UNIVERSITY OF OTTAWA

DOCTORAL THESIS

Essays on International Trade and Environment

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A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

in the

Faculty of Social Science
Department or Economics

November 19, 2024

Declaration of Authorship

I, Jintao FU, declare that this thesis titled, "Essays on International Trade and Environment" and the work presented in it are my own. I confirm that:

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Abstract

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Essays on International Trade and Environment

by Jintao FU

This dissertation employ applied microeconomics techniques with a specific emphasis on international trade and environmental economics in China. In Chapter one,I investigates the impact of China environmental regulation since 2015 on middle-aged people's health, using data from the China Family Pannel Studies (CFPS). My findings suggest a significantly positive impacts on health benefits. In Chapter two, I employs a Shift-Share instrument variable to investigate the long-term effect of China's export expansions on human capital accumulation, highlighting the benefits of trade shocks and costs of trade-induced pollution shocks. In Chapter three, I study the causal relationship of international coal boom on human capital. My results show that the high school students in coal-abundant prefectures experience a significant reduction in university attainments and cognitive test scores and improvements in labor market outcomes.

Acknowledgements

First and foremost, I would like to express my deepest appreciation to my thesis supervisor, Nicholas Rivers, for his rigorous academic training, continuous support, and kindness. His timely comments and feedback on this dissertation and throughout my doctoral studies have been invaluable. I am deeply indebted to my supervisor for his consistently dispelling my negative thoughts and guiding me back on the right track during difficult moments, for in spiring me to set high goals, and for generously sharing his time and wisdom, setting an exceptional example as both a person and a researcher.

Also, I thank my thesis committee, composed of internal examiners Jason Garred, Myra Mohnen and Louis-Philippe Beland for their suggestions, ideas, and recommendations during my first and second thesis workshops and thesis defense, as well as during department seminars. I also thank Werner Antweiler for agreeing to evaluate my thesis as an external examiner and for his comments and suggestions. I extend my appreciation to all faculty members and my colleagues at the University of Ottawa, Carleton University, and the participants in various seminars, including CREEA, CEA, and department seminars.

Lastly, I could not have undertaken this journey without the support of my parents, who believed in me and taught me to dream big and supported me all the funding those years. I also want to thank all my dear friends, Jing Cui, Pu Sun, Qiwei Yu, Yani Zhang, Yuyang Zi who always share with me life's joys and challenges.

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Chapter 1

Environmental Regulation and Household Well-Being: Evidence from China's Key Region Policy

1.1 Introduction

Over the past decades, tremendous efforts have been invested into the environmental regulation around the world. How these environmental policies affect the pollution level and household welfare, and how to understand any distributional effects of environmental regulation are at the core of both academic and policy field. Although the existing evidence about the impact of pollution control in developing countries is extensive, the evidence on "environmental justice" is piecemeal and indirect.

Among those policies, "China's War on Pollution" since 2014 received large attention in recent studies (e.g., Karplus, Zhang, and Almond, 2018; Greenstone et al., 2021; Greenstone et al., 2022; Dong, Tian, and Wen, 2022; Buntaine et al., 2022; Heo, Ito, and Kotamarthi, 2023; Yao et al., 2022; Xie, Yuan, and Zhang, 2023).[1] Although extensive literature documents its effectiveness, we have little evidence on how it induced welfare improvements and distributional effects.

This paper examines the legislation of the "Key Region Policy" (henceforth, KRP), a pivotal component of China's "War on Pollution" (Greenstone et al., 2021; Greenstone et al., 2022) and sheds lights on whether China's efforts in combatting pollution have indeed yielded tangible reductions in pollution concentrations, and if so, how this regulation-induced pollution reduction affects the local household well-being?

China's "War on Pollution" represents a comprehensive policy framework encompassing a multitude of environmental initiatives, for example, nationwide automatic air quality monitoring system (Karplus, Zhang, and Almond, 2018; Greenstone et al., 2022; Dong, Tian, and Wen, 2022; Buntaine et al., 2022; Xie, Yuan, and Zhang, 2023) and Key Region Policy (Karplus, Zhang, and Almond, 2018; Heo, Ito, and Kotamarthi, 2023).[2] The centerpiece of China's War on Pollution is the establishment of China's air quality standard and designation of the key region prefectures, which directly requires key region prefectures to achieve the reduction targets using the data from automatic monitoring system.

[1] In the national congress meeting on March 4, 2014, Premier Li Keqiang emphasized "We will resolutely declare war against pollution as we declared war against poverty" (`https://news.cctv.com/2014/03/13/VIDE1394694915322164.shtml`).

[2] During the China's War on Pollution, several other policies were proposed to control different pollutants and target on specific industries. See the policy review by Karplus, Zhang, and Zhao, 2021 for example.

In this paper, I use the variation of regulation stringency in different prefectures by leveraging on legislation of "Key Region Policy" through the *Amendment of Atmospheric Pollution Prevention and Control Law* in 2015. This Amendment is interesting for several reasons.[3] First, the legislation of KRP separates the prefectures by key region and non-key region prefectures, which derives a comparison for my reseach design. This is achieved through its mandate that obliges all key region prefectures across China to adhere to the *National Ambient Air Quality Standards* and achieve an annual pollutant threshold of below 35 $\mu g/m^3$, which provides the geographic and time variation for identification (see, e.g., Karplus, Zhang, and Almond, 2018; Liu, Tan, and Zhang, 2021). [4] In the event that key region prefectures fail to meet the prescribed pollutant thresholds, the respective prefectural governments are compelled to devise detailed plans and implement measures aimed at attaining the stipulated limits.[5] According to the KRP, a substantial 82% of them fall short of compliance with the prevailing air quality standards, exhibiting pollutant concentrations that significantly surpass the prescribed air quality thresholds. Hence, I posit that this designation as a key region holds the predictive capacity for future reductions in pollution levels while simultaneously engendering heightened regulatory stringency. This paradigm bears resemblance to the concept of "Non-attainment status" delineated within the Clean Air Act Amendment (see, e.g., Chay and Greenstone, 2005; Isen, Rossin-Slater, and Walker, 2017).

Second, China has made substantial and concerted investments in pollution control initiatives since 2013, providing an opportune context for scrutinizing the regulatory effects on household welfare. Calculations derived from Greenstone et al., 2021 reveal that China achieved a remarkable reduction in pollution levels within just a five-year timeframe, in contrast to the United States, where a comparable reduction spanned over a decade. Hence, it becomes feasible to conduct an assessment of the health-related welfare impacts, even in circumstances where pollution concentrations remain elevated in China.

Third, as one of the world's largest developing economies, China places substantial reliance on its manufacturing sectors for economic growth while concurrently grappling with pronounced social inequality issues. In this context, it becomes imperative to ascertain whether environmental regulations might yield distributional effects among households, a matter of considerable policy relevance. Environmental justice (EJ), a concept less explored within the Chinese context, warrants increased attention. Consequently, an evaluation of the impacts stemming from this newly enacted policy would augment the existing body of literature on environmental regulation in China (Tanaka, 2015; Liu, Tan, and Zhang, 2021) as well as in other developing nations (Greenstone and Hanna, 2014; Do, Joshi, and Stolper, 2018).

To gauge the causal impact on welfare, I employ a difference-in-differences (DID) research design, contrasting welfare outcomes between key region prefectures and their non-key region counterparts. This utilization of prefecture-level geographic variation generated by the policy shock is analogous to the approaches adopted in prior studies, such as the use of the Non-Attainment status in the United States (Isen, Rossin-Slater, and Walker, 2017; Deschenes, Greenstone, and Shapiro, 2017), CWS

[3] see, `https://www.mee.gov.cn/ywgz/fgbz/fl/201404/t20140425_271040.shtml`

[4] The standard for $PM_{2.5}$ required each prefecture's 24-hour and annual $PM_{2.5}$ concentration lie below 75 $\mu g/m^3$ and 35 $\mu g/m^3$. In comparison, the NAAQS in the United States and Canada currently contain a 24-hour $PM_{2.5}$ standard set at 35 $\mu g/m^3$ and below 30 $\mu g/m^3$.

[5] In accordance with legal provisions, should the key region prefectures fail to meet the prescribed air quality standards, they are mandated to achieve pollutant levels below these standards within the timeframe specified by the State Council or the Ministry of Ecology and Environment.

in Canada(Cherniwchan and Najjar, 2022) and Key regions within China (Karplus, Zhang, and Almond, 2018; Liu, Tan, and Zhang, 2021).

In terms of policy efficacy, my findings yield evidence that the Key Region Policy reduced $PM_{2.5}$ concentrations by 4.75 $\mu g/m^3$, constituting a decline of approximately 7.6 percentage points. I proceed to gauge household well-being through the lens of infant and middle-aged people's health, as both demographic groups exhibit heightened susceptibility to the deleterious effects of air pollution. For infant health, the KRP has resulted in substantial improvements, evidenced by an 4.95 percentage point reduction in low birthweight cases, a 4.79 percentage point decrease in preterm births. Simultaneously, the empirical evidence pertaining to the middle-aged people demographic indicates a reduction of 2.51 percentage points in chronic respiratory diseases and a 3.4 percentage point decline in pollution-related chronic ailments.

In order to elucidate the dimensions of environmental justice, I segment the sample according to occupational categories and subsequently demonstrate that working-age people individuals engaged in "dirty jobs" have realized more pronounced improvements in health outcomes attributable to the policy. This is quantified by a more substantial reduction in chronic respiratory diseases. Given the distinct work environments of these individuals (i.e., manufacturing plant), they contend with heightened levels of pollution exposure. Consequently, these manufacturing workers have experienced more substantial health benefits stemming from the improvement in air quality.

I delve deeper into the mechanisms driving these outcomes by conducting an analysis of both industrial firms and household adjustment behaviors, with detailed findings available in the Appendix 1.8. Firstly, I leverage data extracted from the China Statistical Yearbook dataset, revealing that the Key Region Policy (KRP) has led to a reduction in both the number and output value of industrial firms operating within these designated areas. Subsequently, I present evidence indicating that the KRP has also stimulated public engagement in information-seeking related to pollution and fostered avoidance behaviors, such as the increased purchase of anti-haze masks and air purifiers. These behaviors by firms and individuals have garnered significant attention in recent studies (Liu, Tan, and Zhang, 2021; Greenstone et al., 2022; Buntaine et al., 2022; Xie, Yuan, and Zhang, 2023).

Drawing upon the comprehensive analysis presented above, I leverage the estimated coefficients to conduct a back-of-the-envelope calculation of the health-related benefits. My findings indicate that the observed enhancements in birth outcomes result in substantial economic gains, amounting to USD $4 billion in savings attributable to the reduction in premature births in the year 2017. Furthermore, the observed reduction of 2.03 percentage points in the chronic respiratory disease rate among the middle-aged population equates to annual savings of USD $17.3 billion for middle-aged individuals across China for the year 2017.

This paper contributes to three strands of literature. First, this study informs the burgeoning literature on environmental regulation and its ramifications on public health, by focusing on a large developing country with high pollution and leveraging on the most stringent regulation policy. The China's War on Pollution provides an interesting background and would complement the health benefits documented in prior literature on developed countries (e.g., Deschenes, Greenstone, and Shapiro, 2017; Bishop, Ketcham, and Kuminoff, 2018; Hollingsworth and Rudik, 2021; Marcus, 2021; Hansen-Lewis and Marcus, 2022). Although this paper resonates with prior work on China's environmental regulation, previous studies mainly employed early policies from 1998-2006 (Tanaka, 2015; Liu, Tan, and Zhang, 2021). The KRP policy in this paper receives much attention in recent studies, but they mainly focus on firm behavior and employment (Karplus, Zhang, and Almond, 2018; Liu, Tan, and Zhang, 2021; Dong, Tian, and Wen, 2022), international spillover effects on Korea (Heo, Ito, and Kotamarthi, 2023), people's information search and public participation (Greenstone et al., 2022; Buntaine et al., 2022). Adding to this literature, my study documents that China's War on Pollution had measurable impacts on population health. Leveraging the availability of the latest wave of China's nationally representative survey dataset, namely the China Family Panel Studies (CFPS) dataset 2020, I bolster the robustness of these findings by employing a comprehensive array of measures encompassing infant birth outcomes and the health status of the middle-aged people. Besides, this paper also investigates the legislation of KRP and use this for causal inference, which induces exogenous regulation stringency on key region prefectures. This identification approach also contributes to recent studies that employ the automatic pollution monitoring station for identification (Greenstone et al., 2022; Buntaine et al., 2022; Xie, Yuan, and Zhang, 2023).

Second, my research contributes to a large literature examining the environmental justice and distributional effects of pollution exposure. Existing studies have documented low-socioeconomic-status (SES) households are more likely to live near emission source and thus face larger exposure to air pollution. Previous studies have documented heterogeneous effect of environmental policy on household, including the racial differences (Zivin and Singer, 2023; Currie, Voorheis, and Walker, 2023), socioeconomic differences and income differences (Bento, Freedman, and Lang, 2015; Hausman and Stolper, 2021; Marcus, 2021; Cassidy, Hill, and Ma, 2022; Hansen-Lewis and Marcus, 2022) and work type differences (Curtis, 2018; Liu, Tan, and Zhang, 2021). These uneven results receive much policy attention with attempts to provide more assistance to those groups who bear more health risks and labor market costs during regulation. My heterogeneous results contribute to this literature by showing that individuals who take the pollution-intensive jobs would receive more health benefits due to the improved pollution quality in their working areas and less work hours. In this regard, my paper connects to the literature on the loss of manufacturing workers under regulation (e.g., Walker, 2013; Curtis, 2018; Liu, Tan, and Zhang, 2021), which have documented that those workers bear more labor market costs due to the unintended unemployment effects and reduced income caused by regulation.

Third, this paper also explores the role of information search and avoidance behaviors in reducing the negative effects of pollution. Using the information on family essentials documented in CFPS dataset and China's Baidu Index, I measure the avoidance behaviors with people's search for anti-haze masks and air purifiers, reduction of outdoor physical exercises and work hours. My estimates indicate that the KRP policy significantly increases these avoidance behaviors and thus help protect health. This is consistent with findings in prior studies that show information search and avoidance behavior determine the effect of pollution (Zhang and Mu, 2018; Ito and Zhang, 2020; Marcus, 2021; Greenstone et al., 2022; Hansen-Lewis and Marcus, 2022; Xie, Yuan, and Zhang, 2023).

The remainder of the paper is structured as follows: Section I briefly reviews the relevant institutional background. Section II analyzes the history of KRP and variation source. Section III introduces the identification and specification. Section IV describes my data and characterizes my treatment and control groups with summary statistics and despriptive evidence. Section V presents and discusses estimated effects on a variety of health outcomes. Section VI exploits the robustness checks. Finally, Section VII provides a simple benefit analysis and then concluding remarks.

An online Appendix contains detailed descriptions of data sources and includes additional analysis.

1.2 Policy Background

An optimal research scenario would entail a controlled experiment wherein environmental regulations are randomly allocated to each prefecture, allowing for a straightforward comparison of regulatory outcomes. While the selection of key region prefectures under this policy lacks the element of randomization, it is noteworthy that the legislative enactments of the Amendment provides a variation for regulatory stringency between key region and non-key region prefectures. In the ensuing discussion, I provide a comprehensive institutional background and elucidate why this framework may provide a credible opportunity to establish a robust linkage between environmental regulation and the health outcomes.

1.2.1 China's War on Pollution

Among the past decades, the year of 2013 could be seen as one of the watersheds in the development of environmental regulation in China (Greenstone et al., 2021; Karplus, Zhang, and Zhao, 2021).This pivotal year witnessed a culmination in pollution levels, prompting intensified media coverage and official government warnings, thereby augmenting societal demands for improved air quality. Concurrently, within the broader context of China's ambitious "War on Pollution", a suite of stringent regulatory policies was introduced. The Key Region Policy was formally enshrined through the Amendment of Atmospheric Pollution Prevention and Control Law in 2015. In addition to the KRP policy, two related environmental regulation policies were also proposed and aimed to reduce the $PM_{2.5}$ concentrations during the period from 2013 to 2017, namely the "Action Plan on Air Pollution Prevention and Control (2013-2017)" and the "Three-Year Action Plan for Winning the Blue Sky War (2018-2020)" (Karplus, Zhang, and Zhao, 2021).[6]

In Table 1.1, I demonstrate a series of environmental policies spanning the critical period from 2012 to 2017. The Chinese government embarked on this trajectory by delineating the key region prefectures in 2012, followed by the expeditious release of the National Ambient Air Quality Standards (NAAQS) within the same year. [7] Concurrently, a network of monitoring stations was established. Subsequently, legislative measures were instituted, mandating compliance with the NAAQS for all designated key region prefectures, as guided by the data emanating from the monitoring stations.

While it is recognized that all those supportive policy details can play a role in mitigating pollution concentrations, my primary focus in this analysis centers on the compelling aspect that key region prefectures are legally compelled to adhere to National Ambient Air Quality Standards (NAAQS) through the legislative framework established by the Amendment. This legal requirement serves as the cornerstone of my identification strategy. Other studies have delved into the influence of political incentives (Wu and Cao, 2021) and the efficacy of automated local pollution monitoring stations (Greenstone et al., 2022; Xie, Yuan, and Zhang, 2023) under the framework of China's War on Pollution.

[6] The official website for the action plan on air pollution prevention and control is: https://www.gov.cn/zhengce/content/2013-09/13/content_4561.htm

[7] The NAAQS policy could be seen on its official website https://www.mee.gov.cn/gkml/hbb/bwj/201203/t20120302_224147.htm

1.2.2 History of Key Region Policy

Key Region Policy (1998 version).- This concept was first proposed in 1998 in an official document (known as the "Two Control Zones policy") of the Ministry of Environmental Protection (MEP) with the intention to improve the air quality of some key prefectures (Tanaka, 2015; Chen, Li, and Lu, 2018; Liu, Tan, and Zhang, 2021). The central government designated 47 prefecture-level prefectures as the key region prefectures, and 66 prefectures were added in 2000. Although Liu, Tan, and Zhang, 2021 show that the 1998 version of Key Region Policy significantly reduced the firm-level SO_2 emissions since 2002, the overall pollution level in China was still climbing. This is because environmental regulation authorities (i.e., the Ministry of Environmental Protection) do not gain much political support and enforcement power during this policy period from 2001-2007, so the local environmental authorities were unable to inspect and decide the local pollution-intensive industries. This could be seen from the stylized fact that the overall pollution level in China is still climbing and peaks around year of 2013, though the SO_2 emission drop sharply since 2002 as shown in Figure 1.1.

Key Region Policy (2012 version).- This renewed policy is called the "*Key-Region Air Pollution Prevention: the Twelfth-Five Years Planning*" and proposed by Ministry of Environmental Protection, National Development and Reform Commission and Ministry of Finance at December, 2012.[8] Specific targets for average annual concentrations of PM2.5, PM10, SO2, and NO2 have been established at 35, 70, 60, and 40 $\mu g/m^3$, respectively. I summarize more policy details in the Appendix 1.8.

Prior to 2013, the landscape of environmental regulation at the prefecture level in China was marked by notable limitations, primarily stemming from constraints in financial resources and executive authority, largely due to a lack of comprehensive legislation. It was evident that many local governments recognized the significance of environmental regulation, yet they were also compelled to strike a balance with the imperative of fostering economic growth. Additionally, the intricate nature of pollution problems, along with the far-reaching consequences of pollution spillover, rendered it challenging for any single prefecture to effectively manage and control regional pollution levels. In response to these challenges, the central government adopted a strategic approach that prioritized addressing systemic environmental issues. This strategy hinged upon collaborative efforts among key region prefectures, implying that these jurisdictions were tasked with achieving identical pollution reduction goals while adhering to the same stringent regulatory standards.

Amendment of Atmospheric Pollution Prevention and Control Law.- After the proposition and the updated *National Ambient Air Quality Standards* in 2012 and the equipment of monitoring stations in key region prefectures, the Key Region Policy was legislated through the *Amendment of Atmospheric Pollution Prevention and Control Law* in Augest, 2015 (counterpart of the Clean Air Act Amendments in the U.S.).[9] This Amendment formally established the mechanism of regional collaboration in pollution control, which requires key region prefectures to move together with same

[8] See the policy in the official website on https://www.gov.cn/gongbao/content/2013/content_2344559.htm

[9] In August 2015, the 6th session of the 13th standing Committee of the National People's Congress passed this Amendment. The procedure of the law could be seen by the link: https://climate-laws.org/geographies/china/laws/law-on-the-prevention-and-control-of-atmospheric-pollution. And the official version of the law is from the Ministry of Ecology and Environment https://www.mee.gov.cn/ywgz/fgbz/fl/201811/t20181113_673567.shtml.

reduction targets. According to the Amendment, all key region prefecture governments should include air pollution prevention and control in their economic and social development planning and design concrete plans to reach the environmental quality standards. In addition, all the prefectures specified in the key region areas must follow the new version of NAAQS and achieve the pollutant limits, which induce higher level of regulation stringency on key region prefectures.[10] This requirment could be seen from the policy details in Appendix 1.8.

1.2.3 The Selection Process of Key Region Prefectures

Why does China's Key Region Policy is substantial and necessary for pollution control? This is based on the fact that air pollution is increasingly showing regional characteristics. Due to uneven economic development, the willingness and financial investment in environmental protection as well as the level of environmental management and environmental pollution control vary greatly from place to place. Hence, joint prevention and control of air pollution would be an effective mechanism for reducing regional air pollution. The legislation law in 2015 established this regional management mechanism from a legal perspective.

The list of key region prefectures (2012 version, 113 prefectures) is specified through "*Key-Region Air Pollution Prevention: the Twelfth-Five Years Planning*". The key region prefectures are composed of 113 prefecture-level cities in 19 provinces primarily located in the greater Beijing–Tianjin–Hebei area, the Pearl River Delta, the Yangtze River Delta and in some key prefectures across China (See the Figure 1.2).[11] And the sample prefectures are similar to the 1998 first version (47 prefectures) and 2001 second version (66 prefectures as complements).

Overall, the selection of these 113 key region prefectures was grounded in a multifaceted assessment encompassing air pollution concentrations, comprehensive economic evaluations, and industrial compositions spanning the years 2010 and 2012. The key region prefectures collectively encompasses 14% of China's total land area while accommodating nearly 48% of its populace. In terms of pollution concentrations, they are responsible for 71% of the overall economic output, 52% of coal consumption, and emissions comprising 48% of sulfur dioxide, 51% of nitrogen oxides, and 42% of nitrogen oxides. In terms of pollution intensity, the emission intensity per unit area within these regions ranges from 2.9 to 3.6 times the national average. Furthermore, a substantial 82% of the key region prefectures fall short of meeting the air quality standards outlined by the National Ambient Air Quality Standards (NAAQS) when they were specified as key region prefectures in 2012.

The sample in this paper includes 46 key region prefectures and 80 non-key region prefectures due to the household survey data limitation (both CFPS and CHARLS dataset), which covers parts of Chinese prefectures. Among them, I choose the prefectures that are designated as key region prefectures as the treatment group and the others as control group. In Figure 1.2, I depict the key region prefectures and non-key region prefectures in the map of China. Prefectures shaded in darker green are subject to heightened regulatory pressure and are henceforth referred to as the treatment group in this analysis. The discernible variation in regulatory stringency serves as a foundational element for my identification strategy.

[10] See the NAAQS official website: `https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/dqhjbh/dqhjzlbz/201203/t20120302_224165.shtml`

[11] Due to the limitation of my household survey data, I delete several prefectures and only plot the prefectures with data.

1.2.4 Why Do Key Region Prefectures Face Higher Regulation Stringency?

Since 2015, prefectures situated within key regional areas have been subject to a more elevated level of environmental regulatory stringency in comparison to their counterparts. I summarize several approaches in this subsection.

NAAQS

While the NAAQS (new 2012 version) applies to any location, stricter standards can be set in those key region prefectures due to the legislation. The variation comes from the fact that the Amendment require all key region prefectures listed in the KRP to comply with the *National Ambient Air Quality Standard* and finish the reduction targets by the time required by the State Council and provincial-level government.[12] This requirment could be seen from the policy details in Appendix 1.8.

Automatic Pollution Monitoring Stations and Information Disclosure

On one hand, the automatic pollution monitoring stations were required to be equipped among key region prefectures. According to KRP, the Capital Economic Zone (Beijing-Tianjin-Hebei area), the Yangtze River Delta and the Pearl River Delta must complete the construction of regional ambient air quality monitoring systems by the end of 2012, and other key region prefectures need to complete by the end of 2015. Greenstone et al., 2022 documents that the first wave of stations incorporates 74 key polluting prefectures (496 stations) by January 1, 2013, and those prefectures are the key region prefectures in Capital Economic Zone, the Yangtze River Delta and the Pearl River Delta areas. The prefectures specified in the second wave are another 116 prefectures (449 stations), which are mainly located in national key environmental prefectures predetermined in 2007 and the national model prefectures for environmental protection. [13] The introduction of automatic local pollution monitoring stations (Greenstone et al., 2022; Xie, Yuan, and Zhang, 2023) publishes realtime of every pollutant in all prefectures, which can reduce the pollutant data manipulation and increase the public attention. Therefore, monitoring stations equipped by key region prefectures can bring higher level of regulation stringency.

On the other hand, the Amendment requires key region prefectures make the pollution information public to the society. Two recent paper exmine the role of pollution information disclosure and public appeals on environmental regulation (Greenstone et al., 2022; Buntaine et al., 2022). More policy details can be seen in the Appendix 1.8.

Political Incentives

The incorporation of environmental performance targets for local officials promotion (Chen, Li, and Lu, 2018; Wu and Cao, 2021) is another seminal "top-down" command-and-control type approach for environmental protection. If the key region prefectures do not satisfy the pollutant targets, the local government leader would face serious punishment from the political system. Furthermore, in the case of key region prefectures that fall short of meeting their reduction targets, it becomes incumbent upon them to formulate meticulous regulatory strategies and future-oriented plans geared towards attaining these goals. This political impetus aligns

[12] The Amendment does not specify the accurate time for the target to be achieved for prefectures.

[13] The range of key region prefectures is less than the prefectures with automatic pollution monitoring stations. But the first wave and second wave covers all key region prefectures.

with the principles observed in the implementation of the Clean Air Act Amendments (CAAA) as discussed by (Chay and Greenstone, 2005; Isen, Rossin-Slater, and Walker, 2017). In a broader perspective, non-compliant prefectures face the prospect of being documented for their non-adherence, potentially affecting the prospects of local officials during comprehensive evaluations and promotions within the party system (Liu, Tan, and Zhang, 2021; Wu and Cao, 2021; Yao et al., 2022).[14]

Assessment of Polluting Industry

Finally, industries within key region prefectures face more stringent standards, with a particular focus on enhancing energy efficiency and minimizing pollutant emissions, as mandated by the KRP framework. According to the KRP, all incumbent firms, in response, must make judicious investments in abatement measures to ensure compliance with these rigorous environmental quality standards. Moreover, prefectural authorities are legally obligated to establish emission limits for existing industrial facilities located within key region prefectures.

[14] Prior research has extensively documented the influence of political considerations on local mayors and party secretaries in ameliorating local pollution concentrations, primarily due to the heightened emphasis placed on environmental quality evaluations by higher tiers of government.

1.3 Research Design

Although the KRP policy designated key region prefectures and required them to reduce the pollution level and finished reduction targets, it is the *Amendment of Atmospheric Pollution Prevention and Control Law* that officially requires key region prefectures to comply with the National Ambient Air Quality Standard (GB3095-2012).[15]

To estimate the causal effect of KRP regulation on air quality and health outcomes, I employ DID design and exploit variation from the legislation timing (i.e., Augest, 2015) and regulation stringency between key region and non-key region prefectures. Following prior literature which employs regulation policy and legislation as a quasi-experiment design (e.g., Chay and Greenstone, 2005; Isen, Rossin-Slater, and Walker, 2017; Curtis, 2018; Liu, Tan, and Zhang, 2021; Marcus, 2021; Hollingsworth and Rudik, 2021; Hansen-Lewis and Marcus, 2022; Currie, Voorheis, and Walker, 2023), I exploit this legislation-induced variation of stringency of pollution regulation for identification.

1.3.1 Identification

The pursuit of causal inference regarding the impact of regulatory measures hinges upon the premise that the legislation singularly triggers alterations in regional pollution concentrations while leaving other factors unaffected. Moreover, this legislative action must serve as a reliable predictor of prospective changes in local pollution levels. Consequently, I face two primary empirical challenges: (i) measurement error; and (ii) endogeneity.

First, there are several ways to measure the regulation stringency difference in literature. To avoid the measurement error, I directly choose the key region prefectures specified by the policy as the treatment group. The inital results in the Table 1.4 confirm that the key region status can predict future pollution reduction in key region prefectures. This approach is also used in previous studies on Key Region Policy (e.g., Karplus, Zhang, and Almond, 2018; Liu, Tan, and Zhang, 2021). For pollution measure, I avoid the official report and choose the satellite data provided by Van Donkelaar et al., 2021. And for household welfare measures, I use survey dataset which provides direct measures of infant birth outcome, physician-diagnosed chronic disease and self health status, and household income and working hours. These measures from the survey dataset are commonly used in labor, health and environmental economics to measure income, health and so on (e.g., Chen and Fang, 2021; Huang and Zhang, 2021; Deng and Lindeboom, 2022).

Second, the key identification assumption in this paper relies on the fact that the non-key regions provide valid counterfactual changes in individual well-beings indicators for the key region prefectures, had they not been treated, conditional on covariates. Two potential hypotheses may violate this assumption: (1) there is a systematic difference in preexisting trends in well-being measurements; and (2) the key region status is not orthogonal to factors explaining any changes in well-being in the post-treatment period. Therefore, I conduct several indirect tests. First, I use data from years prior to KRP legislation to examine pretrends in prefecture-level covariates and outcomes on Figure 1.6 with their F-test results and p-values, finding little evidence of statistically significant differences between treatment group and control group. Second, I also test whether key region status is correlated with changes in the observable characteristics of households and prefecture economic outcomes in

[15] Although KRP (2012 version) emphasized joint prevention and control of air pollution, this is not effective due to lack of legal support.

the years after the KRP went into effect, and I find little evidence in support of such a hypothesis. The results are presented in the robustness check section 1.6.5.

1.3.2 Estimating the impacts of Key Region Policy

I first estimate the effect of key region status on the regional pollution concentration and then on middle-aged people well-being. In an ideal research setting, the Key Region status is randomly assigned across prefectures, creating variation uncorrelated with baseline characteristics. In the absence of a randomized controlled trial, I use a difference-in-differences approach to examine the policy effectiveness, and the model is as follows:

$$Pollution_{ct} = \alpha + \beta \text{KeyRegion}_c \times \text{Post}_t + X'_{ct}\delta + \mu_c + \eta_t + \varepsilon_{ct} \tag{1.1}$$

In Specification 1.1, I use $Pollution_{c,t}$ to denote the pollution level in prefecture c in year t, which is obtained from the database provided by Van Donkelaar et al., 2021. The $KeyRegion_c$ is the treatment variables which equals 1 if the prefecture is specified as Key Rregion Prefecture through Key Region Policy. $Post_t$ is the time indicator equals 1 after the legislation year (i.e., Augest, 2015). The coefficient of interest is β, which is the interaction of the key region exposure with the post-treatment variable. The control vector X_{ct} contains GDP per capita, population, share of secondary industry over the gdp, share of labor in manufacturing industry and fiscal expenditure. In Figure 1.6, I examine trends of those characteristics between the two groups and show that they are all not affected by KRP. μ_c and η_t are prefecture fixed effect and year fixed effect.

In some results, my econometric specification controls for prefecture-level socio-economic characteristics in year of 2013 (pre-policy year) interacted with policy year (i.e., $\text{Post}_t \times Z'_{c,2013}\gamma$).[16] These characteristics may affect the region pollution concentrations and household welfare, and they could also potentially be correlated with the upper level government's choice of key region prefectures. Specifically, I control the prefecture GDP per capita, population size, number of beds in hospital, fiscal expenditure, fiscal revenue and average wages in the year of 2013.

Second, I employ the following equation to further examine the effect of regulation on people's health outcome:

$$y_{ict} = \alpha + \beta \text{KeyRegion}_c \times \text{Post}_t + X'_{ict}\delta + \mu_c + \eta_t + \varepsilon_{ict} \tag{1.2}$$

where y_{ict} denotes individual-level well-being measurement, representing individual who resides in prefecture c and is surveyed in year t. A set of control variables is denoted by X_{ict}, including individual socioeconomic indicators such as age, age's square, gender, marriage status, education level, rural/urban type and family size. Following Huang and Liu, 2023, I control all of these variables because they are strongly related to health status and healthcare utilization. By doing this, this specification can avoid omitted variables and increase the accuracy of regression results. I also include the prefecture-level socio-economic characteristics in year of 2013 (pre-policy year) interacted with policy year (i.e., $\text{Post}_t \times Z'_{c,2013}\gamma$) in some columns. Specifically, I control GDP per capita and hospital beds per 10,000 persons, which can affect infant and middle-aged people's health outcomes.

The parameter β should capture any changes in individual well-being before and after the regulations, between the key regions treatment group and non-key regions

[16] I employ the following equation $Pollution_{ct} = \alpha + \beta \text{KeyRegion}_c \times \text{Post}_t + X'_{ct}\delta + \text{Post}_t \times Z'_{c,2013}\gamma + \mu_c + \eta_t + \varepsilon_{ct}$ in some columns.

since 2015. If the air pollution regulation contributed to significant improvements in household welfare among key regions prefectures relative to non-key regions prefectures, I should observe a significant β. Prefectures-specific time invariant characteristics are denoted by μ_c. τ_t is the survey-year fixed effects and can be used to control for the shocks common to all prefectures in a given year.[17] And ε_{ict} is an unobservable error term. Standard errors are clustered at the prefecture level. Because most of the surveys take place in June or July (i.e., summer vacation), I ignore the month fixed effects and regard the survey year .[18] For all regression, I use a weighted regression to reduce the dominance of individual living in large cities in the estimation results. Specifically, all regressions are weighted by the number of population for each prefectures in 2013 to control for the potential concern of uneven distribution of survey participants across different prefectures. In the Appendix 1.8, I report the unweighted regression results.

To exploit the impact on infant birth outcome, I use the cohort DID regression, which takes the following form:

$$y_{ict} = \alpha + \beta \text{KeyRegion}_c \times \text{Post}_{it} + X'_{ict}\gamma + \mu_c + \delta_{pt} + \varepsilon_{ict} \tag{1.3}$$

where outcome y_{ict} denotes the low birthweight and preterm birth rate for infant i, born in prefecture c and cohort year t. And $Post_{it}$ is a variable that equals 1 if the infant i was born after the legislation of Key Region Policy since year of 2015. In my regression, the vector X_{ict} contains both individual and household characteristics, such as gender, urban/rural type, household size, parents'age, education and income when having infants.

The difference to the baseline regression is the δ_{pt}, which is now the province-birth year cohort fixed effects ranging from year of 2011 to 2020. This province-birth cohort fixed effects is important because it represents the cohort year time-varying fixed effects within the province. The standard errors are clustered by prefecture of birth to account for correlations in outcomes between infants in the same prefecture. In some specifications, I also report the estimation results controlling prefecture controls $Z_{c,2013}$ in the initial year interacted with post year dummy.

1.3.3 Event study

I also examine the identification assumption using an event-study type analysis:

$$y_{ict} = \alpha + \sum_{t=2009}^{2020} \beta_t \text{KeyRegion}_c \times \text{Year}_t + X'_{ict}\gamma + \mu_c + \eta_t + \varepsilon_{ict} \tag{1.4}$$

where β_t captures the extra time effect on well-being. Since the legislation year is 2015, I drop the year of 2014 for this test. The hypothesis is that there is no significantly different trend between the key regions and non-key regions before the implementation of the regulation policy. In Figure 1.5, I plot the coefficient β_t in an event study study, and the result suggests an insignificant effect before the policy year and a decreasing trend since 2015. One potential threat to this specification

[17] For the baseline regression using CFPS dataset, the year fixed effect includes the year of 2010, 2012, 2014, 2016, 2018 and 2020, which is also the survey year of biennial survey dataset. For the data from CHARLS, I include year of 2011, 2013, 2015 and 2018.

[18] Following Huang and Zhang, 2021, I do not incorporate the individual fixed effect in the main regression results, because individual fixed effects may exaggerate the attenuation bias caused by measurement errors. Additional regression results with individual fixed effect are reported in the Appendix 1.8.

could arise if local KRP implementation is correlated with changes in alternative socioeconomic conditions. For further identification check, I also show that several socioeconomic variabes present the similar trends during policy period in Figure 1.6 with their *p*-values. I also report the F-test of pre-treatment coefficients in the baseline regressions in Table 1.4.

1.4 Data and Descriptive Evidence

In this study, I amalgamate data sourced from multiple key repositories spanning the period from 2010 to 2020, incorporating the ground-level fine particulate matter ($PM_{2.5}$) measures, the China Family Panel Studies (CFPS), and the China Health and Retirement Longitudinal Study (CHARLS) survey dataset. The CFPS dataset furnishes essential household-level variables pertaining to children's birth outcomes and measures of the middle-aged people's health, while CHARLS is distinctly tailored to the assessment of the health status among the middle-aged people demographic. It is worth noting that these two survey datasets have gained widespread recognition and adoption within the scholarly discourse of labor economics, development economics, health economics, and environmental economics (See, e.g., Zhang, Zhang, and Chen, 2017; Ao, Dong, and Kuo, 2021; Huang and Zhang, 2021; Yao et al., 2022; Xie, Yuan, and Zhang, 2023).

China Family Panel Studies (CFPS).- The CFPS dataset is a nationally representative sample of Chinese communities, families, and individuals that covers 25 of China's 31 provinces/regions and 162 prefectures. The waves of survey I use are 2010, 2012, 2014, 2016, 2018 and 2020. Since most surveyed households do not respond during each wave, this is an unbalanced panel dataset. I have 100,618 observations aged 45 and above, and 11,573 observations of infants from this dataset.

China Health and Retirement Longitudinal Studies (CHARLS).- The CHARLS is also a commonly used dataset which aims to collect the information of people ages 45 and older. This survey is the Chinese equivalent of Health and Retirement Survey (HRS) in US. The CHARLS dataset started in 2011, and this study uses the 2011, 2013, 2015 and 2018 waves of the CHARLS. Finally, I have 75,105 observations aged 45 and above from CHARLS dataset.

Pollution Data: My pollution measure is the ground-level fine particulate matter ($PM_{2.5}$) for 1998-2021 provided by Van Donkelaar et al., 2021, who combined Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWIFS instruments with the GEOS-Chem chemical transport model and then calibrated them to global ground-based observations using a Geographically Weighted Regression (GWR). I use their data because it provides the most comprehensive measure of air pollution across China's geography and over time, and this satellite data can avoid data manipulation (Karplus, Zhang, and Almond, 2018; Greenstone et al., 2022). The AOD measures the extinction of the solar beam by dust and haze and can be used to predict pollution even in areas lacking ground-based monitoring stations (Van Donkelaar et al., 2021).[19] I then match this high resolution ($0.01° \times 0.01°$) data to each Chinese prefectures by their horizontal and vertical coordinates.

Infant health: The infant birth outcome has been shown to be sensitive to air pollution and is essential for later life outcomes (Isen, Rossin-Slater, and Walker, 2017; Currie and Walker, 2019). Infant health is also ideal for the measurement and avoidance of endogeneity, because infant health is affected during the gestation period and is less affected by parental health outcomes. I choose the low birthweight and prematurity as two measures of infant birth outcome.[20] The CFPS dataset provides a wide set of household information including year and month of birth, place of birth, and whether individuals were born in a rural area. I separate those samples by rural areas and urban areas. The reason for this intervention is because that the NAAQS specifies two different level of pollution limits for urban areas and rural areas (see

[19]More data details can be seen from their database website `https://sites.wustl.edu/acag/`

[20]Following commonly used medical recommendations, low birthweight is defined as birthweight below 2,500 grams, preterm birth is defined as a gestation less than 37 weeks.

Appendix 1.8 for details). This is also because urban pollution is more severe, thus the urban sample should be more sensitive to the pollution reduction and reflect the reliable estimates.

Middle-aged people health: I draw on sample from CHARLS dataset and CFPS dataset aged 45 and older to denote the health change for the middle-aged people. Previous studies show that the middle-aged people is also sensitive to the pollution exposure (Zhang, Zhang, and Chen, 2017; Ao, Dong, and Kuo, 2021) and environmental regulation (Lai, 2017; Hollingsworth and Rudik, 2021; Hansen-Lewis and Marcus, 2022). Because the question in these two survies are not the same, I report the regression results in two tables with different outcoems. In CFPS dataset, the outcome of interest for middle-aged people include chronic respiratory disease (yes=1) and another general chronic (yes=1). In CHARLS dataset, I define pollution-related chronic (yes=1) for middle-aged people. Detailed questions are reported in the Appendix Table 1.19. I choose these three outcomes as the most important variables to represent the household health status impacted by pollution changes.[21] The CHARLS dataset reports the asthma information, so I also report the outcomes of asthma in the sample from CHARLS dataset.

In addition to these pollution-related outcomes, I include several comprehensive health measures. Following Lai, 2017, Chen and Fang, 2021 and Huang and Zhang, 2021, I choose several commonly used measures with four main dimensions: Activities of Daily Living (ADL), Cognitive ability, Self-reported overall health condition and Medical expenditure.[22]

Individual controls: Both CFPS and CHARLS dataset provide detailed individual information, including gender, age, education years, marital status, rural/urban type, income and family size. The socioeconomic information can help me capture family heterogeneity across different prefectures. For impacts on middle-aged people, I include the above variables; For impacts on birth outcomes, I also control for infant gender and parental characteristics. By incorporating these socioeconomic variables into regression, I could control for individual characteristics that may affect their health status.

Table 1.2 and 1.3 contain descriptive statistics on the variables used in my analysis. The average municipal-level pollution concentration is about 59.88 $\mu g/m^3$ in the treatment group and approximately 43.97 $\mu g/m^3$ in the control group during the whole sample period (2009 to 2020). The summary statistics for socio-demographic variables by treatment show that the key region cities have higher chornic rate and respiratory rate, also middle-aged people's health and infant birthoutcome is worse in those areas.

Before the estimation results, I first plot the raw data. Figure 1.3a plots the trends of the pollution level between key region cities and non-key region cities from 2009 to 2020. This figure suggests that the whole $PM_{2.5}$ pollution concentration decreased since 2014. In order to discern the magnitude of this reduction across the two groups,

[21] The CHARLS survey provides detailed information about the incidence of 14 different types of illness in the last 4 weeks, including hypertension, dyslipidemia, diabetes, cancer, chronic lung diseases, liver disease, heart attack, stroke, kidney disease, stomach disease, emotional problems, memory-related, arthritis and asthma. The CFPS survey provides detailed chronic disease codes diagnosed by physicians during last 6 months, including respiratory and other chronic disease. The pollution-related chronic indicator from CHARLS dataset consists of the hypertension, asthma and lung disease, while the chronic indicator from CFPS dataset is defined by all chronic diseases.

[22] These measures are also employed in existing medical and toxicology literature, though the mortality is a more convincing measure for calculating the lower bound of welfares. The CHARLS and CFPS dataset do not provide mortality information, so here I mainly focus on the comprehensive health measures.

Figure 1.3b highlights that while the pollution levels in key region areas and non-key region areas exhibited similar high levels during the pre-policy period, there was a pronounced decline in pollution levels in key region prefectures starting around 2014-2015. Figure 1.3b, which sets both trends to commence at zero, accentuates the negative values on the y-axis, indicating significant pollution reductions. This outcome underscores that the heightened regulation stringency in key region areas has led to substantial pollution abatement. In summary, these figures illustrate that, subsequent to the enactment of the Key Region Policy, pollution reduction in key region areas exhibited a more precipitous decline. Consequently, this differential pollution reduction, driven by varying degrees of regulatory stringency, serves as the foundation for our identification strategy.

To help with visualizing the relationship between the environmental regulation and health outcomes before reporting my regression results, Figure 1.4 presents binned scatter plots of changes in infant, children and middle-aged people's health outcomes.[23] Panels (a) and (b) substantiate the presence of an positive association between infants' birth outcomes and the decline in PM2.5 concentrations. The prefectures experienced larger pollution reduction would also have larger reduction on infants' birth outcomes. Panels (c) and (d) imply a similar positive correlation between chronic respiratory ailments and pollution levels, both in the context of children and the middle-aged people. And panels (e) and (f) draw upon evidence from the CHARLS dataset, underscoring a positive relationship between the prevalence of middle-aged people asthma and general chronic conditions and reductions in PM2.5 levels.

[23] I first calculate the change of $PM_{2.5}$ reduction for each prefectures from 2010 to 2020, and then divide them into 20 bins.

1.5 Results

In this section, I present the estimates for pollution reduction and health improvements.

1.5.1 Impacts on Pollution

Pretrends analysis (1): Event study.- I commence by conducting an examination of the policy's impact on regional $PM_{2.5}$ concentrations. In order to establish the validity of the strong identification hypothesis, which posits that, in the absence of the Key Region Policy, the treatment group would have followed a trajectory similar to that of the control group, I initiate the assessment by scrutinizing this identification assumption. Figure 1.5 illustrates the coefficients and accompanying 95 percent confidence intervals pertaining to KeyRegion-Year interactions derived from regression analyses of $PM_{2.5}$ concentrations spanning the period from 2009 to 2020. As depicted in Figure 1.5, prior to the policy's enactment, the coefficients associated with KeyRegion-Year interactions exhibit no statistically significant deviation from zero. This observation underscores the notion that key region and non-key region locales shared analogous trends in pollution emissions. However, following the policy's implementation, a discernible shift becomes apparent, as the coefficients for KeyRegion-Year interactions become negative values. This shift signifies a substantial reduction in $PM_{2.5}$ concentrations within the treatment group relative to the control group, lending credence to the policy's efficacy in curbing pollution levels. I also report the F-test of pre-treatment coefficients in Table 1.4, and all four columns indicate that the pre-treatment coefficients are close to zero with significance.

Pretrends analysis (2): Descriptive evidence.- Second, I provide the initial evidence and plot the economic indexes over the calendar years for both treatment group and control group. Figure 1.6 illustrates the trajectories of various measures, encompassing the logarithm of GDP per capita, population size, fiscal expenditure, the quantity of hospital beds, the number of physicians, and wage levels. Importantly, the temporal trends between key region and non-key region jurisdictions exhibit a striking parallelism, implying a lack of substantial disparities in prefecture-level economic metrics. To further substantiate these findings, I conduct F-tests to assess the parallelism of trends and report their associated p-values within each figure. Taken collectively, both the statistical tests and the visual evidence converge to indicate the absence of significant nonparallel trends.

DID results.- The Difference-in-Differences (DID) findings pertaining to the environmental performance, as delineated in Equation (1), are presented in Table 1.4. The baseline outcome in column (1) incorporates solely prefecture fixed effects and year fixed effects. The estimate for the interaction term KeyRegion $\times$ Post exhibits statistical significance, signifying that the more stringent Key Region Policy has led to a reduction in pollution levels by 4.57 $\mu g/m^3$, equating to a reduction of roughly 7.6 percent.[24] Given the fact that most of China's policies were designed at the provincial-level with consideration of regional socioeconomic status, I also control for prefecture controls in column (2) and then add the initial prefecture characteristics interacted by post dummy in column (3). As I add prefecture-specific socioeconomic characteristics in column (3), the coefficient does not meaningfully change. The inclusion of prefecture-specific socioeconomic characteristics is important for my identification since it help guard against the possibilities that my specification ignore any important prefecture changes other than regulation stringency. The column

[24] The mean number of $PM_{2.5}$ in key region is 59.88, so the percent change is 7.6 percent.

(4) replaces the year fixed effects with the province-by-year fixed effects to capture the policy factors at the province level, and the results show that Key Region Policy led to a 1.28 $\mu g/m^3$ fall in $PM_{2.5}$. The lower magnitude of reduction indicates that the pollution reduction effect is more likely to be driven by the province-level difference, i.e., some provinces are more polluting-intensive. In sum, all these results offer evidence that the KRP is effective at reducing prefecture-level $PM_{2.5}$ concentrations in key region prefectures since its implementation.

To ascertain the extent of the impact of key region status on pollution reduction, I offer a straightforward comparison of coefficients spanning both the pre-policy era (i.e., from 1998 to 2008) and the policy implementation period, as detailed in the Appendix section 1.8. During this pre-policy era (i.e., from 1998 to 2008), China witnessed a rapid escalation in pollution levels, with a significant portion of this pollution emanating from key region areas. Thus, a comparison between the impact of key region status on pollution increase and pollution reduction can provide robust insights into magnitude. In the Appendix section 1.8, parallel magnitudes observed in these coefficients serve as compelling evidence that the Key Region Policy (KRP) has played a significant role in driving down pollution levels. This magnitude aligns consistently with the trends observed during the initial phase of rapid pollution growth.

1.5.2 Impacts on Health Outcomes

Infant Birth Outcome

Figure 1.7 illustrates an event study depicting the impact of the Key Region Policy on the probability of low birthweight and preterm birth, focusing on infants born between 2011 and 2019.[25]

Panel (a) and (b) document the trend of low birthweight for urban/rural sample, which both show that KRP does not significantly reduce low birthweight rate. In terms of preterm birth rate, panel (c) demonstrates a more pronounced reduction in preterm birth rates within urban samples. It's important to note that while there is no immediate and drastic decline in the probability immediately following the legislation year, I contend that this observation is rooted in several factors. First, China is still at high pollution levels, and newborns are still exposed to health risks during their gestation period spanning from 8 to 11 months. Further evidence need to be provided to complement this study when China's pollution concentrations are further reduced, leveraging new data sources.

My main results on urban infants can be found in Table 1.5, Panel A. Column (1) and (4) are the baseline estimates with prefecture and birth-cohort year fixed effects, and the results demonstrate that the Key Region Policy does not significantly reduce the low birthweight but reduce the preterm rate. Columns (3) and (6) within Table 1.5 unveil evidence that the Key Region Policy exerts a substantial and statistically significant influence on diminishing the likelihood of low birthweight and prematurity rates, as I add prefecture characteristics and family size.[26] In terms the magnitude, column (2) shows that KRP decreases low birthweight rate by 4.95 percentage point reduction and a 4.79 percentage point decrease in preterm. The mean value of low birthweight rate and preterm birth rate for urban infants are 0.0400 and

[25] I delete the infant sample born in year of 2020 to avoid the unexpected effect of COVID-19.

[26] I use GDP per capita and hospital beds per 10,000 persons interacted with pre-policy year (i.e., $\text{Post}_t \times Z'_{c,2013}\gamma$).

0.0435, and for rural infants are 0.072 and 0.059. Although my estimated coefficient is large, I think this may due to the small sample size.

In panel B, I restrict the sample on rural infants and show that KRP does not significantly reduce the two birth outcomes for them as shown in column (3) and (6). The reason I separate the sample into urban/rural group is that previous studies show that urban and rural infant face different economic and health conditions, which may induce different health outcomes (Huang and Liu, 2023). It is worth noting that KPR policy increases the low birthweight rate for rural infants in column (1) to (5), and this may be due to the difference on the parental investment or regional health care conditions between rural infants and urban infants. And the significant difference betwwen the rural areas and urban areas may contribute to the opposite sign of coefficients.

Middle-aged people Health

In this subsection, I explore the impacts of the Key Region Policy on the old people. To obtain a larger sample size covering more key region prefectures, I restrict the sample in CFPS who are at least 45 years of age and use CHARLS dataset to as complements.[27]

I initiate the analysis by examining the event-study effects using CFPS dataset. Figure 1.8 presents the event-study estimates, utilizing the chronic respiratory disease rate as the dependent variable. The prevailing downward trends observed in middle-aged people's health outcomes strongly indicate that the Key Region Policy can effectively forecast alterations in the respiratory rates of the middle-aged people when compared to the years preceding the legislation year.

To investigate the impact of the Key Region Policy (KRP) on the health of the middle-aged people, I conduct regressions with various health outcomes as dependent variables, as outlined in Table 1.6. In Columns (1) and (2), I assess chronic respiratory diseases and general chronic indicators. The initial two columns of Table 1.6 reveal a substantial and statistically significant negative effect of the KRP on the probability of individuals having chronic respiratory diseases and a general chronic condition, with reductions of 2.03 percentage point and 0.37, respectively. Turning to the comprehensive self-rating health status in Columns (3) and (4), the regression results suggest that the KRP led to a higher likelihood of individuals rating their own health status more negatively, although the significance level is not reached. Besides, column (4) indicates a decrease of 1.94 percentage point in individuals rating their health status as "bad" health.[28] Additionally, in Column (6), it is indicated that the KRP has a non-significant positive impact on medical expenditure for the middle-aged people. This may be attributed to the tendency of the middle-aged people to invest more in their health status as they age.

Table 1.7 provides a comprehensive overview of the impact of the Key Region Policy on health outcomes for individuals eligible by age, utilizing data from the CHARLS dataset. In Column (1), the results reveal that the KRP significantly reduces the probability of individuals experiencing chronic diseases related to pollution by 3.4 percentage point among the middle-aged people. For this analysis, the pollution-related chronic indicator is defined as one if the middle-aged people report any of the following chronic diseases: asthma, lung diseases, and hypertension. Existing medical literature has extensively documented the adverse effects of pollution on lung health, including conditions such as asthma and occupational lung diseases.

Columns (2), (3), and (4) provide a more detailed breakdown of the chronic disease results, focusing on asthma, lung chronic diseases, and hypertension. Specifically, the KRP is found to significantly reduce the rate of asthma by 1.38 percentage point. However, it is worth noting that there is a non-significant increase of 0.22 percentage point in lung chronic diseases. In contrast, Column (4) demonstrates that the KRP primarily led to a significant reduction in the prevalence of hypertension among the middle-aged people, with a decrease of 3.22 percentage point. Columns (5) and (6) introduce measures of Limitations in Activities of Daily Living (ADL) and Limitations in Instrumental Activities of Daily Living (IADL), which help describe individuals' difficulties in performing daily activities. The negative coefficients in

[27]CFPS has a larger sample size, covering individuals at all ages; while CHARLS focuses on the middle-aged people ages over 45.

[28]The self-rating variable ranges from 1 to 5 when individual reports 1 (excellent), 2 (very good), 3 (good) and 4 (fair). And I define bad health binary variable equals one if the answer is 5 (poor).

these columns suggest that improved air quality is associated with increased physical activity in daily life and a reduction in such limitations.

In addition to difference-in-differences models, I complement the main analysis using the RD approach. The RD method offers a demanding test of the effect of the regulation stringency induced by NAAQS threshold after its legislation. Given that a substantial 82% of the designated key region prefectures failed to meet the prescribed threshold set by the National Ambient Air Quality Standards (NAAQS) upon their designation in 2012, I employ a Regression Discontinuity (RD) design using the precise air quality standard threshold (i.e., an annual $PM_{2.5}$ level below 35 $\mu g/m^3$) to discern the impact of key region status on public health. The results in Appendix 1.8 reveal a discernible discontinuity in both pollution reduction and public health outcomes among the prefectures designated as key region prefectures in 2015.

To corroborate the impact of key region status on public health outcomes, I also examine the Stable Unit Treatment Value Assumption (SUTVA). This critical assumption stipulates that "the potential outcomes for each individual i are independent of the treatment status of other individuals." In subsection 1.6.1, I adopt a approach by refining the sample and eliminating neighboring prefectures. The majority of the results maintain consistency in both magnitude and statistical significance.

In the online Appendix Table 1.28 and 1.29, I regress the middle-aged people people outcomes in an unweighted regression. The impact on chronic respiratory disease rate is -0.0193 in the unweighted regression, which is similar to the -0.0203 in the main text. The impact on pollution-related chronic rate from the CHARLS dataset is -0.0185 in the unweighted regression, which is also similar to the -0.0340 in my main results.

As a further check of the robustness of our main results, I exploit the longitudinal component of the sample by controlling for individual fixed effects and report the results in Table 1.30 and 1.31 in the online Appendix. The results are consistent in general (For chronic respiratory rate and pollution-related chronic rate, the coefficients are -0.0128 and 0.0141 in the individual fixed effect regression, and -0.0203 and -0.0340 in the main regression).

1.5.3 Who are Lost? DID Results across Work Types

In this section, I delve into the nuanced impact of environmental regulation on local populations based on their occupational categories. Recent scholarship underscores the importance of considering environmental justice in policy implementation, as environmental regulations may exert divergent effects on households characterized by varying socio-economic statuses and involvement in distinct economic sectors (see, e.g., Bento, Freedman, and Lang, 2015; Curtis, 2018; Liu, Tan, and Zhang, 2021; Marcus, 2021; Cassidy, Hill, and Ma, 2022; Currie, Voorheis, and Walker, 2023; Zivin and Singer, 2023).

I exploit the fact that individuals whose jobs have different pollution intensities are affected differently under environmental regulation. Specifically, workers in sectors such as manufacturing, mining, construction, and transportation are expected to face more pronounced regulatory pressures due to the inherent characteristics of these industries, which are recognized as substantial contributors to $PM_{2.5}$ concentrations and have been subject to heightened scrutiny under the Key Region Policy.[29]

[29]These industries were chosen because they were viewed as major contributors to the $PM_{2.5}$ concentrations and were also emphasized in the content of Key Region Policy. By the requirement of Key

Consequently, the stringent regulatory environment has translated into elevated unemployment rates and diminished incomes for individuals employed in the manufacturing sector (see, e.g., Walker, 2013; Curtis, 2018; Liu, Tan, and Zhang, 2021).

On the other hand, those workers are directly exposed to the pollutants emitted from manufacturing firms and work outside with longer work hours. The chronic respiratory diseases rate in my sample for manufacturing worker and others is 0.095 and 0.091, respectively. And for weekly working hours, manufacturing workers work 51.428 hours per week on average, while others work 44.413 hours. To disentangle how the marginal effects of pollution exposure differ across the population in China, I examine whether individuals employed in the manufacturing sector experience disproportionately disparate impacts from the Key Region Policy.

I first choose the sample of working-age middle-aged people during the age of 45-60 years old, then I estimate Equation 1.2 by separating the sample as manufacturing workers and others according to their self-reported work type.[30] In Table 1.8, The dependent variables in Table 1.8 remain consistent with the previously discussed baseline results. The regression outcomes reveal that the KRP led to an 11.84% decrease in the chronic respiratory disease rate among manufacturing workers and a 6.08% reduction among individuals in other occupations. This disparity suggests that individuals in more pollution-intensive roles derive greater benefits from environmental regulation, as evidenced by their more substantial reductions in respiratory disease and chronic ailment rates.

Figures 1.9 and 1.10 provide robust confirmation that working-age middle-aged people individuals employed in manufacturing occupations experience more favorable health outcomes, as indicated by a diminished chronic respiratory rate and a lower rate of general chronic diseases. In summation, these outcomes underscore that manufacturing workers in China have witnessed more pronounced enhancements in air quality within their workplaces compared to their counterparts in other vocations, thereby yielding more substantial health improvements.

The existing body of empirical research predominantly highlights the regulatory costs borne by workers. In contrast, my results contribute a complementary dimension by elucidating the health benefits conferred upon this demographic, thus offering a comprehensive perspective to the extant literature (e.g., Curtis, 2018; Liu, Tan, and Zhang, 2021).

1.5.4 Mechanisms

Having established that the KRP has reduced pollution concentrations and improved public health, I now investigate diverse mechanisms underpinning these outcomes in Appendix 1.8. My analysis reveals that pollution emission control, information dissemination, and household adaptive behaviors collectively contribute significantly to the observed enhancements in health outcomes. In terms of the magnitudes, I find that the KRP has larger effects on the reduction of log of firms' output value. And for information search, the effects on search for mask are larger.

Region Policy, these industries and jobs need to be regulated carefully with an additional focus in each cities.

[30] I define the worker worktype if the individual works in the manufacturing, mining, construction, and transportation sector.

1.6 Robustness Check

I now provide a thorough discussion of the different threats to the validity of my estimates: I first consider potential failures of the key region status, then I discuss identification and endogeneity issues in my DID specification.

1.6.1 Stable Unit Treatment Value Assumption (SUTVA)

In this part, I analyze the key identification assumption of my KRP research design: the Stable Unit Treatment Value Assumption (SUTVA). The SUTVA requires that non-key region households are not affected by the key region prefectures. In other words, the realized health outcomes of an individual in key region prefectures depends only on the treatment value of that policy in key region prefectures, and not on the treatment value of any other policies on non-key region prefectures. I employ several approaches to assert that the KRP does not exert an impact on potential health determinants within the control group.

Nonetheless, there are several interdependencies between my treated and control groups, and these connections could potentially violate the Stable Unit Treatment Value Assumption (SUTVA). Firstly, one concern arises from the possibility that the Key Region Policy (KRP) may have spillover effects on households residing in non-key region prefectures. For instance, if a key region prefecture reduces its manufacturing sector's output and employment due to the KRP, this could result in the manufacturing sector relocating to non-key region prefectures, subsequently increasing manufacturing output, labor supply, and work intensities in these areas. Such a shift in the manufacturing sector could potentially impose health burdens on households in non-key region prefectures. Consequently, the pass-through health costs within my research design might be underestimated as I do not account for the health burden experienced by non-key region households. The excess work intensities could hinder the worker's health outcomes (Fan, Lin, and Lin, 2020). Secondly, the general equilibrium effects can also influence non-key region prefectures through an alternate pathway. For example, the non-key region prefectural governments could glean valuable insights from the successful environmental abatement and management strategies implemented in key region prefectures. Consequently, this learning process might enhance the health benefits experienced in non-key region areas.

In summary, should the first set of negative effects predominate, the actual health benefits stemming from the Key Region Policy could be more modest than my initial estimate. Conversely, if the second set of positive effects prevails, the true impact of pollution reduction and the ensuing health benefits would be more substantial. Besides, the pollution in key region areas can migrate to non-key region areas.

Restrict the control group

To avoid potential SUTVA violations, I restrict the sample and contemplate alternative control groups to rule out potential spillover effects from the KRP on household living in non key region areas. I test whether there is any spillover effect by excluding from the control group sample non key region prefectures in the neighborhoods of the treated group.

After deleting the neighboring prefectures, I obtain 46 key region prefectures and 50 non key region prefectures (i.e., I delete 30 neighboring prefectures).

In Table 1.9, I replicate the baseline specification. The sign and significance of the coefficient of interest are in line with the main results documenting that our main analysis is not affected by downward bias due to a violation of SUTVA. For a comparison, the magnitude of KRP on pollution reduction in the main text is -4.3428 (column (2) of Table 1.4), and the magnitude is -4.4294 after deleting the neighboring prefectures. Also, for middle-aged people health outcome, the respiratory and bad health rate decrease by 2.03% and 1.94% in column (1) and (4) of Table 1.6, which are close to the coefficients after deleting the neighboring prefectures. Overall, the pollution reduction effects and health benefits are slightly larger after deleting the neighboring prefectures, and the coefficient, sign and significance are in line with the main results.

Figure 1.11 depicts the event-study trends for the impact on $PM_{2.5}$ and middle-aged people respiratory. Again, I obtain significant effects of KRP on pollution reduction and middle-aged people health improvements.

1.6.2 Random selection

In the first robustness check, I randomly select the key regions and regress the pollution level on the treatment variables 500 times.

Figure 1.12 show that the 500 times coefficient is close to zero, while the actual estimates is negative 4.57. As one can see, the distribution of the coefficient is more like a normal distribution, with the mean close to 0. This gives us more convincing evidence about the plausibility of my identification strategy. Therefore, I could infer that the Key Region Policy significantly reduce the pollution level.

1.6.3 Alternative chronic diseases

I also explore the heterogeneous effects on various categories of chronic diseases as a robustness check. The CFPS and CHARLS surveys offer comprehensive insights into the prevalence of chronic ailments, encompassing 14 distinct types of illnesses reported within the last 4 weeks.

In columns (1)-(3) of Table 1.10, I conduct estimations regarding three chronic diseases other than chronic respiratory disease using the CFPS dataset. My findings suggest that the Key Region Policy does not exert a statistically significant impact on the likelihood of contracting these three chronic diseases. Subsequently, columns (4)-(6) present the results for cancer, liver, and kidney illnesses employing the CHARLS dataset. Once again, the coefficients fail to attain statistical significance, signifying an absence of discernible effects on these specific illnesses. In sum, the non-significant outcomes pertaining to alternative chronic diseases and illness categories provide additional affirmation of the KRP's efficacy in diminishing pollution-related chronic diseases.

1.6.4 Alternative pretreatment period

Table 1.11 and 1.12 offer insights into the outcomes of the primary model estimation during the pre-treatment period, while adhering to the same specifications utilized in the previous analyses. These results suggest that the pre-trends of these outcomes do not exhibit statistically significant associations with the timing of the policy's introduction. Insignificant coefficients observed in columns (2), (3) and (5) of Table 1.11 indicate that the KRP implemented during the pre-period does not yield improvements in middle-aged people health outcomes. Likewise, columns (1) to (2) in Table 1.12 convey that the pre-period KRP implementation fails to generate improvements in the health outcomes of infants.

1.6.5 Alternative confounding factors

To rule out the potential concern that my findings may be driven by family-level or prefecture-level unobservable factors that influence all individuals, here I perform a number of tests by estimating the KRP on a set of economic indicators.

Family Characteristics.- The concern at the family-level arises due to the possibility that the enactment of the Key Region Policy might be correlated with alterations in family characteristics, which could confound the estimation of infant health outcomes. For instance, if the KRP legislation coincided with an increase in conceptions among families with a higher inclination for prenatal care in key regions, the results obtained could potentially reflect shifts in family composition rather than the impacts stemming from the air quality improvements brought about by the KRP. Additionally, it could influence individuals' health-related behaviors, such as smoking habits, when examining health outcomes among the middle-aged people. Hence, I initially present evidence indicating that urban family characteristics, as measured by household income, do not exhibit simultaneous changes with policy exposure. This is demonstrated in column (2) of Table 1.13.

Finally, I also report the impacts on smoking status for middle-aged people using both CFPS and CHARLS dataset in column (3). The estimate suggests that there is little effect on smoking behaviors. All of these show there is no evidence of a systematic change in underlying family and individual characteristics that corresponds to the policy variation.

Local economic change.- Additional confounding factors may arise from changes in regional economic characteristics, such as variations in healthcare infrastructure, the number of physicians available, and local wage levels. If the implementation of the KRP or other potentially confounding policies leads key region prefectures to increase local investments in healthcare or raise local wages, it could introduce bias into the DID estimates of the KRP's health effects. Increased healthcare resources can provide residents with better medical care, while higher wages may boost people's willingness to invest in improved air quality and defensive health measures, consequently enhancing their overall health status. These time-varying, unobservable characteristics could systematically vary with the observed timing of policy implementation. To address this concern, I perform regressions of a set of prefecture-level economic indicators on the KRP, aiming to assess whether these economic variables introduce bias into my estimates. The regression results are presented in columns (1) to (4) of Table 1.14. Overall, I do not find that the KRP significantly affects those prefecture health care infrastructure, fiscal expenditure or average wages.

Figure 1.13 illustrates the event study estimates for these factors. In general, the regression results reveal a lack of statistical significance, indicating that the KRP does not bring about substantial improvements in regional health infrastructure, as depicted in panels (a) and (b). Furthermore, the key region prefectures do not exhibit significant alterations in their fiscal expenditure or the logarithm of wages, as evidenced in panels (c) and (d). Taken together, these findings provide robust reassurance that the observed health improvements attributable to the KRP are not the result of systematic changes at the prefecture level.

Another concern is about migration in my regression. If the factors affecting migration are correlated with the timing of the implementation of the KRP and outcomes such as income and health, then the estimates will be biased. In Appendix 1.8, I rely on the migration status documented in the CFPS survey dataset and show that the timing of the KRP is not correlated with migration.

1.7 Interpretation and Policy Implications

1.7.1 Assessing the benefits

My results provide the ex-post health outcome evaluation of China's War on Pollution. To gauge the magnitude of the implied effects of this broad policy framework, I conduct a simple benefit analysis for the legislation of Key Region Policy, with the caveat that data restrictions prevent us from measuring all health outcomes and costs.

First, leveraging the pollution measurements and my estimated effects – namely, the 4.57 units of predicted fine particulate matter reduction resulting from the Key Region Policy, which corresponded to a 3.59 percentage point decrease in preterm birth infants – I conducted an analysis about its health benefits using birth data from the China Statistical Yearbook. Specifically, I examined the number of newborns in key region prefectures for the years 2017, 2018, and 2019, which amounted to 5368838, 4542177, and 4113095, respectively. Calculating against the 2017 baseline, my findings indicate that China's War on Pollution resulted in approximately 192741 fewer preterm birth infants in the year 2017 alone. Furthermore, I use the median total hospitalization charge for China's preterm estimated by Zhu et al., 2020. Considering the average medical expenditure for caring for premature babies in China is $20,770.7 USD, the economic implications of this health improvement translates into significant figures, with around $4 billion for premature births in the year 2017.

Second, as demonstrated in column (1) of Table 1.6, the observed average decrease in the chronic respiratory disease rate amounts to a 2.03 percentage points. Considering that the average medical expenditure for managing respiratory conditions in China stands at $3123 USD and the middle-aged people population in China numbered approximately 240 million by the close of 2017, these findings translate into substantial annual cost savings of $17.3 billion USD for middle-aged people in China.[31]

My estimates shed light on the consequences of the stringent Key Region Policy for health benefits. These health benefits underscore the significant societal gains associated with improved air quality. There are some limitations in my benefits analysis. One is measurement errors in reported annual medical expenditure and the caring costs. My estimates may be susceptible to bias due to data limitations, particularly the absence of comprehensive administrative health expenditure data for specific diseases. Additionally, it's worth emphasizing that this study does not undertake the task of estimating the social cost associated with this regulation. However, the health benefits elucidated herein, particularly concerning infant birth outcomes, offer informative contributions to the broader discourse surrounding China's efforts in combatting pollution. Further research and calculations can serve as complementary additions to our understanding of the multifaceted impacts of China's environmental policies.

1.7.2 Comparison of magnitude

In this section, I contextualize the magnitudes of my effect sizes by drawing parallels to existing research on similar relationships. Specifically, I refer to the health benefits of infant birth outcomes estimated by scholars such as Currie and Walker, 2011, Marcus, 2021, and Hansen-Lewis and Marcus, 2022. This study reveals a 4.79

[31] I use the estimated expenditure data from the website: `https://www.pharmacytimes.com/view/us-hospitalization-costs-for-respiratory-syncytial-virus-are-highest-worldwide`

percentage point decline in the preterm birth rate. These findings suggest that the mitigation of high pollution levels in China has yielded health benefits that align with those observed in previous research.

1.8 Conclusion

As a pivotal component within the framework of China's War on Pollution, the legislation of the Key Region Policy offers a vital context for assessing the efficacy and health-related advantages of environmental regulation. The prefectures designated as key regions under this policy are central contributors to pollution levels across China. Leveraging the most recent waves of data from the China Family Panel Studies (CFPS) and the China Health and Retirement Longitudinal Study (CHARLS), I undertake a comprehensive analysis to explore the causal impact of environmental regulation on various health outcomes, including infant birth outcomes, as well as the health statuses of the middle-aged people. This study initially demonstrates that the Key Region Policy yields a significant reduction in pollution levels within key region prefectures relative to non-key prefectures, with a reduction of approximately 4.57 $\mu g/m^3$, equivalent to approximately 7.6 percent.

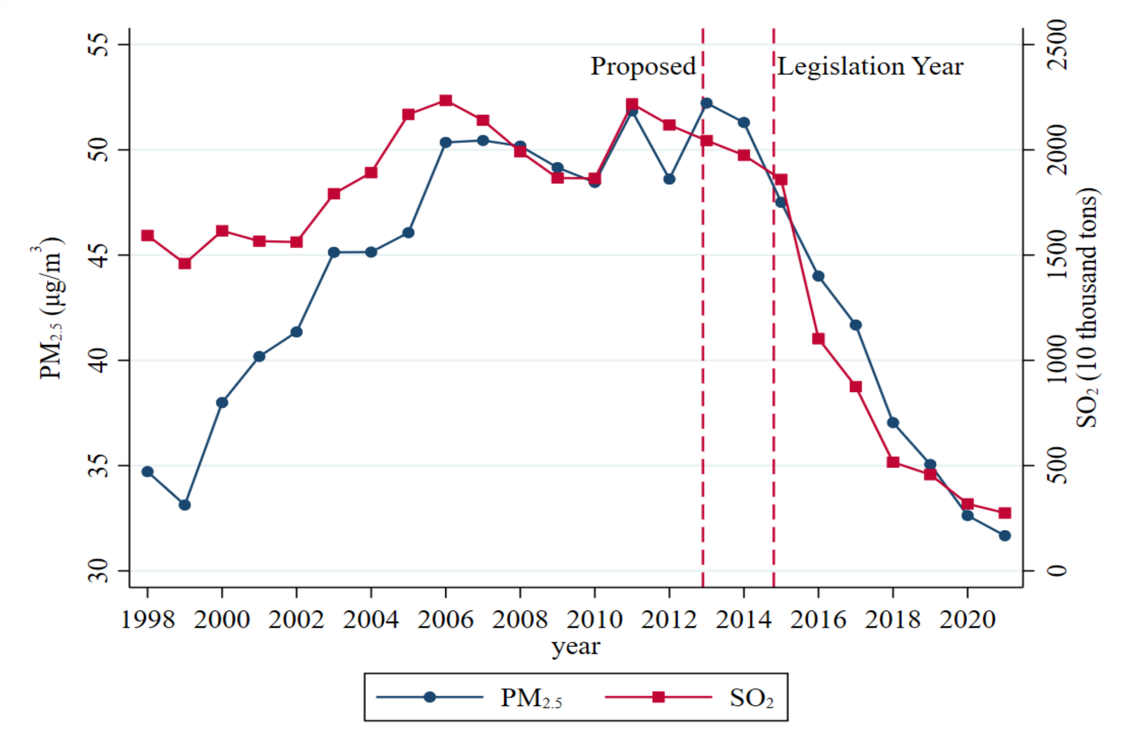
Furthermore, the DID results suggest that the Key Region Policy exerts a substantial impact, leading to an approximately 4.95 percentage point reduction in the incidence of low birthweight and a 4.79 percentage point decrease in preterm births among infants. Simultaneously, among the middle-aged people population, the empirical evidence indicates reductions of 2 percentage point and 3.4 percentage point in respiratory diseases and pollution-related chronic ailments, respectively. Moving forward, my econometric analyses on environmental justice unveil that individuals employed in the manufacturing sector experience more pronounced health benefits arising from improved air quality, as evidenced by a more substantial decline in chronic respiratory disease rates.

Lastly, this study delves into multifaceted mechanisms underlying these health improvements. It becomes evident that the closure of polluting firms plays a pivotal role in diminishing pollution concentrations. Moreover, individuals' information-seeking and avoidance behaviors exhibit a positive association with the Key Region Policy, further contributing to the observed positive outcomes.

My research makes a contribution to the expanding body of literature centered on China's environmental regulations. It accomplishes this by placing a particular emphasis on the pivotal role played by the introduction of the Key Region Policy as a cornerstone of China's broader efforts in combatting pollution (i.e., China's War on Pollution), beginning in 2014. By examining the effectiveness and associated health benefits of this policy, my study adds insights to the existing evidence on China's War on Pollution. Moreover, this paper serves as a valuable complement to the literature by illuminating how environmental regulations in China contribute to the reduction of health disparities, especially concerning workers compared to individuals in other employment categories.

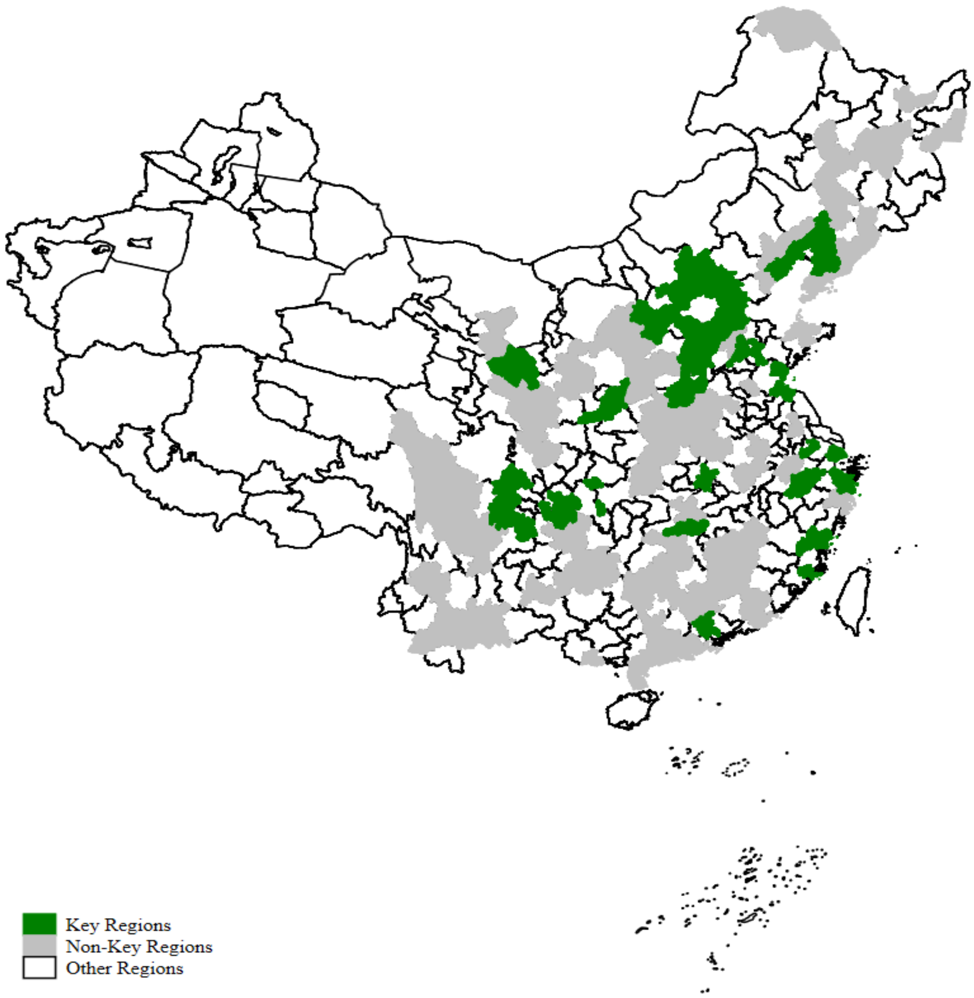
Figure

FIGURE 1.1: $PM_{2.5}$ and SO_2 Trends in China



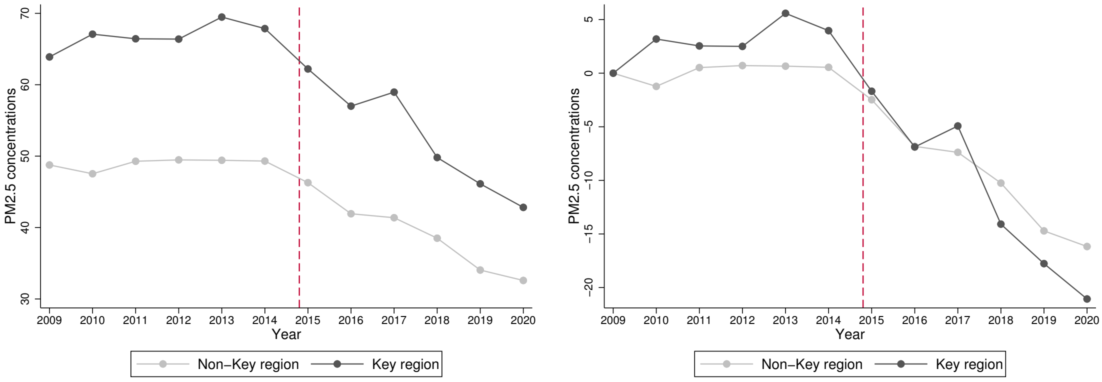
Notes: This figure plots the average annual pollution concentrations of $PM_{2.5}$ ($\mu g/m^3$) and SO_2 (10 thousand tons) over time from 1998 to 2021. Data of $PM_{2.5}$ is from the Atmospheric Composition Analysis Group in Washington University in St.Louis calculated by Van Donkelaar et al., 2021, and SO_2 is from China Statistical Yearbook collected and published by National Bureau of Statistics of China (NBS).

FIGURE 1.2: The distribution of Key Region Prefectures in China



Notes: All 46 key region prefectures and 80 non-key region prefectures are included in my survey dataset (i.e., CFPS and CHARLS). The blank area is not available in these two datasets.

FIGURE 1.3: $PM_{2.5}$ Trends Between Key Region and Non-Key Region Prefectures

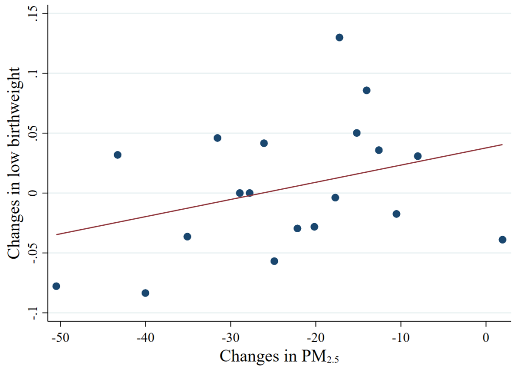


(A) $PM_{2.5}$ Trends

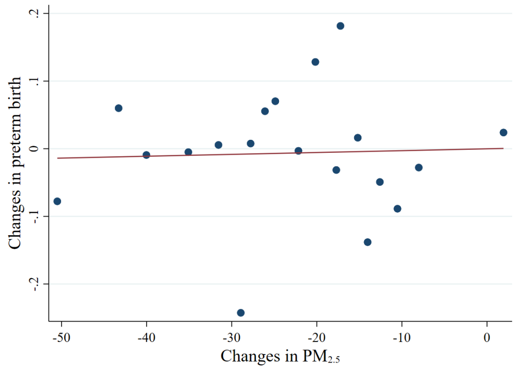
(B) $PM_{2.5}$: 0 as the benchmark

Notes: Panel (a) plots trends of ambient $PM_{2.5}$ concentrations between key region prefectures and non-key region prefectures across time. Panel (b) sets the starting unit at 0 $\mu g/m^3$, and thus the negative values on the y-axis indicate the reduction of $PM_{2.5}$ concentrations since year of 2009

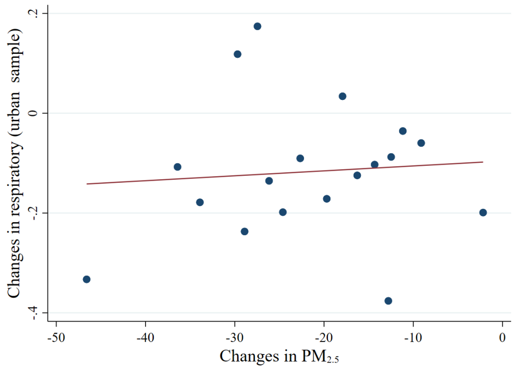
FIGURE 1.4: Binned scatter plots: Pollution reduction and health outcome improvements (2010 to 2020)



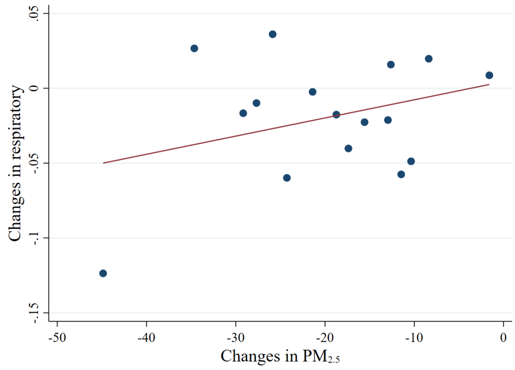
(A) Low birthweight



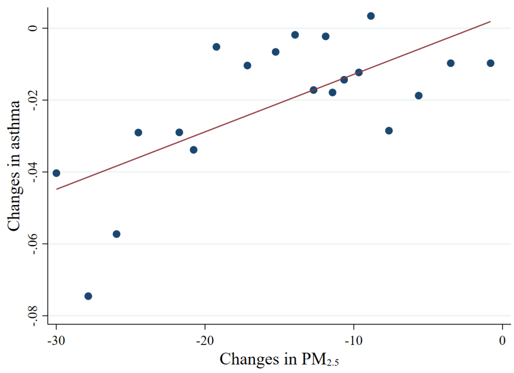
(B) Preterm



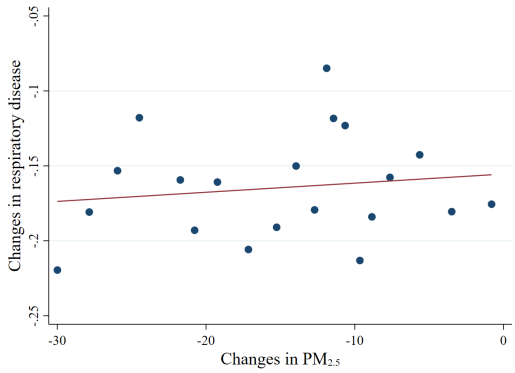
(C) Children respiratory



(D) Middle-aged people respiratory (CFPS dataset)



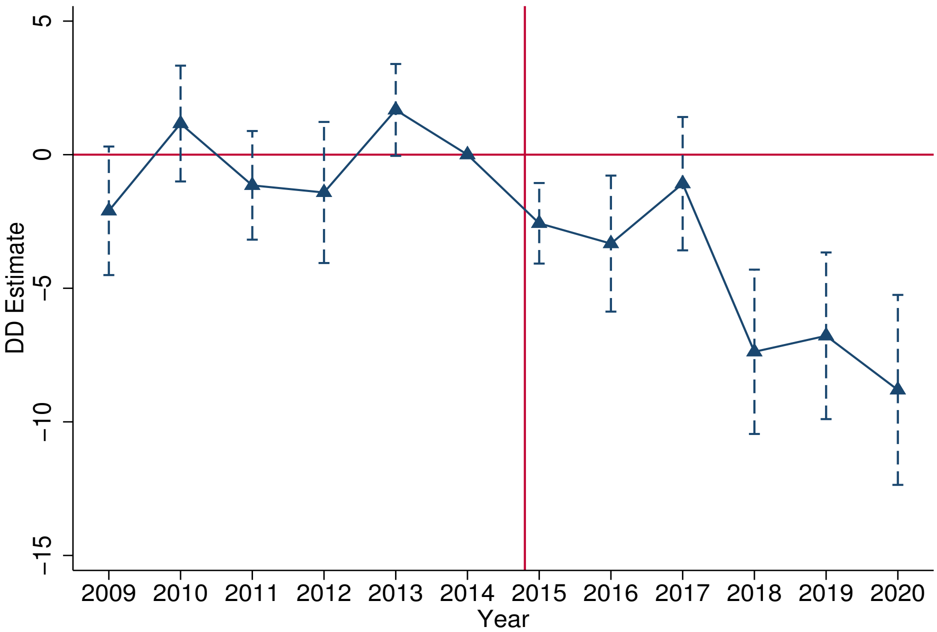
(E) Middle-aged people asthma (CHARLS dataset)



(F) Middle-aged people chronic (CHARLS dataset)

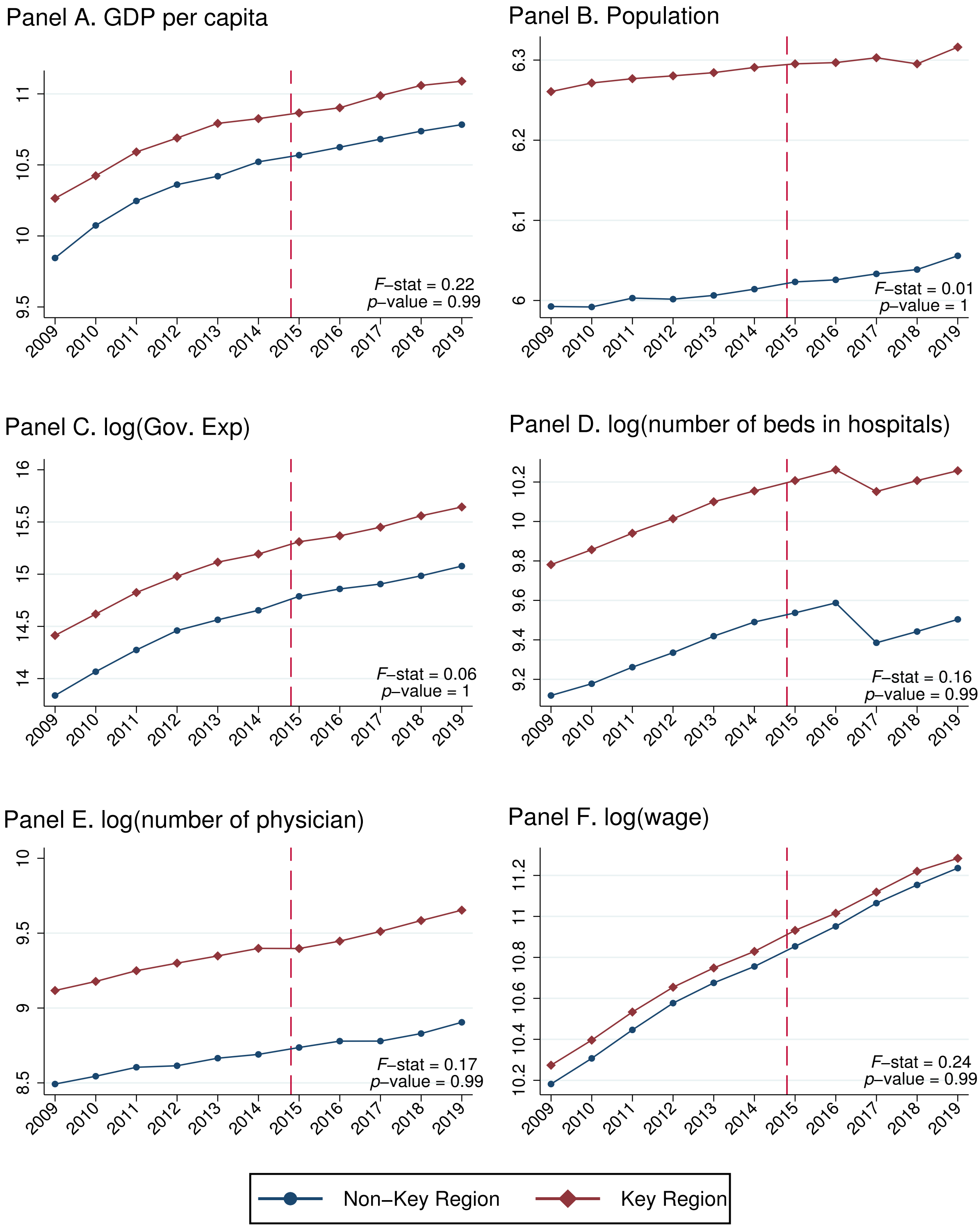
Notes: The panels plot relationship between change of prefecture $PM_{2.5}$ concentrations and prefecture-level health outcomes based the survey dataset from 2010 to 2020. Panels (a), (b), (c), and (d) rely on the CFPS dataset, while Panels (e) and (f) draw upon the CHARLS dataset. The line is the linear fitted line weighted by the 2013 population for each prefecture.

FIGURE 1.5: Event study of KRP on pollution



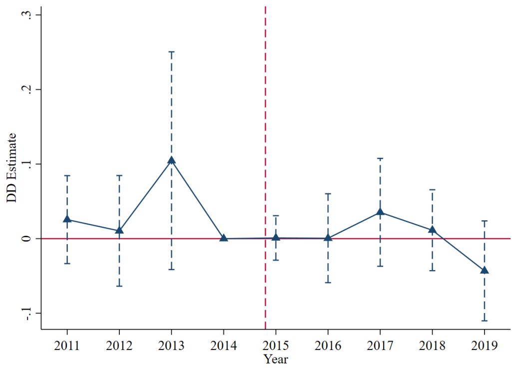
Notes: This figure plots the estimated coefficients of KeyRegion × Year dummy variables. The regression controls for year fixed effects, prefecture fixed effects and annual prefecture-specific economic controls. The dependent variable is ambient $PM_{2.5}$ concentrations. Brackets denote 95 percent confidence intervals, calculated from robust standard errors clustered at the prefecture level. The regression is weighted by the number of population in 2013 for each prefectue. The reference year is 2014.

FIGURE 1.6: Examination of Pretrends in Key Region Cities and Non-Key Region Cities

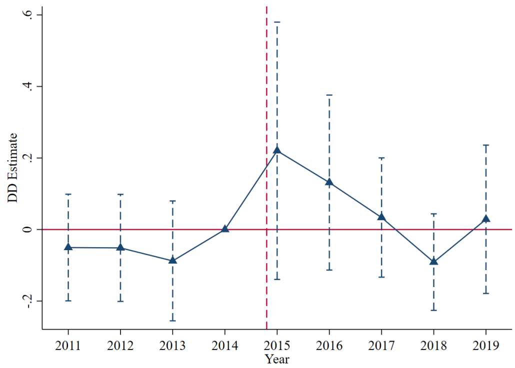


Notes: The economic indexes from different prefectures are from the China City Statistical Yearbooks. Each figure plots the mean values of the logarithm of the economic indexes from 2009 to 2019. The vertical line indicates the legislation of the Key Region Policy. The p-values are shown to test the equality of coefficient estimates for prefectures located in key region and non key region prefectures.

FIGURE 1.7: Event-study of Impacts on Infant Birth Outcomes

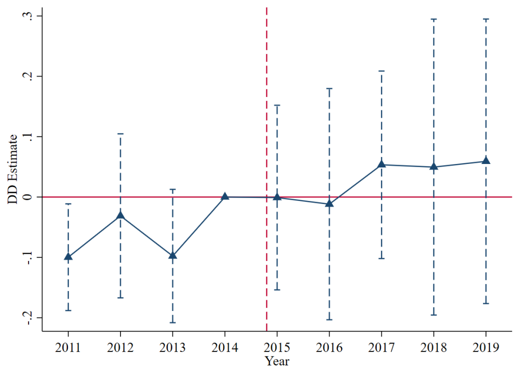


(A) Urban Infant: Low Birthweight



(B) Rural Infant: Low Birthweight

(C) Urban Infant: Preterm Birth



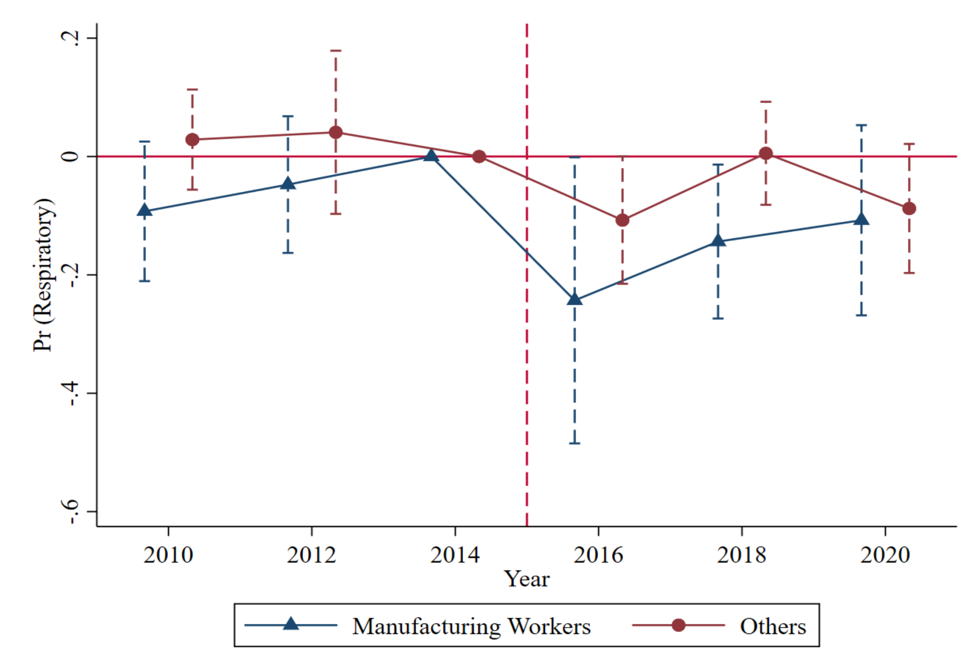
(D) Rural Infant: Preterm Birth

Notes: The panels plot event study estimates of Key Region Policy on infant birth outcome across rural/urban type. The regression includes prefecture fixed effects, cohort year fixed effects, and controls for the gender type and family size. All regressions are weighted by the number of population in that prefecture. Coefficients are denoted by the dots and the vertical line and whiskers denote the 95 percent confidence interval of the estimates.

FIGURE 1.8: Event-study of the Impacts on Chronic Respiratory Disease (CFPS)

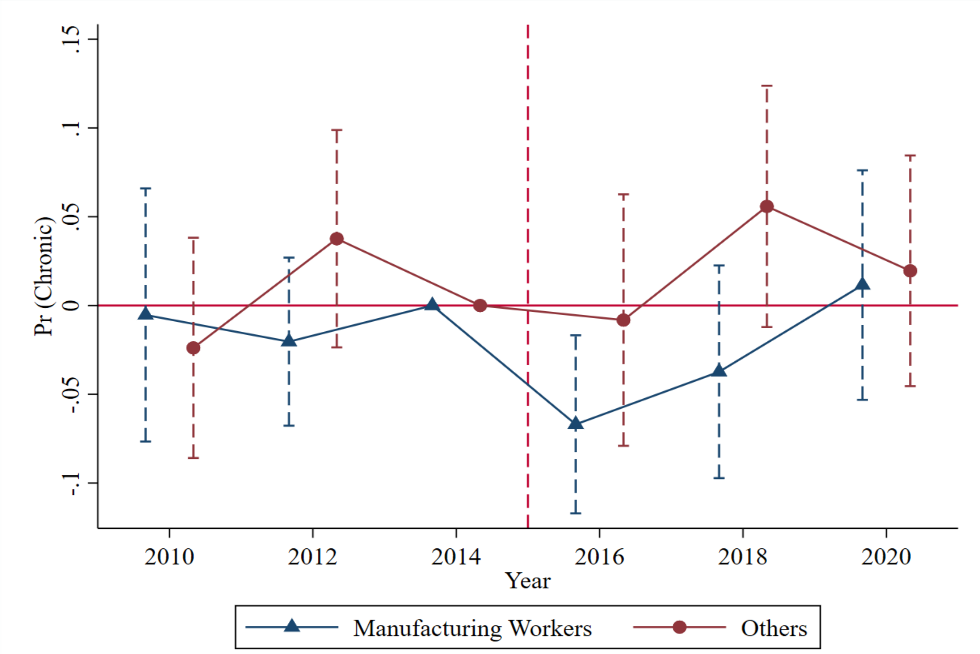
Notes: This figure plots event study estimates of Key Region Policy on chronic respiratory disease rate. The regression includes year fixed effects, prefecture fixed effects, and controls for the age, age's square, gender type, rural/urban type, education, marriage status and family size. The regression is weighted by the number of population in 2013 for each prefecture. Coefficients are denoted by the dots and the vertical line and whiskers denote the 95 percent confidence interval of the estimates. These solid trend lines reveal a distinct downward trend starting in 2015 for respiratory rate.

FIGURE 1.9: Impacts on Chronic Respiratory Disease by Job



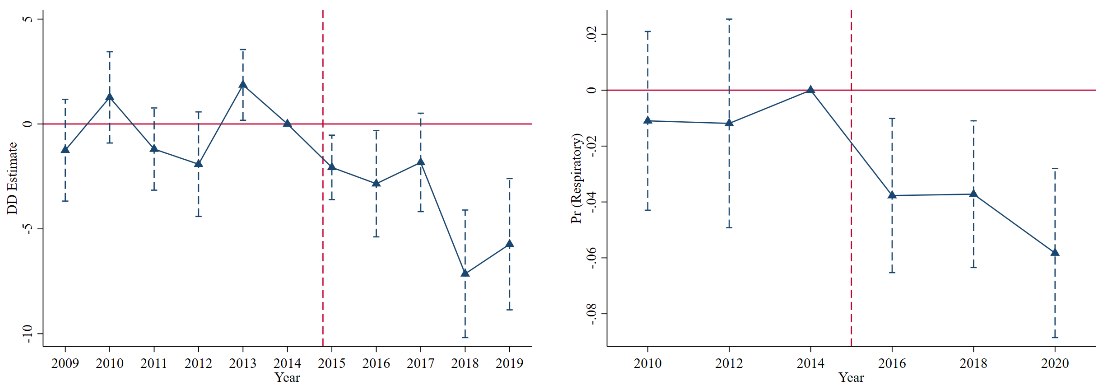
Notes: This figure plots event study estimates of Key Region Policy on working-age middle-aged people respiratory rate using the CFPS dataset. The regression includes year fixed effects, prefecture fixed effects, and controls for the age, age's square, gender type, rural/urban type, education, and marriage status. The regression is weighted by the number of population in 2013 for each prefecture.

FIGURE 1.10: Impacts on All Chronic Disease by Job



Notes: This figure plots event study estimates of Key Region Policy on working-age middle-aged people all chronic rate using the CFPS dataset. The regression includes year fixed effects, prefecture fixed effects, and controls for the age, age's square, gender type, rural/urban type, education, and marriage status. The regression is weighted by the number of population in 2013 for each prefecture.

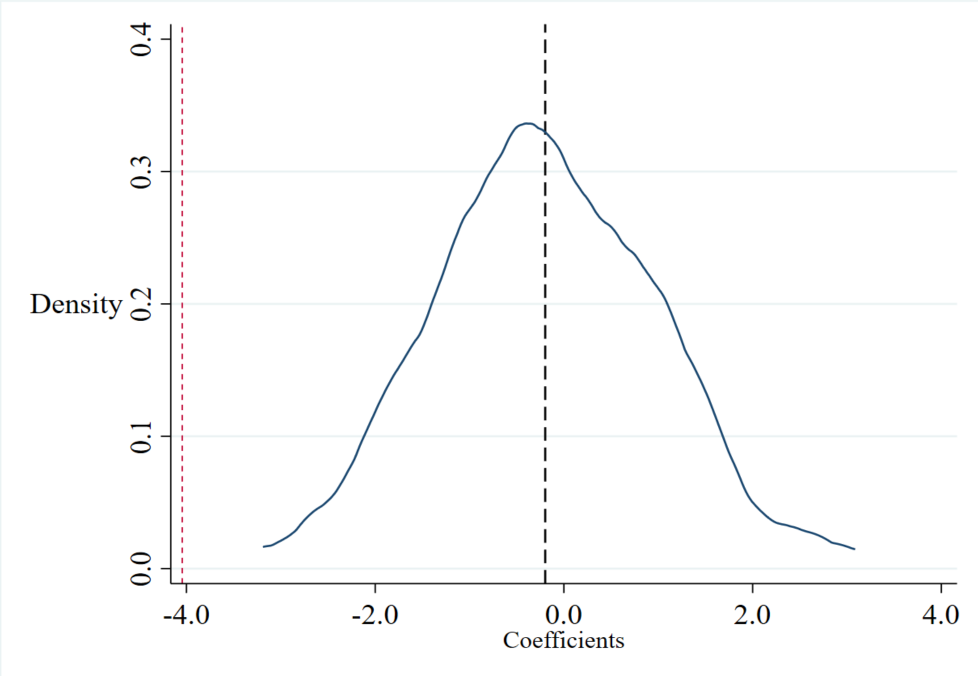
FIGURE 1.11: Event-study of Impacts on Pollution and Respiratory (SUTVA)



(A) $PM_{2.5}$ (B) Respiratory

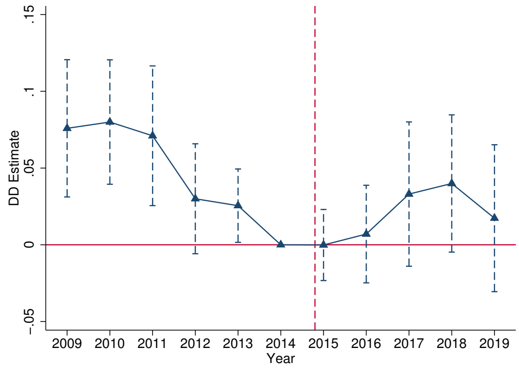
Notes: This figure plots event study estimates of KRP on $PM_{2.5}$ concentrations between 2009 and 2019 and middle-aged people respiratory rate using CFPS data set between 2010 and 2020. The regression includes year fixed effects, prefecture fixed effects, and controls, and are weighted by the population size in the pre-policy year. Both regressions are clustered at prefecture level.

FIGURE 1.12: Placebo Tests: The effect of KRP on pollution

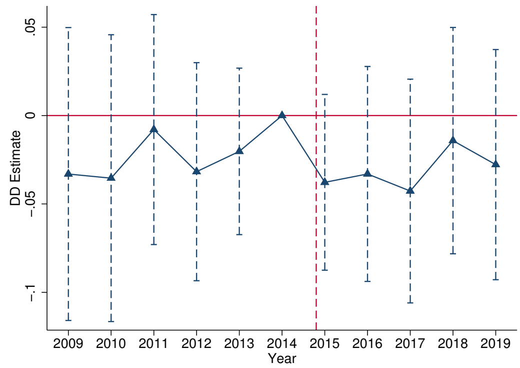


Notes: This figure shows the results of a robustness check for Table 1.4, which examines the role of key region in explaining the reduction in overall pollution concentrations. In this figure, I conduct a placebo exercise, where I randomly re-assign key region status to each prefectures. The figure shows the results of 500 replications of this placebo exercise. The distribution of these standard deviations is plotted in blue solid line. The true value is shown in the red line.

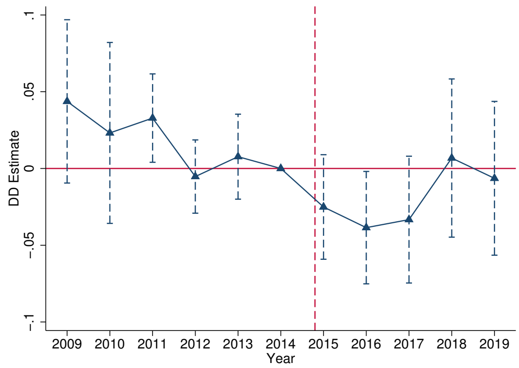
FIGURE 1.13: Robustness Check on Prefecture Characteristics



(A) Log (number of beds in hospitals)



(B) Log (number of physician)



(C) Log (government expenditure)

(D) Log (wage)

Notes: This figure plots the estimated coefficients of KeyRegion × Year dummy variables. The regression controls for year fixed effects, prefecture fixed effects and annual prefecture-specific economic controls. Brackets denote 95 percent confidence intervals, calculated from robust standard errors clustered at the prefecture level.

Table

TABLE 1.1: Evolution of environmental regulation in China since 2012

Policy	Year	Main content
Twelfth Five-Year Plan on Air Pollution Prevention and Control in Key Regions	2012.12	Established "Key Regions"
Action Plan on Air Pollution Prevention and Control	2013.9	Set NAAQS, Mainly focus on Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta region
China's War on Pollution	2014.3	(1) recognizing $PM_{2.5}$ as a primary pollutant; (2) pollution reduction as political evaluation
Air Quality Monitoring System	2013-2014	Automated monitoring system must be introduced
Amendment of Atmospheric Pollution Prevention and Control Law	2015.8	Key regions must comply with NAAQS
Three-Year Action Plan for Winning the Blue Sky War	2018-2020	Reduction of sulphur dioxide, nitrogen oxide and $PM_{2.5}$ density

TABLE 1.2: Summary Statistics

	Key Region		Non-Key Region	
	Mean	SD	Mean	SD
Prefecture-level characteristics				
$PM_{2.5}$ ($\mu g/m^3$)	59.88	18.6	43.97	15.34
Panel A. Middle-aged people health (CFPS dataset)				
Individual characteristics				
Chronic	0.228	0.420	0.223	0.416
Respiratory	0.096	0.294	0.088	0.283
Feel uncomfortable	0.328	0.469	0.382	0.486
Bad health	0.190	0.392	0.232	0.422
CES-D score	3.313	3.265	4.024	3.484
Depression	0.054	0.227	0.080	0.272
Log of Medical Expenditure	7.328	1.760	7.127	1.719
Controls				
Age	60.28	10.58	59.48	10.49
Male	0.473	0.499	0.478	0.499
Marriage	0.823	0.380	0.802	0.398
Education Years	6.393	4.69	4.942	4.72
Log of Individual Income	8.437	1.916	7.787	2.096
Rural *hukou*	0.576	0.494	0.731	0.443
Panel B. Middle-aged people health (CHARLS dataset)				
Individual characteristics				
Chronic	0.255	0.435	0.246	0.431
Asthma	0.025	0.158	0.029	0.169
Lung	0.063	0.243	0.083	0.276
ADL	0.082	0.275	0.097	0.296
IADL	0.120	0.325	0.172	0.377
Controls				
Age	60.80	10.17	60.53	10.12
Male	0.483	0.499	0.481	0.499
Marriage	0.821	0.382	0.793	0.405
Education Years	9.55	6.34	8.79	6.72
Smoking status	0.223	0.416	0.223	0.416
Rural *hukou*	0.672	0.469	0.704	0.456

Notes: This table shows summary statistics for the pollution concentration and household welfare outcomes between 2009 and 2020. The sample is separated by the key region status. The calculation of these health outcomes are defined in the main text. The health outcomes and individual-level characteristics are abstracted from the CFPS and CHARLS database. The prefecture-level characteristics are from China Statistical Yearbook. The pollution concentration is accessed from the database calculated by Van Donkelaar et al., 2021 and then matched with China cities.

TABLE 1.3: Summary Statistics - Infant Health

	Key Region		Non-Key Region	
	Mean	SD	Mean	SD
Panel C. Infant Birth Outcome				
Birth weight (gram)	3278.628	497.00	3209.168	555.06
Gestation period (month)	9.54	0.67	9.42	0.63
Low Birth Weight	0.043	0.203	0.062	0.241
Prematurity	0.056	0.231	0.047	0.213
Controls				
Male	0.505	0.499	0.533	0.498
Rural	0.338	0.473	0.649	0.477

TABLE 1.4: The Effects of KRP on Pollution Concentrations

Variables	$PM_{2.5}$			
	(1)	(2)	(3)	(4)
KeyRegion × Post	-4.5743***	-4.3428***	-4.2998***	-1.2890**
	(1.1767)	(1.0921)	(0.9114)	(0.6029)
Observations	2,064	2,064	2,064	2,020
R-squared	0.9335	0.9341	0.9378	0.9791
Controls		X	X	X
Prefecture Characteristics			X	X
Prefecture FE	X	X	X	X
Year FE	X	X	X	
Province-Year FE				X
F-test of	6.48***	6.28***	7.74***	4.47***
pre-treatment coefficient	(0.0000)	(0.0000)	(0.0000)	(0.0007)

Notes: All regressions are weighted by the number of population in 2013 for each prefecture. Standard errors are clustered at the prefecture level. The control variable vector contains GDP per capita, population, share of secondary industry over the gdp, and share of labor in manufacturing industry. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.5: The Effects of KRP on Infant Birth Outcomes

Variables	Low Birthweight (Yes=1)			Preterm Birth (Yes=1)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Urban infants						
KeyRegion × Post	-0.0410	-0.0495	-0.0831**	-0.0443*	-0.0479**	-0.0974***
	(0.0297)	(0.0340)	(0.0396)	(0.0236)	(0.0240)	(0.0262)
Observations	1,121	981	981	1,483	1,325	1,325
R-squared	0.1568	0.1784	0.1793	0.1099	0.1264	0.1280
Panel B. Rural infants						
KeyRegion × Post	0.1437**	0.1530**	0.0761	0.0729	0.0814	-0.0132
	(0.0555)	(0.0595)	(0.0494)	(0.0566)	(0.0595)	(0.0566)
Observations	1,160	1,044	1,044	1,598	1,460	1,460
R-squared	0.1148	0.1251	0.1286	0.0971	0.0994	0.1095
Family Characteristics		X	X		X	X
Prefecture Characteristics			X			X
Prefecture FE	X	X	X	X	X	X
Birth-Cohort FE	X	X	X	X	X	X

Notes: The sample is from the CFPS (2010-2020) for infants born between 2011 and 2019. The covariatesin the regressionsin each column include dummies for gender, birth cohort fixed effect and prefecture fixed effect. I also control for the family size in column (2), (3), (5) and (6). All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.6: The Effects of KRP on Middle-aged People's Health: CFPS Sample

Data	CFPS				
Variables	Respiratory (Yes=1) (1)	Chronic (Yes=1) (2)	Self-rating (Good=1, Bad=5) (3)	Bad Health (Yes=1) (4)	Ln.Med (Log) (5)
KeyRegion × Post	-0.0251***	-0.0005	0.0204	-0.0229***	0.0163
	(0.0076)	(0.0132)	(0.0395)	(0.0082)	(0.0618)
Observations	19,134	83,689	71,752	71,752	37,528
R-squared	0.0239	0.0428	0.2512	0.1055	0.1066
Prefecture FE	X	X	X	X	X
Year FE	X	X	X	X	X

Notes: The sample is from the CFPS (2010-2020) for individuals aged 45 and over. The covariatesin the regressions in each column include dummies for gender, age, age's square, education years, marriage status, urban/rural type, family size, survey year and prefecture fixed effect. All regressions are weighted by the number of population for each prefectures in 2013 to control for the potential concern of uneven distribution of survey participants across different prefectures. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.7: The Effects of KRP on the Middle-aged People: CHARLS Sample

Data	CHARLS					
Variables	Pollution Chronic (Yes=1) (1)	Asthma (Yes=1) (2)	Lung (Yes=1) (3)	Hypertension (Yes=1) (4)	ADL (Yes=1) (5)	IADL (Yes=1) (6)
KeyRegion × Post	-0.0340**	-0.0138	0.0022	-0.0322*	-0.0116	-0.0203
	(0.0163)	(0.0124)	(0.0127)	(0.0193)	(0.0112)	(0.0141)
Observations	34,357	33,772	32,829	29,633	44,273	65,260
R-squared	0.0746	0.0217	0.0366	0.0621	0.0590	0.1447
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: The sample is from the CHARLS (2011-2018) for individuals aged 45 and over. The covariates in all columns include dummies for gender, age, age's square, education years, marriage status, urban/rural type, survey year and prefecture fixed effect. All regressions are weighted by the number of population in 2013 for each prefectures. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.8: The Effects of KRP on Household Outcomes by Work Type: CFPS Dataset

Variables	Respiratory	Chronic	Badhealth	Respiratory	Chronic	Badhealth
Worktype	Manufacturing Worker			Other worktype		
	(1)	(2)	(3)	(4)	(5)	(6)
KeyRegion $\times$ Post	-0.1184***	-0.0225	0.0153	-0.0608***	0.0299	-0.0516***
	(0.0410)	(0.0231)	(0.0213)	(0.0186)	(0.0242)	(0.0164)
Observations	1,100	7,436	5,888	3,440	17,209	15,239
R-squared	0.1334	0.0374	0.0669	0.0478	0.0429	0.0966
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: The sample is from the CFPS (2010-2020) for individuals aged 45 and over. The covariatesin the regressions in each column include dummies for gender, age, age's square, education years, marriage status, survey year and prefecture fixed effect. All regressions are weighted by the number of population for each cities in 2013 to control for the potential concern of uneven distribution of survey participants across different prefectures. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.9: Robustness check - SUTVA

Data		CFPS	
Variables	$PM_{2.5}$	Respiratory (Yes=1)	Bad health (Yes=1)
	(1)	(2)	(3)
KeyRegion $\times$ Post	-4.4294***	-0.0349***	-0.0245***
	(1.0909)	(0.0094)	(0.0082)
Observations	1,833	15,150	56,223
R-squared	0.9327	0.0231	0.1038
Prefecture FE	X	X	X
Year FE	X	X	X

Notes: The sample is from the CFPS (2010-2020) for individuals aged 45 and over. The covariates in all column include dummies for gender, age, age's square, education years, marriage status, log of income, survey year and prefecture fixed effect. All regressions are weighted by the number of population in 2013 for each prefectures to control for the potential concern of uneven distribution of survey participants across different prefectures. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.10: Robustness: Impacts on Alternative Chronic Diseases

Data	CFPS			CHARLS		
Variables	Circulatory (Yes=1) (1)	Digestive System (Yes=1) (2)	Infectious (Yes=1) (3)	Cancer (Yes=1) (4)	Liver (Yes=1) (5)	Kidney (Yes=1) (6)
KeyRegion × Post	0.021	-0.004**	0.000	-0.004	-0.002	0.006
	(0.016)	(0.002)	(0.005)	(0.003)	(0.006)	(0.007)
Observations	62,998	62,998	62,998	30157	29851	29590
R-squared	0.246	0.010	0.042	0.007	0.015	0.026
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: The sample in column (1) to (3) is from the CFPS (2010-2020) for individuals aged 45 and over. The sample in column (4) to (6) is from the CHARLS (2011-2018) for individuals aged 45 and over. All regressions are weighted by the number of population for each prefectures in 2013. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.11: Placebo Tests - Main Model Estimation in Pre-Period

Data		CFPS			
Variables	$PM_{2.5}$	Respiratory	Chronic	Bad Health	Self-Rating
	(1)	(2)	(3)	(4)	(5)
Panel A: Suppose policy in 2012					
KeyRegion × Post	-1.267**	0.0058	0.0082	-0.0465**	0.0096
	(0.549)	(0.0107)	(0.0197)	(0.011)	(0.048)
Panel C: Suppose policy in 2011					
KeyRegion × Post	-0.748	0.0058	0.0067	-0.0465**	0.0096
	(0.536)	(0.010)	(0.0216)	(0.011)	(0.048)
Prefecture FE	X	X	X	X	X
Year FE	X	X	X	X	X

Notes: The sample in column (1) is from the pollution dataset. The sample in column (2) to (5) is from the CFPS (2010-2020) for individuals aged 45 and over. The covariates in the regressions in each column include age and its square, and dummies for gender, education level, marriage status and log of income. All regressions are weighted by the number of population for each prefectures in 2013. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.12: Placebo Tests - Main Model Estimation in Pre-Period

Data	CFPS Infant (Urban Sample)	
Variables	Low Birth Weight	Prematurity
	(1)	(2)
Panel A: Suppose policy in 2012		
KeyRegion × Post	-0.005	-0.0229
	(0.052)	(0.032)
Panel B: Suppose policy in 2011		
KeyRegion × Post	-0.138	-0.0337
	(0.133)	(0.0238)
Prefecture FE	X	X
Year FE	X	X

Notes: The sample in column (1) to (2) is from the CFPS (2010-2020). All the standard errors are clustered at the prefecture level in parentheses. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.13: Robustness Check on Parental Characteristics

Data	CFPS		CFPS&CHARLS
Variables	Log of Income (RMB:Yuan)		Smoking (Yes=1)
	(1)	(2)	(3)
	Rural	Urban	
KeyRegion × Post	-0.342***	0.087	0.0054
	(0.088)	(0.066)	(0.007)
Observations	20299	12620	62568
R-squared	0.540	0.429	0.411
Prefecture FE	X	X	X
Year FE	X	X	X

Notes: In column (1) and (2), the income data is from the CFPS with individuals aged over 45. The smoking behavior data is from both CFPS and CHARLS with individuals aged over 45. The covariates in all regressions are the same as the baseline regression. All regressions are weighted by the inverse of the number of population for each prefecture. All the standard errors are clustered at the prefecture level in parentheses. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.14: Robustness Check on Prefecture Characteristics

Data	China Statistical Yearbook			
Variables	Hospital beds (Log)	Physician (Log)	Government Exp (Log)	Wage (Log)
	(1)	(2)	(3)	(4)
KeyRegion × Post	-0.027	-0.010	-0.036	-0.018
	(0.017)	(0.027)	(0.025)	(0.012)
Observations	2064	2064	2064	2063
R-squared	0.979	0.951	0.979	0.954
Prefecture Characteristic Control	X	X	X	X
Prefecture FE	X	X	X	X
Year FE	X	X	X	X

Notes: In column (1) and (4), the data is from the China Statistical Yearbook 2009 - 2019. These prefecture-level regressions in each column include GDP per capita, population, share of labor in manufacturing industry and fiscal revenue. All the standard errors are clustered at the prefecture level in parentheses. All columns absorb prefecture fixed effect and year fixed effect. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.15: Comparison of magnitude

Variables	Low Birth Weight			
Literature	Currie and Walker, 2011	Marcus, 2021	Hansen-Lewis and Marcus, 2022	This Paper
Policy	E-Zpass	Underground storage tank	Maritime emissions standards	War on Pollution
Pollutant	NO_2	Lead	$PM_{2.5}$	$PM_{2.5}$
Pollution Reduction	10.8%	16.5%	4%	4.95%
Variables	Preterm Birth			
Literature	Currie and Walker, 2011	Marcus, 2021	This Paper	
Pollutant	NO_2	Leak	$PM_{2.5}$	
Magnitude	10.8%	7%-8%	4.79%	

Appendix

Policy Details

National Ambient Air Quality Standards

Table 1.16 presents the current ambient air quality standards in China, as specified in the version of GB 3095-2012. These standards were phased-in beginning in 2012 for Key Region Prefectues (i.e., the treatment group in this paper) and were legislated in 2015. Class 2 standards apply to urban areas and Class 1 apply to rural areas.

TABLE 1.16: Concentration Limit of Ambient Air Pollutants

Pollutant	Averaging time	Limit		Unit
		Class 1	Class 2	
SO_2	Annual	20	60	$\mu g/m^3$
	24 Hours	50	150	$\mu g/m^3$
	Hourly	150	500	$\mu g/m^3$
NO_2	Annual	40	40	$\mu g/m^3$
	24 Hours	80	80	$\mu g/m^3$
	Hourly	200	200	$\mu g/m^3$
CO	24 Hours	4	4	mg/m^3
	Hourly	10	10	mg/m^3
PM_{10}	Annual	40	70	$\mu g/m^3$
	24 Hours	50	150	$\mu g/m^3$
$PM_{2.5}$	Annual	15	35	$\mu g/m^3$
	24 Hours	35	75	$\mu g/m^3$

Notes: This table presents the current ambient air quality standards in China, as specified in GB 3095-2012. These standards were phased-in beginning in 2012 for some prefectures and by 2016 for all prefectures nationwide.

Table 1.17 and 1.18 present the 2010 Annual $PM_{2.5}$ for each key region prefectures documented in the Key Region Policy. The average annual $PM_{2.5}$ concentration is 84.83 $\mu g/m^3$ for key region prefectures in 2010.

TABLE 1.17: Pollutant level for key region prefectures in 2010 (part I)

Prefecture	2010 Annual $PM_{2.5}$	Prefecture	2010 Annual $PM_{2.5}$
Beijing	121	Tianjin	96
Shijiazhuang	98	Tangshan	85
Qinhuangdao	64	Handan	90
Baoding	84	Chengde	53
Cangzhou	78	Hengshui	79
Xingtai	82	Zhangjiakou	60
Langfang	78	Shanghai	79
Nanjing	114	Wuxi	88
Xuzhou	88	Changzhou	97
Suzhou	90	Nantong	97
Lianyungang	90	Huaian	95
Yancheng	122	Yangzhou	96
Zhenjiang	97	Taizhou	87
Suqian	99	Hangzhou	98
Ningbo	96	Wenzhou	85
Jiaxing	93	Huzhou	86
Shaoxing	95	Jinhua	67
Quzhou	65	Zhoushan	61
Taizhou	80	Lishui	71
Guangzhou	69	Shenzhen	57
Zhuhai	49	Foshan	64
Jiangmen	57	Zhaoqing	58
Huizhou	51	Dongguan	63
Zhongshan	51	Shenyang	101
Anshan	105	Fushun	94
Benxi	69	Yingkou	73
Liaoyang	66	Tieling	78
Jinan	117	Qingdao	99
Zibo	110	Zaozhuang	99
Dongying	89	Yantai	81
Weifang	99	Jining	116
Taian	97	Weihai	67
Rizhao	89	Laiwu	107
Linyi	97	Dezhou	89
Liaocheng	93	Binzhou	97
Heze	93	Wuhan	108
Huangshi	91	Ezhou	83
Xiaogan	101	Huanggang	71

TABLE 1.18: Pollutant level for key region prefectures in 2010 (part II)

Prefecture	2010 Annual $PM_{2.5}$	Prefecture	2010 Annual $PM_{2.5}$
Xianning	94	Changsha	83
Zhuzhou	81	Xiangtan	95
Chongqing	102	Chengdu	104
Zigong	81	Mianyang	82
Yibin	78	Luzhou	86
Deyang	65	Nanchong	61
Suining	71	Neijiang	52
Leshan	79	Meishan	83
Guangan	59	Dazhou	69
Ziyang	62	Fuzhou	73
Xiamen	65	Quanzhou	68
Putian	64	Sanming	91
Zhangzhou	72	Nanping	72
Longyan	83	Ningde	53
Taiyuan	89	Datong	75
Shuozhou	75	Xinzhou	61
Xian	126	Xianyang	94
Tongchuan	99	Baoji	98
Weinan	112	Lanzhou	155
Baiyin	99	Yinchuan	94
Wulumuqi	133	Changji	82
Wujiaqu	73		

Key Region Prefectures and NAAQS

The following Figure 1.14 is an example of a "higher level of regulation stringency" for key region prefectures, which I choose from NAAQS.

The extracted paragraph in Chinese and its English translation (from Google Translate, lightly edited) are included.

Original:

FIGURE 1.14: The NAAQS and Key Region Prefectures

7 实施与监督

7.1 本标准由各级环境保护行政主管部门负责监督实施。

7.2 各类环境空气功能区的范围由县级以上（含县级）人民政府环境保护行政主管部门划分，报本级人民政府批准实施。

7.3 按照《中华人民共和国大气污染防治法》的规定，未达到本标准的大气污染防治重点城市，应当按照国务院或者国务院环境保护行政主管部门规定的期限，达到本标准。该城市人民政府应当制定限期达标规划，并可以根据国务院的授权或者规定，采取更严格的措施，按期实现达标规划。

Translation:

"7 Implementation and Regulation

7.3: According to the provisions of the Air Pollution Prevention and Control Law of the People's Republic of China, key region prefectures that have not met this standard must meet this standard within the time limit prescribed by the State Council or the environmental protection administrative department of the State Council. The prefecture government shall formulate a compliance plan, and may, in accordance with the authorization or regulations of the State Council, adopt more stringent measures to achieve the standard compliance plan on time."

Key Region Prefectures, Monitoring Station and Information Disclosure

The following Figure 1.15 from the Amendment documents the requirement of mandatory disclosure of pollution information for key region prefectures. I also provide an English translation (from Google Translate, lightly edited) for this requirement.

Original:

FIGURE 1.15: Mandatory Disclosure of Pollution Information

第九十一条 国务院生态环境主管部门应当组织建立国家大气污染防治重点区域的大气环境质量监测、大气污染源监测等相关信息共享机制，利用监测、模拟以及卫星、航测、遥感等新技术分析重点区域内大气污染来源及其变化趋势，并向社会公开。

Translation:

"**Chapter 91:** The Ministry of Ecology and Environment shall organize the establishment of a relevant information sharing mechanism for atmospheric environmental quality monitoring and air pollution source monitoring mechanisms in key region prefectures. And the ministry shall use monitoring, simulation, and new technologies such as satellites, aerial surveys, and remote sensing to analyze the sources of air pollution and its changing trends in key region areas. And this will be made public to society."

A Comparison of Key Region Prefecture and Nonattainment County

To address concerns about the endogeneity of pollution exposure, an extensive literature employs the Nonattainment status as the predictor (i.e., instrumental variable) of reduction in the pollution concentrations for identification under the context of US Clean Air Act (See, e.g., Greenstone 2002; Chay and Greenstone 2005; Auffhammer, Bento, and Lowe 2009; Isen, Rossin-Slater, and Walker 2017; Currie, Voorheis, and Walker 2023). This research design comes from the fact that nonattainment designation led to significant and persistent declines in ambient pollution concentrations in the years after the law went into effect. In China, the pollutant concentrations in those key region prefectures exceed the air quality standards before the legislation year, and thus this status can predict the changes of pollution level and cause exogenous higher regulation stringency. While for the non-key region prefectures, the restrictions on polluters are less stringent like the attainment counties in US.

How the status specified by the regulation induces significant incentive or punishment for local government? Similar to the consequences of nonattainment status in US, the prefectures in China must develop a pollutant-specific plan and explain how they will improve air quality and come into compliance if they fail to achieve the pollutant limits. Besides, China's political system can induce huge personal promotion incentives for local governments (Chen, Li, and Lu, 2018; Wu and Cao, 2021).

To validate my key region status as an efficient prediction about the pollution reduction, I need to show that the KRP can predict the pollution reduction given other factors. I report this result in the first main regression results in sectoion 5.1

and argue that China's Key Region Policy can also strongly predict local pollution change. Thus, it can be used as the treatment variable for a DID research design.

Data Description

CFPS

China Family Panel Studies (CFPS): The CFPS is a biennial survey and is designed to be similar to the U.S. Panel Study of Income Dynamics. The first national wave was conducted in collaboration with the Institute of Social Science Survey at the Peking University and the Survey Research Center at the University of Michigan from April to August 2010. The five main parts of the questionnaire include data on communities, households, household members, adults, and children. This study used the 2010, 2012, 2014, 2016, 2018 and 2020 waves.

CHARLS

China Health and Retirement Longitudinal Studies (CHARLS): The CHARLS aims to collect a nationally representative sample of Chinese residents ages 45 and older to serve the needs of scientific research on the middle-aged people. The baseline national wave of the CHARLS was fielded in 2011. The individuals are followed up every two years. This study used the 2011, 2013, 2015 and 2018 waves.

Table 1.19 and 1.20 describe several main questions employed in this paper.

In the paper, I choose use Respiratory variable to denote Chronic Respiratory diseases, which are documented in the Table 1.20.

TABLE 1.19: Variable and Questionnaire in CFPS and CHARLS

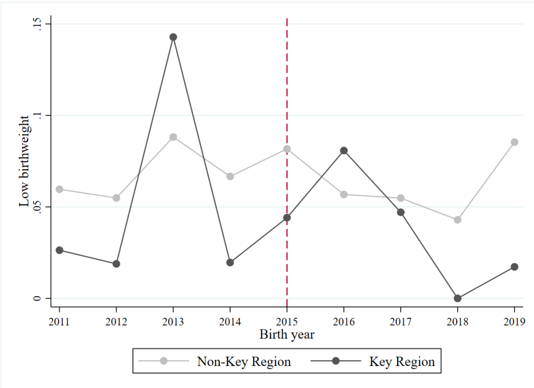
Variables	Questionnaire in survey
Panel A. CFPS	
Chronic	During the past six months, have you had any doctor-diagnosed chronic disease? (1-yes; 0-no)
Respiratory	If the chronic question is yes, then what is the doctor-diagnosed chronic disease?
Self-Rating Health	What do you evaluate your current health status? (1-very good, 5-bad)
Bad Health	Self-rating health takes the value "Unhealth".
Outpatient	Have you visited doctors last 6 months? (1-yes; 0-no).
Inpatient	Were you hospitalized last year due to illness/injury? (1-yes; 0-no).
Log of Medical Expenditure	What is your total medical expenditure last year?
Panel B. CHARLS	
Chronic	Diagnosed with Chronic Lung Diseases by a Doctor (1-yes; 0-no).
Asthma	Diagnosed with Asthma by a Doctor (1-yes; 0-no)
Lung Chronic	Diagnosed with Lung Chronic by a Doctor (1-yes; 0-no)
Self-Rating Health	Self-Reported Health Status (1-5)
Log of Medical Expenditure	Total Medical Cost of Hospitalization and Inpatient
Panel C. CFPS Infant	
Birth weight	What is the infant's birth weight?
Gestation period	What is the infant's gestation period?

Notes: These codes are compiled from CFPS disease codebook.

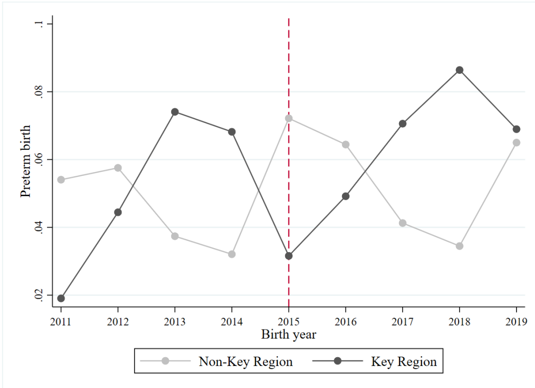
Trends of variable of interests

Figure 1.16 plots the trends of variable of interests in this paper. Overall, all four figures show a more better health improvements for key region households.

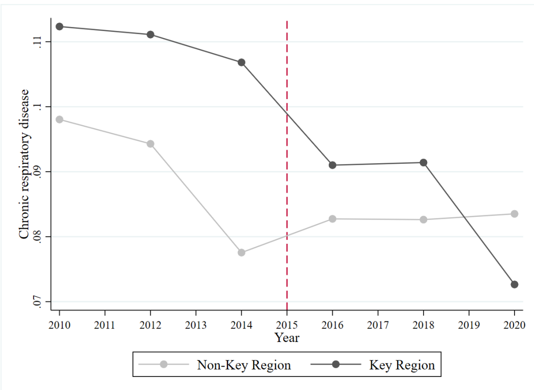
FIGURE 1.16: Trends of variable of interests



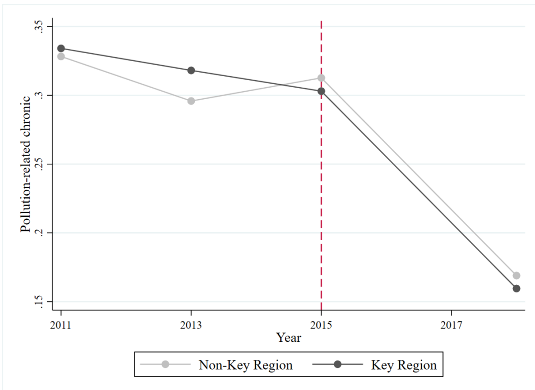
(A) Low birthweight



(B) Preterm birth



(C) Chronic respiratory disease



(D) Pollution-related chronic

Notes: This figure plots the trends of variable of interests in this paper. Panel (a) and (c) use data from CFPS data set, while panel (d) employ data from CHARLS data set.

TABLE 1.20: Chronic Respiratory diseases variable in CFPS dataset

Disease Code	Respiratory Diseases
12.70	Acute nasopharyngitis
12.71	Acute upper respiratory infections of the pharyngitis, tonsillitis and tracheitis
12.72	Influenza
12.73	Pneumonia
12.74	Chronic rhinitis, nasopharyngitis and pharyngitis
12.75	Emphysema
12.76	Other chronic obstructive pulmonary disease (copd, including chronic bronchitis, etc.)
12.77	Asthma
12.78	Other diseases of the respiratory system including acute lower espiratory infections and chronic sinusitis

Notes: These codes are compiled from CFPS disease codebook.

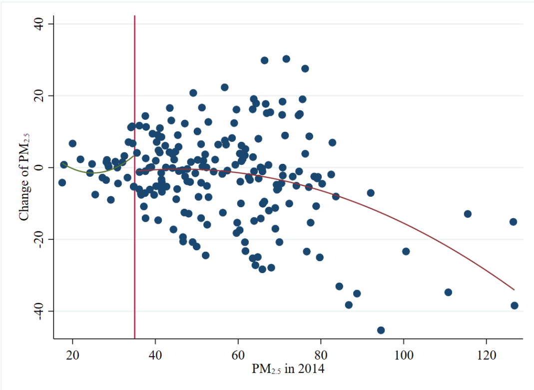
Additional RD Estimates

I now turn to the estimation results with RD design by leveraging on the pollutant cutoff specified by the China NAAQS, i.e., annual $PM_{2.5}$ should be below 35 $\mu g/m^3$. To clearly document the sharp jump in the cutoff point, here I employ the China official $PM_{2.5}$ numbers documented by its automatic pollution monitoring stations since 2013.

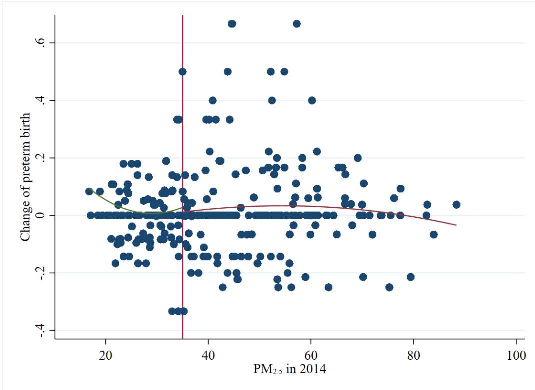
As described in the institution background section, I begin with the graphical illustration of the RD design. The Figure 1.17 plots the change of total pollution concentrations (panel (a)), low birthweight (panel (b)), preterm birth (panel (c)), and middle-aged people asthma (panel (d)) against the pollution limits, 35 $\mu g/m^3$. The x-axis represents each prefecture's pollution in year of 2014. Overall, these trends show that for the prefectures who has average pollution concentrations above 35 $\mu g/m^3$ in year of 2014 would experience sharp reduction of pollution levels, preterm birth and asthma, as shown by the clear jump pollutant at the cut-off.

After presenting the initiao sharp jump in the pollution limit, I further analyze the effect of this jump on the main dependent variables in the main text. Figure 1.18 and Table 1.21 provide the rd estimates by using the 35 $\mu g/m^3$ as the threshold. The figure shows that the infant low birthweight and preterm birth significantly drop in the prefectures whose pollution level is above the threshold. While for middle-aged people's health outcomes in CFPS, the results are not significant. In panel(e) and (f), the pollution-related chronic and lung chronic sharply drop. In the Table 1.21, the magnitude of effects on low birthweight and preterm birth (6.5% and 5.8%) is slightly less than the DID estimates in the main text (11.7% and 9.9%). The column (3) shows the impacts on pollution-related chronic (7.07%), while the DID estimates in the main text is (3.4%). Overall, these estimates are close to the DID estimates in the main text, though without significance.

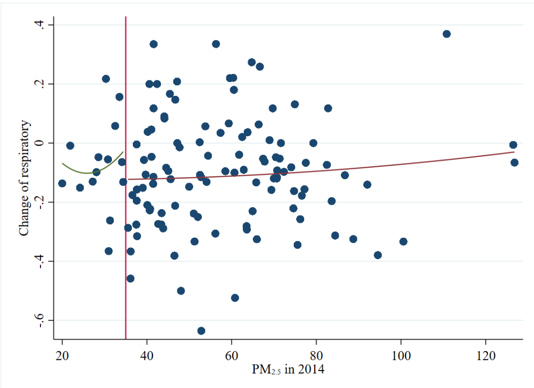
FIGURE 1.17: Relationship between change of welfare and pollution concentrations in 2014



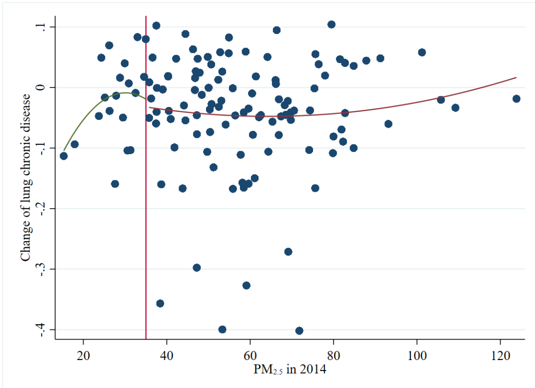
(A) Pollution Concentrations



(B) Infant: Preterm birth



(C) Children: Respiratory



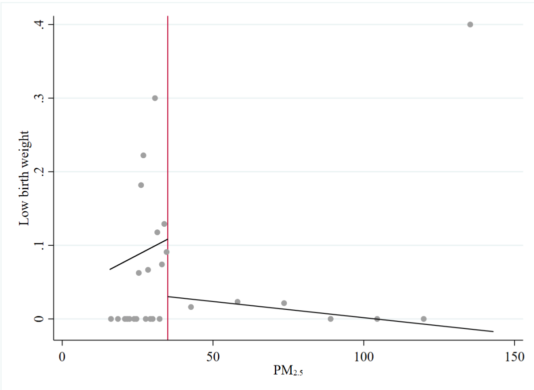
(D) Middle-aged people Lung (CHARLS)

TABLE 1.21: The RD Estimates of Pollution Concentrations Cutoffs

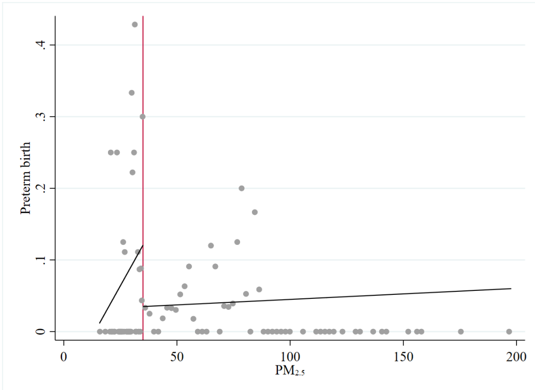
Dataset	CFPS		CHARLS
Variables	Low birth weight	Preterm birth	Chronic
	(1)	(2)	(3)
RD in $PM_{2.5}$	-0.06503	-0.05803	-0.0707
	(0.0465)	(0.0501)	(0.057)
Observations	1022	1451	2316
Bandwidth (PM)	6.011	6.760	2.465
Prefecture FE	X	X	X

Notes: All regressions include the basic control variables as in the main text. All standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

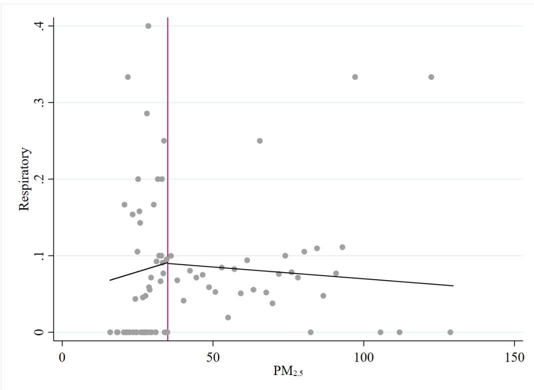
FIGURE 1.18: Regression Discontinuity of KRP



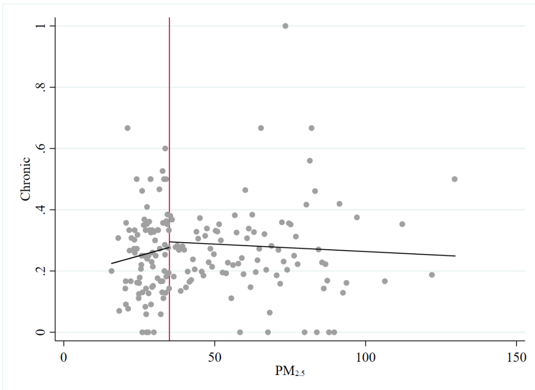
(A) Infant: Low Birthweight



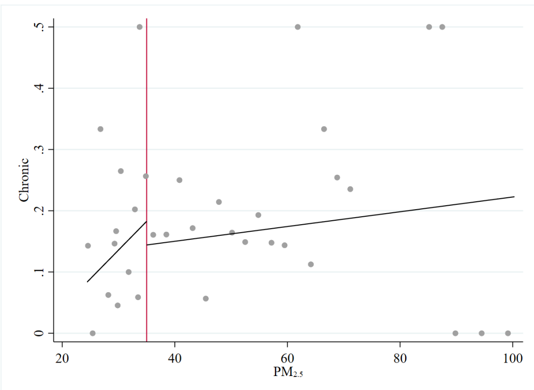
(B) Infant: Preterm



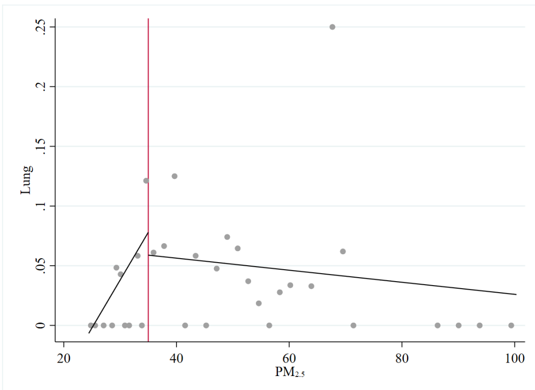
(C) Middle-aged people Respiratory (CFPS)



(D) Middle-aged people Chronic (CFPS)



(E) Middle-aged people Chronic (CHARLS)



(F) Middle-aged people Lung Chronic (CHARLS)

Additional Heterogeneous Results

Sample by pollution intensity.- If better health outcomes are indeed caused by regulation-induced pollution reduction, then the impact should concentrate mainly on individuals who are more exposed to ambient pollution. Therefore, the people who live in high pollution areas should be more likely to have pollution-related diseases. To test this prediction, I estimate whether the effects of KRP on individual health benefits vary across quartiles of the pollution intensity distribution.

Table 1.22 documents those results. Column (1) indicates that prefectures with the relatively high pollution intensity reduced pollution most. Column (2) and (3) of Table 1.22 show that the middle-aged people in the most polluting-intensive area (i.e., Q4) have larger probability to report the reduced respiratory rate and chronic rate. Column (5) also shows that infants in the most polluting-intensive area have higher probability to report the reduced preterm birth rate.

TABLE 1.22: Heterogeneity in KRP's Effects By Pollution Intensity

Data	All Cities	CFPS middle-aged people		CFPS Infant	
Variables	$PM_{2.5}$ ($\mu g/m^3$)	Respiratory (yes =1)	Chronic (yes =1)	Low Birthweight (Yes =1)	Preterm (Yes =1)
	(1)	(2)	(3)	(4)	(5)
KeyRegion × Post × Q_1	1.784	-0.024	0.0506	-0.009	0.010
	(1.752)	(0.032)	(0.034)	(0.033)	(0.045)
KeyRegion × Post × Q_2	-1.954**	-0.035	0.0278	0.014	0.0004
	(0.845)	(0.067)	(0.061)	(0.025)	(0.024)
KeyRegion × Post × Q_3	-3.432***	-0.051	0.0152	-0.007	0.004
	(0.914)	(0.034)	(0.026)	(0.016)	(0.016)
KeyRegion × Post × Q_4	-1.337	-0.093**	-0.139***	-0.002	-0.0380*
	(1.450)	(0.038)	(0.049)	(0.012)	(0.019)
Prefecture FE	X	X	X	X	X
Year FE	X	X	X	X	X

Notes: The column (1) report the prefecture-level $PM_{2.5}$ reduction affected by Key Region Policy across different pollution intensity. The column (2) to (3) employ the individuals aged over 45 from CFPS dataset. The column (4) to (5) employ the infants birth outcomes from CFPS dataset. The covariates in the regressions in each column is the same as in the main text. All the standard errors are clustered at the prefecture level in parentheses. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

A Comparison with Pre-Policy Period

Table 1.23 provides the effect of Key Region Policy on pollution concentrations in the early period of China between 1998 and 2008, which is the period when the pollution significantly increased. Following Liu, Tan, and Zhang, 2021, I denote the policy year as the 2001 and the results show that the KRP increased the pollution level by 3.32 $\mu g/m^3$. According to the above estimates in the main text, the KRP in my policy period decreased the pollution by 4.57 $\mu g/m^3$. The similar magnitude indicates that the KRP policy significantly help reduce the pollution level and this magnitude is consistant with the early pollution fast-growing period.

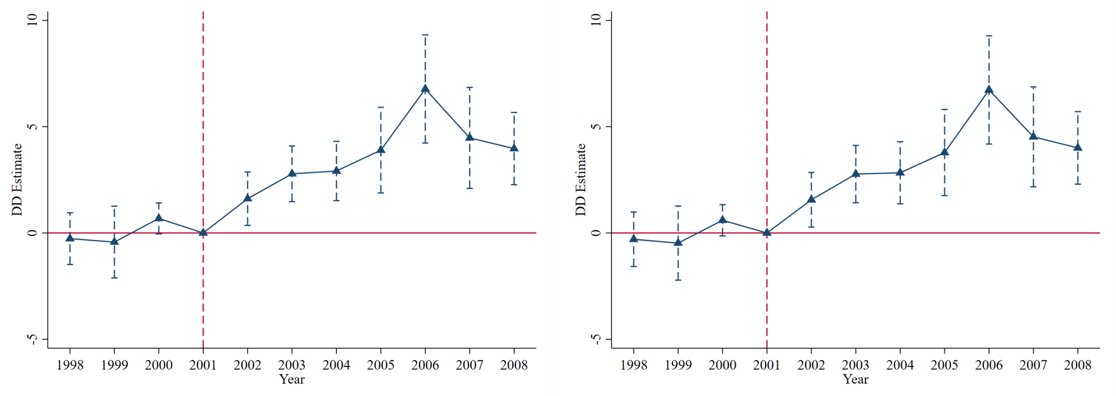
Figure 1.19 further provides dynamic graph of the pollution change in the early period, and the trends suggest that the key region prefectures significantly increased their pollution concentrations. And this effect is more pronounced since the year of 2001. An understanding about the difference between my results and the findings documented by Liu, Tan, and Zhang, 2021 is that my results focused on the $PM_{2.5}$ change, which differs with the reduction of SO_2 in their paper.

TABLE 1.23: The DID Estimates of Regulation on Pollution Concentrations (1998-2008)

Variables	$PM_{2.5}$	
KeyRegion × Post	3.3266***	3.3254***
	(0.8988)	(0.8840)
Observations	2,937	2,937
R-squared	0.9438	0.9449
Prefecture FE	X	X
Year FE	X	X

Notes: KeyRegion equals 1 if a prefecture is denoted as the Key region prefectures for controling pollution; otherwise, KeyRegion equals 0. Post equals 1 for all years after 2001; otherwise, Post equals 0. All regressions are weighted by the number of population, and all the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

FIGURE 1.19: Event-study of Impacts on Pollution (1998-2008)



(A) Regression without controls (B) Regression with controls

Notes: This figure plots event study estimates of KRP on $PM_{2.5}$ concentrations between 1998 and 2008. The regression includes year fixed effects, prefecture fixed effects, and controls.

Mechanisms Analysis

Having substantiated the positive impact of improved air quality resulting from the Key Region Policy on infant and middle-aged people's health, I proceed to investigate diverse mechanisms underpinning these outcomes. My analysis reveals that pollution emission control, information dissemination, and household adaptive behaviors collectively contribute significantly to the observed enhancements in health outcomes.

The Amendment of Atmospheric Pollution Prevention and Control Law directs several approaches that key region prefectures need to follow. First, it necessitates that these key region prefectures engage in a meticulous assessment of industrial parks, development zones, and regional industries which may carry huge pollutants and then assess them with consideration. This industry-based solution of pollution reduction would cause direct adverse effects on local manufacturing sectors, both on productions and emissions. In addition, the Amendment compels key region prefectures to establish comprehensive mechanisms encompassing atmospheric environmental quality monitoring, air pollution source tracking, and related information sharing systems. These newly established technologies are subsequently employed to scrutinize the origins and patterns of air pollution within key region areas, with the findings being made transparent to the broader society and households.[32] Therefore, this paper examines the two main mechanisms and their subsequent impacts on household health outcomes.

Shutdown of Polluting Firms in Key Region Areas

The manufacturing firms account for the most part of pollution emission in China. To comply with the required pollution limits, local government set several standards for those industrial firms, which induce those firms to shut down their production lines, reduce the output or invest the abatement technology. Liu, Shadbegian, and Zhang, 2017, Chen et al., 2018, Karplus, Zhang, and Almond, 2018 and Liu, Tan, and Zhang, 2021 show that the China environmental regulation effectively induce firms

[32] See, https://www.mee.gov.cn/ywgz/fgbz/fl/201811/t20181113_673567.shtml

to employ multiple approaches to reduce their emissions. Therefore, this would further increase the regional household health outcomes.

The China statistical yearbook documents the number of "enterprise above designated size" and its annual output value. This firm definition is a commonly used statistical term to identify the industrial firm with annual main business income above 20 million RMB (280 000 USD). Therefore, one direct mechanism is to examine these large industrial firm's performance among key region cities affected by KRP.

To investigate the role of local industrial firms in pollution and health improvements, I examine whether KRP affects the number and value of output of industrial firms. Columns (1) and (3) of Table 1.24 report the results separately. Here I find that the number of industrial firms drop by 9.47 percentage point and value of output drop by 9.68 percentage point after legislation. Figure 1.20 plots event study estimates for each of these industrial firm outcomes, along with 95-percent confidence intervals. The reslts from Panel (a) and (b) suggest that there are no clear pre-trends for both measures. The number and output value of industrial firms in key region cities decrease relative to control group since year of 2015. For the prefecture level outcomes, Column (5) to (8) show that the unemployment rate increased and the employment share of secondary sector decreased, both of which indicate the KRP induced negative changes of labor market composition among key region prefectures. Overall, the results here align with evidence that environmental regulation increases the local unemployment and casued labor supply transition (Walker, 2013; Liu, Shadbegian, and Zhang, 2017; Curtis, 2018; Liu, Tan, and Zhang, 2021). The Panel (c) and (d) in Figure 1.20 examine the event study, and the trends show that the unemployment rate increased since 2011 and the employment in secondary sector decreased.

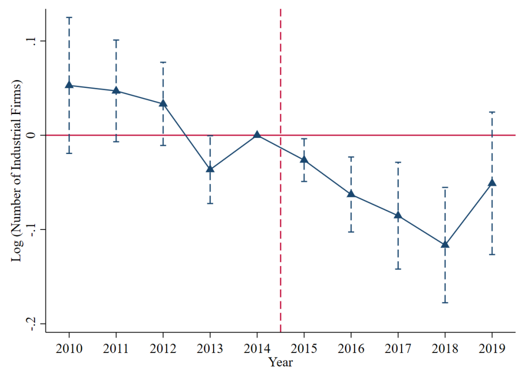
The lack of evidence of firm-level employment data is a hopeful one in light of recent work. Liu, Shadbegian, and Zhang, 2017 and Liu, Tan, and Zhang, 2021 show that firms would choose to upgrade their technology and invest in abatement with less labor demand, and thus households have to adjust to this labor market shock. Although these evidence do not focus on the same period in this paper, their results would be more inspiring for any future studies that employ firm data to investigate on the Key Region Policy.

TABLE 1.24: Mechanisms - Shutdown of Industrial Firms

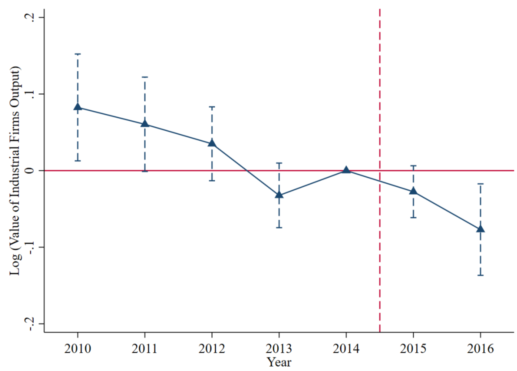
Variables	Number		Value		Unemp		Share of secondary	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KeyRegion × Post	-0.0947***	-0.0540*	-0.0968***	-0.1069***	0.0841**	0.0818*	-1.8872*	-1.0475
	(0.0329)	(0.0291)	(0.0371)	(0.0302)	(0.0407)	(0.0461)	(0.9611)	(0.9608)
Observations	3,158	3,158	2,303	2,303	3,157	3,157	3,163	3,163
R-squared	0.9750	0.9764	0.9843	0.9850	0.8928	0.8935	0.8761	0.8787
Control		X		X		X		X
Prefecture FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X

Notes: The sample is China Statistical Yearbook from 2009-2019. The two columns control for the GDP per capita, population, share of secondary industry over the gdp, share of labor in manufacturing industry and fiscal expenditure, year fixed effects and prefecture fixed effects. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

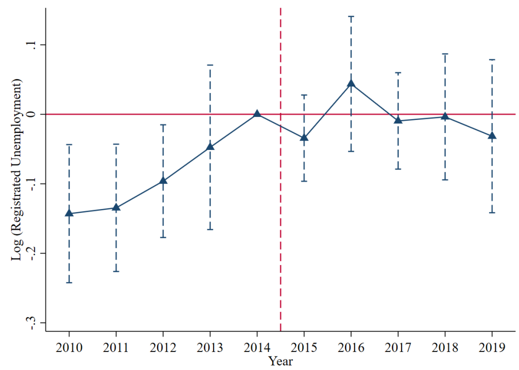
FIGURE 1.20: Mechanisms - Prefecture Characteristics



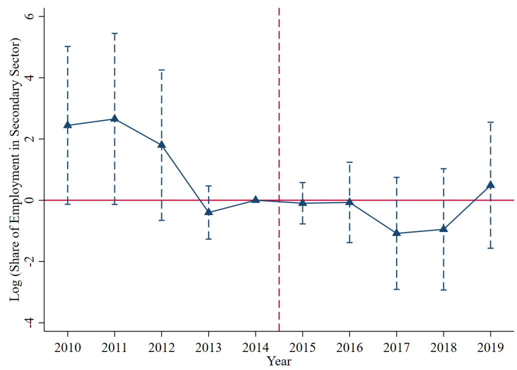
(A) Log (number of industrial firms)



(B) Log (value of industrial firms output)



(C) Log (registrated unemployment)



(D) Log (share of employment in secondary)

Notes: The panels plot event study estimates of Key Region Policy on regional industrial firm's performance and prefecture unemployment and share of secondary sector. Data is from China Statistical Yearbook 2009-2019. The data on value of output of industrial firms is only available before year of 2016. The regression controls for year fixed effects, prefecture fixed effects and annual prefecture-specific economic controls. Brackets denote 95 percent confidence intervals, calculated from robust standard errors clustered at the prefecture level.

Information and Avoidance Behaviors

Recent literature documents that the environmental regulation can induce people's responsive behavior (Marcus, 2021; Xie, Yuan, and Zhang, 2023; Buntaine et al., 2024). Following Greenstone et al., 2022, I choose China Baidu's search indices for "anti-haze mask" and "air filters" to measure behavioral responses through online searches. Besides, I also complement people's search of pollution intensity and to measure household's attention on environment issues, for example, "haze" and "environmental pollution". Following Xie, Yuan, and Zhang, 2023, I normalize the dependent variable by dividing it by the population count per 10,000 individuals in each respective prefecture.

The findings are displayed in columns (1) through (4) of Table 1.25, indicating a statistically significant increase attributable to the KRP in regional individuals' information search regarding haze and environmental pollution. Moreover, the CFPS dataset includes information on whether households owned an air purifier as of the survey year, starting with the questionnaire introduced in the 2018 wave. The cross-sectional OLS estimation in column (5) indicates that individuals residing in key region cities are statistically more inclined to possess air purifiers in their homes.

TABLE 1.25: Mechanism: information search and avoidance behavior

Data	Baidu Search Index				CFPS
Variables	Haze (1)	Env. Pollution (2)	Anti-Haze Mask (3)	Air purifier (4)	Air Purifier (5)
KeyRegion					0.036***
					(0.003)
KeyRegion × Post	0.039***	0.015***	11.830***	2.163***	
	(0.009)	(0.003)	(2.434)	(0.360)	
Observations	1,751	1,751	1,778	1,778	12,369
R-squared	0.823	0.926	0.904	0.684	0.007
Prefecture FE	X	X	X	X	X
Year FE	X	X	X	X	

Notes: *** p<0.01, ** p<0.05, * p<0.1.

Lifestyle Change

In this subsection, I complement the evidence of lifestyle change such as sleep hours and work hours as mechanisms for the health channel. As a response to environmental regulation, the individual may change their lifestyle by reducing the work hours and having better sleep. Therefore, it is direct to examine whether or not the decreased pollution concentration induce better sleeping quality and less working hours. The less working hours come from the guess that stringent environmental regulation may induce local manufacturing firms reduce labor demand.

The CFPS documents the individual information on sleeping and working time. I find that the middle-aged people who takes the manufacturing job change their lifestyle as a response to environmental regulation by doing less physical exercises and exercises hours, which is documented in column (1) in Table 1.26. Column (2) indicates that the non-manufacturing workers do not work less since the environmental regulation. And one explanation is that the manufacturing firms may choose upgrade their abatement technology and thus reduce the labor demand for manufacturing workers (Liu, Shadbegian, and Zhang, 2017; Curtis, 2018; Liu, Tan, and Zhang, 2021). Figure 1.21 help visualize this adjustment behavior on work hours, which suggests that manufacturing workers spend less hours on weekly work hours and other type of workers.

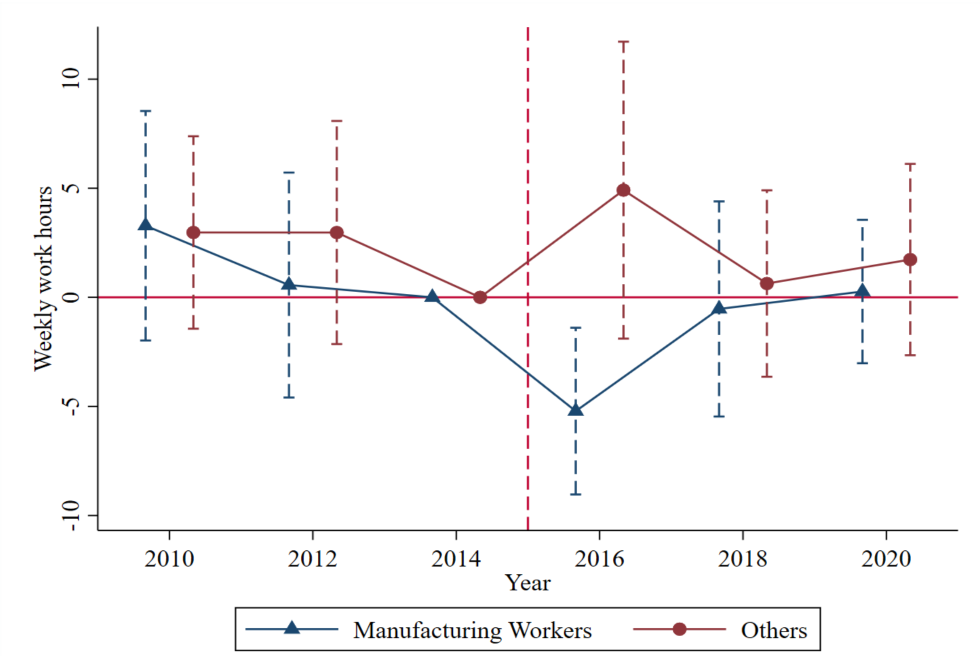
Previous studies document the negative effect of pollution on less sleep (Heyes and Zhu, 2019). Thus, decreased pollution concentrations bring better sleeping quality and can help improve middle-aged people health status. This idea is further ensured in the column (2) of Table 1.27. The column (4) also documents that the urban middle-aged people reduced their weekly work hours, which can help increase their health outcomes. Overall, the sleeping time and weekly work hours among the middle-aged people could be a mechanism explaining the health benefits of reduced pollution induced by Key Region Policy.

TABLE 1.26: Mechanism - Lifestyle Change

Data	CFPS		
Variables	Weekly Work Hours		
	(Hours)	(Hours)	(Hours)
Sample	Worker	Other	All Sample
	(1)	(2)	(3)
KeyRegion × Post	-3.2693*	0.9171	-0.4593
	(1.7790)	(1.5460)	(0.7887)
Observations	5,659	10,436	33,061
R-squared	0.1215	0.0865	0.1034
Prefecture FE	X	X	X
Year FE	X	X	X

Notes: The sample is from the CFPS (2010-2020) for individuals aged 45 and over. The covariates in all column include dummies for gender, age, age's square, education years, marriage status, log of income, survey year and prefecture fixed effect. All regressions are weighted by the number of population for each prefectures to control for the potential concern of uneven distribution of survey participants across different prefectures. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

FIGURE 1.21: Impacts on Weekly Work Hours by Job



Notes: This figure plots event study estimates of Key Region Policy on working-age middle-aged people weekly work hours. The regression includes year fixed effects, prefecture fixed effects, and controls for the age, age's square, gender type, rural/urban type, education, and marriage status. The regression is weighted by the number of population in 2013 for each prefecture.

TABLE 1.27: Mechanism - Lifestyle Change

Data	CFPS			
Variables	Sleep Hours		Weekly Work Hours	
	(Hours)		(Hours)	
	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)
KeyRegion × Post	-0.128	0.272*	-0.4198	-4.542***
	(0.133)	(0.146)	(1.527)	(1.635)
Observations	18814	12154	8649	5384
R-squared	0.152	0.200	0.142	0.079
Prefecture FE	X	X	X	X
Year FE	X	X	X	X

Notes: The sample is from the CFPS (2010-2020) for individuals aged 45 and over. The covariates in all column include dummies for gender, age, age's square, education years, marriage status, log of income, survey year and prefecture fixed effect. All regressions are weighted by the number of population for each prefecture to control for the potential concern of uneven distribution of survey participants across different prefectures. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

Additional Robustness Checks

Unweighted Regression Results

Table 1.28 and 1.29 present the results without weighting, which are fairly consistent with our above results.

TABLE 1.28: Effects of the KRP on the health outcomes, without weighting (CFPS)

Variables	Respiratory (1)	Chronic (2)	Self-rating (3)	Bad Health (4)	Ln.Med (5)
KeyRegion × Post	-0.0193**	-0.0039	-0.0020	-0.0235***	0.0425
	(0.0076)	(0.0120)	(0.0306)	(0.0078)	(0.0460)
Observations	19,983	89,060	76,511	76,511	39,979
R-squared	0.0263	0.0474	0.2442	0.1127	0.0964
Prefecture FE	X	X	X	X	X
Year FE	X	X	X	X	X

Notes: The sample is from the CFPS (2010-2020) for individuals aged 45 and over. The covariatesin the regressions in each column include dummies for gender, age, age's square, education years, marriage status, urban/rural type, family size, survey year and prefecture fixed effect. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.29: Effects of the KRP on the health outcomes, without weighting (CHARLS)

Variables	Pollution Chronic (1)	Asthma (2)	Lung (3)	Hypertension (4)	ADL (5)	IADL (6)
KeyRegion × Post	-0.0185	-0.0008	0.0148*	-0.0304*	-0.0139	-0.0071
	(0.0176)	(0.0067)	(0.0082)	(0.0166)	(0.0096)	(0.0090)
Observations	36,828	36,201	35,158	31,727	47,613	69,926
R-squared	0.0727	0.0176	0.0358	0.0595	0.0653	0.1476
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: The sample is from the CHARLS (2011-2018) for individuals aged 45 and over. The covariates in all columns include dummies for gender, age, age's square, education years, marriage status, urban/rural type, survey year and prefecture fixed effect. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

Individual Fixed Effects

Table 1.30 and 1.31 present the results using individual fixed effects. The results show no material difference compared with those in the main text.

Selective Migration

One common concern of estimation of health benefits of environmental regulation is selective migration (Currie, Greenstone, and Moretti, 2011; Currie and Walker, 2011). The assumptions necessary to identify health effects would be violated if the

TABLE 1.30: Effects of the KRP on the health outcomes, Individual Fixed Effects Controlled (CFPS)

Variables	Respiratory (1)	Chronic (2)	Self-rating (3)	Bad Health (4)	Ln.Med (5)
KeyRegion × Post	-0.0128	-0.0062	-0.0017	-0.0268**	-0.0222
	(0.0118)	(0.0143)	(0.0478)	(0.0103)	(0.0757)
Observations	13,291	78,498	66,197	66,197	31,206
R-squared	0.6605	0.4068	0.6738	0.5446	0.6334
Prefecture FE	X	X	X	X	X
Year FE	X	X	X	X	X

Notes: The sample is from the CFPS (2010-2020) for individuals aged 45 and over. The covariatesin the regressions in each column include dummies for gender, age, age's square, education years, marriage status, urban/rural type, family size, survey year and individual fixed effect. All regressions are weighted by the number of population for each prefectures in 2013. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

TABLE 1.31: Effects of the KRP on the health outcomes, Individual Fixed Effects Controlled (CHARLS)

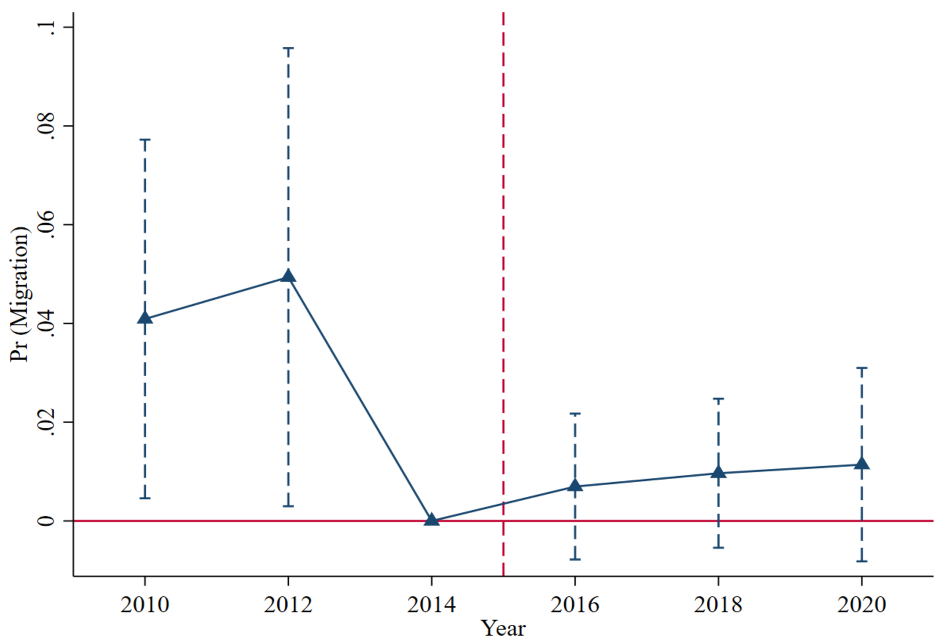
Variables	Pollution Chronic (1)	Asthma (2)	Lung (3)	Hypertension (4)	ADL (5)	IADL (6)
KeyRegion × Post	-0.0141	-0.0098	0.0295	0.0145	-0.0151**	-0.0232*
	(0.0322)	(0.0101)	(0.0229)	(0.0337)	(0.0074)	(0.0138)
Observations	30,722	29,882	28,550	24,630	40,373	65,358
R-squared	0.5325	0.4979	0.5179	0.5277	0.4310	0.4751
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: The sample is from the CHARLS (2011-2018) for individuals aged 45 and over. The covariates in all columns include dummies for gender, age, age's square, education years, marriage status, urban/rural type, survey year and individual fixed effect. All regressions are weighted by the number of population for each prefectures in 2013. All the standard errors are clustered at the prefecture level. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

Key Region Policy causes mothers with systematically different unobserved health endowments to move closer to the key region prefectures. In order to guard against the possible effects of selective migration, I estimate the impacts of KRP on migration decision.

Following Huang and Zhang, 2021, I choose the variable of whether migrating to another prefecture as the measure of selective migration from the CFPS dataset. The results are shown in Figure 1.22, and the trends of migration indicate that KRP does not significantly induce more migrations since 2015.

FIGURE 1.22: Event Study Plots of Key Region Policy on Migration



Notes: This figure plots event study estimates of Key Region Policy on people's migration decision using CFPS dataset for individuals aged 45 and over. The regression includes year fixed effects, prefecture fixed effects, and controls for the age, age's square, gender type, education years, and marriage status.

Adding control

In Table 1.32, I reestimate the effect of KRP on middle-aged people's health. And Column (1) to (3) suggest that the results are robust when I add the family control and prefecture control step by step.

And in Figure 1.23, I add the event study figure of the urban and rural sample. Also, I use the original data to plot the trends of disease in Figure 1.24.

Propensity score matching strategy

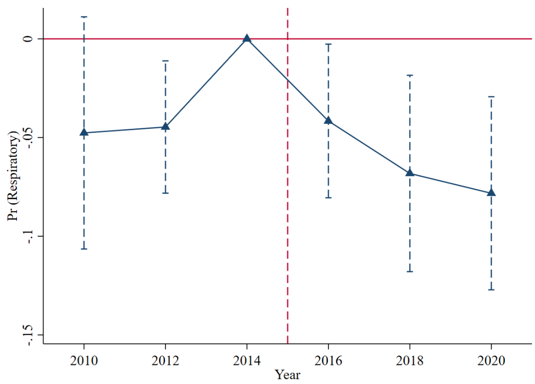
In my maintext, I only incorporate 46 KRP prefectures due to data limitation. One may concerns that this selection may not be at random. Therefore, I use the propensity score matching strategy to argue that the 46 sampled regions are representative of the entire 116 KRP regions. PSM involves a logistic regression where the dependent variable equals 1 for key region prefectures and 0 otherwise. Independent variables include pre-treatment characteristics hypothesized to influence the propensity

TABLE 1.32: Effects of the KRP on Middle-aged People Health (CFPS)

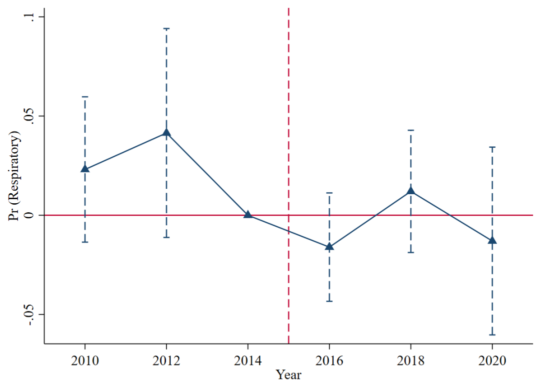
Variables	Respiratory			Bad Health		
	(1)	(2)	(3)	(4)	(5)	(6)
KeyRegion × Post	-0.0253***	-0.0251***	-0.0302**	-0.0236***	-0.0229***	-0.0114
	(0.0075)	(0.0076)	(0.0123)	(0.0083)	(0.0082)	(0.0096)
Observations	19,134	19,134	19,134	71,758	71,752	71,752
R-squared	0.0237	0.0239	0.0240	0.1049	0.1055	0.1056
Prefecture Control			X			X
Family Control		X	X		X	X
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: The sample is from the CFPS (2010-2020) for individuals aged 45 and over. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

FIGURE 1.23: Event-study of Impacts on Chronic Respiratory Disease Rate



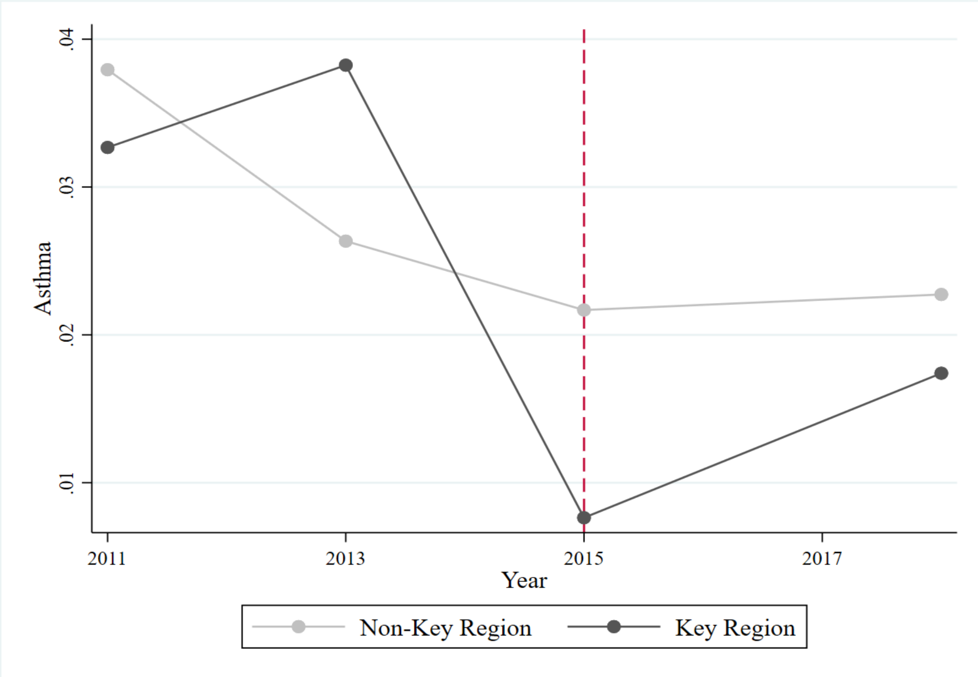
(A) Urban sample



(B) Rural sample

Notes: This figure plots event study estimates of KRP on $PM_{2.5}$ concentrations between 2009 and 2019 and middle-aged people respiratory rate using CFPS data set between 2010 and 2020. The regression includes year fixed effects, prefecture fixed effects, and controls, and are weighted by the population size in the pre-policy year. Both regressions are clustered at prefecture level.

FIGURE 1.24: Trend of Asthma For Middle-aged People (CHARLS)



Notes: This figure plots trend of asthma for middle-aged people using CHARLS dataset for individuals aged 45 and over.

to be in the treatment group. Specifically, I incorporate variables from 2011, encompassing a prefecture's population, GDP per capita, fiscal revenue, share of secondary industry, employment share, and SO_2 concentration.

Figure 1.25 illustrates the biases between treated and untreated prefectures before and after matching. It reveals a substantial reduction in biases across most indicators between the two groups post-matching. Ultimately, I identify 49 treated prefectures matched with 49 untreated prefectures.

In Table 1.33, column (1) presents the effects on pollution concentrations, while columns (2) to (6) report findings related to health outcomes using the CFPS sample. Columns (1) and (2) reveal statistically significant negative coefficients, with minimal deviation in magnitude compared to the baseline results. Table 1.34 reproduces the health outcomes using the CHARLS sample. Columns (1) and (2) affirm the robustness of the results.

TABLE 1.33: The effects of KRP on pollution and health (PSM-DID)

Variables	PM2.5	Respiratory	Chronic	Self-rating	Bad Health	Ln.Med
	(1)	(2)	(3)	(4)	(5)	(6)
KeyRegion × Post	-3.9086***	-0.0258**	-0.0314*	-0.0043	-0.0232**	0.0218
	(1.1458)	(0.0115)	(0.0163)	(0.0429)	(0.0103)	(0.0637)
Observations	1,074	8,503	38,497	32,951	32,951	17,175
R-squared	0.9370	0.0340	0.0419	0.2210	0.1044	0.0780
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: Column (1) estimates the effects on pollution, and column (2) to (6) estimates the effects on health using CFPS data set. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 1.25: Prefecture characteristics bias before and after matching

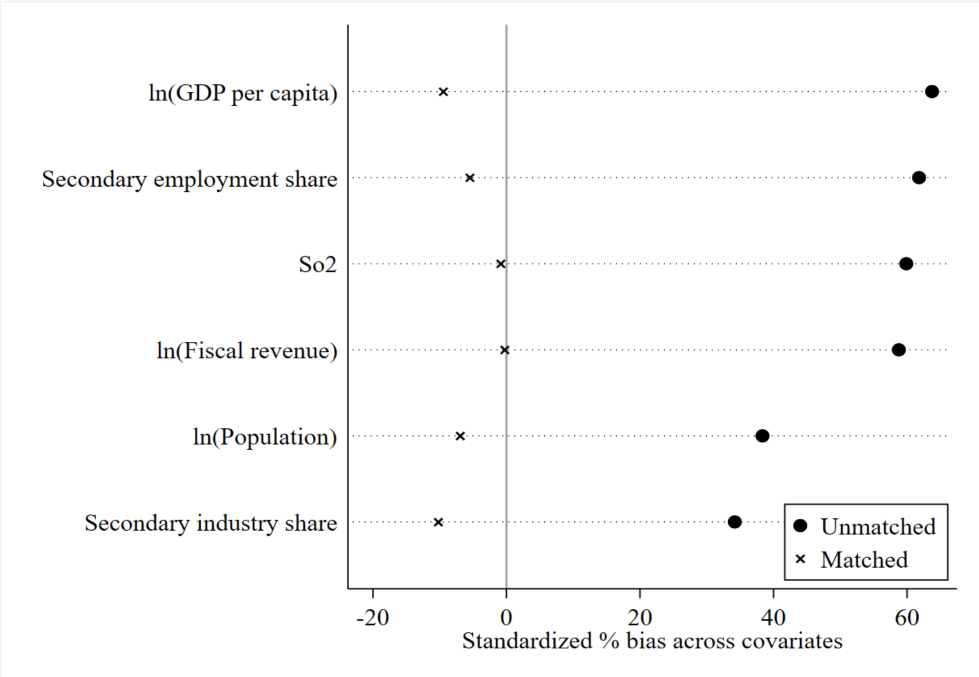


TABLE 1.34: The effects of KRP on health (PSM-DID)

Variables	Pollution Chronic (Yes=1) (1)	Asthma (Yes=1) (2)	Lung (Yes=1) (3)	Hypertension (Yes=1) (4)	ADL (Yes=1) (5)	IADL (Yes=1) (6)
KeyRegion × Post	-0.0360*	-0.0161**	-0.0174	-0.0166	-0.0201	0.0134
	(0.0199)	(0.0062)	(0.0118)	(0.0188)	(0.0128)	(0.0108)
Observations	17,604	17,289	16,860	15,164	22,378	33,589
R-squared	0.0659	0.0191	0.0307	0.0536	0.0589	0.1365
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: The sample is from the CHARLS (2011-2018). *** p<0.01, ** p<0.05, * p<0.1.

Alternative pollutant

Table 1.35 reports the effects of KRP policy on alternative pollutants in China, which complements the baseline results in Table 1.4.

TABLE 1.35: The Effects of KRP on Alternative Pollution Concentrations

Variables	SO_2			NO_2		
	(1)	(2)	(3)	(4)	(5)	(6)
KeyRegion × Post	-0.3366***	-0.2702***	-0.1454*	0.0358	0.0507	-0.0005
	(0.0945)	(0.0843)	(0.0862)	(0.1140)	(0.1039)	(0.1231)
Observations	1,993	1,993	1,993	639	632	632
R-squared	0.8796	0.8826	0.8891	0.4477	0.4622	0.4665
Controls		X	X		X	X
Prefecture Characteristics			X			X
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: All regressions are weighted by the number of population in 2013 for each prefecture. Standard errors are clustered at the prefecture level. The control variable vector contains GDP per capita, population, share of secondary industry over the gdp, and share of labor in manufacturing industry. Significance at the 1%, 5%, and 10%, levels are denoted by ***, **, and *, respectively.

Chapter 2

Long-Term Effect of Export Expansion on Human Capital: Evidence from China

2.1 Introduction

How does trade liberalization affect household welfare? Previous casual evidence shows that the economic windfall induced by trade expansion significantly increases regional productivity, wages, employment and GDP per capita (Han et al., 2016; Lu and Yu, 2015; Erten and Leight, 2021). However, these economics benefits come with environmental costs, and extensive literature documents that the pollution caused by trade expansion increases infant mortality, damages worker's health status and reduces human capital accumulation (Li et al., 2019; Lin and Long, 2020; Chen et al., 2020; Fan, Lin, and Lin, 2020; Bombardini and Li, 2020; Gong et al., 2023). Although these studies provide causal links between trade liberalization and contemporaneous measures of economic and environmental well-being, there is less evidence on trade expansion's effects in a longer period.

This paper investigates the following inquiry within the framework of China's accession to the World Trade Organization (WTO): What is the impact, if any, of early-life exposure to trade liberalization on health and cognitive outcomes approximately 15 years later, specifically during adolescence? The focal point of this study is China's expansive trade activities, given its status as the largest manufacturing economy globally and the presence of relatively high pollution levels. While China's trade policies and export expansions yield substantial economic and productivity gains, they are accompanied by environmental challenges. To assess the benefits and costs of trade-induced pollution, comprehensive evidence on firms, households, and regional development is necessary. On one hand, China's WTO accession leads to heightened emissions from firms and elevated regional pollution levels, as documented in previous research (Chen et al., 2020; Chen, Shao, and Zhao, 2023; Bombardini and Li, 2020), potentially detrimentally impacting individuals' well-being. Conversely, recent investigations indicate that trade liberalization may contribute to a reduction in emissions from firms (Cherniwchan, Copeland, and Taylor, 2017; Forslid, Okubo, and Ulltveit-Moe, 2018; Cui et al., 2020; Rodrigue, Sheng, and Tan, 2022; Lin, Huang, and He, 2023). The mixed evidence makes it intriguing to analyze how the trade shock and trade-induced pollution shock could impact long-term outcomes, which is essential for policy evaluations.

This study extends the work of Bombardini and Li, 2020 by delving into the enduring ramifications of trade expansion on health and cognitive test performance, examining both trade shocks and trade-induced pollution shocks. To ascertain the causal influence of these shocks, a shift-share (Bartik-style) instrumental variable for trade shock is constructed, leveraging foreign countries' tariffs on Chinese export goods to estimate export flows. Each prefecture's exposure to trade shock is then determined by weighting the estimated export flows according to its initial employment share, akin to methodologies employed in prior studies (Autor, Dorn, and Hanson, 2013; Bombardini and Li, 2020; Tian, 2022). In assessing trade-induced pollution shock, industry-specific SO_2 emission intensity is interacted with the trade shock. Health outcomes and cognitive test scores are evaluated using data from the China Family Panel Studies (CFPS) spanning from 2010 to 2020, tracing the effects into later adolescence across seven birth cohorts from 1999 to 2005.

In this study, I incorporate measures of trade shock and trade-induced pollution shock. The prefecture-level trade shock measures the extent to which a prefecture initially specializes in industries that subsequently experience substantial export growth. This measure is constructed using a shift-share framework, which combines the initial industry shares with changes in trade flows over time. Additionally, the trade-induced pollution shock incorporates each industry's emission intensity into the trade shock measure. This captures the interaction between export expansion and pollution intensity: prefectures with a higher initial employment share in industries facing significant export shocks and displaying high emission intensity are expected to encounter elevated pollution levels. In the empirical analysis, I employ regression models to examine the relationship between early-life exposure to the two measures and a range of long-term human capital indicators. By doing this, I can explore the coefficients associated with each measure and their implications for human capital development over time.

One threat to identification is that trade shock within each prefecture may influence households' behavior changes that are not captured in my specification. Simultaneity arises from the fact that export flows are not only influenced by regional economic conditions like GDP growth but also have feedback effects on these variables. This mutual determination can complicate the analysis of export flows and their impact on regional welfare. Additionally, omitted variable bias may occur if important factors affecting both export flows and regional welfare, such as productivity improvements, are not included in the analysis. This omission could lead to biased estimates of the relationship between export flows and welfare outcomes. To address this potential endogeneity, I construct an instrumental variable (IV) for Chinese export flows in which I leverage the tariffs reported by the rest of the world. By regressing actual export flows on these reported tariffs, I estimate the fitted value of Chinese export flows. The fundamental assumption here posits that the tariffs imposed by foreign countries do not directly influence domestic household behaviors within China. Consequently, the estimated fitted value of export flows varies across prefectures in China, reflecting regional disparities in trade exposure.

Another empirical obstacle lies in establishing the link between childhood circumstances and later-life outcomes, which requires detailed household information and insights into migration status. Leveraging the comprehensive household data available in the CFPS dataset, I narrow down the sample to households that have remained in their original prefectures.[1]

Therefore, I uncover substantial effects of exposure to trade expansion during gestation and early childhood on adolescent health and cognitive development. Specifically, exposure to trade shock correlates with a 0.025 standard deviation reduction in

[1]By restricting the sample to exclude selective migration, I can obtain the causal effects on human capital accumulation. For example, if children's parents with higher education levels are more likely to migrate to regions with trade liberalization, I would capture education rather than trade liberalization.

the unhealthiness index, which comprises self-reported health, hospitalization, and underweight indicators, alongside a 0.022 standard deviation increase in the cognitive index, encompassing verbal and math test scores among adolescents. Furthermore, exposure to trade-induced pollution shock corresponds to a 0.002 standard deviation increase in the unhealthiness index and a 0.002 standard deviation decrease in the cognitive index. Besides, the benefits of these shocks are more pronounced among low socioeconomic status (SES) families in terms of health and cognitive outcomes. Additionally, I delve into the potential mechanisms driving these long-term benefits of trade shock and trade-induced pollution shock by examining their contemporaneous effects on regional health and education infrastructure investment and exporter's SO_2 emissions. I find that trade shock is positively related to improved health and education resources. In addition, I also find the trade-induced pollution shock is linked to a reduction in regional firms' SO_2 emissions.[2]

This paper contributes to three main strands of literature. Firstly, it adds to the body of research examining the long-term health and human capital implications of trade liberalization (Kim and Kose, 2014; Dix-Carneiro and Kovak, 2017; Li et al., 2019; Lin and Long, 2020; Dai, Huang, and Zhang, 2021; Erten et al., 2023). China initiated significant trade liberalization efforts in the late 1990s, providing a unique opportunity to assess its effects over extended timeframes. My findings build upon the seminal work of Bombardini and Li, 2020, which conducted contemporaneous analyses on how China's trade expansion affected infant mortality through income and pollution channels. They observed a negative correlation between changes in pollution resulting from export expansion and shifts in infant mortality rates. Extending their analysis, my paper examines these relationships over a longer horizon and discovers that trade shock significantly improve adolescents' health and cognitive test scores, while trade-induced pollution shock negatively affects those outcomes. Furthermore, the recent study by Erten et al., 2023 also investigates the long-term consequences of China's WTO accession on children's mental health, and they document a decline in the incidence of severe depression during adolescence. My paper supplements their findings by incorporating both trade shock and trade-induced pollution shock and employing an alternative measure of prefecture-level exposure to trade shock.

While prior research has demonstrated that trade shock can diminish completed years of schooling, cognitive abilities, wages, and noncognitive outcomes among young children (Li et al., 2019; Lin and Long, 2020; Dai, Huang, and Zhang, 2021), much of this work centers on the opportunity cost of education and labor market dynamics.[3] In contrast, my findings focus on an earlier exposure period for children and affirm the role of trade liberalization in bolstering cognitive scores.

Secondly, this paper contributes to the literature on the long-term effects of pollution exposure. Previous research has extensively documented the impact of significant pollution sources (Almond, Currie, and Duque, 2018; Arenberg and Neller, 2023; Deryugina and Reif, 2023), environmental regulations (Isen, Rossin-Slater, and Walker, 2017; Barreca, Neidell, and Sanders, 2021), mining activities (Goltz and Barnwal, 2019; Benshaul-Tolonen, 2019; Maffioli, 2022), and lead exposure (Almond,

[2] This finding aligns with the literature showing that trade liberalization is decreased emissions (Rodrigue, Sheng, and Tan, 2022; Lin, Huang, and He, 2023).

[3] The rationale behind this is that the additional economic opportunities generated by trade liberalization may incentivize young adults to forego further education and join manufacturing production, driven by heightened labor demand and wages. Consequently, this reduction in years of education can translate into lower wages and entry into more basic job positions over the long term.

Currie, and Duque, 2018; Grönqvist, Nilsson, and Robling, 2020) on children's human capital. For instance, Benshaul-Tolonen, 2019 illustrate how large-scale gold mining in Africa led to harmful pollution, yet also coincided with a decrease in local infant mortality rates by over 50% amid rapid economic growth. Similarly, Goltz and Barnwal, 2019 demonstrate that while mining activities generate wealth, they also correlate with a higher incidence of health conditions associated with heavy metal toxicity. This study complements existing research by examining both the economic benefits and environmental costs induced by trade shock. A recent study by Gong et al., 2023 reveals that $PM_{2.5}$ resulting from trade shock increases all-cause and cardiorespiratory mortality. By employing the individual-level survey data set, this paper provides the positive effects of trade shock on health.

Lastly, this paper contributes to a burgeoning literature that assesses the causal impact of early childhood health interventions on long-term outcomes (Hoynes, Schanzenbach, and Almond, 2016; Billings and Schnepel, 2018; Huang, Lei, and Sun, 2021; Bianchi, Lu, and Song, 2022; Akresh, Halim, and Kleemans, 2023; Barham, Kuhn, and Turner, 2023). Traditionally, prior studies have investigated the roles of various interventions such as safety nets (Hoynes, Schanzenbach, and Almond, 2016), cash transfers (Bronchetti, Christensen, and Hoynes, 2019; González and Trommlerová, 2022), health insurance (Huang and Liu, 2023), public health programs (Hoehn-Velasco, 2021), nutrition programs (Lundborg, Rooth, and Alex-Petersen, 2022; Deng and Lindeboom, 2022), computer-assisted learning (Bianchi, Lu, and Song, 2022), and education (Akresh, Halim, and Kleemans, 2023). For instance, Hoynes, Schanzenbach, and Almond, 2016 and Billings and Schnepel, 2018 delve into the benefits of early-life health interventions. This paper adds to this body of literature by providing further evidence that exposure to trade shock during early life significantly enhances children's cognitive outcomes during adolescence.

Section 2.2 of this paper provides background on China's WTO accession. Section 2.3 explains the two channels of trade shock in a conceptual framework. Section 2.4 describes various data sources and measurements. Section 2.5 discusses my empirical framework. Section 2.6 presents empirical results, and Section 2.7 analyzes the mechanisms. Section 2.8 provides additional robustness checks. And Section 2.9 concludes.

2.2 Background

2.2.1 China's WTO and tariff reduction

Over the past twenty-five years, China has undergone a remarkable process of structural transformation alongside rapid economic expansion. Concurrently, there has been a significant surge in China's manufacturing exports, which escalated from 2% to 19% of global manufacturing exports (Erten and Leight, 2021). China has consistently pursued economic liberalization since the early 1990s, epitomized by its accession to the World Trade Organization (WTO) in 2001. Before its accession to the World Trade Organization (WTO), during the period from 1995 to 2001, the annual nominal growth rate of exports to the US was approximately 14%. However, following its WTO accession, spanning from 2002 to 2008, this rate surged to 25% (Liu and Ma, 2020).

China's WTO accession precipitated substantial alterations in its tariff regime. Preceding its WTO membership, China navigated a landscape of bilateral trade agreements with select partners, affording preferential treatment to specific trading allies. However, upon WTO entry in 2001, China assumed the obligation to grant Most Favored Nation (MFN) status to all WTO members, necessitating tariff reductions, quota eliminations, and the dismantling of other trade impediments on imports from fellow WTO nations.[4] In essence, China's WTO accession precipitated a paradigm shift in its trade policy, notably in its MFN treatment approach, fostering heightened trade liberalization and deeper entrenchment within the global economic framework.

Figure 2.1 illustrates the trajectory of average tariff rates imposed by foreign countries on Chinese manufacturing exports from 1998 to 2005. Initially, China's simple average applied tariff stood at 11% in 1998, progressively diminishing to 7% by the conclusion of 2005. The blue line denotes data sourced from the WITS Trains database, while the red line reflects my computed figures elucidated in Section 2.5 Equation 2.9. Despite both sets of tariff data indicating a marked decline in tariffs on Chinese exports, the reduction trajectory following WTO accession displayed fluctuations. This dynamic can be attributed to a transitional phase during which tariffs on Chinese exports remained relatively elevated as nations acclimated to China's newfound status as a WTO participant. Throughout this interim period, some countries retained higher tariff levels on Chinese exports until they fully assimilated the alterations in trade regulations.

Moreover, Figure 2.1 delineates China's average tariff reduction, which underwent a relatively stable phase from 1997 to 2001, followed by another gradual reduction in 2002, culminating in a plateau by 2005. This pattern ensued as part of China's commitment to join the WTO, which entailed a sweeping and widespread average tariff reduction from 42.9% to 17% between 1992 and 1997. Subsequently, there was minimal fluctuation in tariffs until China's WTO accession at the close of 2001. In early 2002, China commenced fulfilling its tariff reduction obligations as a WTO member. [5]

2.2.2 Trade and human capital accumulation

The preceding context highlights the profound impact of China's accession to the WTO on its economic and social landscape. Given China's significant population size and the pressing environmental challenges it faces, this study delves into how the WTO accession during individuals' early years influences their health and educational outcomes during adolescence.

For instance, trade liberalization has been associated with economic advantages and employment prospects for local households (Erten and Leight, 2021; Fei, 2022; Khanna et al., 2023). Moreover, parental economic status plays a crucial role in shaping children's long-term human capital accumulation (Almond, Currie, and Duque, 2018; González and Trommlerová, 2022). From this view, we may expect trade liberalization help improve people's long term human capital outcoems. However, existing literature on trade and the environment presents mixed findings, suggesting a link between trade and increased pollution levels (Chen et al., 2020; Chen, Shao, and Zhao, 2023), as well as the emergence of cleaner manufacturing firms (Rodrigue, Sheng, and Tan, 2022; Lin, Huang, and He, 2023). Additionally, early-life environmental exposures have been connected to later labor market outcomes and human

[4]For instance, China was provisionally granted Normal Trade Relations (NTR) status, subject to an annual review by the U.S. Congress. Had China lost its MFN status, the prevailing average tariff rate, standing at 4% in 2000, would have surged to 31% (Handley and Limão, 2017).

[5]Lu and Yu, 2015 report that China's weighted average tariffs on foreign goods decreased from 9.1% to 6.4% between 2001 and 2004, aligning closely with my analysis of foreign countries' tariffs on Chinese exports, which reduced from 9% to 7%.

capital development (Isen, Rossin-Slater, and Walker, 2017; Grönqvist, Nilsson, and Robling, 2020).

Thus, I initiate my analysis by documenting preliminary evidence concerning China's tariff reductions and the subsequent changes in human capital indicators among Chinese adolescents following its WTO accession.

2.2.3 Descriptive evidence

Here, I present a descriptive analysis examining the relationship between each prefecture's exposure to tariff cuts and the health and cognitive indices at the prefecture level, as depicted in Figure 2.2. The figure illustrates the changes in health and cognitive variables between 1999 and 2005 against the changes in each prefecture's exposure to tariff cuts during the same period. The unhealthiness index and the cognitive index utilized in this analysis are derived from the CPFS survey dataset, with detailed construction outlined in Section IV. The changes in exposure to trade shocks are computed based on Equation 2.5, wherein prefectures are categorized into 20 bins according to their variations in trade shock.

Overall, as depicted in panel (a), prefectures exhibiting higher exposure to tariffs cuts (situated to the right side of the x-axis) demonstrate a reduced increase in the unhealthiness index. Meanwhile, panel (b) reveals that prefectures with greater exposure to tariffs cuts experience a more substantial increase in the cognitive index. Although the F-test and t-value do not indicate statistical significance for both coefficients, the signs of these coefficients offer preliminary evidence suggesting that tariffs cuts may contribute to improvements in health and cognitive scores.

2.3 Conceptual Framework

The descriptive findings above suggest that prefectures with greater exposure to tariff reduction exhibit better adolescents' health outcomes and cognitive outcomes. To elucidate the mechanisms through which trade shock during early life influences human capital in adolescence, I introduce a conceptual framework termed "early-life tariff exposure with pollution channel and economic channel," building upon insights from Aguilar-Gomez et al., 2022 and Arenberg and Neller, 2023.

Given the focus of this study on the effects of early-life trade shock, I employ a two-period utility function to model the impact of early-life shocks on human capital outcomes. First, in the infant period, childhood health (h_1) is determined as a function of genetic endowments (h_0), trade shock income channel (i_1) and trade shock environment channel (p_1), so that ($h_1 = h_1(h_0, i_1, p_1)$). Specifically, I use the following equation to show the effect of tariff reduction:

$$h_1 = h_1(h_0, i_1(\tau), p_1(\tau)) \tag{2.1}$$

where τ represents the average trade tariffs, which can influence human capital through both the income channel and pollution channel of trade shock. Specifically, $i_1(\tau)$ denotes the income channel, capturing the effects of foreign demand on regional firms' revenues, subsequently affecting the child's household income (Lu and Yu, 2015; Erten and Leight, 2021). Because infants do not have job and income, I assume this income channel is from their parents' investment. The environmental channel p_1 indicates that tariff reduction can impact local pollution concentrations (Chen et al., 2020; Chen, Shao, and Zhao, 2023; Rodrigue, Sheng, and Tan, 2022; Lin, Huang, and He, 2023). And pollution can further affect child's health. Hence, the decrease in export tariffs manifests two effects on the contemporaneous health outcomes of children:

$$\frac{\partial h_1}{\partial \tau} = \underbrace{\frac{\partial h_1}{\partial i_1}\frac{\partial i_1}{\partial \tau}}_{\textit{Income channel}} + \underbrace{\frac{\partial h_1}{\partial p_1}\frac{\partial p_1}{\partial \tau}}_{\textit{Pollution channel}} \tag{2.2}$$

In this paper, I do not clearly specify the sign of each channels because of mixed evidence on the two effects. On one hand, the reduction of trade tariffs can influence foreign demand, firm productivity, and regional labor market outcomes (Amiti and Konings, 2007; Lu and Yu, 2015; Brandt et al., 2017; Fieler, Eslava, and Xu, 2018; Tombe and Zhu, 2019; Fiorini, Sanfilippo, and Sundaram, 2021). Previous studies have demonstrated that this can ultimately lead to increases in local wages, labor demand, and employment (Han et al., 2016; Erten and Leight, 2021), and better parental economic conditions can potentially improve children's health outcomes, as indicated by $\frac{\partial h_1}{\partial i_1}\frac{\partial i_1}{\partial \tau} < 0$. However, the income channel may also have adverse effects on health. For instance, extensive research on the "China shock" suggests that this trade channel can intensify regional import competition, thereby potentially compromising workers' health due to unemployment (Autor, Dorn, and Hanson, 2013; Pierce and Schott, 2020). Moreover, another study by Fan, Lin, and Lin, 2020 suggests that China's WTO accession has exacerbated mental health issues among workers.

For the pollution channel, the reduction of trade tariffs can increase local pollution concentrations through more production, potentially adversely affecting health $\frac{\partial h_1}{\partial p_1}\frac{\partial p_1}{\partial \tau} > 0$. This health effect encompasses mortality rates (Chen et al., 2020; Bombardini and Li, 2020; Gong et al., 2023). However, recent research suggests that the reduction of trade tariffs can also lead to decreases in emissions from regional firms (Cherniwchan, Copeland, and Taylor, 2017; Rodrigue, Sheng, and Tan, 2022; Lin, Huang, and He, 2023). Given that firms' emissions contribute significantly to regional pollution concentrations, we can hypothesize that such reductions may ultimately improve health $\frac{\partial h_1}{\partial p_1}\frac{\partial p_1}{\partial \tau} < 0$.

In the second period, individuals pursue schooling (e), with educational outcomes being contingent on childhood health and contemporaneous shocks.[6] A considerable body of literature elucidates the connection between early-life health shocks and children's long-term educational achievements (Almond, Currie, and Duque, 2018; Zhou and Wang, 2023; Villadsen et al., 2023). Hence, I assume educational attainment e depends on health status in the initial phase h_1, and current health status h_2:

$$e = e(h_1; h_2) = e\left(h_0, i_1(\tau), p_1(\tau); h_2\right) \tag{2.3}$$

Because health is seen as a positive input into the educational outcomes, i.e., $\frac{\partial e}{\partial h_1} > 0$, the educational attainment in adolescence is affected by childhood trade shock from two channels:

$$\frac{\partial e}{\partial \tau} = \underbrace{\frac{\partial e}{\partial h_1}\frac{\partial h_1}{\partial i_1}\frac{\partial i_1}{\partial \tau}}_{\textit{Income channel}} + \underbrace{\frac{\partial e}{\partial h_1}\frac{\partial h_1}{\partial p_1}\frac{\partial p_1}{\partial \tau}}_{\textit{Pollution channel}} + \underbrace{\frac{\partial e}{\partial h_2}\frac{\partial h_2}{\partial \tau}}_{\textit{Contemporaneous channel}} \tag{2.4}$$

In Equation 2.4, it is evident that reductions in trade tariffs influence educational outcomes via both the income channel and the trade-induced pollution channel in the first two terms. Based on the preceding analysis, the enduring impact of early-life trade shocks on educational outcomes during adolescence remains ambiguous due to conflicting evidence regarding the effects of tariff reductions on pollution. Referencing insights from Bombardini and Li, 2020, Figure 2.3 is employed to elucidate the comprehensive framework of this study, depicting the relationship between export tariffs and long-term human capital outcomes through both the pollution and economic channels. In addition, the tariffs reduction can have the contemporaneous effects on adolescents' health, as shown in extensive trade shock literature (Pierce and Schott, 2020; Fan, Lin, and Lin, 2020; Guerrico, 2021). Because this paper focuses on the impacts of early-lefe trade shock, I will ignore the details about the contemporaneous effects on adolescents.

2.4 Data and Measurement

Having established the conceptual framework, I now transition to the empirical analysis. The data utilized in this study comprises trade exports, tariffs, health indicators, cognitive test scores, SO_2 emission intensity, and prefecture characteristics, sourced from various databases.

[6]While all citizens are mandated to complete a minimum of nine years of schooling (i.e., nine-year compulsory education), households have the option to select schools with varying educational resources.

2.4.1 Export shock and tariffs

I employ product-level bilateral trade data sourced from WITS (UN Comtrade), documented at the 6-digit level within the "Harmonized System" (HS92) for the time-frame spanning 1997 to 2005. This dataset encompasses export values in thousand US dollars from China to 200 countries worldwide. To ensure compatibility with other industry-level datasets, I subsequently convert HS product codes into 4-digit International Standard Industrial Classification (ISIC) Rev.3 codes using the WITS Concordance. Tariff data faced by Chinese exporters in each country, at the 4-digit ISIC Rev.3 level, is obtained from the TRAINS database for the period spanning 1997 to 2005. Finally, to streamline the analysis, I convert the 4-digit ISIC codes of exports and tariffs into 3-digit CSIC codes utilizing the Industrial Classification for National Economic Activities (GB/T 4754-2002).

As shown in the conceptual framework, I define two channels of trade shock using the measurement proposed by Bombardini and Li, 2020. First, I construct economic channel of trade shock ExpShock as follows:

$$\text{ExpShock}_{ct} = \sum_k \frac{L_{ck,1990}}{L_{k,1990}} \frac{\Delta X_{kt}}{L_{c,1990}} \tag{2.5}$$

In this context, $\frac{L_{ck,1990}}{L_{k,1990}}$ denotes the employment share of industry k in prefecture c in the year 1990, where $L_{k,1990}$ represents the total national employment of industry k in the same year. To capture each prefecture's export endowments during the period leading up to WTO accession, I utilize the labor share from the initial year preceding the outcome period. ΔX_{kt} signifies the annual change in total export values for industry k in year t. Consequently, $\frac{\Delta X_{kt}}{L_{c,1990}}$ indicates the annual change in export values (in thousand USD dollars) per unit of labor. In essence, prefectures characterized by a greater proportion of products undergoing significant export expansion would exhibit heightened exposure to trade shock. And this variable represents the income channel of trade liberalization, which measures the dollar value of export expansion per worker (i.e., $1000 per worker).

Second, I measure pollution effect of pollutant SO_2 induced by trade exposure for each prefecture c in year t by adding each industry's emission intensity $\gamma_k^{SO_2}$ in initial year 1999 to Equation 2.5:

$$\text{PollShock}_{ct}^{SO_2} = \sum_k \gamma_k^{SO_2} \frac{L_{ck,1990}}{L_{k,1990}} \frac{\Delta X_{kt}}{L_{c,1990}} \tag{2.6}$$

This $\text{PollShock}_{ct}^{SO_2}$ variable measures the pounds of SO_2 associated with export expansion measured on a per worker basis. The interpretation is as follows: different industries exhibit varying emission intensities. Consequently, industries experiencing greater increases in export flows will generate higher emissions when these flows are interacted with their respective emission intensities. I weight this industry-emission intensity by each prefecture's initial labor employment share. This implies that prefectures with more emission-intensive industries will experience a larger trade-induced pollution shock if those industries are more exposed to trade. Thus, this variable can capture each prefecture's exposure to emission induced by trade shock.[7]

[7] As a robustness check, I also report the results using alternative emission intensity.

2.4.2 Household data

China Family Panel Studies (CFPS): To examine the longer-term effects of trade expansion on human capital, I rely primarily on the CFPS, which includes six survey waves in 2010, 2012, 2014, 2016, 2018, and 2020. The CFPS survey has been widely used to analyze the long-term impact on household human capital (see, e.g., Li et al., 2019; Deng and Lindeboom, 2022; Bianchi, Lu, and Song, 2022; Huang and Liu, 2023). To measure adolescents' human capital, I employ health and cognitive test outcomes.

Health: I collect information on several health outcomes of adolescents from their answers in the survey of CFPS 2010–2020. First, I use self-assessed general health status, rated on a 5-point scale (excellent, very good, good, fair, or poor). I construct a binary bad health indicator that takes the value of 1 if the adolescent reports poor and 0 otherwise. My second measure of health is hospitalization, which indicates whether the adolescent has been admitted to a hospital due to illness (i.e., spent the night at the hospital) during the previous year. The third measure I analyze is an indicator of whether the adolescent is underweight, which equals 1 if individual's BMI score is less than 18. I also construct unhealthiness index by taking the first principal component from a principal components analysis (PCA) on the three health measures.[8]

Cognitive tests: I use two cognitive test scores which have been extensively employed in prior literature (e.g., Li et al., 2019; Bianchi, Lu, and Song, 2022; Huang and Liu, 2023; Kim and Wang, 2023): a verbal test score, based on 34 verbal questions, and a math test score, based on 24 mathematics questions, administered in CFPS 2018. Both cognitive scores are standardized and calculated as age-specific z-scores. [9] Again, I construct cognitive index by taking the first principal component from a principal components analysis (PCA) on the math and verbal test.

I also consider several control variables, including individual's gender, and urban/rural status.

2.4.3 Emission intensity

I compute industry emission intensity utilizing data on pollution emissions and output from the Annual Environmental Survey of Polluting Firms (AESPF) in 1999.[10] This dataset, administered by the Ministry of Ecology and Environment (MEE), offers comprehensive insights into firms' environmental practices.

The AESPF provides detailed information on various aspects of firms' environmental performance, encompassing metrics such as emissions of primary pollutants (e.g., annual SO_2 emissions per firm in kilograms), the presence of pollution abatement equipment, and energy consumption. Therefore, I calculate each firm's SO_2 emission intensity and subsequently aggregate these values based on the CSIC 3-digit codes.[11]

[8] PCA forms the basis of multivariate data analysis based on projection methods. The first principal component is the line that minimizes the sum of squared distance between a data point and the line, and accounts for as much variation in the data as possible. So I use this method to construct two indices in this paper.

[9] Only CFPS 2010, 2014 and 2018 survey document the test scores for children, and I use CFPS 2018 to obatain cross-sectional comparison.

[10] The data in 1999 serves as the initial year before the WTO accession for pollution measure construction. Because I can not obtain the earlier data in 1990, I use the data in 1999 to calculate the emission intensity.

[11] The 3-digits industry employed in this paper is listed in the Appendix Table 2.16.

In this paper, the pollution intensity of pollutant SO_2 for each firm f in year 1999 can be calculated as follows:

$$\gamma_f^{SO2} = \frac{P_f^{SO2}}{Y_f} \tag{2.7}$$

Here, P_f^{SO2} represents the total SO2 emissions of firm f in year 1999, while Y_f denotes the total output in thousand US dollars of firm f during the same period. Upon computing the emission intensity for each firm, I aggregate these values by Chinese Industrial Classification (CIC) 3-digit codes to derive the emission intensity γ_k^{SO2} for each industry k. Additionally, I incorporate other pollutant total emissions (such as NO_2 and $PM_{2.5}$) in the robustness checks.

2.4.4 Sample

I limit the sample to cohorts born between 1999 and 2005, ensuring that individuals fall within the age range of 13 to 19 years old across all five waves. Consequently, the dataset comprises approximately 17,377 observations. However, due to incomplete reporting of wordtest and mathtest scores by some individuals, the sample size for the cognitive test analysis is relatively modest. Table 2.1 presents an overview of the key variables examined in this study.

2.5 Research Design

In this section, I delineate my specification and identification strategy. To discern the impact of exposure to trade expansion on children's life trajectories, I predominantly rely on the changes in tariffs induced by WTO accession as a pivotal determinant of future export activities (Kovak, 2013; Dix-Carneiro, Soares, and Ulyssea, 2018; Tian, 2022).

2.5.1 Specification

Employing the two regressors, I estimate the ordinary least squares (OLS) specifications:

$$y_{ict} = \alpha + \beta \text{ExpShock}_{ct} + \theta \text{PollShock}_{ct}^{\text{SO}_2} + X'_{ict}\delta + \mu_c + \eta_t + \varepsilon_{ict} \tag{2.8}$$

where y_{ict} is one of long-run health and cognitive attainments for individual i born in prefecture c in year y.[12] The right hand variables of interest are ExpShock_{ct} and $\text{PollShock}_{ct}^{\text{SO}_2}$, measuring the income shock and pollution shock due to trade exposure, respectively.[13] X'_{ict} controls children's gender and rural/urban type. μ_c and η_t are prefecture and birth year fixed effects. Because the population sizes in each prefecture vary substantially, I weight the regression by the CFPS survey weights. Standard errors in my baseline estimates are clustered at the province-level, an approach that allows for correlation of errors within provinces, and which therefore yields conservative estimates of statistical significance. Because this paper focuses on the early life shocks experienced by different cohorts, I utilize their birth years for

[12] Because I use only 2018 wave of CFPS data set to measure test scores, I drop the survey year fixed effect in test score specification. And I include the survey fixed effect in health specifications.

[13] Following Bombardini and Li, 2020, I use the variable ExpShock_{ct} to proxy the trade-induced income benefits.

matching purposes. For instance, my sample includes cohorts born between 1999 and 2005, which I align with the export shocks occurring from 1999 to 2005 based on their respective birth years. The dependent variable concerning cognitive outcomes is recorded in the year 2018, while health outcomes are documented across all waves of data collection.

2.5.2 Identification strategy: an instrumental variable approach

After controlling for prefecture fixed effects and individual characteristics, there remains a concern that ExpShock_{ct} and $\text{PollShock}_{ct}^{SO_2}$ might still be endogenous and correlated with other unobserved variables. The presence of omitted variables suggests that China's WTO accession and other policy changes could concurrently influence exports and the long-term health and education outcomes of children.

To mitigate these identification concerns, I adopt a strategy from prior literature that substitutes domestic policy changes with international policy changes. For instance, Autor, Dorn, and Hanson, 2013 utilize exports from China to other developed countries excluding the US to construct the Bartik instrument for each US county. Another approach, employed by Li, 2018, Bombardini and Li, 2020 and Fei, 2022, utilizes predicted exports estimated by global tariffs as instruments. This method assumes that changes in external tariffs fall under a country's own jurisdiction and are politically determined by foreign countries. Consequently, these tariffs are considered exogenous to China's internal shocks and are uncorrelated with the economic conditions in China.

I follow Bombardini and Li, 2020 and estimate the trade flows of China using the tariff data set. First, I construct an industry-level tariff faced by Chinese exporters with weighted average of tariffs imposed by different countries, as follows:

$$\text{ExTariff}_{kt} = \sum_j \frac{X_{jk,t-2}}{X_{k,t-2}} \tau_{jkt} \tag{2.9}$$

where τ_{jkt} denotes the tariff of industry k (3-digit CSIC) imposed by country j in year t. The weights are determined by the country j's share in China's total exports in industry k in the year of $t-2$, which uses the export values from two years earlier. [14]

I posit that the growth in total exports can be explained by a decrease in the level of tariffs faced by exporters, so I adopt the following specification to estimate the trade flows:

$$lnX_{kt} = \theta ln(1 + \text{ExTariff}_{kt}) + \eta_k + \phi_t + \varepsilon_{kt} \tag{2.10}$$

where η_k and ϕ_t are industry and year fixed effects. I report the results of this regression in Figure 2.4, where the estimated coefficient implies that a 1% decrease in the tariff faced by exporters increases exports by 3.5%. My estimate is within the range of gravity equation estimates of the effect of bilateral trade frictions as in Bombardini and Li, 2020 who obtain the coefficients with 7.8%. The larger magnitude in their results may be caused by a more pronounced export surge and tariff reduction in their sample period (1985-1995).[15]

[14] Equation 2.9 uses the trade flows ahead the tariff year to avoid endogeneity as in Bombardini and Li, 2020.

[15] The average tariffs declined from 43.2% to 23% over the period from 1985 to 1995. In my sample period from 1999 to 2005, the average tariffs fell from 17% to 9.8%.

I then obtain the fitted value of the logarithm of exports by taking the exponential of such predicted value to obtain $\hat{X}_{kt}$, which serves as instrument in my paper:

$$\hat{X}_{kt} = exp\left(\hat{\eta}_k + \hat{\phi}_t + \hat{\theta} ln(1 + \text{ExTariff}_{kt})\right) \tag{2.11}$$

I plot the trends of the original exporting data X_{kt} and the fitted value of exporting value $\hat{X}_{kt}$ in panel (a) of Figure 2.5. The two parallel trends show that my estimated trade flows data fits the original data well. The panel (b) of Figure 2.5 presents binned scatter plots of first stage from the IV specification. I use the residualized variables to remove variation that can be attributed to the fixed effects. Panel (b) confirms that there is a tight relationship between the (residualized) predicted export shock IV ($\widehat{\text{ExpShock}}_{ct}$) and the original export shock variable (ExpShock_{ct}).

I then employ instrumental variables that are constructed using predicted exports derived in Equation 2.13 and 2.12. The two instrumental variables and the IV specification are constructed as follows:

$$\widehat{\text{ExpShock}}_{ct} = \sum_k \frac{L_{ck,1990}}{L_{k,1990}} \frac{\Delta \hat{X}_{kt}}{L_{c,1990}} \tag{2.12}$$

$$\widehat{\text{PollShock}}^{SO_2}_{ct} = \sum_k \gamma_k^{SO_2} \frac{L_{ck,1990}}{L_{k,1990}} \frac{\Delta \hat{X}_{kt}}{L_{c,1990}} \tag{2.13}$$

$$y_{ict} = \alpha + \beta \widehat{\text{ExpShock}}_{ct} + \theta \widehat{\text{PollShock}}^{SO_2}_{ct} + X'_{ict}\delta + \mu_c + \eta_t + \varepsilon_{ict} \tag{2.14}$$

The right hand variables of interest are the Bartik-IV $\widehat{\text{ExpShock}}_{ct}$ and $\widehat{\text{PollShock}}^{SO_2}_{ct}$, measuring the income channel and pollution channel due to trade exposure, respectively.

2.6 Results

2.6.1 OLS results

I first present the OLS estimation results in Table 2.2 of Equation 2.8. I include the trade shock and trade-induced pollution shock in each specification.

Column (1) and (4) confirm that export shock significantly improve health outcomes in terms of decreased hospital admissions and unhealthiness index, while trade-induced pollution shock increase the two outcomoes. Column (5) to (7) indicate that trade shock increase the math and verbal test $z-$ score and cognitive test index, while trade-induced pollution shock decrease those cognitive test scores. The standard deviation of unhealthiness index is 1, so a one-standard-deviation more positive export shock would decrease the unhealthiness index by 0.0235, and a one-standard-deviation more pollution shock would increase the index by 0.0015. In addition, a one-standard-deviation more positive export shock would increase the cognitive test index by 0.0292, and a one-standard-deviation more pollution shock would decrease the index by 0.0027.

2.6.2 IV results: health

I next turn to the results for health and cognitive test outcomes by using IV estimation in Table 2.3. Column (1), (2) and (4) in Table 2.3 show that a one standard deviation increase in trade shock significantly improve the people's health in long term, which reduce unhealthiness index by 0.025; while a one standard deviation increase trade-induced pollution shock increase this index by 0.002, respectively. Another way to express the magnitude is to use the change of 1000 USD to describe the magnitude. Taking the IV estimation in column (4) of Table 2.3 as the baseline, an increase of $1,000 in a prefecture's export per worker would reduce 25 additional unhealthiness index and an increase of $1,000 in a prefecture's export-induced pollution per worker would induce 2 additional unhealthiness index.

Additionally, Panel (a) of Figure 2.6 plots coefficients of each component of unhealthiness index. This indicates that the reduction of unhealthiness index is mainly through less child's hospital admission rate and better self-rating health conditions. As a comparison, Huang and Liu, 2023 finds that the exposure to NCMS in early childhood is associated with an unhealthiness index that is approximately 0.29 standard deviations lower, a 11.9-percentage-point decrease in the likelihood of not being in good health, a, 5.5-percentage-point decrease in the risk of hospitalization, and a 10.4- percentage-point decrease in the probability of being underweight in adolescence.

The associated first stage estimates are reported in Panel B. There is a positive correlation between ExpShock and PollShock, and their instruments $\text{Exp}\widehat{\text{Shock}}$ and $\text{Poll}\widehat{\text{Shock}}$. As suggested by Angrist-Pischke F-statistics, both instruments are strong.

2.6.3 IV results: cognitive test

The reults in Table 2.4 indicate that trade exposure during the early-life increases adolescent cognitive performance in long term as shown in column (3), (6) and (7). One-standard-deviation more trade shock would raise the cognitive test index by 0.022, and a one-standard-deviation more trade-induced pollution shock would decrease the index by 0.002. To describe the magnitude, an increase of $1,000 in a prefecture's export per worker would induce 22 additional cognitive index and an increase of $1,000 in a prefecture's export-induced pollution per worker would reduce 2 additional index.

The IV regression results are similar to the OLS results in magnitude. Panel (b) in Figure 2.6 plots the impacts on two test scores and the cognitive test index, and it indicates positive effects of trade shock and negative effects of trade-induced pollution shock. Overall, my results are comparable to other estimates on China human capital accumulation. For example, Li et al., 2019 shows that a 1-percentage-point reduction in the tariff rate is associated with a 0.283 standard deviation reduction in math test scores, so trade liberalization from 1990 to 2010 resulted in a 1.415 standard deviation reduction in cognitive abilities.

2.6.4 Heterogeneous effects

By Parental income: I further use parents' income to proxy household socioeconomic status before the China's WTO accession. Table 2.5 reports the effects on cognitive test socres separately for children with parents below a 25^{th} percentile income or above 75^{th} percentile income. The effects are more significant and larger in the parents with low income as shown in column (1) and (3). Consistent with Almond, Currie, and Duque, 2018, these findings suggest that trade shock in early childhood could help reduce socioeconomic disparities in cognitive test outcomes. Besides, the trade-induced pollution shock are also more pronounced among them, suggesting that those people face more pollution exposure and bear more trade-induced pollution costs.

2.7 Mechanisms

The positive effects of trade shock and the negative effects of trade-induced pollution shock on children's long term health and cognitive outcomes suggest that trade liberalization has deep influence on human capital accumulation through two channels. Given the main results presented above, it is essential to understand the specific mechanisms through which exposure to trade expansion in early childhood can lead to an improvement in adolescent outcomes. I investigate the role of regional health and education development and firms' emissions in Table 2.6 and estimate the contemporaneous effects of trade liberalization on those measures. I choose these three main roles because they are related directly to people's long-term health and cognitive outcomes. Early life health infrastructure can improve long-term health, and the better education resources can improve the education outcomes. Specifically, the variable bed denotes the log of number of hospital bed, and the variable doctor denotes the log of number of local doctors. The variable elementary school denotes the number of elementary school per capita. I also used the exporter's SO_2 emissions in column (4). The health and education data are from the China City Statistical Yearbook, and the SO_2 emissions data are from the Annual Environmental Survey of Polluting Firms (AESPF) .

In columns (1) and (2), I find evidence that trade shock is correlated with more hospital bed numbers and doctor numbers. Column (3) indicates that trade shock increases elementary school per capita, which can explain why trade shock can increase people's long term cognitive outcomes. Because both of them are at log scale, the magnitude suggests that a $1,000 increase in exports per worker would lead to 0.1% increase in the number of hospital bed, and 0.6% increase in the number of elementary school teacher. In column (4), I find that trade shock reduces local firms' SO_2 emissions. This negative results can explain why the magnitude of trade-induced pollution shock is less than the trade shock.

Also, this finding aligns with the literature showing that trade liberalization decreased emissions (Rodrigue, Sheng, and Tan, 2022; Lin, Huang, and He, 2023). For example, Rodrigue, Sheng, and Tan, 2022 show that exporting reduces emissions-intensity by at least 36 percent across air pollutants, and abatement equipment, product scope and capital-vintage can account for this clean-up. And Lin, Huang, and He, 2023 show that decrease in trade policy uncertainty can reduce emission intensity of Chinese exporting firms. Overall, these results show that trade shock induce more health and education infrastructure investment and less emissions, which can improve people's long term human capital outcomes.

2.8 Robustness

I conduct a variety of robustness tests to ensure that the effects of export shock and pollution shock do not qualitatively change much.

2.8.1 Using different birth cohorts

My sample includes all individuals born between 1999 and 2005, which are exposed to China's WTO accession at early life. Here, I show that pre-WTO birth cohorts are not significantly affected by the early life trade shock. Therefore, I incorporate individuals born between 1988 and 1995, who were of schooling age during the exposure to the trade shock. The lack of significance among the older cohorts suggests that trade shock and trade-induced pollution shock influence individuals primarily during their early life stages. The coefficients presented in Table 2.7 do not attain significance, further affirming the influence of early life trade shock. The trade-induced pollution shock in column (2) to (4) is much smaller than my main results (0.002), implying that trade has little effect on their cognitive outcomes.

2.8.2 Alternative measure of pollution

In the main text, I use the SO_2 emission intensity for each industry interacted by the trade shock to measure each prefecture's trade-induced pollution shock. As suggested by Bombardini and Li, 2020, Chinese prefectures are exposed to very different sulfur dioxide and particulate matter concentrations. And SO_2 concentration over time show even more heterogeneity. This variation can help us capture the effects of trade-induced pollution shocks. Also, Liu, Tan, and Zhang, 2021 argues that the SO_2 is the main target of the central government of China for air pollutants control, and COD is mainly for water pollutants control. Here, I test the role of trade-induced pollution shock by using NO_2 and $PM_{2.5}$ in 1999 to measure emission intensity, and the construction is as the same as in Equation 2.7:

$$\gamma_f^{NO2} = \frac{P_f^{NO2}}{Y_f} \tag{2.15}$$

$$\gamma_f^{PM2.5} = \frac{P_f^{PM2.5}}{Y_f} \tag{2.16}$$

Column (1), (4), (5) and (8) in Table 2.8 confirm that the trade-induced pollution shock constructed by NO_2 and $PM_{2.5}$ also have significant influence on unhealth index and cognitive test outcomes.

2.8.3 Balance test

To utilize the shift-share instrumental variable, it is essential that the assumption of identification holds, wherein the shock at the industry level remains uncorrelated with a weighted average of the unobservable local shocks, with the weights reflecting the significance of the industry in the local economy (Borusyak, Hull, and Jaravel, 2022). To assess this, I conduct a balance test analysis. For this purpose, I select GDP per capita, the share of manufacturing employment, exports as a percentage of GDP, per capita fiscal expenditure, and per capita educational expenditure in 1995 as the prefecture characteristics. I then regress these prefecture characteristics on the export shock, pollution shock, and the year dummies, employing average industry exposure as weights. Standard errors are clustered by 2-digit CSIC codes.

Table 2.9 presents the coefficients and standard errors, revealing the absence of statistical significance in the coefficients. Specifically, in columns (3) and (4), I observe that the pollution-export shocks exhibit no statistically significant correlation with any of the prefecture characteristics. This suggests that the pollution-export shocks are not concentrated in prefectures that underwent a relatively rapid increase in GDP per capita. These findings indicate that both export shock and pollution shock could be considered as effectively randomly assigned across industries. Consequently, this provides supportive evidence that the CSIC 3-digit product-level export shocks fulfill the necessary conditions for treatment balance.

2.8.4 Alternative specification

Here, I implement an alternative method for clustered standard errors. I present the estimation results using clustered standard errors at the prefecture level in Table 2.10. Column (1) and (2) replicate the baseline findings, clustered at the prefecture level, demonstrating the robustness of the statistical inference. In column (3) and (4), I display the regression outcomes using unweighted regression, which align with the baseline results. Overall, both specifications indicate that trade shock decrease the unhealthiness index and trade-induced pollution shock can decrease cognitive test scores.

2.8.5 Additional policy

Between 1997 and 2005, various noteworthy environmental policies were implemented and garnered considerable research attention, including the “Two control zone (TCZ)" environmental regulation policy. Tanaka, 2015 demonstrates that the TCZ policy introduced in 1998 represents one of the earliest large-scale regulatory endeavors in a developing nation, leading to a reduction in infant mortality rates.

To mitigate concerns regarding the potential impact of these policies on children’s long-term health and cognitive test scores, I introduce a control variable at the prefecture level. This variable takes a value of one for TCZ prefectures. Table 2.11 presents the regression outcomes with the TCZ prefecture dummy. The results suggest that the adding TCZ policy does not significantly change my baseline estimates in terms of sign and magnitude. Also, the column (1) suggests that the environmental regulation policy can improve health.

2.9 Conclusion

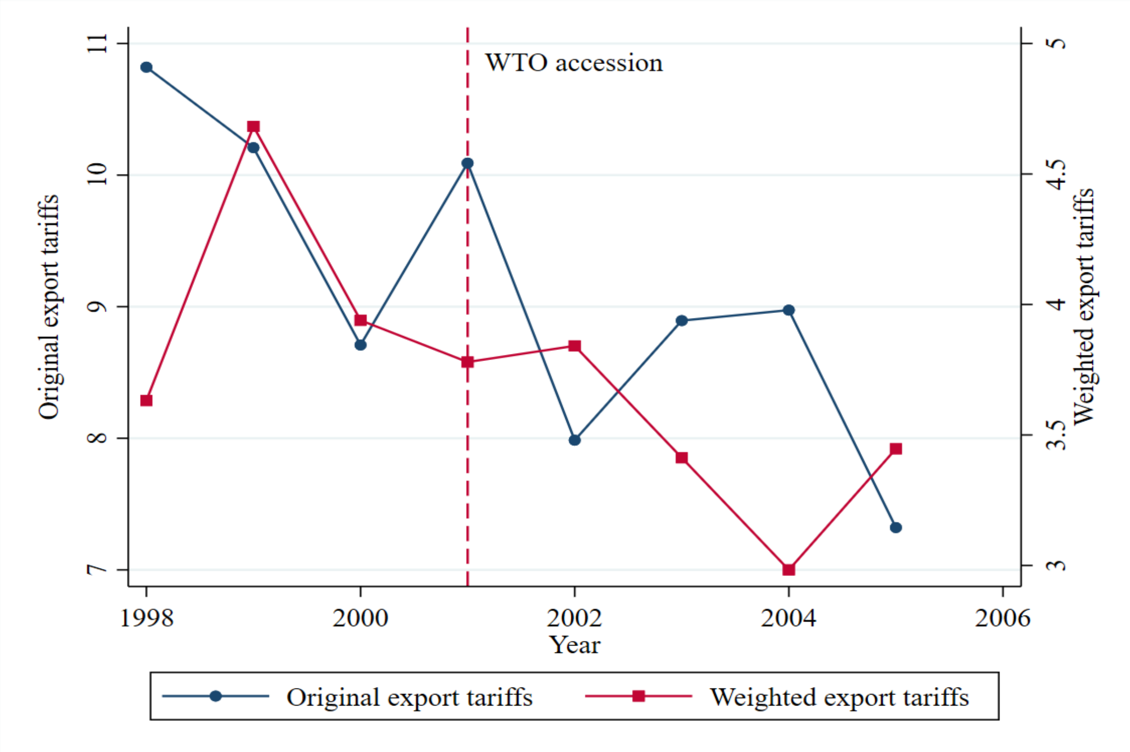
Recent evidence suggests the economic windfall in early childhood would positively influence lifetime success. The trade liberalization cause both economic benefits and pollution concentrations in local. I contribute to this growing literature by providing new evidence on the effects of early-life trade expansion on long term human adolescents’ health and cognitive tests through both trade shock and trade-induced pollution shock.

Compared to those with no exposure, cohorts exposured to trade shocks exhibit a 0.025 standard deviation decrease in unhealthiness index and a 0.022 standard deviation increase in cognitive index among adolescents. In addition, the exposure to trade-induced pollution shock leads to a 0.002 standard deviation increase in a composite health index and a 0.002 standard deviation decrease in cognitive index. I also find heterogeneous effects across household socioeconomic status. I find that low-SES children benefit more from the trade expansion in terms of health and cognitive outcomes. Further investigation indicates that improvements in regional elementary school per capita and decreased firms' SO_2 emissions can be potential mechanisms behind the longer-term benefits of the trade expansion.

My findings contribute to several on-going literature and provide important policy implications. First of all, the investigation of long term effects of trade expansion and trade-induced pollution shock can help us understand the true benefits of costs of trade liberalization. For example, my results emphasize the positive effects of trade expansion on cognitive test scores, which support the policy for trade liberalization in developing countries. In addition, thie paper also provides the evidence that trade-induced pollution can negatively affect people's long term health and education outcomes, and is more pronounced among household with low social economic status.

Overall, my findings suggest that early-life trade shock have positive effects on children's long term health and cognitive scores. However, since the measure of trade-induced pollution shock is derived from directly interacting emission intensities with export shocks, it becomes challenging to compare the two magnitudes and draw conclusions regarding the net social welfare implications of export expansion. This paper recognizes that the findings related to the two channels of export expansion merely indicate their significant effects. Therefore, a crucial task for future research will be to employ a life-cycle quantitative model to analyze in greater detail the benefits and costs associated with these two channels.

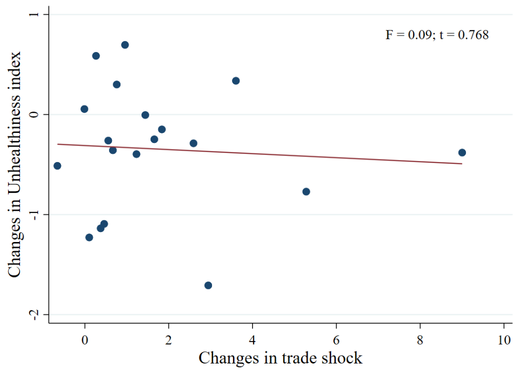
FIGURE 2.1: Trends of tariffs on Chinese exporting goods



Notes: This figure plots the annual exporting tariffs (1998 to 2005) on China's exporting goods reported by the rest of the world in blue line and the calculated tariffs from Equation 2.9 in red line. Data is from WITS Trains database.

Figures

FIGURE 2.2: Scatter plots of export tariffs against human capital

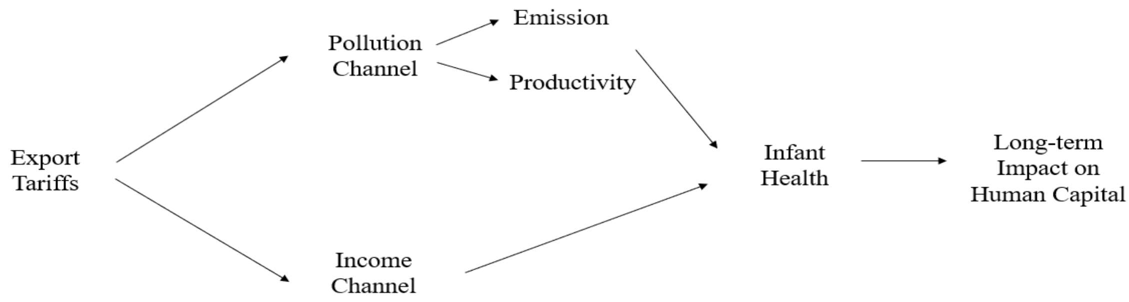


(A) Unhealthiness index

(B) Cognitive index

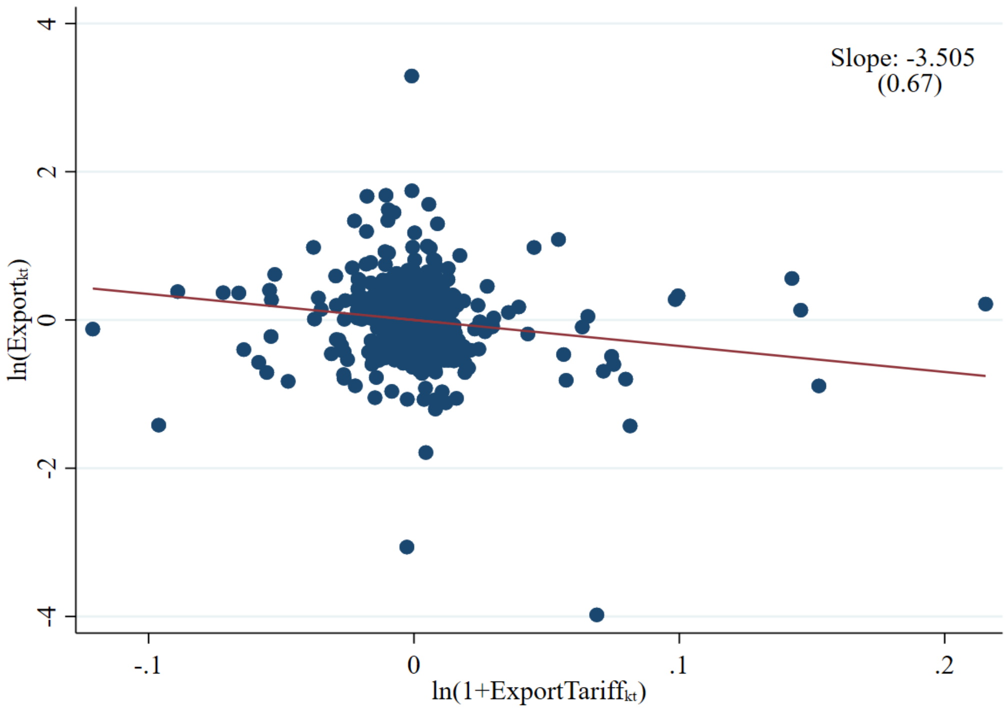
Notes: This figure utilizes data from the CFPS dataset by calculating the mean index for each prefecture and then computing the difference between the years 1999 and 2005.

FIGURE 2.3: Mechanism relating Export Shocks to Long-term Human Capital



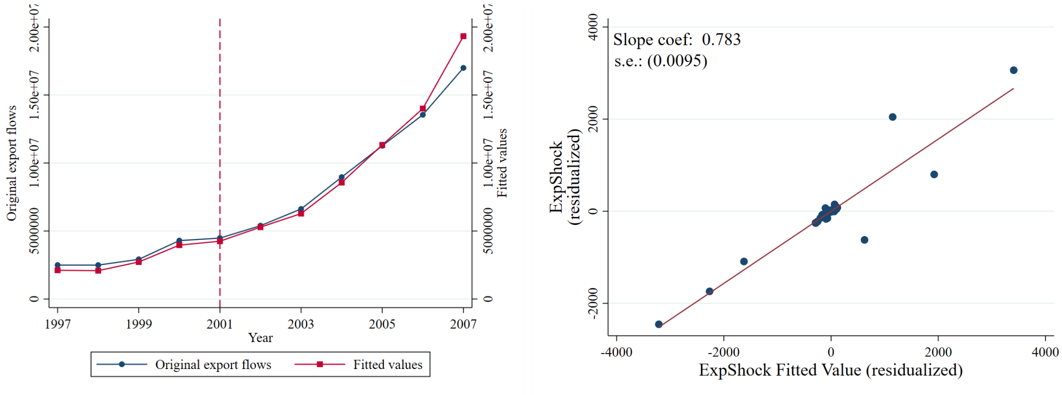
Notes: This mechanism graph follows the pollution channel and income channel analyzed in Bombardini and Li, 2020 with an extension to a long-term impact.

FIGURE 2.4: The relationship between Log(Export) and Log(1+Export Tariff)



Notes: The figure displays the residual scatter plot based on regression 2.10. The regression coefficient is -3.5059 with standard error 0.67 and p-value 0. The data of export and tariff cover 148 3-digit CSIC industries over the period 1999 to 2005.

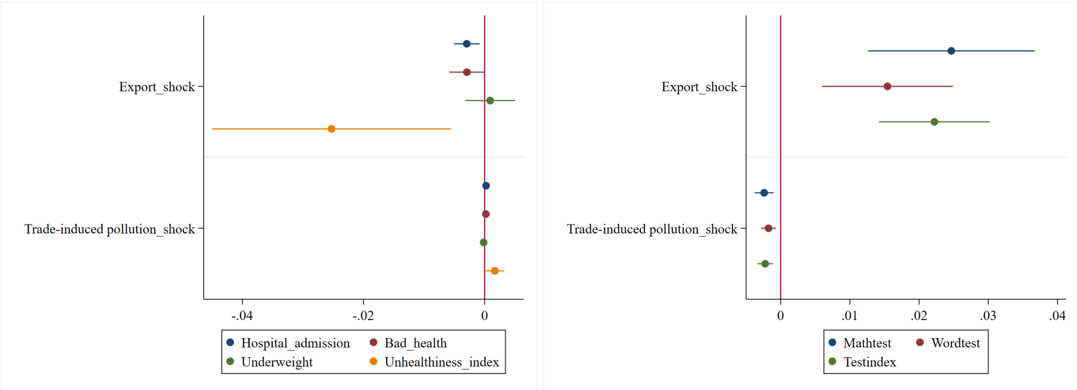
FIGURE 2.5: Trends and scatter plots between original data and fitted value



(A) Trends (B) First stage scatter plots

Notes: Panel (a) plots the original exporting value from the data and my estimated fitted value from the Equation 2.11. Panel (b) plots the first stage scatter plots.

FIGURE 2.6: IV Estimates of Trade Liberalization on Unhealthy and Cognitive Index



(A) Unhealthiness Index (B) Cognitive Index

Notes: Panel (a) plots the IV estimates of trade liberalization on each components of unhealthiness index. Each component is a dummy variable, and the index is a z-score index. Panel (b) plots the effects on each components of cognitive test score index, and all of them are constructed by z-score index.

Tables

TABLE 2.1: Summary Statistics

	Mean	Standard Deviation	N
Panel A Prefecture-level variables			
ExpShock ($1000 per worker)	4.758	17.447	17,377
$\widehat{\text{ExpShock}}$ ($1000 per worker)	5.412	17.483	17,377
PollShock^{SO_2} (pounds per worker)	45.191	228.001	17,377
$\widehat{\text{PollShock}}^{SO_2}$ (pounds per worker)	45.380	217.696	17,377
SO_2 emission intensity	17.511	30.687	17,377
Panel B Health and cognitive outcomes			
Hospital (0-1)	0.062	0.241	12,018
Bad health (0-1)	0.019	0.139	5,430
Underweight (0-1)	0.322	0.467	5,468
Math test scores (0-24)	15.259	4.887	2,012
Word test scores (0-34)	26.871	5.608	2,012
Panel C Additional variables			
Males	0.524	0.499	17,377
Rural	0.622	0.484	17,377
Age	12.761	4.211	17,377
Log of parents' education (0-16)	6.069	3.714	17,174
Log of parents' income (1-12)	8.883	1.253	16,943

Notes: The sample comes the CFPS data set, UN Comtrade and Annual Environmental Survey of Polluting Firms (AESPF) of China.

TABLE 2.2: OLS regression results

Panel A: Health results				
Variable:	Hospital	Bad health	Underweight	Unhealthiness Index
	(1)	(2)	(3)	(4)
ExpShock	-0.0029**	-0.0023	0.0016	-0.0235**
	(0.0011)	(0.0015)	(0.0026)	(0.0102)
PollShock	0.0002**	0.0002	-0.0001	0.0015*
	(0.0001)	(0.0001)	(0.0002)	(0.0008)
Observations	9,064	3,825	3,607	3,607
R-squared	0.0398	0.0512	0.1079	0.0623
Panel B: Cognitive results				
Variable:	Math	Verbal	Cognitive Index	
	(5)	(6)	(7)	
ExpShock	0.0296***	0.0231***	0.0292***	
	(0.0063)	(0.0044)	(0.0034)	
PollShock	-0.0028***	-0.0022***	-0.0027***	
	(0.0006)	(0.0004)	(0.0004)	
Observations	1,687	1,687	1,687	
R-squared	0.1572	0.1362	0.3103	
Individual Control	X	X	X	X
Prefecture FE	X	X	X	X
Cohort FE	X	X	X	X

Notes: The sample in panel (a) comes from CFPS (2010-2020) and sample in panel (b) comes from CFPS (2018), and both include adolescents aged 13–19 who were born between 1999 and 2005. All regressions are weighted by the CFPS survey weights. All the standard errors are clustered at the province level. The individual characteristics include gender and rural/urban type.

TABLE 2.3: Trade liberalization and adolescent health (IV)

Variable:	Hospital (Yes=1) (1)	Bad health (Yes=1) (2)	Underweight (Yes=1) (3)	Unhealthiness index (z-score) (4)
Panel A: IV Estimates				
ExpShock	-0.003***	-0.003**	0.001	-0.025**
	(0.001)	(0.001)	(0.002)	(0.010)
PollShock	0.000***	0.000*	-0.000	0.002**
	(0.000)	(0.000)	(0.000)	(0.001)
Observations	9,064	3,825	3,607	3,607
R-squared	0.018	0.003	0.008	0.004
Fstat ExpShock	9575	5782	4451	4451
Fstat PollShock	8667	8331	7269	7269
Individual Control	X	X	X	X
Prefecture FE	X	X	X	X
Cohort FE	X	X	X	X
Panel B: First Stage Estimates				
Dependent variable:	ExpShock	PollShock		
$\widehat{\text{ExpShock}}$	0.8338***			
	(0.011)			
$\widehat{\text{PollShock}}$		0.866***		
		(0.0018)		
Observations	4,782	4,642		
R-squared	0.939	0.938		

Notes: The sample comes from CFPS (2010-2020) and includes adolescents aged 13–19 who were born between 1999 and 2005. All regressions are weighted by the CFPS survey weights. All the standard errors are clustered at the province level. The individual characteristics include gender and rural/urban type.

TABLE 2.4: Trade liberalization and adolescent cognitive performance (IV)

Variable:	Math (z-score)			Verbal (z-score)			Index (z-score)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: IV Estimates							
ExpShock	-0.000		0.025***	-0.003		0.015***	0.022***
	(0.009)		(0.006)	(0.006)		(0.005)	(0.004)
PollShock		-0.000	-0.002***		-0.001*	-0.002***	-0.002***
		(0.000)	(0.001)		(0.000)	(0.001)	(0.001)
Observations	1,687	1,687	1,687	1,687	1,687	1,687	1,687
R-squared	0.008	0.009	0.011	0.015	0.015	0.016	0.144
Fstat ExpShock	488.5		19574	488.5		19574	19574
Fstat PollShock		10009	17415		10009	17415	17415
Individual Control	X	X	X	X	X	X	X
Prefecture FE	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X
Panel B: First Stage Estimates							
Dependent variable:	ExpShock	PollShock					
$\widehat{ExpShock}$	0.940***						
	(0.0014)						
$\widehat{PollShock}$		0.894***					
		(0.0024)					
Observations	674	674					
R-squared	0.943	0.940					

Notes: The sample comes from CFPS (2018) and includes adolescents aged 13–19 who were born between 1999 and 2005. All regressions are weighted by the CFPS survey weights. All the standard errors are clustered at the province level. The individual characteristics include gender and rural/urban type.

TABLE 2.5: Heterogeneity - by parental income: IV Estimates

Variable:	Low SES household (25th percentile)			High SES household (75th percentile)		
	Math (z-score)	Verbal (z-score)	Cognitive Index (z-score)	Math (z-score)	Verbal (z-score)	Cognitive Index (z-score)
	(1)	(2)	(3)	(4)	(5)	(6)
ExpShock	0.095***	0.096***	0.097***	-0.003	0.017	0.009
	(0.037)	(0.023)	(0.028)	(0.012)	(0.015)	(0.011)
PollShock	-0.009***	-0.010***	-0.009***	0.001	-0.000	0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Observations	339	339	339	510	510	510
R-squared	0.038	0.064	0.202	0.022	0.028	0.192
Fstat ExpShock	148.5	148.5	148.5	17079	17079	17079
Fstat PollShock	1062	1062	1062	1640	1640	1640
Individual Control	X	X	X	X	X	X
Prefecture FE	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X

Notes: The sample comes from CFPS (2018) and includes adolescents aged 13–19 who were born between 1999 and 2005. All regressions are weighted by the CFPS survey weights. All the standard errors are clustered at the province level. The individual characteristics include gender and rural/urban type.

TABLE 2.6: Mechanisms: IV Estimates

Variable:	Bed	Doctor	Elementary school	SO_2
	(1)	(2)	(3)	(4)
ExpShock	0.001*	0.001	0.006*	-0.008*
	(0.001)	(0.001)	(0.004)	(0.005)
Observations	1,702	1,721	1,721	1,587
R-squared	0.004	0.001	0.013	0.007
Fstat ExpShock	463.6	465.2	465.2	363.1
Prefecture Control	X	X	X	X
Prefecture FE	X	X	X	X
Year FE	X	X	X	X

Notes: The sample comes from China City Statistical Yearbook (1999-2005). Column (4) uses data from Annual Environmental Survey of Polluting Firms (AESPF) in China. All the standard errors are clustered at the province level. The prefecture characteristics include population size.

TABLE 2.7: Robustness - pre-WTO cohort (1988-1995)

Variable:	Unhealthiness Index (z-score)	Math (z-score)	Verbal (z-score)	Cognitive Index (z-score)
	(1)	(2)	(3)	(4)
ExpShock	0.001	-0.003	0.002	-0.001
	(0.027)	(0.003)	(0.002)	(0.002)
PollShock	-0.00009	0.0003*	0.0004*	0.0005**
	(0.002)	(0.000)	(0.000)	(0.000)
Observations	5120	4,017	4,017	4,017
R-squared	0.007	0.027	0.022	0.032
Fstat ExpShock	2316	248.3	248.3	248.3
Fstat PollShock	1396	2009	2009	2009
Individual Control	X	X	X	X
Prefecture FE	X	X	X	X
Cohort FE	X	X	X	X

Notes: The sample in column (1) comes from CFPS (2010-2020) and sample in columns (2) to (4) come from CFPS (2018) and were born between 1988 and 1995. All regressions are weighted by the CFPS survey weights. All the standard errors are clustered at the province level. The individual characteristics include gender and rural/urban type.

TABLE 2.8: Robustness - alternative measaure of emission intensity

Variable:	Unhealth	Math	Verbal	Cognitive Index	Unhealth	Math	Verbal	Cognitive Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ExpShock	-0.027**	0.029***	0.017***	0.025***	-0.023***	0.026***	0.017***	0.023***
	(0.011)	(0.007)	(0.005)	(0.004)	(0.009)	(0.005)	(0.006)	(0.004)
PollShock^{NO2}	0.006**	-0.010***	-0.007***	-0.009***				
	(0.003)	(0.003)	(0.002)	(0.002)				
$\text{PollShock}^{PM2.5}$					0.002**	-0.003***	-0.002***	-0.003***
					(0.003)	(0.003)	(0.002)	(0.002)
Observations	3,607	1,687	1,687	1,687	3,607	1,687	1,687	1,687
R-squared	0.004	0.011	0.016	0.144	0.004	0.011	0.017	0.144
Fstat ExpShock	4815	28102	28102	28102	3171	17195	17195	17195
Fstat PollShock	6862	22474	22474	22474	8267	24221	24221	24221
Individual Control	X	X	X	X	X	X	X	X
Prefecture FE	X	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X	X

Notes: The sample in columns (1) and (5) are from CFPS (2010-2020) and sample in other columns are from CFPS (2018) and includes adolescents aged 13–19 who were born between 1999 and 2005. All regressions are weighted by the CFPS survey weights. All the standard errors are clustered at the province level. The individual characteristics include gender and rural/urban type.

TABLE 2.9: Robustness - Balance Test of Product-level Shocks

	ExpShock		PollShock	
	Coefficient	S.D.	Coefficient	S.D.
	(1)	(2)	(3)	(4)
Manufacturing employment share	0.01539	(0.0842)	-0.0227	(0.0556)
Observations	10,400		10,400	
Log GDP per capita	0.00522	(0.00687)	-0.00452	(0.00429)
Observations	9,920		9,920	
Fiscal expenditure per capita	0.18962	(7.9183)	-0.99740	(5.2219)
Observations	10,240		10,240	
Educational expenditure per capita	0.02279	(1.2803)	-0.1772	(0.8450)
Observations	10,120		10,120	
Log of average wages	3.6910	(11.934)	-3.0837	(7.7936)
Observations	10,400		10,400	

Notes: This table reports coefficients and standard errors from regressing CSIC 3-digits product-level export shocks on each product specific weighted average of initial prefecture characteristic in year 1995 (pre-trend in outcome) and year fixed effects. All regressions are weighted by the simple average of the exposure to product-level shock across prefectures. Standard errors are clustered at the CSIC 2-digit level.

TABLE 2.10: Robustness - alternative cluster and unweighted regression

Variable:	Unhealthiness Index	Cognitive Index	Unhealthiness index	Cognitive Index
	(1)	(2)	(3)	(4)
	Cluster in prefecture		Unweighted regression	
ExpShock	-0.025**	0.022	-0.007	0.010**
	(0.011)	(0.015)	(0.008)	(0.005)
PollShock	0.002**	-0.002*	-0.000	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	3,607	1,687	3,254	2,012
R-squared	0.004	0.144	0.004	0.104
Fstat ExpShock	2499	913.8	61281	344.4
Fstat PollShock	6177	5100	1536	2997
Individual Control	X	X	X	X
Prefecture FE	X	X	X	X
Year FE	X	X	X	X

Notes: The sample in columns (1) and (3) comes from CFPS (2010-2020) and sample in columns (2) and (4) comes from CFPS (2018) in and includes adolescents aged 13–19 who were born between 1999 and 2005. Panel (a) cluster in prefecture level, and panel (b) is unweighted. The individual characteristics include gender and rural/urban type.

TABLE 2.11: Robustness - TCZ control

Variable:	Unhealthiness index	Cognitive Index
	(1)	(2)
ExpShock	-0.025**	0.022***
	(0.010)	(0.004)
PollShock	0.002**	-0.002***
	(0.001)	(0.001)
TCZ	-0.128***	0.055
	(0.016)	(0.051)
Observations	3,607	1,687
R-squared	0.004	0.144
Fstat ExpShock	4451	19574
Fstat PollShock	7269	17415
Individual Control	X	X
Prefecture FE	X	X
Cohort FE	X	X

Notes: The sample in column (1) comes from CFPS (2010-2020) and sample in column (2) comes from CFPS (2018), and the sample includes adolescents aged 13–19 who were born between 1999 and 2005. All regressions are weighted by the CFPS survey weights. All the standard errors are clustered at the province level. The individual characteristics include gender and rural/urban type.

TABLE 2.12: Robustness - Additional impacts

Variable:	Migration (1)	Good health (2)
ExpShock	0.00668	0.1066***
	(0.0039)	(0.0226)
Observations	5,890	11,948
R-squared	0.150	0.840
Individual Control	X	X
Prefecture FE	X	X
Cohort FE	X	X

Notes: The sample comes from CFPS (2010-2020) and includes adolescents aged 13–19 who were born between 1999 and 2005. All regressions are weighted by the CFPS survey weights. All the standard errors are clustered at the province level. The individual characteristics include gender and rural/urban type.

TABLE 2.13: Robustness - sample by rural and urban hukou type

Variable:	Unhealthiness Index		Cognitive Index	
	(1)	(2)	(3)	(4)
	Rural	Urban	Rural	Urban
ExpShock	-0.018*	-0.012	-0.004	0.025***
	(0.010)	(0.016)	(0.012)	(0.009)
PollShock	0.001*	0.001	-0.000	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,220	1,387	856	831
R-squared	0.004	0.002	0.140	0.138
Fstat ExpShock	1384	3284	6362	2568
Fstat PollShock	7138	1666	5558	2036
Individual Control	X	X	X	X
Prefecture FE	X	X	X	X
Year FE	X	X	X	X

Notes: The sample in column (1) and (2) come from CFPS (2010-2020) and sample in column (3) and (4) comes from CFPS (2018) and includes adolescents aged 13–19 who were born between 1999 and 2005.

TABLE 2.14: Robustness - sample by gender type

Variable:	Unhealthiness Index		Cognitive Index	
	(1)	(2)	(3)	(4)
	Boy	Girl	Boy	Girl
ExpShock	-0.024	-0.030***	0.019*	0.042**
	(0.017)	(0.011)	(0.010)	(0.021)
PollShock	0.002	0.002**	-0.002**	-0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
Observations	1,803	1,804	860	827
R-squared	0.001	0.012	0.108	0.164
Fstat ExpShock	10667	1935	14191	2146
Fstat PollShock	22871	2200	7049	2634
Individual Control	X	X	X	X
Prefecture FE	X	X	X	X
Year FE	X	X	X	X

Notes: The sample in column (1) and (2) come from CFPS (2010-2020) and sample in column (3) and (4) comes from CFPS (2018) and includes adolescents aged 13–19 who were born between 1999 and 2005.

TABLE 2.15: Robustness - sample by manufacturing worktype

Variable:	Unhealthiness Index		Cognitive Index	
	(1)	(2)	(3)	(4)
	Worker	Others	Worker	Others
ExpShock	0.016	-0.056**	-0.135***	0.031***
	(0.024)	(0.024)	(0.048)	(0.009)
PollShock	-0.005*	0.004**	0.011**	-0.002***
	(0.003)	(0.002)	(0.005)	(0.001)
Observations	363	1,138	158	446
R-squared	0.029	0.019	0.304	0.145
Fstat ExpShock	2912	9599	220.1	9104
Fstat PollExpShock	1890	5991	569.3	10291
Individual Control	X	X	X	X
Prefecture FE	X	X	X	X
Year FE	X	X	X	X

Notes: The sample in column (1) and (2) come from CFPS (2010-2020) and sample in column (3) and (4) comes from CFPS (2018) and includes adolescents aged 13–19 who were born between 1999 and 2005.

Appendix

Industrial classifications

Because this paper employs several sources which use different industrial classification standards, here I present the mapping approach and basic statistics for my dataset.

The employment share is from China Population Census 1990 and the emission intensities are from Annual Environmental Survey of Polluting Firms (AESPF) 1999, which use 3-digit CSIC codes. Those CSIC codes have three versions, CSIC1984, CSIC1994 and CSIC2002, and I mainly use CSIC2002 (GB/T4754-2002) version. The trade tariff data and trade flows data on China reported by every country is from WITS Trains dataset using ISIC revision 3. Therefore, I build the concordances which map ISIC revision 3 codes to 3-digit CSIC codes, and then calculate each prefecture's exposure to trade shock and trade-induced pollution shock.

This paper focuses on the manufacturing sectors exposed to trade shocks. Consequently, I exclude the manufacturing 2-digit codes from 13 to 16 because these codes pertain to agricultural, food, and tobacco industries, which are not considered trade-exposed. Certain digit codes are also excluded due to asymmetric matching issues between the China Population Census, firm-level emission data, and ISIC revision data. For instance, industry code 21 represents furniture manufacturing in CSIC2002 but is categorized as paper-related manufacturing in ISIC revision 3, while industry code 36 is listed as furniture manufacturing in ISIC revision 3. Additionally, industries 32 and 33 are not listed in this Table because they correspond to ferrous and nonferrous metal smelting in CSIC2002. These industries are listed under code 27 in ISIC revision 3, and I have included them in this Table. Overall, due to asymmetric codes across multiple data sources, I match industries by their function and names, which may result in some missing codes in Table 2.16. Nonetheless, this paper aims to retain all essential manufacturing products whose 2-digit codes are between 17 and 43 in CSIC2002. I also include industries 40, 41, 42, and 43 as they are regarded as manufacturing industries for communication devices, instrumentation, crafts, and waste resources.

Finally, my sample includes 83 manufacturing industries in 3-digit CSIC codes as listed in Table 2.16:[16]

Trade liberalization and adolescent health

Table 2.17 provides additional estimates of trade liberalization on cognitive performance. And I separately regress long term cognitive outcomes on early life exposure. Overall, those estimates are not significant, suggesting that my baseline specification should capture both trade shock and trade-induced pollution shock.

Multicollinearity

In this section, I test the multicollinearity concern between $\widehat{\text{ExpShock}}$ and $\widehat{\text{PollShock}}$. First, I present the correlation coefficient between the two variables as shown in Table 2.18. The coefficient is 0.82 which induces the concern that those two variable could have multicollinearity issue. I also examine the two measure's relations in Figure 2.7.

[16]This table does not fully replicate the CSIC2002 (GB/T4754-2002) version but instead presents the codes used in this paper from multiple sources.

TABLE 2.16: Classification for 3-digit CSIC codes

2 digit	3 digit
17	171 172 173 174 175 177 178 179
18	180 181 182 189
19	191 193 194 199
20	201 202 209
22	222 224 226 227 228 229
24	241 243 245 249
25	251 252 254
26	261 262 263 264
27	271 273 274 275 279
28	281 282 283
29	290
30	301 303 305 306 307
31	311
34	341 342
35	351
36	361 362 363 365
37	372 375 377
38	381 384 386 387 388
40	401 402
41	411 413 414 416 418
42	421 423 428 429
43	431 433 435 436 438 439

Notes: The industry code and corresponding industry name is from CSIC2002 version combined with ISIC revesion 3.

TABLE 2.17: Trade liberalization and adolescent cognitive performance (IV)

Variable:	Hospital		Bad health		Underweight		Unhealthiness index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ExpShock	-0.0005		-0.0007		-0.0008		-0.0071	
	(0.0008)		(0.0005)		(0.0013)		(0.0052)	
PollShock		0.0000		-0.0000		-0.0001		-0.0003
		(0.0000)		(0.0000)		(0.0001)		(0.0003)
Observations	9,064	9,064	3,825	3,825	3,607	3,607	3,607	3,607
R-squared	0.0177	0.0176	0.0026	0.0025	0.0075	0.0075	0.0032	0.0028
Fstat ExpShock	439.5		258.2		327.1		327.1	
Fstat PollShock		5389		10352		14302		14302
Individual Control	X	X	X	X	X	X	X	X
Prefecture FE	X	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X	X

Notes: The sample comes from CFPS (2010 to 2020). All regressions are weighted by the CFPS survey weights. All the standard errors are clustered at the province level.

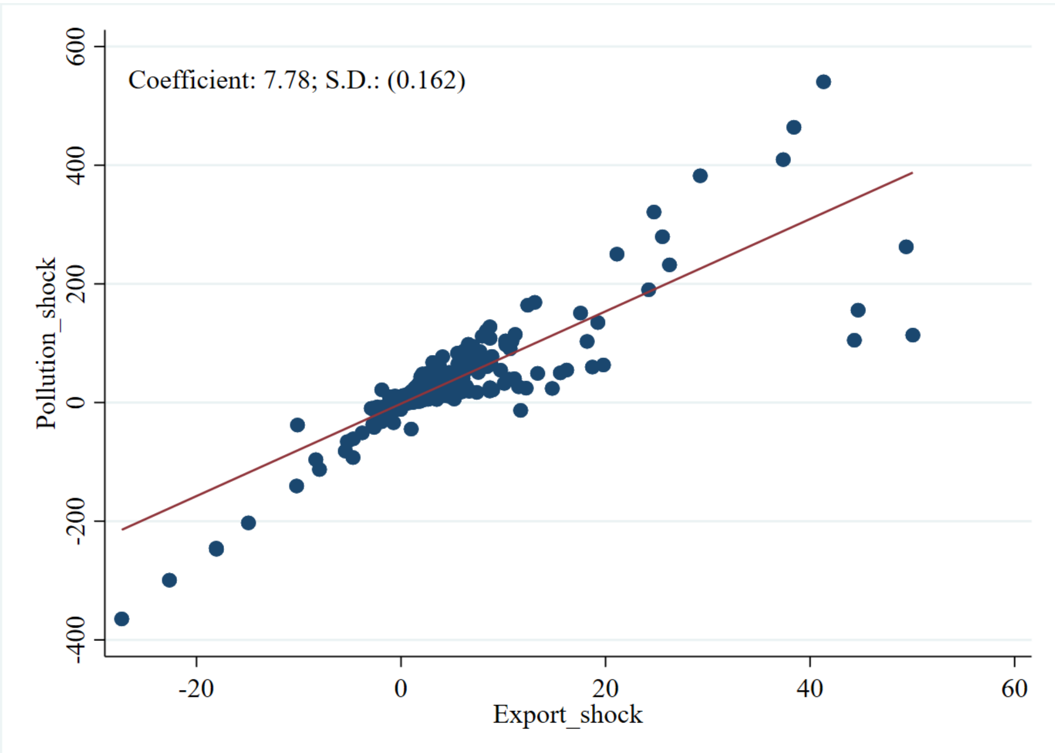
I then test the two variable in a regression and report the mean value of variance inflation factor (VIF), which is a measure of the amount of multicollinearity. The result is 2.55 and indicates that the multicollinearity issue is not too serious in my specification.

Following Bombardini and Li, 2020, I also calculate the PollShock^{PCA} that use the principal component analysis of SO_2, NO_2 and $PM_{2.5}$. I argue that this comprehensive measure of pollution chock has less correlations with trade shock variable as shown in Table 2.20 and smaller mean VIF value in Table 2.21. And I also report the regression IV estimates in Table 2.22, which suggests that trade shock still decrease unhealthiness index and trade-induced pollution shock increase this index. Also, the trade-induced pollution shock decrease long term cognitive test scores. Overall, those results complement additional evidence to the main text.

TABLE 2.18: Correlation coefficient

Variable:	$\widehat{\text{ExpShock}}$	$\widehat{\text{PollShock}}$
$\widehat{\text{ExpShock}}$	1	
$\widehat{\text{PollShock}}$	0.8261	1

FIGURE 2.7: The relationship between Export shock and Pollution shock



Notes: The figure displays relationship between Export shock and Pollution shock.

Test for nonlinear regression models

In this paper, because the three health measures all take dummy variable (yes-1, no-0). This may cause the concern that my IV specification can't capture the linear

TABLE 2.19: VIF results

Variable:	VIF	1/VIF
$\widehat{\text{ExpShock}}$	3.81	0.262
$\widehat{\text{PollShock}}$	3.77	0.265
male	1.01	0.994
rural	1.34	0.744
age	2.38	0.420
2000	1.73	0.579
2001	1.48	0.675
2002	1.66	0.602
2003	1.67	0.597
2004	2.32	0.430
2005	2.67	0.373
Mean VIF	2.55	

TABLE 2.20: Correlation coefficient

Variable:	$\widehat{\text{ExpShock}}$	$\widehat{\text{PollShock}}^{\text{PCA}}$
$\widehat{\text{ExpShock}}$	1	
$\widehat{\text{PollShock}}^{\text{PCA}}$	0.0668	1

TABLE 2.21: VIF results

Variable:	VIF	1/VIF
$\widehat{\text{ExpShock}}$	1.32	0.757
$\widehat{\text{PollShock}}^{\text{PCA}}$	1.22	0.820
male	1.01	0.991
rural	1.27	0.786
age	2.40	0.416
2000	1.71	0.584
2001	1.49	0.670
2002	1.64	0.608
2003	1.64	0.609
2004	2.35	0.426
2005	2.75	0.364
Mean VIF	1.71	

TABLE 2.22: Robustness - alternative measure of emission intensity

Variable:	Unhealthiness Index	Cognitive Index
	(1)	(2)
IV Estimates		
ExpShock	-0.008**	-0.001
	(0.003)	(0.003)
PollShock^{PCA}	0.024**	-0.033***
	(0.011)	(0.008)
Observations	3,607	1,687
R-squared	0.004	0.144
Fstat ExpShock	7865	14673
Fstat PollShock	25479	39239
Individual Control	X	X
Prefecture FE	X	X
Cohort FE	X	X

Notes: The sample comes from CFPS (2010 to 2020). All regressions are weighted by the CFPS survey weights. All the standard errors are clustered at the province level.

change. Specifically, I use the IV-probit model to re-estimate the results. Column (1) in Table 2.23 indicates that 1% increase in trade shock decrease the hospital rate by 1.82%, and trade-induced pollution shock increase hospital rate by 0.16%. This indicates that pollution shock plays a moderate rale compared to the trade shock. I also provide the Wald and AR p-value about those results, both suggest the power of my IV. Besides, I add the probit model regression results and obtain the logistic predicted probabilities. Then I compare this predicted probabilities with the fitted value obtained from the OLS linear model as shown in Figure 2.8. The two fitted values show a comparable trend. And this suggests that my orginal specification can caputure the effects on those dummy variable.

TABLE 2.23: IV-Probit model results

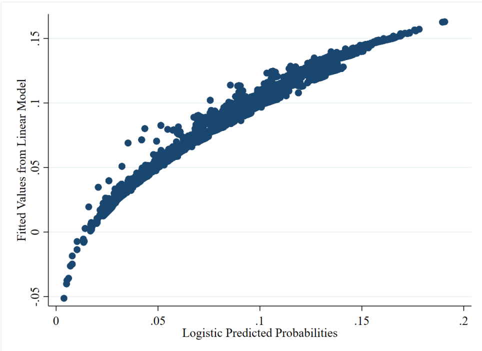
Variable:	Hospital	Bad health	Underweight
ExpShock	-0.0182**	-0.0181	0.0253**
PollShock	0.0016**	.0024	-0.0025**
Observations	10,435	4,509	4,260
Weak IV test:			
AR p-value	0.1034	0.3061	0.0180
Wald p-value	0.1035	0.3063	0.0180

Notes: The table replicates the results on Table 2.3 using IV-probit model.

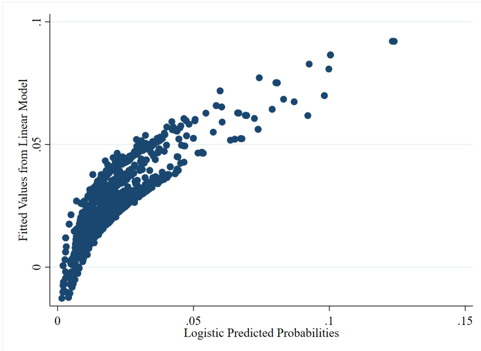
Wild-p value

Here, bootstrap p-values are calculated using the wild boostrap method with 1000 repetitions. And I report the results in the following Table 2.24.

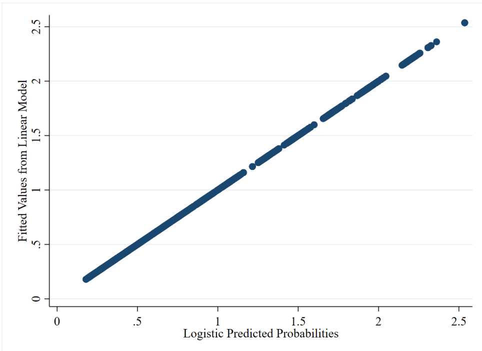
FIGURE 2.8: Scatter plots of fitted value from linear model and probit model



(A) Hospital



(B) Bad health



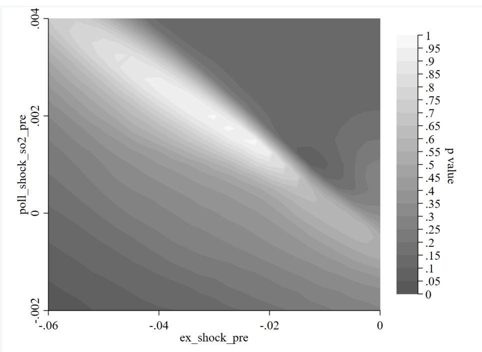
(C) Underweight

TABLE 2.24: Bootstrap p-values

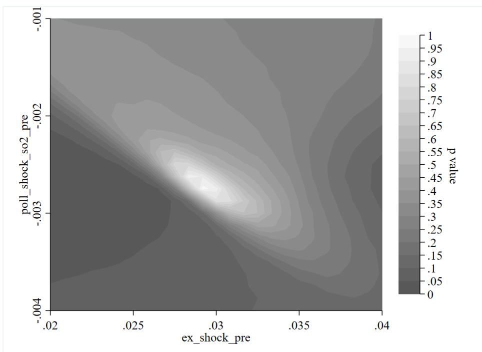
Variable:	Unhealthiness index	Cognitive index
Bootstrap *p*-value	0.13	0.01

Notes: The table replicates the results on Table 2.3 and 2.4.

FIGURE 2.9: Bootstrap p-values



(A) Hospital

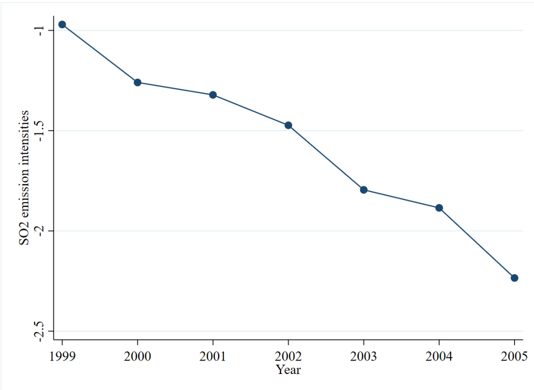


(B) Bad health

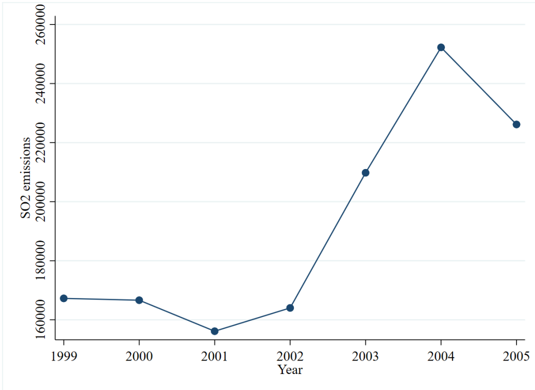
Trends of emission intensity

To examine whether there is technique effect from innovation (i.e., whether $\gamma_t$changes with the time t), I also plot the trends of the emission intensities in Figure 2.10. I find that the emission intensities are decreasing, which can not reflect the initial year of pollution effects. So I use the initial year pollution intensities.

FIGURE 2.10: Trends of SO2 emission intensities and concentrations



(A) Intensities



(B) Concentrations

Notes: Panel (a) and (b) plot the trends of SO2 emission intensities and concentrations.

Magnitudes

Another method to gauge the importance of export growth on reducing unhealthiness index is to compare the sample at the 25th and the 75th percentile of trade export shock distribution. I first separate the sample by their change of trade export shocks during 1999 and 2005, and then I mark the prefectures at the 75th percentile as the prefectures more exposed to trade shocks. I use this comparison to explore the counterfactual: what if the WTO accession never happened? The columns (2) and (4) in Table 2.25 show that the household from the prefectures more exposed to trade export shocks present larger effects magnitudes.

A timeline of the model stages

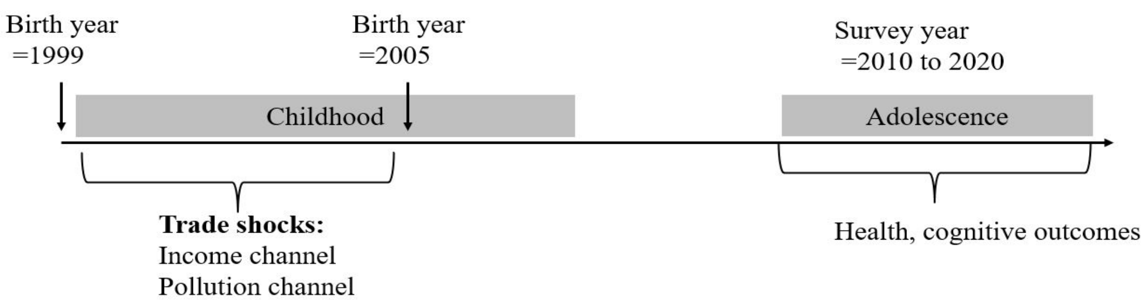
To help understand the timing period of this research, Figure 2.11 illustrates the life cycle of an individual. From birth year 1999 to 2005, the child lives with her parents and does not make any choices. The trade shocks affect them through income channel and pollution channel in each birth year (i.e., during the parenting stage). In survey period 2010 to 2020, individuals enter adolescence where they study in high school stages. And this paper links the trade shocks in birth year to the outcomes in adolescence by using an instrumental variable method.

TABLE 2.25: Heterogeneous - sample by export shock distribution

Variable:	Unhealthiness Index		Cognitive Index	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
ExpShock	0.007	-0.011**	-0.051	0.018
	(0.096)	(0.005)	(0.060)	(0.012)
PollShock	0.002	0.001*	-0.005	-0.002***
	(0.006)	(0.000)	(0.006)	(0.001)
Observations	1,084	450	516	212
R-squared	0.008	0.022	0.110	0.154
Fstat ExpShock	1027	116.2	1421	544.5
Fstat PollShock	1216	846.7	1351	1556
Individual Control	X	X	X	X
Prefecture FE	X	X	X	X
Year FE	X	X	X	X

Notes: The sample in columns (1) and (3) is from the low export shock (25th percentile), and sample in columns (2) and (4) is from the high export shock (75th percentile).

FIGURE 2.11: A timeline of the model stages



Notes: The figure displays how the trade shocks during the parenting stage affect their health and cognitive outcomes in adolescence.

Chapter 3

Resource Windfalls and Human Capital Accumulation: Evidence from China

3.1 Introduction

Are resource booms a blessing or a curse for local household human capital accumulation (Sachs and Warner, 2001)? At first glance, natural resources might seem to promote economic development and attract enhanced educational resources. However, recent studies suggest that resource booms can hinder human capital accumulation (Mejía, 2020; Mosquera, 2022; Kovalenko, 2023). One explanation is that resource booms elevate the opportunity cost of education by increasing labor demand, thereby causing high school students to face a critical trade-off between immediate employment and long-term investment in skills and education to enhance future earnings. This economic phenomenon aligns with the Dutch disease theoretical model by Corden and Neary, 1982, which posits that a natural resource boom can contract the manufacturing sector through crowding out and real exchange rate appreciation. For instance, the resource sector can attract labor away from manufacturing and services into energy due to higher wages in resource sectors (Smith, 2019). Consequently, some individuals may find it optimal to drop out of high school or college to enter the workforce. While the current literature provides substantial evidence on the impacts of natural resource booms, there is limited evidence specific to China.

I address this gap by analyzing the impact of coal mining on students' schooling decisions, cognitive test scores, and labor market outcomes in China. This analysis is particularly warranted for several reasons. First, China has been the largest consumer of coal worldwide over the past decade, accounting for over 50% of global coal use.[1] And China surpassed the US in 2005 as the leading energy producer and became the highest energy consumer in 2009. Second, China's geographic features create sources of regional variation in exposure to the coal boom's effects. Specifically, the coal industry is predominantly located in regions distant from provincial economic centers, which are typically characterized by limited educational resources. These resource-abundant prefectures heavily rely on the resource sector and lack diversified economic structures. Consequently, resource booms may temporarily reduce university attainment rates, as immediate employment opportunities in the resource sector become more attractive compared to pursuing further education. Third, in 2004, the international trade volume of coal experienced a significant surge,

[1] See the website: `https://www.iea.org/energy-system/fossil-fuels/coal`

with total exports reaching 755 million tons—an increase of 32.9 million tons compared to the previous year. Among these, thermal coal exports amounted to 541 million tons, reflecting an increase of 24.7 million tons and a growth rate of 4.8%, which accounted for 71.7% of the total international coal trade volume. This international coal price surge can induce more workers to extract those resources due to higher wages and labor demand in a very short period of time. Therefore, understanding how economic conditions affect educational attainment decisions has important policy implications in China.

According to Chinese law, nine years of compulsory education (encompassing primary school and junior high school) are mandatory, and individuals must complete these stages. Upon completion, students aged around 15 can independently decide whether to attend senior high school or enter the labor market. Three years after senior high school, around the age of 19, students can choose whether to take the national examination for university admission. Therefore, I compare the educational attainment of individuals who reached the age of 19 after the coal boom with those who reached 19 before 2004. Given that individuals typically complete high school and make decisions regarding college education at the age of 19, my aim is to examine how the coal boom affects high school graduates' decisions about college education. Additionally, I include an analysis of cohorts aged 16, the earliest age at which individuals can independently decide about their schooling and enter the labor market.[2]

For the research design, I utilize the surge in international coal prices since 2004 and the geographic distribution of coal deposits to assess the causal effects of coal mining. The international coal price experienced a significant increase between 2004 and 2010. The identification strategy hinges on the assumption that the rise in international coal prices disproportionately affects areas with high potential for coal mining.[3] To measure coal-prefecture status, I identify 45 coal prefectures based on the lists documented in the China Mining Statistical Yearbook 2003, categorizing them according to their historical deposits. These coal prefectures constitute the treatment group for measuring geographic variation in exposure to the coal boom, while other prefectures in my sample are denoted as control groups.

I utilize data from the 0.3% sample of the 2010 China Population Census and the China Family Panel Studies (CFPS) from 2010, 2012, and 2014. My research design leverages the global coal price surge beginning in 2004 as a temporal shock and exploits the heterogeneous exposure to this boom across different regions based on their coal deposits. Specifically, the cohort difference-in-differences (DID) approach compares individuals who turned 19 during the coal boom starting in 2004 with those who turned 19 before 2004, across coal-abundant and other prefectures. First, I analyze educational outcomes using the 2010 China Population Census, focusing on high school cohorts who turned 19 between 1994 and 2010. This analysis is supplemented with CFPS data, which includes cognitive test results and annual income data. Additionally, the 2010 China Population Census records current employment status. Following the methodologies of Lin and Long, 2020 and Kovalenko, 2023, I focus on the pre-existing student population who reported no migration in the baseline specification and examine how the coal boom affects their migration in Appendix 3.6. The sample reporting no migration suggests that they are affected by

[2]Following the methodology of Lin and Long, 2020, I select these two cohorts as they represent critical ages for making significant educational decisions.

[3]I also consider the possibility that some prefectures use coal as an important input for manufacturing or electricity. In the robustness check, I report the effects on these prefectures and find no significant evidence.

regional economic shocks.

My analysis reveals that exposure to the coal boom for cohorts aged 19 after the onset of the shock significantly impacts educational attainment, cognitive performance, and income. Specifically, high school students in coal prefectures exhibited reduced university enrollment and lower grade levels. The estimates indicate that the coal boom resulted in a 2.7 percentage point decrease in university attainment rates. Utilizing the CFPS data set, which documents students' cognitive test scores, I find that the coal boom led to a reduction in math test scores by 0.0458 standard deviations, measured approximately 5 to 10 years later.

To evaluate the rationality of these behaviors, I further examine labor market outcomes and find that the coal boom increased annual income by 16.32 percentage points and employment rates by 4.18 percentage points for affected cohorts, measured approximately 5 to 10 years later. The earnings gains for these students, relative to their peers in other areas, indicate that the decision to forgo education does not appear detrimental within a ten-year period. These positive effects on labor market outcomes are consistent with recent findings on the oil boom in Canada (Morissette, Chan, and Lu, 2015) and the fracking boom in Texas (Kovalenko, 2023).[4] Furthermore, I demonstrate that the main findings are robust to alternative model specifications.

There are several concerns regarding the identification assumption. Firstly, the international coal price surge could be endogenous due to China's domestic economic boom since 2001, potentially biasing my estimates. To address this limitation, I provide additional measurements of the temporal shock by directly using the international coal prices in the robustness check section, and the results remain largely unchanged. Secondly, the identified effects could be driven by pre-existing trends among the earlier cohorts. To mitigate this concern, I incorporate initial year characteristics interacted with trends in the robustness check section and examine the balance tests of initial year economic characteristics between coal prefectures and other prefectures.

This paper contributes to the extensive literature examining the impact of natural resource booms on human capital accumulation. Recent studies have explored the fracking boom in the US (Bartik et al., 2019; Kovalenko, 2023), coal extraction (Esposito and Abramson, 2021), oil and gas booms (Morissette, Chan, and Lu, 2015; Zuo, Schieffer, and Buck, 2019; Cai, Maguire, and Winters, 2019; Mosquera, 2022), and the effects of mining on human capital formation (Mejía, 2020; Esposito and Abramson, 2021; Agüero et al., 2021). The findings of this study provide evidence that coal booms may result in reduced cognitive test outcomes. This is consistent with Esposito and Abramson, 2021, who demonstrated a decline in the share of individuals with a university education due to coal mining in Europe. Similarly, Mejía, 2020 found that gold mining reduces standardized test scores and college attainment rates.

My findings also contribute to understanding the long-term effects of resource booms on wealth accumulation by demonstrating that such booms increase income in the medium term. Kovalenko, 2023 illustrates that the decision of low-ability students to invest less in schooling is rational given the higher long-term income prospects resulting from resource booms. Similarly, Mosquera, 2022 finds that the long-term decline in college completion rates aligns with rational individual behavior, as the income gains for low-skilled workers sufficiently compensate for reduced

[4]Due to data limitations, my analysis does not capture longer-term outcomes, preventing predictions about future earnings and decisions.

human capital accumulation. In this context, my results suggest that rural and low socioeconomic status (SES) families in China may also benefit from this rational decision to drop out of school.

Finally, this paper makes a significant contribution to the literature on coal mining in China. Recent research has underscored the pivotal role of coal mining in economic development, while also highlighting substantial social costs, including accidents (Jia and Nie, 2017; Shi and Xi, 2018), air pollution and climate change (Chu et al., 2023), and implications for political institutions (Hong and Yang, 2024). Additionally, studies such as Hou et al., 2020 and Zeng et al., 2019 have addressed issues of sustainable development within coal-prefecture regions in China. Building upon this body of work, my paper extends these findings by focusing on the critical role of human capital accumulation in shaping future development trajectories.

Section 3.2 of this paper provides background on China's coal boom. Section 3.3 describes data sources, measurements and empirical framework. Section 3.4 presents empirical results, and Section 3.5 provides additional robustness checks. And Section 2.6 concludes.

3.2 Background

Global commodity markets have experienced a pronounced price surge since the mid-2000s (Kovalenko, 2023). As illustrated in Figure 3.1, the global coal price index began a sharp ascent from 2004 onward. By 2011, coal prices had reached \$129.607 per ton, representing a 363.6% increase from 2003 levels. This study leverages the temporal shock induced by this coal price surge to evaluate the short- and medium-term impacts of the coal boom.

China's rapid economic expansion and industrialization, driven by export growth following its accession to the World Trade Organization (WTO) in late 2001, catalyzed an accelerated phase of urbanization and industrial development. This period of heightened economic activity and rising global resource prices spurred growth in the resource sector. Drawing on data from the China Energy Statistical Yearbook (2000-2020), I detail the trajectory of coal production and consumption in China. Figure 3.2 illustrates significant increases in both coal production and consumption since 2004, marking the onset of the coal boom within this period.

3.3 Material and methods

3.3.1 Data and measurement

Coal prefectures

Building on the methodologies of Zeng et al., 2019 and Hou et al., 2020, this study designates 45 prefectures as treatment groups, identified as coal-rich based on the list provided in the China Mining Statistical Yearbook 2003. And the other 99 prefectures are denoted as control group. Detailed information on these prefectures is presented in Appendix Table 3.12, and their geographic distribution is illustrated in Figure 3.8.

Education outcomes

To assess educational attainment, I leverage a 0.3% sample from the 2010 China Population Census, administered by the National Bureau of Statistics of China. This dataset provides granular, individual-level information including year of birth, region of residence, urban versus rural dwelling, gender, ethnicity, and educational attainment.

In this analysis, I concentrate on individuals aged 19, a crucial developmental stage when they transition from high school and confront the decision between enrolling in higher education or entering the labor market. This decision is of paramount importance due to the demanding nature of college entrance examinations, marking a significant milestone following the completion of senior high school.[5] As shown in Table 2.1, the university/college attainment rate during the sample period from 1994 to 2010 was 20.5%, markedly lower than the 44.6% rate observed at the high school level. Given that the minimum legal working age in China is 16, coinciding with the end of compulsory schooling, individuals can make independent educational decisions from age 16. Accordingly, I incorporate a robustness check to evaluate whether the coal mining boom has a significant impact on the cohort aged 16.

Educational outcomes for high school students are assessed using data on educational attainment from the 2010 China Population Census. The census provides a categorical measure of current educational levels, ranging from 1 to 7.[6] For the purpose of this study, “university attainment" is defined as attaining a university or college degree or currently being enrolled in university or college, denoted as 1. Conversely, “high school attainment" is defined as having completed or currently being enrolled in senior high school, also denoted as 1.

To address potential confounding effects arising from population mobility and migration, I exclude individuals who have relocated from their original registered residence regions. Migration status is assessed based on discrepancies between current and registered residence, including the duration of any absence. As detailed in Appendix 3.6, I analyze the impact of the coal boom on selective migration. [7] Consequently, the final analytical sample consists of 308,418 individuals who were 19 years old between 1994 and 2010.

[5]Under the Compulsory Education Law, nine years of schooling is mandated, typically concluding by ages 15 or 16. Following an additional three years of high school education, students face the critical choice of pursuing college education upon reaching age 19.

[6]The corresponding educational levels are as follows: 1 = no schooling, 2 = primary school, 3 = junior high school, 4 = senior high school, 5 = college, 6 = university, 7 = graduate education.

[7]In the population census, respondents are queried about their current residence in relation to their registered residence, along with the length of any absence. Individuals who have consistently retained their registered residence status are included in the final sample, thereby excluding those who have migrated.

I also depict the trends of university attainment for both coal prefectures and other prefectures in Figure 3.3. Overall, the data illustrates a rising trend in university attainment among cohorts aged 19 prior to 2001 in both types of prefectures. However, for cohorts aged 19 between 2004 and 2007 in coal prefectures, they demonstrate a relatively decreasing trend in terms of university attainment compared to other prefectures. From 2007 onward, both groups show a resurgence in university attainment.

Cognitive test outcomes

To examine the medium-term effects of coal boom on cognitive test scores, I use data from China Family Panel Studies (CFPS) with two cognitive test scores: a verbal test score, based on 34 verbal questions, and a math test score, based on 24 mathematics questions, administered in CFPS 2010 and 2014. Both cognitive scores are standardized and calculated as age-specific z-scores. I then construct a cognitive index by taking the first principal component from a principal components analysis (PCA) on the math and verbal test, denoted by Testscore in the results part. I also restrict the sample to non-migrant (non-migrant from birth to survey time) and the sample to those who had reached 19 years old between 1994 and 2010.

Labor market outcomes

Following Kovalenko, 2023, I consider two labor market outcomes. First, I create indicators for being employed or not using the China Population Census, which documents whether the individual works last week. Second, I use their current annual wages documented in CFPS data set in three survey waves in 2010, 2012 and 2014. Within the estimation sample, 66.1% of respondents are employed, with an average annual wage of 9.427 on a logarithmic scale.

Descriptive statistics for these variables are presented in Table 3.1.

3.3.2 Specification

In line with past work (Mosquera, 2022; Kovalenko, 2023), I employ a cohort difference-in-differences model to investigate the impact of coal booms on human capital accumulation. The baseline regression equation is formulated as follows:

$$Y_{ict} = \alpha + \beta \text{Coal}_c \times \text{Boom}_t + X_{ict}\gamma + \mu_c + \tau_t + \varepsilon_{ict} \tag{3.1}$$

where Y_{ict} denotes the schooling decisions and future human capital outcomes for individual i in cohort t living in prefecture c. The cohort t denotes the years when cohorts were 19 years old.[8] The dummy variable Coal_c identifies whether a prefecture is designated as a coal-based prefecture, using prefecture lists sourced from the China Mining Statistical Yearbook 2003. These listings are based solely on historical coal deposits, which are determined by geographical factors and therefore assumed to be strictly exogenous to human capital decisions. Following Bazillier and Girard, 2020, I measure the resource boom period Boom_t in two alternative ways: (1) a year dummy that equals 1 during the period from 2004 to 2010, corresponding to years of elevated coal prices, and 0 before 2004;[9] (2) the natural logarithm of the international coal price, utilized as a robustness check in Section 3.5.3. In the main text, I

[8] This matching approach ensures each individual is aligned with the cohort's age of 19 during the boom year.

[9] I choose this period because of higher price level compared to the pre-boom period.

denote Boom_t equals 1 if the cohort t turned 19 years old after 2004. The reason I focus on age 19 is that cohorts aged 19 would start university attainment, and they are considered fully treated. I choose the period between 2004 and 2010 as the coal boom period due to higher international coal prices and domestic coal production in this period as shown in Figure 3.1 and 3.2. Also, the two figures show that extraction activity and employment in resources sectors were largely unchanged until the mid-2000s. Consequently, the treatment group comprises individuals reaching 19 in 2004, whose educational decisions may have been influenced by the coal boom, while the control group consists of those who turned 19 before 2003 and were thus unaffected by the coal boom during their initial opportunity to make educational choices.

The vector X_{ipt} encompasses individual-level covariates, incorporating gender, and urban/rural *hukou* type. I also include the log of population size. In all regressions, prefecture fixed effects μ_c are included to mitigate time-invariant disparities between prefectures. Additionally, cohort fixed effects τ_t are incorporated to capture time-invariant differences among cohorts of high school students. Standard errors are clustered at the prefecture level.

3.4 Results

3.4.1 Education attainment

My research design's key identifying assumption is that the coal boom is the only factor causing differential trends in outcomes across treated and control regions. To examine this, I initially conduct an event study on university attainment in Figure 3.4. This allows me to evaluate if there are significant differences in outcomes between the treatment and control groups before the coal boom and to ascertain the persistence of treatment effects over time. All estimates are relative to the last untreated cohort of students who turned 19 in 2003. During the pre-boom period, the estimates do not reveal differential pre-existing trends, which lends support to the validity of my identifying assumptions. Subsequently, the post-boom estimates for the probability of university attainment indicates a negative trajectory. This pattern is consistent with the gradual impact of the coal boom on educational outcomes.

I present the results in Table 3.2. Columns (1) demonstrates a statistically significant negative effect of the coal boom on university attainment. Specifically, the exposure to coal boom in a prefecture reduced student's university attainment rate by 2.71 percentage points. This effect size is comparable to similar studies in the literature.[10] The data description indicates that the mean value of university attainment is 20.5%, while the estimation results yield a significant figure of 13.2%.Column (2) suggests that the effect on high school attainment is not statistically significant, suggesting that the coal boom has not substantially increased the opportunity cost of high school education. In column (3), I report that the coal boom also decreased the grade level by 0.0566. The mean value of grade level is 3.751, so this effect takes 1.5%.

[10]For instance, Mosquera, 2022 documented that exposure to the oil boom decreased college completion rates by 2.9 percentage points among treated cohorts in Ecuador. Mejía, 2020 finds estimated effect of mining on college attainment oscillates between 0.6 percentage points and 1.9 percentage points. Kovalenko, 2023 finds that students in an area with average fracking potential experienced a 4.4 percentage point decrease in the probability of public university attainment.

3.4.2 Cognitive outcomes

In addition to analyzing school attendance, I estimate the medium-term impacts of the coal boom on students' cognitive test scores using the CFPS dataset from 2010 and 2014. Figure 3.5 presents the event study findings, indicating that cohorts reaching age 19 from 2006 onwards exhibit negative coefficients and a declining trend in math test scores and cognitive index. Table 3.3 displays the DID estimates. Column (1) demonstrates that the coal boom is associated with reductions in math test scores, with the dependent variable normalized to age-specific z-scores. The coal boom corresponds to a 0.0458 standard deviation reduction in math test scores and a 0.0427 standard deviation reduction in the cognitive index. Column (2) shows that the effect of coal boom exposure results in a 0.0373 standard deviation decrease in verbal test scores, although this result is not statistically significant. Overall, my findings that coal mining negatively affects students' academic performance align with Mejía, 2020, who report that mining reduces math test scores by 0.019 standard deviations.

3.4.3 Labor market outcomes

Prior literature suggests that natural resource abundance often correlates with expanded job markets, potentially raising the opportunity costs of pursuing higher education. Whether individuals choose to forego further education in this context hinges on the economic calculus of lifetime earnings. Specifically, if the financial gains from increased wages among lower-skilled workers are substantial enough, they may offset the long-term implications of diminished human capital accumulation (Mejía, 2020; Mosquera, 2022).

Here, I analyze the medium-term effects of coal boom on employment status and earnings, which is around 5 to 10 years after coal boom. I begin by presenting an event study on the logarithm of income and employment status in Figure 3.6. Panel (a) illustrates that cohorts reaching 19 years old between 2005 and 2007 experienced an increase in the logarithm of income due to the coal boom, and panel (b) demonstrates an increase in the rate of having any employment for cohorts aged 19 after 2004. The estimates in the preboom period do not show differential preexisting trends, which provides support for the effects of coal boom on students' labor market outcomes.

Column (1) of Table 3.4 indicates that the coal boom has a positive effect on the medium-term log of annual income for the affected cohorts. Column (2) suggests an increase in employment rates. The magnitudes of the effects indicate that coal boom increases people's annual income by 16.32 percentage points and employment rate by 2.65 percentage points. This magnitude is similar to other studies examining the labor market effects of the fracking boom in the US by Kovalenko, 2023, who finds that students in commuting zones would be estimated to experience a 6 percentage points increase in quarterly earnings and a 5 percentage point increase in the probability of employment.

3.4.4 Heterogeneous effects

Education outcome

To further assess the impacts of coal boom on human capital accumulation, I analyze differences between rural and urban areas because they have large difference in obtaining higher education resources. Table 3.5 presents the estimates of two separate regressions for individuals from rural and urban areas. In column (1), I find that sample from rural areas report larger reduction in university attainment. In column (7), I find significant and negative effects of the coal boom shock on test score among 19-year-old cohorts from rural backgrounds. And these results are not significant for urban samples.

Furthermore, I stratify the sample by parents' education levels as a proxy for socioeconomic status, categorizing low parental education as below the mean and high parental education as above the mean. Columns (2), (4), and (6) in Table 3.6 reveal that these negative effects are particularly pronounced among households with lower socioeconomic status, indicated by low parental education. These findings suggest that the additional economic benefits are more likely to induce high school students from rural areas and low socioeconomic status backgrounds to enter the labor market and forgo higher education.

I believe this may be due to the limited opportunities for higher education available to rural individuals, stemming from the small number and low quality of high schools and teachers in these areas. For many students, even if they wish to dedicate more time to their studies, gaining admission to reputable universities or colleges proves challenging. Consequently, they often opt to leave high school in pursuit of higher income opportunities outside of academia. Another explanation is that individuals from low socioeconomic status (SES) backgrounds in rural areas may prioritize increasing their income as much as possible in order to support their families financially. Attending university or college entails not only tuition fees and living expenses but also the opportunity cost associated with potential wages lost during that period.

Labor market outcomes

I also investigate the effects on labor market outcomes. Columns (1) and (3) of Table 3.7 reveal that the positive impact on the natural logarithm of income is particularly pronounced among the rural sample and households with low socioeconomic status. This result corroborates the finding that students from rural areas and low socioeconomic backgrounds benefit more from the coal boom.

Overall, the preceding analysis corroborates the presence of heterogeneous effects among youths with varying personal characteristics, aligning with the findings of Lin and Long, 2020, which indicate that rural students are more likely to drop out of school and enter the labor market following China's WTO accession. One explanation is that most universities and colleges are situated in urban areas, while rural farmers are generally poorer than urban residents. Consequently, the opportunity cost of pursuing higher education is greater in rural areas compared to urban areas.

3.5 Additional robustness results

3.5.1 Random selection

I first employ a placebo test where I create “fake" coal prefectures by reshuffling the prefectures in my original data set. If the coal prefecture effectively capture the resource windfalls rather than other confounding factors, I anticipate that the placebo analysis using these “fake" coal prefectures will yield statistically insignificant estimates. I repeat the baseline specification in column (1) of Table 3.2.

Figure 3.7 illustrates the distribution of p-values for the estimated coefficients of university attainment across these 500 iterations. In the majority of cases, the p-values exceed 10%, indicating that the use of randomly selected prefectures as coal prefecture status fails to produce significant estimates. This placebo test demonstrates that coal prefecture effectively generates exogenous variation.

3.5.2 Alternative measure of coal prefecture

Additionally, to enhance robustness, an alternative proxy for resource-abundant prefectures is employed. Following Shao et al., 2020, the measure utilized is the prefecture's labor share dedicated to mining relative to total labor, indicative of the prefecture's intensity of dependence on coal:

$$\text{Mining Share} = \frac{\text{Mining Employment}}{\text{Total Employment}} \tag{3.2}$$

I use the data from China City Statistical Yearbook in 2001 to construct the mining share. This prefecture-level indicator in Equation 3.2 is utilized to gauge each prefecture's mining intensity. Prefectures positioned at the 75$^{\text{th}}$ percentile of this indicator are categorized as coal prefectures (treatment group), while those at the lowest 25$^{\text{th}}$ percentile are assigned a dummy variable value of zero, defining them as non-coal-dependent prefectures (control group). In total, 86 prefectures are designated as coal-dependent (treatment group), and 67 prefectures as non-coal-dependent (control group). This selection criterion is grounded in the concentration of labor and capital inputs within the resource sector during periods of resource boom. Thus, the absorptive capacity of the resource sector vis-à-vis production factors serves as a significant reflection of the extent of the resource sector boom.

Column (1) of Table 3.8 replicates the primary findings, indicating persistent declines in university attainment among high school students in coal abundant prefectures. However, the declines in students' cognitive outcomes as shown in columns (2) to (4) are not observed and without significance.

3.5.3 Alternative specifications: international coal price

I conduct supplementary tests employing an alternative measure of the boom period. Instead of designating 2004 as the initial year of the boom, I adopt a method similar to Mejía, 2020 and Gradstein and Klemp, 2020, using the logarithm of international coal price as an indicator of the boom period. Although China produces the largest volume of coals around the world, most of the output supplies the domestic rather than the international market. Moreover, the domestic price was higher than the average of imported coals due to the high transportation cost within China. As a result, China is a price-taker in the global coal market. Columns (1) in Table 3.9 present the estimation results, indicating that the coal boom is associated with declines in education outcomes. Also, the column (6) suggests that the coal boom improves the probability of having any employment.

3.5.4 Adding initial year characteristics

Additionally, to mitigate potential confounding factors that might affect different cohorts differently, especially prevalent in coal prefectures, I include initial year characteristics such as GDP per capita, population size, fiscal expenditure, and secondary employment share in 2003. Specifically, I incorporate region-specific controls by interacting initial prefecture characteristics with the post-coal boom dummy variable ($Z_c \times \text{Boom}_t$) to account for time-varying regional factors that could confound the analysis. The results presented in columns (1) to (4) in Table 3.10 demonstrate that the impact of the coal boom on youth education outcomes remains statistically significant, while the effects on labor market outcomes are not significant.

3.5.5 Alternative cohort

The above analysis focuses on the impacts on cohort aged 19 during my sample period. Here, I compare the school attainment of individuals who reached the key age of 16 after coal boom period with those reaching 16 before, as this is the earliest time individuals can make their own decisions regarding education, including the option to quit school.

Table 3.11 presents the results from estimating Equation 3.1 with the 16-year-old cohorts in the sample. The coefficient in column (1) is not significant, indicating that the coal boom does not significantly influence the university decisions of these younger cohorts. However, columns (2), (4), and (6) reveal that the coal boom negatively impacts cognitive test scores and positively affects labor market outcomes for this cohort. This is because cohorts aged 16 in 2004 would be 19 in 2007, meaning they are partially affected by the coal boom (Kovalenko, 2023). Overall, the insignificant result in column (1) further substantiates the findings regarding higher education attainment for the 19-year-old cohorts.

3.6 Conclusion

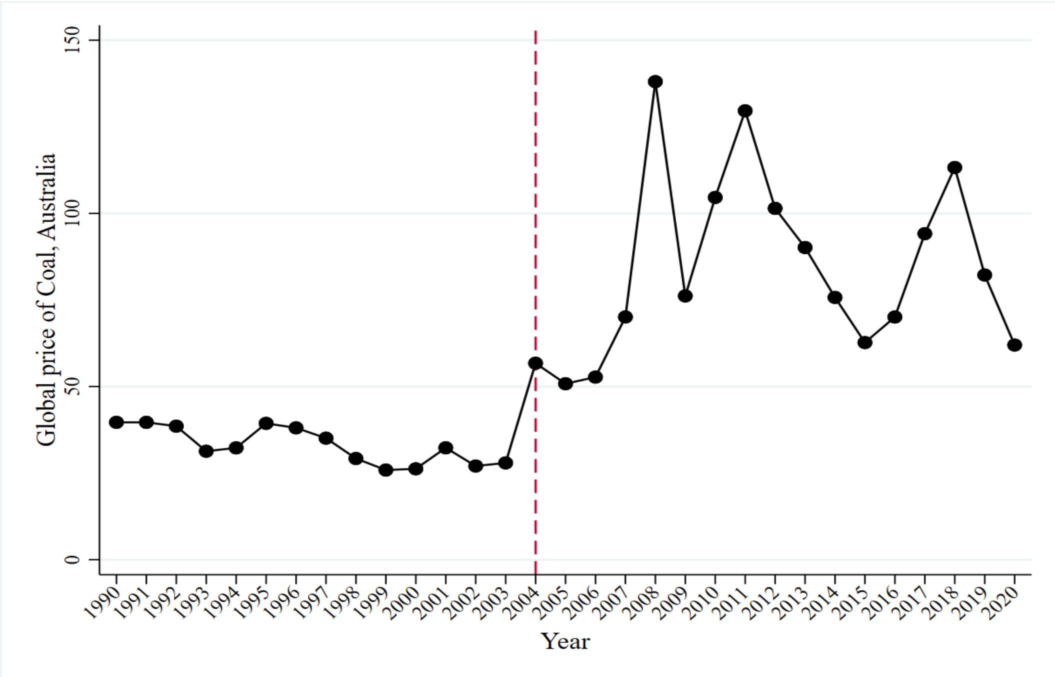
This paper provides empirical evidence on the long-term effects of the global coal boom starting from 2004, particularly examining its impact on human capital accumulation. Using matched data from China's population census and CFPS data set, this study investigates how coal-abundant prefectures in China have been affected in terms of educational, cognitive and labor market outcomes.

The findings indicate a significant negative impact of the coal boom on high level education attainment among high school students, evidenced by reduced university attainment rates and lower cognitive test scores. Additionally, the analysis of labor market outcomes reveals an increase in the income and an increase in employment rates among affected individuals. These results suggest rational decision-making behaviors in response to economic incentives, consistent with similar findings by Mosquera, 2022 and Kovalenko, 2023.

The paper also acknowledges several limitations that may provide avenues for future research. A primary caveat is the use of the coal boom period starting in 2004 as the treatment period. While this approach complements existing literature on natural resource booms (Mosquera, 2022; Kovalenko, 2023), the coal price surge could be largely attributed to China's economic expansion. In this regard, my definition of the boom period may be endogenous, potentially biasing the estimates. Moreover, this study examines the medium-term effects on labor market outcomes for high school students, but the research sample does not extend far enough to capture longer-term results. Future research could benefit from new data sources to provide a more comprehensive evaluation of China's coal boom.

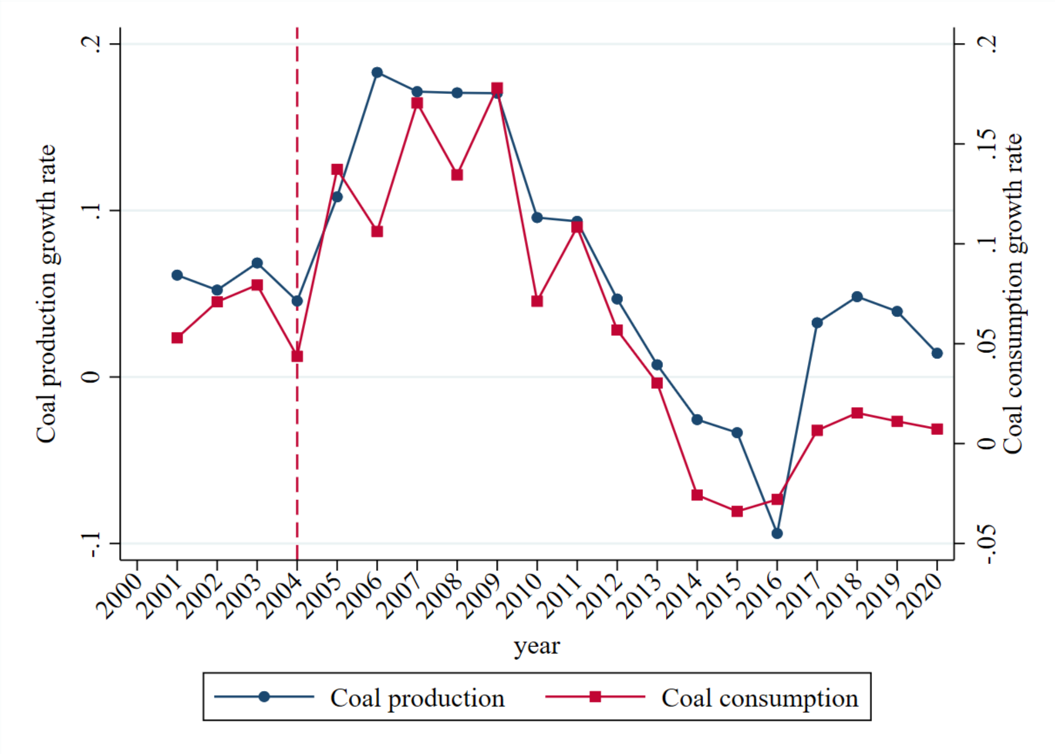
Figures

FIGURE 3.1: Trend of international coal price, Australia



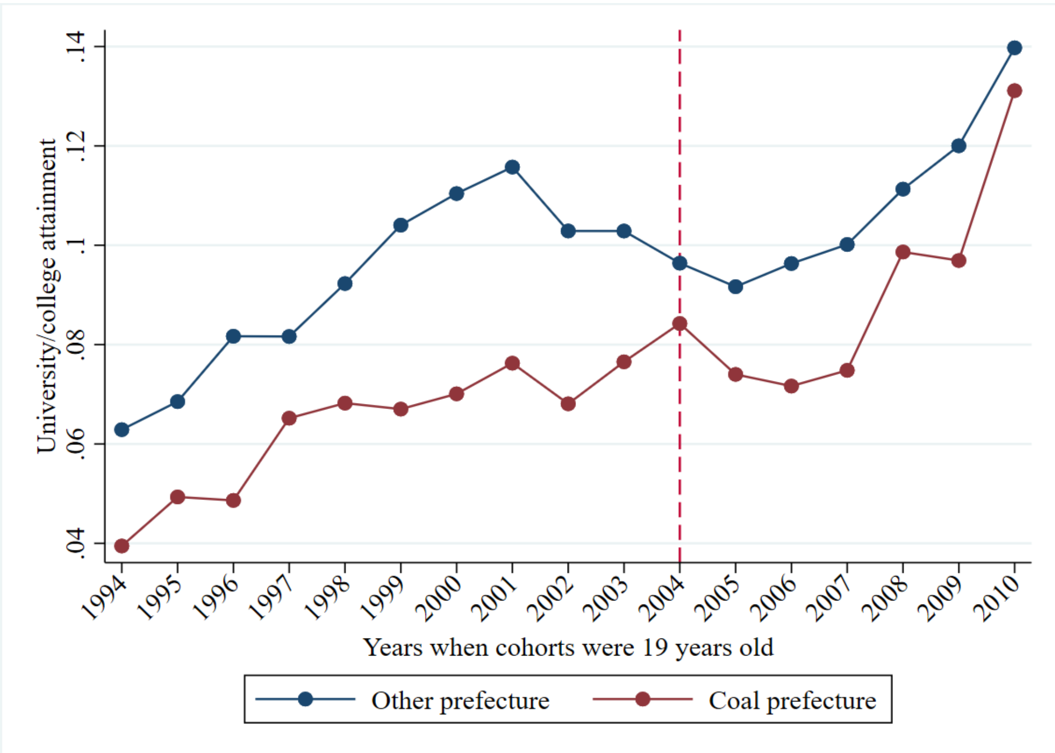
Notes: The Australia coal price is accessed from International Monetary Fund. And prices are period averages in nominal U.S. dollars, and unit is dollars per metric ton without seasonally adjusted.

FIGURE 3.2: Coal production and consumption growth in China



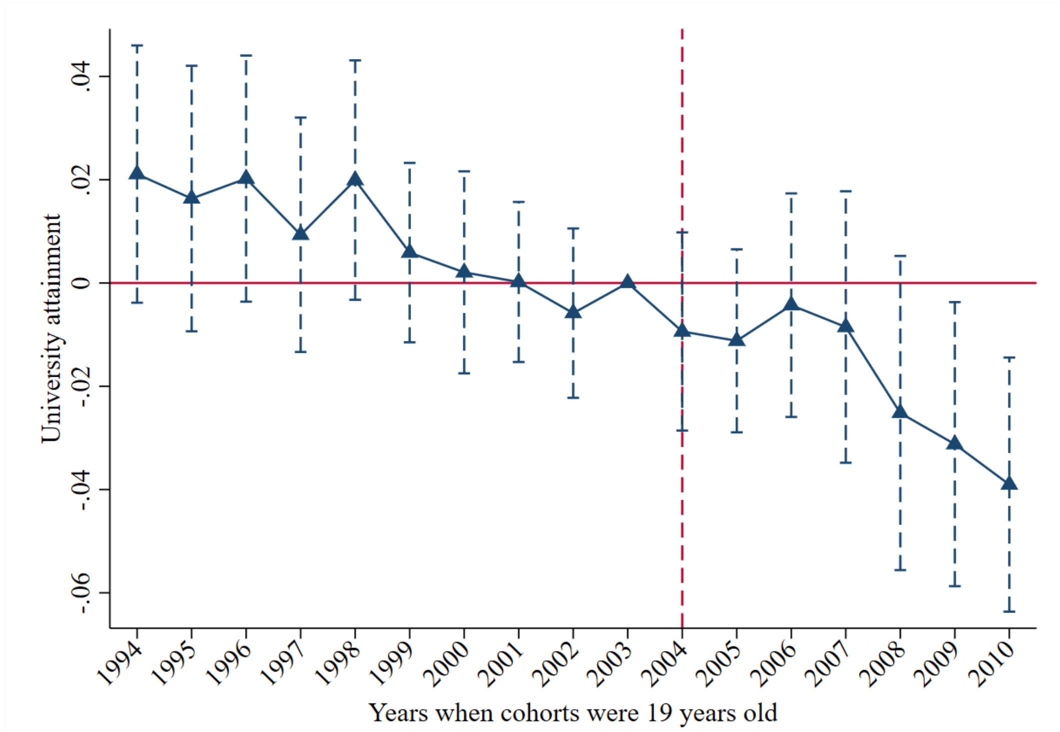
Notes: The data is from China Energy Statistical Yearbook.

FIGURE 3.3: Trend of Chinese students' university attainment



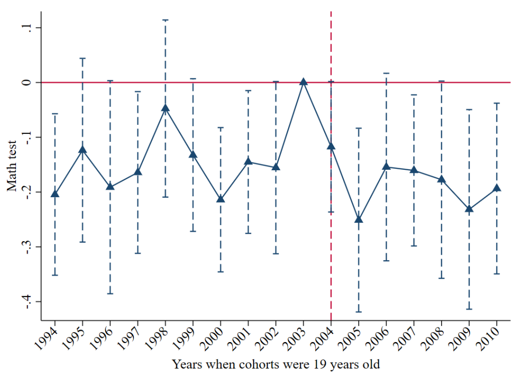
Notes: The data is from 2010 China Population Census, and x-line represents the year when cohorts were 19 years old.

FIGURE 3.4: Event study: university attainments

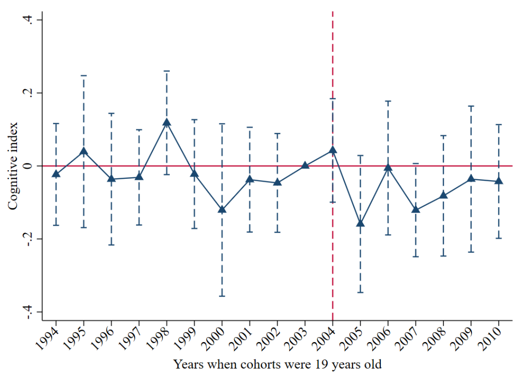


Notes: The figure presents the estimated coefficients of the interaction terms between coal prefecture dummy and the 19-year-old cohort dummy for each year.

FIGURE 3.5: Event study: cognitive test scores



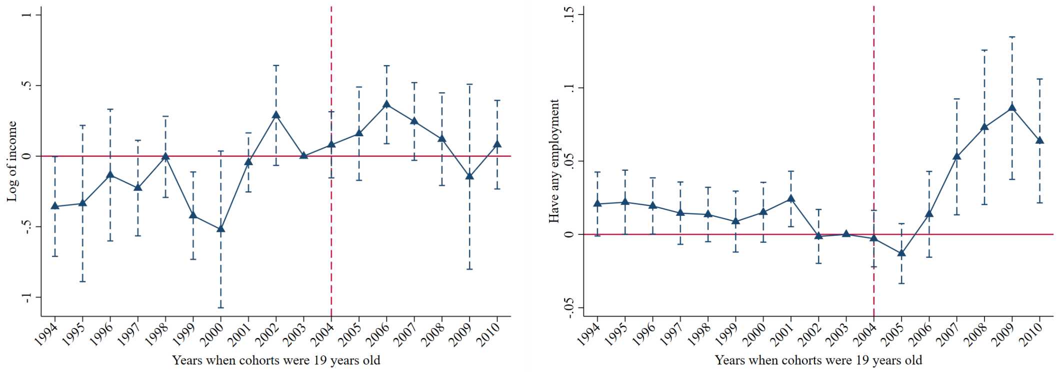
(A) Math test scores



(B) Cognitive index

Notes: This event study figure replicates the effect of coal boom on cognitive index using the CFPS data set. The red dashed line represents the start of coal boom year.

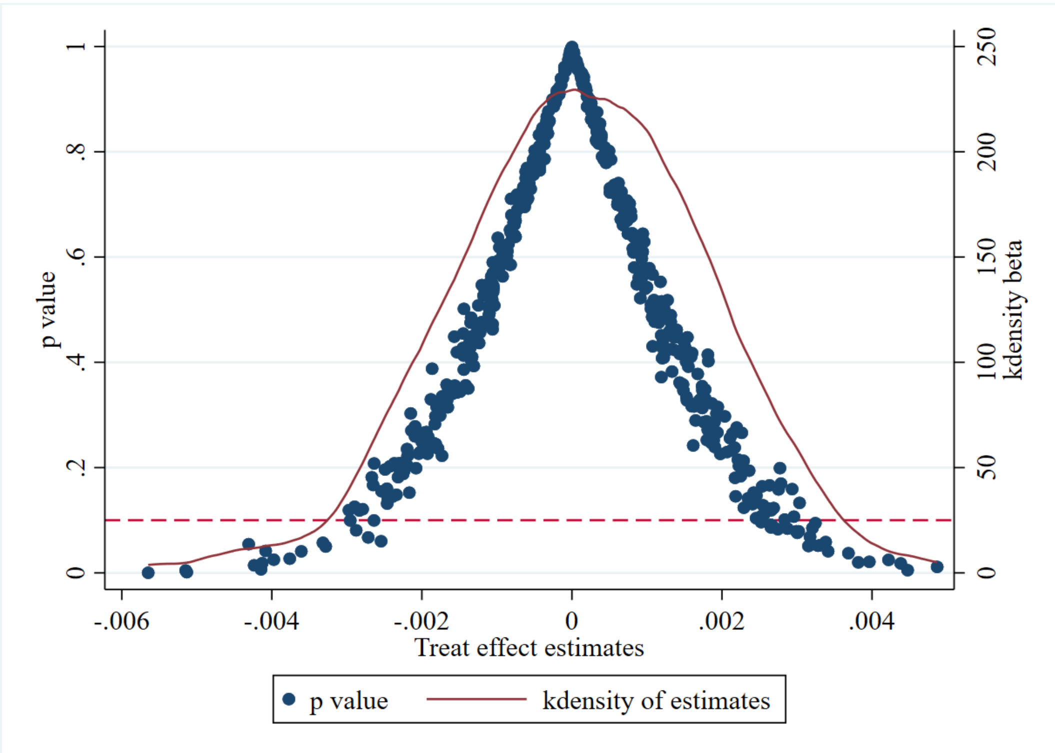
FIGURE 3.6: Event study: labor market outcomes



(A) Log annual income (B) Have any employment

Notes: Panel (a) examines the effect of coal boom on log of income using the CFPS data set. Panel (b) examines the effect of coal boom on employment rate using the China Population census data. The red dashed line represents the start of coal boom year.

FIGURE 3.7: Placebo Tests: The effect of coal boom on university attainment



Notes: This figure presents the robustness check results for column (1) of Table 3.2. The red dashed line represents the p-value threshold at the 0.1 level.

Tables

TABLE 3.1: Summary statistics

	N	Mean	Standard Deviation
Panel A Coal boom			
Coal prefecture (Yes=1)	308,418	0.248	0.432
International coal price	308,418	59.843	35.054
Panel B Education attainments			
University/college attainment	308,418	0.205	0.404
High school attainment	308,418	0.446	0.497
Grade level (1-7)	308,418	3.751	1.146
Panel C Cognitive scores			
Math test score	9,376	14.548	5.477
Verbal test score	9,376	24.529	7.305
Panel D Labor market outcomes			
Log of annual income	7,682	9.427	1.399
Have any employment (Yes=1)	308,418	0.661	0.473

Notes: The sample comes the 0.3% of 2010 China Population Census and CFPS data set (2010 to 2014).

TABLE 3.2: Population census education attainment estimates

Variable:	University attainment	High school attainment	Grade level
	(1)	(2)	(3)
Coal × Boom	-0.0271***	-0.0110	-0.0566***
	(0.0093)	(0.0084)	(0.0206)
Observations	265,811	265,811	265,811
R-squared	0.3489	0.3930	0.4440
Individual Control	X	X	X
Prefecture FE	X	X	X
Year FE	X	X	X

Notes: The sample comes from China Population census for cohorts who aged 19 in year 1994 to 2010. All the standard errors are clustered at the prefecture level. *** p<0.01, ** p<0.05, * p<0.1

TABLE 3.3: CFPS cognitive estimates

Variable:	Mathtest	Wordtest	Testscore
	(1)	(2)	(3)
Coal × Boom	-0.0458*	-0.0373	-0.0427
	(0.0274)	(0.0345)	(0.0281)
Observations	9,216	9,216	9,216
R-squared	0.7018	0.4570	0.6791
Individual Control	X	X	X
Prefecture FE	X	X	X
Year FE	X	X	X

Notes: The sample comes from CFPS data set (2010 and 2014). All the standard errors are clustered at the prefecture level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 3.4: Labor market outcomes

Variable:	Log annual income	Have Any employment
	(1)	(2)
Coal $\times$ Boom	0.1633*	0.0265
	(0.0942)	(0.0163)
Observations	7,403	265,811
R-squared	0.3304	0.1827
Individual Control	X	X
Prefecture FE	X	X
Year FE	X	X

Notes: Column (1) uses sample from CFPS data set (2010 to 2014). Column (2) uses sample from China Population census data set. All the standard errors are clustered at the prefecture level. *** p<0.01, ** p<0.05, * p<0.1

TABLE 3.5: Heterogeneous effects on cognitive outcomes: by urban/rural

Variable:	University		Mathtest		Wordtest		Testscore	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coal × Boom	-0.0436**	-0.00838***	-0.0528	-0.0019	-0.0492	0.0323	-0.0631**	0.0222
	(0.0197)	(0.0017)	(0.0320)	(0.0487)	(0.0428)	(0.0719)	(0.0298)	(0.0501)
Observations	92,239	170,362	6,192	3,017	6,192	3,017	6,192	3,017
R-squared	0.0928	0.0184	0.6391	0.5811	0.4013	0.3697	0.6242	0.6015
Individual Control	X	X	X	X	X	X	X	X
Prefecture FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X

Notes: The sample in column (1) is from Population census. The sample in columns (2) to (8) comes from CFPS data set (2010 and 2014). All the standard errors are clustered at the prefecture level. *** p<0.01, ** p<0.05, * p<0.1

TABLE 3.6: Heterogeneous effects on cognitive outcomes: by parental education

Variable:	Mathtest		Wordtest		Testscore	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Coal × Boom	0.0072	-0.1126***	0.0505	-0.1601**	0.0346	-0.1488***
	(0.0424)	(0.0412)	(0.0356)	(0.0635)	(0.0356)	(0.0480)
Observations	5,492	3,699	5,492	3,699	5,492	3,699
R-squared	0.6319	0.6221	0.3723	0.4108	0.6071	0.6197
Individual Control	X	X	X	X	X	X
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: The sample comes from CFPS data set (2010 and 2014). All the standard errors are clustered at the prefecture level. *** p<0.01, ** p<0.05, * p<0.1

TABLE 3.7: Heterogeneous effects on labor market outcomes

Variable:	Log of income				Have any employment	
	Rural	Urban	Low	High	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)
Coal × Boom	0.2018**	-0.2430*	0.2119**	0.1095	0.0014	0.0101
	(0.0988)	(0.1422)	(0.1004)	(0.1382)	(0.0088)	(0.0208)
Observations	4,892	2,504	4,438	2,962	171,139	94,671
R-squared	0.2821	0.3716	0.3286	0.3047	0.1121	0.2966
Individual Control	X	X	X	X	X	X
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: Column (1) to (4) use CFPS data set and column (5) and (6) use China Population census for cohorts who aged 19 in year 1995 to 2010. All the standard errors are clustered at the prefecture level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 3.8: Robustness: using mining share

Variable:	University	Mathtest	Wordtest	Testscore	Log of income	Employment
	(1)	(2)	(3)	(4)	(5)	(6)
MiningShare × Boom	-0.0283*	0.0182	0.0013	0.0134	0.1522	0.0387
	(0.0174)	(0.0334)	(0.0466)	(0.0388)	(0.1569)	(0.0263)
Observations	117,272	4,704	4,704	4,704	3,744	117,272
R-squared	0.3475	0.7071	0.4826	0.7012	0.3434	0.1790
Individual Control	X	X	X	X	X	X
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: Column (1) and (6) use China Population census data set. Column (2) to (5) use CFPS data set (2010 and 2014). All the standard errors are clustered at the prefecture level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 3.9: Robustness: using international coal price

Variable:	University	Mathtest	Wordtest	Testscore	Log of income	Employment
	(1)	(2)	(3)	(4)	(5)	(6)
Coal × Price	-0.0267***	-0.0390	0.0282	-0.0018	0.1106	0.0418**
	(0.0094)	(0.0289)	(0.0378)	(0.0312)	(0.0831)	(0.0181)
Observations	265,811	6,488	6,488	6,488	7,403	265,811
R-squared	0.3489	0.7013	0.4416	0.6691	0.3303	0.1829
Individual Control	X	X	X	X	X	X
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: Column (1) and (6) use China Population census data set. Column (2) to (5) use CFPS data set (2010 and 2014). All the standard errors are clustered at the prefecture level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 3.10: Robustness: adding initial year characteristics

Variable:	University	Mathtest	Wordtest	Testscore	Log of income	Employment
	(1)	(2)	(3)	(4)	(5)	(6)
Coal $\times$ Boom	-0.0169**	-0.0606**	-0.0590	-0.0716**	0.0532	-0.0034
	(0.0083)	(0.0305)	(0.0404)	(0.0330)	(0.0726)	(0.0134)
Observations	265,811	9,216	9,216	9,216	7,403	265,811
R-squared	0.3499	0.7021	0.4573	0.6796	0.3336	0.1868
Initial year Control	X	X	X	X	X	X
Individual Control	X	X	X	X	X	X
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: Column (1) and (6) use China Population census data set. Column (2) to (5) use CFPS data set (2010 and 2014). All the standard errors are clustered at the prefecture level. *** p<0.01, ** p<0.05, * p<0.1

TABLE 3.11: Robustness: impacts on 16 years old cohorts

Variable:	University	Mathtest	Wordtest	Testscore	Log of income	Employment
	(1)	(2)	(3)	(4)	(5)	(6)
Coal × Boom	-0.0035	-0.0909**	-0.0525	-0.0788*	0.1163	0.0531***
	(0.0069)	(0.0423)	(0.0537)	(0.0467)	(0.1033)	(0.0176)
Observations	260,195	8,989	8,989	8,989	12,530	260,195
R-squared	0.3410	0.6590	0.4263	0.6501	0.3001	0.3105
Individual Control	X	X	X	X	X	X
Prefecture FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: Column (1) and (6) use China Population census data set. Column (2) to (5) use CFPS data set (2010 and 2014). All the standard errors are clustered at the prefecture level. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Prefecture list

TABLE 3.12: 45 coal mining prefectures in 2003

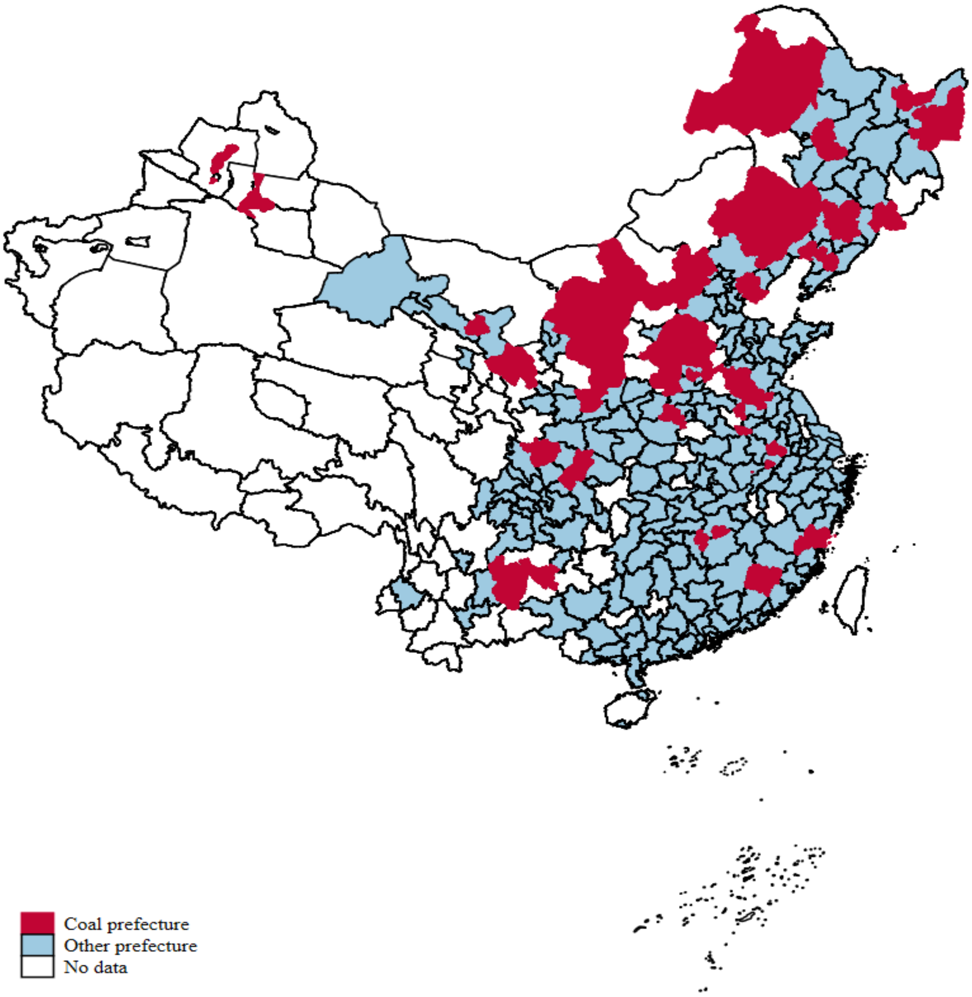
Prefecture name	Province	Prefecture name	Province
Luquan (Shijiazhuang)	Hebei	Handan	Hebei
Tangshan	Hebei	Datong	Shanxi
Tongliao	Neimenggu	Huhehaote	Neimenggu
Baotou	Neimenggu	Ordos	Neimenggu
Hulunbeier	Neimenggu	Chifeng	Neimenggu
Wuhai	Neimenggu	Jixi	Heilongjiang
Qitaihe	Heilongjiang	Hegang	Heilongjiang
Daqing	Heilongjiang	Diaobingshan (Tieling)	Liaoning
Beipiao (Chaoyang)	Liaoning	Fuxin	Liaoning
Anshan	Liaoning	Panjin	Liaoning
Fushun	Liaoning	Baishan	Jilin
Pingdingshan	Henan	Jiaozuo	Henan
Puyang	Henan	Zaozhuang	Shandong
Zoucheng (Jining)	Shandong	Yulin	Shannxi
Tongchuan	Shannxi	Huainan	Anhui
Huaibei	Anhui	Tongling	Anhui
Maanshan	Anhui	Daye (Huangshi)	Hubei
Xinyu	Jiangxi	Fuding (Ningde)	Fujian
Longyan	Fujian	Gejiu (Honghe hani)	Yunnan
Lanzhou	Gansu	Jinchang	Gansu
Baiyin	Gansu	Shizuishan	Ningxia
Geermu	Qinghai	Wulumuqi	Xinjiang
Kelamayi	Xinjiang		

Notes: The sample comes from the China Mining Statistical Yearbook 2003.

Map

Figure 3.8 depicts the distribution of coal-prefecture treatment groups alongside the control groups utilized in this study.

FIGURE 3.8: The distribution of coal prefectures in China



Notes: The distribution of coal prefectures is based on the China Mining Statistical Yearbook 2003.

Balance test

Here, I examine whether there are time-varying shocks specific to areas and whether they are correlated with student outcomes. In Table 3.13, I show changes in student and local economic characteristics between 1995 and 2003. The corresponding two-tailed p-value is is larger than 0.05, indicating that the difference of means in economic conditions between coal prefectures and other prefectures equals 0. Therefore, I do not find any economically meaningful differences in trends across regions.

TABLE 3.13: Summary Statistics

	Changes, 1995-2003		
	Coal prefecture	Others	p-values
	(1)	(2)	(3)
University attainment rate	0.076	0.088	0.433
High school attainment rate	0.084	0.106	0.166
Grade level	0.312	0.403	0.083
Log of income	-0.042	0.213	0.171
Employment rate	0.067	-0.035	0.115
GDP per capita	5903.307	6994.495	0.112
Share of secondary emoloyment	14.23621	13.53421	0.572

Notes: The table reports means for student and prefecture characteristics from 1995 to 2003. Column (3) reports the p-values associated with the null hypothesis of equivalent means across the groups.

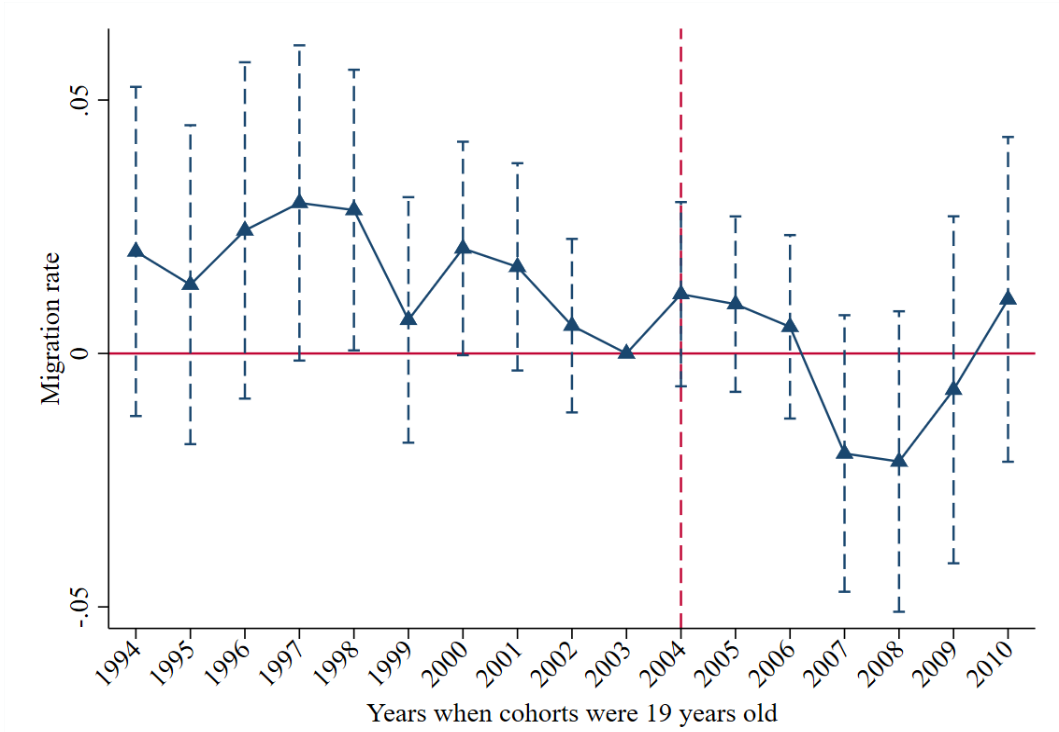
Selective Migration

Another concern is that the results could be biased by selective migration. Systematic migration into booming areas, driven by improved labor market opportunities, has the potential to alter the population composition, thereby biasing the results. To address this issue, I follow Lin and Long, 2020 and Kovalenko, 2023, focusing on high school students who have lived in the area since birth, thus excluding potential migrants from my sample. I also estimate the impact of the coal boom on migration rates. Figure 3.9 indicates no statistically significant effect of the coal boom on the probability of moving out of one's birth prefecture. Moreover, individuals residing in coal-prefectures exhibit lower migration rates in 2007 and 2008. This result corroborates the validity of my identification strategy.

Trends since 2010

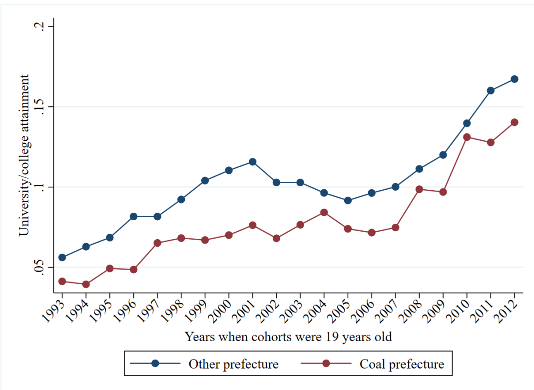
Here, I further examine what happens after 2010 in Figure 3.10, as the coal industry went into a slump. To do this, I first use the new Population Census 2015 to look at the university/college attainment trends. I find that coal workers do not abandon the industry and pursued new opportunities. The trend is similar to the previous period. I also use the China City Statistical Yearbook to examine the mining employment trends in each prefectures in panel (b), and the results show that the mining employment decrease since 2014. So, this means that this estimated effect is transitory during that period (2005-2015) and not permanent.

FIGURE 3.9: Event study: migration rate

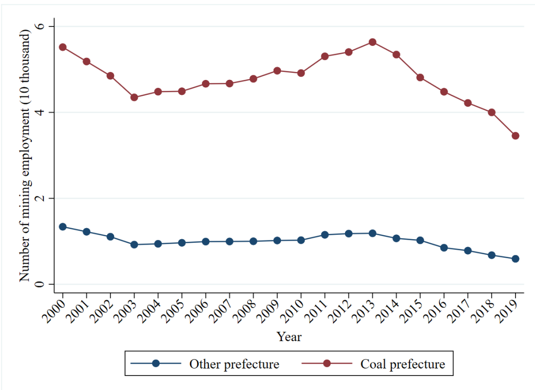


Notes: This event study figure estimates the effect of coal boom on high school students' migration rates using the China Population census data.

FIGURE 3.10: Trends of university attainment and mining employment



(A) University attainment



(B) Mining employment

Notes: This two figures plot the trends of university attainment rate using 2015 China Population Census and prefecture-level mining employment using China City Statistical Yearbook.

Suppose alternative policy year

TABLE 3.14: Population census education attainment estimates: suppose alternative policy year

Variable:	University attainment	High school attainment	Grade level
	(1)	(2)	(3)
Panel A: Suppose in 2002			
Coal × Boom	0.0225***	0.0217***	0.0425**
	(0.0073)	(0.0079)	(0.0080)
Panel B: Suppose in 2001			
Coal × Boom	0.0219***	0.0229***	0.0625**
	(0.0072)	(0.0080)	(0.0188)
Individual Control	X	X	X
Prefecture FE	X	X	X
Year FE	X	X	X

Notes: The sample comes from China Population census for cohorts who aged 19 in year 1994 to 2010. All the standard errors are clustered at the prefecture level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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