, satellite remote sensing data are raster data, allowing access to air pollutant data for the entire residential area or study area, and are therefore more representative and complete (Zhang et al., 2017). Most scholars use satellite remote sensing data from the National Aeronautics and Space Administration's (NASA's) MERRA-2 product (Deschenes et al., 2020; Chen et al., 2022), which has global coverage of remote sensing data and records atmospheric signature data from 1980 to the present.

Based on the above analysis, we chose to use $PM_{2.5}$ data from NASA's MERRA-2 product for 288 prefecture-level cities in China in 2018 as the air pollution variable. The raster data was extracted using ArcGIS 10.8 based on the administrative area of each prefecture-level city, and the obtained data was used to perform an inverse extrapolation of $PM_{2.5}$ (Buchard et al., 2016) with the following formula:

$$PM2.5 = DUST2.5 + SS2.5 + BC + 1.4 \times OC + 1.375 \times SO4 \quad (1)$$

$PM_{2.5}$ is the main cause of haze pollution (van et al., 2010). $PM_{2.5}$ pollutants are small in diameter, tend to carry more toxic substances compared with other types of pollutants, and hover in the air for a relatively longer period of time, making it easier for them to penetrate indoors and have an impact on human health (Chang et al., 2016). Therefore, the choice of $PM_{2.5}$ pollution as the air pollution variable is more conclusive. In the robustness check section, we use AQI data from ground-based monitoring stations of the Chinese Ministry of Environmental Protection as replacement air pollution indicator data to test the robustness of the regression results.

(2) Household commercial health insurance participation behaviour (*CHI*, *CHIE*)

The household commercial health insurance participation behaviour studied in this paper is divided into two types, namely, whether the household has commercial health insurance (CHI), and the extent of household commercial health insurance participation (CHIE). CHI is a dummy variable with sample data from the 2019 CHFS, and CHI is 1 if a household member has purchased commercial health insurance and 0 if no household member has purchased commercial health insurance. CHIE is defined as the proportion of premium expenditure on commercial health insurance by household members to total household income in the previous year.

(3) Residents' concern

Based on the summary and analysis of the literature review on residents' concern, we selected the following potential channels as residents' concern: pollution reporting, protective behaviors, and healthy depreciation.

Pollution reporting generally appears before the occurrence of risk, with the aim of reducing the probability of risk occurrence. Based on the air pollution study from a pollution reporting perspective (Sun et al., 2021b; 2021a), we use the reporting of environmental pollution by residents in each region in 2018 as the pollution reporting variable, which includes the total number of reports (reports), WeChat channel reports (WeChat) and Internet channel reports (web); Protective behaviors generally appear in the process of risk occurrence, aiming to reduce the harm caused by the risk. Based on the air pollution study from a defensive investment perspective (Ito and Zhang, 2020), we use the defensive investment behaviors of Chinese household residents on respirable dust and haze in 2018 as protective behaviors (PB) variable, such as purchasing air purifiers, masks, green plants, and fresh air systems, etc., with PB taking the value of 1 if they have protective behaviors and 0 otherwise.; Healthy depreciation is the loss of health capital after the risk occurs. Based on studies of the effects of air pollution on physical and mental health (Zheng et al.,

TABLE 1 Variable definitions.

Variable name	Variable description
CHI	Whether family members purchased commercial health insurance in the last year
CHIE	Percentage of total household income spent on commercial health insurance premiums in the last year
$PM_{2.5}$	$PM_{2.5}$ data represent air pollution status
AQI	Air quality index
TI	Annual frequency of thermal inversions in residential areas in the last year
age	Age of household head
edu	Education level of household head
gender	Gender of household head
marry	Marital status of household head
health	Physical condition of household head (self-assessment)
SI	Household head's participation in social insurance
risk	Risk attitude of household head
job	Unemployment of household head
hospital	Whether the household head has been hospitalised in the last year
internet	Whether the household head has a mobile phone with Internet access
income	Total household income in the last year
asset	Total household assets in the last year
consump	Total household consumption in the last year
debt	Whether the household had any debts in the last year
card	Whether the household has credit cards
rural	Area in which the household lives
old	Number of people aged 60 and over in the household
kid	Number of people aged 14 and under in the household

2015; Liu et al., 2017; Chen et al., 2018; Zhang et al., 2018), We use whether Chinese household residents had medical expenditures in 2018 as a healthy depreciation (HD) variable, with HD taking the value of 1 if they had medical expenditures and 0 otherwise.

(4) Control variable

Appropriate control variables are added to obtain better estimation results and to solve the problem of omitted variables. Household participation behaviour in commercial health insurance is influenced by a wide range of factors, so we referred to the results of related studies (Zietz, 2003; Hussels et al., 2005; Outreville, 2013) and combined the characteristics of the sample data to set two sets of control variables, one for household characteristics and the other for the personal characteristics of the household head.

The control variables for household characteristics include total household income, total household assets, total household consumption, total household debt, credit card, whether the household residence is in a rural area, the proportion of the household population aged 60 or above, and the proportion of the household population aged 14 or below. The Control variables for the personal characteristics of the household head include age, health, hospital behaviour, gender, marital status, educational attainment, social insurance participation, risk attitude, unemployment and internet.

(5) Instrumental variable (*TI*)

The instrumental variable should be highly correlated with the independent variable and should not directly affect the dependent variable. On the basis of satisfying this condition, thermal inversions can solve the air pollution endogenous problem to some extent (Fu and Gu, 2017; Fu et al., 2018; Chen et al., 2020). We therefore chose to use thermal inversion (TI) as the instrumental variable to address the endogenous issue in conjunction with the household sample data characteristics.

The thermal inversion data were obtained from NASA's MERRA-2 product, dataset code M2I6NPANA. The raw data were global atmospheric temperatures at 42 barometric levels, collected at a frequency of 6 h/time, and we used ArcGIS10.8 to extract the 2018 data based on the administrative area of prefecture-level cities. The percentage of days in a year when

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thermal inversions occur in prefecture-level municipalities is the instrumental variable.

Table 1 describes the definition of each variable.

4.2 Model construction

The first question discussed is whether air pollution affects household participation in commercial health insurance, i.e., whether air pollution motivates households to purchase commercial health insurance or if it acts as a disincentive. There are only two states of household participation in commercial health insurance, namely, insured and non-insured states, which are dummy variables. The Probit model is therefore chosen to estimate the effect of air pollution on whether households take out commercial health insurance, while the thermal inversion instrumental variable is introduced to control for endogeneity in the model, resulting in the construction of the following IV-Probit model:

$$pollution_i = \tau_0 + \tau_1 Z_i + \tau_3 X_i + \varepsilon_i \quad (2)$$

$$Pr(CHI_i = 1) = \phi(\alpha_0 + \alpha_1 Pollution_i + \alpha_2 X_i + \varepsilon_i) \quad (3)$$

Where i denotes the ith household; CHI_i represents whether anyone in the household has commercial health insurance; $pollution_i$ is air pollution, denoted by $PM_{2.5}$; Z_i indicates the instrumental variable; X_i stands for the control variable; ε_i signifies the residual term; and α_1 is the coefficient to be estimated.

The second question discussed is the extent to which air pollution affects household participation in commercial health insurance., i.e., whether air pollution positively or negatively affects household investment in commercial health insurance as a proportion of total income. The number of households with commercial health insurance in the data sample selected for this paper is small (i.e., the ratio of commercial health insurance premium expenditure to total income is truncated), and the thermal inversion instrumental variable is introduced to control for endogeneity in the model; therefore, the IV-Tobit model is chosen to estimate the impact of air pollution on household participation in commercial health insurance by constructing the following IV-Tobit econometric model:

$$pollution_i = \vartheta_0 + \vartheta_1 Z_i + \vartheta_3 X_i + \varepsilon_i \quad (4)$$

$$CHIE_i^* = \beta_0 + \beta_1 Pollution_i + \beta_2 X_i + \varepsilon_i \quad (5)$$

$$CHIE_i^* = max(0, CHIE_i^*) \quad (6)$$

Where i denotes the ith household; $CHIE_i$ is the proportion of household members' total income spent on commercial health insurance premiums; $Pollution_i$ represents air pollution, denoted by $PM_{2.5}$; Z_i indicates the instrumental variable; X_i stands for the control variable; ε_i signifies the residual term; and β_1 is the coefficient to be estimated.

The third question discussed is a mechanistic test of air pollution and household commercial health insurance participation behaviour, i.e., whether residents' concern is a channel through which air pollution affects household commercial health insurance participation behaviour. We draw on previous empirical research approaches to mechanism testing (Alesina and Zhuravskaya, 2011). Based on the IV-Probit and IV-Tobit models we constructed, we added residents' concern as a potential channel variable in the regression process and made mechanism tests and transmission direction judgments based on the changes in the estimated coefficients. When the estimated coefficient of the effect of air pollution becomes smaller after the residents' concern is added as an additional control variable in the benchmark regression, it is judged that residents' concern is a potential channel for air pollution to affect household commercial health insurance participation behaviour and has a positive transmission effect. Conversely, when the estimated coefficient of the effect of air pollution becomes larger, then residents' concern is judged to be a potential channel through which air pollution affects household commercial health insurance participation behaviour, but with a negative transmission effect (The models are not repeated here)

TABLE 2 Descriptive statistics.

Statistic	Observations	Mean	St. Dev	Min	Max
CHI	32,645	0.034	0.182	0	1
CHIE	32,645	0.002	0.020	0	0.955
$PM_{2.5}$	32,645	35.240	10.763	2.537	62.817
AQI	32,645	70.248	18.871	33.449	114.124
TI	32,645	0.706	0.209	0.041	0.997
age	32,645	56.419	13.750	17.000	101.000
edu	32,645	0.147	0.354	0	1
gender	32,645	0.753	0.431	0	1
marry	32,645	0.970	0.169	0	1
health	32,645	0.395	0.489	0	1
SI	32,645	0.941	0.236	0	1
risk	32,645	0.052	0.222	0	1
job	32,645	0.353	0.478	0	1
hospital	32,645	0.170	0.375	0	1
internet	32,645	0.701	0.458	0	1
income	32,645	86,597.500	1.97e+05	0	1.21e+07
asset	32,645	1.15e+06	1.25e+07	0	2.10e+09
consump	32,645	82,821.063	9.43e+05	1,356.000	1.70e+08
debt	32,645	0.523	0.499	0	1
card	32,645	0.033	0.179	0	1
rural	32,645	0.347	0.476	0	1
old	32,645	0.885	0.893	0	4
kid	32,645	0.430	0.747	0	7

5 Results and discussion

5.1 Descriptive statistics

Table 2 reports the descriptive statistics of the matched sample data.

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TABLE 3 Regression results.

	1)	2)	3)	4)
	CHI	*CHI*	*CHIE*	*CHIE*
$PM_{2.5}$	0.274***	0.560***	0.0495***	0.115***
	(0.049)	(0.117)	(0.009)	(0.024)
age	0.0389***	0.0387***	0.0102***	0.0101***
	(0.010)	(0.010)	(0.002)	(0.002)
age2	−0.000521***	−0.000521***	−0.000130***	−0.000130***
	(0.000)	(0.000)	(0.000)	(0.000)
edu	0.196***	0.186***	0.0300***	0.0280***
	(0.038)	(0.038)	(0.007)	(0.007)
gender	−0.265***	−0.260***	−0.0449***	−0.0439***
	(0.034)	(0.034)	(0.007)	(0.007)
marry	−0.0497	−0.0594	−0.00454	−0.0068
	(0.083)	(0.082)	(0.015)	(0.015)
health	0.0476	0.0443	0.0146**	0.0139**
	(0.032)	(0.032)	(0.006)	(0.006)
SI	0.000885	0.00473	0.00025	0.0012
	(0.070)	(0.069)	(0.013)	(0.013)
risk	0.0835*	0.0923*	0.0124	0.0145
	(0.051)	(0.050)	(0.009)	(0.009)
job	−0.134***	−0.127***	−0.0182**	−0.0168*
	(0.047)	(0.047)	(0.009)	(0.009)
hospital	−0.00049	0.00403	0.00434	0.00541
	(0.049)	(0.049)	(0.010)	(0.010)
internet	0.354***	0.360***	0.0716***	0.0732***
	(0.068)	(0.068)	(0.015)	(0.015)
asset	0.0754***	0.0707***	0.0155***	0.0145***
	(0.013)	(0.014)	(0.003)	(0.003)
income	0.122***	0.121***	0.00929***	0.00905***
	(0.016)	(0.016)	(0.002)	(0.002)
consump	0.0964***	0.102***	0.0176***	0.0191***
	(0.023)	(0.023)	(0.005)	(0.005)
debt	0.00729	0.0244	0.00069	0.00456
	(0.033)	(0.033)	(0.006)	(0.006)
card	0.359***	0.357***	0.0641***	0.0640***
	(0.055)	(0.055)	(0.011)	(0.011)
rural	−0.149***	−0.128***	−0.0302***	−0.0255***
	(0.043)	(0.044)	(0.009)	(0.009)
old	−0.0848***	−0.0874***	−0.0166***	−0.0172***

(Continued on following page)

TABLE 3 (*Continued*) Regression results.

	1)	2)	3)	4)
	(0.025)	(0.025)	(0.005)	(0.005)
kid	−0.0234	−0.0199	−0.00526	−0.0045
	(0.021)	(0.021)	(0.004)	(0.004)
Wald test		6.88***		10.16***
Pseudo R2	0.180		0.261	
F-value		319.73		319.73
Observations	32,645	32,645	32,645	32,645

Household clustering robust standard errors in brackets; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

5.2 Analysis of main empirical results

First, we need to test the endogeneity of the regression model as a prerequisite for the effective use of instrumental variables. Table 3 reports the Wald tests for the IV-Probit and IV-Tobit models, both of which are significant at the 1% level, indicating that the dependent variables are endogenous and that instrumental variables should be used. In addition, the one-stage F-values for both regression models are greater than 10, indicating that the instrumental variable passes the Cragg-Donald test, rejecting the weak instrumental variable hypothesis, and suggesting that thermal inversion is a qualified instrumental variable.

Table 3 reports the results of our regressions. Columns 1) and 3) show the regression results for the Probit and Tobit models, while columns 2) and 4) show the regression results for the IV-Probit and IV-Tobit models. Comparing these, we find that the regression results with the addition of instrumental variables are still significant and that the regression coefficients are larger, suggesting that the Probit and Tobit models are endogenous and thus underestimate the effect of air pollution on household participation in commercial health insurance. Therefore, we chooses to use the regression results of the IV-Probit and IV-Tobit models to estimate the marginal effects. The IV-Probit model estimates the effect of air pollution on the likelihood of household participation in commercial health insurance with a regression coefficient of 0.358 and a marginal effect of 0.0149, which indicates that for every 1% increase in $PM_{2.5}$ concentration, the likelihood of household participation in purchasing commercial health insurance rises by 1.49%. The IV-Tobit model estimates the effect of air pollution on household participation in commercial health insurance with a regression coefficient of 0.115 and a marginal effect of 0.1148, which indicates that for every 1% increase in $PM_{2.5}$ concentration, household expenditure on commercial health insurance as a proportion of total income rises by 11.48%. Our estimates are consistent with the results of Jia and Yan (2022) on the relationship between air pollution and household commercial health insurance. So, air pollution increased the likelihood of household participation in purchasing commercial health insurance and household expenditure on commercial health insurance as a proportion of total income, verifying Hypothesis 1a.

The regression results of the control variables show that total household income, total household assets and total household consumption have a positive impact on household participation in commercial health insurance, and that the likelihood of purchasing commercial health insurance increases as total household income increases. Tian and Dong (2022) study found that in terms of the financial status of the family, the total consumption of the household has a positive and significant effect on the breadth and depth of health insurance. This is consistent with our finings. Credit card ownership has a positive impact on household commercial health insurance participation behavior. Living in a rural area has a negative impact on household participation in commercial health insurance, probably because commercial health insurance is less widespread in rural areas and the income and education level of rural residents are lower than those of urban residents. The proportion of the population that is elderly has a negative impact on household participation in commercial health insurance, suggesting that as China ages, the demand for commercial health insurance decreases.

The regression results for the age, quadratic age, unemployment, education, gender and internet of the household head are significant. The regression results are positive for age and negative for the quadratic age, indicating that the household's need for commercial health insurance changes from increasing to decreasing as the age of the household head increases. The regression coefficients for educational attainment indicate that the educational attainment of the household head has a positive effect on household participation in commercial health insurance. The regression coefficients for gender show that the male head of household reduce the household's commercial health insurance participation behaviour. The regression coefficients for unemployment show that the unemployment of household head reduce the household's commercial health insurance participation behaviour. The regression coefficients for internet indicate that the use of the Internet by the household head has a positive effect on household participation in commercial health insurance.

6 Mechanisms

The Residents' concern is an important channel linking air pollution to commercial health Insurance's sustainable development. The residents' concern in this paper include pollution reporting, protective behaviors, and healthy

TABLE 4 Results of the mechanism test with CHI.

	1)	2)	3)	4)	5)	6)
		reports	*Wechat*	*web*	*PB*	*HD*
	CHI	*CHI*	*CHI*	*CHI*	*CHI*	*CHI*
$PM_{2.5}$	0.560***	0.565***	0.644***	0.627***	0.512***	0.555***
	(0.117)	(0.113)	(0.123)	(0.127)	(0.119)	(0.118)
concerns		−0.027*	−0.00851**	−0.0227**	0.120***	0.0829**
		(0.021)	(0.022)	(0.027)	(0.038)	(0.034)
Wald chi2	6.88***	8.62***	13.07***	12.90***	5.79**	6.63***
F-value	319.73	691.30	737.47	1,057.28	313.21	304.62
Control	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,645	32,645	32,645	32,645	32,645	32,645

Household clustering robust standard errors in brackets; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

depreciation. Below we explore three potential channels through which air pollution might affect the commercial health insurance's sustainable development: pollution reporting, protective behaviors, and healthy depreciation.

Table 4 reports the results of the mechanism test with CHI as the dependent variable. Column 1) is the benchmark regression and reports the results of the regression of air pollution on whether households participate in purchasing commercial health insurance. Columns (2)–(6) show the regression results for total number of reports, WeChat channel reports, Internet channel reports, protective behaviors and healthy depreciation as additional control variables, respectively. Comparing the regression results in columns (2)–(6) with the benchmark regression results, respectively, we found that the regression coefficients all became larger or smaller and were significant. This indicates that residents' concern is a potential channel through which air pollution affects household participation in the purchase of commercial health insurance.

Comparing the regression results of column 2), column 3) and column 4) with the benchmark regression results, we found that the regression coefficients were significantly higher. The regression coefficient of $PM_{2.5}$ in the benchmark regression is 0.560, while the regression coefficients of column 2), column 3) and column 4) are 0.565, 0.644 and 0.627, respectively, which are all significant. This indicates that the total number of reports, WeChat channel reports and Internet channel reports play a negative transmission role of air pollution affecting household participation in the purchase of commercial health insurance.

Comparing the regression results of column 5) and column 6) with the benchmark regression results, we found that the regression coefficients were significantly lower. The regression coefficient of $PM_{2.5}$ in the benchmark regression is 0.560, while the regression coefficients of column 5) and column 6) are 0.512 and 0.555, respectively, which are both significant. This suggests that protective behaviors and healthy depreciation play a positive transmission role of air pollution affecting household participation in the purchase of commercial health insurance. The above results verify hypothesis 1b.

Table 5 reports the results of the mechanism test with CHIE as the dependent variable. The regression results in Table 5 are similar to Table 4, which indicates that residents' concern is a potential channel through which air pollution affects the extent of household commercial health insurance participation.

The column 2), column 3) and column 4) show significantly higher regression coefficients compared to the benchmark regression. The regression coefficient of the benchmark regression is 0.115, while the regression coefficients of column 2), column 3) and column 4) are 0.124, 0.130 and 0.127, all of which are highly significant. This indicates that the total number of reports, We Chat channel reports and Internet channel reports play a negative transmission role of air pollution affecting the extent of household commercial health insurance participation.

The regression coefficients in columns 5) and 6) are significantly higher compared to the benchmark regression. The regression coefficient of the benchmark regression is 0.115, while the regression coefficients of columns 5) and 6) are 0.107 and 0.114 and are highly significant. This indicates the positive transmission effect of protective behaviors and healthy depreciation on the effect of air pollution on the extent of household commercial health insurance participation. The above results verify hypothesis 2a.

7 Robustness test

7.1 Substitution of independent variables

To test the robustness of the empirical regression results, we chose to use AQI, which can reflect the level of air pollution, instead of the original independent variables. Data on AQI was obtained from ground-based monitoring stations in China. The regression results after replacing the independent variables are reported in Table 6. Panel A shows the regression results of the IV-Probit model. It can be seen that the regression coefficients of AQI indicator is

TABLE 5 Results of the mechanism test with CHIE.

	1)	2)	3)	4)	5)	6)
		reports	*Wechat*	*web*	*PB*	*HD*
	CHIE	*CHIE*	*CHIE*	*CHIE*	*CHIE*	*CHIE*
$PM_{2.5}$	0.115***	0.124***	0.130***	0.127***	0.107***	0.114***
	(0.024)	(0.023)	(0.025)	(0.026)	(0.024)	(0.024)
concerns		−0.00827**	−0.0048**	−0.00835**	0.0168***	0.0153**
		(0.004)	(0.004)	(0.005)	(0.007)	(0.007)
Wald chi2	10.16***	10.87***	15.84***	15.42***	9.03***	9.87***
F-value	319.73	691.30	737.47	1,057.28	313.21	304.62
Control	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,645	32,645	32,645	32,645	32,645	32,645

Household clustering robust standard errors in brackets; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

TABLE 6 Regression results after replacing the independent variables.

	1)	2)	3)	4)	5)	6)
		reports	*Wechat*	*web*	*PB*	*HD*
Panel A	*CHI*	*CHI*	*CHI*	*CHI*	*CHI*	*CHI*
AQI	0.470***	0.506***	0.569***	0.541***	0.429***	0.466***
	(0.105)	(0.105)	(0.111)	(0.113)	(0.107)	(0.106)
concerns		0.0315**	0.0541***	0.0437**	0.131***	0.0769**
		(0.015)	(0.016)	(0.018)	(0.037)	(0.034)
Wald chi2	4.29**	6.40***	9.48***	9.91***	3.98**	4.21**
F-value	600.27	603.46	674.20	868.68	585.59	572.27
Panel B	*CHIE*	*CHIE*	*CHIE*	*CHIE*	*CHIE*	*CHIE*
AQI	0.0971***	0.102***	0.114***	0.109***	0.0907***	0.0964***
	(0.021)	(0.021)	(0.022)	(0.022)	(0.021)	(0.021)
concerns		0.00361*	0.00783**	0.00509*	0.0189***	0.0140**
		(0.003)	(0.003)	(0.003)	(0.007)	(0.007)
Wald chi2	6.62**	8.38***	11.65***	11.80***	6.28**	6.54**
F-value	600.27	603.46	674.20	868.68	585.59	572.27
Control	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,645	32,645	32,645	32,645	32,645	32,645

Household clustering robust standard errors in brackets; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

close to the regression coefficients of the original independent variables and is significant at the 1% level. Panel B presents the regression results of the IV-Tobit model. It can be seen that the regression coefficients of AQI indicators is close to the regression coefficients of the original independent variables and is significant at the 1% level. The above results prove that the regression results are robust.

7.2 Excluding the effects of natural selection bias

As some residents are more sensitive to air pollution or more aware of risk prevention, they may choose to migrate to cities with good air quality, which may make the regression results biased and produce a natural selection bias. Therefore, we excluded the sample

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TABLE 7 Regression results of excluding the migrated sample.

	1)	3)	4)	5)	6)	7)
		reports	*Wechat*	*web*	*PB*	*HD*
Panel A	***CHI***	***CHI***	***CHI***	***CHI***	***CHI***	***CHI***
$PM_{2.5}$	0.556***	0.558***	0.641***	0.622***	0.507***	0.551***
	(0.120)	(0.116)	(0.126)	(0.130)	(0.122)	(0.120)
concerns		−0.0291*	−0.00736**	−0.0209*	0.126***	0.0908***
		(0.021)	(0.023)	(0.028)	(0.039)	(0.035)
Wald chi2	5.73**	6.79***	11.27***	11.01***	4.71**	5.50**
F-value	308.41	672.55	719.62	1,028.60	301.43	293.88
Panel B	***CHIE***	***CHIE***	***CHIE***	***CHIE***	***CHIE***	***CHIE***
$PM_{2.5}$	0.1139***	0.122***	0.128***	0.126***	0.106***	0.1130***
	(0.024)	(0.025)	(0.026)	(0.027)	(0.024)	(0.024)
concerns		−0.00889**	−0.0047	−0.00797	0.0179**	0.0165**
		(0.004)	(0.004)	(0.005)	(0.008)	(0.007)
Wald chi2	8.37***	8.27***	13.09***	12.73***	7.32***	8.10***
F-value	308.41	672.55	719.62	1,028.60	301.43	293.88
Control	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,600	31,600	31,600	31,600	31,600	31,600

Household clustering robust standard errors in brackets; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

of households with migration behaviors. The migration rate of the valid sample was 3.21%, the number of samples with migration behaviors was 1,045, and the overall valid sample was 32,645, leaving 31,600 after processing. This indicates that the migration rate of Chinese residents is not high. Table 7 reports the results of the regression excluding the migrated sample. Panel A and panel B show the regression results for the IV-Probit and IV-Tobit models, respectively, which are consistent with our benchmark regression results, indicating the robustness of the regression results.

8 Conclusion

Due to the negative physical and psychological effects of air pollution on residents, the burden of medical expenses increases as a consequence, and the wellbeing of residents is negatively impacted. In order to combat the effects of these problems, in addition to tackling environmental pollution, commercial health insurance can help to alleviate the pressure on residents' healthcare costs. It provides an effective way to reduce the financial burden of healthcare associated with air pollution and can help to improve family wellbeing. It is therefore important to study the relationship and mechanism between $PM_{2.5}$ and commercial health insurance participation, not only to help residents understand the negative effects of air pollution so that countermeasure policies can be formulated to improve household welfare, but also to provide a reference for the sustainable development of commercial health insurance for insurance companies. Using data from van et al., 2010 and through matching it with $PM_{2.5}$ data by city, we investigated the impact and mechanisms of air pollution on household commercial health insurance participation behaviors using the IV-Probit and the IV-Tobit models. The final conclusions obtained are as follows.

The marginal effect of $PM_{2.5}$ pollution on the likelihood of household participation in commercial health insurance is that for every 1% increase in $PM_{2.5}$ concentration, the likelihood of a household purchasing commercial health insurance increases by 1.49%. The marginal effect of $PM_{2.5}$ pollution on household participation in commercial health insurance coverage is that for every 1% increase in $PM_{2.5}$ concentration, the proportion of total household income spent on commercial health insurance increases by 11.48%.

Residents' concern is an important channel linking air pollution to Household commercial health insurance participation behaviors, where pollution reporting plays a negative transmission role, protective behaviors play a positive transmission role, and healthy depreciation plays a positive transmission role.

The above findings pass the two robustness tests of replacing the independent variables and excluding selectivity bias, proving the credibility of the regression results and conclusions. We therefore make the following policy recommendations in conjunction with the empirical findings. In order to improve the health and welfare status of the population, the cooperation between social insurance and commercial health insurance should be strengthened in China, and publicity and advisory services on commercial health insurance should be provided to the population so as to increase their awareness of risk prevention and sensitivity to $PM_{2.5}$ pollution and thus encourage their active participation in commercial health insurance. Insurance companies should innovate according to different influencing factors, such as air pollution level, residents' background, residents' education level, and different mechanisms, such as pollution reporting, protective behaviors and health depreciation, in order to ensure the sustainable development of commercial health insurance, relieve the pressure of medical expenses and improve the health of residents.

We were limited by cross-sectional data to examine the relationship between air pollution and commercial health insurance over time. In addition, we used a single type of air pollution and did not comprehensively examine the impact of air pollution on commercial health insurance. It is hoped that in future studies, panel data can be constructed and comprehensive air pollution data can be collected for the study, making the results more accurate.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

TR: formal analysis, investigation, and validation. QZ: conceptualization, methodology, and writing—original draft and editing. WW: mechanisms and writing—revising and editing. XD: conceptualization and writing—review and editing. All authors contributed to the manuscript and approved the submitted version.

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Conflict of interest

Author TR was employed by the company Huatai Insurance Agency and Consultant Service Ltd. QZ China Export and Credit Insurance Corporation.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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