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Essays on Fine Particulate Matter, Health and Socioeconomic Factors in China

Jingyuan Di

A thesis submitted for

Doctor of Philosophy

Department of Economics and Finance

Durham University

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Abstract

The thesis contains three empirical essays that investigate the relationship between health, economic growth, and health in China.

The first chapter investigates the relationship between air pollution and economic growth, based on Environmental Kuznets Curve (EKC). We examine the EKC hypothesis based on data in Beijing from 2008 to 2017, with quarterly data. Land use and dummy variables for seasons are controlled. The results confirm an "N" shaped EKC in Beijing, with the first turning point at 60,000 RMB and the second point at 132,000 RMB. The "N" shaped EKC indicates that although air pollution is decreasing now, the pressure for the future is high.

The second chapter explores the effects of income and air pollution on health at individual level. The air pollution includes ambient $PM2.5$ concentration level, and household air pollution. Ambient concentration comes from official observing sites, and household air pollution is measured with dummy variables on energy consumption and active and negative smoking. The household air quality data, along with data at individual level, comes from micro dataset called CHARLS (Chinese Health and Retirement Longitude Survey), together with socio-economic factors, Probit models are employed to investigate the health effect of income and air pollution, and spatial probit models are also deployed due to the high spatial correlation of air pollution. It is found that the health of individuals is affected by the local air pollution and income, and the pollution from neighbouring cities.

The third chapter focuses on the effect of income, exposure level of air pollution on health. Compared with concentration level, exposure level is a better description of human interaction with air pollution. With the Mass Balance Equation, household air concentration is a function of ambient concentration and emission of household pollutant sources. Two scenarios, window open and closed, are considered due to the difference of air exchange rate and penetration rate. We find that poor lung health is associated with high exposure level and low income in both scenarios. Exposure reduction should not only include the ambient concentration target set by the government, and improvement on the household emissions, such as kitchen extraction and transfer from coal and crop residual to electricity and natural gas.

Declaration

The work in this thesis is based on research carried out at the Durham University Business School. No part of this thesis has been submitted elsewhere for any other degree or qualification and it is all my own work unless referenced to the contrary in the text.

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Dedicated to

My parents, Mrs Li Zheng and Mr Chengwen Di

Acknowledge

I am grateful to everyone that I have met in the journey of PhD study. It is all of you that shape and enrich my study at Durham University.

First, I want to say thank you to my supervising team, Dr Laura Marsiliani and Dr Thomas Renström. Your devotion to work, patience to students and moral standards serve as a model to follow. I remember the days that I first came to UK, and almost cried in Thomas' office hour because of confusion about the modules. I remember the days when Laura and I discussed about the research topics, of which the symbol is the coolness of wind in the golden autumn of Millhill Lane. I remember the first time to attend a research roundtable, seminar teaching and job interview, which was encouraged and supported by the supervisors.

Secondly, I want to thank everyone who provided feedback on my research. Special thanks to Professor Riccardo Scarpa and Professor Tooraj Jamasb for their annual reviews. Presenting my research ideas publicly at the research roundtable in 2018 was a turning point, and I am grateful for all the constructive feedback received. Attending conferences such as EAERE 2020, ARENA 2021, and CEAC 2021, as well as participating in summer schools like the 15th NIPE summer school on spatial econometrics and the Applied Energy summer school on the energy-emission-water nexus, have broadened my knowledge and enhanced my methodology.

Third, I want to say thank you to my friends. I am grateful to Dr Xiaoxiao Ma, Dr Changhyun Park, and Dr Jiunn Wang for their tutoring. My friends, Tao Chen, Zhaodong He, Dr Sizhe Hong, Shan Jia, Dr Xiao Liang, Weidong Lin, Xiao Liu, Kaisheng Luo, Haoran Sun, Xuan Yin and Wenrui Zhang who has endowed the dullness of the study with research idea challenge, entertainment, and food. My friends prior to the study shares a different daily to give a glance of another possibility of fate: Tiande Ding, Hongrui Gao, Chong Li, Jingde Liu, Xin Pei and Zhong Yu. The friendship lasts long.

Lastly, I want to express my deepest gratitude to my parents. You have been my first and best teachers and friends. I cannot imagine who I would be without your guidance and unwavering support. Because of you, I wake up every day filled with happiness and a sense of purpose, ready to make a meaningful contribution to society. I am also grateful for the financial support you have provided, which has laid the foundation for my personal growth and leisure.

I came to Durham in 2016 as a master student and continued as a PhD student since 2017. I have spent a longer time in Durham than other places outside my home. The moments of happiness and challenges that I experienced here will always be cherished.

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Chapter 1

Introduction

The rise of China's economy in recent decades has been influenced by both domestic and international factors. The implementation of the open-up and reform policy has facilitated labor migration, while China's participation in organizations like the World Trade Organization (WTO) has provided access to a vast market. This economic growth has required the influx of capital, technology, and raw materials, along with a highly educated workforce, contributing to the steady development of the Chinese economy. As a result, people's wealth has increased, accompanied by a rise in life expectancy.

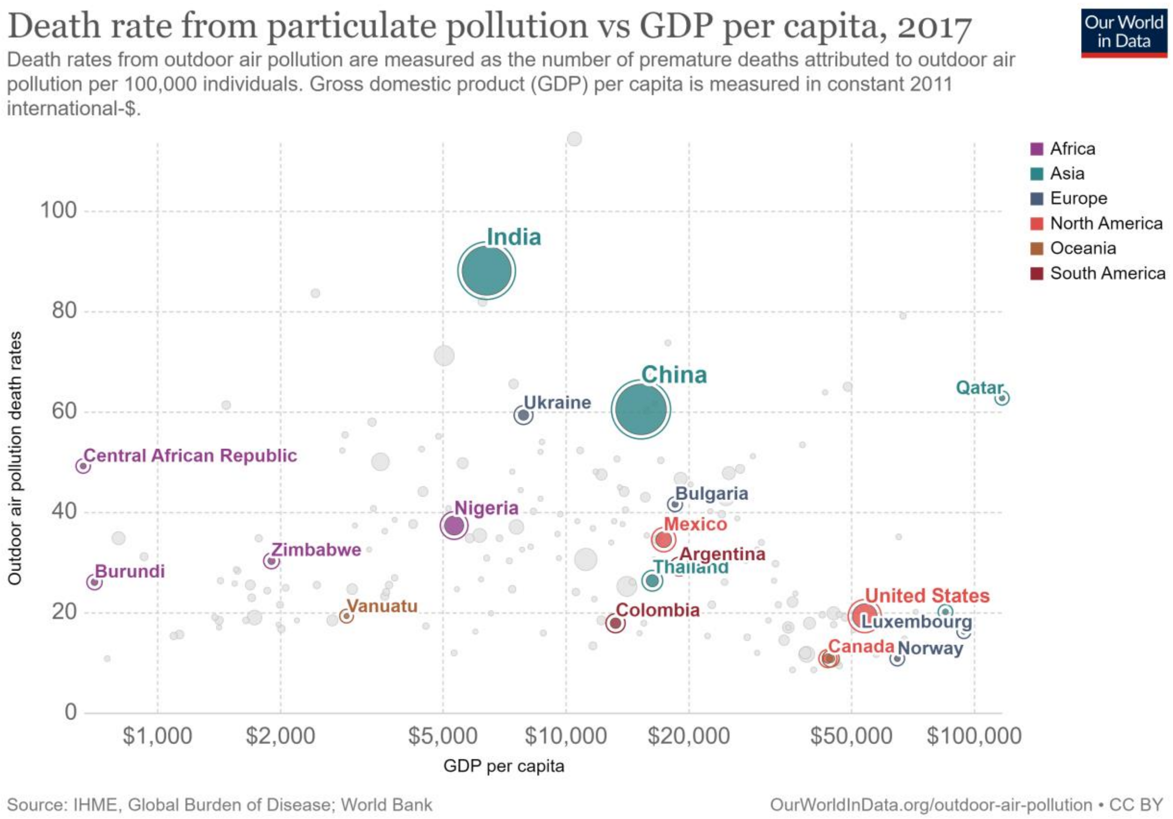

Figure 1: Death rate from outdoor air pollution and GDP per capita

However, China's economic expansion has also come with significant environmental challenges. China is currently the largest emitter of greenhouse gases globally, and the country faces severe environmental issues related to soil, air, and water pollution. Figure 1 illustrates the death rate caused by outdoor air pollution compared to GDP per capita internationally. In China, the mortality rate attributed to outdoor air pollution is significantly higher than in other countries at similar levels of economic development, such as Mexico, Argentina, and Thailand. Despite having a similar GDP per capita to these countries, China experiences a much higher death rate from outdoor air pollution. This disparity indicates that China is grappling with a serious air pollution problem that is taking a toll on public health.

1.1 Definition of $PM_{2.5}$

$PM_{2.5}$, which refers to fine inhalable particles with diameters of 2.5 μm or smaller, poses significant health risks due to its pathogenicity. Several factors contribute to the harmful effects of PM2.5, including its size, composition, solubility, and ability to produce reactive oxygen species. The large surface area of PM2.5 enables it to carry toxic substances, while its small diameter allows it to reach the deepest parts of the respiratory tract. Once accumulated in the lungs, PM2.5 can also affect other organs through air exchange.

Animal studies have demonstrated the impact of PM2.5 on the respiratory system. For instance, research conducted on rats has shown that PM2.5 negatively affects the function of alveolar macrophages[1], which are responsible for defending against bacteria (Jalava et al., 2007). Consequently, rats exposed to PM2.5 exhibit reduced resistance to bacterial infections (Phipps et al., 2010).

The mechanism through which PM2.5 affects the human respiratory system can be summarized in the following aspects: Firstly, the surface of PM2.5 can carry free radicals, metals, and organic components, leading to the production of reactive oxygen species that oxidize lung cells. Secondly, PM2.5 can disrupt calcium homeostasis, activating and damaging inflammatory reactions. Lastly, PM2.5 induces the

[1] Alveolar macrophages "are the most abundant innate immune cells in the distal lung parenchyma, located on the luminal surface of the alveolar space. They are the first to encounter incoming pathogens and pollutants and to help orchestrate the initiation and resolution of the immune response in the lung." (Joshi et al., 2018)

overexpression of transcription factor genes and inflammation-related cytokine genes, causing inflammatory injury (Xing et al., 2016). These processes collectively contribute to the adverse health effects associated with exposure to PM2.5.

PM 2.5 is one of the air pollutants contributing to the air quality index. Other air pollutants are Nitrogen dioxide (NO_2), Sulphur dioxide (SO_2), Ozone (O_3), Carbon monoxide (CO), and PM 10. The formation of these pollutants is related to industrial processes and traffic exhausts, with the combustion of fossil fuels. And the health effects of the pollutants are mainly respiratory systems. (US EPA, 2018)

The emissions of NO_2 and SO_2 occur through similar processes such as the combustion of fossil fuels and industrial activities. However, there are distinct sources for each of these air pollutants. SO_2 emissions are commonly associated with metal production, paper manufacturing, and chemical production industries. Additionally, volcanic activity is a natural source of SO_2 emissions. On the other hand, NO_x emissions primarily originate from traffic-related sources such as vehicle exhaust and biomass burning.

Short-term exposure to both pollutants can have adverse effects on the respiratory system, leading to difficulties in breathing. Individuals with asthma, particularly children, are more susceptible to the harmful effects of these pollutants.

In terms of environmental effects, both NO_2 and SO_2 can cause damage to trees and plants. They can harm foliage and inhibit growth. These pollutants can also contribute to the formation of acid rain, which can have detrimental impacts on ecosystems, including aquatic life. Furthermore, they can contribute to reduced visibility by forming haze and smog.
It is important to implement measures to reduce emissions of both NO_x and SO_2 to mitigate their detrimental effects on human health and the environment. This can be achieved through the implementation of emission controls, the use of cleaner fuels, and the promotion of sustainable practices in various sectors.

The primary sources of carbon monoxide (CO) emissions in outdoor air are vehicles, including cars, trucks, and other machinery that burn fossil fuels. However, it is important to note that various sources within homes can also release CO, impacting indoor air quality. These sources include unvented kerosene and gas space heaters, faulty chimneys and furnaces, and gas stoves.

Breathing air with a high concentration of CO can have detrimental effects on human health. CO binds to haemoglobin in the blood, reducing its ability to transport oxygen to critical organs such as the heart and brain. This can lead to symptoms such as dizziness, confusion, and unconsciousness. In severe cases, it can be fatal when exposed to very high levels of CO, which can occur indoors or in enclosed environments.

Ozone is not emitted directly into the air; instead, it is formed due to chemical reactions between nitrogen oxides (NOx) and volatile organic compounds (VOCs). These reactions occur when emissions from various sources, such as cars, power plants, industrial facilities, and other pollution sources, interact with sunlight. The sunlight acts as a catalyst for the formation of ozone.

Exposure to elevated levels of ozone can have negative effects on human health. Symptoms commonly associated with ozone exposure include coughing, sore throat, and difficulty breathing. Individuals with pre-existing respiratory conditions, such as asthma, may experience an increase in the frequency and severity of asthma attacks when exposed to high levels of ozone.

1.2 $PM_{2.5}$ and other air pollution in the recent Five-Year Plan

The 10th Five Year Plan (FYP) implemented from 2000 to 2005 had a specific focus on reducing

Sulphur Dioxide (SO_2) emissions from power plants. The plan aimed to decrease SO_2 emissions in "two control zones" by 20%. Dust pollution resulting from deforestation and desertification was also monitored during this period. The subsequent 11th FYP provided a more detailed air control policy that included mandatory measures for specific industries. Newly scheduled coal power plants were required to install anti-sulphur devices, while existing plants had to be equipped with such devices as well. The policy expanded to cover additional industries like steel, iron, non-ferrous metals, and construction materials. The plan also addressed issues related to fine particulate matter, smog, dust, and emissions from vehicles, as summarised by He et al. (2020).

During the early 2000s, the primary targets of air pollution policy in China were sulphur and dust, which were closely linked to the energy structure and environmental challenges of that time. China heavily relied on coal as an energy source due to its abundant coal resources but limited petroleum reserves, resulting in substantial sulphur emissions. Dust storms, a major problem during the early spring, were caused by construction sites without proper covering or moisture and desertification due to deforestation and over-cultivation.

In the 12th FYP, the list of monitored pollutants expanded to include nitrogen oxides (NO_x) and odor. Beyond coal power plants, thermal power plants were included, and all power plants were mandated to install NO_x removal devices. The plan set a clear environmental target stating that the number of days with an air quality index lower than 100 should exceed 80% of the year. Additionally, a prevention and control mechanism was proposed, emphasizing the need for regional collaboration.

Table 1: Air pollution in the FYP from 2000

Five-Year Plan	Duration	Pollutant Mentioned	Target	Plan
10th FYP	2000-2005	Dust	N.A	Natural forest protection and Grain for Green
		Sulphur Dioxide	20% reduction	Air pollution control project in "Two control areas" and key cities
11th FYP	2006-2010	Sulphur Dioxide	N.A	Anti-sulphur devices for power plant with coal Integrated governance on the industries of steel and iron production, non-ferrous metal, and construction materials production
		Smog, dust, fine particulate matter	N.A	Enhance the control over emission from vehicle
12th FYP	2011-2015	Sulphur Dioxide and Nitrogen Dioxide	N.A	Anti-sulphur and nitrogen devices for thermal power plant, steel and iron production, non-ferrous metal, chemical engineering, and construction materials
		Particular matter	N.A	
		Vehicle emission	N.A	
		odour pollutant	N.A	
		The number of days with heavy pollution	< 20% of the year	Air pollution joint prevention and control mechanism
13th FYP	2016-2020	The number of days with heavy pollution	25% reduction	
		Fine particulate matter	N.A	Monitoring regulation on the environmental performance of transports and fuel oil
				popularize LNG usage in urban areas
		Dust	N.A	Regulation on road and construction sites
				Ban on combustion of straw and crop residual
		VOC in key areas	10% reduction	Integrated governance
		Emission of vehicle	N.A	Higher standard of emission and petrol quality
				Replacement of the out-of-standard vehicles
14th FYP	2021-2025	PM2.5	10% reduction	
		O3	stop the rise	
		The number of days with heavy pollution	should decrease to 0	
		VOC	10% reduction	
		Nitrogen Dioxide	10% reduction	Integrated governance

Source: author’s work

The 13th FYP covering the period from 2016 to 2020, and the 14th FYP from 2021 to 2025, have expanded the scope of air pollution control beyond power plants and sulphury emissions to include a wider range of industries and pollutants. The 14th FYP introduced several measures for the domestic energy sector and agriculture. Urban residents were encouraged to replace coal with coal gas, and regulations were implemented to address dust pollution from roads and construction sites. The combustion of crop residues and straw was also banned. In terms of industrial production, a new pollutant, Volatile Organic Compound (VOC), was added to the monitoring list. Industries associated with VOC emissions, such as petroleum and related chemical industries, gas stations, and transportation, were required to reduce their VOC emissions. The 14th FYP set a target of a 10% reduction in PM2.5 and aimed to prevent an increase in O3 levels. The target for VOC and NOx reduction was set at 10% by the end of the FYP. VOC emissions from industries such as coating, painting, and pharmaceutical production were included in the monitoring efforts. In northern China, clean heating with stove improvements was promoted as a primary measure for reducing domestic emissions. Industries other than power plants were encouraged to adopt new technologies to lower their emissions.

Besides the FYPs, there are two air pollution control plans, which are Air Pollution Prevention and Control Action Plan (2013-2017), and Three Year Plan of Action for winning the War to Protect Blue Sky (2017-2020). The plan for 2013-2017 was aimed at a 10% reduction of PM_{10} compared with the concentration in 2012, and $PM_{2.5}$ concentration for Beijing-Tianjin-Hebei, the Delta of Yangtze River and the Delta of Zhu River should decrease by 25%, 20% and 15%. The following plan for 2017-2020 set a target of a 15% reduction of SO_2 and NO_x, and 18%

$PM_{2.5}$ reduction for cities that did not meet the between 2013 and 2017.

The Ambient Air Quality Standards in China have undergone several updates since its first version in 1982. The initial version, GB 3095-82, provided limitations on six pollutants, including total suspended particulates and floating dust particles. In 1989, the standard was updated to include PM10 as a measure of coarse particles, with a daily concentration constraint of 15 μg/m3. The 1996 update, GB 3095-96, clarified floating dust as inhalable particulate matter. In 2012, the latest version, GB 3095-2012, introduced PM2.5 as a pollutant with an 8-hour average limit, and updated the limit for PM10, as explained by Guo (2019).

The changes in the Ambient Air Quality Standards reflect the evolving environmental concerns and the government's response to address them. The focus has shifted from sulfur dioxide and dust to PM and volatile organic compounds (VOCs). The scope of regulation has expanded from power plants to a wider range of industries, and there is increased emphasis on domestic energy consumption. Additionally, there has been a transition from city-specific actions to collaboration among multiple cities.

The figure below illustrates the annual CO2 emissions per capita from 2000 to 2019. The emissions have increased significantly since 2000, with a slight reduction observed from 2014 to 2015. After this fluctuation, emissions have continued to rise at a slower pace, reaching approximately 7.6 tons per capita in 2019. The air pollution control policies and plans have been effective in curbing the rapid growth of emissions seen in the early 2000s, leading to a more gradual increase in recent years.

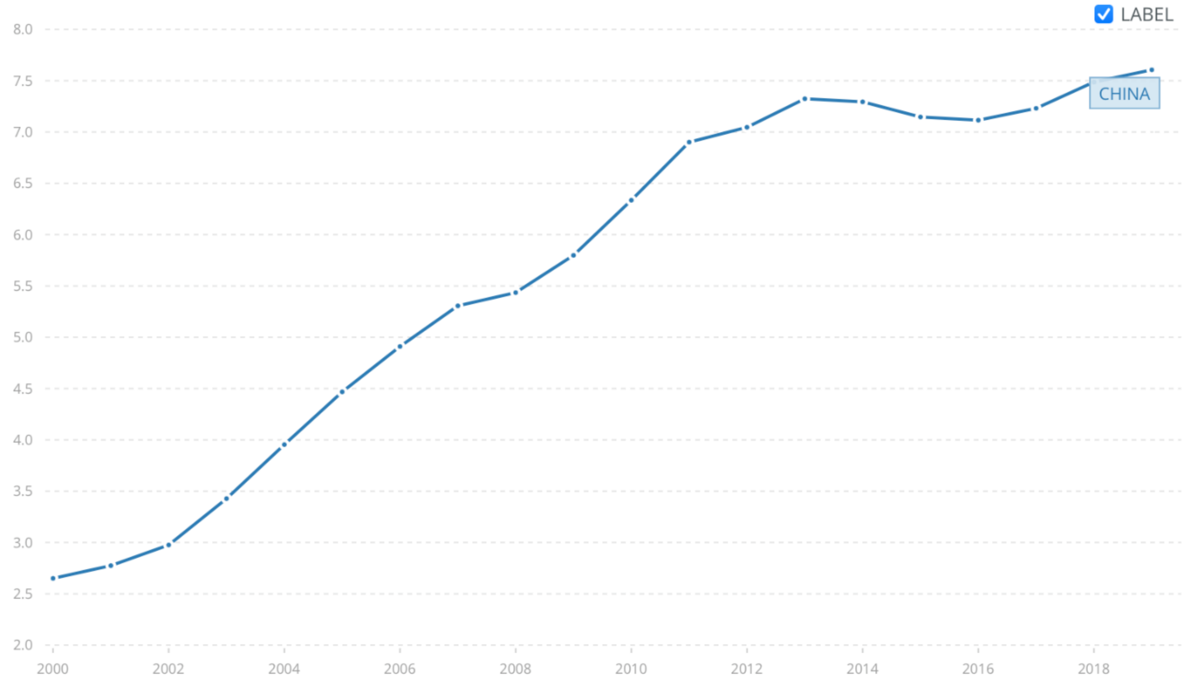

Figure 2: CO2 Emission per capita in China: 2000-2019

Beijing's experience in air pollution control serves as an example of effective measures that have contributed to air quality improvement. With heavy industrialization being a major source of pollution in water, soil, and air, diversifying the economy has been a wise strategy. One specific focus has been on vehicle emission control, implementing higher emission standards to reduce emissions from transportation.

The "carrot and stick" approach, which involves providing incentives and implementing regulations for private enterprises, has proven to be an effective method in controlling pollution. Transparency of data plays a crucial role in enabling public participation and awareness. Cross-boundary collaboration and multidisciplinary efforts are essential for effective air protection measures.

Overall, Beijing's experience highlights the importance of implementing various strategies, including industry diversification, vehicle emission control, incentivizing private enterprises, promoting data transparency, and fostering collaboration among different stakeholders and disciplines. These approaches have contributed to significant improvements in air quality in Beijing and can serve as valuable lessons for other regions facing similar challenges. (He et al., 2019)

1.3 PM data posted by the US embassy in Beijing

The public awareness of PM 2.5 in China can be attributed to the conflict between the air quality observations reported by the US Embassy in Beijing and the official records. Since 2008, the US embassy has been recording and publishing air quality data for PM_2.5 and Ozone (O3) in Beijing. This data was made available to the public through the creation of a Twitter account called BeijingAir.

On December 4, 2011, the US Embassy's record showed a PM 2.5 concentration of 522 μg/m3, which was too high to convert into the Air Quality Index (AQI). This discrepancy between the US Embassy's data and the official reports, along with public complaints about poor air quality on social media, put pressure on the government to address the issue. As a response to public opinion, the Minister of Environmental Protection included PM 2.5 in the updated air quality standards in February 2012. Since 2013, the concentration of PM 2.5 has been monitored, initially in 74 important cities and later extended to all cities by 2015.

Prior to 2011, PM 2.5 was not included in the list of monitored pollutants, with the focus mainly on sulphur dioxide. The absence of PM 2.5 observation resulted in a significant gap between the data reported by the US Embassy and the Chinese observing sites. The publication of PM data by the US Embassy played a crucial role in raising public awareness of this pollutant, leading the government to take immediate actions to address public concerns. The inclusion of PM 2.5 as a monitored pollutant in the 11th Five Year Plan (2006-2010) had received less attention at the time, but the event involving the US Embassy data significantly increased the popularity and importance of monitoring PM 2.5 in China.[2]

1.4 Environmental Kuznets Curve hypothesis

The Kuznets Curve has been widely used to describe the trajectory of income inequality, suggesting that inequality initially increases with economic development before eventually decreasing. Similarly, the Environmental Kuznets Curve (EKC) hypothesis describes the relationship between economic development and air pollution. According to this hypothesis, pollution levels initially increase as a result of economic growth and industrialization but eventually decrease after reaching a turning point.

Andreoni and Levinson (2001) provided a microfoundation for the EKC hypothesis using a static model. They formulated individual utility as a linear function of consumption and

[2] The author believes that the public would know PM and related damage, and the government would include PM in the monitoring list, if the US embassy did not post the hourly record. It could take few years, but it would come eventually.

pollution, with pollution being influenced by consumption and environmental efforts. The budget constraint incorporates consumption and environmental effects. The solution to the utility-maximizing problem follows a standard Cobb-Douglas solution, and the slope of the EKC represents the derivative of pollution with respect to the budget. The relationship exhibits an inverted U shape when the power parameter is negative, indicating diminishing returns to pollution abatement efforts.

Numerous empirical studies have applied the EKC hypothesis to analyze the relationship between economic development and air pollution. Li, Wang, et al. (2016) examined the EKC in China using panel data from 1996 to 2012 for air, soil, and water pollution and found robust support for the hypothesis. Dong et al. (2018) estimated the turning point of CO2 emissions in China to be 96,000 CNY in 2028 and highlighted the role of nuclear and renewable energy in reducing emissions. Xu (2018) criticized EKC research in China, suggesting that it neglects aggregation bias, leading to an underestimation of emissions. While there is considerable EKC research describing and predicting air pollution emissions, many of the results are not robust. Stern (2017) described the EKC as the dominant approach among economists for modeling aggregate pollution emissions and ambient concentration.

Urbanization is the ongoing process of population inflow into cities, resulting in an increasing percentage of the population residing in urban areas. In China, urbanization is occurring at an unexpected rate as more people are relocating to urban areas in search of improved job prospects, educational opportunities, and better access to healthcare for their families and elderly relatives. The urbanization rate has risen from under 20% in 1980 to over 50% in 2011, and it is projected to exceed 75% by 2035.

The urbanisation could influence environment as industrialisation does, and more energy consumption due to the increasing amount of residents. The agglomeration of the population leads to a heavy burden for the environment. Emitted mainly by artificial sources, PM 2.5 is one of the indictors that measuring the environment effect of urbanisation.

The concept of the Urban EKC recognizes the need to consider ambient pollution within the EKC framework. This involves incorporating variables that shed light on the relationship between ambient pollution and economic growth in urban areas, such as urban transport emissions, particulate matter in urban areas, municipal solid waste, population density, and characteristics of the transport network. Various studies have explored the Urban EKC in different countries and regions, including Hilton and Levinson (1998) for 47 countries, Day and Grafton (2003) for Canada, Orubu and Omotor (2011) for African countries, Asahi and Yakita (2012) and Hossain and Miyata (2012) for urban areas in Japan, Kim et al. (2016) for South Korea, and Sinha and Bhattacharya (2016) for India.

The first chapter of the thesis focuses on examining the EKC hypothesis in Beijing using PM 2.5 observations provided by the US embassy and economic and geographic data from the statistical yearbook. The research findings suggest an N-shaped EKC, indicating that the PM 2.5 concentration is projected to increase to higher levels, even after a period of fluctuation.

1.5 Environment income and health

Epidemiological studies have extensively investigated the health effects of air pollution, particularly focusing on the associations between particulate matter (PM) and human health. The impacts of PM on cardiovascular and cerebrovascular diseases have been well-documented. It is believed that PM can trigger systemic inflammation, activate coagulation, and directly enter the systemic circulation, thereby contributing to the development of cardiovascular and cerebrovascular diseases. The influence of PM on the cardiovascular system has strong supporting evidence, with both long-term and short-term exposure showing effects on mortality and morbidity. However, the evidence for the effects of PM on the cerebrovascular system is relatively weaker compared to cardiovascular issues. On the other hand, the impact of PM on the respiratory system is well-established, and numerous studies have demonstrated its adverse health effects. These associations hold true across different populations and regions (Anderson et al., 2012).

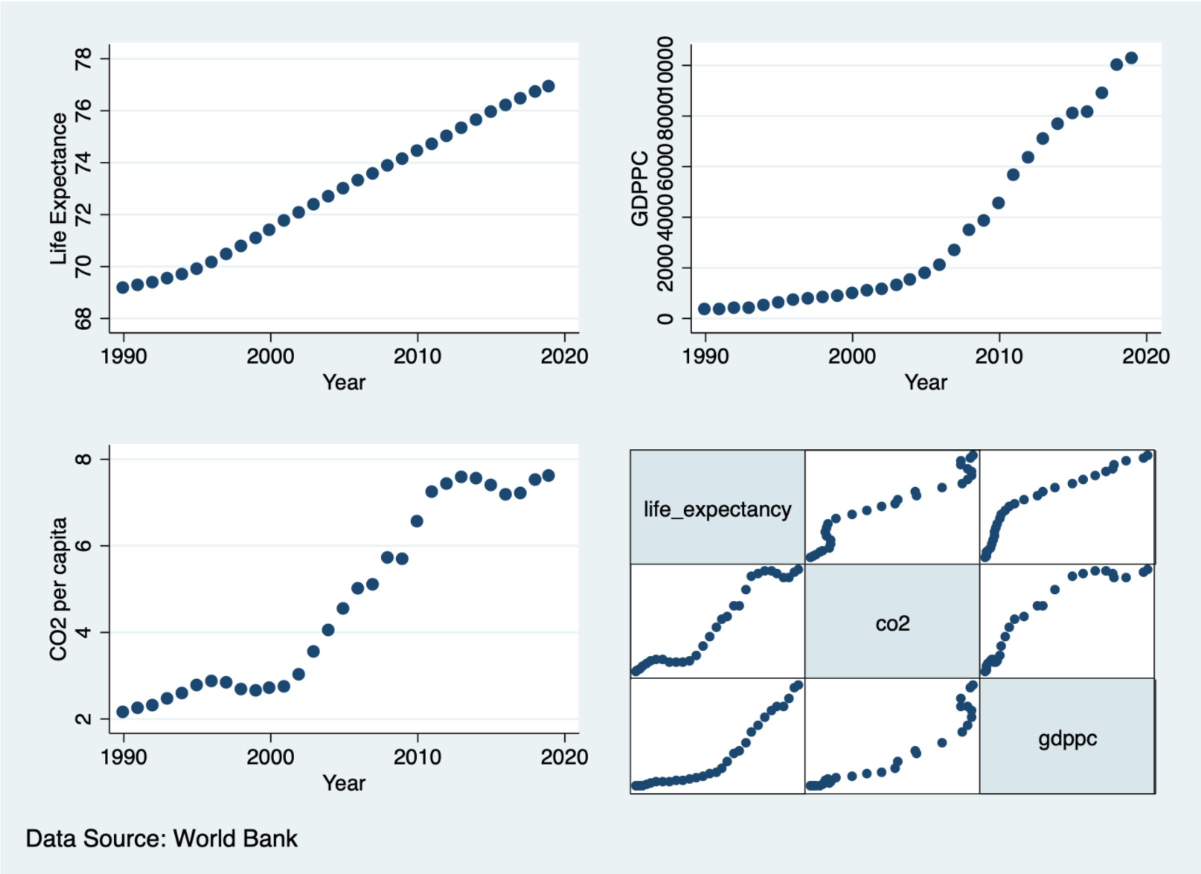

Figure 3: Life expectancy, GDPpc and CO2 per capita in China

Figure 3 illustrates the time trajectory of CO2 emissions per capita, GDP per capita, and life expectancy in China since 1990, as well as the correlation between these factors. The graphs show that life expectancy and GDP per capita have shown a steady growth over time, indicating improved economic conditions and health in China. The trend for CO2 emissions is more complex, with a peak in 2013 and 2014, followed by a decline in the subsequent years. However, since 2017, CO2 emissions have started to increase again. The correlation graph demonstrates a positive relationship between GDP per capita and both life expectancy and CO2 emissions

The EKC hypothesis provides a framework for understanding the relationship between economic growth, environmental pollution, and health outcomes. However, there is a research gap in understanding how individuals' health is influenced in fast-developing countries with high economic growth and high pollution levels. Ebenstein et al. (2015) conducted a regression analysis that incorporates health as a result of both pollution and income, where income is assumed to be a function of pollution.

$$H = H(I(P), P)$$

where H is the health outcome, and I, P refers to the income and pollution. Income is assumed to be a function of pollution.

$$\frac{dH}{dP} = \frac{dH(I,P)}{dP} + \frac{dH(I,P)}{dI}\frac{dI}{dP}$$

The second and third chapters of the study build upon this framework. In the second chapter, the focus is on investigating the health effects of air pollution and household income at the individual level, with control variables such as demographic and geographic factors. Air pollution is measured using PM2.5 records, considering both ambient air pollution and household air pollution. The endogeneity issue is addressed for household air pollution by introducing the price of electricity as an instrument. Additionally, spatial probit models are employed to estimate the health effects of air pollution from neighboring cities.

The third chapter extends the analysis from the second chapter by examining the health effects of air pollution and income using a different income indicator: the cash held by households. Air pollution exposure is measured using PM2.5 concentration, taking into account different microenvironments such as the kitchen, bedroom, and outdoors. Household concentration is calculated using the Mass Balance approach, considering ambient air pollution and household pollution sources. The study incorporates various scenarios, including different window conditions, to account for air exchange rates and penetration rates. The findings indicate that poor health is associated with high exposure levels and low income.

Overall, these chapters contribute to understanding the complex relationship between air pollution, income, and health outcomes in a fast-developing country, taking into account individual-level observations and various control variables.

The structure of the thesis is as below: Chapter one is the introduction of the thesis, which overviews the $PM_{2.5}$ and related regulations in China. Chapter two is an empirical analysis on the relationship between air pollution and economic growth, based on one single city, Beijing in China from 2008 to 2015. Chapter three investigates the association between individual health, income and air pollution, based on CHARLS data in 2015. Chapter four calculates the individual exposure level of $PM_{2.5}$, and estimates the health effects of exposure and income. Chapter five concludes the thesis, and proposes the future research.

Chapter 2

The relationship between growth and the environment in Beijing, using PM2.5 concentrations.

Acknowledgements: We wish to thank Riccardo Scarpa, the seminar participants at Durham University, two anonymous referees and an associate editor for valuable comments that greatly improved this chapter. The first author is also grateful to the China Scholarship Council for financial support while undertaking this research.

Jingyuan and Laura designed the research question, and collected and analysed the data. Jingyuan, Chong, and Laura wrote up the work.

2.1 Introduction

The environmental Kuznets curve (EKC) hypothesis states that economic growth leads to degradation and pollution but, beyond a certain level of income per capita, it is conducive to an improvement in environmental quality (an inverted U-shaped relationship). The EKC hypothesis has become a powerful tool in analysing the empirical relationship between growth and the environment. The literature on the EKC has relentlessly proliferated since the seminal contribution of Grossman and Krueger in 1991, to take into account different pollutants and control variables.[3]

A recently published paper by Stern and Zha (2016) highlights two very recent developments in the extensive literature on EKC hypothesis, namely the importance of ambient pollution concentrations and the opportunity offered by newly recorded particular matter (PM2.5) at urban level.

The need to consider ambient pollution within the EKC framework is embedded in the concept of Urban EKC. The urban dimension is generally captured by including variables shedding light on the relationship between ambient pollution and economic growth, such as emissions from urban transport, suspended particular matter in urban areas, municipal solid waste, population density, characteristics of transport network etc. Examples of studies within the Urban EKC literature are Hilton and Levinson (1998) for 47 countries, Day and Grafton (2003) for Canada,

[3] See for example, the country level studies by Grossman and Krueger (1995), Shafik and Bandyopadhyay (1992), Panayotou (1992, 1993 and 1995), Cropper and Griffiths (1994), Bhattarai and Hamming (2001), Markandya et al. (2006), Plassmann and Khanna (2006).

Orubu and Omotor (2011) for African countries, Asahi and Yakita (2012) and Hossain and Miyata (2012) for the urban areas of Yokkaichi and Toyohashi, Japan, Kim, S. J., et al. (2016) for South Korea and Sinha and Bhattacharya (2016) for India.

Nevertheless, to our knowledge, most of the research on the Urban EKC is based on China either at province or city level, as China is experiencing a remarkable urbanisation growth, coupled with consistently high energy consumption and pollution (Dhakal, 2009).[4] Since the early 2000s, studies on the urban EKC in China have been undertaken with regularity and include a wide range of environmental and urban indicators. Results also support a variety of estimated EKC, from the standard inverted U-shape to the more unusual U-shape and N-shape.

As data for PM2.5 concentrations have only recently become available with sufficient frequency[5], EKC studies using PM2.5 as an indicator of ambient pollution are scarce (Stern and Zha, 2016; Hao and Liu 2016). Yet PM2.5 concentrations have been proven to be extremely harmful to human health[6] by affecting respiratory and cardiovascular functions and causing cancer, and to ecological systems.

In this chapter, we examine the relationship between income and the environment in Beijing using PM2.5 concentrations as our chosen environmental indicator. In addition to being the

[4] The percentage of population living in urban areas has increased in China from 40% in 2005, to 57.3% in 2016, with 790 million residents in urban areas (see https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS).
[5] Only recently, concentrations of PM2.5 have been regulated and regularly recorded. Although some measurement of PM2.5 concentration was undertaken in the US already in the late 1990s, the US implemented daily standards in 2007, followed by Japan in 2009, Russia in 2010 and more recently by the EU and South Korea in 2015.
[6] See Sørensen et al. (2003), Cohen et al. (2005), US EPA (2009), Janssen et al. (2011).

national capital of China, Beijing is identified in the latest Chinese national plan[7] as one of 35 major cities in terms of size and economic significance. These cities, with less than 20% of the national population, account for 40% of total energy consumption and are characterized by high pollution levels. As PM 2.5 is considered an ambient pollutant, we include relevant local variables such as green space, and length of road network as controls. By using a recently available dataset for PM2.5 from the Mission China Air Quality Monitoring Programme (MCAQMP) which possesses high reliability[8], we are able to provide the first EKC analysis of a Chinese city for the medium run. Contrary to most of the existing literature, our analysis supports an N-shaped EKC relationship[9]. The first turning point is about 60,000 CNY per year while the second turning point is about 132,000 CNY per year. The income at the second turning point is just above the current average income of Beijing residents. The improved environment quality in the last several years can mainly be attributed to the implementation of stringent government environmental policy while the latest spur in pollution may be a consequence of the stimulus growth policies implemented since late 2014[10]. These results suggest that in the next decades, it may be extremely challenging to achieve stable growth rates and high air quality in China. Therefore, we expect that the EKC curve for Beijing would be an N shape, and Beijing is in the process between two turning points. The concentration levels are decreasing, and could be upward rising again in the future, based on the industrial structure.

[7] See http://www.mlr.gov.cn/tdsc/djxx/djjc/201004/t20100401_143692.htm. Beijing has been listed as one of the main observation cities since 2008, by the Ministry of Housing and Urban-Rural Development

[8] Official data from China has been found not to be reliable as air quality measurements are related to the career progression opportunities of officials and therefore may be prone to manipulation (See Chen et al., 2012 and Ghanem and Zhang, 2014).

[9] Other EKC studies that find an N-shaped EKC, although in a different setting, are Shafik and Bandayopadhyay (1992), Grossman and Krueger (1993), Selden and Song (1994) Panayotou (1997).

[10] See Bloomberg 2015 *China Stimulus Kicks in to Help Keep 2014 Growth Near Target*, https://www.bloomberg.com/news/articles/2015-01-19/china-gdp-beats-estimates-leaving-2014-expansion-close-to-target

This chapter proceeds as following: Section 2 surveys the existing literature on the Urban EKC hypothesis for China; Section 3 describes the data used in this chapter; Section 4 focuses on the empirical model and the econometric methodology; Section 5 presents the results from the empirical analysis; Section 6 includes some policy implications for Beijing and section 7 concludes and offers suggestions for future research on the Urban EKC.

2.2 Survey of the Existing Literature on the Urban EKC in China

To our knowledge, the first study that addresses the existence of EKC in China is De Groot et al. (2004). They use data from 30 provinces from 1982 to 1997 and include waste water, water gas, and solid waste, as environmental indicators and a regional specific intercept. Their results support a typical EKC for water gas, an N-shaped relationship for solid waste, and a monotonically decreasing relationship for waste water.

Shen (2006) conduct the EKC hypothesis research for 31 Chinese provinces. It includes five pollutants, Sulphur Dioxide (SO2) and Fall Dust for air, Organic Pollutants, Arsenic, and Cadmium for water, with population density, industrial share and abatement expense as control variables. The results suggest an EKC relationship for water pollutants and for SO_2, but no relationship for Fall Dust.

Liu, X. et al. (2007) examine the EKC hypothesis in Shenzhen, based on the data from 1989 to 2003. They included a large number of pollutants for several environmental media, including major rivers and near-shore water. The results show that production induced pollution supports the canonical EKC hypothesis, while consumption related pollutants do not.

Brajer et al. (2008) test the relationship between SO_2 and per capita income based on the city level data in China from 1990 to 2004, with population density as control. Using different econometric methods, both the inverted U-shaped and N-shaped EKC are supported.

Based on the Chinese provincial data from 1985 to 2005, Song et al. (2008) investigate the EKC hypothesis between GDP per capita and three environmental indicators: waste water, waste gas, and solid waste, without adding control variables. Their results assert that all these three environmental indicators follow an inverted U-shape EKC relationship and the turning point for waste gas is lower than the other two indicators

Diao et al. (2009) analyse the relationship between GDP per capita and a number of industrial pollutants, with environmental policies, investment strategies, and contribution to GDP as control variables, for Jiaxing city. An inverted U-shape relationship is observed for industrial waste water, industrial waste gas, SO2, and industrial dust. The turning points for the pollutant are generally lower than previous studies in China and lower than the turning points in developed countries and can be explained by the early local government policies against industrial pollution.

Shaw et al. (2010) examine the EKC hypothesis for 99 cities in China from 1992 to 2004. Air pollution includes SO_2, Nitrogen Oxide (NOx) and particle deposition, and control variables include population density, contribution of secondary industry to GDP, and a policy variable. The conclusion shows only SO_2 supports an inverted U shape, while NO_X increases as income grows.

He and Wang (2012) analyse the impact of economic structure, development strategy and environmental regulation on the shape of the EKC, using the city level data from 1990 to 2001. The relationship between environmental indicators, SO2, NOx, total suspended particles (TSP) and GDP per capita are examined, with openness, regulation, population density, area, and capital/labour ratio as control variables. Openness, measured by FDI, always increases the level of the three pollutants, and capital abundance increases the concentration of TSP but decreases the concentration of NOx.

Luo et al. (2014) support a negative linear relationship between Gross Regional Product (GRP) per capita and particulate matter 10 (PM10) concentrations in all province capitals for the last decade. However, only the PM10 concentrations in the central parts of China are significantly related to GRP.

Sun and Yuan (2015) examine the relationship between GDP per capita and three environmental indicators, industrial SO2, industrial soot, and industrial sewage discharged, based on data for 287 cities in China from 2003 to 2008. Population density, area and variables standing for agglomeration are used as control variables. Their results show an N-shaped EKC for all three pollutants with industrial agglomeration having a significant influence on regional environmental quality.

Zhang et al. (2016) analyse the relationship between a comprehensive air quality index (API) and wealth based on the data for 26 capital cities and 4 municipalities in China from 2002 to 2010. As control they include population size, urbanization level, industrialization level, green coverage level, and pollution control investment. The economic level shows an inverted U shape EKC and the turning point is about 63,000 CNY.

Wang and Ye (2017) illustrate the monotonic increasing relationship between Carbon Dioxide (CO2) emission and GDP per capita using city-level data and employing a spatial lag model and a spatial error model. As a novelty from the previous literature, Wang and Ye include dummy variables for coastal and central cities.

Finally, the latest developments in the literature include the use of particulate matters 2.5 data. Stern and Zha (2016) use PM 10 and PM 2.5 data from the years 2013 and 2014 for 50 Chinese cities to regress pollution growth on the GDP growth. They find U-shaped relationship which however turns to be statistically insignificant. Similarly, based on data for 73 Chinese cities in 2013, Hao and Liu (2016) examine the influence of GDP per capita, population density, transport, and industry on air quality. All estimation models, OLS, spatial lag model (SLM) and spatial error model (SEL) support a U-shaped EKC.

Given the fast-paced developments in connection to the Urban EKC hypothesis and the growing interest for China, as a key player in the global economy, we expect this literature to expand considerably in the next few years. This Chapter intends to contribute to this literature by focusing on the case of Beijing.

2.3 Data

In this chapter, the urban unit of reference is the city of Beijing and the pollutant used for the analysis is PM2.5 concentrations, whose source is local. The controls are also local level variables such as population, green space and the length of road network. In the proceedings of this chapter we precisely define the urban area, the data and all issues surrounding their measurements.

The reason why the chapter focuses on Beijing rather than other cities can be explained from several perspectives. Firstly, Beijing, as the capital of China, has all the attributes of an ideal unit of investigation for the EKC Hypothesis. Indeed, the city attracts large amounts of labour, capital, and intelligence resources which contribute to the rapid urban development, but also the degradation of the city's air quality. Secondly, Beijing is due to undergo an ambitious urban restructuring plan as highlighted in the city development plan for the year 2035[11]. Beijing will raise its profile as the political centre of China by focusing on developing its tertiary sector rather than industrial production and agriculture and restricting granting permanent residency rights to highly skilled workers. Heavy industries have already been relocated to the

[11] See Beijing government (2017): *Beijing General Urban Plan 2020-2035.* http://zhengwu.beijing.gov.cn/gh/dt/t1494703.htm

neighbouring provinces such as Hebei and Tianjin to decrease the effects of sulphur dioxide and particulate matter[12]. Therefore, the findings of this chapter may inform the city planners of the likely environmental impact of further development projects in the city. Thirdly, the availability of data for Beijing is higher than for other cities.

2.3.1 Definition of Urban Area

According to the China City Statistical Yearbook, 2016, the Beijing metropolitan area includes 16 districts (see Figure 4). Dongcheng and Xicheng Districts are the core parts of Beijing, historically dating back to the Qing Dynasty[13]. Together with the four surrounding districts of Haidian, Chaoyang, Fengtai and Shijingshan, they are referred to as the Urban Six District. In 1949, six more districts were added to the Beijing metropolitan administrative area: Shunyi, Changqing, Mentougou, Fangshan, Daxing, and Tongzhou. As the 2035 city plan indicates, these districts are becoming increasingly important, with the city administrative offices being gradually moved to this suburban area. In 2000, four more districts in the north of Beijing were included in the Beijing metropolitan area.

Recently, the newly-published city planning encourages residents to move away from the Urban Six Districts to other districts, in order to enjoy better living conditions and lower house prices. Therefore, nowadays, many workers still need to commute daily to the Urban Six Districts for work. As one of the major sources for local PM2.5 concentrations is transport (Zíková et al.,

[12] One example is the Shougang Group, one of the largest steel companies located in Beijing that started moving to Hebei since 2005 in the preparation for the Olympic Games of 2008.

[13] In 2010, the districts of Dongcheng (1 in the map in Figure A) and Chongwen (3 in the map) were merged into the Dongcheng district, and the districts of Xuanwu (2 in the map) and Xicheng (4 in the map) were merged into the Xicheng district.

2016), it makes sense to include all 16 districts of Beijing into our investigation area.

According to the statistic Yearbook of China, the acreage of Beijing did not change from April 2008 to June 2017, despite the implementation of a few changes affecting the district borders[14]. Therefore, acreage is not considered as a variable in this paper. Also, as acreage is fixed we only use population and not population density to capture the effects of urbanisation.

Figure 4: Beijing Metropolitan Area

Source: http://www.dsac.cn/file/attached/image/20150720/20150720164446_6118.jpg

2.3.2 Data Description

Data for environmental quality PM2.5 concentrations are from the Mission China Air Quality Monitoring Programme (MCAQMP) available online at

[14] One is the consolidation of the four central districts into two, Dongcheng and Xicheng, in 2008; another is the establishment of a new district, Xiong'an, in 2017.

http://www.stateair.net/web/historical/1/1.html, which started as a means to provide reliable information about air quality in China for US expats. The observation site is in the US Embassy, which is located in the Chaoyang District, one of the busiest downtown areas in Beijing. Air quality recordings from the embassy site are less frequents than recordings from the official national sites, nevertheless, they are the longest publicly available recorded data for PM2.5 in Beijing having started in April 2008. In addition, a recent study (Zhang and Mu, 2017) finds that the data for PM2.5 from the Chinese Ministry of Environmental Protection are correlated with the data from the US Embassy, hence we expect our results not to be biased.

Our dataset contains the data from April 2008 to May 2017, typically with one observation per hour. Tables 2 and 3 below give a brief summary of the data and their descriptive statistics. Our indicator for pollution is the quarterly average of PM 2.5 concentrations from the second quarter of 2008 to the second quarter of 2017 (the longest interval we have data for). There are 37 observations in total.

The data for population and GDP are from the Statistic Yearbook of Beijing. Quarterly data for GDP are available, while for the population defined as the number of residents in Beijing metropolitan area, observations are annual. By calculating the growth rate of population each year, interpolation is used for the population. For other variables, including the length of road network and green space, we use the same interpolation method to generate more data points for our regression analysis.

As both the data for PM2.5 and GDP present the problem of seasonality (see graphs 5 and 6) we smooth the series by applying the moving average method.

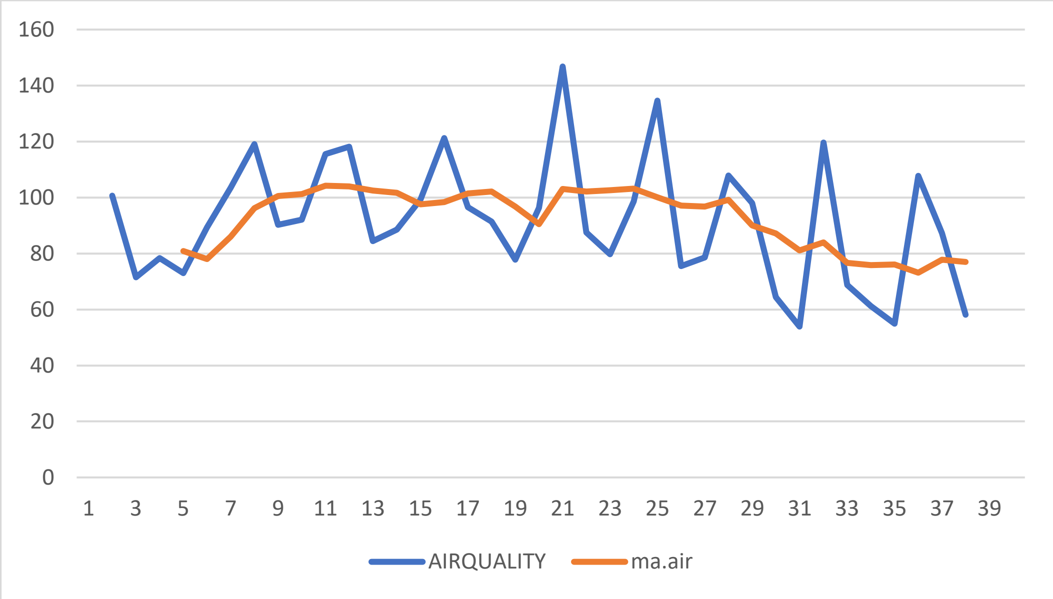

Figure 5: Seasonal Effects of PM 2.5

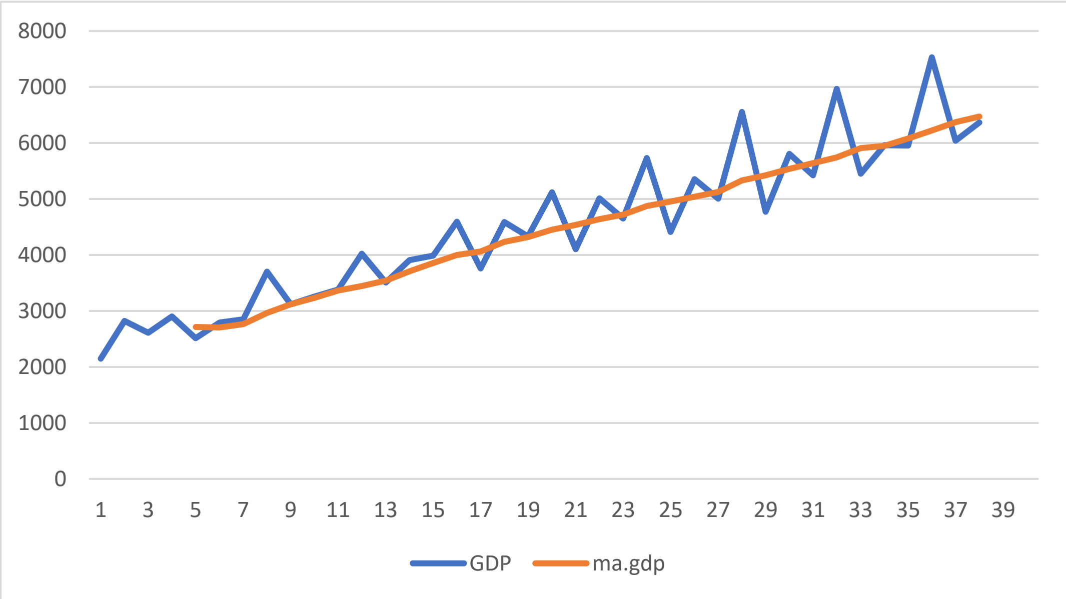

Figure 6: Seasonal Effects of GDPPC

Other variables of interest are green space (Zhang et al. 2016) and the length of roads as those have been identified in the literature as having an impact on urban pollution. Green space, or parks, play an essential role in ameliorating air quality in a city. Yin et al. (2011) estimate that the vegetation in Shanghai contributes to 9.1% of TSP removal. Tallis et al. (2011) estimate that the removal of PM 10 by urban trees in the Greater London Authority is between 0.7% and 1.4%. The longer road length is supposed to serve more vehicles. Vehicles and dust from the road are a major source of PM 2.5 in urban areas (Cassady et al., 2004); furthermore, increasing highways capacity is found to be positively related to the vehicle mileages, suggesting a positive correlation with emissions as well (Noland, 2000).

Table 2: Data Description

Data	Source	Website	Frequency	Time span
PM 2.5	US Embassy	http://www.stateair.net/web/historical/1/1.html	hourly	Since April 2008
Populat.	Beijing Macroeconomics Database	http://www.bjhgk.gov.cn/	yearly	1949-2016
GDP	Beijing Bureau of Statistics	http://www.bjstats.gov.cn/tjsj/yjdsj/GDP/2018/	quarterly	Since Q1 2005
Green Space	Beijing Macroeconomics Database	http://www.bjhgk.gov.cn/	yearly	Since 1975
Length of road network	Beijing Macroeconomics Database	http://www.bjhgk.gov.cn/	yearly	2003-2016
T	Time trend: T= year-2007			
Quarter1	Dummy Variable; =1 when the data is in the 1st quarter; =0 in 2,3,4 quarter			
Quarter2	Dummy Variable: =1 when the data is in the 2nd quarter; =0 in 1,3,4 quarter			
Quarter3	Dummy Variable: :=1 when the data is in the 3rd quarter; =0 in 1,2,4 quarter			

Table 3: Descriptive Statistics

Variable	Mean	Std. Dev	Min	Max	No. of observation
Air quality	91.6	21.5	53.9	146.8	37
Population	2029.2	141.0	1732.6	2174.1	37
GDP	4564.6	1301.1	2511.9	7531.5	37
GDP per capita	2.2	0.5	1.4	3.5	37
Green space	15.3	0.9	13.2	16.4	37
Length of road network	14.0	0.6	13.3	15.2	37

2.4 Model and Methodology

The empirical model used in this paper is based on Grossman and Krueger (1995), which is one of the earliest works on the EKC hypothesis. The model proposes a theoretical framework to analyse the impact of various factors on the environment within an economic growth context. And the model has been extensively tested empirically, both by the authors themselves and by subsequent researchers. This empirical validation helps establish the model's credibility and demonstrates its usefulness in explaining real-world phenomena.

A reduced form methodology was proposed to investigate the relationship between economic development and environment quality, together with characteristics of city as socio-economic control variables. The reduced form of the EKC hypothesis can be expressed as:

$$\mathrm{ma.airquality} = \beta_0 + \beta_1(ma.gdp/population) + \beta_2(ma.gdp/population)^2 + \beta_3(ma.gdp/population)^3 + \beta_4 Z + \varepsilon$$

where $\mathrm{ma.airquality}$ is measured by PM 2.5 concentrations; $ma.gdp\ /population$ is Beijing per capita GDP. For completeness we include both the squared and cubic values of $ma.gdp\ /population$. As control variables, we use: Greenspace (including public parks); Length of the road network (the length of road per capita, an indicator for transport activities); Year, a linear time trend; 3 dummy variables, one per quarter to capture the seasonal effects of pollution (with Q4 being our omitted dummy). We perform OLS estimations.

In the EKC literature, the most common shape for the relationship between income and pollution is an inverted u-shape pattern, which means β_3 should be insignificant, while β_1, β_2 should be significant with $\beta_1 > 0$ and $\beta_2 < 0$. For other patterns the coefficients take on the signs reported in Table 4 below (Song et al., 2008):

Table 4: EKC Patterns

Pattern	β1	β2	β3
N shape	>0	<0	>0
Inverted N shaped	<0	>0	<0
Inverted U shape	>0	<0	Insignificant
U shape	<0	>0	Insignificant
Monotonously increasing	>0	Insignificant	Insignificant
Monotonously decreasing	<0	Insignificant	Insignificant

2.5 Results

Table 5 below presents the results of 4 OLS regressions. Regressions 3 and 4 use logs of all the variables, regressions 2 and 4 do not include green space and the length of road as those are found to be highly correlated with GDP.

Table 5: OLS results for EKC

	1 ma.airquality	2 ma.airquality	3 log(ma.airquality)	4 log(ma.airquality)
Intercept	-503.07	-540.84***	5.75	2.45***
	(707.62)	(113.17)	(12.00)	(0.46)
ma.gdp/population	856.87	921.88***	8.574	8.16***
	(679.09)	(168.75)	(6.96)	(2.04)
(ma.gdp/population)^2	-406.99	-439.26***	-11.39	-11.01***
	(313.36)	(87.31)	(9.38)	(3.22)
(ma.gdp/population)^3	55.26	60.54***	3.34	3.52**
	(43.72)	(13.24)	(3.51)	(1.35)
T	17.9	17.58**	0.22	0.16*
	(18.25)	(7.49)	(0.20)	(0.08)
Quarter1	-12.88	-12.71**	-0.16	-0.11*
	(14.43)	(5.90)	(0.16)	(0.06)
Quarter2	-10.51	-9.77**	-0.13	-0.08*
	(9.97)	(4.51)	(0.11)	(0.05)
Quarter3	-6.89	-6.69**	-0.08	-0.06
	(5.92)	(3.24)	(0.06)	(0.04)
Greenspace	-0.02	----	-0.56	
	(23.36)		(3.82)	
Lengthofroadnetwork	629.32	----	0.41	
	(31330)		(2.49)	

Standard error in parenthesis;
One, two, or three asterisks indicate significance levels at 10%, 5%, or 1% respectively.

All four regressions (although the coefficients in the regression 1 and 3 are not statistically significant) show an N-shaped relationship between air quality and income, with positive coefficient for the per capita GDP and GDP cubic and negative for GDP square. The N-shaped EKC relationship is consistent with the findings of Grossman and Krueger (1991, 1995). The existing literatures based on Chinese cities have also reported an N-shaped EKC relationship, such as De Groot et al. (2004) for solid waste, Brajer et al. (2008) for SO2, and Sun and Yuan (2015) for SO2, industrial soot and industrial sewage. As far as we know, this is the first work to report a N shape with PM 2.5 as an environmental indicator in one single city.

In regression 2, all coefficients are significant, and the goodness of fit is high (R^2=0.86), indicating that regression 2 is a good description of the EKC relationship in Beijing. The first turning point is reached at 15,272 CNY (2009 Q4) per quarter or 60,000 CNY per year and the second turning point will be reached at 33,500 CNY per quarter or 132,000 CNY per year. When income is in the interval of the first and second turning point, PM 2.5 decreases as income grows. From the second turning point onwards, pollution starts increasing again as income increases. The income in Beijing in 2017 Q2, the last quarter in our dataset was 29,280 CNY, which is slightly lower than the income associated with the second turning point. It suggests that Beijing will shortly reach the second turning point and it is possible that the environment will worsen as income grows, if tailored structural policies or stricter environmental policies are not implemented.

The negative coefficients of the seasonal variables Q1-Q3 suggests that air quality is worse (higher PM2.5 concentrations) in Q4, which may be explained by the start of the winter season in Beijing and therefore higher use of fossil fuels (including coal) for central heating. This effect is also well highlighted in the previous literature (see He et al. 2002; Duan et al. 2006 and Zhao et al. 2009).

The coefficients of time trend in all four regressions are positive, indicating that the pollution will rise as time passes. The reason may be due to the low-energy efficiency of the Beijing economy (China Eenergy Development Report, 2008) which calls for urgent energy efficiency reforms.

The coefficients for green space and length of road network, although insignificant, present the expected sign (see regressions 1 and 3). The concentration of PM 2.5 is positively related to the length of road network, suggesting that longer roads lead to more vehicles and therefore higher air pollution. The coefficient of green space is negative and suggests a small reduction in pollution by a unitary increase in green space. One potential explanation for these variables being insignificant is that they are highly correlated to GDP per capita, and GDP per capita is positively related to air pollution. As shown in Table 6 below, Variance Inflation Factors (VIF) of green space and the length of the road network are greater than 30, suggesting multicollinearity. We therefore proceeded to eliminate those two variables from regressions 2 and 4 in which most of the coefficients are significant and of the correct sign.

Table 6: VIF for Regressions

	regression 1		regression 2		regression 3		regression 4	
	Uncentred	Centred	Uncentred	Centred	Uncentred	Centred	Uncentred	Centred
C	782956	NA	22381	NA	1882737	NA	2877.4	NA
MA_GDP /POPULATION	3535771	129066	249800	9563	387370	25224	35555	2367
MA_GDP /POPULATION)^2	4218520	526737	385991	50319	531688	100334	69254	13304

MA_GDP /POPULATION)^3	508581	117572	56837	13644	63205	19401	10634	3313
T	19497	2960	3854	595	20349	3089	3433	530
Q1	89	65	16	11.8	92	67	14	11
Q2	38	29	9	7	39	30	8	6
Q3	13	10	4	3	13	10	4	3
GREEN SPACE	203792	370			1426623	358		
LENGTH OF ROAD	72262	691			2019113	728		

2.6 Discussion and Policy Implications

In Panayotou (1997) some intuitions are given for the occurrence of the first turning point. When income reaches a relatively high level, consumers' demand for environmental goods, such as energy efficient housing and cars increases. Furthermore, more resources can be devoted by the government towards environmental protection further decreasing the degradation[15].

This research examines the relationship between PM2.5 concentration and GDP per capita in Beijing based on a time series data, and found an N shaped curve. New evidence supports some different shape of the EKC hypothesis, indicating that more attention should be paid to environmental pressure. Wu et al. (2018) suggests that the shape of the EKC hypothesis is inverted N shape in the Eastern China, and inverted U shape in the middle part of China,

[15] Panayotou (1997) found that improvements in the quality of institutions (policies) by 10% will lead to a 15% reduction in SO_2 emissions. Bhattarai and Hammig (2001) found that the quality of official policies is negatively related to deforestation.

exhibiting huge regional gaps. And Ding et al. (2019) examined the Beijing-Tianjin-Hebei region, and found an inverted U shape pattern. They found that the region is still in before the turning point, suggesting the air quality would worse as economy grows.

The Beijing government has placed air pollution control as a priority since 1998, and a variety of measures have been significantly implemented ever since. These measures include clean energy promotion, on-road vehicle constraints, industrial construction upgrading, an air quality monitoring and forecasting system, and education aiming at public awareness of air quality. Examples of the pollution control policies are: The 'Green Olympic' implemented for the 2008 Beijing Olympics Games[16], and the 'Beijing Clean Air Action Plan 2013-2017' which includes reduction of the PM 2.5 emissions.

Furthermore, the dependency of the city on coal has been lessened by restructuring the power generation process and by phasing out the coal-based boilers for domestic heating (UNEP 2016). For power generation, coal was the major source until 2005, when natural gas was introduced in the production process. Consequently, the total thermal coal consumption in Beijing decreased from 9 million tonnes in 2005 to 6.4 million tonnes in 2013. By 2013, natural gas accounted for 35% of the total energy consumption for the thermal power sector. This coupled with the promotion of the end-of-pipe control technologies led to a substantial decline in PM 2.5 emissions in 2013 compared with 1998 levels (UNEP 2016). The process of removing coal-based boilers in Beijing started with small boilers (in 1998), boilers under 14MW capacity

[16] Our dataset starts in 2008, therefore we do not have a sufficient data span to test the so-called Olympic Games effect on air pollution.

(2003-2008), and finally with all other coal-based boiler types (2009-2013) in the urban six areas. In the more suburban areas, the small size boilers were replaced or connected to large size boilers (2006-2009). Besides, the boiler operators are given incentives to innovate. In 2013, the reduction of PM 2.5 emissions from removing the coal-based boilers was about 20 thousand tonnes with respect to the 1998 levels.

The control of transport emissions includes emission control on new and in-use vehicles, fuel quality improvement, promotion of clean and new energy sources, and better traffic management.

Perhaps the most interesting result of this chapter is that Beijing is fast approaching a second turning point. This is often explained in the literature by the so-called scale effect of further increasing economic growth. In recent years the Chinese government has continuously implemented mini-stimulus policies to boost decreasing the GDP growth rates[17]. One of the sectors benefitting from these policies has been the housing industry. The People's Bank of China eased the lending requirement and cut the interest rates in 2016. In addition, to help estate developers raise money for their new projects, the China Securities Regulatory Commission also lifted the restrictions on bond and stock sale since 2016 (Bloomberg 2016[18], Bloomberg 2018[19]). As a result, investments in the real estate have increased since 2016. In Beijing and

[17] See Independent UK 2016: *China's economic growth remains strong but increasing risks revealed:* https://www.independent.co.uk/news/business/news/china-economic-growth-gdp-global-economy-slowdown-stimulus-brexit-a7138111.html

[18] See Bloomberg 2016 *China Banking Official Urges Cut to Required Reserve Ratio:* https://www.bloomberg.com/news/articles/2016-12-28/china-banking-official-says-required-reserve-ratio-should-be-cut

[19] See Bloomberg 2018 *China to Ease Bad-Loan Provision Rules to Support Growth:*

Shanghai, more than 50% of investment comes from real estate. The housing stimulus vows also to boost the related industries, including upstream steel and cement, and downstream furniture and textile. Although the growth rate of GDP from 2014 to 2016 was still lower than in the previous years, the growth rate stopped decreasing in 2016 and started to increase at a rate of 6.7% in 2016, and 6.9% in the first and second quarters of 2017. One can therefore speculate that the second turning point in Beijing can be generated by the scale effect associated with an increase in GDP growth in the last couple of years. This has profound implications for policymakers in Beijing and suggests that environmental degradation may become serious if the growth is further enhanced and more stringent environmental protection is not implemented.

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https://www.bloomberg.com/news/articles/2018-03-06/china-is-said-to-ease-bad-loan-provision-rules-to-support-growth

2.7 Conclusion

This study contributes to the literature on the Urban EKC by examining the relationship between growth and air degradation for Beijing. We focus on the relationship between per capita GDP and PM2.5 concentrations using the quarterly data from 2008 to 2017 and including some local variables of interest as controls. The data for PM2.5 concentrations are publicly available courtesy of the US embassy, which is deemed to be reliable and provide the earliest continuous records of the PM 2.5 concentrations.

Our estimation results support an N-shaped pattern for environment and per capita income in Beijing. Determining the shape of the EKC is important for policy making. Our analysis suggests that after a period of economic growth coupled with improved air quality, Beijing may now be on the verge of a reverse path, where a stimulus to growth causes environmental degradation.

Our analysis has concentrated only on the effect of a few control variables. Further research at city level can include, among others, the share of the manufacturing sector to capture the effect of structural policies towards the protection of the environment (Shen 2006; Diao et al., 2009; Shaw et al., 2016; Kim et al., 2016), the intensity of local resident's campaigns as a proxy for residents' environmental sensitiveness (Asahi and Yakita, 2012), public environmental investment (Diao et al., 2009; Shen 2006; Zhang et al., 2016) and other environmental policies (Diao et al., 2009; He and Wang, 2012; Shaw et al., 2010).

This work follows the methodology proposed by Grossman and Krueger (1995) which was designed for a multi-country level empirical study. The model has been improved to describe the local emission of air pollution, where the length of the road and the area of green space are introduced as indicators of traffic and construction sites, which are local main contributors of PM 2.5 in Beijing. The model can be extended to other cities in developing countries, especially in the progress of industrial structure upgrade.

Finally, the major constraint on our analysis has been the availability of city level data for pollution. The air quality data at city level has been publicly accessible since 2015, and more research based on the cross sectional and panel data could investigate the urban EKC hypothesis in China.

Spatial econometrics provide a powerful tool to measure the spillover effects of air pollution and economic development. The diffusion of air pollution across city boundary, and the transformation of heavy polluted industries can be measured as spatial effects. Based on Moran's I index and spatial econometrics, Du et al. (2018) measure the spillover effects of urbanization on PM concentration in the Beijing-Tianjin-Hebei area, and show that the PM concentration increase by 0.138% and 0.340% as a result of local and nearby urbanization. Feng at al. (2020) measures the effects of regulations on air pollution, and find that the air quality is affected by the air regulations of local and nearby cities. The cities with poor air regulation tend to be shelter of pollution, and the local air improvement can be offset by the pollution from nearby cities.

We expect more research to emerge for Chinese cities as the official data quality keep improving.

Chapter 3

The Impact of Household and Ambient Air Pollution and Socio-Economic Factors on Adult Health in China: A Spatial Econometrics Approach

3.1 Introduction

Over the past few decades, China has experienced rapid economic growth, leading to significant improvements in health outcomes. Life expectancy has increased from 66.8 years in 1980 to 76 years in 2016 (World Bank, 2019). However, along with economic development, pollution levels, particularly from industrial activities, have also risen. Han et al. (2018) reported that pollution levels in one-third of selected Chinese cities exceed the recommended standards set by the World Health Organization.

This has raised concerns about the impact of pollution on public health and whether it could hinder the progress made in increasing life expectancy. A report by Landrigan et al. (2018) suggests that pollution is a significant contributor to non-communicable diseases, including chronic obstructive pulmonary disease (COPD), and predicts a more than 50% increase in deaths due to ambient air pollution by 2050. Another study in China published in The Lancet by Wang Q et al. (2019) estimates that the implementation of pollution reduction targets outlined in the 13th Five Year Plan could potentially prevent around 240,000 premature deaths from COPD.

The adverse impact of air pollution on health has been extensively documented in epidemiological research. The availability of fine particulate matter (PM2.5) data in many countries has prompted further investigation into the health effects of this pollutant. Brauer et al. (2012) found a significant global burden of disease associated with ambient air pollution. Landrigan et al. (2018) established a causal link between PM2.5 exposure and various health conditions, including myocardial hypertension, congestive heart failure, cardiovascular mortality, COPD, and lung cancer.

In China, numerous studies have linked PM2.5 exposure to depression (Wang R et al., 2019), allergic rhinitis (Chu et al., 2019), respiratory disease risk (Chen and Wu, 2019), respiratory mortality (Song et al., 2019), COPD and asthma-related hospital admissions (Xie et al., 2019).

However, most of these studies have not adequately controlled for important socio-economic and demographic variables, such as individual income and age, which are crucial for fully assessing the impact of pollution on health. In the context of China, recent empirical research has shown a positive correlation between health and individual income or consumption. For instance, studies have found that greater household wealth is associated with higher life satisfaction (Lei et al., 2018), better health-related quality of life (Tan et al., 2018), improved health literacy (Tang et al., 2019), and an inverse U-shaped relationship between household income and Body Mass Index (BMI) (Yao and Asiseh, 2019). However, the connection between income and pollution has been largely overlooked in this body of literature.

This paper aims at bridging the two stands of literature above by investigating the relationship between health, pollution, individual income and other socio-economic and demographic variables in China.

This paper aims to bridge the gap between these two strands of literature by examining the relationship between health, pollution, individual income, and other socio-economic and demographic variables in China. We utilize cross-sectional data from the China Health and Retirement Longitudinal Study (CHARLS) for the year 2015. We investigate the effects of income, ambient air pollution (AAP) measured by average annual PM2.5 concentrations, and household air pollution (HAP) measured by cooking fuel, on the incidence of lung disease (LD) in adults. Probit regression analysis is employed to estimate the relationship while controlling for demographic factors such as marriage, gender, age, and other socio-economic variables including education. To address potential reverse causality issues, where individuals with lung disease may opt for cleaner cooking fuels, we utilize the province-level electricity price as an instrumental variable (IV).

Additionally, we incorporate spatial econometrics techniques to account for the possibility of spatial dependence in PM2.5 concentrations, as pollution can cross boundaries between nearby cities, and health outcomes may be influenced by neighboring areas due to commuting patterns (Chen X et al., 2017).

To the best of our knowledge, Chen X et al. (2017) is the only paper that utilizes spatial econometric techniques to examine a similar research question, specifically the relationship between mortality, pollution measured by SO2, and GDP per capita in Chinese cities. However, our study differs by focusing on a different source of pollution, PM2.5, which is more relevant to respiratory diseases. Furthermore, we specifically consider individual income (instead of GDP per capita) and individual-level control variables (rather than city-level variables). Our findings indicate that both ambient air pollution (local and spatial) and household air pollution have negative effects on health. We also emphasize the positive impact of higher income on health.

Additionally, factors such as being underweight, smoking, second-hand smoking, living in urban or southern China, and using natural gas instead of biomass fuel for cooking are found to influence individual health and the likelihood of LD.

The structure of the paper is as follows: Section 2 presents a literature review of studies investigating the relationship between air pollution and health, as well as the link between health, income, and socio-economic factors in China. Section 3 introduces the probit model with non-spatial and spatial econometric features. Sections 4 and 5 describe the data and present the results. The final section concludes the paper.

3.2 Literature Review

In this section we review the existing literature for China that focuses on the relationship between health and several variables of interest for our study, namely ambient air pollution (AAP), household air pollution (HAP) and socio-economic and demographic variables.

3.2.1 Effect of AAP on health

Emerging evidence in China reveal the health effect of air pollution, from $PM_{2.5}$ concentration in a single city or multiple cities. Wang et al. (2019) finds a negative effect of long-term exposure to $PM_{2.5}$ concentration on mental health in Jinan City. Yang, Guo, Morawska, et al. (2019) estimate that increasing $PM_{2.5}$ concentration of $10\ ug/m^3$ results in 1.06% increase in cardiovascular.

Chu et al. (2019) find a positive correlation between exposure to $PM_{2.5}$ concentration and risk of developing allergic rhinitis in Nanjing City. Zhang et al. (2019) confirm the correlation with childhood asthma in Hefei city. Xie et al. (2019) find a correlation between $PM_{2.5}$ concentration and hospital admission for respiratory diseases in Shenzhen city, and Zhang et al. (2019) finds the same correlation for Beijing. Several papers report a correlation between $PM_{2.5}$ concentration and mortality due to respiratory problems and hypertension in several cities (e.g., Cai et al., 2019, Yu et al., 2019, Hu et al., 2018, and Wu et al., 2018).

3.2.2 Effect of HAP on health

Household air pollutants include cooking combustion of biomass fuel with poor ventilation, second-hand smoking, formaldehyde derived from furniture, and nitrogen oxides from natural gas appliances (Guan et al., 2016). According to the World Health Organization, HAP leads to 3.7 million premature deaths globally and is a leading health risk in developing countries (Sidhu et al., 2017). In China, household air pollution is the top risk factor for premature death (Lelieveld et al., 2015) and causes more adverse health effects than ambient air pollution (Yang et al., 2010).

Chronic obstructive pulmonary disease (COPD) is one of the diseases caused by household air pollution. The overall incidence of COPD in China among non-smokers is estimated to be 5.2% of the population and is positively correlated with advanced age, lower body mass index (BMI), being male, exposure to smoking, and lower levels of education (Zhou et al., 2009). The improvement of household stoves in Xuanwei County, China, led to a 42% reduction in COPD in men and a 25% reduction in women, and the long-run effect was significantly positive, resulting in a lower relative risk (Chapman et al., 2005).

Based on survey in two areas in Yunnan Province, the overall incidence of COPD is 9.4%, and this increase with rural areas, smoking and use of biomass fuel (Liu. S et al., 2007). Zhou et al. (2014) estimates the effect of transformation from biomass fuel to biogas, and the project of kitchen ventilation improvement and biogas usage leads to improved household air pollution and reduction of COPD risk. [20]

3.2.3 Effect of Income on Health

There are some hypotheses on the relationship between health and income, which are supported by empirical studies. The Absolute Income Hypothesis states that there is a positive relationship between income and health, and that higher income can provide better health status. Evidence can be found in Adeline and Delattre (2017) , Carrieri and Jones (2017) and Mackenbach et al. (2005) .

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[20] There exist some papers on measuring and estimating household air quality in China. Zhang et al. (2019) measure daily average household air pollution concentration in northern China in living rooms and kitchens. Other papers measure household $PM_{2.5}$ concentration controlling for different fuel used for cooking and heating. For solid fuels, examples include wood and coal in Guizhou (Wang et al., 2011), crop residual and wood in Hebei (Zhong et al., 2012); crop residues in Shaanxi (Zhang et al., 2014) and in Yunnan by (Hu et at., 2014). And measurement of change in energy consumption includes coal and wood in Guizhou (Alnes et al., 2014), crop residuals and coal in Henan (Wu et al., 2015); coal and wood in Shanxi (Huang et al., 2017); and wood in Guizhou (Du et al., 2017). And based on field measurement of indoor air pollution measurement, a meta-analysis (Chen et al., 2018) estimate the average exposure of household air pollution.

The Income Inequality Hypothesis assumes that the individual health gets affected by the income inequality in a society. Strong version of the Income Inequality Hypothesis says that all individuals are affected by the income inequality. And the weak version of the Income Inequality Hypothesis asserts that individuals with low income suffer more from inequality than those with high income. Empirical evidence supporting the strong version can be found in studies conducted by Kennedy et al. (1998) in the US, Wagstaff et al. (2003) in Vietnam, and van Doorslaer et al. (2004) and Adeline and Delattre (2017) in Europe. The weak version finds support in studies by Hildebrand and van Kerm (2009), Li and Zhu (2006), and Mellor and Milyo (2002).

Dalstra et al. (2005) examine the prevalence of chronic disease and socioeconomic factors in eight European countries, with education as socioeconomic indicator. The prevalence of most diseases is found to be higher in the group with lower socioeconomic status, excluding cancer, kidney disease, skin disease (which no association with socioeconomic status are found) and allergy (which is found to be higher in higher socioeconomic status). The chronic respiratory disease was found to be higher in lower socioeconomic status group, of which the odd ratio is 1.33 and 1.19 in the group of male and female, and 1.24 for the overall population.

Mika et al. (2020) investigate the association between socioeconomic status and physical and mental health conditions based on two Finnish cohort studies and one UK cohort study. The socioeconomic status is measured in three indicators: the first one is score based on the proportion of people with low education background, unemployment rate, and rate of people living in rental properties; the second indicator is educational attainment which is based on two categories: high (tertiary qualification, college or university) and low (other qualifications, including none). The third indicator is an index named "British civil service occupational grade" which is related with salary, occupational prestige, level of responsibility at work and future pension. lifestyle factors including smoking, alcohol consumption, physical inactivity and obesity are adjusted. Low socioeconomic status is associated with increased risk for 18 diseases, including chronic obstructive bronchitis.

Tan et al. (2018) conducted a study to examine the association between absolute household income and health-related quality of life in China. They utilised cross-sectional data from the 2008 National Health Service Survey conducted in Shaanxi Province. The findings emphasized the significance of income on health outcomes. After adjusting for sociodemographic factors, the low-income group exhibited a significantly lower health index compared to the higher-income group. Additionally, the study revealed that income played a role in influencing health information gain.

In a separate research by Tang et al. (2019), the correlation between income and health literacy, as well as the increased risk of poor health among the low-income group in Guangzhou in 2013, was examined. The study aimed to explore the relationship between income and health literacy, shedding light on the heightened susceptibility to health issues experienced by individuals with lower incomes.

Contrasting the aforementioned studies that focused on specific regions, Lei et al. (2018) adopted a national database, the China Family Panel Study, to investigate the positive impact of higher household income and consumption on life satisfaction and mental health. Utilizing probit analysis, the study explored the association between income, consumption, and subjective well-being on a broader scale.

Yao and Asiseh (2019) delved into the connection between body mass index (BMI) and family income, utilising micro-level panel data from China spanning from 1991 to 2011. Their findings provided support for a linear relationship between household income and individual BMI.

3.2.4 Effect of Ambient and Household Air Pollution on Health

Income and air pollution are primary factors associated with human health. Kattan et al. (1997) examined the characteristics of children with asthma and found that lower-income households may face challenges in asthma care, leading to increased vulnerability to the severity of air pollution. Samet et al. (2000) estimated the association between daily mortality rates and PM10, with education, income, and race as control variables. Their findings suggested that a 10 μg/m3 increase in PM10 led to a 0.51% and 0.68% increase in mortality from all causes and cardiovascular and respiratory causes, respectively.

Pope et al. (2015) reviewed the health gains in life expectancy in the US and found that reductions in air pollution and increases in income contributed to the increase in life expectancy. Allen et al. (2016) examined the effects of income and air pollution on life expectancy and aging using cross-sectional data at the county level in the US. The linear results revealed an association between health outcomes and air pollution and income, suggesting that reduced levels of air pollution and increased income are beneficial for health. Non-linear results indicated that the group with income over $40,000 gained more health benefits compared to the group with income less than $40,000. Additionally, the effects of income and air pollution were found to be attenuated when smoking and obesity were controlled for.

There are only a few papers estimating the joint effect of air pollution and economic factors on health in China. Chi et al. (2019) measured individual exposure to both household and ambient PM2.5 and examined 43 patients with chronic obstructive pulmonary disease (COPD) and their healthy spouses as a control group. They used iron as a trace element to distinguish between the sources of pollutants and employed mixed-effects models with lagged days. The results showed that the health effects of household and ambient PM2.5 differ among the population, with forced expiratory volume influenced by household PM2.5 during heating seasons and diastolic blood pressure influenced more by ambient PM2.5.

Lin et al. (2018) measured individual exposure to air pollution using cross-sectional data from six cities and estimated the prevalence of asthmatic and allergic symptoms among preschool children. Air pollution factors included household dampness, renovation materials, parental smoking as household air pollution (HAP), and PM2.5 and O3 as ambient air pollution (AAP). Other demographic factors were also controlled for. The study included more than 30,000 children from 205 kindergartens. The results supported the association between high ambient PM2.5, HAP, and the prevalence of asthmatic and allergic disorders. Children living in suburban areas and households with dampness were found to be at higher risk. However, the study did not analyze household income at the individual level, but rather at the city level based on city statistical yearbooks. Therefore, the study could not examine the direct effect of income on individual health. Additionally, this paper concluded that the income effect on health differs across different cities, which limits further discussion on the relationship between health and household income.

In addition to AAP, HAP, and income, age has been found to be related to health outcomes. The effect of PM2.5 on COPD varies across different age groups, with individuals aged 50 and older being more sensitive to PM2.5 (Chen G et al., 2019). The prevalence of COPD is reported to be 21.2% for individuals aged 60-69 and 35.5% for those over 70 (Wang et al., 2018).

3.2.5 Ambient air pollution concentration: spatial econometrics approach

Spatial econometrics provides a method for measuring transboundary externalities of air pollution and is considered necessary in the field of environmental and resource economics (Anselin, 2013). Air pollution, due to its high mobility, often exhibits interregional characteristics, with haze and fog occurring simultaneously in multiple areas. This spatial correlation of air pollution has been empirically observed in China, where PM concentrations have shown significant spatio-temporal correlation in regions such as Beijing-Tianjin-Hebei, Shandong Peninsula, the middle part of the Yellow River, and the Guangdong-Hong Kong-Macau area (Xu et al., 2019; Fang et al., 2019).

Researchers have applied spatial econometric techniques to study the effects of air pollution on health. For example, Chen et al. (2017) estimated the spatial effect of SO2 and soot on lung cancer mortality using a spatial Durbin model based on data from 106 cities over the period of 2006 to 2012. Hao and Liu (2016) investigated the Environmental Kuznets Curve hypothesis by examining the relationship between GDP per capita and PM2.5 concentration using spatial lag and spatial error models based on data from 73 cities in 2013. Feng et al. (2018) demonstrated the negative impact of local and neighbouring air pollution on public health using a spatial autoregressive model based on city-level data.

Given the spatial nature of air pollution and its potential impact on individual health, employing spatial econometric techniques is essential when estimating the effects of air pollution and income on individual health. These techniques allow for the consideration of spatial dependencies and provide a more accurate understanding of the relationship between these variables.

3.3 Data

3.3.1 Data source

The individual records utilized in this research are obtained from the China Health and Retirement Longitudinal Study (CHARLS). This survey is known for providing high-quality data for research on adult and elderly individuals in China. It encompasses a wide range of locations, including 150 cities and 450 villages from 28 provinces across the country. The sample consists of more than 10,000 households (or family units) and over 17,000 interviewees.

The CHARLS questionnaire comprises 10 modules, covering various aspects of life. These modules include demographics, family structure and transfers, health status and functioning, biomarkers, health care and insurance, work, retirement and pension, income and consumption, assets at both the individual and household levels, and community-level information. For this particular research, data from three modules are employed: demographics, health status and biomarkers, and income.

The national wave of the CHARLS survey has been conducted in multiple years, including 2018, 2015, 2013, and 2011. For this research, the analysis is based on the cross-sectional data from the year 2015. The CHARLS dataset provides comprehensive individual-level information on socioeconomic factors and physical and mental health, making it a valuable resource for numerous scholarly works. Previous studies utilizing this dataset have explored various topics, such as the impact of social engagement on self-rated health status and mental distress (Liu et al., 2019; Ma and Piao et al., 2020), the relationship between chronic diseases and mental health (Jiang et al., 2020), the morbidity rate and socioeconomic factors (Jiang et al., 2019), the influence of migration on health (Hou et al., 2019), a comparison of grandparenthood in Western Europe and China (Zhang et al., 2020), and the connection between medical insurance and health equity (Fan et al., 2020).

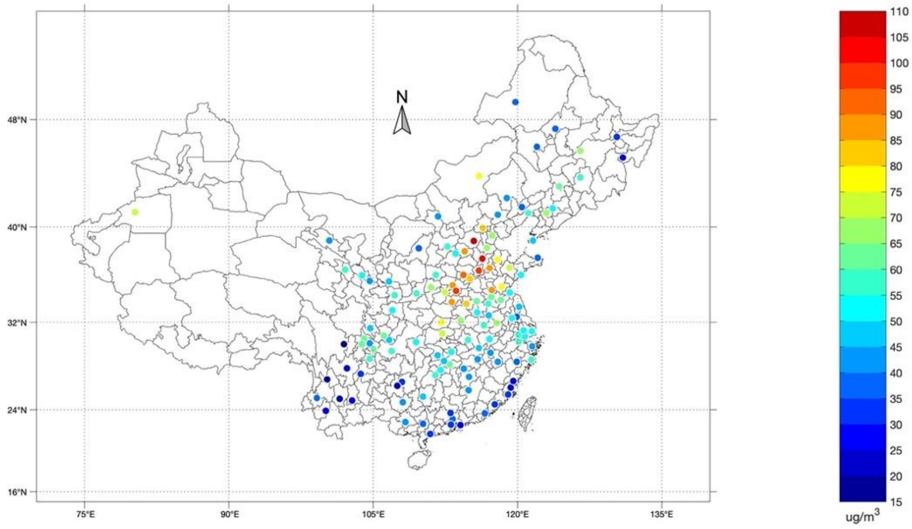

Figure 7: PM Concentration at city level

In Figure 7, the annual average concentrations of PM at the city level are visualized. The colors on the map represent varying levels of ambient air pollution, ranging from cool colors indicating lower concentrations to hot colors indicating higher concentrations. The map highlights that the highest concentration levels (depicted by brown and red points) are found in the central part, specifically the Beijing-Tianjin-Hebei area. Conversely, lower concentration levels (represented by indigo and blue points) can be observed in the southeast and northeast regions. The concentration levels gradually decrease from the central area towards the boundaries, indicating a strong spatial relationship.

3.3.2 Data Description

The dependent variable in this research is lung disease (LD), obtained from the biomarker module of the CHARLS dataset. Demographic factors are derived from the demographic background, individual income, and pension sectors. Housing characteristics provide variables related to household air pollution (HAP). Education information is matched from waves in 2011 and 2013. The document named PSU[21] provides city names and community IDs, facilitating the linkage between location and ambient air pollution levels. The research takes into account changes in administrative divisions and includes cities with the same spelling but located in different provinces.

For the volume of observations, HAP data from 2015 are utilized because limited air pollution records are available for 2014 and earlier years. The monthly average of HAP at the city level is obtained from the *Airstudy* dataset, which collects daily atmospheric records in China. The annual average pollution concentrations at the city level are calculated and matched with individual records based on the city name.

Table 7 gives the definition of variables in this chapter.

Table 7: Variable definition

Variables	Definition
LD	=1 if the individual self reports to be diagnosed with lung disease =0 otherwise
Income	average household income measured in 1,000 CNY per year, sum of income, cash deposit, government bonds and stock
PM25	annual ambient PM 2.5 concentration at city level measured in ug/m^3
Cooking	=1 if the fuel is less polluted, as electricity, liquefied gas and others =0 if the fuel for cooking is coal, wood and crop residue
Smoke	=1 if the individual has smoked more than 100 cigarettes, including pipe, self-rolled and chewed tobacco; =0 otherwise
SHS	Second Hand Smoking =1 if the individual has never smoked but lives with a smoking individual; =0 if the individual smoking, or no one has smoked at home
Gender	=1 if the individual is female; =0 if the individual is male
Marriage	=1 if the individual is married in law or in fact =0 otherwise

[21] Note: There was one city named Xiangfan in the first wave of CHALRS 2011 but the city is cancelled due to change of administration division. Also some cities shares the same spelling but different pronunciations (such as Suzhou in Anhui province and Suzhou in Jiangsu, and Taizhou in Zhejiang province and Taizhou in Jiangsu province)

Age	= the year of survey (2015) – the birth year
Edu	The education level of the individual: from 0 (illiberally) to 11 (Ph.D.)
BMI[22]	Body mass index, equal to height square divided by weight
Overweight	=1 if BMI >28.5 [23] ; =0 otherwise
Underweight	=1 if BMI < 18.5: =0 otherwise
Residential factors	
Urban	=1 if the individual is living is urban areas; =0 if the individual is living in rural areas
Coastal	=1 if the individual is living in coastal areas; =0 if the individual is living in continental areas
Northern	=1 if the individual is living in the northern part; =0 if the individual is living in the southern part

[22] BMI is not included in the regression, because health is not a monotonic function but a proper range of BMI. Therefore, we introduce two dummy variables, Overweight and Underweight, to measure it

[23] The standard of overweight and underweight comes from Criteria of Weight for Adults (National Health Commissions of China, 2013)

Table 8 reports the data statistics, including number of observation (N), mean, standard deviation (sd), and extreme values (min, max). The mean of LD, which is a dummy variable, is small (0.08), indicating that slightly over 8% of individuals reported to be diagnosed with lung disease. The percentage is consistent with the reported prevalence of 8.2% people over 40 years old of COPD in China (Yang et al., 2020)

Table 8: Descriptive Statistics

VARIABLES	N	MEAN	SD	MIN	MAX
LD	8,335	0.0812	0.273	0	1
Income	8,335	36.78	95.39	0.001	3,081
PM25	8,335	51.15	18.00	14.54	98.08
Smoke	8,335	0.370	0.483	0	1
SHS	8,335	0.189	0.391	0	1
Cooking	8,335	0.479	0.500	0	1
Gender	8,335	0.428	0.495	0	1
Marriage	8,335	0.891	0.312	0	1
Old	8,335	0.275	0.447	0	1
Edu	8,335	4.295	2.026	0	11
Overweight	8,335	0.289	0.453	0	1
Underweight	8,335	0.0408	0.198	0	1
Urban	8,335	0.474	0.499	0	1
Coastal	8,335	0.418	0.493	0	1
Northern	8,335	0.494	0.500	0	1

In terms of individual factors, the mean income is 36,000 Chinese Yuan. The mean gender variable is 0.43, indicating that 43% of the individuals in the sample are female. The average educational level is 3.49, which falls between primary school (3) and junior high school (4).

Regarding health-related factors, only 3% of the individuals are underweight, while 42% are overweight, with a BMI (Body Mass Index) higher than 28.5. Additionally, 31% of the individuals are smokers, while another 16% are exposed to second-hand smoking.

Residential factors provide information on individuals' residential locations. Approximately 47% of the individuals live in urban areas, 42% in coastal areas, and 49% in northern areas of China. These proportions reflect a reasonable distribution across urban-rural, coastal-continental, and northern-southern regions, each representing around 50% of the sample.

Housing characteristics include dummy variables related to the sources of household air pollution (HAP). For instance, 48% of individuals use clean fuel for cooking.

Ambient air pollution (AAP) factors encompass the annual concentrations of air pollution. The level of PM2.5 is indicated as 51, which exceeds the threshold set by the World Health Organization (WHO) of 10 ug/m3.

To account for province-specific effects, province dummy variables are created. There are 28 provinces, leading to the generation of 27 dummy variables to mitigate multicollinearity issues.

3.4 Model

The fundamental model, explained in section 4.1, describes health as an outcome determined by income, household air pollution (HAP), ambient air pollution (AAP), and other control variables. The effects of air pollution and income on health are estimated using a probit model.

In section 4.2, the simultaneity between cooking fuel and health is addressed. High HAP can lead to lung disease, and individuals with lung disease tend to switch to clean energy for household cooking. To account for endogeneity, a two-stage probit model is employed. In the first stage, the price of electricity is introduced as an instrumental variable, representing the cost of clean cooking fuel.

In section 4.3, spatial econometrics is utilized as a practical method to evaluate the effects of air pollution from nearby cities. This approach considers the spatial correlation of air pollution and its impact on individual health.

3.4.1 Fundamental Model

As a result of economic growth, higher income is associated with higher health status, as living conditions improve, health education is pervasive and quality of and access to health care increase among the population. However, high growth especially at the early stages of development results in higher pollution which in turn negatively affect health.

We follow a longevity-based model by Ebenstein et al. (2015), which estimates the relationship between (ambient) air pollution and life expectancy in China. We consider the following relation, that health (H) of individual i is a function of income (I) and pollution (P),

$$H_i = H(I_i, P_i)$$

Two sources of air pollution, household air pollution (HAP) and ambient air pollution (AAP), are considered. HAP is specified in terms of cooking fuel and second-hand smoking. Annual averages of PM2.5 concentration are used to represent AAP. The model controls for determinants of individual health, such as smoking, gender, marriage, and geographic location following Feng et al. (2018). The final model is given as:

$$HEALTH_i = H(Income_i, HAP_i, AAP_i, Demographis_i, Geographics_i)$$

A probit model is employed to estimate the above empirical relationship. Binary models are widely used in health economics to assess the likelihood of a certain disease from survey data (See AM Jone, 2009, Miratitlles et al., 2015 , and Kim, M. et al 2016). Such as hospital choice in Italy (Berta et al., 2016)

An index function restricts the way in which the response probability depends on x: $p(x)$ is a function of x via the index $x\beta$, and the function $G(x\beta)$ maps the index $(x\beta)$ into the response probability $p(x)$.

$$p(x) = P(y = 1|x) = G(x\beta)$$

where x is a vector of independent variables, and β is a vector of coefficients.

Let y^* be an unobserved continuous variable of a measure of lung disease by a non-random component $x\beta$ and a random component ϵ, which is:

$$y^* = x\beta + \epsilon$$

And if y^*exceed a threshold, then the individual will be diagnosed with the lung disease. We can only observe the outcome of lung disease but cannot observe the latent variable y.

$$y = \begin{cases} 1, & y_i^* \geq 0 \\ 0, & otherwise \end{cases}$$

where y_i is equal to one when $y^* > 0$, zero otherwise. We assume that the disturbance term, $\epsilon_i \sim N(0,1)$, follows standard normal distribution. The response probability of y writes:

$$P(y = 1|x) = P(y^* > 0) = P(x\beta + \epsilon > 0) = P(\epsilon > -x_i'\beta) = G(x\beta)$$

In the probit model, the function $G(x\beta)$ is given as:

$$G(x\beta) = \Phi(\mathrm{x\beta}) = \int_{-\infty}^{x\beta} \phi(v)dv$$

where $\phi(v)$ is the standard normal density

$$\phi(v) = (2\pi)^{-1/2} \exp\left(-z^2 / 2\right)$$

To estimate the probit model by maximum likelihood, the log-likelihood function for individual i is needed. And the density of y_i can be written as :

$$f(y|x_i; \beta) = [G(x_i\beta)]^y[1 - G(x_i\beta)]^{1-y},$$

The log-likelihood for the individual i is a function of vector of independent variables:

$$l_i(\beta) = y_i \log\big(G(x_i\beta)\big) + (1 - y_i)\log\left(1 - G(x_i\beta)\right)$$

The log likelihood is given as follows

$$\mathcal{L}(\beta) = \sum_{i=1}^{n} y_i \log\left(\Phi(x_i'\beta)\right) + \sum_{y_i=1}^{n} (1 - y_i)\log\left(1 - \Phi(x_i'\beta)\right)$$

Then we estimate the coefficient $\hat{\beta}$ with maximum likelihood estimation (MLE).

3.4.2 Endogeneity

Endogeneity is a significant issue in estimating health outcomes as it arises when the independent variable is correlated with the error term. Several factors can contribute to endogeneity, including omitted variables, selection bias, model misspecification, and simultaneity. In this study, the problem of simultaneity is particularly relevant as both health outcomes and the choice of cooking fuels may be determined simultaneously.

Health outcomes are influenced by air pollution, and the choice of cooking fuels can be influenced by individuals' health conditions. For instance, individuals with lung disease may be more inclined to reduce respiratory burdens and opt for less-polluted fuels for cooking. This creates a simultaneous relationship between health and HAP.

The equations below give simultaneous functions of health and HAP:

$$LD = 1 \; if \; LD^{*} = \beta_1 HAP + \beta_2 x_1 + u_1 > 0$$

$$HAP = 1 \; if \; HAP^{*} = \alpha_1 Health + \alpha_2 x_2 + v_2 > 0$$

where x_1, x_2 is a vector of exogeneity variables. $Health^{*}, HAP^{*}$ are latent function. The equations below express the endogenous variables ($Health, HAP$) in terms of exogenous variables:

$$LD^{*} = \frac{\beta_2 x_1 + \alpha_2 \beta_1 x_2 + u_1 + \beta_2 v_2}{1 - \alpha_1 \beta_1}$$

$$HAP^{*} = \frac{\alpha_1 \beta_2 x_1 + \alpha_2 x_2 + \alpha_1 u_1 + v_2}{1 - \alpha_1 \beta_1}$$

The covariance of u_1 and HAP is not zero, leading to endogeneity issue:

$$E(HAP^{*}, u_1) = Cov(HAP, u_1) = \frac{\alpha_1}{1 - \alpha_1 \beta_1} E(u_1^2) \neq 0$$

A two-step correction for endogeneity is used here with introduction of electricity price as instrument variable (IV). The electricity ($ELEP$) is assumed to be a factor of the choice of cooking fuels, and not related with the individual health. The equations on $Health^{*}, HAP^{*}$ is rewritten in a reduced form:

$$LD = 1\ if\ \gamma_1 x_1 + \gamma_2 HAP + e_1 > 0$$

$$HAP = 1\ if\ \delta_1 x_2 + \delta_2 ELEP + e_2 > 0$$

where (e_1, e_2) is independent of (x_1, x_2), and $\rho_1 = corr(e_1, e_2) \neq 0$. The joint distribution of $(Health, HAP)$ is:

$$P(Health = 1|HAP = 1, x_2, ELEP) = \mathrm{E}[\mathrm{P}(\mathrm{Health} = 1|\mathrm{e}_2, \mathrm{x}_2, \mathrm{ELEP})|\mathrm{HAP} = 1, \mathrm{x}_2, \mathrm{ELEP}]$$

$$= E\{\Phi\left[(\gamma_1 x_1 + \gamma_2 HAP + \rho_1 e_2) / (1 - \rho_1^2)^{\frac{1}{2}}\right] |HAP = 1, x_2, ELEP\}$$

$$P(Health = 0|HAP = 1, x_2, ELEP) = 1 - P(Health = 1|HAP = 1, x_2, ELEP)$$

Similarly, the likelihood function for Health when HAP is equal to 0 can be written as:

$$P(Health = 1|HAP = 0, x_2, ELEP) = \mathrm{E}[\mathrm{P}(\mathrm{Health} = 1|\mathrm{e}_2, \mathrm{x}_2, \mathrm{ELEP})|\mathrm{HAP} = 0, \mathrm{x}_2, \mathrm{ELEP}]$$

$$P(Health = 0|HAP = 0, x_2, ELEP) = \mathrm{E}[\mathrm{P}(\mathrm{Health} = 0|\mathrm{e}_2, \mathrm{x}_2, \mathrm{ELEP})|\mathrm{HAP} = 0, \mathrm{x}_2, \mathrm{ELEP}]$$

In this study, the probit model is used to estimate the relationship between health outcomes and household air pollution (HAP) using the command BIPROBIT in STATA. The model takes into account the four possible outcomes: (Health, HAP), and the log-likelihood function is used for maximum likelihood estimation (MLE).

To ensure the validity of the instrumental variables used in the model, two conditions need to be satisfied: instrument relevance and instrument exogeneity.

Instrument relevance refers to the extent to which the instrument variables are correlated with the endogenous variable (HAP) in the first stage of the model. If the instrument variables are weak, they explain little of the variation in HAP, leading to weak instruments. Weak instruments can result in imprecise estimates and biased inference. The paper will conduct tests to assess the relevance of the instruments and ensure they adequately explain the variation in HAP.

Instrument exogeneity implies that the instrument variables are not correlated with the error term in the model. If there is correlation between the instruments and the error term, it can lead to overidentification and inconsistent results. To ensure instrument exogeneity, the paper will test for the absence of correlation between the instruments and the error term.

By testing for both weak instrument relevance and instrument exogeneity, the study aims to validate the instrumental variables used in the model and ensure the reliability of the estimation results. Valid instruments are crucial for addressing the endogeneity issue and obtaining unbiased estimates of the effects of HAP on health outcomes.

3.4.3 Heteroscedasticity

Heteroscedasticity refers to variance of residuals is not equal for all observations. The error term represents unobserved factors that affect the health. This research assumes that the consciousness of self-protection from air pollution is an unobserved factor. $PM_{2.5}$ is a recent concern for individuals in China, especially for over 40 years old in this dataset. The consciousness of air pollution is not compulsory for everyone, but is determined by the learning ability. Education level can be a proxy for the self-protection. The error term in the index function decrease as the education level increases:

$$Var(e) = e_i^2 \neq e^2$$

To overcome the heteroscedasticity, the variance of error term is written as:

$$e_i^2 = (\exp(\gamma\ edu))^2$$

And the index function will be given as:

$$\Pr(y = 1) = \Phi(\beta x/[\exp(\gamma\ edu)]$$

As suggested by Wooldridge et al. (2004), heteroscedasticity in $Var(e|x)$ entirely changes the functional form for $P(y = 1|x)$, and it makes little sense to care the consistency of β.

3.4.4 Spatial econometrics

There are economic reasons of employing spatial models. As stated by LeSage and Pace (2009), SAR models can be utilized when the decision by individuals at various geographic location are made based on the choices of neighbour agents, such as the health status among children who live in neighbouring regions. For individuals in this work, health is treated as results of personal choices including resident location, air improvement and lifestyle. The reason for SLX utilisation can be straightforward as the air pollution in one city will pose adverse effects on individual health in neighbouring cities, and other variables will also the spillover effect influences. For SEM, spatial error term can distinguish the spatial correlation in unobserved attributes due to the similarity of the neighbouring regions.

A general nonlinear nesting model with binary dependent variable can be written as:

$$y^* = \rho W_1 y^* + \beta x + \theta W_2 x + u, \qquad u = \lambda W_3 u + v$$

$$y = 1\ if\ y^* > 0$$

y^* is the latent variable and y is the observed binary variable. x is the exogeneous variables and u is the disturbance term. W_1, W_2, W_3 are known non-negative spatial weight matrix. Wy^* denotes the endogenous interaction effect among the latent variable, Wx the exogenous interaction effects among the independent variables and Wu is the interaction effects among the disturbance term of the different units. The parametres $\rho, \beta, \theta, \lambda$ are unknow parametres to be estimated, in which ρ is called spatial autoregressive coefficient, λ the spatial autocorrelation coefficient, and θ spatial lag of X.

The spatial weight matrix are assumed to be equal, $W_1 = W_2 = W_3 = W$. The element w_{ij} of spatial weight matrix describe the spatial relationships of two individuals i, j.

$$W = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{pmatrix}$$

The diagonal element is set to be zero $w_{ii} = 0$, as the individual i cannot be treated as the neighbour of its own. And the elements w_{ij} $i \neq j$ is generated as below:

$$w_{ij} = \begin{cases} 1, & d_{ij} \leq 200 \\ 0, & d_{ij} > 200 \end{cases}$$

Individuals ij is treated as neighbours ($w_{ij} = 1$) if the distance between them is no more than 200 kilometres, and non-neighbours otherwise. And d_{ij} is the distance between individual i j based on the latitude and longitude.

$$d_{ij} = distance(individual_i, individual_j)$$

In regression analysis, the basic model translates into inclusion of spatial spillover effects: spatial lagged of dependent variable, Y, (resulting in Spatial Autoregressive model, SAR), or spatial lagged of independent variables, X, (resulting in Spatial Lagged of X model, SLX), or spatial error structure, ε, (resulting in Spatial Error model, SEM). Also, SAC[24] model includes both spatial error term and dependent variable and Spatial Durbin Model (SDM) include spatial lagged of dependent and

[24] This model is denoted by LeSage and Pace without pointing out what this acronym stands for (Elhorst, 2014).

independent variables.

Due to the complication of spatial weight which is a $8{,}335 \times 8{,}335$ matrix, we are considering following models based on a linear regression. The MATLAB Toolbox by LeSage[25] provide models for binary regression, but the calculation involves huge amount of workload via Monte Carlo Simulation.

$$SAR\colon \mathrm{y} = \alpha + \rho\,\mathrm{W}\,\mathrm{y} + X\beta + \varepsilon$$

$$SLX\colon \mathrm{y} = \alpha + X\beta + WX\theta + \varepsilon$$

$$SEM\colon y = X\beta + \mu, \mu = \gamma W\mu + \varepsilon$$

Moran's I index is calculated before employing spatial econometrics to evaluate whether the pattern is clustered, dispersed or random. The following statistics is estimated. The value of the index is from -1 to +1, and for a null hypothesis with no spatial correlation, the expected value approaches 0.

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}\,(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

[25] The toolbox is available at [Econometrics Toolbox for MATLAB (spatial-econometrics.com)](spatial-econometrics.com)

3.5 Results

3.5.1 Probit Result

Table 9 reports the results of the non-spatial probit models, which estimate the individual health as a result of income, AAP, HAP and other control variables. Column 1 gives the result of regression on AAP, HAP and Income, and column 2 include the demographic factors based on the column (1). Column (3) gives the results with more geographic factors than column (2). The pseudo R^2 increases from 0.06 to 0.10, indicating a higher level of goodness-to-fit. The increasing Pseudo R square indicates an improvement from null model to fitted model[26]. And the value of Pseudo R^2 of 0.2 to 0.4 represents an excellent fit (McFadden 1977[27]) , and in this paper the R square is around 0.1, which is a proper estimation.

Table 9: Results for non spatial probit models

	(1) AAP&HAP	(2) Demographic	(3) Geographic	(4) Endogeneity	(5) Heteroscedasticity
Income	-0.0025***	-0.0013**	-0.0011**	-0.0013***	-0.0008**
	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0004)
PM25	0.0035	0.0039	0.0045*	0.0016	0.0039**
	(0.0024)	(0.0024)	(0.0024)	(0.0015)	(0.0018)
SHS	0.2432***	0.3579***	0.3524***	0.1053**	0.2780***
	(0.0607)	(0.0732)	(0.0732)	(0.0483)	(0.0643)
Smoke	0.5561***	0.4615***	0.4546***	0.3216***	0.3445***
	(0.0476)	(0.0559)	(0.0560)	(0.0432)	(0.0578)
Cooking	-0.0360	0.0023	0.0065	-1.5305***	-0.0009
	(0.0436)	(0.0448)	(0.0449)	(0.0691)	(0.0344)
IV					
Electricity				-0.0002	
				(0.0002)	
N	8335	8335	8335	8335	8335
pseudo R^2	0.0667	0.1010	0.1022	n.a.	n.a.
LR test	n.a	n.a.	n.a.	86.377***	5.52**

z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1
The full table is attached in the appendix, see table A

[26] Note: Stata reports McFadden R square as pseudo R square, which is $R^2 = 1 - \frac{\ln \hat{L}\,(M_{full})}{\ln \hat{L}((M_{intercept})}$, where $\hat{L}$ is the estimated likelihood, M_{full} and $M_{intercept}$ are model with and without predictors, which can be treated as the sum of squares total and sum of squares error. The ratio of the likelihood suggests the level of improvement over the intercept model. Source: https://stats.oarc.ucla.edu/other/mult-pkg/faq/general/faq-what-are-pseudo-r-squareds/ UCLA

Column (1) to (3) provides a strong negative impact of income on LD, suggesting that individuals with higher income tends to have lower possibility of LD. The effects of air pollution are consistent with existing literature, that high level of AAP concentration, and HAP concentration leads to high possibility of LD. The HAP is always significant while the AAP is only significant in the column(3).

The column (4) considers the endogeneity in the regression as the choice of clean energy and LD can be simultaneous functions. Column (4) utilizes the price of electricity as instrument variable. The price of electricity is for residential use, and it is regarded as an indicator of price of clean energy, which is assumed to be correlated with the choice of cooking fuel but uncorrelated with LD. In the first step, the effect of electricity price is negative, suggesting that a high price of clean energy leads to polluted energy and less clean energy. In the second step, the effect of cooking is significantly negative. This result means that a choice of cooking with clean energy contributes to less LD. Compared with the result in column (3), endogeneity leads to overestimate the coefficient.

The column (5) consider heteroscedasticity due to the education level, and the coefficient is slightly lower than the column (3), due to consider the education level in the variance of error term. The cooking is significantly negative whereas positive in column (3), which is consistent with the literatures. The LR test with 5% significance shows that the regression with heteroscedasticity should be better than column (3).

Table 10 presents subgroup results based on the regression in column (3), which includes demographic and geographic factors. The effects of HAP, AAP, and property on health are estimated for subgroups with different vulnerability to lung disease.

Across all subgroups, the coefficient of INCOME is consistently negative, indicating that a higher economic status is associated with a lower likelihood of LD. This finding aligns with the results in Table 3. Additionally, the effects of second-hand smoke (SHS) and active smoking on LD remain consistent with Table 3, indicating that both active smoking and exposure to SHS contribute to a higher probability of LD.

The results for PM2.5 are more complex. In the subgroup of young people (age <45 years old), the coefficient of PM2.5 is insignificantly negative. However, in all other subgroups, the coefficient is positive, though not always statistically significant. This suggests that the relationship between PM2.5 and LD varies across different vulnerability groups, with some subgroups showing a positive association and others not exhibiting a significant relationship.

The differences in health outcomes between males and females can be attributed to both pathological and socioeconomic factors. One contributing factor is the anatomical differences between males and females. Even when lung sizes are equivalent, males generally have larger lungs and conducting airways compared to females. Experimental animal data have supported the role of sex hormones in lung development, with androgens and estrogens exerting both inhibitory and stimulatory effects. For instance, adult male mice tend to have larger lung volumes but smaller volume-to-body mass ratios compared to females.

Studies have observed that the gender difference in COPD may vary between developed and developing countries. For instance, a study conducted in Canada by Tan et al. (2015) found no gender difference in COPD risk factors among ever-smokers. On the other hand, biomass fuel combustion has been associated with COPD in developing countries rather than in developed countries.

In the context of China, Li et al. (2019) investigated the association between the use of solid fuels for cooking and the prevalence of COPD. They found that the joint effect of fuel type and sex showed a higher hazard ratio for females in the solid fuel group, while the ratio was lower in the solid fuel group for males. This suggests that solid fuel use for cooking has a greater impact on COPD risk for females in China. This finding can be explained by the fact that females in China tend to spend more time in housework and cooking, resulting in prolonged exposure to indoor pollutants. The prolonged exposure to particulate matter (PM) and other air pollutants generated during cooking and fuel combustion contributes to adverse health outcomes.

Existing literature supports the notion that both ambient and household air pollution have an impact on health outcomes. However, most of these studies are based on aggregate data rather than individual-level analysis. Several studies have found correlations between air pollution and various health indicators, including respiratory disease mortality, hospital admissions, and incidence of asthma. For example, studies by Yang, Guo, and Morawska (2019), Xie et al. (2019), Zhang et al. (2019), Chapman et al. (2005), Zhou et al. (2009), and Zhang et al. (2019) have demonstrated associations between air pollution and these health outcomes.

The health effect of HAP is supported by the empirical research by Chapman et al. (2005) and Zhou et al. (2009). And the health effect of cooking is consistent with the results of Liu S et al. (2007) and Zhou et al. (2014). The health effect of income in this chapter supports the absolute income hypothesis, that a higher income is correlated with better health status. The effect of income is supported by Let et al. (2018), Tan et al. (2018), and Tang et al. (2019).

Overall, the existing literature supports the idea that both ambient and household air pollution have detrimental effects on health outcomes. The gender differences in health outcomes, particularly regarding COPD, are influenced by physiological and socioeconomic factors. Females in China, in particular, are more susceptible to adverse health effects due to their prolonged exposure to indoor pollutants resulting from activities such as housework and cooking.

Table 10: Results for non spatial probit models: subgroup

VARIABLES	(1) GENDER =0	(2) GENDER =1	(3) GDPPC <= 50	(4) GDPPC > 50	(5) EDU: LOW	(6) EDU: HIGH	(7) NORTHERN =0	(8) NORTHERN =1
Income	-0.001*	-0.001	-0.001	-0.002**	-0.003**	-0.001	-0.001	-0.002**
	(-1.79)	(-1.46)	(-1.02)	(-2.06)	(-2.15)	(-1.50)	(-1.05)	(-2.11)
PM 2.5	0.004	0.007*	0.003	0.009*	0.009***	-0.000	0.015***	0.001
	(1.25)	(1.68)	(0.82)	(1.69)	(2.64)	(-0.09)	(3.00)	(0.37)
SHS	0.406	0.452***	0.310***	0.435***	0.261***	0.498***	0.363***	0.321***
	(1.52)	(5.11)	(3.24)	(3.77)	(2.83)	(4.02)	(3.77)	(2.81)
Smoke	0.449***	0.496***	0.478***	0.430***	0.371***	0.556***	0.432***	0.472***
	(7.14)	(3.72)	(6.73)	(4.62)	(4.84)	(6.49)	(5.67)	(5.64)
Cooking	-0.022	0.072	0.021	-0.030	0.023	-0.015	0.022	0.001
	(-0.38)	(0.95)	(0.36)	(-0.40)	(0.37)	(-0.22)	(0.37)	(0.02)
Constant	-1.835***	-1.734***	-1.531***	-1.775***	-1.612***	-1.691***	-1.867***	-1.545***
	(-9.74)	(-7.80)	(-7.88)	(-7.13)	(-8.75)	(-5.44)	(-6.21)	(-6.78)
Observations	4,736	3,571	4,736	3,599	4,172	4,134	4,214	4,121
Pseudo R-squared	.0962	.1215	.0999	.1061	.0985	.1094	.10564	.0882

VARIABLES	(9) COASTAL=0	(10) COASTAL=1	(11) URBAN=0	(12) URBAN=1	(13) AGE<=45	(14) 45<AGE<65	(15) AGE>=45
Income	-0.001	-0.001	-0.002*	-0.001	-0.002	-0.001*	-0.001
	(-1.53)	(-1.62)	(-1.80)	(-1.55)	(-0.29)	(-1.67)	(-1.30)
PM 2.5	0.008**	0.002	0.002	0.009*	-0.010	0.001	0.007*
	(2.02)	(0.56)	(0.73)	(1.84)	(-0.23)	(0.45)	(1.92)
SHS	0.359***	0.324***	0.299***	0.410***	3.165**	0.384***	0.127
	(3.97)	(2.59)	(2.98)	(3.72)	(2.15)	(3.78)	(1.04)
smoke	0.504***	0.348***	0.550***	0.342***	-	0.395***	0.399***
	(7.30)	(3.62)	(7.06)	(4.03)	-	(5.18)	(4.55)
Cooking	-0.012	0.051	-0.019	0.065	0.508	-0.015	0.041
	(-0.22)	(0.67)	(-0.30)	(0.93)	(0.65)	(-0.26)	(0.59)
Constant	-1.813***	-1.622***	-1.798***	-1.606***	-4.600*	-1.255***	-1.630***
	(-10.19)	(-6.71)	(-9.00)	(-6.73)	(-1.83)	(-6.11)	(-7.28)
Observations	4,848	3,487	4,382	3,901	187	5,189	2,293
Pseudo R-squared	.0987	.0789	.1080	.1130	.3778	.0674	.0535

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.2 in the appendix reports the probit result of subgroups. Column (3) and (4) present the results of individuals living in cities with different GDP per capita levels. It can be found that the average marginal effects of Income in the high GDP city is higher than that of low GDP city -0.0015 vs-0.0007, suggesting that for unity of income, the health effect of income is higher in the cities with high GDP than those with low GDP.

The results are supported by existing literatures. For instance, Allen et al. (2016) conducted a study investigating the impacts of income and air pollution on life expectancy and aging. Their research revealed non-linear relationships, suggesting that individuals with an income over 40,000 USD experienced greater gains in life expectancy compared to those with an income below 40,000 USD. Additionally, when accounting for factors such as smoking and obesity, the effects of income and air pollution were found to be weakened.

3.5.2 Spatial Probit Results

Table 11: Results for spatial models: SAR

	coefficient	direct effect	indirect effect	total effect
Income	-0.0001***	-0.000099	-0.000082	-0.000181
	(-3.201663)	(-3.246219)	(0.062391)	(0.007364)
PM 2.5	0.000271**	0.000273	0.000195	0.000467
	(2.029822)	(2.077927)	(0.025213)	(0.018305)
SHS	0.034198	0.034377	0.027698	0.062075
	(4.214293)	(4.113392)	(0.019815)	(0.000228)
smoke	0.085744***	0.085745	0.070065	0.155809
	(13.0339)	(12.776897)	(0.009038)	(0)
Cooking	-0.008178***	-0.008246	-0.007207	-0.015453
	(-1.391905)	(-1.441672)	(0.256217)	(0.181706)
rho	0.436978***			
	-4.579523			

Note:
t statistics in parentheses;
* p<0.1 ** p<0.05 *** p<0.01

Before having a spatial regression, Moran I index is computed to check the spatial correlation in the residuals. The statistic is 7.7054 > 1.96, indicating that we should reject the null hypothesis that there is no spatial correlation, and confirm the existence of spatial correlation in the models.

Table 11 presents the results of SAR model, where the endogenous variable Wy is included and ρ represents a function of neighboring values of dependent variable. In this research, although LD is a result of air pollution, not a result of communicative disease, the introduction of spatial effects of y describes the spatial correlation of the residuals, which is a regional disease due to geographic reasons. A positive ρ suggests that LD is spatially correlated, which can be explained by the special occupation in specific regions with extreme high exposure of the air pollution, such as coal miners. The positive coefficient of WY lend support to Guo et al. (2016) that LD is also highly spatiotemporally related.

The results of income and air pollution is consistent with the probit models in table 3, that income can decrease the possibility of LD, and $PM_{2.5}$, smoking and SHS contribute to higher possibility of LD. Turning cooking fuel to clean energy can also decrease the possibility of LD. Both negative direct and indirect effect suggest that local individuals' health is not only affected by local $PM_{2.5}$, also by AAP from nearby cities. This finding is consistent with Wang et al. (2015) and Nacul et al. (2011) who found spatial correlation between COPD and ambient air pollution in China and the UK, respectively.

Table 12: Results for spatial models: SEM

	Coefficient
Income	-0.000097***
	(-3.113813)
PM 2.5	0.000242*
	(1.653277)
SHS	0.034429***
	(4.217608)
smoke	0.085391***
	(12.880045)
Cooking	-0.008846
	(-1.497499)
lambda	0.882***
	(14.00873)

Note:
t statistics in parentheses;
* p<0.1 ** p<0.05 *** p<0.01

Table 12 gives results on the SEM model. Based on the SAR results, there is suspect about the spatial correlation of the error term in the basic probit models. A significant λ , indicates spatial dependence in error term, and is sometimes due to omitting key variables. The λ helps account for explanatory variables, which is not included in the regression, but is associated with the dependent variable.

Table 13 shows the spatial results of SLX model with the spatial effects of independent variables. The direct effect describes the local effect of the variable and the indirect effect is the spillover effects. The local effect of income is negative but the spillover effect is insignificantly positive. The effect of AAP is negative but insignificant. For smoking and cooking both direct and indirect effects are significant, suggesting that the individuals who smoke and cooking with clean energy are spatially correlated. The smoking behaviour of individuals can be spatially related as a result of local government actions aiming at reducing smoking in the public. And anti-public smoking policy can be regional due to a competitiveness of neighbouring government.

Table 13: Results for spatial models: SLX

	Direct effect	Indirect effect
Income	-0.00010488***	0.0012955
	(0.000031196)	(0.0024265)
PM 2.5	-0.00012261	-0.0011463
	(0.0001826)	(0.0018865)
SHS	0.029115	-3.6647
	(0.0081671)	(0.94007)
smoke	0.081823***	1.9089***
	(0.0066205)	(0.50145)
Cooking	-0.0078186***	-0.071995***
	(0.0060024)	(0.12664)

t statistics in parentheses;
* p<0.1 ** p<0.05 *** p<0.01

In summary, the spatial models (SAR, SEM, SLX) account for the spatial spillover effects of the dependent variable (y), the error term (e), and the independent variables (x). The local effects of the variables are consistent with the non-spatial models, while the indirect effects may vary. Table 11 highlights the spatial correlation in the error term, which could be influenced by omitted variables such as pneumoconiosis in coal miners, a region-specific and occupation-related disease. Table 12 confirms the spatial correlation in the error term and suggests the omission of key variables. Table 13 considers the spatial effects of independent variables, and most of the estimates align with the non-spatial results, particularly regarding the spillover effects of PM2.5 and the reduction of HAP, which may be influenced by organized public policies.

3.6. Conclusion

In this paper, we estimate the effect of ambient and household air pollution and income on lung disease in China, while controlling for socio-economic and demographic factors. The individual data used in this study are derived from the CHARLS 2015 survey and are linked to the PM2.5 concentration levels based on the city names. We employ a basic probit model, taking into account endogeneity and heteroscedasticity. Additionally, spatial econometrics is employed to address pollution spillover effects and the potential omission of key variables. We include the annual average of ambient PM2.5 concentration levels as a measure of ambient air pollution (AAP), and cooking with clean fuels and second-hand smoking as measures of household air pollution (HAP). Smoking is also considered as a factor.

Our results reveal that both HAP and AAP have a significant positive impact on lung disease (LD), indicating that individuals residing in areas with high ambient and household air pollution levels are more likely to be diagnosed with LD. On the other hand, income is found to be negatively related to the disease, suggesting that higher income can protect individuals from LD. Furthermore, geographic location has a significant impact on LD, with individuals residing in urban areas being more susceptible. Smoking and aging over 65 years old are also identified as key factors contributing to lung disease. The spatial models we employ take into account the potential omission of key variables and estimate the spatial effects of HAP and AAP.

Our analysis emphasizes the crucial role of individual income in mitigating the negative health effects of pollution. While China's rapid economic growth raises concerns about its pollution generation, higher individual income associated with this growth may help alleviate the detrimental effects on individual health. It is important for China to implement policies that effectively control pollution while simultaneously promoting higher living standards and redistributing income to the broader population.

In addition to the above findings, it is important to acknowledge some limitations of our study. Firstly, the use of cross-sectional data from the CHARLS 2015 survey limits our ability to establish causal relationships between air pollution, income, and lung disease. Longitudinal data would provide more robust evidence of the temporal relationship between these variables.

Secondly, the reliance on self-reported data introduces the possibility of recall bias and measurement error. Participants may not accurately recall their exposure to air pollution or their health status, leading to potential inaccuracies in the analysis. Future research could benefit from incorporating objective measures of air pollution and medical examinations to validate the self-reported information.

Thirdly, the absence of air pollution regulation as a variable ignores the effect of government, which plays important roles in the air quality improvement in China. Including air quality policy in the analysis would provide valuable insights into the efforts to reduce PM2.5 concentration levels and improve health outcomes for individuals. In future studies, it would be beneficial to incorporate regulatory measures as a dummy variable, especially with the availability of subsequent CHARLS data. Additionally, certain key cities have implemented strict air pollution regulations, which present an opportunity for comparing regions with and without such regulations. For instance, the Beijing-Tianjin-Hebei area enforces stringent air quality policies, while neighbouring provinces could serve as a benchmark for air pollution levels and their impact.

Chapter 4

Estimation of individual's Exposure Level to $PM_{2.5}$ and the Association between Individual Health, Exposure and Wealth in China

4.1 Introduction

Air pollution poses a significant threat to public health, leading to 4.2 million deaths attributable to exposure to ambient air pollution and 3.8 million deaths linked to household air pollution in 2016 (WHO, 2021a). Additionally, the proportion of deaths attributed to chronic obstructive pulmonary disease (COPD) is reported to be 18% for ambient air pollution (WHO, 2021a) and 20% for household air pollution (WHO, 2021b). In China, it is estimated that air pollution was responsible for 1.24 million deaths in 2017, with over 851,000 deaths attributable to ambient PM2.5 and 271,000 deaths associated with household air pollution from solid fuel (Yin et al., 2020).

Particulate Matter 2.5, commonly referred to as PM2.5, refers to airborne particles with a diameter smaller than 2.5μm. This pollutant primarily originates from human activities, such as industrial processes, transportation, construction, as well as natural sources like dust. Compared to larger particulate matter, such as PM10, PM2.5 poses a greater hazard to human health. The interaction between humans and PM2.5 primarily occurs through inhalation and ingestion pathways (Kampa & Castanas, 2008). This research specifically focuses on self-reported lung diseases influenced by PM2.5 exposure.

Table 14 presents the air quality standards for PM2.5 concentration in various countries and regions. In most countries and regions, including China, the annual mean standard for PM2.5 concentration is set at 15ug/m3. The World Health Organization (WHO) sets a more stringent standard at 5ug/m3, which is the lowest value in the table. In China, it is projected that the population-weighted mean of PM2.5 concentration will decrease to 34ug/m3 by 2030, resulting in a reduction of 217,000 deaths (Wang Q et al., 2019).

Table 14: Concentration Standard in Countries and Regions

Country/Organisation	Measured as:	Standard ug/m^3
China	annual mean	15
	24hour mean	35
European Union	annual mean	20
India	annual mean	40
	24hour mean	60
Japan	annual mean	15
	24hour mean	35
United Kingdom	annual mean	20
United States	annual mean	12
	24hour mean	35
WHO	annual mean	5
	24hour mean	15

While concentration standards provide an important measure, a more comprehensive assessment of PM2.5 is achieved through exposure assessment. Concentration merely describes the local abundance of a pollutant, whereas exposure accounts for the interaction between the pollutant and humans. Concentration can be quantified through air monitoring, whereas exposure measurement requires an additional factor—time allocation. Concentration only reflects the volume of air pollution at a given location, thus obscuring exposure variability across populations in terms of spatial and temporal dimensions. Furthermore, refining exposure characterization provides valuable insights when estimating exposures based on central site monitor measurements (Özkaynak et al., 2013). From an exposure modeling perspective, exposure can be quantified as a function of relevant human factors and pollutant concentrations in microenvironments (US EPA, 2021).

Health inequality, stemming from income inequality, has been addressed through various government initiatives. Poverty alleviation has been a key strategy, facilitated by rapid and consistent economic growth, leading to a reduction of 770 million individuals living below the World Bank's extreme poverty threshold of $1.9 per day. Additionally, targeted support has been provided to geographically disadvantaged areas and individuals with low socioeconomic conditions. Concurrently, health outcomes have shown improvement, with life expectancy at birth increasing from 66 years in 1978 to 77 years in 2019, and infant mortality declining from 54 to 6.8 per thousand infants.

The terms "left-behind children" and "left-behind elderly" refer to individuals who reside alone at home while their parents or caregivers are absent due to migration for work. Previously, individuals from economically deprived regions would remain at home, taking care of children and elderly family members. However, with better employment opportunities and higher salaries available in cities, migrant workers now spend most of their time away from home. Administrative restrictions, such as the hukou system, hinder the transfer of education and pension benefits to other cities, resulting in children and the elderly being left behind. Left-behind children are more susceptible to depression (Wang et al., 2019), engage in unhealthy behaviours such as smoking and drinking (Yang et al., 2016), and face challenges in high school enrolment (Yang & Banasak, 2020) due to the absence of parental guidance. Furthermore, the health of the elderly is negatively affected by this phenomenon (Li et al., 2020). However, left-behind individuals often experience better nutrition (Shi et al., 2020) and academic outcomes (Chen et al., 2014; Bai et al., 2018) due to increased household income compensating for the lack of parental supervision.

Addressing health inequality goes beyond income inequality, as the separation of parents and children introduces more problems than poverty itself. The government's efforts to improve transportation infrastructure enable the delivery of local goods, including agricultural products. Infrastructure development and traffic construction contribute to poverty reduction by facilitating business growth in underdeveloped regions. Moreover, these infrastructure projects generate employment opportunities for low-skilled workers and ensure access to safe water and energy in low-income areas (World Bank and DRC PRC, 2022).

Our research builds upon four national epidemiological studies on chronic pulmonary obstructive disease (COPD) conducted in China. The initial study was conducted in 2007, followed by studies by Yin et al. (2011), Wang et al. (2018), and Fang et al. (2018). The prevalence of COPD ranges from 2.9% (Yin et al., 2011) to 13.8% (Fang et al., 2018), with variations attributed to differences in sample age and diagnostic methods. Fang et al. (2018) included individuals aged 40 and above and employed spirometry to confirm pulmonary health, whereas Yin et al. (2011) used a self-reporting diagnostic approach with a sample of individuals aged 15 to 69. Wang et al. (2018) remains the sole study incorporating ambient PM concentration. In terms of economic factors, Fang et al. (2018) classified cities into three categories based on economic development, while Yin et al. (2011) classified individuals into low-income (below 8,400), medium-income (8,400 - 20,000), and high-income (over 20,000) categories.

In our research, we approximated individual exposure levels and examined the association between exposure and lung health in China. We considered three microenvironments: ambient, kitchen, and bedroom. Ambient concentration data was directly obtained from air monitoring records, while household microenvironment concentration levels (kitchen and bedroom) were estimated using the Mass Balance method, incorporating factors such as air exchange, penetration, and deposition based on existing research. Household PM2.5 sources included fuel combustion, emissions from Chinese-style cooking, and smoking. Time allocation data was derived from the CHARLS dataset and a report on housework in China, accounting for gender and age subgroups. Probit models were employed to estimate the effects of socioeconomic factors and exposure levels on individual lung diseases, with demographic and geographic variables included as control variables. The results indicate that income and exposure level have average marginal effects of 0.000639 and -0.0233, respectively. Robustness checks were conducted by considering various model specifications and addressing endogeneity issues. The findings suggest a significant negative relationship between exposure to PM2.5 and lung health, with income also exhibiting a positive association.

The research introduces several novel aspects:

- Time Allocation: In contrast to existing exposure models such as Hazardous Air Pollutant Exposure Model (HAPEM) and Stochastic Human Exposure and Dose Simulation (SHEDS) that rely on population census data for time allocation, this research directly utilizes dataset information and a statistical report on average time spent in cooking. By incorporating precise time allocation data, this study provides a more accurate representation of daily activities in China.
- Choice of Microenvironments: The selection of microenvironments in this research is based on existing literature on Chinese households, specifically focusing on the kitchen and bedroom. These microenvironments closely align with the daily activities of the Chinese population. Considering the demographic characteristics of the sample, ambient microenvironments such as transportation and occupation are not included since the majority of the sample comprises elderly individuals who are retired. Additionally, relevant data related to work and transportation are not available in the CHARLS dataset.
- Binary Model Linking Exposure and Health: To the best of our knowledge, this research is the first to establish a link between individual exposure levels and individual health using a binary model. By employing a binary model, this study offers a unique perspective on the relationship between exposure and health outcomes, providing valuable insights into the potential health effects associated with individual exposure levels.

The research is structured as follows: Section 1 presents the introduction to the research, Section 2 conducts literature review on the individual exposure measurement, the health effect of $PM_{2.5}$ and epidemiology of COPD. Section 3 outlines the methodology on the calculation of concentration levels and employ probit models to estimate the health effect of exposure levels. Section 4 gives the data source and data description. Sector 5 presents the results and Sector 6 concludes this research.

4.2 Literature Review

4.2.1 Measurement of Household Air Concentration

The measurement of individual exposure levels has been a subject of research since the 1980s. Ott (1981) criticizes the use of fixed monitoring site data in "exposure" research, as it is unrealistic to assume that individuals stay in the same location throughout the day. Exposure is a combination of an individual's presence and the concentration of pollutants in the environment. Duan (1982) compares four models of human exposure to air pollution. The first model is a simple microenvironment monitoring approach that focuses on pollutants at fixed sites. The second model is a replicated microenvironment monitoring approach that takes into account the frequency of site visits. The third model is an integrated personal monitoring approach that collects personal exposure levels using air quality samplers and incorporates regression analysis to determine exposure based on time allocation in different microenvironments. Finally, the fourth model is continuous personal monitoring, which requires recording daily activities and concentration levels in each microenvironment. The more advanced models, such as continuous personal monitoring, require more data on time and concentration compared to the simpler models. Time allocation data can be easily collected through self-reported records, while the measurement of pollutant concentrations is a critical aspect of exposure assessment.

Ambient (outdoor) air pollution measurements can be obtained from monitoring sites, where records are maintained. On the other hand, household (indoor) concentrations can be directly measured using personal monitoring devices or indirectly estimated using predictive models based on location characteristics. The direct measurement method provides results that are closer to the mean population exposure level but is expensive and time-consuming. In contrast, the indirect measurement method is more suitable for studying large populations as it can rely on existing monitoring sites, reducing the cost of time and labour.

Researchers have focused on examining the discrepancy between direct and indirect measurements.

Empirical analyses have been conducted in various locations such as Los Angeles (Kim & Kwan, 2019), Xining (Tan et al., 2020), and Beijing (Ma and Li et al., 2020) to investigate this gap. The differences observed in exposure level measurements are associated with population characteristics. Socially disadvantaged groups tend to experience higher exposure levels due to their limited daily activities. Therefore, it is necessary to consider the effects of socio-economic factors in the indirect measurement of individual exposure levels.

Studies comparing direct and indirect methods have investigated the gap between these approaches and have shown that, at least for PM2.5, there is good agreement between the indirect method and direct measurements (Cattaneo et al., 2010; Gerharz et al., 2013).

Empirical analyses conducted in China provide support for a strong correlation between indirect and direct measurements of air pollution exposure, with a particular focus on cooking emissions in rural areas. Huang et al. (2017) conducted a study in the summer of 2011 in rural areas of Shanxi province, China, using portable samplers to investigate individual exposure levels of particulate matter (PM). The results showed a strong correlation between direct and indirect measurements, with the indirect measurements being approximately one-third lower than the direct measurements. Liu et al. (2018) measured PM levels in rural central China and found that individual exposure was more closely correlated with household air pollution than ambient air pollution. Shen et al. (2014) measured polycyclic aromatic hydrocarbons (PAHs) in rural areas of East China and demonstrated that the indirect measurement was lower than the direct levels. (Du et al., 2018)

Ozkaynak et al. (2013) proposed alternative methods to improve air quality records obtained from central site monitors, considering the increasing complexity of methodology and input data. One commonly used exposure approach is Land Use Regression (LUR), which estimates exposure levels based on land use information and considers air pollutants such as traffic and industrial emissions. Air quality models predict pollutant concentrations using designated models that incorporate various physical processes. Statistical approaches combine multiple exposure estimation methods, while remote sensing or satellite data can be integrated with air quality models or geographic variables. Human exposure models account for concentrations in microenvironments and consider human behavior factors, taking into account multiple factors that influence individuals' personal exposure from both indoor and outdoor sources. This method requires extensive data input, as it considers various determinants of exposure. However, it tends to provide more accurate measurements of individual exposure.

4.2.2 Estimation of Exposure

The US Environmental Protection Agency (EPA) has developed several simulation tools for estimating population exposure levels, including the Hazardous Air Pollution Exposure Model (HAPEM), the Stochastic Human Exposure and Dose Simulation (SHEDS), and the Air Pollutants Exposure Model (APEX). These models rely on census data to simulate a representative population and incorporate modelled air pollution data along with daily activities (Isakov et al., 2009). While the estimation from these complex models can sometimes provide more accurate results than concentration levels from central site monitors, their effectiveness depends on the research design. For instance, ecological studies typically require population-level data input, whereas individual-level studies necessitate exposure estimates based on individual-level data.

In this research, the existing methods mentioned above are not employed for several reasons. Firstly, the CHARLS dataset used in this study provides data on time allocation and household fuel sources, which are fundamental for estimating individual exposure levels. Secondly, the time allocation patterns of individuals, particularly elderly Chinese individuals, significantly differ, with a preference for staying indoors rather than outdoors. Thirdly, this difference can be attributed to poorer physical conditions and a cultural preference for indoor activities. Therefore, the author believes that estimating exposure levels using the CHARLS dataset can provide a better description compared to general methods based on the US census.

Probabilistic models, such as the INDAIR model developed by Dimitroulopoulou et al. (2006), are employed to estimate household air pollution concentrations. This probability model considers the change in concentration over time, taking into account the gap between household and ambient concentrations. It incorporates parameters such as the rate of air exchange, deposition, and emission rate. The quality of the data used in the model simulation is crucial, and the parameter inputs are assumed to follow a normal or log-normal distribution with known means and deviations. The research concludes that household sources make significant contributions to air pollution concentrations.

4.2.3 COPD Research on Factors Globally

Figure 8 from Agusti and Faner (2018) proposes that COPD is the result of dynamic interactions between genetic factors and environmental exposures that occur throughout a person's lifetime, starting before birth. The figure depicts two physiological processes: lung development (represented by a green triangle) and lung injury (represented by a red triangle). The area between these two processes represents health-life expectancy, depicted by a rainbow triangle at the top of the figure. The arrow indicates that better or worse situations lead to longer or shorter life expectancy.

The Global Initiative for Chronic Obstructive Lung Disease (GOLD) report identifies key risk factors for COPD. While smoking is the leading environmental risk factor, it is important to note that even among heavy smokers, less than 50% develop COPD. Genetic factors, such as certain genes associated with reduced lung function, also contribute to an increased risk of COPD. Additionally, siblings of severe COPD patients have been shown to be at a significant risk of developing airflow obstruction (McClosky et al., 2001).

Age is a well-established risk factor for COPD, and the relationship between aging and the disease is complex. Aging leads to weakened respiratory muscles, reduced effectiveness of coughing, and impaired mucociliary clearance, which can contribute to acute exacerbations of COPD (Brandsma et al., 2017). The prevalence of COPD generally increases with age, with a higher prevalence observed in older age groups (Landis et al., 2014).

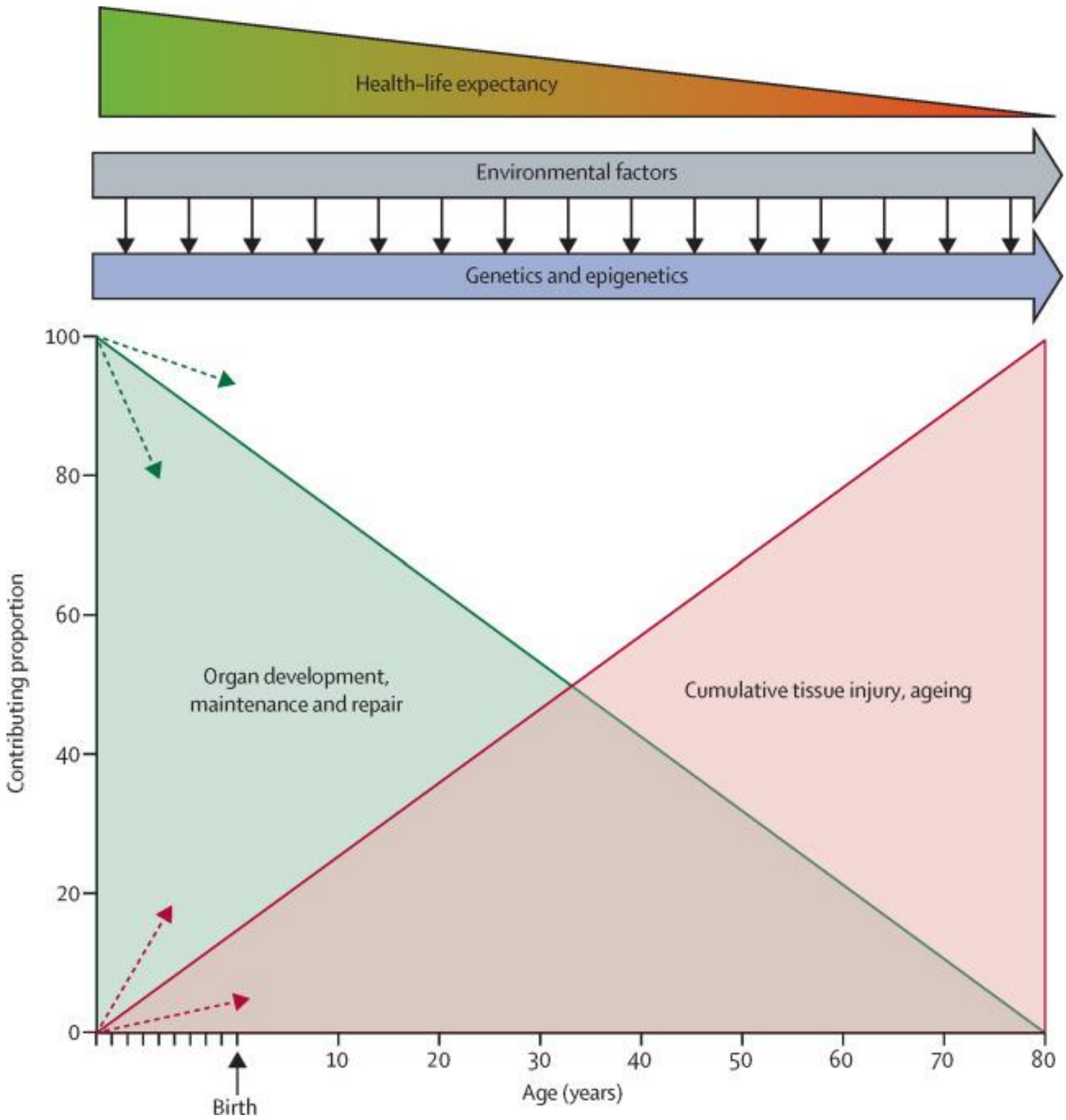

Figure 8: Health as a result of lung development and damage

Gender is also recognized as a risk factor for COPD. In most countries, the prevalence of COPD is higher among males compared to females, although in some regions, such as the United States, the prevalence is higher among females. This discrepancy may be attributed to increased tobacco and biomass fuel consumption in females (Gut-Gobert et al., 2019). Some research suggests that females may be more susceptible to the damaging effects of smoking, leading to a higher risk of COPD even with similar tobacco consumption as males (Martinez et al., 2007). However, LoMauro and Aliverti (2018) argue that the size of the lungs, rather than gender itself, contributes to lung dysfunction.

Smoking, both active and passive, remains the leading cause of COPD. It causes respiratory symptoms, lung function abnormalities, and a decline in Forced Expiratory Volume in one second (FEV1). Additionally, environmental tobacco smoke can increase the pulmonary burden of inhaled particles and gases. Smoking during pregnancy can also negatively impact fetal lung growth, development, and the immune system.

Approximately 25% to 45% of COPD patients have never smoked, indicating that factors other than smoking play a significant role in the development of the disease. These factors include indoor and outdoor air pollution, occupational exposures, a history of childhood respiratory diseases, such as asthma and pulmonary tuberculosis, and low socioeconomic status (Salvi & Barnes, 2009).

Occupational exposure to dust, gas, or fumes has been associated with decreased respiratory function and an increased risk of COPD (Rodriguez et al., 2008; Blanc et al., 2009). Certain occupations with high exposure to pollutants have been linked to a significant increase in COPD risk, both in the general population and among non-smokers (De Matteis et al., 2019).

In developing countries, high indoor air pollution concentrations resulting from the combustion of biomass fuel in poorly-performing stoves contribute to COPD, particularly among women. The use of liquid petroleum gas for cooking has been associated with lower pollutant concentrations and a decreased risk of COPD (Liu et al., 2009; Chapman et al., 2005; Shen et al., 2009). Heating, an important aspect of household air pollution, has been estimated to contribute significantly to air pollution and associated health burdens (Chen et al., 2018).

Studies in various countries have shown similar associations between COPD and non-smokers, highlighting risk factors such as age, education level, occupation, cooking, passive smoking, childhood hospitalization, and low body mass index (Lamprecht et al., 2011; Tan et al., 2015; Lee et al., 2015; Hagstad et al., 2015).

4.2.4 Research Linking Health and Exposure

The research mentioned highlights the significant impact of air pollution on health, particularly in relation to household air pollution (HAP) in China. Aunan et al. (2018) estimated the annual population-weighted personal exposure level in China, finding that the mean exposure level was 151 µg/m3, with 62-74% of this attributed to solid fuel use as part of HAP. The study estimated that from 2010 to 2013, PM2.5 exposure resulted in approximately 1.1 million premature deaths. This number could be even higher if deaths were separately calculated for household and ambient exposures. Aunan and Wang (2010) employed a similar methodology and estimated that the transition to cleaner household fuels led to a decrease of 52 µg/m3 in PM2.5 exposure from 2000 to 2010.

Shen et al. (2019) estimated a population-weighted exposure level of approximately 70 µg/m3, with rural emissions contributing 21% to the total exposure level. The study also estimated that the energy transition resulted in the avoidance of 130,000 premature deaths. Aunan et al. (2019) suggested the inclusion of HAP in air pollution policies and emphasized the need for public attention to the contribution of HAP to overall air pollution exposure.

These findings underscore the importance of addressing household air pollution as a significant contributor to health issues related to air pollution in China. The research supports the notion that reducing HAP through the transition to cleaner household fuels can have a substantial positive impact on public health.

4.2.5 Epidemiologic Study on COPD in China.

This subsection includes the existing literature on the epidemiological study of COPD in China. Based on a review of COPD (Zhu et al., 2018) and findings from Google Scholar, there are four national epidemiological studies conducted in China.

Zhong et al. (2007) initiated the first national COPD epidemiologic study in China, encompassing seven provinces and involving over 20,000 individuals aged 40 and older. The study reported an overall prevalence rate of 8.2%. Risk factors considered in the study included demographic factors, occupational exposure, residence, and smoking-related behavior.

Yin et al. (2011) examined the effects of socioeconomic status on COPD using a national sample of individuals aged between 15 and 69. The study reported a crude prevalence rate of 2.9%, which was significantly lower than the rates reported by Zhong et al. (2007) and the other two studies. This substantial discrepancy can be attributed to several factors, including self-reported diagnosis, underreporting of physical conditions by COPD patients, and undiagnosed cases of COPD. Consequently, the study explored the association between self-reported COPD and socioeconomic factors. The findings indicated that household income and educational level were the primary contributors to COPD after controlling for the influence of demographic and regional factors.

Another national study conducted by Wang et al. (2018) in more than ten provinces in China investigated the prevalence of COPD. The research identified a range of socioeconomic factors, as well as ambient and household air pollution, as risk factors for COPD. These factors included gender, age, being underweight, having a history of respiratory disease in both the interviewee and their parents, education, smoking history, and exposure to annual mean particulate matter.

In a cross-sectional survey carried out by Fang et al. (2018) on a national sample of individuals aged 40 and older from 2014 to 2015, the study found that socioeconomic factors and exposure to air pollution were significant risk factors for COPD. The effects of these variables were particularly pronounced among urban residents and were influenced by the economic development experienced in their respective regions. Additionally, education level, smoking status, history of hospital visits during childhood, indoor exposure to biomass cooking or heating, workplace exposure to chemicals, and BMI were also identified as risk factors. Furthermore, the prevalence of COPD varied across regions, with the highest rates observed in the southwest and the lowest in central China.

The table 15 summarises the national epidemiological studies on COPD in China.

The existing literature primarily focuses on two main areas: (1) the impact of air pollution concentration on health, with most studies conducted at the regional or city level, and (2) the importance of economic factors, which are often mentioned in relation to COPD. Thus, utilizing data from the CHALRS dataset, this research aims to address the following question: How does individuals' health contemporarily relate to income and air pollution?

To answer this question, this chapter firstly estimate the exposure level of PM 2.5, and investigate the relationship between PM exposure and health status. Variables related to pulmonary health, including demographics such as age and gender, socioeconomics such as income and education are controlled. Besides, considering the regional difference in life style and climate, dummy variables related with provinces are introduced.

Table 15: National epidemiological study on COPD in China

Author	Year	Diagnosis	Size	Age	Sample region	Prevalence	Risk factors				
							Demographics	Disease history	Economics	Occupation	PM
Zhong et al., 2007	2002-2004	spirometry	20245	>=40	7 provinces	8.2	Yes	Yes		Yes	
Yin et al., 2011	2007	self-report	49363	15-69	161 disease surveillance point	2.9	Yes	Yes	Yes (household)		
Fang et al., 2018	2014-2015	spirometry	66752	>=40	605 disease surveillance point	13.6	Yes	Yes	Yes (city level)	Yes	
Wang et al., 2018	2012-2015	spirometry	50991	>=20	10 provinces	8.6	Yes	Yes			Yes

4.3 Method of Exposure Estimation

The exposure addresses the interaction between the human activity and concentration, and can be expressed with a function of concentration and time allocation in each microenvironment, which demonstrated below:

$$E_i = \sum_{j}^{J} C_j t_{ij} \, , j = 1,2,3$$

where E_i is time-weighted integrated exposure for individual i over a period; $C_{i,j}$ is the concentration level in microenvironment j, and t_{ij} is the time spent in the microenvironment i, and J is the total microenvironments individual i moves through during the period. A microenvironment refers to a space with homogenous concentration level with physical boundary.

4.3.1 Concentration Calculation

There are two approaches to assess indoor concentration levels. The direct approach is to carry a personal air monitoring device, and the indirect approach is to calculate the exposure based on literature. A personal monitor measures the individual real-time concentration level and collects the most reliable information about the pollution. However, the studies with the personal device are often conducted as non-representative pilot studies due to amount of labour and time required to undertake the study, in addition to the monetary cost. Taking the device and collecting the data requires a considerate research design to minimize the influence on the participants, and the commitment of the researchers. Furthermore, there are problems with the privacy as the device track the individuals location and movement.

Due to the data availability, the direct approach for the concentration information is not feasible, and this study employs the indirect approach to approximate the concentration levels in microenvironments.

Following Dockery (1979), the indoor air mass is defined as four parts: penetration for outdoor air into the room through windows, doors and ventilators; air flow out of the room which reduces the household air pollution; pollution removed by the air filters and other methods; and pollution produced in the room. Therefore, the equation for household air concentration is given as

$$dQ_h = PC_a dt - qC_i dt - KQdt + SVdt$$

where Q_h is the mass of household air pollutant, P is the penetration of ambient air pollutant, $C_a \text{ } and \text{ } C_h$ are concentrations of ambient and household pollutant. q is the volume of airflow into and out of the household, K is the rate of deposition and S is the household pollutant production rate. V is the volume of the room and $a = q/V$ is the air change rate.

Dividing the equation by the V,

$$dC_h = PaC_a dt - (a + K)C_h dt + SVdt$$

Defining average value over the period from t_1 to t_2 as

$$\overline{C_h} = \frac{1}{t_2 - t_1}\int_{t_1}^{t_2} C_h \, dt$$

$$\overline{C_a} = \frac{1}{t_2 - t_1}\int_{t_1}^{t_2} C_a \, dt$$

$$\bar{S} = \frac{1}{t_2 - t_1}\int_{t_1}^{t_2} S \, dt$$

and the equation is integrated over the period, and we assume P, V, K are constant, the average household concentration is:

$$\overline{C_h} = \frac{P\,a}{a + K}\overline{C_a} + \frac{1}{(a + K)}\,\bar{S} + \frac{C_h(t_1) - C_h(t_2)}{(t_2 - t_1)(a + K)}$$

We assume that $C_h(t_1) = C_h(t_2)$ as the household concentration level will converge to a constant. The household concentration level can be approximated as:

$$\overline{C_h} = \frac{Pa}{(a + K)}\overline{C_a} + \frac{1}{(a + K)}\bar{S}$$

The household concentration level depends on two parts: ambient air pollutant C_a, which is determined by airflow, and the pollutant S produced and decayed in the room.

Ji and Zhao (2005) measure the air exchange rate a, penetration rate P and deposition rate K based on experiments. In this paper average value of the parameters are utilized. That is, 0.17, 0.95 and 0.36 respectively. For the robustness of the results, the scenario with the window open are also investigated.

Table 16: Parameters for Mass Balance, following Ji and Zhao (2005)

Parameters	Window	Mean	Min	Max
Air exchange rate, a	Closed	0.17	0.03	0.83
	Open	2.3	1	5
Penetration rate, P	Closed	0.95	0.90	0.97
	Open	1	1	1
Deposition rate, K	-	0.36	0.21	0.63

The air exchange rate is defined as the rate of air flow into and out of a building (Q) over the volume of the room V , that is to say $a = Q/V$. Air exchange rate is a determinate factor for the exposure model. This is because people spend most of the time within an enclosed building. Empirical works have provided air exchange rates, and these results vary due to the country, season, the built year and floor area (Breen et al., 2014).

Table 17: Parameters of mass-balance model in other research

	Air exchange rate	penetration rate	deposition rate	Region, Country
Breen et al., 2010	0.68	0.84	0.21	Central North Carolina, US
Breen et al., 2014	0.64	0.90	1.0	Detroit, US
Breen et al., 2015	0.67	0.84	0.21	Central North Carolina, US
Breen et al., 2018	0.28	0.84	0.21	Central North Carolina, US
Bruke et al., 2001	0.52	0.95	0.33	Philadelphia, US
Chen et al., 2020	0.232	0.902	0.194	Beijing, China

Ozkaynak et al., 1996	1	1	0.39	California, US
Gerharz et al., 2013	0.57[28]	1	0.39	Munster, Germany
Tran et al., 2017	0.2	0.84	0.33	North of France

The table 17 above presents the parameters from previous research. The parameters of air exchange rate are higher than the one we employ in this work, and only Chen et al., and Tran et al., 2017 are close to what we choose. The huge difference in air exchange rate is related to the residential building difference: there is no air leakage for most house in China, leading to a lower level of infiltration and air exchange rate. (Cheng and Li, 2018).

Based on the parameters provided by Ji and Zhao (2005), the concentration level for microenvironments can be approximated as the equation below:

$$c_i = \begin{cases} 0.32 * c_{ambient} + 1.96 * Source, & window\ close \\ 0.85 * c_{ambient} + 0.38 * Source, & window\ open \end{cases}$$

Three microenvironments relevant to individuals' daily activities are identified: the bedroom, kitchen, and outdoors. Each of these microenvironments corresponds to specific activities: sleeping and entertainment, cooking, and outdoor activities. Smoking is identified as the source of PM2.5 in the bedroom, while cooking and fuel combustion contribute to pollutant emissions in the kitchen. Therefore, the concentration in the bedroom and kitchen can be calculated using the following functions:

$$c_{bedroom} = \begin{cases} 0.32 * c_{ambient} + 1.96 * S_{smoke}, & window\ close \\ 0.85 * c_{ambient} + 0.38 * S_{smoke}, & window\ open \end{cases}$$

[28] The air exchange rate of $PM_{2.5}$ is not given but the rate of PM_{10} follows log-normal distribution with mean 0.57.

$$c_{kitchen} = \begin{cases} 0.32 * c_{ambient} + 1.96 * (S_{cooking} + S_{fuel}), & window\ close \\ 0.85 * c_{ambient} + 0.38 * (S_{cooking} + S_{fuel}), & window\ open \end{cases}$$

Ji and Zhao (2005) estimated that one cigarette per day contributes 0.8 ug/m^3 to 24-hour average indoor concentration. We assume the medium level of cigarette consumption of 10 per day in the bedroom, therefore the emission rate for $PM_{2.5}$ is calculated as:

$$S_{smoking} = 0.8ug/(m^3 * 1\ cigarrete)\ *\ 10\ cigarette\ = 8\ ug/m^3$$

Household pollutant emission for kitchen, $S_{cooking}$, is based on the average value of Chinese cooking from Chen et al. (2018), which is 2.056 microgram per cubic metres per minutes. We convert per minute to per hour, with a multiplier 60, and the emission rate per hour is $123.36ug/m^3$.

$$S_{cooking} = 2.056\ ug/m^3/\ minute = 123.36ug/m^3$$

Gerharz et al. (2013) also considered cooking as a source of indoor air pollutants and set the parameter at 102 µg/m3, slightly lower than the value used in this study. The difference can be attributed to the cooking practices in China, which often involve stir-frying and deep-frying, leading to higher particulate emissions (Zhao & Zhao, 2018).

Furthermore, the fuel used for cooking is considered based on Li et al. (2016). They found that fuel combustion, particularly with coal, is a major contributor to household air pollution concentration and individual exposure. The parameter for cooking with coal is assumed to be 80 μg/m3, indicating that the contribution of cooking with coal is 80 μg/m3.

$$S_{fuel} = 80\ ug/m^3$$

The table 18 provides statistics about the concentration level in each microenvironments. The outdoor concentration level is directly reported on the government website, and the bedroom and kitchen concentrations are calculated based on the functions and parameters above.

Table 18: concentrations for microenvironments

Table 18a: concentrations for microenvironments window closed

Microenvironment	Mean	SD	Min	p50	Max
Outdoor	54.72	20.07	15.75	54.33	106.3
Bedroom	21.24	9.290	4.880	18.81	48.62
Kitchen	258.0	6.220	246.0	257.9	274.0

Table 18b: concentration for each microenvironments window open

Microenvironment	Mean	SD	Min	p50	Max
Outdoor	54.72	20.07	15.75	54.33	106.3
Bedroom	47.34	17.10	13.39	46.32	93.35
Kitchen	93.25	17.06	60.13	92.92	137.1

In the scenario with closed windows, the mean concentration in bedrooms is 21 μg/m3, and in kitchens, it is 258 μg/m3. The bedroom concentration is lower than the ambient level because the contribution from smoking is relatively small compared to other sources.

In the scenario with open windows, the mean difference in concentration for each microenvironment is lower compared to the closed windows scenario. This is because opening the window increases the air exchange rate and penetration rate, leading to the dispersion of indoor emissions and lower concentrations. The outdoor mean concentration remains the same in both scenarios, as the air exchange and penetration rates do not influence the outdoor concentration. In the scenario with open windows, the mean concentration is 47 μg/m3 in the bedroom and 93 μg/m3 in the kitchen, closer to the outdoor concentration.

Comparing these estimations with fieldwork conducted by Li, Cao et al. (2016) that measured household concentrations, the results are reasonable. Li et al. reported outdoor concentrations of 80±49 μg/m3 and kitchen concentrations of 213±50 μg/m3 with coal and 65±42 μg/m3 with gas. The bedroom concentration was 102±65 μg/m3, significantly higher than the ambient concentration. In this study, microenvironments are defined as spaces with boundaries and similar concentrations, and the bedroom is assumed to be affected by smoking and ambient air pollutants. Fuel combustion and cooking emissions are considered as sources only in the kitchen, not the bedroom.

4.3.2 Time Allocation

The time spent in each microenvironment is another aspect of the research. Based on self-reported time allocations for sleeping and outdoor activities, as well as statistical reports on housework for different age and gender groups, the time allocation for each microenvironment is estimated. In the CHARLS dataset, activity durations are reported in ranges rather than exact numbers, such as 2 to 4 hours or 4 to 6 hours. The mean value of each range is selected, resulting in an estimated average duration of 3 and 5 hours for outdoor activities.

Table 19 provides statistical results for housework time across different age and gender groups. As shown in the table, housework time generally increases with age, except for the subgroup aged between 40 and 49, which represents the maximum age for promotion. The time spent on housework for the age groups of 50-59 and 60+ is significantly higher than that of younger groups, as retirement age for males and females is typically around 55 and 50, respectively. This provides more available time for housework, and some individuals also take on child care responsibilities.

Table 19: Time allocation for housework by age and gender

Age	Male	Female
20-24	0.7	1.08
25-29	0.97	1.62
30-39	1.38	2.23
40-49	1.07	2.12
50-59	1.85	3.42
60+	2	3.65

Since the time allocation is approximated, the sum of time allocations for each individual may not always equal 24 hours. To address this, the time allocation is standardized using an inflation factor, resulting in a new time allocation denoted as "standardized time allocation." The new time allocation is noted as t_i^*:

$$Inflation\ Factor = \frac{24}{\sum_i^3 t_i}$$

$$t_i^* = t_i * inflation\ factor$$

Table 20 presents the statistical report of time spent in each microenvironment. The mean time spent outdoors is 8 hours per day, while the time spent indoors is 16 hours, with approximately 4.45 hours in the kitchen and 11.30 hours in the bedroom. These time allocation results reflect the general daily life pattern of the Chinese population. The time spent indoors (kitchen and bedroom) accounts for around two-thirds of a day, consistent with other research on individual exposure levels (WHO, 2005).

Comparing these findings with recent research conducted in the US by Spalt et al. (2013), which surveyed the time allocation of multi-ethnic elderly individuals, the average indoor time for the elderly is approximately 121 hours per week (17 hours per day), while Chinese elderly individuals spend 18.6 hours per day indoors. The age peaks in Spalt et al. (50-60 and 60-70) coincide with the age peak in this research, making the results comparable for understanding the reliability of time allocation in this study. However, there are several factors that may contribute to misspecification in the Spalt et al. study. The sample is limited to Chinese elderly individuals in the US, which may introduce biases due to the small sample size. The US elderly population typically benefits from greater socioeconomic advantages, and language barriers may result in less time spent due to communication limitations with their children and grandchildren. Therefore, the sample with an average indoor time of 17 hours may provide a more reliable time allocation than this research.

Table 20: Time allocation

Microenvironment	Mean	SD	Min	Max
Outdoor	8.25	4.18	0	21.28
Kitchen	4.45	1.96	0	18.78
Bedroom	11.30	3.54	0	20.77

4.3.3 Exposure Level

Graph 9 describes the distribution of individual exposure levels in 24 hours. Graph 1 does not include the cooking fuel as a pollutant source for the kitchen. However, Graph 2 considers the contribution of coal as cooking fuel to kitchen concentration and, therefore, exposure level. The exposure level with cooking fuel is smoother than the one without fuel.

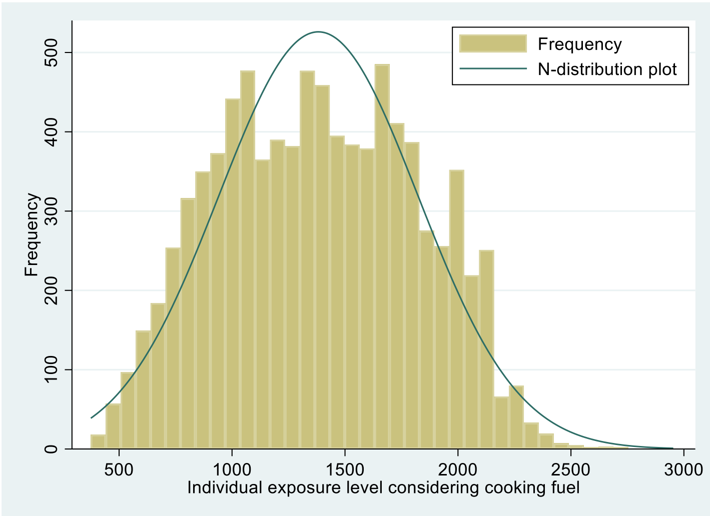

Figure 9: Exposure level considering the cooking fuel

4.3.4 Exposure and Health

A binary probit model is employed to estimate the effects of income and exposure on health. The dependent variable, y_i is defined as the self-reported chronic lung disease, which is:

$$y_i = \begin{cases} 1, if\ individual\ reported\ to\ be\ diagnosed\ with\ chronic\ lung\ disease \\ 0, others \end{cases}$$

An index model which restricts how the response probability depends on x, and $G(x\beta)$ maps the index into response probability.

$$P(y = 1|x) = G(x\beta) = p(x)$$

where x is a vector of independent variables, and β is the coefficient for the model.

In the probit model, the index model is assumed as:

$$G(z) = \Phi(z) = \int_{-\infty}^{z} \phi(v)dv$$

where $z = x\beta$, and $\phi(z) = (2\pi)^{-1/2}\exp\left(-z^2/2\right)$

The probit model is estimated by maximum likelihood and the density of y_i given x_i is written as:

$$f(y|x_i : \beta) = [G(x_i\beta)]^y[1 - G(x_i\beta)]^{1-y}, y = 0, 1$$

The log-likelihood for individual i is given as:

$$l_i(\beta) = y_i \log[G(x\beta)] + (1 - y_i)\log\left[1 - G(x\beta)\right]$$

And the log-likelihood for the sample with N observation is

$$L(\beta) = \sum_{i}^{N} l_i(\beta)$$

4.4 Data Description and Statistics

4.4.1 Data Source

The data used in this research is derived from two primary sources: the China Health and Retirement Longitudinal Study (CHARLS) dataset and air quality records from the AQISTUDY.

China Health and Retirement Longitudinal Study (CHARLS) aims to collect a representative sample of residents aged 45 and older. The baseline wave was set in 2011, with 17,500 individuals from around 10,000 household, from 150 urban areas and 450 rural areas. The sample of the follow-up survey was held every two years, and existing data are for 2011, 2013, 2015 and 2018. This research is based on a cross-sectional data, which is the wave 3 in 2015.

There are 7 sectors in the survey, covering Demographic Background, Family, Health Status and Functioning, Health Care and Insurance, Work, Retirement and Pension, Income, Expenditures and Assts, and Housing Characteristics. Demographic factors, such as age, gender, and marriage status, come from sector of Demographic Background. Education level is matched with previous waves in 2011 and 2013. Variables related to lifestyle and health conditions were sourced from the Health Status and Functioning sector. Household income data were obtained from the Income, Expenditures and Assets sector, and variables related to household energy consumption were derived from the Housing Characteristics sector.

Ambient air pollution concentration data were sourced from the AQISTUDY website. The data represents the annual average PM2.5 concentration at the city level. Initially, PM2.5 concentration data were available for 113 "key environment protection" and "representative environmental protection" cities in 2013. By 2015, data for all cities were included in the study. Since no PM2.5 data were available before 2015, the research relied on cross-sectional data from that year.

The research sample used in this study consisted of 5,017 observations, which is significantly lower than the total sample size of 17,500 individuals in the CHARLS dataset. The observation loss occurred due to several reasons. First, the data were presented in modules, and merging the data led to a slight loss of observations. Second, in Wave 3, many individuals reported the same educational level as in previous waves, resulting in a moderate loss of observations during the data merging process. Third, according to the CHARLS questionnaire, only one individual per household was required to answer the time allocation section, leading to approximately a 50% loss of observations. Finally, extraordinary values or errors in demographic factors were adjusted or corrected to minimize data loss. These cleaning and adjustment processes contributed to a slight loss of data.

4.4.2 Variable Definition and Statistical Report

The table 21 defines the variables. The dependent variable, Lung Disease is defined as the self-reported chronic lung disease

The "Income" variable represents the amount of cash held by the household, measured in thousand CNY (Chinese Yuan). It indicates the financial resources available to the household.

The "Gender" variable is a dummy variable that denotes the gender of individuals. For example, it may be set to 1 for males and 0 for females.

"Marital Status" is also a dummy variable. It is equal to 1 if the individual is married and living with their spouse, and 0 if the individual is single, divorced, widowed, living alone, or living with someone without civil registration.

"Underweight" and "Obesity" are dummy variables indicating whether an individual is underweight or obese, respectively. They are likely based on specific criteria or measurements.

The "Smoking" variable is another dummy variable. It is set to 1 if the individual is currently smoking and 0 if the individual has never smoked or has quit smoking.

Table 21: Variable definition

Variable	Definition
Lung Disease	=1 if the individual has been diagnosed with chronic lung disease =0 otherwise
Exposure	exposure level of individuals, the sum of products of concentration and time in each microenvironment
Wealth	The average cash that household holds (in 10,000 CNY)
Rural	=1 if the individual lives in rural areas; =0 otherwise
GDPpc	The GDP per capita of the city in which the individual lives (measured in 10,000 CNY)
Education	the level of education, range from 1 (illiterate) to 11 (Ph.D.)

Edu	=0 if the education level is lower than 5 (high school) =1 otherwise
Marital Status	=1 if the individual is married and living with spouse = 0 others
Underweight	=1 if the BMI of individual is lower than 18.5 =0 others
Obesity	=1 if the BMI of individual is higher than 30 =0 others
Gender	=1 if the individual is male = 0 if the indivdual is female
Old	= 1 if the age of individual is higher than 65 =0 otherwise
Smoke	=1 if the individual has been smoking =0 others

The table 22 presents the statistical report of the variables. The dependent variable, lung disease is dummy variable with an average of 0.11, indicating that 11% of individuals reported being diagnosed with Chronic Lung Disease.

The exposure level is $76ug/m^3$with the window open, and $58ug/m^3$ with the window closed. The difference between these two exposure level rise from the air exchange rate and penetration rate. When window is open, the air flow between outdoor and indoor is more, with higher air exchange rate and penetration rate. The high air exchange leads to diffusion of household combustion, and household concentration is less affected by the combustion, leading to a lower level of concentration.

The average of income is 0.21 (thousand CNY). The education is 0.32 suggesting that 32% of individuals holds a high school degree and higher. The other variables, marital status, whether the participant is underweight or obese, age and smoking are dummy variables, and the mean suggests the proportion of these features in the observation.

Table 22: Statistic Report

Variable	Mean	SD	Min	Max
Lung Disease	0.110	0.320	0	1
Exposure (open)	58.38	18.22	18.71	113.6
Exposure (close)	76.55	19.30	24.90	205.8
Wealth	0.210	0.740	0	20
Rural	0.640	0.480	0	1
GDPpc	4.610	2.540	1.090	15.70
Edu	0.320	0.470	0	1
Marital Status	0.830	0.370	0	1
Underweight	0.0600	0.230	0	1
Obesity	0.0500	0.210	0	1
Gender	0.470	0.500	0	1
Old	0.300	0.460	0	1
Smoke	0.270	0.450	0	1

4.5 Result

The results with the window closed are reported in the tables 23, where province dummy variables are included as an indicator of geographic difference. It is estimated that the poor health condition is associated with a higher exposure level, which is statistically significant from column (1) to (5). The results indicate that the increase of the exposure level to $PM_{2.5}$ is associated with a high probability of lung disease.

The average marginal effects of wealth are negative, suggesting that an increase in wealth leads to a lower probability of lung disease. Wealth is insignificant in columns (3) and (5), where demographic factors are included as control variables. The reason for the insignificance can be the partial correlation of wealth and other demographic factors. Living in a rural area, holding a low level of education, being single, and being elderly are significant correlated with wealth (see table in appendix). The correlation suggests that low-income individuals are the ones with low social-economic status.

In columns (4) and (5), Smoke is considered as a determinant for COPD. Smoking and secondhand smoking have been considered in the measurement of exposure, but here smoking is treated as an indicator of an unhealthy lifestyle. The results of smoke is insignificant in the column (4) and (5).

Residence includes two variables: rural and GDP per capital level of the residential city. North, which describes the geographic location of a city, is omitted due to multicollinearity as the introduction of province dummy variables. Living in a rural area and living in a city with a low GDP level are associated with a poor lung disease. The coefficients of Rural are significantly positive in all columns, whereas the coefficients of GDPpc are insignificantly negative. The health gap between urban and rural has been found in Chen et al., 2019[29], which explained that the health gap is a result of the access to health literacy and shortage of specialist doctors.

Table 23: AME results of health with the window closed

	(1)	(2)	(3)	(4)	(5)
Exposure	0.000639**	0.000687***	0.00116***	0.000692***	0.00708***
	(0.000255)	(0.000255)	(0.000298)	(0.000257)	(0.00166)
Wealth	-0.0233*	-0.0211*	-0.0168	-0.0231*	-0.0865
	(0.0126)	(0.0124)	(0.0120)	(0.0126)	(0.0643)
Geographic factors	NO	YES	NO	NO	YES
Demographic factors	NO	NO	YES	NO	YES
Smoke	NO	NO	NO	YES	YES
Province FE	YES	YES	YES	YES	YES
Observations	5,017	5,017	5,017	5,017	5,017

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Demographic factors such as education level, marital status, being underweight, and obesity are included in columns (3) and (5). Education is negative, indicating that a higher level of education leads to a lower probability of lung disease. Marital status is insignificantly negative, indicating that marriage cannot improve or affect individual's health. Being underweight and being obesity are both significantly positive, suggesting that improper BMI is associated with a poor lung health. The obese state is more than a state of mass loading, and BMI is only an

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indirect measurement of metabolic health. The obese state is associated with gut microbiome, cellular metabolism and other functions, which can fundamentally alter the pathophysiology of lung health. (Peters et al., 2018)

The table 24 presents the results when the window is open. The difference between the scenario of the window open and closed are the difference of air exchange rate and penetration rate. Exposure is positive while insignificant, and wealth are negative and significant except in the column (3) and (5). Smoking as a lifestyle is insignificantly positive, and demographic and residential factors are the same as the results when the window is open.

Table 24: AME results with the window open

	(1)	(2)	(3)	(4)	(5)
Exposure	0.000328	0.000416	0.000600	0.000341	0.000701
	(0.000481)	(0.000484)	(0.000488)	(0.000482)	(0.000494)
Wealth	-0.0251**	-0.0230*	-0.0182	-0.0250*	-0.0173
	(0.0128)	(0.0126)	(0.0121)	(0.0128)	(0.0120)
Geographic factors	NO	YES	NO	NO	YES
Demographic factors	NO	NO	YES	NO	YES
Smoke	NO	NO	NO	YES	YES
Province FE	YES	YES	YES	YES	YES
Observations	5,017	5,017	5,017	5,017	5,017

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The difference between results with having the window open and close is the household concentration levels, therefore individual exposure levels. The air exchange rate and penetration rate are higher when window is open than close, suggesting that household concentration level are more close to the ambient $PM_{2.5}$ concentration, and the household source of pollutant can be diffused easily. The emission from household sources diffuse more with the window open than the window closed, and the household source emission make little difference to the household concentration. The household concentration level with window open is more close to the ambient concentration levels.

The results of subgroup regressions are given in the table 25 below. The regression is based on the column (1) in the table 10, which only consider the exposure level with the window closed and household wealth. The subgroup results are consistent with the overall results given in the table above, except the subgroup (old = 1), where exposure and wealth are both insignificant. In the subgroup of gender, lung disease is associated with high exposure level, and low wealth for female. In other subgroups, the results are consistent regardless of significance, that poor pulmonary health is associated with high individual exposure of $PM_{2.5}$ and low income.

Table 25: AME results for subgroups

	Gender		Rural		Edu		Marital Status	
	=0	=1	=0	=1	=0	=1	=0	=1
Exposure	0.0011***	0.0020***	0.000626	0.00066**	0.000480	0.000761*	0.000225	0.00069**
	(0.000323)	(0.000600)	(0.000392)	(0.000331)	(0.000319)	(0.000442)	(0.000662)	(0.000283)
Wealth	-0.0383*	-0.0153	-0.0251	-0.0204	-0.0167	-0.0222	-0.0174	-0.0201
	(0.0203)	(0.0158)	(0.0186)	(0.0166)	(0.0167)	(0.0179)	(0.0543)	(0.0125)
Observations	2,661	2,332	1,799	3,218	3,391	1,598	799	4,161

	Smoke		Old		GDPpc		
	=0	=1	=0	=1	(0,3)	[3,5]	(5,20)
Exposure	0.000351	0.00229***	0.00107***	-0.000581	0.000641	0.000675	0.000736*
	(0.000284)	(0.000615)	(0.000298)	(0.000515)	(0.000488)	(0.000457)	(0.000405)
Wealth	-0.0190	-0.0366	-0.0297*	0.00882	-0.0152	-0.0900**	-0.0107
	(0.0135)	(0.0289)	(0.0153)	(0.0259)	(0.0252)	(0.0371)	(0.0107)
Observations	3,617	1,370	3,475	1,495	1,521	1,649	1,847

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.6 Conclusion

The research based on the CHARLS dataset aims to analyze the association between air pollution exposure levels, household characteristics, and individual health outcomes, specifically focusing on the elderly population in China. The study utilizes a cross-sectional dataset that includes individual activity diaries, household pollution sources, and ambient concentration records from official sites. Two scenarios, with the window open and closed, are considered to account for different air exchange and penetration rates in household microenvironments.

The probit model is employed to estimate the effects of income and exposure levels on lung disease probability, controlling for demographic and residential factors. The findings suggest that individuals with lower income, higher exposure levels, abnormal BMI, and lower education levels have a higher probability of lung disease. Residential factors, such as the GDP per capita level of the residential city and urban residence, show consistent results with previous research but are not statistically significant. The results in both scenarios, with the window open and closed, are generally consistent, although the significance of some variables may differ.

The CHARLS dataset is aimed at the elderly people in China, and they are the people who spend most of their time indoors. The source of cooking and fuel combustion contributes to the concentration in the kitchen, and smoke contributes to the bedroom concentration. Reduction of household air pollution can improve the lung health of the elderly in China, including stove improvement and the fuel transfer from biomass and coal to LNG and electricity.

The study acknowledges several limitations. Firstly, the research only examines two scenarios and more scenarios should be explored, including seasonal variations and different heating systems. Secondly, the influence of the fluctuation of air pollution on health is not well understood, and more research, including biological studies, is needed to explore this aspect. Additionally, the composition of PM2.5 should be considered when assessing its health effects, as different components may have varying levels of toxicity. Future research plans to match individuals with intimate exposure levels from different cities to better understand the relationship between industrial structure, health, and air pollution, with potential policy implications.

Future research will focus on matching of individuals with a close exposure level from different cities. With controlling demographic factors, the health effect of $PM_{2.5}$ exposure can be explained as the various component of the pollutant, which are emitted with local industries. The relationship between industrial structure and health will be explored, and policy implications for a better-health industrial updates can be recommended.

In the literature review section, methods for exposure estimation provided by EPA US are mentioned. As far as the author is aware, there is not a widely used models based on daily patterns of Chinese. Based on CHARLS dataset, we can simulate individual daily pattern, and the model will be more precise with more observations from other datasets. The CHARLS dataset has provided records of wave 4 (2018), and the more waves in years. Panel data can help us better understand the interaction of air pollution and individual health, with observations over long time.

Chapter 5

Conclusion

5.1 Conclusion

The thesis examines the relationship between air pollution, socioeconomic factors, and health in China, with a focus on PM2.5 as the air pollutant. The three chapters investigate different aspects of this relationship.

The first chapter analyses the relationship between PM2.5 concentration and GDP per capita in Beijing, controlling for factors such as green land and road length. The findings reveal an "N" shaped curve, with the first turning point at 60,000 CNY and the second at 130,000 CNY, indicating that air pollution may increase after a certain turning point. This highlights the need for further environmental protection measures in Beijing.

The second chapter examines the association between air pollution, economic factors, and health using microdata from the CHARLS dataset. The study matches PM2.5 concentration with individuals based on city codes. Household air pollution, including cooking fuels and smoking habits, is also considered. Endogeneity and heteroscedasticity issues are addressed, and spatial probit models are used to estimate the spatial effects of air pollution and income. The results demonstrate that individuals' health is positively associated with high income and low air pollution, and air pollution from neighbouring cities has a negative impact on health.

The third chapter focuses on the relationship between health, income, and air pollution and introduces a method to calculate the exposure levels of PM2.5. The household concentration of PM2.5 is estimated using the Mass Balance approach, considering ambient concentration and household emissions. Two household microenvironments, the bedroom and kitchen, are included, and scenarios with open and closed windows are considered. A probit model is employed to estimate the effects of income and exposure on health. The findings indicate that poor lung health is associated with low income and high exposure levels. The current policy target of reducing ambient concentration is effective in reducing exposure to PM2.5, and clean energy use, kitchen extractors, and reduced smoking in the bedroom further minimize individuals' exposure to the air pollutant.

This thesis investigates the health effects of income and air pollution, with socioeconomic factors as control variables. The results are supported by the literature, that better income and lower level of air pollution exposure/ concentration are related with better health status.

Overall, the thesis provides insights into the complex relationship between air pollution, socioeconomic factors, and health in China, shedding light on the importance of environmental protection measures and the impact of income on individuals' health outcomes.

5.2 Future work

Future work in this area could explore the following directions:

- International comparative studies: Utilize datasets similar to CHARLS, such as the English Longitudinal Study of Ageing (ELSA) in England, the Health and Retirement Study (HRS) in the United States, the Survey of Health, Ageing and Retirement in Europe (SHARE), as well as surveys from other developing countries like India, Mexico, and Malaysia. Conducting an international research project on the relationship between air pollution, socioeconomic factors, and health would provide valuable insights and comparisons across different contexts. Matching individual records with air pollution data in these surveys would be a challenge, but efforts can be made to overcome this obstacle. Also dataset based on other countries and regions provide observations of individual health for a long time. Heteroscedasticity can be solved with intertemporal records of health and income.
- Effects of environmental policy: Investigate the impacts of environmental policies implemented by the Chinese government on air quality. Examine the effectiveness of regulations and economic incentives targeted at private enterprises and consumers in reducing air pollution. Focus on key regions where strict air pollution control measures have been implemented. Explore the causality between environmental policies and air pollution levels, taking into account the administrative boundaries and the diffusion of pollutants.
- Development of a daily exposure model for PM2.5 in China: Build a model similar to the models developed by the U.S. Environmental Protection Agency (EPA) for

estimating daily exposure to PM2.5 and other air pollutants. Utilize datasets such as CHARLS and other relevant censuses to model the daily exposure of the Chinese population. Promote the awareness and adoption of the model among researchers by collaborating with top research institutions and universities in China. Establish partnerships with the Ministry of Ecology and Environmental matters to ensure the model's reliability and wide adoption.

Please cite all information retrieved from the Gateway data as follows:

Gateway to Global Aging Data, Produced by the Program on Global Aging, Health & Policy, University of Southern California with funding from the National Institute on Aging (R01 AG030153)

Study Overview | Core Interview | End of Life Interview | Life History | Health Assessment | Self-Completion | HCAP

	HRS	MHAS	ELSA	SHARE	CRELES	KLoSA	JSTAR	TILDA	CHARLS	LASI	MARS
	United States	Mexico	England	20+ European countries & Israel	Costa Rica	Korea	Japan	Ireland	China	India	Malaysia
STUDY OVERVIEW	HRS	MHAS	ELSA	SHARE	CRELES	KLoSA	JSTAR	TILDA	CHARLS	LASI	MARS
Respondent Eligibility											
Age Eligibility	51	50	50	50	Cohort 1: 60 / Cohort 2: 55-65	45	50-75	50	45	45	40
One or all age-eligible	one	one	all	one†	one	all	one	all	one	all	three oldest
Spouse Inclusion	regardless of age	regardless of age	regardless of age	regardless of age	Cohort 1: none / Cohort 2: regardless of age	only if age eligible	none	regardless of age	regardless of age	regardless of age	none
Survey											
Method	in-person/ phone/ self-completion	in-person	in-person/self-completion	in-person/self-completion	in-person	in-person	in-person/self-completion	in-person/self-completion	in-person	in-person	in-person
Sample refreshment											
Waves or frequency	every 3 waves	Waves 3, 5	Waves 3, 4, 6, 7	varies by country	none	Wave 5	none	none	Waves 2,3	none	none
Sample Size											
At baseline	12,652	15,402	12,099	30,779	Cohort 1: 2,827 / Cohort 2: 2,798	10,254	3,742	8,504	17,705	72,262	6,672
At latest released wave	20,912	14,779	10,078	77,263	Cohort 1: 1,855 / Cohort 2: 2,430	6,940	4,021	6,400	19,816	72,262	6,672
Blood-based biomarker											
Type	dbs	venous and dbs	venous	dbs	venous	none	none	venous	venous	dbs	none

dbs: dried blood spots.

† The original Wave 1 sample of SHARE interviewed *all* age-eligible individuals in a household.

* Not all collected waves have been released

Figure 10: Surveys with a Similar Structure to CHARLS

By pursuing these avenues of research, we can deepen our understanding of the complex relationship between air pollution, socioeconomic factors, and health, both within China and in an international context.

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Appendix

Table A2.1: Full results of non spatial probit models

	(1) AAP&HAP	(2) Demographic	(3) Geographic	(4) Endogeneity	(5) Heteroscadasticity
lung					
Income	-0.0025***	-0.0013**	-0.0011**	-0.0013***	-0.0008**
	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0004)
PM25	0.0035	0.0039	0.0045*	0.0016	0.0039**
	(0.0024)	(0.0024)	(0.0024)	(0.0015)	(0.0018)
SHS	0.2432***	0.3579***	0.3524***	0.1053**	0.2780***
	(0.0607)	(0.0732)	(0.0732)	(0.0483)	(0.0643)
Smoke	0.5561***	0.4615***	0.4546***	0.3216***	0.3445***
	(0.0476)	(0.0559)	(0.0560)	(0.0432)	(0.0578)
Cooking	-0.0360	0.0023	0.0065	-1.5305***	-0.0009
	(0.0436)	(0.0448)	(0.0449)	(0.0691)	(0.0344)
gender		-0.1565**	-0.1434**		-0.1234**
		(0.0665)	(0.0668)		(0.0530)
marriage		-0.1968***	-0.1991***		-0.1623***
		(0.0677)	(0.0678)		(0.0565)
old		0.4541***	0.4620***		0.3570***
		(0.0469)	(0.0470)		(0.0547)
edu		-0.0263**	-0.0206*		0.0459**
		(0.0118)	(0.0121)		(0.0217)
underweight		0.2412***	0.2353***		0.2021***
		(0.0907)	(0.0908)		(0.0739)
overweight		0.0198	0.0246		0.0267
		(0.0493)	(0.0494)		(0.0376)
urban_nbs			-0.1134**		-0.0911**
			(0.0476)		(0.0376)
coastal			-0.1131		-0.1508
			(0.1407)		(0.1026)
northern			-0.1399		0.0544
			(0.1542)		(0.2010)
_cons	-1.8227***	-1.7677***	-1.6491***	-0.4457***	-1.4853***
	(0.1620)	(0.1851)	(0.1476)	(0.1129)	(0.1313)
N	8335	8335	8335	8335	8335
pseudo R^2	0.0667	0.1010	0.1022		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Coeffficient of province dummies are omitted

Table A2.2: Full results of non-spatial probit models : subgroups

	(1) Gender = 0	(2) Gender = 1	(3) GDPpc < 50	(4) GDPpc > 50	(5) Edu < 4	(6) Edu >=4	(7) Northern = 0	(8) Northern = 1	(9) Coastal = 0	(10) Coastal = 1	(11) Urban = 0	(12) Urban = 1	(13) age <= 45	(14) Age>45, <65	(15) Age >= 65
Income	-0.0011*	-0.0015	-0.0007	-0.0015**	-0.0027**	-0.0008	-0.0006	-0.0019**	-0.0009	-0.0014	-0.0018*	-0.0009	-0.0024	-0.0010*	-0.0011
	(0.0006)	(0.0010)	(0.0007)	(0.0008)	(0.0012)	(0.0006)	(0.0006)	(0.0009)	(0.0006)	(0.0009)	(0.0010)	(0.0006)	(0.0083)	(0.0006)	(0.0008)
PM25	0.0037	0.0073*	0.0026	0.0087*	0.0088***	-0.0003	0.0146***	0.0010	0.0077**	0.0018	0.0021	0.0087*	-0.0098	0.0014	0.0075*
	(0.0030)	(0.0043)	(0.0032)	(0.0051)	(0.0034)	(0.0036)	(0.0048)	(0.0028)	(0.0038)	(0.0031)	(0.0029)	(0.0047)	(0.0430)	(0.0032)	(0.0039)
SHS	0.4057	0.4517***	0.3100***	0.4349***	0.2612***	0.4984***	0.3633***	0.3205***	0.3592***	0.3237***	0.2990***	0.4099***	3.1651**	0.3840***	0.1270
	(0.2665)	(0.0884)	(0.0957)	(0.1153)	(0.0924)	(0.1239)	(0.0963)	(0.1142)	(0.0904)	(0.1249)	(0.1004)	(0.1103)	(1.4707)	(0.1017)	(0.1222)
smoke	0.4488***	0.4958***	0.4778***	0.4302***	0.3711***	0.5559***	0.4322***	0.4718***	0.5045***	0.3485***	0.5496***	0.3418***	0.0000	0.3949***	0.3986***
	(0.0629)	(0.1331)	(0.0710)	(0.0930)	(0.0767)	(0.0856)	(0.0762)	(0.0837)	(0.0691)	(0.0962)	(0.0778)	(0.0848)	(.)	(0.0762)	(0.0876)
Clean Cooking	-0.0216	0.0716	0.0212	-0.0301	0.0225	-0.0150	0.0220	0.0011	-0.0124	0.0509	-0.0188	0.0651	0.5084	-0.0155	0.0415
	(0.0567)	(0.0754)	(0.0580)	(0.0745)	(0.0605)	(0.0695)	(0.0603)	(0.0677)	(0.0560)	(0.0759)	(0.0620)	(0.0699)	(0.7802)	(0.0604)	(0.0705)
Female	0.0000	0.0000	-0.1145	-0.1865*	-0.1695**	-0.1253	-0.1281	-0.1687*	-0.1110	-0.2021*	-0.0506	-0.2517**	0.5108	-0.2485**	0.0247
	(.)	(.)	(0.0855)	(0.1086)	(0.0848)	(0.1147)	(0.0906)	(0.0998)	(0.0826)	(0.1137)	(0.0937)	(0.0986)	(0.7116)	(0.0979)	(0.1026)
marriage	-0.0572	-0.3530***	-0.1297	-0.3086***	-0.2070**	-0.1492	-0.1556*	-0.2574**	-0.1678**	-0.2507**	-0.1701*	-0.2292**	0.0000	-0.1750	-0.1207
	(0.0917)	(0.1092)	(0.0865)	(0.1100)	(0.0811)	(0.1332)	(0.0896)	(0.1039)	(0.0853)	(0.1120)	(0.0889)	(0.1080)	(.)	(0.1166)	(0.0897)
old	0.4240***	0.5135***	0.4727***	0.4495***	0.4309***	0.5073***	0.5007***	0.4129***	0.4845***	0.4181***	0.3682***	0.5718***	0.0000	0.0000	0.0000
	(0.0581)	(0.0832)	(0.0604)	(0.0763)	(0.0611)	(0.0787)	(0.0628)	(0.0719)	(0.0580)	(0.0808)	(0.0633)	(0.0730)	(.)	(.)	(.)
edu	-0.0072	-0.0351*	-0.0157	-0.0280	-0.0180	-0.0338	-0.0222	-0.0185	-0.0129	-0.0378*	-0.0220	-0.0270	0.3758	-0.0369**	-0.0050
	(0.0165)	(0.0187)	(0.0155)	(0.0200)	(0.0186)	(0.0332)	(0.0161)	(0.0186)	(0.0149)	(0.0211)	(0.0166)	(0.0184)	(0.2975)	(0.0177)	(0.0173)
underweight	0.2732**	0.2148	0.2321**	0.2302	0.1957*	0.3665**	0.1466	0.4139***	0.2077*	0.2803*	0.2640**	0.1947	0.0000	0.1954	0.2822**
	(0.1152)	(0.1506)	(0.1104)	(0.1629)	(0.1100)	(0.1651)	(0.1131)	(0.1526)	(0.1126)	(0.1536)	(0.1131)	(0.1570)	(.)	(0.1588)	(0.1144)
overweight	-0.0160	0.0949	0.0076	0.0447	0.0239	0.0340	0.0200	0.0250	0.0218	0.0183	-0.0103	0.0285	0.4139	-0.0034	0.0582
	(0.0630)	(0.0819)	(0.0642)	(0.0788)	(0.0685)	(0.0732)	(0.0662)	(0.0746)	(0.0605)	(0.0861)	(0.0678)	(0.0748)	(0.7194)	(0.0641)	(0.0832)
urban_nbs	-0.1299**	-0.0898	-0.0872	-0.1521*	-0.1240*	-0.1178	-0.1735***	-0.0594	-0.1342**	-0.0777	0.0000	0.0000	-2.8838	-0.1600**	-0.0484
	(0.0599)	(0.0799)	(0.0618)	(0.0852)	(0.0636)	(0.0751)	(0.0637)	(0.0732)	(0.0582)	(0.0839)	(.)	(.)	(1.7574)	(0.0645)	(0.0747)
coastal	-0.0926	-0.1549	-0.1234	0.0139	-0.1427	-0.0618	-0.3634**	0.0924	0.0000	0.0000	0.0408	-0.2283	0.4957	-0.1540	0.0075
	(0.1826)	(0.2239)	(0.1755)	(0.1962)	(0.1728)	(0.2515)	(0.1691)	(0.2705)	(.)	(.)	(0.1847)	(0.2351)	(1.0832)	(0.1807)	(0.2308)
northern	0.0151	-0.4692*	-0.2748	-0.0706	-0.2846	0.0690	0.0000	0.0000	-0.2392	0.2745	0.0857	-0.4192	0.3701	-0.1780	0.0072
	(0.1885)	(0.2808)	(0.1862)	(0.4956)	(0.1929)	(0.2687)	(.)	(.)	(0.1757)	(0.3226)	(0.1994)	(0.2615)	(2.1368)	(0.2057)	(0.2465)
_cons	-1.8355***	-1.7340***	-1.5306***	-1.7746***	-1.6122***	-1.6905***	-1.8670***	-1.5452***	-1.8130***	-1.6221***	-1.7983***	-1.6059***	-4.5996*	-1.2550***	-1.6302***
	(0.1885)	(0.2224)	(0.1944)	(0.2488)	(0.1843)	(0.3108)	(0.3006)	(0.2278)	(0.1779)	(0.2417)	(0.1998)	(0.2387)	(2.5073)	(0.2055)	(0.2240)
N	4736	3571	4736	3599	4172	4134	4214	4121	4848	3487	4382	3901	187	5189	2293
pseudo R^2	0.0962	0.1215	0.1000	0.1061	0.0985	0.1095	0.1056	0.0883	0.0988	0.0789	0.1080	0.1131	0.3779	0.0675	0.0536
chi2	286.6270	204.7871	292.8205	185.4406	268.8522	210.2345	285.9951	172.6981	311.4988	117.3600	297.5087	216.0273	14.6125	160.9881	106.0443

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: for province dummy variables, due to perfectly predicted failure, some observations are omitted. This omission leads to the sum of N for some subgroups is not equal to the total sum (8335)

Table A3.1: Full result of health and income and exposure with closed window

	(1)	(2)	(3)	(4)	(5)
Exposure	0.000639**	0.000687***	0.001159***	0.000692***	0.001297***
	(0.000255)	(0.000255)	(0.000298)	(0.000257)	(0.000303)
Wealth	-0.023323*	-0.021102*	-0.016819	-0.023075*	-0.015839
	(0.012643)	(0.012412)	(0.011951)	(0.012640)	(0.011787)
Rural		0.025513**			0.018842*
		(0.010146)			(0.010353)
GDPpc		-0.002559			-0.002531
		(0.002367)			(0.002348)
Education			-0.032857***		-0.028271***
			(0.010544)		(0.010829)
Marital Status			-0.013906		-0.014833
			(0.011691)		(0.011689)
Underweight			0.063500***		0.062618***
			(0.016538)		(0.016601)
Obesity			0.049023**		0.049668**
			(0.019963)		(0.019918)
Gender			0.055127***		0.065353***
			(0.010766)		(0.012690)
Old			0.032053***		-0.018729
			(0.009779)		(0.011610)
Smoke				0.015974	-0.102253
				(0.009927)	(0.063392)
pro1	0.044689	0.030924	0.038451	0.044424	0.025506
	(0.032229)	(0.033870)	(0.031994)	(0.032219)	(0.033640)
pro2	0.007730	0.034416	0.018739	0.006785	0.037474
	(0.104153)	(0.104382)	(0.100280)	(0.105040)	(0.099503)
pro3	0.122003***	0.112597***	0.111749***	0.120572***	0.104986***
	(0.039937)	(0.040046)	(0.039668)	(0.039933)	(0.039804)
pro4	0.033529	0.027327	0.039665	0.033215	0.037435
	(0.037570)	(0.037542)	(0.037309)	(0.037550)	(0.037315)
pro5	0.104387***	0.092034**	0.110037***	0.103965***	0.099822***
	(0.034793)	(0.036361)	(0.034496)	(0.034759)	(0.036107)
pro6	-0.035510	-0.028380	-0.029807	-0.035949	-0.022229
	(0.035867)	(0.035959)	(0.035716)	(0.035845)	(0.035874)
pro7	-0.027991	-0.036386	-0.035033	-0.027132	-0.045012
	(0.040054)	(0.040968)	(0.040290)	(0.040039)	(0.041244)
pro8	0.053084	0.041454	0.049487	0.051208	0.042589
	(0.047803)	(0.048696)	(0.047369)	(0.047848)	(0.048297)
pro9	-0.002665	-0.013807	-0.010121	-0.003697	-0.023038
	(0.034491)	(0.035170)	(0.034561)	(0.034480)	(0.035316)
pro10	0.045444	0.045883	0.060763	0.044902	0.059541
	(0.040094)	(0.041133)	(0.039940)	(0.040072)	(0.040981)
pro11	-0.026947	-0.031026	-0.025611	-0.027613	-0.032782
	(0.031700)	(0.032122)	(0.031667)	(0.031684)	(0.032129)
pro12	0.079055**	0.071717**	0.078231**	0.077897**	0.070769**
	(0.035708)	(0.036179)	(0.035437)	(0.035681)	(0.035947)
pro13	0.064633**	0.059378*	0.067663**	0.064201**	0.061398*
	(0.031773)	(0.032476)	(0.031547)	(0.031746)	(0.032265)
pro14	0.001127	0.008181	0.003963	0.001162	0.009660
	(0.035474)	(0.035519)	(0.035181)	(0.035442)	(0.035239)

pro15	0.060075*	0.057125*	0.060347*	0.059652*	0.057573*
	(0.032585)	(0.033457)	(0.032388)	(0.032566)	(0.033278)
pro16	0.027595	0.024721	0.030759	0.024223	0.028735
	(0.038136)	(0.038808)	(0.037786)	(0.038177)	(0.038485)
pro17	0.033059	0.027079	0.042164	0.031455	0.037902
	(0.034672)	(0.034836)	(0.034478)	(0.034676)	(0.034683)
pro18	0.084497***	0.088890***	0.096622***	0.083386***	0.101123***
	(0.032054)	(0.032262)	(0.031883)	(0.032045)	(0.032119)
pro19	0.015378	-0.002586	0.023711	0.013119	0.010668
	(0.051732)	(0.052527)	(0.050862)	(0.051738)	(0.051697)
pro20	0.035166	0.028009	0.036755	0.034101	0.031226
	(0.035091)	(0.035427)	(0.034777)	(0.035076)	(0.035148)
pro21	-0.019561	-0.022020	-0.023303	-0.021390	-0.026585
	(0.031000)	(0.031043)	(0.030954)	(0.031005)	(0.031035)
pro22	-0.037719	-0.010753	-0.021259	-0.036832	-0.002390
	(0.092789)	(0.092996)	(0.094602)	(0.092496)	(0.094973)
pro23	0.039230	0.025860	0.047047	0.038061	0.034496
	(0.035894)	(0.037015)	(0.035551)	(0.035864)	(0.036733)
pro24	0.065962**	0.059136*	0.062754**	0.065772**	0.056405*
	(0.029219)	(0.030175)	(0.029014)	(0.029201)	(0.029985)
pro25	-0.054726	-0.027543	-0.051084	-0.058431	-0.025613
	(0.092415)	(0.092723)	(0.092316)	(0.093016)	(0.091698)
pro26	0.159286***	0.159429***	0.153763**	0.159900***	0.148310**
	(0.060290)	(0.060810)	(0.060269)	(0.060354)	(0.060779)
pro27	0.087643***	0.080650***	0.089469***	0.087139***	0.085467***
	(0.029796)	(0.030842)	(0.029629)	(0.029778)	(0.030753)
Observations	5,017	5,017	5,017	5,017	5,017

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A3.2: Full result of health and income and exposure with open window

	(1)	(2)	(3)	(4)	(5)
Exposure	0.000328	0.000416	0.000600	0.000341	0.000701
	(0.000481)	(0.000484)	(0.000488)	(0.000482)	(0.000494)
Wealth	-0.025098**	-0.023008*	-0.018246	-0.025017*	-0.017272
	(0.012780)	(0.012578)	(0.012119)	(0.012785)	(0.011983)
Rural		0.024115**			0.016423
		(0.010134)			(0.010355)
GDPpc		-0.002634			-0.002660
		(0.002375)			(0.002360)
Education			-0.032899***		-0.028654***
			(0.010576)		(0.010867)
Marital Status			-0.016996		-0.017501
			(0.011684)		(0.011706)
Underweight			0.064983***		0.063717***
			(0.016613)		(0.016687)
Obesity			0.049766**		0.050824**
			(0.019983)		(0.019950)
Gender			0.035778***		0.039705***
			(0.009335)		(0.010901)
Old			0.037902***		0.038549***
			(0.009686)		(0.009739)
Smoke				0.012761	-0.010032
				(0.009847)	(0.011457)
pro1	0.043573	0.029161	0.036497	0.043361	0.022692
	(0.032373)	(0.034083)	(0.032201)	(0.032366)	(0.033935)
pro2	0.009675	0.034043	0.018018	0.009351	0.034419
	(0.104506)	(0.104662)	(0.100874)	(0.105158)	(0.100532)
pro3	0.123325***	0.113859***	0.115057***	0.122328***	0.108138***
	(0.040030)	(0.040162)	(0.039781)	(0.040029)	(0.039942)
pro4	0.033408	0.028446	0.039611	0.033018	0.037498
	(0.038429)	(0.038379)	(0.038247)	(0.038415)	(0.038260)
pro5	0.100899***	0.088380**	0.103784***	0.100295***	0.091981**
	(0.034885)	(0.036416)	(0.034649)	(0.034863)	(0.036218)
pro6	-0.037619	-0.030150	-0.032833	-0.038196	-0.026575
	(0.036445)	(0.036547)	(0.036352)	(0.036436)	(0.036520)
pro7	-0.027603	-0.035990	-0.035332	-0.026919	-0.045418
	(0.040272)	(0.041156)	(0.040598)	(0.040265)	(0.041533)
pro8	0.051792	0.041162	0.047915	0.050000	0.039721
	(0.048885)	(0.049647)	(0.048464)	(0.048939)	(0.049305)
pro9	-0.002559	-0.015728	-0.009075	-0.003086	-0.022871
	(0.037224)	(0.038150)	(0.037391)	(0.037227)	(0.038413)
pro10	0.047538	0.048021	0.063081	0.047153	0.060332
	(0.040353)	(0.041356)	(0.040293)	(0.040336)	(0.041292)
pro11	-0.027435	-0.033696	-0.025326	-0.027731	-0.033578
	(0.034675)	(0.035226)	(0.034684)	(0.034666)	(0.035313)
pro12	0.079562**	0.071151*	0.080252**	0.078825**	0.071925*
	(0.036423)	(0.036966)	(0.036160)	(0.036401)	(0.036751)
pro13	0.065788**	0.059975*	0.069835**	0.065584**	0.062939*
	(0.031849)	(0.032594)	(0.031687)	(0.031829)	(0.032453)
pro14	0.000692	0.007252	0.002965	0.000720	0.007855
	(0.035512)	(0.035557)	(0.035279)	(0.035488)	(0.035336)
pro15	0.060192*	0.057139*	0.059989*	0.059835*	0.056040*

	(0.032755)	(0.033594)	(0.032626)	(0.032744)	(0.033483)
pro16	0.031109	0.027282	0.037325	0.028863	0.033283
	(0.038360)	(0.039092)	(0.038027)	(0.038379)	(0.038803)
pro17	0.032389	0.026248	0.042064	0.031109	0.036856
	(0.034710)	(0.034884)	(0.034583)	(0.034717)	(0.034809)
pro18	0.083590***	0.087793***	0.095231***	0.082629**	0.097949***
	(0.032193)	(0.032388)	(0.032111)	(0.032190)	(0.032348)
pro19	0.013480	-0.004951	0.020535	0.011626	0.005647
	(0.051819)	(0.052671)	(0.050999)	(0.051827)	(0.051908)
pro20	0.033385	0.025808	0.034177	0.032470	0.027370
	(0.035119)	(0.035477)	(0.034880)	(0.035110)	(0.035281)
pro21	-0.019253	-0.023576	-0.022067	-0.020419	-0.026800
	(0.033577)	(0.033775)	(0.033608)	(0.033580)	(0.033863)
pro22	-0.038072	-0.012087	-0.022632	-0.037353	-0.004663
	(0.093663)	(0.093913)	(0.096132)	(0.093484)	(0.096472)
pro23	0.038429	0.024378	0.047278	0.037549	0.033799
	(0.036104)	(0.037301)	(0.035814)	(0.036081)	(0.037072)
pro24	0.064613**	0.057265*	0.060361**	0.064399**	0.052936*
	(0.029266)	(0.030244)	(0.029125)	(0.029255)	(0.030128)
pro25	-0.050628	-0.024989	-0.047492	-0.053038	-0.025393
	(0.092860)	(0.093134)	(0.093801)	(0.093327)	(0.093648)
pro26	0.158439***	0.156403**	0.155006**	0.159070***	0.148539**
	(0.061088)	(0.061707)	(0.061104)	(0.061145)	(0.061792)
pro27	0.085624***	0.079441**	0.086305***	0.084918***	0.081243**
	(0.031206)	(0.032069)	(0.031079)	(0.031201)	(0.032028)
Observations	5,017	5,017	5,017	5,017	5,017

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A3.3: wealth as a result of demographic factors

	Wealth
Rural	-0.0507**
	(0.0238)
GDPpc	0.00656
	(0.00522)
Edu	0.0887***
	(0.0245)
Marital Status	0.0983***
	(0.0284)
Old	-0.0593**
	(0.0238)
Constant	0.139*
	(0.0745)
Province FE	YES
Observations	5,017
R-squared	0.032

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1