Essays on Environmental and Labor Economics

ABSTRACT

ESSAYS ON ENVIRONMENTAL AND LABOR ECONOMICS

By

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This dissertation consists of three essays on Environmental and Labor Economics.

The first chapter estimates the impact of the winter clean heating pilot (WCHP) project on air quality in northern China using staggered models. The primary findings indicate an overall reduction in air pollution levels in northern China attributed to the WCHP. Moreover, the WCHP exhibits heightened effectiveness during the heating period, resulting in a reduction of $PM_{2.5}$ by 13.39 μg/m^3 (14.2%), and PM_{10} by 21.06 μg/m^3 (13.6%). Additionally, the study reveals unintended consequences of the WCHP in mitigating historical disparities in air pollution levels between northern and southern China due to the Huai River policy (HRP). Following the implementation of the WCHP, there is a notable decrease in air pollution levels in northern regions compared to southern areas. Specifically, $PM_{2.5}$ and PM_{10} in northern China exhibit a substantial and greater decrease than in southern China, with reductions of 13.07 μg/m^3 (23%) and 21.31 μg/m^3 (21%), respectively.

Hedonic theory predicts that housing prices should increase as air quality improves from environmental regulations. However, environmental policies also bring substantial costs to influenced industries and affect labor markets, which affect housing markets. The second chapter investigates the effects of environmental regulations on both house values and rents under the

setting of a cap-and-trade program - the NOx Budget Trading Program (NBP), considering both the amenity channel and the labor-market channel. I find that the pass-through of the value of environmental improvements is lower among renters than that of house owners. In addition, house values and rents decrease more in higher manufacturing energy intensity areas due to the negative impact of the NBP on the local labor market. Furthermore, the distributional effects of the NBP are distinctly different between owner-occupants and renters.

The third chapter examines the impact of family size on the labor market behavior and occupational characteristics of employed parents in the United States, utilizing an instrumental variable approach. By leveraging exogenous variation in family size resulting from the sex composition of the first two children, I analyze changes in parents' job flexibility, employer-provided health insurance, and occupational prestige scores. The findings reveal that parents with larger families tend to have occupations characterized by greater flexibility, as indicated by lower scores in the five job features related to flexibility. Additionally, parents tend to hold jobs that offer employer- or union-provided health insurance. Furthermore, the analysis uncovers a noteworthy trend: each additional child corresponds to a 7.8% to 10.2% decrease in the prestige scores of both mothers and fathers. This suggests a discernible shift towards occupations with lower prestige scores as family size increases.

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Chapter I. The Effects of a Clean Heating Policy on Air Quality in China

1.1. Introduction

Winter heating in residential buildings in cold regions has emerged as a significant global energy consumption concern (Deroubaix et al., 2021). The carbon emissions resulting from winter heating, the largest single end-use service related to energy for maintaining warmth, significantly contribute to air pollution (Sovacool et al., 2021). The World Health Organization (WHO) warns that pollution has led to nine out of 10 people breathing polluted air, resulting in seven million deaths annually. Additionally, one-third of deaths from stroke, lung cancer and heart disease are attributed to air pollution[1]. This alarming situation demands urgent attention from climate policymakers and researchers to address the challenge of decarbonizing heating methods. However, the energy crisis that started in 2021 has driven up energy prices, including natural gas and electricity, making heating less affordable for users. Moreover, energy poverty has become more widespread and evident due to the impact of the COVID-19 pandemic (Che et al., 2021). Consequently, the issue of winter heating is no longer confined to developing countries but has become a global problem requiring immediate action and attention.

Particularly, the Chinese government established free or heavily subsidized winter indoor heating by providing free coal for fuel boilers, which is associated with the release of air pollutants from coal combustion. Due to budget constraints, the Chinese government implemented the Huai River policy (HRP) in the 1950s, dividing the north and south by the line formed by the Huai River and Qinling Mountain range[2]. This policy exclusively granted free or subsidized indoor heating to northern China. Consequently, northern China has experienced hazardous air pollution from the coal-fired heating services during winter. This has led to unintended consequences of the HRP, evident in marked disparities in air pollution levels and residents' health between northern and

[1]How air pollution is destroying our health (World Health Organization):https://www.who.int/news-room/spotlight/how-air-pollution-is-destroying-our-health

[2]In subsequent sections of the paper, the terms "Huai River boundary" or "Huai River line" will be employed to indicate the geographical division between northern and southern China.

southern China (Chen et al., 2013; Ebenstein et al., 2017).

Moreover, coal-fired winter heating increased $PM_{2.5}$ level by more than 50% in Beijing (Liang et al., 2015). In response to this concern, China launched the Winter Clean Heating Pilot (WCHP) project in 2017 as part of the *Clean winter heating plan for Northern China (2017-2021)*[3]. The primary objective of the project is to provide subsidies to northern cities, encouraging the energy transition of their heating systems from coal to natural gas or electricity. Mei et al. (2021) find that switching power plants from coal to natural gas in Beijing in 2013 resulted in favorable price premiums to nearby properties, indicating potential economic benefits. Other literature focuses on the impact of the WCHP on air pollution and concludes that it effectively improved air quality in northern China (Zhang et al., 2020; Tan et al., 2023; Zeng et al., 2022). However, the intended and unintended effects of the WCHP project on air pollution in China have not been extensively studied.

This paper is dedicated to a thorough examination of the effects of the WCHP on air pollution in China. The study is designed to address two primary research questions: 1) how does the WCHP impact air pollution derived from winter heating in northern cities? 2) to what extent does the WCHP alleviate the disparities in air pollution levels and human health outcomes between northern and southern China, the unintended consequence originally introduced by the HRP implemented in the 1950s?

First, to examine the impact of the WCHP on air quality in northern China, I analyze city-level annual average air pollution data sourced from the National Urban Air Quality Real-time Publishing Platform. Two distinct empirical methodologies are employed. Initially, the standard two-way fixed effects (TWFE) approach is used to evaluate the overall effects of the WCHP project on air pollution among northern Chinese cities. However, the literature argues that the TWFE estimator equals a weighted average of all possible 2×2 DiDs, which can be problematic in cases with

[3]The report comprehensively covers the heating situation in Northern China, providing insights into guiding principles, targets, and the promotion strategy. More details can be found at:https://chinaenergyportal.org/en/clean-winter-heating-plan-for-northern-china-2017-2021/

more than two time periods and heterogeneous effects (Borusyak et al., 2023; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Imai et al., 2023). Therefore, I utilize Goodman-Bacon decomposition to illustrate the components of the TWFE estimates and reveal the potentially biased terms. Additionally, selection bias may exist in the cities chosen for the WCHP project, while the TWFE approach is valid only if the randomized treatment assumption holds. To overcome these limitations, I introduce staggered models to examine the overall effects of the WCHP and its effects specifically during the heating season. Second, to address the second research question, a regression discontinuity (RD) design based on the cities' distance to the Huai River line is employed. I use the same source of data to investigate whether the WCHP has mitigated the disparities in air pollution levels between northern and southern China due to the HRP.

This paper is pioneering in its approaches to comprehensively study the WCHP by using staggered difference-in-differences (DID), staggered triple differences (DDD), and RD methods. The staggered methods effectively address concerns related to the bias of the TWFE model in estimating the average treatment effects on the treated (ATT) and the possible selection bias inherent in the WCHP project. Notably, the staggered DDD method distinguishes this study by assessing the effects on air quality in northern Chinese cities specifically during winter following the implementation of the WCHP, as opposed to the average effects observed throughout the entire year. Additionally, this research is unique in examining the WCHP's effectiveness throughout its entire duration from 2017 to 2021. The meticulous collection of precise starting and ending dates of winter heating services among 120 northern cities over seven years further enhances the accuracy of both methods, thereby allowing for more accurate estimates. Furthermore, this study stands out for its exploration of the WCHP's unintended effects on disparities in air pollution levels between northern and southern China. Employing an RD design based on the distance to the Huai River line, the research examines the policy's potential to alleviate historical disparities introduced by the HRP implemented in the 1950s. This innovative idea illuminates the WCHP project's capacity to address longstanding regional imbalances caused by historical policies, contributing to a deeper understanding of overlapping environmental policies and their unintended consequences in the context of China.

The staggered DID analysis reveals an overall positive effect of the WCHP on air quality in northern China, resulting in reductions in annual levels of $PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2 by 9.03 $\mu g/m^3$, 13.10 $\mu g/m^3$, 0.347 $\mu g/m^3$, 3.49 $\mu g/m^3$, and 10.56 $\mu g/m^3$, respectively. Additionally, the annual mean of the Air Quality Index (AQI), a comprehensive ambient air pollution index, decreased by 8.05. Moreover, the staggered DDD results indicate significantly higher reductions in $PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, and AQI during the heating season: 13.39 $\mu g/m^3$, 21.06 $\mu g/m^3$, 0.599 $\mu g/m^3$, 5.34 $\mu g/m^3$, 27.94 $\mu g/m^3$, and 14.33, respectively. These reductions are attributed to the exclusive funding for clean heating projects. Furthermore, the study suggests that disparities in air pollution levels stemming from the HRP persist. For instance, PM_{10} rises by 29/35 $\mu g/m^3$ at the boundary in the restricted and full samples, respectively, aligning closely with the findings of 27/32 $\mu g/m^3$ in Ebenstein et al. (2017). However, there is a notable decrease in air pollution levels in northern regions compared to southern areas following the WCHP implementation (e.g., $PM_{2.5}$ and PM_{10} in northern China decreases by 13/18 $\mu g/m^3$ and 21/32 $\mu g/m^3$ more than in southern China after 2017, respectively). These findings highlight the unintended consequences of the WCHP on addressing historical environmental inequalities and regional imbalance, emphasizing the complexity of such interventions and their outcomes.

The rest of the paper is organized as follows. Section 1.2 provides a literature review and background. Section 1.3 describes the data sources. Section 1.4 discusses the empirical strategies. Section 1.5 presents results. Section 1.6 is the robustness check. Section 1.7 concludes the paper.

1.2. Background and Literature Review

1.2.1. Huai River policy (HRP) and Chinese Winter Heating System

Learning from the former Soviet Union's system, the Chinese government initiated a coal-fired winter heating system in the 1950s and gradually expanded it during the planned economy period

(1950s-1980s) (Fan et al., 2020). Due to energy and budget constraints in the 1950s, the Chinese government implemented the Huai River policy (HRP), which defined northern and southern China by the Huai River boundary. The HRP exclusively granted free or subsidized coal for fuel boilers to northern Chinese residents, as the northern regions generally experience a colder and extended winter season, and the government arbitrarily decided on this boundary.

In northern China, there are two different ways to keep buildings warm in winter: the centralized heating system and individual heating devices. In urban areas, the centralized heating system is commonly used. It connects fuel boilers with residential and commercial buildings and consists of boilers, water pipelines that deliver hot water to households and offices, and radiators. The centralized heating service is either provided at zero cost or heavily subsidized by the government (Fan et al., 2020). As mentioned earlier, the state-provided centralized heating service is not offered by local governments in southern China, as the government arbitrarily decided that southern China did not need it. In rural areas, most households use individual coal-fired heating devices at home, such as domestic heating stoves, kangs[4](Zhuang et al., 2009). This study specifically focuses on the effects of the energy transition in the centralized heating system in cities.

The HRP was initially designed to provide more comfortable winters for northern Chinese residents, yet it inadvertently led to environmental issues. Chen et al., 2013 suggest that under the coal-fired heating system, the HRP significantly increased total suspended particulates (TSPs) air pollution in the north, reducing over 2.5 billion life years of life expectancy among the 500 million northern Chinese residents. Additionally, Ebenstein et al. (2017) document that the HRP caused a 46% higher release of PM_{10} during winter heating seasons, leading to shortened lifespans in the north, primarily due to elevated cardio-respiratory mortality rates. Fan et al. (2020) find that initiating a heating service increased weekly air pollution by 36% and caused a 14% higher mortality rate. They also indicate that people in poor and rural areas were more severely affected

[4]A typical Chinese kang in northern China usually has different functions of cooking, bed, domestic heating, and ventilation.

by the rapid deterioration in air quality. Wang et al. (2019) suggest that winter heating contributed to decreased air quality in northern Chinese cities. All these studies provide evidence that the HRP introduced unintended regional imbalances and disparities in air pollution levels and residents' health between northern and southern China.

1.2.2. Winter Clean Heating Pilot (WCHP) Project

As part of the Chinese *Five-Year Clean Air Action Plan*, a *Clean Winter Heating Plan in Northern Region (2017-2021)*(Plan2017) was issued jointly by China's National Development and Reform Commission and other ten state departments in 2017. Focusing on the "2+26" key cities[5] (including Xiong'an New District) in the air pollution corridors of the Beijing-Tianjin-Hebei region, as well as the four provinces[6] where these 26 cities are located, this plan comprehensively promotes clean heating in winter in urban areas, counties, urban-rural areas, and rural areas. According to the plan, "in northern China, Beijing-Tianjin-Hebei and surrounding areas have the most serious air pollution in winter. Also, according to Plan2017, as the air pollution corridors of the Beijing-Tianjin-Hebei region, the '2+26' key cities and the provinces where they are located have relatively strong economic strength. It is necessary and able to take the lead in achieving clean heating" (p.9).

In 2017, to facilitate the implementation of a clean winter heating policy, the Ministry of Finance, the Ministry of Ecology and Environment, the Ministry of Housing and Urban-Rural Development, and the National Energy Administration jointly launched a winter clean heating pilot (WCHP) project in the northern regions. In this project, they identified the first 12 pilot cities among the "2+26" key cities, and a total of six billion yuan in incentive funds had been allocated. Then 23 cities were added to this pilot project in 2018, with 21 cities in the previous four provinces, and 2 cities in another new province (Shanxi Province). In addition, another 8 areas were included

[5]These include the administrative areas: Tianjin; Shijiazhuang, Tangshan, Langfang, Baoding, Cangzhou, Hengshui, Xingtai, and Handan in Hebei Province; Taiyuan, Yangquan, Changzhi, Jincheng in Shanxi Province; Jinan, Zibo, Jining, Dezhou, Liaocheng, Binzhou, and Heze in Shandong Province; Zhengzhou, Kaifeng, Anyang, Hebi, Xinxiang, Jiaozuo, and Puyang in Henan Province.

[6]The four provinces include Hebei Province, Shanxi Province, Shandong Province, Henan Province.

in 2019[7]. 20 new cities were included in 2021[8]. The details of the chosen cities will be presented in Section 1.3 Table 1. The subsidies provided through the WCHP are allocated for three years.

Each April, cities have the opportunity to submit their applications for the WCHP. These applications consist of specific materials, including forms detailing the city's characteristics (such as GDP, population, household structure, etc.) and the current status of winter heating services. Additionally, the submission comprises implementation plans outlining strategies to enhance clean heating and the intended use of subsidies during the funding period[9]. Following this, the four departments will assess and select the cities for inclusion in the WCHP based on the merits of their applications. Selected cities must adhere to the implementation plans and allocate the subsidies exclusively to winter heating projects.

Cities utilize subsidies in various ways, primarily employing three main approaches: 1) using subsidies as rewards or incentives for entities engaged in clean heating projects; 2) directly investing funds from the subsidy into energy transition projects; and 3) offering discounted interest rates on loans or establishing specialized funds through equity investment for clean winter heating projects[10]. Cleaning winter heating projects involve transitioning equipment from coal-fired to natural gas-fired systems, gas storage station initiatives, and projects aimed at reducing emissions from coal-fired and gas-fired boilers, etc.

Several papers have investigated the effectiveness of the WCHP on air pollution in China. For example, employing TWFE model, Zhang et al. (2020) find that the WCHP project leads to a

[7]Dingzhou, and Xinji in Hebei Province; Sanmenxia, and Jiyuan in Henan Province; Tongzhou, Weinan, Baoji, and Yangling Demonstration Zone in Shanxi Province. Since Yangling Demonstration Zone is under the jurisdiction of Xianyang, it is not considered as a new city which was included in 2019 in this paper.

[8]Biejing; Chengde, Qinhuangdao in Hebei province; Xinzhou, Datong, Shuozhou in Shanxi province; Yantai, Weifang, Tai'an in Shangdong province; Xuchang in Henan province; Yulin, Yan'an in Shanxi province; Fuxin in Liaoning province; Jiamusi in Heilongjiang province; Baotou in Inner Mongolia; Haixizhou in Qinghai province; Wuluuqi in Xinjiang province; Liaoyuan in Jilin province; Lanzhou in Gansu province; and Wuzhong in Ningxia province.

[9]Information is from government website:https://www.gov.cn/xinwen/2017-05/20/content_5195490.htm

[10]Information is from government websites, such as http://www.wuzhong.gov.cn/xxgk/gz/bfgfxwj/202112/t20211230_3266529.html

substantial decrease in AQI, $PM_{2.5}$, NO_x, and SO_2 emissions. Similarly, other studies argue that the air quality in northern China has notably improved due to the clean heating policy initiated by the central government (Wang et al., 2019, 2023; Zeng et al., 2022; Tan et al., 2023).

However, existing literature mainly focuses on the overall effects of the WCHP on air pollution. Given that the WCHP project primarily targets winter heating, which is anticipated to be most effective during the heating season, it is crucial to understand the WCHP's impact on air quality during the heating season in northern China. Moreover, most studies have employed standard DID approach rather than staggered models, which could lead to bias in cases involving more than two periods, heterogeneous effects, or potential selection bias when the randomization assumption is not held. Furthermore, it remains unclear whether the WCHP has reduced the disparities in air pollution levels between southern and northern China. This paper aims to address these gaps by using staggered DID and staggered DDD methods to investigate whether the WCHP increases the air quality during the winter in the treated northern cities. Additionally, an RD design will be used to examine whether the WCHP has mitigated the disparities between northern and southern China resulting from the HRP, which is the unintended consequence of the WCHP.

1.3. Data Sources

1.3.1. Air Pollution Data

To study how this cleaning heating pilot program contributes to air quality during the winter heating period in northern China, I collected comprehensive air quality information from the National Urban Air Quality Real-time Publishing Platform[11]. China's Ministry of Environmental Protection administrates this platform. It publishes real-time Air Quality Index (AQI), including $PM_{2.5}$, PM_{10}, O_3, NO_2, SO_2, and CO index for all state-controlled monitoring sites.

To study the effectiveness of the WCHP on air quality in northern China, I firstly use city-level daily air pollution data and the precise starting and ending dates of winter heating service in each

[11] This is the largest real-time air quality monitoring network in China. It includes all municipalities, provincial capitals, and cities with independent planning (Fan et al., 2020).

city to obtain the annual average pollution levels during the heating period and non-heating periods. The city-level daily air pollution data comes from the average of the real-time air pollution data in the platform for each day. Then, I use the annual average data in the staggered DID and staggered DDD models. Since the air pollution Data is only available from May 2014, this paper uses air pollution data from 2015-2021, i.e., we have two pre-treatment years and five post-treatment years. Due to this policy's primary purpose is to decrease $PM_{2.5}$ level, $PM_{2.5}$ is used as the primary air pollution to investigate the policy's effect. Given that air can travel across cities and PM_{10} is heavier than $PM_{2.5}$, I also use PM_{10} as another pollution, more local pollution, to estimate the policy's effect on air quality. In addition, CO, NO_2, and SO_2 emissions are pollution due to coal burning, I include both NO_2 level and SO_2 level in the analysis. As a comprehensive ambient air quality indicator, AQI is included as well.

Therefore, dependent variables to study the effectiveness of the WCHP on air pollution in northern China are air pollution levels of $PM_{2.5}$, PM_{10}, AQI, CO, NO_2 and SO_2. The treatment group and the control group are cities from the north. 56 northern cities[12] in the WCHP are included in the treatment group. 64 northern cities from the same provinces as cities in the WCHP are included in the control group. The details are shown in Table 1.

To study the effects of the WCHP project on the disparities in air pollution levels between northern and southern China, annual levels of $PM_{2.5}$, PM_{10}, AQI, CO, NO_2 and SO_2 are the dependent variables. The treatment group consists of 123 northern cities, including the 56 cities in the WCHP, while the control group includes 152 southern cities. Figure 1 shows all the northern cities included to study the effectiveness of the WCHP in northern China. Figure 2 shows all the northern and southern cities in the study on the disparities between northern and southern China.

[12] 63 cities in total were selected in the WCHP by 2021. Due to data limitations, I can only include 56 northern cities in the treatment group.

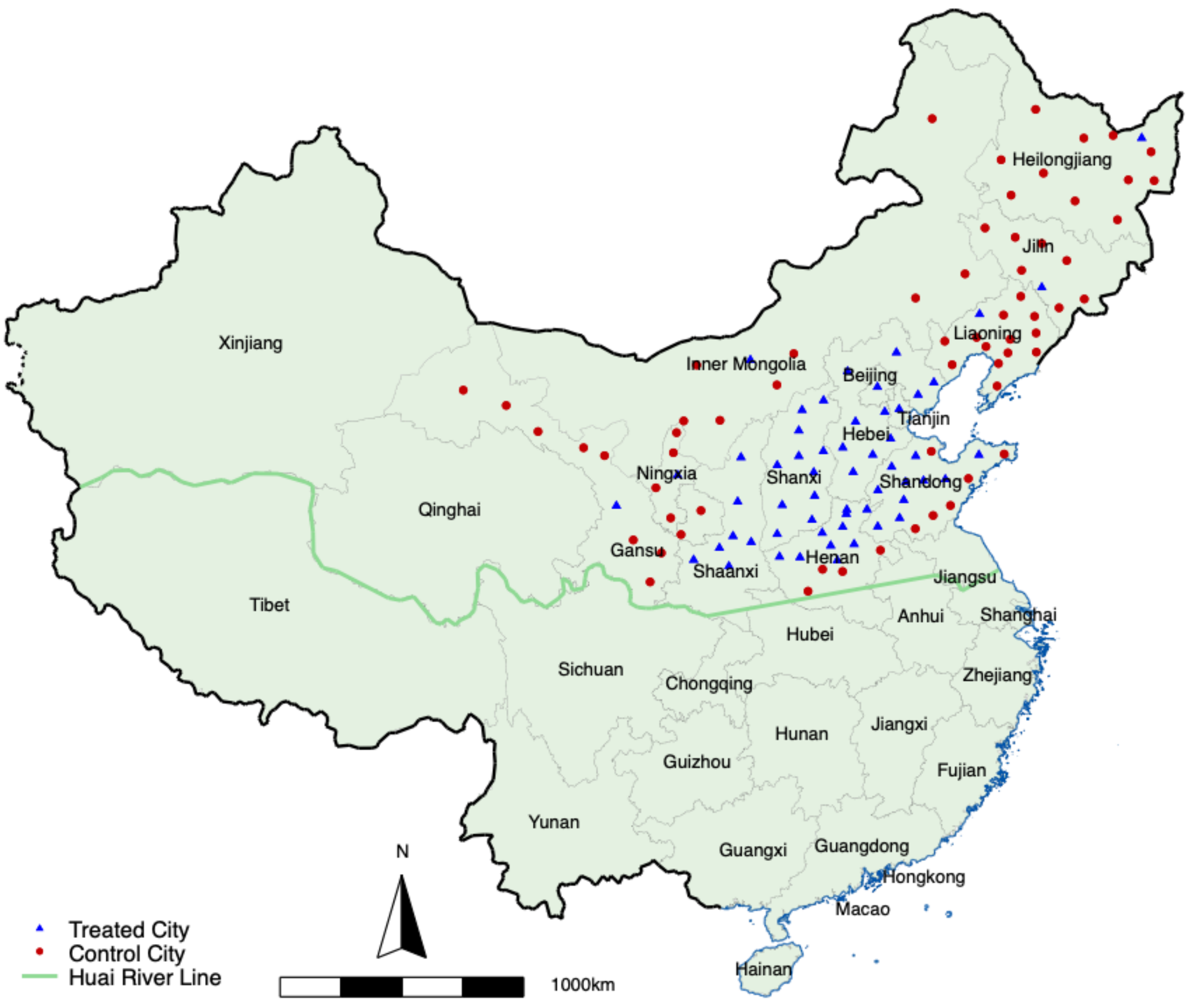

Figure 1. Northern Cities in the Treatment and Control Groups

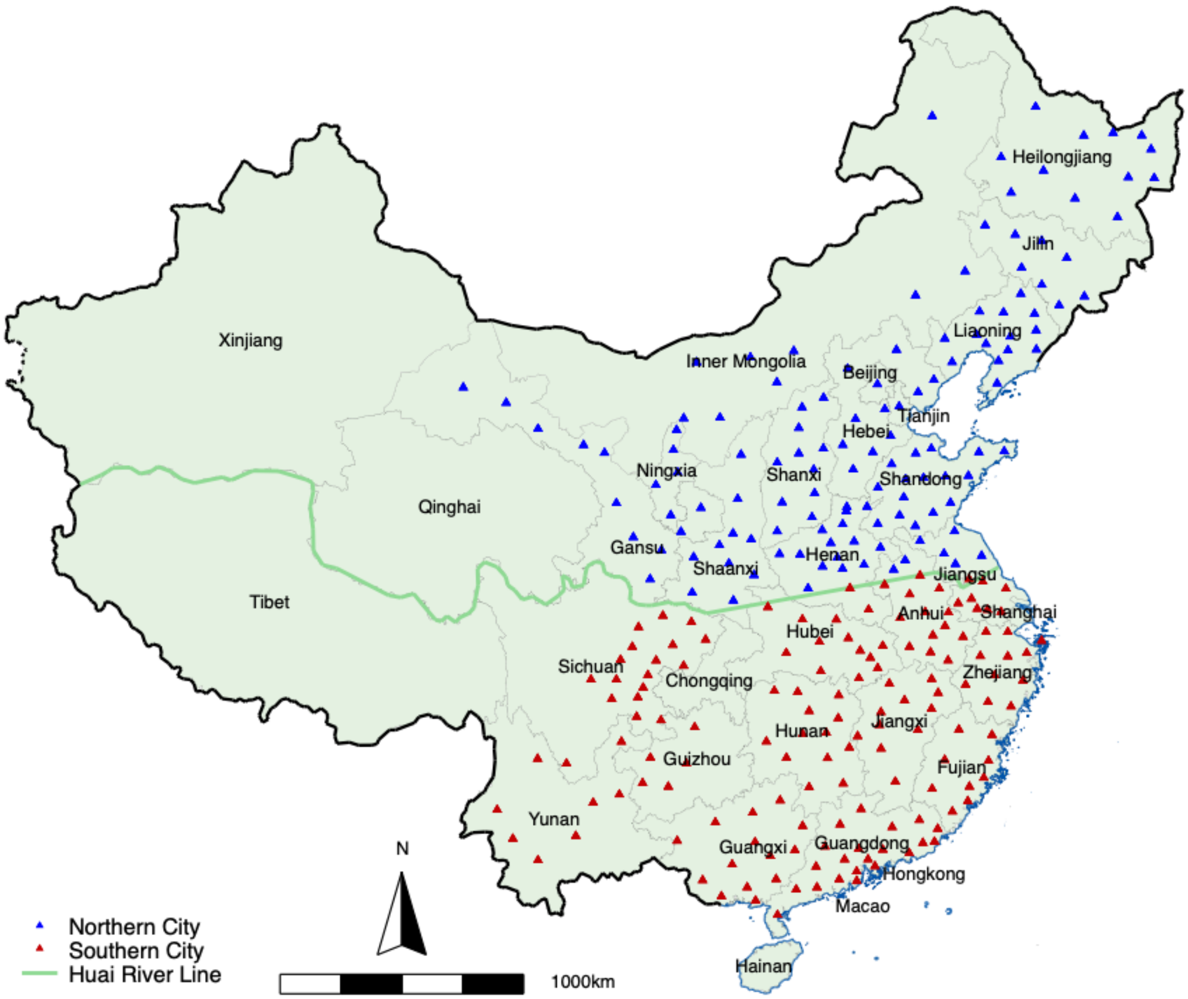

Figure 2. Northern and Southern Cities in the Treatment and Control Groups

Table 1. Treatment Group and Control Group

	Treatment group (56)	Control group (64)
Selected in 2017	Tianjin, Shijiazhuang, Tangshan, Baoding, Langfang, Hengshui, Taiyuan, Ji'nan, Zhengzhou, Kaifeng, Hebi, Xinxiang	Qindao, Zaozhuang, Dongying, Weihai, Rizhao, Linyi, Pingdingshan, Luohe, shangqiu, Zhumadian, Nanyang, Shenyang, Dalian, Anshan, Fushun, Benxi, Dandong, Jinzhou, Yingkou, Liaoyang, Panjin, Tieling, Chaoyang, Huludao, Haerbin, Qiqiha'er, Jixi, Hegang, Shuangyashan, Daqing, Yichun, Qitaihe, Mudanjiang, Heihe, Suihua, Huhehaote, Chifeng, Tongliao, Wuhai, Hulunbei'er, Wulanchabu, E'erduosi, Bayanzhuoer, Changchun, Jilin, Siping, Tonghua, Baishan, Songyuan, Baicheng, Jiayuguan, Jinchang, Tianshui, Wuwei, Zhangye, Pingliang, Jiuquan, Qingyang, Dingxi, Longlan, Yinchuan, Shizuishan, Guyuan, Zhongwei
Selected in 2018	Xingtai, Zhangjiakou, Cangzhou, Yangquan, Changzhi, Jincheng, Jinzhong, Yuncheng, Linfen, Lvliang, Zibo, Jining, Binzhou, Dezhou, Liaocheng, Heze, Luoyang, Anyang, Jiaozuo, Puyang, Xi'an, Xiangyang	
Selected in 2019	Sanmenxia, Tongzhou, Weinan, Baoji	
Selected in 2021	Beijing, Chengde, Qinhuangdao, Xinzhou, Datong, Shuozhou, Yantai, Tai'an, Weifang, Xuchang, Yulin, Yan'an, Fuxin, Jiamusi, Baotou, Liaoyuan, Lanzhou, Wuzhong	

Notes: This is only for studying the Effects of the WCHP in Northern China. There are 63 cities in the WCHP by the year 2021. Due to data availability, I only included 56 cities in the treatment group. Cities in the control group are from the same provinces as the cities in the treatment group.

1.3.2. Weather and Winter Heating Data

Weather information can be obtained from the Global Summary of the Day (GSOD) (Fan et al., 2020). The weather control variables include temperature, dew point, and other relevant weather conditions which can potentially affect air pollution.

According to Plan2017, northern cities usually provide heating services to residents for about four months, starting from November 15 to March 15 of the subsequent year. However, in extremely cold regions such as Harbin in Heilongjiang Province, the heating season can extend from October to April. Local governments have the discretion to determine when to start and end heating services based on weather conditions, especially the temperature. Consequently, the starting and ending dates may vary every year in each city. Fan et al. (2020) suggest that the weekly AQI increased by 36% after turning on the heating system, indicating an immediate deterioration in air quality caused by winter heating service.

Therefore, to better understand the effect of the WCHP on air pollution, obtaining accurate starting and ending dates of the heating service for each city within the treatment and control groups is crucial. I collected this information from official government websites and local news sources[13]. In this paper, the heating period is defined as the duration spanning from the starting date to the ending date of the heating service. Conversely, the remainder of the year is categorized as a non-heating period.

1.3.3. Policy and City Data

The information regarding the WCHP project is sourced from China's government websites[14]. These sources provide lists of selected cities for each year and the corresponding subsidies allocated to each pilot city[15]. The selected cities are eligible to receive subsidies for a duration of three years, with the subsidy varying according to the city's tier. The subsidies are categorized into three levels: tier one cities, directly under the central government, are granted one billion yuan per year; tier two cities are eligible for 700 million yuan per year; and tier three cities can receive 500 million yuan per year. As explained in Section 1.2, the subsidies, intended as capital investments in the cleaning heating projects, aim to have a sustained impact, extending beyond the three-year funding period. Hence, I consider the cities chosen to be consistently treated throughout the program.

The government document *Clean Winter Heating Plan for Northern China (2017-2021)* highlights that one reason for the selection of certain cities and provinces in the WCHP is their relatively robust economy, facilitating the implementation of clean heating plans during winter. As a result, economic indicators such as GDP level, GDP growth rate, and GDP per capita are controlled for this analysis. Notably, secondary industries are known for substantial coal and gas consumption, which leads to increased air pollution. To account for this, the ratio of secondary industries in each city's GDP is included in the analysis. The city-specific information is from the 2015-2021 China City Statistical Yearbook.

[13]For example, http://www.sjz.gov.cn/col/1490076620544/2021/03/31/1617153307709.html

[14]Ministry of Finance of the People's Republic of China: http://www.mof.gov.cn/index.htm. The Central People's Government of the People's Republic of China: http://www.gov.cn/xinwen/2017-12/20/content_5248855.htm

[15]Several local governments provide support and funding to clean winter heating projects. However, comprehensive information regarding these subsidies from local governments remains a challenge. As a result, for the purposes of this paper, the control variable for subsidies solely includes the funding allocated through the WCHP by the central government.

Table 2. Summary Statistics of the Variables in Norther Cities: Pre-WCHP (2015-2016)

	Treat		difference	Control		difference
	Heating Period	Non-heating Period	in means	Heating Period	Non-heating Period	in means
Dependent Variables (Annual: $\mu g/m^3$)						
$PM_{2.5}$	94.348	51.429	42.919	64.323	34.437	29.886
	(29.079)	(14.425)	(3.067)	(23.001)	(12.773)	(2.325)
PM_{10}	154.926	97.736	57.189	110.492	69.889	40.602
	(40.556)	(23.547)	(4.431)	(34.067)	(23.667)	(3.666)
AQI	130.021	81.922	48.098	95.697	61.570	34.126
	(31.967)	(16.797)	(3.412)	(26.293)	(16.455)	(2.742)
CO	2.075	1.182	0.894	1.211	0.768	0.443
	(0.583)	(0.354)	(0.064)	(0.390)	(0.283)	(0.043)
NO_2	51.612	35.705	15.907	36.014	24.380	11.634
	(12.474)	(8.646)	(1.434)	(10.785)	(7.543)	(1.163)
SO_2	64.210	25.055	39.156	46.718	15.916	30.802
	(30.140)	(10.743)	(3.023)	(23.786)	(9.503)	(2.264)
Weather Variables						
Temperature	8.583	193.247	-184.664	-25.150	184.692	-209.843
(0.1 °C)	(30.687)	(21.582)	(3.545)	(46.631)	(18.977)	(4.450)
Dew point	-85.974	109.682	-195.656	-108.484	99.036	-207.520
(0.1 °C)	(34.082)	(29.866)	(4.282)	(45.121)	(36.116)	(5.108)
Precipitation	0.732	2.829	-2.097	1.231	2.752	-1.521
(mm)	(0.569)	(0.659)	(0.082)	(1.341)	(0.956)	(0.146)
Wind Speed	26.947	26.312	0.635	28.100	27.802	0.298
(m/s)	(7.847)	(5.822)	(0.923)	(7.402)	(6.204)	(0.854)
City Characteristics						
GDP	307.472			169.736		
(Billion CNY)	(391.443)			(186.579)		
GDP Growth (%)	6.410			4.907		
	(3.440)			(4.573)		
Ratio of Secondary	47.613			41.568		
Industries (%)	(9.235)			(11.617)		
Observations	112	112		128	128	

Notes: In this table, all the observations are from northern cities. Standard errors in parentheses.

Table 2 presents the summary statistics for air pollution and control variables among northern cities in both the treatment and control groups before the implementation of the WCHP, serving for the study on the effectiveness of the WCHP in northern China. Firstly, the data illustrates substantially higher pollution levels during the heating period compared to the non-heating period in both the treatment and control groups. This indicates a significant increase in air pollution associated with winter heating. Secondly, air pollution levels are higher in the treated cities than those in the control cities during both periods, meaning that air pollution issues are more pronounced in treated cities. Thirdly, the comparison of pollution mean differences between the heating and non-heating periods reveals larger variations in treated cities than in control cities. This suggests that the issue of air pollution resulting from winter heating is more prominent in treated cities. This observation could raise concerns regarding self-selection bias- cities with poorer air quality due to winter heating may have greater motivation to compete for inclusion in the WCHP.

Moreover, the panel depicting city characteristics indicates that the treated cities exhibit a more robust economy, characterized by higher GDP levels and growth rates. This could potentially serve as evidence supporting the selection bias concern that economic status is a criterion for selection in the WCHP. Additionally, the treated cities show a higher concentration of secondary industries. Table A1 presents the description of the statistics among northern cities after the implementation of the WCHP.

1.3.4. Summary Statistics

Table 3 presents the summary statistics for cities in the northern and southern regions. Columns (1) and (2) denote the mean annual pollution levels in the north and south, respectively. The data reveals that the annual average pollution levels in northern cities are much higher than those in southern cities both pre- and post-WCHP. Columns (3) and (4) display the disparities in pollution levels between the heating period and non-heating period. Regardless of the WCHP timeline, these differences show consistently higher pollution levels in northern cities compared to their southern counterparts. This suggests that the winter heating service contributes to increased air pollution

Table 3. Summary Statistics: North and South

	(1) North	(2) South	(3) North	(4) South
	Annual Mean		Difference between Heating period and non-heating period	
	2015-2016, Pre-WCHP (Annual: $\mu g/m^3$)			
$PM_{2.5}$	56.812	44.284	33.188	24.536
	(18.527)	(13.601)	(18.273)	(13.628)
PM_{10}	102.097	69.515	42.330	30.307
	(29.178)	(20.686)	(25.439)	(17.758)
AQI	87.443	65.801	36.913	28.239
	(21.208)	(17.338)	(20.671)	(16.254)
CO	1.235	0.960	0.651	0.288
	(0.431)	(0.246)	(0.406)	(0.193)
NO_2	35.269	27.907	12.963	10.231
	(10.295)	(9.095)	(6.564)	(4.973)
SO_2	34.201	17.923	35.221	4.742
	(15.934)	(7.672)	(22.988)	(5.406)
Observations	246	304	246	304
	2017-2021, Post-WCHP (Annual: $\mu g/m^3$)			
$PM_{2.5}$	42.892	34.720	29.946	22.806
	(13.459)	(10.304)	(16.347)	(13.009)
PM_{10}	83.531	57.010	31.962	24.110
	(24.241)	(15.632)	(20.403)	(16.131)
AQI	73.014	55.520	30.284	24.472
	(17.355)	(13.237)	(18.396)	(15.146)
CO	0.857	0.780	0.389	0.202
	(0.275)	(0.179)	(0.209)	(0.120)
NO_2	30.859	26.012	11.017	9.710
	(9.157)	(8.014)	(5.593)	(5.148)
SO_2	16.295	10.449	12.429	1.864
	(9.424)	(4.530)	(14.083)	(3.113)
Distance to Huai River (degrees °)	5.406	-5.646		
	(3.987)	(3.451)		
Observations	615	760	615	760

Notes: This table includes both northern cities and southern cities. Columns (1) and (2) are the annual pollution levels in the north and south, respectively. Columns (3) and (4) are the differences in pollution levels between the heating period and non-heating period. Distance to the Huai River refers to the degree of latitude north of the Huai River Boundary.

levels during winter in northern cities. The term "Distance to the Huai River" refers to the degree of latitude north of the Huai River Boundary. On average, northern cities are situated approximately 5.4 degrees north of the Huai River boundary, while southern cities are located around 5.6 degrees south of the Huai River boundary.

1.4. Methodology

1.4.1. Methodology to Study the Effects of the WCHP in Northern China

Basic Models. To examine the overall effects of the WCHP on air pollution in northern China, I initially employ a difference-in-differences (DID) strategy. The model used for this assessment is the two-way fixed effects (TWFE), which is presented as follows:

$$Y_{it} = \alpha_0 + \beta Treat_{it} + \gamma X_{it} + \theta_i + \eta_t + \epsilon_{it} \tag{1}$$

where:

• Y_{it} indicates the annual average levels of air pollution ($PM_{2.5}$, PM_{10}, AQI, CO, NO_2 and SO_2) in city i at year t,

• $Treat_{it}$ is an indicator variable, which equals to one if city i is in the WCHP at year t,

• X_{it} is a vector of control variables. These controls include weather-related factors known to correlate with air pollution, such as temperature, precipitation, wind speed, dew point, etc. Additionally, city-specific controls include GDP, GDP per capita, the GDP growth rate, and the ratio of secondary industries for city i at year t,

• θ_i is the city fixed effect, η_t is the year fixed effect,

• ϵ_{it} is the error term, which is clustered by province and heteroscedasticity-robust.

The term $Treat_{it}$ is designed to estimate the average effect of the WCHP on air pollution levels through the whole year in treated cities. β is the interest of the parameter.

Staggered DID Models. Due to the staggered implementation of the WCHP, cities are treated at different times. However, recent literature demonstrates that TWFE linear regression estimates, especially in the case of different treatment timing and heterogeneous effects, may not provide accurate estimates of the causal effects (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Baker et al., 2022; Roth et al., 2023; Borusyak et al., 2023). Typically, these TWFE estimates are variance-weighted averages derived from all possible combinations of "2×2" DiDs. For example, these combinations entail comparing the never-treated group versus the treated groups, the never-treated versus the early-treated group, and the early-treated group versus the late-treated group, etc. (Baker et al., 2022). Some studies suggest that the weights are positive when the treatment effects remain consistent over time. However, some weights may be negative in the presence of heterogeneous effects (e.g., Goodman-Bacon, 2021). That's because the already-treated units in early-treated groups can serve as effective controls, whose outcome changes are subtracted from the later-treated units, thereby reflecting potentially unreliable treatment effects. Consequently, these regressions raise concerns regarding "bad comparisons" within TWFE estimates (Baker et al., 2022).

To gain a more comprehensive understanding of the weighted average treatment effect represented in Equation (1), I utilize the methodologies proposed by Goodman-Bacon (2021). These methodologies assist in illustrating the weights attributed to the 2×2 DiDs and reveal potentially biased terms. Hence, I aim to demonstrate the reasons why the TWFE estimator in Equation (1) may be considered unreliable.

Subsequently, to address potential biases inherent in the standard TWFE estimates and the selection bias arising from the criterion used for inclusion in the WCHP, I employ innovative methods based on staggered DID to estimate the effects (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Borusyak et al., 2023). Abadie (2005) proposes an inverse probability weighting (IPW) method to estimate the average treatment effect on the treated (ATT) within a DID framework, where the randomization assumption is not met and treatment was selective based on observable covariates matrix X. This method, which involves absorbing all the X information into a single scalar as the propensity score, assumes that the parallel trends assumption holds for a treatment and control group only after conditioning on some covariates matrix X. Therefore, this IPW approach presents a viable method to address selection bias within the context of the WCHP. However, it's important to note that this method is specifically applied to repeated cross-section data.

In response to the limitations of TWFE estimates, Callaway and Sant'Anna (2021) introduce three different types of DID estimands for staggered treatment adoption setups. Among these estimands, one draws upon the IPW method introduced in Abadie (2005), extending its application to both panel data and repeated cross-section data, allowing for time-varying covariates (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). Moreover, Sun and Abraham (2021) and Borusyak et al. (2023) highlight potential biases in the coefficients on lead and lag indicators in a dynamic specification when using TWFE. Building upon the procedures of Callaway and Sant'Anna (2021), Sun and Abraham (2021) propose unbiased estimation methods specifically designed for event studies. Furthermore, Borusyak et al. (2023) provide tools for staggered triple differences design.

The integration of these tools not only addresses concerns about selection bias within the WCHP but also mitigates biases evident in TWFE estimates. This comprehensive approach represents a robust strategy for improving the overall estimation methodologies in the context of staggered treatment adoption setups.

Hence, I begin by outlining an event study model based on the method in Sun and Abraham (2021), aiming to understand the dynamic treatment effects of the WCHP and test the assumption of parallel trends conditioning on covariates. The model is as follows:

$$Y_{it} = \alpha_0 + \sum_{t\in[2015,2021]} \sum_{l=-6, l\neq -1}^{4} \delta_{t,l} \mathbb{1}(E_i = t) \times Treat_{it} + \gamma X_{it} + \theta_i + \eta_t + \epsilon_{it} \tag{2}$$

Where Y_{it} is the annual average levels of pollution for city i at year t. η_t and θ_i are the year-fixed effect and city-fixed effect, respectively. E_i denotes the initial treated time for city i; l is the relative period index which represents the periods since treatment. For example, if city i is treated in 2021, then E_i equals 2021, and the relative period index l for this city in the year 2015 is

-6. Relative periods allow us to compare cohorts (never-treated cohort, not-yet-treated cohort, and treated cohort) while holding their exposure to the treatment constant (Sun and Abraham, 2021).

Secondly, I utilize the methodologies and tools proposed by Borusyak et al. (2023) for staggered DID conduct regression in Equation (1), estimating the overall effects of the WCHP.

However, cities participating in the WCHP are mandated to allocate the subsidy exclusively towards winter heating services. This specification implies that the effectiveness of the WCHP should particularly manifest during the heating season. To further explore how the WCHP affects the air quality during the winter, I employ a staggered triple differences (DDD) model (Kang et al., 2023; Strumpf, 2011), and conduct regression using the tools introduced by Borusyak et al. (2023):

$$Y_{it} = \alpha_0 + \beta_1 Treat_{it} + \beta_2 Heating_{it} + \beta_3 Treat_{it} \times Heating_{it} + \gamma X_{it} + \theta_i + \eta_t + \epsilon_{it} \quad (3)$$

In Equation (3), $Heating_{it}$ represents an indicator variable denoting whether city i is in the heating period during year t. All other variables maintain the same definitions as presented in Equation (1). The primary focus lies on the interaction term, $Treat_{it} \times Heating_{it}$, which captures the impact of the WCHP on air pollution specifically during the heating period.

1.4.2. Methodology to Study the Effect of the WCHP in Mitigating the Disparities

To examine whether the WCHP decreases the disparities between northern cities and southern cities in air quality due to HRP, I follow the empirical strategy in Ebenstein et al. (2017) and adopt an RD design based on the distance to the Huai River. This RD design can exploit not only the impact of the HRP that provides free or subsidized coal-fired indoor hearing in northern China and no subsidies in the south but also investigate how this impact changes following the implementation of the WCHP since 2017. Specifically, according to Chen et al. (2013) and Ebenstein et al. (2017), the HRP caused a discontinuous change in air pollution along the Huai River. I separately test whether the HRP is still introducing the discontinuous change. In addition, I test the necessary assumptions for the RD design that any unobserved determinants (e.g. weather conditions) of air pollution change smoothly as they cross the river. If these assumptions hold, a flexible polynomial adjustment in the distance from the river will eliminate all potential sources of bias and enable a causal inference (Chen et al., 2013,Ebenstein et al., 2017). The equation is as follows:

$$\begin{aligned} Y_{it} = \alpha_0 + \alpha_1 North_i + \alpha_2 North_i \times Post_t + \beta_0 f(L_i) + \beta_1 f(L_i) \times Post_t \\ + \beta_2 North_i \times f(L_i) + \beta_3 North_i \times f(L_i) \times Post_t + \gamma_1 X_{it} + \eta_t + \epsilon_{it} \end{aligned} \quad (4)$$

where:

• Y_{it} indicates the annual average levels of air pollution ($PM_{2.5}$, PM_{10}, AQI, CO, NO_2 and SO_2) in city i at year t,

• The indicator variable $Post_t$ is equal to one if year $t \geqslant 2017$ and 0 otherwise,

• $North_i$ is an indicator variable equal to one for location i that is north of the Huai River,

• $f(L_i)$ is a polynomial in degrees of latitude north of the Huai River Boundary,

• X_{it} is a vector of control variables, η_t is year fixed effect,

• ϵ_{it} is the error term.

An alternative estimation strategy for the RD approach involves non-parametric identification of Equation (4). Consider the following setup for estimation using local linear regression:

$$\begin{aligned} Y_{it} = \alpha_0 + \alpha_1 North_i + \alpha_2 North_i \times Post_t + \beta_0 L_i + \beta_1 L_i \times Post_t \\ + \beta_2 North_i \times L_i + \beta_3 North_i \times L_i \times Post_t + \gamma_1 X_{it} + \eta_t + \epsilon_{it} \end{aligned} \quad (5)$$

In Equation (5), L_i is within h latitude degrees of the Huai River, where the optimal h is determined as a function of the data (Calonico et al., 2015a,b).

In Equation (4) and Equation (5), assuming the RD assumptions hold, the coefficient α_1 will provide an unbiased estimate of whether there is a discontinuity in the average annual levels of air pollution just to the north of the Huai River relative to the south. Additionally, the coefficient

α_2 captures the impact of the WCHP on these disparities after the year 2017. I report results from both the parametric RD approach and the non-parametric RD approach. The parametric RD results include both the full sample and the sample restricted to locations within $5°$ latitude of the Huai River. To concentrate comparisons near the discontinuity, the $5°$ restriction serves as an informal method of applying local linear methods involving bandwidths and kernels (Ebenstein et al., 2017).

1.5. Results

1.5.1. Results of the Effects on Air Pollution in Northern Cities

TWFE. Table 4 presents the outcomes of the TWFE estimates in Equation (1). The implementation of the WCHP reduced the annual levels of $PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2 by 6.47 $\mu g/m^3$ (6.9%), 9.453 $\mu g/m^3$ (6.1%), 0.299 $\mu g/m^3$ (14.4%), 2.567 $\mu g/m^3$ (5.0%), and 9.078 $\mu g/m^3$ (14.1%), respectively. Additionally, there was a decrease of 5.602 (4.3%) in AQI. But the estimates for AQI and NO_2 are not statistically significant. These TWFE estimates strongly suggest that the WCHP contributes to improving the air quality in northern China.

The results from the TWFE estimates are lower than those found in the literature. For example, Zhang et al. (2020) suggests that the WCHP reduces $PM_{2.5}$ by 18.59%. One reason for these discrepancies is that most studies cover periods before 2019, whereas my analysis includes more policy-effective years from 2019 to 2021. The air quality in the selected cities varied significantly before the implementation of the WCHP. Generally, cities included in the WCHP in 2017 and 2018 were more polluted than those selected in subsequent years. Consequently, the WCHP likely resulted in a more substantial reduction in air pollution levels in cities treated in 2017 and 2018. These heterogeneous effects contribute to the different average overall effects observed in my study.

Goodman-Bacon Decomposition. As described in Section 1.4, the TWFE estimators represent variance-weighted averages of treatment effects and may have potential bias. To understand the weights better, I use Goodman-Bacon decomposition method (Goodman-Bacon, 2021) to decompose the outcomes derived from the TWFE model into a weighted average of each com-

Table 4. Effects of the WCHP on Air Pollution in Northern China (TWFE Estimates)

	(1) $PM_{2.5}$	(2) PM_{10}	(3) AQI	(4) CO	(5) NO_2	(6) SO_2
β^{TWFE}	-6.467*	-9.453*	-5.602	-0.299***	-2.567	-9.078*
	(2.209)	(3.767)	(2.767)	(0.036)	(1.343)	(3.954)
Observations	840	840	840	840	840	840

Notes: Air pollution data is annual level data. Control variables include weather controls correlated with air pollution (temperature, precipitation, and dew point, etc.), and city characteristics including GDP, the GDP growth rate, and the ratio of secondary industries in each city at t. β^{TWFE} is the coefficient of $Treat_{it}$ in equation (1). Standard errors are clustered by province in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

ponent. For illustrative purposes, I only present results pertaining to $PM_{2.5}$. It's noteworthy that the components and the weights assigned to each component remain consistent across various dependent variables, despite the the overall DID estimates equaling their respective TWFE estimates. As discussed in Section 1.4, the control matrix X_{it} plays a critical role in the context of the WCHP and the parallel trend assumption. Therefore, I integrate X_{it} into the decomposition procedure. The analysis has five different groups, including the never-treated group and four treated groups subjected to varying treatment timings (2017, 2018, 2019, and 2020).

In Figure 3, "Timing groups" refers to all potential comparisons among the four treated groups. "Timing groups vs. Never treated" denotes the comparisons between the four treated groups and the never treated group, with the never-treated group serving as the control group. The "Earlier Treatment vs. Later Comparison" represents the comparisons among the four treated groups, with the later-treated groups serving as the control group. The "Later Treatment vs. Earlier Comparison" is the comparison within the treated groups, with the earlier treated groups being the control group. The horizontal red line in the graph represents the result of the TWFE regression for $PM_{2.5}$. The overall DD estimate equals the TWFE estimate, indicating that the WCHP reduces the $PM_{2.5}$ level by 6.47 $\mu g/m^3$. Table 5 delineates the details of the weights of the Goodman-Bacon decomposition involving covariates. The "Later Treatment vs. Earlier Comparison" component, which includes the "bad comparison" (Baker et al., 2022), demonstrates positive coefficients with a weight of approximately 0.085. This suggests a potential bias in the TWFE regression.

Table 5. Results of Goodman-Bacon Decomposition for $PM_{2.5}$

$PM_{2.5}$	Avg DD Est	Weight
Earlier Treatment vs. Later Comparison	-7.083	0.151
Later Treatment vs. Earlier Comparison	3.631	0.085
Timing groups vs. Never treated	-7.469	0.764

Notes: The Goodman-Bacon decomposition requires that the data is a balanced panel. Timing groups include all potential comparisons among the four treated groups with different treatment timing. Never-treated vs. Timing groups indicate the comparisons between the four treated groups and the never-treated group, serving as the control group, respectively. The within component is the residual component.

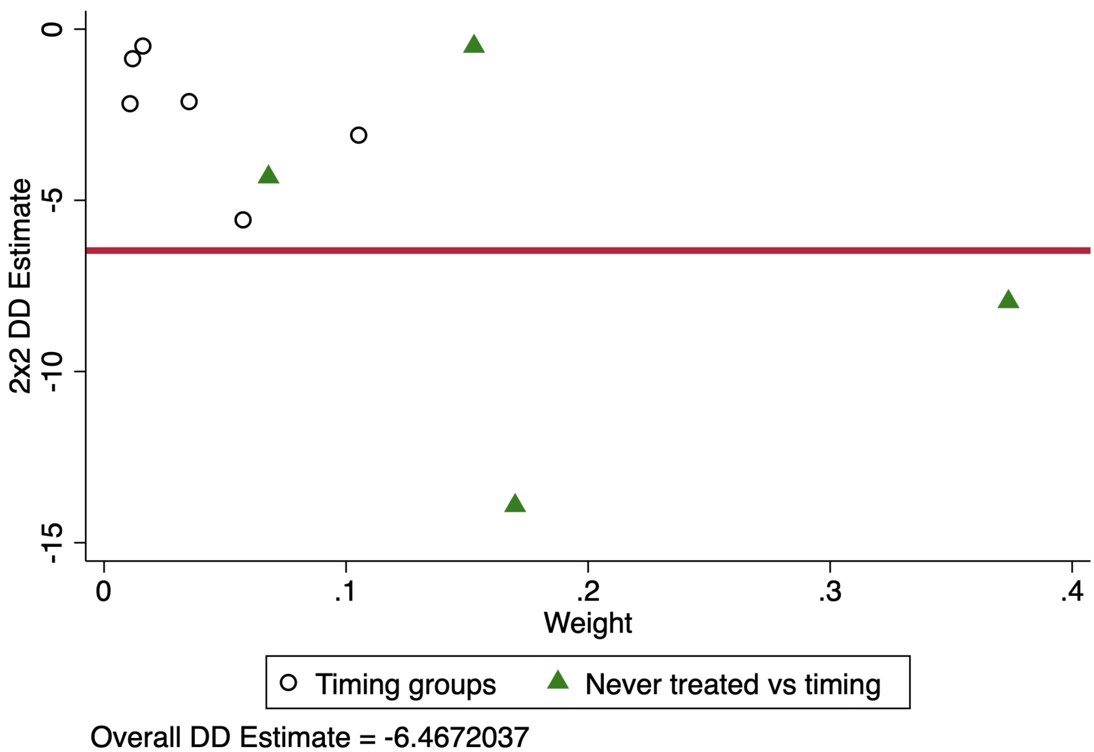

Figure 3. TWFE Decomposition for $PM_{2.5}$

Notes: The figure plots each 2×2 DID components. The horizontal red line represents the TWFE estimate, which equals to the sum of y-axis values weighted by x-axis values.

Event Study. Figure 4 displays the event study plots, demonstrating the validity of the parallel trend assumption conditioned on covariates across all pollution types. Prior to the implementation of the WCHP, the parallel trends conditioning on covariates in air pollution changes for

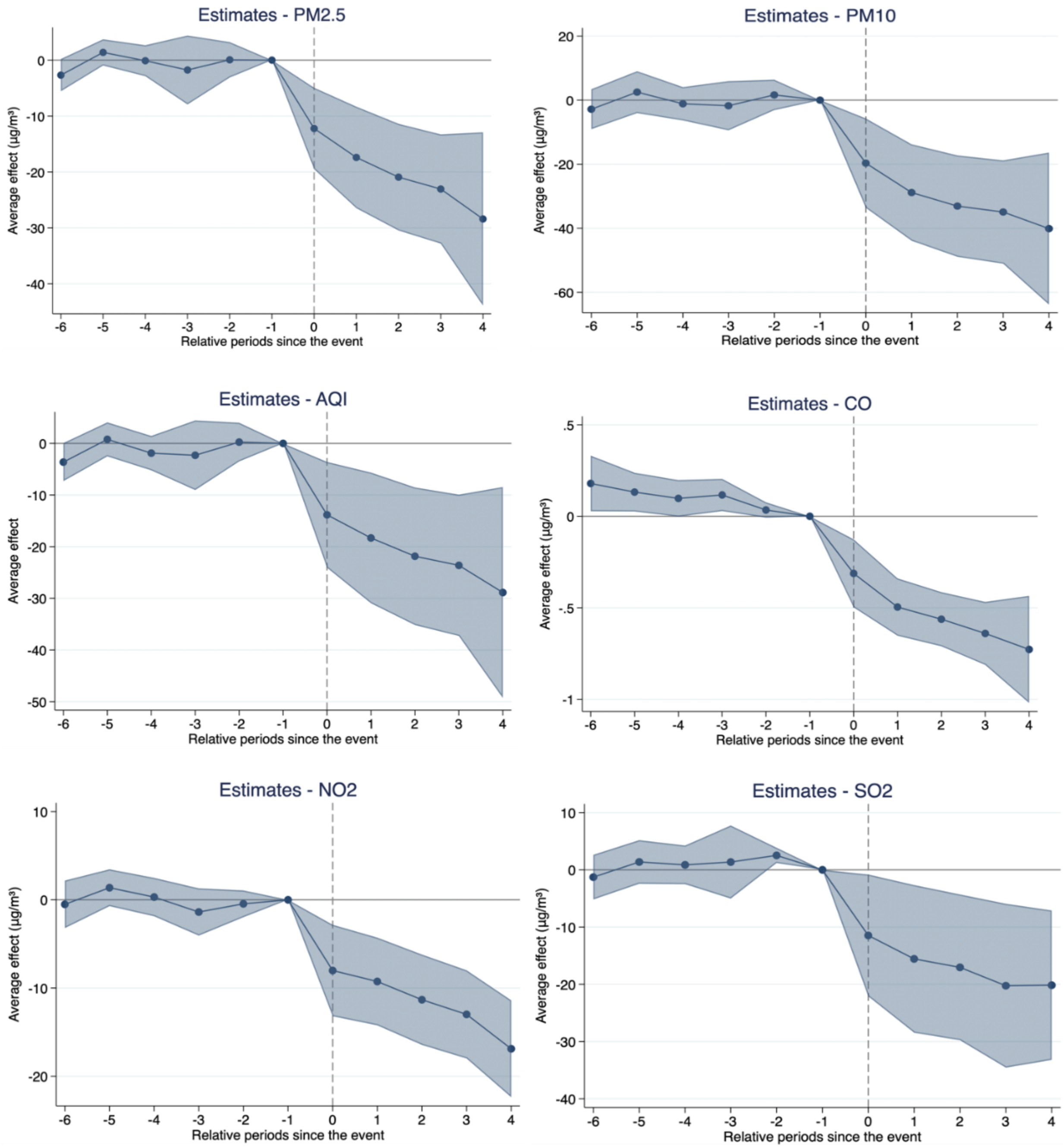

Figure 4. Event Study: Dynamic Effects of the WCHP in Northern China

Notes: The event study is based on the method in equation (3) from Sun and Abraham (2021). Stata commands: $Eventstudyinteract$. The control cohort is the never-treated units. The relative periods represent the periods since treatment. For example, if a city is treated in 2021, then the relative period is -6 for this city in the year 2015.

Table 6. Effects of the WCHP on Air Pollution in Northern China (Staggered Models)

	(1) $PM_{2.5}$	(2) PM_{10}	(3) AQI	(4) CO	(5) NO_2	(6) SO_2
			Panel 1: Staggered DID			
β^{ST}	-9.030***	-13.102***	-8.052**	-0.347***	-3.489**	-10.558***
	(2.015)	(3.321)	(2.530)	(0.025)	(1.091)	(3.039)
Observations	840	840	840	840	840	840
			Panel 2: Staggered DDD			
β^{STT}	-13.385***	-21.059***	-14.330***	-0.599***	-5.354***	-27.940***
	(2.383)	(3.338)	(2.459)	(0.047)	(1.166)	(5.996)
Observations	1680	1680	1680	1680	1680	1680

*Notes:*Air pollution data is annual level. Control variables include weather controls correlated with air pollution (temperature, precipitation, and dew point, etc.) and city characteristics (GDP, the GDP growth rate, and the ratio of secondary industries) in one city in year t. β^{ST} in panel 1 is the coefficient of $Treat_{it}$ (ATT) in equation (1). β^{STT} in panel 2 is the coefficient of interaction term $Heating_{it} \times Treat_{it}$ (ATT) in equation (3). I use the method in Borusyak et al. (2023). The Stata code is $did\_imputation$. Standard errors clustered by province in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

both treated and control cities were observed. Following the WCHP's enactment, a notable dynamic impact on air pollution emerged after 2017, showing a progressive decline in air pollution levels from relative period 1 to relative period 4. The base period, denoted as -1, refers to the years preceding the first-treated for each treated cohort. Period 4 exhibits the most substantial coefficient, indicating the average treatment effect in 2021 among the earliest treated group comprising the 12 cities selected in 2017. Those cities experienced severe air pollution, implying a bigger improvement in air quality after the implementation of the WCHP. Likewise, the coefficient of period 3 reflects the average treatment effect for the 2017 treated group in 2020 and the 2018 treated group in 2021. The coefficients of period 0 to period 3 are the average effect of different treated groups during their respective relative periods. The increasing dynamic treatment effects observed since period 0 indicates heterogeneous effects among treated groups, suggesting potential evidence of invalid TWFE estimates.

Staggered Methodologies. Table 6 reports the results derived from staggered models utilizing the method in Borusyak et al. (2023). In Panel 1, the reported results represent the overall ATT in staggered DID analysis. Similar to the TWFE estimates, the staggered DID estimates exhibit significant negativity, indicating that the WCHP effectively reduces air pollution levels in northern China. Specifically, the WCHP led to reductions in annual levels of $PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2 by 9.03 $\mu g/m^3$, 13.10 $\mu g/m^3$, 0.347 $\mu g/m^3$, 3.49 $\mu g/m^3$, and 10.56 $\mu g/m^3$, respectively. Furthermore, the annual mean of AQI decreased by 8.05 after the implementation of the WCHP.

Panel 2 illustrates the outcomes of staggered triple differences conducting Borusyak et al. (2023) method, detailing the effects of the WCHP on air pollution specifically during the heating season. The ATT during the winter is statistically significant. Compared to those observed effects throughout the entire year, the effects during the heating season have more pronounced magnitudes. The WCHP decreased the levels of $PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2 by 13.39 $\mu g/m^3$, 21.06 $\mu g/m^3$, 0.599 $\mu g/m^3$, 5.34 $\mu g/m^3$, and 27,94 $\mu g/m^3$, respectively. In addition, AQI decreases by 14.33 during the winter, indicating that the WCHP has more substantial effects during the heating season, as the subsidies are restricted exclusively to clean heating projects.

1.5.2. Results of the Effects on Disparities between North and South

Balance Test. In Section 1.4, we discussed that a crucial assumption for the validity of the RD design is that unobserved determinants change smoothly at the Huai River boundary. While a direct test of this identifying assumption is unfeasible, we can examine whether the observable covariates change smoothly at the boundary. This is analogous to the test in randomized control trials where observable determinants of the outcome are expected to be independent of treatment status. In addition, we can examine whether the air pollution levels exhibit discontinuous change over the boundary.

Figure 5 illustrates the variations in weather covariates across the Huai River boundary, including air temperature, dew point, precipitation, wind direction, and wind speed. The weather conditions exhibit a smooth transition on both sides of the Huai River boundary, with no observable distinct discontinuity in weather covariates at the cut-off point.

The fitted values of air pollution levels in Figure 6 reveal observable discontinuities in air

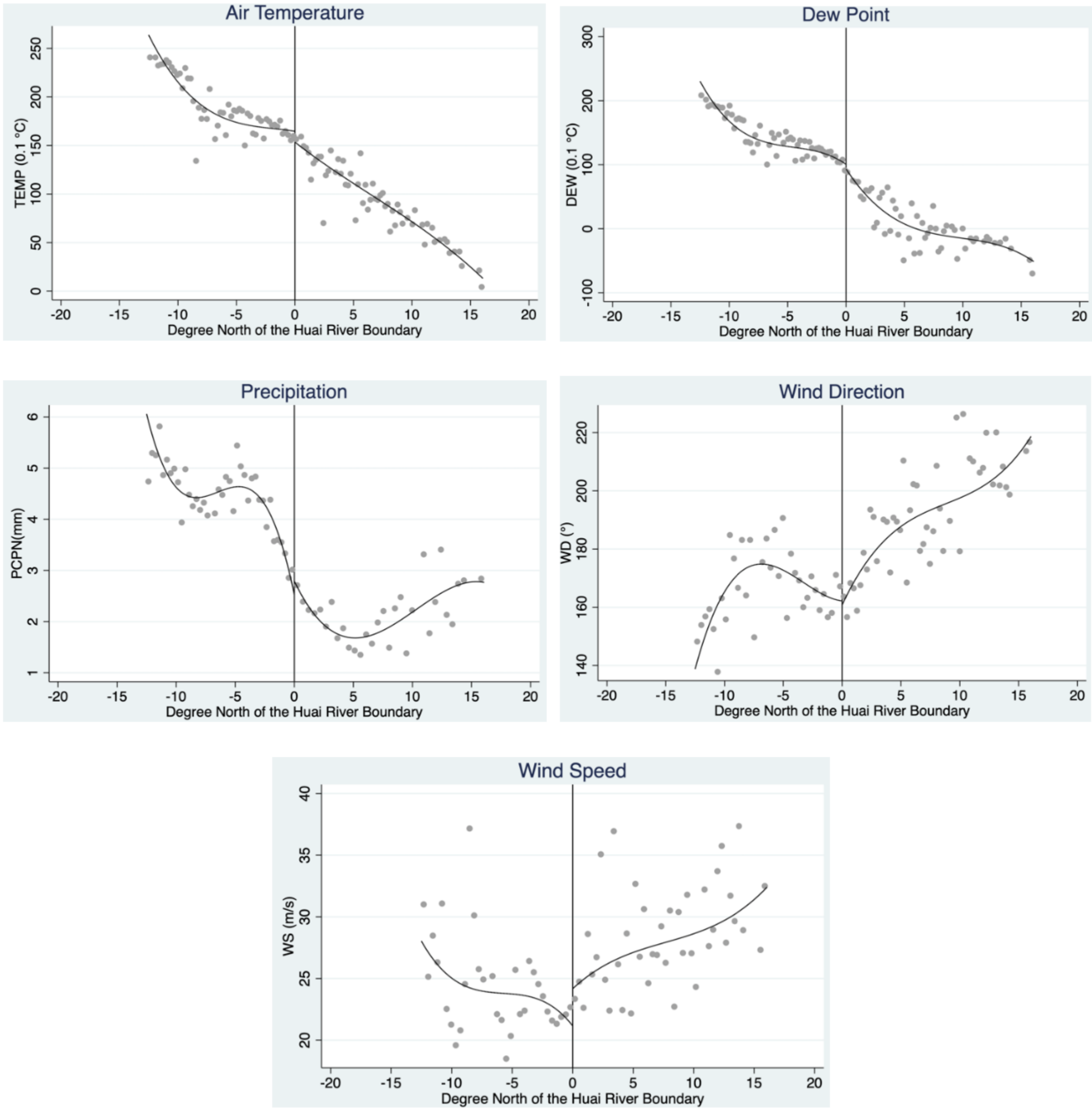

Figure 5. The changes of weather covariates over the Huai River Boundary

Notes: In this figure, weather covariates include air temperature, dew point, precipitation, wind direction, and wind speed. Point 0 on the horizontal axis is the cut-off point, representing the latitude degrees of the Huai River line. The vertical axis represents the indicator values of weather covariates. Fitted values obtained from separate polynomial regressions on the distance from the Huai River for each side of the river (Calonico et al., 2015a,b).

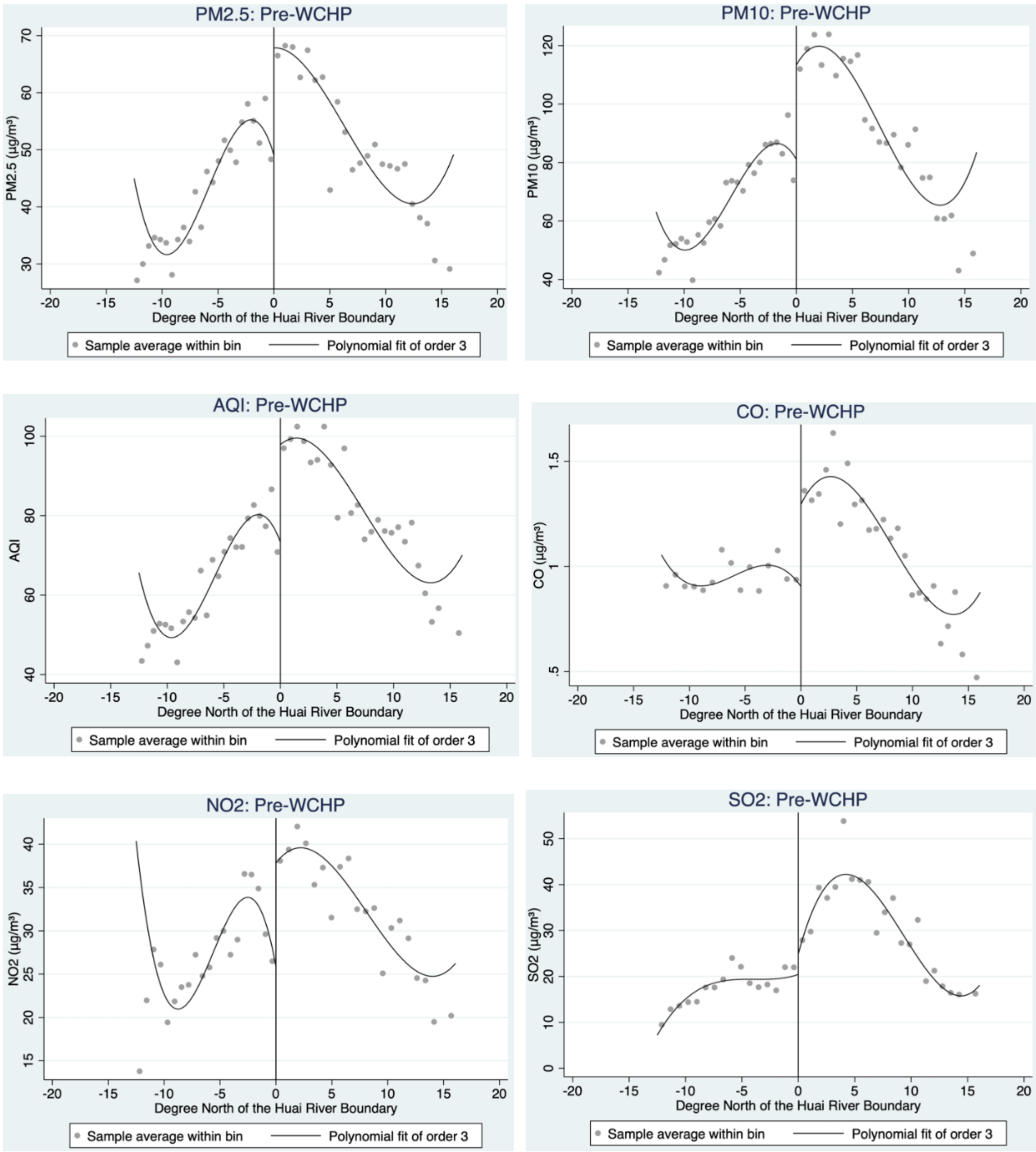

Figure 6. Fitted Values of Air Pollution Levels (Pre-WCHP)

Notes: Fitted values obtained from a polynomial regression of air pollution exposure on distance from the Huai River estimated separately on each side of the river (Calonico et al., 2015a,b). Point 0 on the horizontal axis is the cut-off point, representing the latitude degrees of the Huai River line. The vertical axis represents the indicator values of air pollution levels.

pollution across the Huai River boundary before the implementation of the WCHP. This suggests that the HRP still has a significant impact on the disparities in air pollution levels between northern China and southern China. Therefore, both Figure 5 and Figure 6 provide evidence supporting the validity of the application of the RD design. Figure A1 presents the fitted values of air pollution levels after the implementation of the WCHP in 2017. After 2017, while observable discontinuous changes in the air pollution levels persisted over the Huai River boundary, these discontinuities became significantly smaller than before. This is particularly notable for SO_2, one of the principal emissions resulting from coal combustion, where the difference almost disappeared.

Regression Results. Table 7 presents estimates associated with the north indicator variable and the term $North_i \times Post_t$ using various RD approaches. In Equation (4) and (5), the coefficient α_1 estimates the effect of the HRP on air pollution levels in the north, while α_2 gauges the effect of the WCHP on disparities in air pollution levels between northern and southern cities. Columns (1) and (2) apply the parametric RD approach from Equation (4) using the full sample and a subsample of locations within $5°$ latitude of the Huai River, respectively. These estimates are adjusted for the full set of available covariates, including weather conditions and city characteristics. Column (3) reports the estimated discontinuity at the Huai River using local linear regression with a triangular kernel and bandwidth selected by the method proposed by Calonico et al. (2015a,b). This non-parametric approach selects the most proper bandwidth and places greater weight on locations near the Huai River.

The parametric RD results in columns (1) and (2) reveal that all coefficients associated with the term "$North$" are positive and statistically significant, providing substantial evidence of significant increases in air pollution levels along the Huai River. This indicates the persistence of disparities in air pollution levels between northern and southern China caused by the HRP. For instance, PM_{10} rises by 29/35 $\mu g/m^3$ at the boundary in the restricted and full samples, respectively, aligning closely with the findings of 27/32 $\mu g/m^3$ in Ebenstein et al. (2017). The coefficients for the term "$North \times Post$" are consistently negative and statistically significant, indicating a notable decrease

Table 7. Effects on the Disparities in Air Pollution Levels between North and South

		(1)	(2)	(3)
$PM_{2.5}$	*North*	18.344***	17.054***	22.617***
		(2.198)	(3.602)	(1.626)
	North $\times$ *Post*	-13.073***	-17.282***	-14.185***
		(2.006)	(2.929)	(1.294)
PM_{10}	*North*	33.745***	29.303***	35.372***
		(3.617)	(6.201)	(2.309)
	North $\times$ *Post*	-23.623***	-31.781***	-21.310***
		(3.288)	(4.702)	(2.032)
AQI	*North*	21.922***	20.804***	26.582***
		(2.670)	(4.587)	(1.968)
	North $\times$ *Post*	-12.849***	-19.746***	-13.782***
		(2.394)	(3.534)	(1.534)
CO	*North*	0.548***	0.406***	0.518***
		(0.053)	(0.081)	(0.034)
	North $\times$ *Post*	-0.571***	-0.597***	-0.514***
		(0.048)	(0.062)	(0.031)
NO_2	*North*	9.510***	11.425***	11.270***
		(1.243)	(2.160)	(1.088)
	North $\times$ *Post*	-6.343***	-11.391***	-4.907***
		(1.232)	(1.687)	(0.899)
SO_2	*North*	17.690***	6.890**	13.936***
		(1.915)	(2.342)	(1.216)
	North $\times$ *Post*	-25.104***	-16.412***	-22.368***
		(1.624)	(1.853)	(1.058)
RD Type		Polynomial	Polynomial	LLR
Polynomial Function		Cubic	Cubic	
Sample		Full	5°	

Notes: Air pollution data is annual level. Control variables include weather controls correlated with air pollution (temperature, precipitation, and dew point, etc.) and city characteristics (GDP, the GDP growth rate, and the ratio of secondary industries) in one city in year t. Estimates are α_1 and α_2, the coefficients of $North_i$ and $North_i \times Post_t$ in Equation (4) and (5). Column (1) reports OLS estimates in Equation (4) using the full sample (n=1914). Column (2) reports these estimates for the restricted sample (n=963) of cities within 5° of the Huai River. Column (3) presents estimates from local linear regression (LLR) in Equation (5), with triangular kernel and bandwidth selected by the method proposed by Calonico et al. (2015a) and Calonico et al. (2015b). Standard errors clustered in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

in air pollution levels in northern regions compared to southern areas following the implementation of the WCHP since 2017 (e.g., PM_{10} in northern China decreases by 21/31 $\mu g/m^3$ more than in southern China). This underscores the effectiveness of the WCHP in alleviating the disparities in air pollution levels arising from the HRP. The estimates obtained from the non-parametric approach in column (3) tend to be of similar magnitude.

Furthermore, when compared to the results in column (1), the majority of outcomes in the restricted sample within 5° of the Huai River in column (2) exhibit smaller estimates for "$North$" and larger estimates for "$North \times Post$". This suggests a relatively lesser impact of the HRP on these disparities, while the WCHP has a more pronounced effect in mitigating the disparities in air pollution levels. One plausible explanation is that areas beyond 5° of the Huai River, such as cities in the Harbin province, experience a longer heating season due to lower temperatures and extended winter season. Consequently, these areas witness the most polluted air during winter, diminishing the discernible impact of the HRP when the sample is restricted within 5° of the Huai River. However, around 70% of the selected cities in the WCHP project are situated within 5° of the Huai River, amplifying its effect on reducing the disparities compared to the full sample.

1.6. Robustness Test

1.6.1. Exclusion of Adjacent Cities

As air pollution can transport long distances downwind(Agarwal et al. (2019)), cities adjacent to those included in the WCHP may also benefit from pollution reduction(Deschenes et al., 2017). To isolate the effects of the WCHP specifically among northern cities, I exclude 19 cities from the control group. These cities are either geographically adjacent to treated cities or coastal cities. Table A2 presents results using this modified control group, which align closely with the main findings. The significantly negative coefficients indicate that the WCHP has a positive impact on air quality throughout the year. Notably, its effectiveness is most pronounced during the winter season.

1.6.2. Exclusion of Other Policies

To eliminate potential confounding factors related to policies influences on air pollution trends during the study period, I conduct an investigation into additional environmental policies introduced between 2015 and 2021. Information was sourced from government documents and announcements. Notably, in 2017, various departments, including the Ministry of Environmental Protection and the National Development and Reform Commission, initiated the *2017-2018 Autumn and Winter Action Plan for Comprehensive Control of Air Pollution in Jing-Jin-Ji and Surrounding Areas*. Given the stringent environmental regulations in these regions, coupled with the WCHP project, there is a potential for an overestimation of the WCHP's impact. To address this, cities within Jing-Jin-Ji and surrounding areas were excluded from the sample.

Table A3 presents the findings on the effects of the WCHP on air quality in northern China, consistently revealing significantly negative overall effects on air pollution levels. Furthermore, Panel 2 indicates that the reductions in air pollution levels are higher during the heating season than the whole year. Table A4 shows results excluding other policy confounders, reinforcing the conclusion from the main analysis that the HRP's unintended consequences on regional imbalance persist. Conversely, the WCHP has demonstrated a capacity to reduce disparities in air pollution levels since 2017.

1.6.3. Within the Three-Year Subsidy Duration

As detailed in Section 2, the subsidies provided to selected cities by the WCHP are allocated over a three-year duration, intended primarily for capital investments in clean heating projects (e.g., transition equipment, gas storage stations), suggesting a potential long-term impact beyond the subsidy period. To address any uncertainties observed post-subsidy, I treat the data for treated cities as missing values after the three-year subsidy period. This approach allows for an examination of the WCHP's impact on air pollution levels and disparities resulting from the HRP.

In Table A5, Panel 1 confirms the robust negative overall effects on air pollution found in this study. Panel 2 illustrates the larger effectiveness of the WCHP, particularly during winter. These results align with the main findings. Table A6 presents the unintended consequences of the WCHP on addressing air pollution disparities due to the HRP. The primary findings, indicating that the HRP increases the differences in air quality and the WCHP mitigates these differences after 2017, remain valid.

1.7. Conclusion

The coal-fired winter heating services in northern China have long been a significant source of hazardous air pollutants for northern cities, contributing to increased mortality rates among northern residents. In response to the environmental issue posed by winter heating, the Chinese central government initiated the Winter Clean Heating Pilot (WCHP) in 2017. This program aimed to subsidize the energy transition from coal to natural gas in winter heating, with the overarching goal of mitigating air pollution in northern cities. This study estimates the impact of the WCHP on air quality in northern China. Initially, I employ the Two-Way Fixed Effect (TWFE) method to evaluate the overall effect of the WCHP. Recognizing potential biases inherent in TWFE estimates and the selection bias associated with the WCHP project, I further utilize staggered models.

The staggered DID analysis reveals a positive overall effect of the WCHP on air quality in northern China. This effect is manifested in reductions in annual levels of $PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2 by 9.03 $\mu g/m^3$, 13.10 $\mu g/m^3$, 0.347 $\mu g/m^3$, 3.49 $\mu g/m^3$, and 10.56 $\mu g/m^3$, respectively. Additionally, the annual mean of the Air Quality Index (AQI) decreased by 8.05. Moreover, the staggered DDD results indicate significantly higher reductions in $PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, and AQI during the heating season: 13.39 $\mu g/m^3$, 21.06 $\mu g/m^3$, 0.599 $\mu g/m^3$, 5.34 $\mu g/m^3$, 27.94 $\mu g/m^3$, and 14.33, respectively. These reductions are attributed to the exclusive funding for clean heating projects.

Furthermore, this paper investigates the unintended consequences of the WCHP on reducing the historical disparities in air pollution levels due to the Huai River policy (HRP). Results suggest that disparities in air pollution levels stemming from the HRP persist. For instance, PM_{10} rises by 29/35 $\mu g/m^3$ at the boundary in the restricted and full samples, respectively, aligning closely with the findings of 27/32 $\mu g/m^3$ in Ebenstein et al. (2017). However, there is a notable decrease in air pollution levels in northern regions compared to southern areas following the WCHP implementation (e.g., PM_{10} in northern China decreases by 21/31 $\mu g/m^3$ more than in southern China after 2017). These findings highlight the unintended consequences of the WCHP on addressing historical environmental inequalities and regional imbalance, emphasizing the complexity of such interventions and their outcomes.

The implications of these findings for human well-being are substantial. As suggested by Ebenstein et al. (2017), a sustained exposure to an additional 10 $\mu g/m^3$ of PM_{10} can lead to a 0.64-year decrease in life expectancy. Consequently, the implementation of the WCHP, resulting in an annual decrease in PM_{10} levels by 21.06 $\mu g/m^3$, could contribute to a more than 1.35-year increase in life expectancy in the treated northern cities. This suggests a potential gain of 0.4 billion life-years for the current population of these cities. Furthermore, the observed decrease in PM_{10} levels by more than 21 $\mu g/m^3$ in northern China compared to southern China indicates that the WCHP has mitigated health disparities caused by the HRP by extending life expectancy by 1.34 years, or 0.68 billion life-years in northern China.

Fan et al. (2020) report a 2.2% increase in overall mortality for every 10-point increase in the AQI due to winter heating services. Therefore, the observed 14-point decline in AQI after the implementation of WCHP could potentially decrease mortality by 3.08% in the treated cities, contributing to a 2.77% reduction in overall mortality disparities between northern and southern China.

Secondly, a growing body of evidence highlights that individuals allocate substantial resources to protect themselves from air pollution, constituting additional costs beyond direct mortality and morbidity effects. The willingness of households to pay for the removal of 1 $\mu g/m^3$ of air pollution (PM_{10}) is \$1.34, and \$32.7 to eliminate pollution induced by the HRP (Ito and Zhang, 2020). Consequently, the decrease in air pollution levels (PM_{10}) by 21 $\mu g/m^3$ due to the WCHP can potentially reduce annual household defensive expenditures by \$28.14 for PM_{10} removal and \$686.7

for pollution removal due to the HRP. These reductions in defensive expenditures underscore the economic benefits of the WCHP on household quality of life and society as a whole.

Thirdly, an additional economic benefit of the WCHP may manifest in the housing market. The hedonic theory posits that air quality positively influences the housing market, with residents willing to pay for environmental amenities (Bishop et al., 2020). Mei et al. (2021) suggest an 11% increase in price premiums for properties near Beijing due to reduced air pollutants from coal-to-gas conversion. The focus on the effects of the WCHP on the housing market in future research could further analyze the gains of the policy, considering variations among cities.

Moreover, energy consumption has been rising rapidly, leading to energy-related issues such as power shortages and environmental pollution (Ito and Zhang, 2020). In response, developing countries like China have implemented various energy policies and regulations. The HRP and the WCHP, both related to China's winter heating services, have unintentionally contributed to regional imbalances in air pollution and human well-being. This deeper understanding sheds light on the consequences of overlapping environmental policies in the context of China, which the literature does not study comprehensively.

Chapter II. The Distributional Effects of the NOx Budget Trading Program on Housing Markets

2.1. Introduction

Hedonic theory predicts that air quality improvements positively affect the housing market. A large amount of literature has documented the relationship between air quality and housing prices for amenity reasons, including owner-occupied house values (Bayer et al., 2009; Chay and Greenstone, 2005; Currie et al., 2015) and rents (Davis, 2011). Due to capitalization characteristics, air quality improvements could have different distributional implications on housing values and rents (Grainger, 2012). In the meantime, another important channel – the labor-market channel – should also be considered. Environmental regulations designed for air pollution abatement introduce substantial costs to the affected sources and further impact labor markets (Curtis, 2018; Greenstone, 2002; Greenstone et al., 2012; Kahn and Mansur, 2013; Walker, 2011, 2013). The adverse impact on labor markets, e.g., a decrease in employment, lower wage, may become a negative driver on housing markets (Agarwal et al., 2019). Therefore, the distributional effects of environmental policies on house values and rents, considering both amenity and labor channels, have not been studied; it is determined by the extent of the air quality improvement and the impacts on the local labor markets.

To study this question, this paper explores the NOx Budget Trading Program (NBP), a cap-and-trade system, examining the impact of environmental regulations on the housing and rental markets in regions where implemented the trading program. The NBP was introduced to reduce the emission of NO_x then reduce ground-level ozone concentrations in primarily the eastern U.S. It began in 2003 and was implemented until 2008 in nineteen states in addition to Washington, D.C. (EPA, 2004). NBP dramatically reduced NO_x emissions in the participating states (Deschenes et al., 2017). However, Curtis (2018) shows that NBP imposed substantial costs on manufacturers, then lowered hiring rates and worker wages, especially for young workers between 22 and 34.

Agarwal et al. (2019) investigate the effects of NBP on owner-occupied house values, combining both the amenity and labor market channels. Their study reveals an increase in house prices in low-manufacturing-intensity regions but a decrease in high-manufacturing-intensity regions. I adopt a similar triple differences (DDD) model to isolate the effects of the NBP operations on owner-occupied houses and monthly gross rents through the labor-market channel, utilizing measurements of the manufacturing energy intensity in each county.

The contribution of this paper is particularly focused on the effects of a cap-and-trade program on owner-occupied house values and local rents by using Census and ACS microdata, considering both the amenity and the labor-market channels. Although some manufacturers were directly regulated by the NBP, most manufacturers only suffered indirect costs of the NBP through high utility costs due to the costs of pollution controls. Therefore, I select the manufacturing energy intensity which closely correlates to the actual impact of higher utility costs on manufacturing instead of just manufacturing intensity to identify the effects through the labor markets. In addition, this paper fills the gap by studying the distributional effects of the NBP on housing and rental markets. One limitation of this paper is that the owner-occupied house values and rents from Census data are self-reported data instead of real transaction prices, which could introduce measurement errors (Bishop et al., 2020).

I find that the NBP decreases the NO_2 level during the summertime in NBP states, while the effect on NO_2 emissions does not vary by NBP areas with different manufacturing energy intensities. However, the negative impact of the NBP through the labor-market channel dominates in areas with high manufacturing energy intensities. A one percent (1%) increase in manufacturing energy intensity in 2000 reduces the effect of the NBP on owner-occupied house values and rents by approximately 0.78% and 0.27%, respectively. In addition, the elasticity in owner-occupied housing values is larger than that in rents. This means that the changes in air quality and wages are capitalized into property values, but renters focus more on the current. Furthermore, the distributional effects of the NBP among different groups are distinctly different between owner-occupants and renters.

The rest of the paper is organized as follows: Section 2.2 provides policy background and literature review; Section 2.3 is the data sources and summary statistics; Section 2.4 discusses the empirical strategy; Section 2.5 shows the results; Section 2.6 presents robustness checks; Section 2.7 is the conclusion.

2.2. Background and Literature Review

2.2.1. Ambient Pollution

NO_x would form ground-level ozone with sunlight, heat, and humidity. The ozone would be visible as the largest component of smog, a large cloud of pollution, which would later precipitate into acid rain. High levels of ozone would form between May and September, triggered by the sunlight and high heat of the summer when it breaks down nitrogen oxides (NO_x). Ground-level ozone is detrimental to health in even small quantities.

The EPA had successfully reduced the emission of sulfur oxides (SO_x) with an earlier cap and trade, which contributed to smog and acid rain. However, NO_x is more difficult to address, since there are significantly more sources of NO_x than SO_x, which is primarily from coal power plants. Thus, the NBP program represents a significant environmental regulation and a more diverse market for cap and trade.

2.2.2. The NOx Budget Trading Program

The NO_x Budget Trading Program followed the existing SO_x cap and trade system. The prior system established a large existing system for reporting and collection of data for emissions of SO_x, NO_x, flow rate, and either O_2 or CO_2 from individual pollution sources. It was meant to address some of the shortcomings of the SO_x program, and it represented a more complex program since there were significantly more emission sources than SO_x which focused on coal power plants. This program established a framework for reducing emissions of NO_x.

The NBP is a market-based cap-and-trade program implemented primarily in the eastern United States, aiming to reduce emissions of nitrogen oxides (NO_x) from power plants and industrial sources, to decrease the ground-level ozone and nitric acid (EPA, 2004). An initial version of the

NBP operated from 1999 to 2002 and led to a small reduction in emissions of NO_x during the summer, which is unlikely to affect the analysis of the 2003-2008 NBP effects (Deschenes et al., 2017). The NBP was implemented strictly in 2003 and was replaced by the ozone season NO_x program under the Clean Air Interstate Rule in 2009 (EPA, 2004). This market operated exclusively during the summer period, running from May 1st to September 30th, with the participation of 2,500 electricity-generating units and industrial boilers.

There were eight states[16] in addition to Washington, D.C. in the program in 2003. 11 states[17] joined in 2004. In 2003, the EPA allocated about 150,000 tons of NO_x allowances, and 650,000 tons in 2004. From the years 2005-2008, about 550,000 tons were allocated each year (EPA, 2009b). Each state received permits and decided how to allocate the permits to related sources. The affected sources could either trade the permits in the open markets or bank allowances for the future. In each year, about 250,000 tons of allowances were saved unused for the subsequent years (EPA, 2009a). Approximately seventy percent of units complied by reducing emissions, for example, using low NO_x burners. About thirty percent of units complied exclusively by holding emission permits (EPA, 2009b). The mean of NO_x permit price in the market was $2,523 per ton, with 2015 as the reference year (Deschenes et al., 2017).

2.2.3. Literature Review

It is widely believed that ambient air quality can have an impact on the local housing market. Based on the openings and closings of industrial plants data, Currie et al. (2015) show that plant openings cause an 11 percent decrease in housing value within 0.5 miles and bring about $4.25 million losses to these households. A large body of literature on the effects of CAAA on the housing market exists. In Chay and Greenstone (2005) paper, the results indicate that due to the air quality improvement induced by the mid-1970 total suspended particulates (TSPs) non-attainment

[16]The eight states are Connecticut, Delaware, Maryland, Massachusetts, New Jersey, New York, Pennsylvania, and Rhode Island.

[17]The 11 states are Alabama, Illinois, Indiana, Kentucky, Michigan, North Carolina, Ohio, South Carolina, Tennessee, Virginia, and West Virginia. Only a few counties in Alabama and Michigan were included in the market. In 2007 one region in Missouri and Georgia participated.

designation, those regions experienced a $45 billion aggregate increase in the housing market. Bento et al. (2015) argue that the CAAA creates heterogeneous effects of air quality improvements and favors lower-income households for those households in the lowest quintile of the income distribution receive benefits from house price appreciation twice as much as those in the highest quintile.

Homeowners have a significant barrier to moving with the high US home sale transaction costs, which are among the highest in the world. These losses cannot be effectively mitigated by homeowners because of the high transaction costs of selling. Unlike homeowners, renters are much more mobile, and they can respond relatively quickly to worsening ambient air quality by moving.

The ambient air quality also has a strong influence on rents. Davis (2011) shows that compared to neighborhoods with similar characteristics, housing values and rents would decrease if there were plants within 2 miles around the neighborhoods, with some larger decreases within 1 mile and for large-capacity plants. Grainger (2012) explores the impact of the reduction in PM_{10} due to the 1990 CAAA on rents and finds that the estimated percentage effect is about only half as large as that of owner-occupied housing values.

While there are undeniable benefits associated with increased health resulting from environmental regulations aimed at reducing pollution, it's crucial to acknowledge the challenges faced by regulated plants and industries. A prevailing argument suggests that these regulations can lead to job losses within the affected industries (Walker, 2011). A growing body of literature is dedicated to exploring the adverse effects of environmental regulations on local labor markets. The primary purpose of these regulations is to internalize the costs of pollution on the polluters, thereby facilitating a more efficient allocation of resources towards reducing NOx emissions. However, it's important to note that the costs of pollution remediation are primarily borne by larger employers, as they are the ones directly subjected to regulation.

Some papers have looked at the environmental regulations' impact on regulated industries, concluding negative effects on industry employment and economic activities (Greenstone, 2002; Henderson, 1996). Walker (2011) finds that the early 1990 emissions standards decreased employment persistently in regulated sectors. The increase in the plant-level job destruction rate accounted for those changes in employment, suggesting a related significant work-level adjustment cost for involuntary job loss. Walker (2013) extends the study to the transitional costs associated with reallocating workers to other sectors in the context of new regulations. The paper concluded that workers in newly regulated plants experienced significant long-run forgone earnings, which were driven by non-employment and lower earnings in future employment.

The cap-and-trade market allocation of NO_x reduction costs reduced the overall costs of compliance compared with mandated across-the-board reductions for all covered NO_x emitters covered by NBP, but it imposed significant costs that were passed down to primarily power users or large industrial users. The energy market usually passes through most costs with a profit margin onto the ratepayers, and it increases costs for large energy users. Thus, manufacturing energy intensity has a direct link to increased utility costs that impose costs on employers. Unfortunately, these energy consumers were not automatically allowed to pass through their costs to their customers, and these employers collectively sought to lower costs which included a reduction in force.

The biggest losers in employment are younger workers and some minorities who are more likely to have less seniority. Although employers would not generally reduce existing employee wages, there is a two-fold impact on the younger workers who bear the largest employment declines and lower new hire wages after the regulations took effect.

Curtis (2018) how the NOx budget treading program affected labor markets in the manufacturing sector. His findings show that overall employment experienced a drop by 1.3% in the manufacturing sector, with a loss of up to 4.8% in energy-intensive industries, given the larger costs associated with more energy-intensive industries. In addition, Curtis shows that young workers experienced a larger decline in employment, and the wages of new employees decreased after the program began.

Agarwal et al. (2019) specifically investigate the effect of NOx Budget Trading Program in both the amenity channel and labor market channel. They suppose that this environmental regulation may act as a double-edged sword on the housing market in the implemented regions since it could have positive effects for the decrease in pollution levels while negative effects on labor markets reducing housing demand. Their findings show that house prices increased in the regulated areas with low manufacturing intensity, while the housing market became weak in the regulated areas with high manufacturing intensity. In addition, they find a deteriorating situation in the mortgage market in high-manufacturing-intensity areas, such as a decline in loan application volume, an increase in rejection rate, and a higher probability of loan default.

However, few studies particularly focus on the effects of the NBP on both owner-occupied house value and local rents. This paper aims to study how the NBP affects house valuations and local rents differently. Furthermore, instead of using manufacturing intensity, it distinguishes the effects between the amenity channel and the labor-market channel by manufacturing energy intensity regions. This allows more accurate results by tracking the major increased costs among those energy-intensive manufacturing industries. In addition, it investigates the distributional effects of environmental regulations between renters and homeowners.

Manufacturing energy intensity reflects a clearer representation of the impacts of cap and trade over manufacturing intensity. Not all manufacturers consume significant amounts of energy compared with the value of their output. The NBP only covers larger employers with significant pre-existing NO_x emissions, which means that most manufacturers are not directly regulated by the NBP. However, all manufacturers are subject to a rise in utility costs to reflect costs of compliance with NO_x regulations. If the manufacturer is large enough to have their own power-generating facilities, then they should be subject to the NBP directly, which would still be reflected in their manufacturing energy intensity. Manufacturing intensity may show the hotspots of NO_x compliance costs, but it ignores most of the impact on the economy. Thus, manufacturing energy intensity reflects the actual impact of costs of compliance on the manufacturing and other users' energy across the board.

The application of manufacturing energy intensity may have limitations, particularly in areas located closest to coal power plants. Those power plants have typically been operating for decades, and minor changes to clean up the environment near the plant are always welcome. However, its impact on the housing and rent markets would be muted, since there is such a large stigma being so close to these plants.

2.3. Data Sources

2.3.1. Housing Data

Housing data is sourced from the American Community Survey (ACS) and U.S. census microdata on IPUMS USA. IPUMS USA data provides decennial census microdata spanning from 1790 to 2010, as well as ACS microdata from 2000 to the present. Notably, county identification is unavailable from 2001 to 2004. Therefore, I utilize data from the 2000 census and the 2005-2008 ACS to study the effects on different manufacturing energy intensity areas. In this study, the pre-treatment period is 2000, and the post-treatment period is 2005-2008. Given that the NBP was implemented from 2003 to 2008 and subsequently replaced by the ozone season NO_x program in 2009, this timeframe ensures that the analysis remains unaffected by the influence of the ozone season NO_x program.

The main dependent variables are owner-occupied house value and monthly gross rent. Other housing characteristics (e.g., the number of bedrooms), demographic information, educational attainment, and income for individuals and households are available. In addition, tenancy information is obtained.

The treatment group includes the NBP participating states which implemented the NBP in 2003 and 2004. I do not include the participating counties in Michigan because only a few counties joined the program. Puerto Rico and non-continental states, i.e., Alaska and Hawaii are not included in the empirical analysis. I expect that Puerto Rico and Hawaii as islands would have distinctly different impacts on the housing market since it is harder to move to escape pollution on islands. Alaska is a very big state, but its population is mainly concentrated in a few cities with only 19% of the population living in rural areas. Puerto Rico, Hawaii, and Alaska are also tourist destinations with limited housing availability for residents, which led to significant effects on housing values rather than long-term housing. So, it is much more difficult to relocate because of the rise of Airbnb and other short-term rentals that severely limit mobility. Since NO_x can travel downwind for a long distance (Streets et al., 2001), the adjacent states may benefit from pollution reduction (Deschenes et al., 2017). I exclude the states that are adjacent to NBP regions, i.e., Arkansas, Florida, Georgia, Iowa, Maine, Mississippi, Missouri, New Hampshire, Vermont, and Wisconsin (Agarwal et al., 2019). Therefore, their employers should receive a benefit instead of the costs of compliance or costs of buying NO_x credits.

2.3.2. County Characteristics

County-year-level employment information can be obtained from the County Business Patterns (CBP) produced by the U.S. Census Bureau. Other county characteristics like payroll, the number of establishments etc., are provided by CBP.

Energy usage information is provided by the NBER-CES Manufacturing Industry Database. This database contains annual industry-level data from 1958-2018 on output, input costs, employment, and so on. Following the instruction in Curtis (2018), I calculate the energy intensity index for each industry by dividing the total energy expenditure by the total value of shipments for the industry. To avoid the endogeneity issue that NBP operation may affect the manufacturing energy intensity index, I use the year 2000 as the reference year for the manufacturing energy intensity index. To measure the manufacturing energy intensity for a county, I assume that the county has L labor force with m and n workers in M and N manufacturing industries, respectively. I calculate the manufacturing intensity followed by Agarwal et al. (2019): $ManInt = \frac{m+n}{L}$. In addition, I assume that the energy-intensity index for M and N industries are p and q, respectively. Then, the manufacturing energy intensity for this county is computed as follows: $EnInt = (p * \frac{m}{m+n} + q * \frac{n}{m+n}) \times ManInt = (p * \frac{m}{m+n} + q * \frac{n}{m+n}) \times \frac{m+n}{L} = p * \frac{m}{L} + q * \frac{n}{L}$.

Table 8. Descriptive Statistics

	(1) Owner-Occupied House	(2) Monthly Gross Rent
Value ($)	241,061.813	893.098
	(165,474.656)	(493.437)
Age	48.383	39.900
	(17.274)	(16.810)
Female	0.525	0.530
	(0.499)	(0.499)
Married	0.634	0.379
	(0.482)	(0.485)
White	0.755	0.568
	(0.430)	(0.495)
Black	0.092	0.167
	(0.290)	(0.373)
American Indian/Alaska Native	0.005	0.009
	(0.073)	(0.092)
Asian	0.065	0.086
	(0.246)	(0.280)
Other Race	0.082	0.171
	(0.274)	(0.376)
High School or Less	0.402	0.509
	(0.490)	(0.500)
Some College	0.303	0.274
	(0.459)	(0.446)
Bachelor's Degree or Higher	0.296	0.217
	(0.456)	(0.412)
Income	38,158.040	24,395.563
	(47,414.293)	(33,418.673)
Unemployment	0.029	0.056
	(0.169)	(0.229)
Bedroom	3.071	1.902
	(0.810)	(0.999)
Observations	3,864,776	1,945,960

Notes: The sample is 2000 Census data and 2005-2008 ACS data with county identifications.

Table 9. Energy Intensity Index

(1) NAICS	(2) Description	(3) Energy Intensity	(4) Employment (1000s)
311	Food	1.46%	1,505.80
312	Beverage & Tobacco Product	0.70%	174.60
313	Textile Mills	3.46%	336.90
314	Textile Product	1.33%	229.80
315	Apparel	0.99%	520.30
316	Leather & Allied Product	0.95%	69.20
321	Wood Product	1.82%	586.50
322	Paper	4.19%	548.40
323	Printing & Related Support Activities	1.18%	830.50
324	Petroleum & Coal Products	3.05%	101.20
325	Chemical	3.43%	890.20
326	Plastics & Rubber Products	2.11%	1,080.20
327	Nonmetallic Mineral Product	4.78%	521.90
331	Primary Metal	5.57%	577.90
332	Fabricated Metal Product	1.60%	1,814.90
333	Machinery	0.76%	1,396.30
334	Computer & Electronic Product	0.55%	1,652.80
335	Electrical Equipment, Appliances	0.92%	591.10
336	Transportation Equipment	0.60%	1,837.40
337	Furniture & Related Product	0.97%	640.80
339	Miscellaneous	0.78%	745.60

Notes: The energy intensity data are sourced from the NBER-CES Manufacturing Industry Database for the year 2000.

Table 10. Manufacturing Energy Intensity (County Level)

(1) Variable	(2) Mean	(3) Standard Deviation	(4) Min	(5) Max
Manufacturing Intensity	0.223	0.091	0.006	0.691
Manufacturing Energy Intensity	0.118	0.048	0.003	0.366
Observations	3,218,512	3,218,512	3,218,512	3,218,512

Notes: Data is from the CPB for the year 2000. Manufacturing intensity and manufacturing energy intensity are calculated by the methods in Section 2.3.

2.3.3. Summary Statistics

Table 8 shows the summary statistics from 2000 to 2008. From the table, we can see that the average owner-occupied house value is approximately \$241,062, and the average monthly gross rent is \$893. Caucasians are the only race that has a higher proportion of owner-occupied homes than that of renting homes. Other races all have a higher proportion of renting homes than occupying houses. 63.4% of house owners are married, but only 37.9% of renters are married. People who own their houses tend to have higher education attainment and income, and the unemployment ratio is lower than renters.

Energy-intensity index for each manufacturing industry in 2000 is presented in Table 9. Industries of Primary Metal, Nonmetallic Mineral Products, Paper, Chemical, and Petroleum & Coal Products have the highest energy expenditure proportion, with more than 3% energy intensity. While the Beverage & Tobacco Product, Machinery, Computer & Electronic Product, and Transportation Equipment consumed the least energy compared to their total value of inputs. Those industries with the highest level of energy intensity could suffer the most increased cost from the NBP implementation, passing through the losses to the workers.

Table 10 presents the manufacturing intensity and manufacturing energy intensity at the county level. These metrics are calculated as previously described. The table reveals that the average employment in manufacturing industries at the county level is approximately 22.3% of the total employment. Additionally, the mean county-level manufacturing energy intensity is 11.8%.

2.4. Methodology

I use a difference-in-differences (DID) approach to examine the overall effects of the emission market on owner-occupied house values and monthly gross rents.

Specifically, I estimate the following model:

$$Y_{ict} = \beta(Post_t \times NBP_c) + \gamma X_{it} + \mu_c + \lambda_t + \mu_c \times t + \mu_c \times t^2 + \epsilon_{ict} \tag{6}$$

Where the dependent variable is the logarithm of owner-occupied house values or monthly rents for individual i in county c in the year t. $Post_t$ is a dummy variable that equals one after NBP initiation. The NBP_c is an indicator that equals one if county c participated in the NBP. The coefficient of interaction term $Post_t \times NBP_c$ is the interest to estimate the average effect of the emission market on house values and rents in NBP regions. The matrix of control variables, X_{it}, includes demographics and property characteristics. μ_c indicates the county fixed effects. λ_t represents the year fixed effects. To control for nonlinear changes in the determinants of house values and rents, vectors of the county-specific linear and quadratic time trends are added. ϵ_{ict} represents the error term.

To examine the parallel trend assumption of the DID model, I employ an event study model. In the event study, I utilize 2000 Census data and 2001-2008 ACS data with no county identifications. This enables the incorporation of multiple pre-treatment periods and facilitates the estimation of parameters β_{2000},...,β_{2008}. In addition, this model can measure the dynamic effect of the NBP operation each year, providing additional useful information. The event study model is:

$$Y_{i\alpha t} = \sum_{k=2000, k\neq 2002}^{2008} \beta_k[\mathbb{1}(t=k) \times NBP_\alpha] + \gamma X_{it} + \mu_\alpha + \lambda_t + \mu_\alpha \times t + \mu_\alpha \times t^2 + \epsilon_{i\alpha t} \quad (7)$$

Where the dependent variable is the logarithm of values of owner-occupied house value or monthly gross rent for individual i in state α in the year t. $Post_t$ is a dummy variable that equals one after the NBP initiation. The NBP_α is an indicator that equals one if the state participated in the NBP. μ_α indicates the state fixed effects. State-specific linear and quadratic time trends are added. $\mathbb{1}(t = k)$ is an indicator variable equal to one if year t is the specific year from 2000 to 2008. The year 2002 is the reference year. I plot the β_k in event study figures to visualize the dynamic effects of the NBP. Furthermore, the event study graphs provide an opportunity to assess whether there were pre-NBP trends.

As the hedonic models predict, the value of owner-occupied houses and the rent should increase once the ambient air quality becomes better. While the quantitative analysis suggests that the sign of β is ambiguous. Specifically, it may be positive because air pollution decreases which boosts the housing market. However, the negative effects of the NBP on the labor market among those energy-intensive manufacturing industries.

As we discussed in Section 2.2, 2,500 electrical generating units and industrial boilers were included in the NBP market, which could cause an increase in transitioning equipment costs and energy prices. The manufacturing energy-intensive industries in each county would reflect the greatest effect of the NBP operation on the labor market by suffering the spike in energy input costs. Therefore, to further explore how much the house values and rents are affected in areas with different business patterns, I adopt a triple differences (DDD) model to isolate the effect of the NBP operations on the owner-occupied houses and monthly gross rents through the labor-market channel.

The DDD estimator exploits three sources of variation in the emission and housing market. First, it compares the pre and post-periods of the NBP's implementation. Second, it estimates the differences between counties that participated in the NBP and the ones that did not participate in the operations and were not adjacent to an NBP state. Third, it can isolate the impact on the markets in different manufacturing energy intensity areas. The model is as follows:

$$
\begin{aligned}
Y_{ict} = \beta(Post_t \times NBP_c \times EnInt_c) + \eta(Post_t \times NBP_c) + \delta(Post_t \times EnInt_c) + \\
\gamma X_{it} + \mu_c + \lambda_t + \mu_c \times t + \mu_c \times t^2 + \epsilon_{ict} \quad (8)
\end{aligned}
$$

Where $EnInt_c$ denotes the logged ratio of the manufacturing energy intensity in county c in 2000[18]. Other variables have the same definitions as in equation (6). The coefficient of interaction term $Post_t \times \ NBP_c \times EnInt_c$ is to estimate the effect of the emission market on house

[18] I use a transformation with a logarithm of manufacturing energy intensity plus one.

values and rents with different manufacturing energy intensities. An alternative specification is to use a binary variable, $HighEnInt_c$, in equation (8), denoting whether the manufacturing energy intensity of county c is above average. This specification enables the investigation of the heterogeneous effects of the NBP on the housing and rental markets between regions with higher and lower manufacturing energy intensities.

The main hypothesis is that the higher the manufacturing energy intensity a county has, the more likely the labor-market channel on house prices and rents dominates, leading to a negative coefficient β on house prices and rents.

2.5. Results

In this section, I begin by presenting the event study graph to test the parallel trend assumption and the results of the overall effects on the housing and rent markets. Then, I show the key findings of this paper, the NBP's effects on the housing and rental markets across counties with different manufacturing energy intensities, which demonstrates that the NBP could affect those markets through both amenity and labor-market channels.

2.5.1. Overall Effect of the NBP

Before using the DID analysis, Figure 7 presents a visual graph on the dynamic effects of the NBP on owner-occupied house values and monthly gross rents year by year. Note that 2000-2008 data are used in the event study as discussed in Section 2.4. Before the implementation of the NBP, the trends in owner-occupied house values in the treatment group and the control group were not significantly different, which indicates that the two groups had parallel trends before 2003. However, the effects of the NBP on the housing price values are unclear. The parallel trend assumption for the monthly gross rents also holds. In addition, the rents in the NBP regions seem to grow faster than those in non-NBP regions. The event study results indicate that the NBP impacts the owner-occupied house values and rents differently.

Table 11 presents the results of the overall effects on owner-occupied house values and monthly gross rents from Equation (6). As I mentioned previously, I can only use the data in the years of

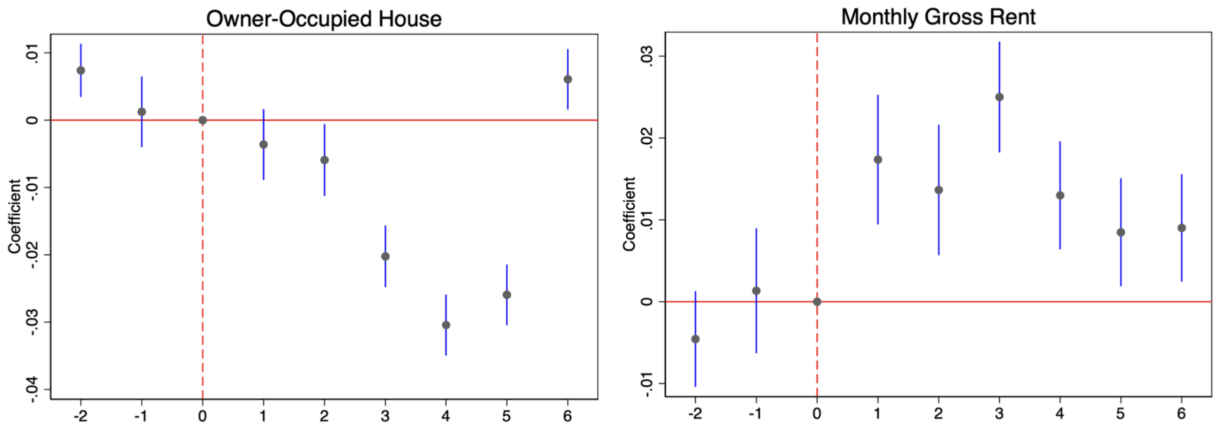

Figure 7. Event Study for House Values and Rents

Notes: In the event study, 2000 Census data and 2001-2008 ACS data with no county identifications are utilized.

2000, and 2005 to 2008, due to the limitations on county identification. Column (1) shows the results with control variables. In column (2), I add county fixed effects to the regression. Column (3) presents the results with both county fixed effects and year fixed effects. County-specific linear and quadratic trends are included in column (4). The majority of estimations yield statistically insignificant results, with the exception of those presented in column (2) for both housing and rental markets and column (4) for the rental market. Although whether the owner-occupied house prices gain or lose is unclear, the results show that the monthly gross rents increase more in the NBP regions, which is consistent with the hedonic theory. However, the gain is not significantly different from zero.

2.5.2. Heterogeneous Effects by Manufacturing Energy Intensity

Table 12 shows the results of monthly gross rents and owner-occupied house values from Equation (8). Panel 1 presents the effects on owner-occupied house values. Each column shows the results from the specifications with different components. The sign of the coefficients on $Post \times NBP$ indicates that the NBP increases the house prices in NBP regions when removing consideration of manufacturing energy intensity related employment. However, the coefficients of $Post \times NBP \times EnInt$ are significantly negative, suggesting that the higher the manufacturing

Table 11. Overall Effects of NBP on Owner-Occupied House Values and Rents

	Owned-Occupied House Value (3,864,776 observations)			
	(1)	(2)	(3)	(4)
Post × NBP	0.086	0.465***	-0.066	-0.023
	(0.212)	(0.035)	(0.084)	(0.063)
	Monthly Gross Rent (1,945,960 observations)			
	(1)	(2)	(3)	(4)
Post × NBP	0.027	0.272***	0.019	0.038***
	(0.091)	(0.008)	(0.019)	(0.010)
Control	Y	Y	Y	Y
State Fixed Effects	N	Y	Y	Y
Year Fixed Effects	N	N	Y	Y
County Trend	N	N	N	Y

Notes: The sample is 2000 Census data and 2005-2008 ACS data with county identifications. Logarithm of monthly gross rents and house values are used. Standard errors in parentheses, clustered by state. * p<0.05, ** p<0.01, *** p<0.001

Table 12. Heterogeneous Effects by Areas with Manufacturing Energy Intensity

	Panel 1: Owned-Occupied House Value (3,857,514 observations)			
	(1)	(2)	(3)	(4)
Post × NBP × EnInt	-4.265***	-5.409***	-0.899***	-0.776***
	(0.025)	(0.020)	(0.028)	(0.028)
Post × NBP	0.581***	0.609***	0.034***	0.069***
	(0.002)	(0.002)	(0.003)	(0.003)
Post × EnInt	3.078***	4.130***	-0.379***	-0.628***
	(0.011)	(0.007)	(0.021)	(0.021)
	Panel 2: Monthly Gross Rent (1,944,329 observations)			
	(1)	(2)	(3)	(4)
Post × NBP × EnInt	-2.188***	-2.180***	-0.325***	-0.274***
	(0.029)	(0.029)	(0.037)	(0.037)
Post × NBP	0.312***	0.286***	0.053***	0.065***
	(0.003)	(0.003)	(0.004)	(0.004)
Post × EnInt	1.814***	2.041***	-0.185 ***	-0.054***
	(0.010)	(0.007)	(0.024)	(0.025)
County Fixed Effects	Y	Y	Y	Y
Control	N	Y	Y	Y
Year Fixed Effects	N	N	Y	Y
County Trend	N	N	N	Y

Notes: The sample is 2000 Census data and 2005-2008 ACS data with county identifications. The logarithm of rent and house value are used. Standard errors in parentheses, clustered by county. * p<0.05, ** p<0.01, *** p<0.001

energy intensity in a county, the more house prices were negatively affected by the NBP. Column (4) suggests that a 1% increase in manufacturing energy intensity in 2000 reduced the effect of the NBP on owner-occupied house value by around 0.78%.

Panel 2 shows the results for the monthly gross rents. Like owner-occupied house values, the coefficients of $Post \times NBP$ are significantly positive, suggesting that the NBP has increased the gross rents in the regulated areas without considering the employment in manufacturing energy-intensive industries. While the $Post \times NBP \times EnInt$ term shows that the rent is negatively affected by the NBP through the labor market channel. In column (4), it indicates that a 1% increase in manufacturing energy intensity in 2000 would reduce the effect of the NBP on rent by around 0.27%.

All the results indicate that as the manufacturing energy intensity increases, the effect of the NBP operation through the labor-market channel would dominate that from the amenity channel. The increasing costs for the energy-intensive industries will impact workers' wages, and the decreased wages will drag the housing and rental markets down more than the improved ambient air quality would boost the markets.

In addition, the impact of environmental regulations on owner-occupied house values is greater than the effect on the rental market. The magnitude of the changes in the owner-occupied house values is larger. It suggests that the house owners may consider the future and capitalize air quality improvements or wages into housing values, whereas renters would pay for current air improvement or wage declines immediately. In other words, the pass-through value of better ambient air quality for renters may be incomplete, for the smaller percentage increase in rent than that of owner-occupied housing values. However, the "penalties" through the labor-market channel for having higher manufacturing energy intensity in a region are also less in rents than in owner-occupied house values.

2.5.3. Heterogeneity Analysis

To further explore the distributional effects of the NBP on the housing market and rents, I analyze the impact on different groups. Table 13 shows the results of heterogeneous effects by groups. In panel 1, the owner-occupied house values have a bigger decline among individuals under 35 than those over 35, with a decline of 0.83% and 0.72%, respectively. It matches with the results in Curtis (2018) study, which demonstrates that younger workers see the largest employment decline in energy-intensive manufacturing industries due to the costs imposed by NBP. In addition, workers with lower education attainment suffer greater levels of property value depreciation. The housing market prices have multiple drivers of value, and the college-educated groups are more likely to live in areas where amenities influence values more than the labor channel, mitigating declines in their housing values. Furthermore, the owner-occupied housing values decrease in a significantly larger magnitude among the low-income group than the high-income group, since the low-income group is more dependent on the prevailing manufacturing wages than the high-income group.

Panel 2 presents the heterogeneous effects on rents. Similar to owner-occupied housing values, rents decrease more among younger people since they are more mobile and willing to move, and after reaching the age of 35 and above, older workers face challenges in moving from childcare, family, and other considerations. Therefore, the impact of younger workers' wage losses on rents is realized faster since they are more mobile and have a lower perceived value of air quality improvements. There exists an apparent paradox where higher educated and higher income groups had a larger decline in rents than poorer and lower educated groups in the NBP-affected areas. This can be attributed to the higher educated and higher income group's willingness to move away from declining rental markets, and the remaining ones in the declining housing market can get steeper discounts with less demand for the higher rent units in a declining rental market. Thus, there are distinct effects on different groups in the rental market, which diverge from the effects seen in the owner-occupied housing market.

Table 13. Heterogeneous Effects by Different Groups

	Age (Under 35)	Age (Over 35)	Bachelor's Degree or Higher	Less than Bachelor's Degree	Income (High)	Income (Low)
	Panel 1: Owned-Occupied House Value					
	(1)	(2)	(3)	(4)	(5)	(6)
Post × NBP × EnInt	-0.827***	-0.715***	-0.407***	-0.940***	-0.005	-0.963***
	(0.061)	(0.036)	(0.055)	(0.036)	(0.115)	(0.039)
Observations	969,238	2,888,276	1,139,760	2,717,754	251,598	2,514,321
	Panel 2: Monthly Gross Rent					
	(1)	(2)	(3)	(4)	(5)	(6)
Post × NBP × EnInt	-0.739***	-0.644***	-0.802***	-0.439***	-0.304	-0.502***
	(0.056)	(0.062)	(0.077)	(0.048)	(0.222)	(0.048)
Observations	958,853	985,476	421,123	1,523,206	45,178	1,595,662

Notes: The sample is 2000 Census data and 2005-2008 ACS data with county identifications. Logarithm of rent and house value are used. Standard errors in parentheses, clustered by county. * p<0.05, ** p<0.01, *** p<0.001

Table 14. NBP Effects on NO_2 Emissions

	NO2 in Summertime (Unit: $\mu g/m^3$)			
	(1)	(2)	(3)	(4)
Post × NBP × EnInt		-0.002	-0.002	-0.002
		(0.002)	(0.002)	(0.002)
Post × NBP	-4.403***	-3.120	-2.807	-2.570
	(1.185)	(2.015)	(2.003)	(1.980)
Post × EnInt		0.009	0.026	0.013
		(0.052)	(0.018)	(0.025)
County Fixed Effects	Y	Y	Y	Y
Control	Y	Y	Y	Y
Year Fixed Effects	Y	N	Y	Y
County Trend	Y	N	N	Y
Observation	6,286,250	6,286,250	6,286,250	6,286,250

Notes: The sample is 2000 Census data and 2005-2008 ACS data with county identifications. * p<0.05, ** p<0.01, *** p<0.001

In general, the results show that rents among different groups are less responsive to the NBP operation than owner-occupied housing value. This is because the elasticity of rents to air quality/income is smaller than the elasticity of owner-occupied housing value (Grainger, 2012). The larger percentage changes in the housing values reflect a change in the imputed capitalized value of rents, and the owner-occupants are unable to avoid modest declines in value because of the high transaction costs related to selling the houses.

2.5.4. Mechanisms

One may question whether the heterogeneous effects on house prices and rents are driven by varying impacts of air pollution abatement in NBP regions with different characteristics. For instance, low-manufacturing-energy-intensity areas may experience a more substantial reduction in pollution emissions compared to regions with high manufacturing energy intensities. In addition, pollution emissions might even increase in high-manufacturing-energy-intensity areas, potentially contributing to the negative effects of the NBP on housing and rental markets in those areas. To test this idea, I investigate the NBP's influence on NO_2 emissions during summertime using equations (6) and (8).

Table 14 presents the effects of the NBP on NO_2 emissions during summertime. Column (1) shows the estimation of equation (6), which assesses the overall effects of the NBP operations. It indicates that NO_2 emissions decrease by more than 4.4 $\mu g/m^3$ (16.9% by annual mean) in NBP regions. Columns (2) to (4) report the estimations of Equation (8) with different components added. The results suggest that the NBP effect on NO_2 emissions during summertime does not vary across areas with different manufacturing energy intensities. Therefore, NO_2 emissions were consistently reduced in NBP states, with no evidence of heterogeneous effects on pollution emissions among areas with different manufacturing energy intensities. This finding supports our main conclusion that the effects on the housing and rental markets through the labor-market channel may provide a better explanation for the analysis.

2.6. Robustness Test

2.6.1. Heterogeneous Effects by High/Low Energy Intensity

Another specification involves introducing a binary variable, $HighEnInt_c$, into equation (8), indicating whether the manufacturing energy intensity of county c exceeds the average. This specification enables the investigation of the heterogeneous effects of the NBP on the housing and rental markets between regions with higher and lower manufacturing energy intensities.

Table A7 suggests that owner-occupied house values decrease by approximately 2.6% - 4.5% more in NBP areas with manufacturing energy intensities higher than average, compared to NBP areas with manufacturing energy intensities below the average. Similarly, in the rental market, NBP regions with higher manufacturing energy intensities experience 1.3% - 2% more declines than those with lower manufacturing energy intensities. Therefore, it appears that the negative effect from the labor-market channel exceeds the positive effect from the amenity channel if the NBP regions have higher manufacturing energy intensities.

2.6.2. Heterogeneous Effects by Manufacturing Intensity

As Agarwal et al. (2019) suggests, I can measure the local manufacturing intensity by calculating the ratio between manufacturing employment and the total labor force in one county. For example, a county has a L labor force with m and n workers in M and N manufacturing industries, respectively. Then, the manufacturing intensity for this county is computed as follows: $\frac{m+n}{L}$. To avoid the possible effect on the manufacturing intensity of NBP after the market's initiation, I use the ratio in 2000 as an exogenous measurement of manufacturing intensity for each county.

Table A8 shows a similar conclusion as our main results. The magnitude of changes in both owner-occupied housing values and rents is more pronounced using manufacturing energy intensity than manufacturing intensity. Although NO_x regulations regulate both manufacturers and power plants, there is only a relatively small set of manufacturers directly regulated by NBP, whose manufacturing energy intensity would also capture the impact on their business. Because most manufacturers are excluded from direct regulation by NBP, the impact on the manufacturing sector is primarily the increase in energy costs. The measurement of manufacturing intensity does not accurately address the energy-intensive differences in manufacturers, basically manufacturing intensity would understate the NBP effects by failing to track the impact of the main increased cost driver. For example, a cardboard box folding plant and an aluminum manufacturer may employ the same amount of employees, but the aluminum plant will continue to need vast quantities of higher-cost electricity after NBP, which electrical costs represent a high percentage of the value of the production from the aluminum plant than the de minimis amount of energy used by the box folding plant. Thus, manufacturing energy intensity is a better measurement of the effects of NBP on manufacturers than simply looking at the number of manufacturing employees in an area.

2.6.3. Rust Belt States

Illinois, Indiana, Michigan, Ohio, and Pennsylvania are Rust Belt states. These states have experienced a dramatic economic decline and population loss for decades (e.g., Glaeser and Gyourko, 2005). There was a very significant decline in industrialization, manufacturing, population, and coal mining. All these states participated in the cap-and-trade program, and they were included in my main study. However, this may affect the estimation of treatment effects. In the main regression, I have controlled the state/county-specific trends to partly reduce the potential concern.

To further reduce heterogeneity, I exclude these states from the treatment group for the robustness check. Table A9 shows the results.

2.7. Conclusion

NBP affects the housing and rental markets through both the amenity and labor-market channels. When the manufacturing energy intensity in an area is high, the labor market's impact dominates. A one percent (1%) increase in manufacturing energy intensity in 2000 reduces the effect of the NBP on owner-occupied house values and rents by approximately 0.78% and 0.27%, respectively.

The magnitude of changes in owner-occupied housing values is larger than that in rents. This means that the changes in air quality and wages are capitalized into property values, while the magnitude of changes in rents are not as large as with owner-occupied house values. The elasticity of rents for air quality/income is smaller than the elasticity of owner-occupied housing value (Grainger, 2012).

The impact of NBP varied based on the demographics of various groups. Younger workers saw the largest decline in their property values and rents due to the NBP operation. For owner-occupied housing, the factors of being in groups under 35 years of age, income below $40,000, and having less than a bachelor's degree show a very similar and substantial decline in property values related to NBP. The group with a bachelor's degree has a more modest negative impact, but the group earning over $100,000 per year has the smallest decline in property values related to NBP. This high-earning group generally lives in different neighborhoods than low-income groups even if they are in the same county.

The rental market reflects a more dynamic market than the owner-occupied housing market since there is much more turnover in rental units. In an apparent paradox, the higher income and higher educated groups received a greater percentage decline in rents from NBP than lower income and lower educated groups. The higher income and higher educated groups are more likely to be able to move in response to a declining neighborhood especially if they are only renting. Although declining rents could give them more discretionary income, the impact of a slightly lower rent does not outweigh continuing to live in a declining area for higher-income groups.

Moreover, this paper provides evidence that environmental policies, such as cap-and-trade systems, have redistributive effects beyond their direct impact on amenity air quality. With the widespread adoption of environmental regulations, policymakers need to have a comprehensive understanding of their impacts not only on the environment but also on other sectors.

While this paper sheds light on the distributional effects of the cap-and-trade program on the housing and rental markets, emphasizing the heterogeneous effects primarily stem from the varying impacts on the labor markets across regions with different manufacturing energy intensities, it does not explicitly identify the effects from the amenity channel. To isolate the pollution abatement effect, it is insufficient to solely rely on pollution emissions in the analysis. Pollution levels can be endogenous due to positive correlations with local housing prices and economic activities (Grainger, 2012). Deschenes et al. (2017) argue that the NBP implementation can serve as a reliable instrumental variable to address endogeneity concerns. However, studies such as Curtis (2018), along with the present paper, demonstrate that the NBP not only affects amenity air quality but also impacts the local labor market. Consequently, the NBP may not be a valid instrument when considering the labor market. A promising avenue for future research lies in exploring valid IVs to isolate the effects of both the amenity and labor-market channels.

Chapter III. The Effects of Family Size on Parents' Occupational Characteristics: Evidence from the U.S.

3.1. Introduction

Bearing and raising children takes tremendous effort, keeping parents from developing their careers, especially mothers. The impact of family size on parents' labor market behavior has been an important research topic that interests labor economists. Previous literature has documented the effect of children number in a family on parents' labor supply (Agüero and Marks, 2008; Angrist and Evans, 1998; Bloom et al., 2009; Bronars and Grogger, 1994), wages (Korenman and Neumark, 1990; Livermore et al., 2011), and working hours (Angrist and Evans, 1998; Bronars and Grogger, 1994; Vere, 2011).

This study goes further on how family size affects parents' decisions on their occupation changes (Chen et al., 2021; Abendroth et al., 2014), which is a less discussed topic in this field. There are occupational status losses for the women in the long term after they have their first child (Abendroth et al., 2014). Chen et al. (2021) find that the number of children has negative effects on the labor supply of mothers. In addition, compared with fathers in Mainland China, fathers in Taiwan are more likely to change to occupations with lower prestige scores if the family size increases.

Apart from the changes in labor supply and working hours, once parents have children, they may have different job preferences than non-parents (Becker, 1991), accepting a desirable job with lower wages (Miller, 2004). The purpose of this paper is to examine the causal effect of family size on parents' occupational changes by analyzing occupational characteristics such as job flexibility, employer-provided health insurance, and prestige scores.

Individuals' occupational prestige is an explicit indicator of socioeconomic status (SES) (Nakao and Treas, 1994), reflecting how society evaluates the social status of a job (Fujishiro et al., 2010) and symbolizing social hierarchy (Krieger et al., 1997). Occupational prestige can be measured by occupational prestige scores, a scale that rates a job based on the belief of that job's worthiness. On the one hand, parents may want to keep their high prestige jobs to set a good example for their children or obtain more social resources for the family. On the other hand, parents may switch to a lower prestige job to save time and energy for their children (Chen et al., 2021). Therefore, occupational prestige score can be one of the occupational characteristics to study in parents' occupational change.

This paper contributes to the literature on how the number of children affects working parents' occupational characteristics in the U.S., using sibling-sex composition as an instrumental variable. Most of the literature that studies occupational characteristics focuses on the effects of occupational characteristics on gender differences regarding wages (Goldin, 2014; Yu and Kuo, 2017; Magnusson and Nermo, 2017; Wang-Cendejas and Bai, 2018; Lordan and Pischke, 2022). To the best knowledge, this is the first paper to focus on the family size's effects on parents' occupational characteristics. I use the Census Bureau microdata and American Community Survey (ACS) microdata in IPUMS USA. Occupational characteristics include a flexible schedule of working time, benefits from employers, and occupational prestige scores. I follow the same method in Goldin (2014) to measure occupational flexibility using five occupational features. These five occupational features are time pressure, contact with others, establishing and maintaining interpersonal relationships, structured vs. unstructured work, and freedom to make decisions. Benefits from employers are mainly measured by health insurance through employer/union. Instead of the Standard International Occupational Prestige Scale (SIOP) used in Chen et al. (2021) paper, I use the occupational prestige scores based on U.S. versions of the prestige scale.

The results indicate that parents with larger families are more inclined to have occupations offering greater flexibility and employer/union-provided health insurance. Additionally, each additional child is associated with a decrease in the prestige scores of all mothers (7.8%) and married fathers (10.2%), suggesting a shift towards occupations with lower prestige scores. These findings contribute to our understanding of the relationship between family size and labor market behavior, highlighting the importance of considering family dynamics in employment decisions. Understanding these dynamics can inform policies aimed at supporting working parents and designing family-friendly workplace practices.

The rest of the paper is organized as follows. Section 3.2 reviews the literature. Section 3.3 describes data. Section 3.4 discusses empirical strategies. Section 3.5 is the results. Section 3.6 is the robustness check. Section 3.7 concludes the paper.

3.2. Literature Review

An understanding of the relationship between family size and parents' labor market behavior is essential, given its implications for workforce participation, gender equality, and family well-being.

A large body of literature has examined how children influence parents' labor supply. Angrist and Evans (1998) employ sibling-sex composition as an instrumental variable, revealing that children lead to a reduction in female labor supply, particularly among impoverished and less educated women. Notably, husbands' labor market behavior exhibits little changes in response to an expanding family size. In addition, Bloom et al. (2009) assert that a birth can decrease a woman's labor supply by nearly two years over her reproductive lifespan. They also find that reduced fertility increases the ratio of working-age individuals to the total population, thereby augmenting a country's physical and human capital per capita. Moreover, Zhang (2017) find that the negative effects on female labor supply tend to decrease over time as children mature, and the incremental effects of adding another child diminish as the total number of children in a family increases.

The effects on labor-force participation vary among women of different groups. Bronars and Grogger (1994) estimate the short-run and life cycle impacts of unplanned children on unwed mothers, utilizing twin births as a natural experiment. Their findings indicate that unplanned births lead to substantial decreases in labor force participation and welfare recipiency among all unwed mothers in the short run, with the black women cohort experiencing significant and enduring declines in the probability of eventual marriage or family earnings. Conversely, married mothers exhibit less pronounced negative impacts. Agüero and Marks (2008) explore the effects among women who are not actively controlling their fertility, utilizing infertility as an instrument. They find no evidence to suggest that having children acts as a barrier to participation in the paid labor force among these women.

Moreover, the number of children has a significant impact on parental wages. Korenman and Neumark (1990) argue that there exists a substantial negative relationship between the number of children and wages. Livermore et al. (2011) observe a motherhood wage penalty of approximately 5 percent for having one child, escalating to 9 percent for two or more children. This wage penalty gradually manifests over time, primarily due to reduced wage growth, rather than an immediate decline following childbirth. Cukrowska-Torzewska and Matysiak (2020) assert that a motherhood wage gap of approximately 3.6-3.8% persists among mothers compared to their childless counterparts. However, the relationship between fatherhood and wages seems to be more indicative of a selection process rather than a causal one, even in societies with strong male-breadwinner traditions (Mari, 2019).

Family size can impact parents' occupational selection, which is less studied. In addition to changes in labor supply and working hours, the preferences of parents regarding employment may diverge from those of non-parents (Becker, 1991), often prioritizing job desirability over wages (Miller, 2004). The impact of family size on parents' occupational changes is less studied. Cukrowska-Torzewska and Matysiak (2020) have identified that the wage gaps associated with having one child are primarily driven by mothers opting for occupations with lower pay scales. Abendroth et al. (2014) demonstrate that motherhood incurs not only a wage penalty but also a reduction in occupational status, with substantial and lasting declines observed for women following the birth of their first child. Chen et al. (2021) reveal that the number of children negatively impacts the labor force participation of mothers. Additionally, fathers in Taiwan exhibit a greater propensity than their counterparts in Mainland China to transition into occupations with lower prestige scores as family size increases.

However, the impact of the number of children on parents' occupational characteristics remains an underexplored area in research. This paper aims to fill this gap by examining how increasing family size influences the occupational changes of working parents. It focuses on factors such as occupational characteristics (e.g., flexibility), job attributes (e.g., employer-provided health insurance), and occupational prestige scores.

3.3. Data Sources and Summary Statistics

3.3.1. Dataset

Data comes from the American Community Survey (ACS) and U.S. census microdata on IPUMS USA. IPUMS USA includes decennial censuses microdata from 1790 to 2010 and ACS microdata from 2000 to the present. It provides information about the number of children in a family, demographics, occupation, and health insurance, etc. I use 2000 census decennial microdata and 2001-2021 ACS microdata.

Occupation characteristics are sourced from O*NET, a database offering detailed insights into the attributes, requirements, and features of various occupations. This includes information on work activities, work context, and other attributes, each rated on a scale from 0 to 100 to measure the job characteristics. The latest version of O*NET aligns with the 2018 Standard Occupational Classification (SOC). To ensure compatibility, I use the ACS-SOC crosswalk table to match the occupations in O*NET with Census occupations by following Goldin (2014). In addition, I match different versions of ACS occupation codes with the 2018-onward ACS version for comprehensive alignment.

3.3.2. Sample

Firstly, the sample is constrained to employed parents since job characteristics can only be observed for individuals holding employment. Secondly, I narrow down the sample to households with a minimum of two children, thereby excluding those with no children or fewer than two children throughout the observation period. Additionally, I further restrict the sample to households where the oldest child is younger than 18 years old, as children above 18 are more likely to be employed or have relocated to different households. For fathers, I utilize a married sample, following the approach adopted by Angrist and Evans (1998).

3.3.3. Dependent Variables

Flexibility is measured using five distinct features from the O*NET: time pressure (the frequency of strict deadline requirements), contact with others (the extent of interpersonal interaction necessary for job performance), establishing and maintaining interpersonal relationships (the ability to develop and sustain cooperative working relationships over time), structured vs. unstructured work (the degree of task autonomy), and freedom to make decisions (the level of decision-making autonomy without supervision). Each characteristic is rated on a scale from 0 to 100.

Time pressure is a measure of the importance of strict deadlines and the requirement to follow rigid time schedules at work. A high-time-pressure job is difficult to manage with multiple children unless at least one parent has a flexible job or no job. Contact with others is a measure of the need to keep in contact with others through face-to-face meetings, telephone calls, or otherwise. The requirement to maintain contact reduces flexibility. Establishing and maintaining interpersonal relationships is a measure of how much a job requires business networking and relationship maintenance. Networking and maintaining additional business relationships make the job inherently less flexible and may require dedication of significant time. Structured versus unstructured work is the ability of the employee to determine the method and manner of work. A manufacturing assembly job would be a highly structured job with little flexibility but whose labor is highly fungible, but a poet would generally have a very unstructured work with more flexibility and low fungibility. Freedom to make decisions is the autonomy given to the worker. This is a reflection of the skill and trust granted by an employer to determine the nature and scope of work, and the greater freedoms granted generally mean that the employee has a higher managerial rank and fewer substitutions. All of these five features measure how much a job impacts the lives of employees and show how the employees value different aspects of their jobs.

Employer-provided benefits are primarily gauged by the presence of health insurance coverage obtained through an employer or union. A logistic regression is employed to measure the impact of increasing family size on parents' occupations. The IPUMS microdata provides insights into individuals' health insurance coverage through an employer or union. However, it is important to note that data on employer- or union-provided health insurance is only available from the year 2008 onward.

Public perception of occupational prestige changes over time. Prestige scores for working parents are determined based on U.S. occupational prestige scores derived from evaluations of occupational titles in the General Social Survey (GSS), conducted by the National Opinion Research Center (NORC) at the University of Chicago (Nakao and Treas, 1990). These scores range from 0 (lowest) to 100 (highest).

The top five occupations with the highest scores are physicians, astronauts, professors of physics in a college or university, college or university president, professors of psychology in a college or university. I employ the 1990 version[19] which is the latest version used by IPUMS USA. The mothers' and fathers' occupational prestige scores are calculated separately.

3.3.4. Instrumental Variable

Numerous theoretical studies support the notion that fertility and labor supply are jointly determined (Goldin, 1994; Schultz and Schultz, 1982). Furthermore, certain unobservable characteristics, such as ambition or talent, can influence both fertility and labor force participation (Agüero and Marks, 2008). Thus, fertility and parents' labor supply can affect each other. Consequently, employing family size as an independent variable to investigate its causal effect on parents' labor market behavior could lead to an endogeneity issue.

[19]The 1990 version is the one most widely used. The sample of 1,500 in 1989 GSS was randomly divided into 12 subsamples, with 125 respondents each (among these 12 subsamples, 10 were used to study occupational prestige scores, and the other two for a related study on ethnic prestige). Each subsample was asked to evaluate 40 occupation titles that were same to all subsamples, and a set of 70 titles which was unique for every subsample, "i.e., 40 rated by the full sample and 700 rated by one or another of the ten subsamples" (Nakao and Treas, 1994, p. 3). Adopting the same method in Hodge et al. (1964), Nakao and Treas (1994) asked the respondents to judge an occupation using an "occupational prestige ladder". The ladder consisted of nine stacked boxes in a vertical column, with box 1 labeled as "BOTTOM", box 5 as "MIDDLE", and box 9 as "TOP". Then respondents could place the cards in the boxes, with a single occupational title listed on each card. The nine rungs of the ladder were scored in 12.5-point intervals from 0 to 100 in order. Thus, respondents' answers were converted to a scale ranging from 0 (lowest) to 100 (highest). The prestige score for an occupation is the average score of all the raters.

Given that children's gender is essentially assigned randomly, parents' career decisions cannot influence the sex of their offspring. Angrist and Evans (1998) pioneered the use of the sex composition of the first two children as an instrumental variable for family size. They posit that the preference for a mixed gender composition among parents is a commonly observed phenomenon, with parents of same-sex siblings being more inclined to have a third child. Through surveys on desired fertility and subsequent studies on actual fertility among couples with two children, Westoff and Potter (2015) find that parents with two same-sex children desired offspring of mixed gender. Subsequently, these parents tended to have more children than those with two mixed-sex children.

Labor markets are dynamic, reflecting both employer demand and employee job choices. Wages and quality of life variables serve as proxies for employees' job ranking preferences. However, parental occupational changes are significantly influenced by the number of additional children. We can isolate the incremental changes in parental occupations based on variables unrelated to employer job demand by considering parents' preference for additional children based on a desire for heterogeneous gender composition. Since sibling sex composition is independent of parents' labor market supply and market demand but closely tied to family size, it serves as a plausible instrumental variable for family size to address the endogeneity problem in this paper. The instrumental variable is a dummy variable equal to one if the first two children are of the same sex and zero otherwise.

3.3.5. Summary Statistics

Table 15 presents some demographic and labor-supply variables of employed parents with two or more children, including all women, married women, and married men. As shown in Table 15, among parents with two or more children, approximately 54% of their first two children share the same sex. Furthermore, it is noteworthy that the average wages and weekly working hours for married men surpass those of both all women and married women.

Table 16 depicts the impact of child sex and gender composition on fertility. The first panel presents the sex preferences in parents with at least one child by indicating the likelihood of them

Table 15. Summary Statistics, Parents with 2 or More Children

	(1) All women	(2) Married women	(3) Married men
Number of children	2.412 (0.714)	2.406 (0.707)	2.480 (0.791)
Same sex (=1 if first two children were the same sex)	0.548 (0.498)	0.545 (0.498)	0.539 (0.498)
Age	38.464 (7.369)	38.766 (7.062)	40.404 (7.676)
Family income ($)	95,871.519 (93,659.118)	109,818.310 (97,460.706)	107,052.513 (100,879.332)
Wage ($)	36,051.412 (44,149.810)	37,632.013 (46,280.564)	68,201.676 (76,605.121)
Usual hours worked per week	35.977 (12.006)	35.591 (12.286)	45.446 (10.781)
Observations	2,382,979	1,934,965	2,749,200

Notes: The sample only includes parents who were employed in the survey year.

Table 16. Fraction of Families that Had Another Child by Parity and Sex of Children

	All women (3,995,816 observations)		Married women (3,080,794 observations)		Married men (4,158,914 observations)	
	Fraction of sample	Fraction that had another child	Fraction of sample	Fraction that had another child	Fraction of sample	Fraction that had another child
(1) one boy	0.511	0.593 (0.000)	0.514	0.623 (0.000)	0.513	0.653 (0.000)
(2) one girl	0.489	0.588 (0.000)	0.486	0.619 (0.000)	0.487	0.649 (0.000)
Difference (1) – (2)	–	0.005*** (0.000)	–	0.004*** (0.001)	–	0.004*** (0.000)
	All women (2,382,979 observations)		Married women (1,934,965 observations)		Married men (2,749,200 observations)	
	Fraction of sample	Fraction that had another child	Fraction of sample	Fraction that had another child	Fraction of sample	Fraction that had another child
(1) both same sex	0.492	0.322 (0.000)	0.491	0.320 (0.000)	0.492	0.361 (0.000)
(2) one boy, one girl	0.508	0.293 (0.000)	0.509	0.288 (0.000)	0.508	0.327 (0.000)
Difference (1) – (2)	–	0.029*** (0.001)	–	0.032*** (0.001)	–	0.034*** (0.001)

Notes: The sample only includes parents who were employed in the survey year. Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

having a second child based on the sex of their first child. The data across all three samples indicates a nearly equal probability of parents opting for a second child, regardless of whether their first child is a boy or a girl.

The second panel of Table 16 shows the relationship between the proportion of parents having a third child and the sex composition of the first two children. Across all three samples, the data suggests that parents with two children of the same sex are more likely to expand their family with a third child compared to those with a mixed-sex composition among their first two children. Specifically, the probability of having a third child is approximately 3% higher if the parents' first two children are the same gender than a boy and girl combination. This observation underscores the potential utility of the same-sex composition of the first two children as a viable instrumental variable for family size in empirical analyses.

3.4. Methodology

To study the effects of family size on employed parents' occupational characteristics, I employ a similar empirical methodology in Chen et al. (2021). The basic model is described as follows:

$$Y_{it} = \alpha_0 + \alpha_1 Size_{it} + \alpha_2 X_{it} + \epsilon_{it} \tag{9}$$

Where Y_{it} occupational characteristics among working parents (both mothers and fathers) in family i at year t, including the logarithm of scores for the five occupational occupational features (time pressure, contact with others, establishing and maintaining interpersonal relationships, structured vs. unstructured work, and freedom to make decisions), and the logarithm of prestige scores; $Size_{it}$ denotes the endogenous fertility measure of interest (child quantity); X_{it} is a vector of control variables including mother's or father's age and age squared, mother's age at giving birth to the first child, race, education, state fixed effects, etc.; ϵ_{it} is the error term.

Employer-based health insurance is a binary variable that equals one if the working parent's employer provides health insurance. Specifically, $Y_{it} = 1$ when there is employer-based health insurance, and $Y_{it} = 0.$ otherwise. I use a Logit model to study the impact of family size on the likelihood of an employed parent having a job with health insurance provided by an employer or union. The equation is as follows:

$$logit\{p(Y_{it} = 1|Size_{it}, X_{it})\} = \alpha_0 + \alpha_1 Size_{it} + \alpha_2 X_{it} + \epsilon_{it} \tag{10}$$

In these basic models (9) and (10), the coefficient α_1 indicates the impact of the number of children in a family on the occupational characteristics of mothers or fathers. Family size is endogenous due to the potential bidirectional relationship between childbearing and job choices. Consequently, the estimated coefficient α_1 here may not provide an accurate measure of the true effect.

To address this endogeneity concern, I adopt the methodology outlined in Angrist and Evans (1998) and employ 2SLS. Specifically, I utilize the sex composition of the first two children as an instrumental variable for family size. This instrument is justified by the empirical observation that parents with two children of the same gender are more likely to expand their family further. Importantly, the gender of the first two children is exogenous, as it is not subject to parental choice. The first stage is described as:

$$Size_{it} = \beta_0 + \beta_1 Z_{it} + \beta_2 X_{it} + \gamma_{it} \tag{11}$$

In equation (11), Z_{it} denotes the binary instrument – "same-sex". Z_{it} equals 1 if the first two children are same-sex. Otherwise Z_{it} equals 0. The remaining variables maintain the same definitions as in equation (9). By introducing this instrumental variable, we aim to enhance the precision of our estimation regarding the impact on working parents' occupational characteristics.

Table 17. Effects on Parents' Job Flexibility

	All women		Married women		Married men	
	Panel 1: More than two children					
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Same sex (first stage)		0.056***		0.061***		0.062***
		(0.003)		(0.003)		(0.003)
	Panel 2: Five features of job flexibility					
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Time pressure	-0.006***	-0.016*	-0.006***	-0.014*	-0.000	0.009
	(0.001)	(0.007)	(0.001)	(0.006)	(0.000)	(0.005)
Contact with others	-0.003***	-0.003	-0.003***	-0.008*	-0.000	-0.022***
	(0.000)	(0.005)	(0.000)	(0.004)	(0.001)	(0.004)
Interpersonal relationships	-0.001*	-0.026***	-0.001	-0.022***	0.000	-0.038***
	(0.000)	(0.006)	(0.000)	(0.005)	(0.001)	(0.006)
Structured vs. unstructured	-0.002***	-0.045***	-0.001**	-0.037***	-0.000	-0.021***
	(0.000)	(0.005)	(0.000)	(0.004)	(0.001)	(0.004)
Freedom to make decisions	-0.001	-0.055***	-0.001	-0.044***	-0.001	-0.026***
	(0.000)	(0.006)	(0.000)	(0.006)	(0.000)	(0.004)
Observations	2,382,979	2,382,979	1,934,965	1,934,965	2,749,200	2,749,200

Note: The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.5. Results

3.5.1. Job Flexibility

Table 17 presents both the OLS and 2SLS results, depicting the impact of family size on parents' job flexibility. In general, the OLS estimations are considerably smaller than the 2SLS estimations, indicating that the OLS results are biased due to the endogeneity of the number of children.

Panel 1 shows the results of the first stage. Across the three groups, there is a significant positive relationship between having an additional child and a homogeneous gender of the first two children. If the first two children are the same gender, then it will increase the probability of the parent's decision to have another child by approximately 6%.

Panel 2 presents the effects of increasing family size on working parents' job features. In general, the scores of the five features decline with three or more children, especially among women. For example, an additional child would decrease the freedom to make decisions in your job by

Table 18. Effects on Job Choices Based on Employer/Union-Provided Health Insurance

	All women		Married women		Married men	
	Panel 1: More than two children					
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Same-sex (first stage)		0.056***		0.061***		0.062***
		(0.003)		(0.003)		(0.003)
	Panel 2: Health Insurance from Employers/Unions					
	Logit	IV	Logit	IV	Logit	IV
Family size/same sex	0.202***	0.240*	0.230***	0.359**	0.244***	0.124
	(0.010)	(0.094)	(0.015)	(0.123)	(0.014)	(0.82)
Observations	1,523,365	1,523,365	1,221,340	1,221,340	1,686,327	1,686,327

Note: The baseline is the jobs with no health insurance provided by an employer/union. Information on health insurance has been available since the year 2018. The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

5.5%, which would generally reflect a lower level of managerial responsibility. The factor of contact with others has diminished as the least impactful of the five features in part because of additional means of communicating such as online conferencing software (Zoom, Webex, etc.) and widescale adoption of cellphones. The disparate impact on women reinforces the earning power gap between men and women since women already face career gaps from pregnancy. From a family economic standpoint, decreased earnings from the mother would result in the lowest aggregate decrease in family income.

Additional children have a significant impact on the job choices of all parents, but married men tend to experience the smallest impact, reflecting their typically higher earning power compared to women. Consequently, the burden of the impact of additional children falls disproportionately on mothers. These impacts are observable across all parental groups and job features, indicating that the presence of additional children influences the occupational decisions of parents.

3.5.2. Employer-Provided Health Insurance

Table 18 delves into the results regarding parents' occupational characteristics based on whether they receive health insurance from employers or unions. The findings indicate that with more children, both mothers and fathers tend to favor jobs offering insurance coverage from their employers

Table 19. Effects on Parents' Occupational Prestige Scores

	All women		Married women		Married men	
	Panel 1: More than two children					
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Same sex (first stage)		0.056***		0.061***		0.062***
		(0.003)		(0.003)		(0.003)
	Panel 2: Prestige scores					
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Family size/same sex	-0.007***	-0.078***	-0.008***	-0.072***	-0.003	-0.102***
	(0.001)	(0.008)	(0.001)	(0.009)	(0.002)	(0.015)
Observations	2,652,302	2,652,302	2,136,994	2,136,994	2,986,665	2,986,665

Note: The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

or unions, which can provide better coverage for their families and children. Historically, health insurance was used to provide additional non-taxed employee benefits to lower wage demands, and before the American Care Act, it was essential to maintain continuous employer-based health coverage to avoid coverage exclusions for pre-existing medical conditions. Even now, employer-based health insurance is a key factor in parents' choice of employment since healthcare constitutes a major US household expense, and uninsured healthcare costs are 200-400% higher than insurance reimbursement rates. However, married couples only need one good health insurance plan from one spouse's employer, since you typically only carry a single health plan at a time. The results show that the availability of healthcare coverage for women is a strong deciding job factor compared with married men.

3.5.3. Occupational Prestige Scores

Table 19 shows the effects of family size (i.e., the number of children an employed parent has) on parents' occupation prestige scores. Both OLS estimates and 2SLS estimates are significantly negative, except for the OLS result of married men. The magnitude of 2SLS estimates is still larger. For 2SLS estimates, the same sex of the first two children is utilized as an IV. The results reveal the negative effects of family size on parents' prestige scores across all three samples. This implies that each additional child negatively impacts the prestige scores of both mothers and fathers by

7.8% and 10.2% respectively, suggesting a shift towards occupations with lower prestige scores. Specifically, the effect is more pronounced among married fathers. With one or two children, it is logistically possible for one parent to deal with sick children, but with three children, it is much more likely that two children will be sick at the same time increasing the burden on both parents. Although additional children might be seen as lineally increasing family expenses, families selecting a third child could be willing to trade additional income for more time with children, since a third child is not an economic benefit to the parents outside of agrarian societies. Also, larger families can reduce child-rearing expenses (shared clothes, sibling babysitting, etc), resulting in reduced incremental costs of a third child.

3.5.4. Heterogeneity Analysis

I analyze heterogeneous effects on the parents' job characteristics among different groups. I use one of the five job features – time pressure – as an example to illustrate the heterogeneous effects on parents' job flexibility. The 2SLS estimates in Table 20 show that parents with more children would prefer to have jobs with lower time pressure, while those who are less educated tend to choose jobs with even lower time pressure than more educated parents. Among all races, Black and Asian parents are the only two races whose job time pressure significantly declines after having more children. Asian mothers' time pressure on the job sees the largest magnitude with an approximately 12% – 14% decline. Moreover, compared with mothers, the impact on fathers' job time pressure is smaller.

Tables A10, A11, A12, and A13 present how an increasing family size impacts the other four job features. They have similar trends as time pressure.

Table 21 shows the results of the impacts on working parents' employer-based health insurance. Both the less educated and more educated parents prefer a job with employer-based health insurance, with the more educated groups showing larger ratios to switch jobs from ones without employer-based health insurance. White and Asian parents are more likely to have jobs with health insurance provided by an employer, while mothers are more inclined to have jobs that offer health

Table 20. Heterogeneous Effects on Parents' Job Flexibility (Time Pressure)

	Less than bachelor's degree		Bachelor's degree or higher		White		Black		Asian		Other races	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
All women	-0.005***	-0.023*	-0.007***	-0.016**	-0.008***	-0.012	-0.004***	-0.057*	-0.007	-0.131*	0.003***	0.001
	(0.001)	(0.010)	(0.000)	(0.006)	(0.001)	(0.008)	(0.001)	(0.027)	(0.004)	(0.050)	(0.001)	(0.025)
Observations	1,435,926	1,435,926	947,053	947,053	1,857,503	1,857,503	212,219	212,219	34,253	34,253	258,047	258,047
Married women	-0.006***	-0.017	-0.007***	-0.017**	-0.009***	-0.007	-0.003**	-0.039	-0.007	-0.125**	0.004***	-0.027
	(0.001)	(0.009)	(0.000)	(0.006)	(0.001)	(0.007)	(0.001)	(0.024)	(0.003)	(0.044)	(0.001)	(0.027)
Observations	1,082,738	1,082,738	852,227	852,227	1,572,774	1,572,774	109,876	109,876	32,031	32,031	206,308	206,308
Married men	-0.001*	0.021**	0.001***	-0.009	-0.001*	0.005	-0.001	0.042*	0.008***	-0.010	0.003***	0.024
	(0.001)	(0.007)	(0.000)	(0.006)	(0.000)	(0.006)	(0.001)	(0.021)	(0.002)	(0.038)	(0.001)	(0.015)
Observations	1,688,385	1,688,385	1,060,815	1,060,815	2,245,527	2,245,527	143,573	143,573	38,387	38,387	302,863	302,863

Note: The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21. Heterogeneous Effects: Job Choices Based on Employer/Union-Provided Health Insurance

	Less than bachelor's degree		Bachelor's degree or higher		White		Black		Asian		Other races	
	Logit	IV	Logit	IV	Logit	IV	Logit	IV	Logit	IV	Logit	IV
All women	0.191***	0.209*	0.232***	0.677***	0.215***	0.432***	0.193***	-0.391	0.214***	2.091**	0.159***	-0.173
	(0.010)	(0.106)	(0.013)	(0.193)	(0.012)	(0.105)	(0.011)	(0.225)	(0.032)	(0.740)	(0.012)	(0.235)
Observations	838,217	838,217	685,148	685,148	1,163,570	1,163,570	139,238	139,238	25,272	25,272	181,095	181,095
Married women	0.219***	0.383*	0.247***	0.552**	0.248***	0.395**	0.232***	0.173	0.235***	1.975**	0.148***	0.036
	(0.015)	(0.160)	(0.015)	(0.208)	(0.017)	(0.138)	(0.017)	(0.398)	(0.034)	(0.633)	(0.015)	(0.211)
Observations	605,567	605,567	615,773	615,773	976,045	976,045	69,135	69,135	23,552	23,552	143,595	143,595
Married men	0.244***	0.021	0.235***	0.525***	0.255***	0.137	0.237***	-0.161	0.149***	0.909	0.198***	-0.021
	(0.015)	(0.110)	(0.015)	(0.157)	(0.017)	(0.097)	(0.016)	(0.370)	(0.036)	(0.656)	(0.010)	(0.151)
Observations	957,737	957,737	728,590	728,590	1,352,212	1,352,212	87,895	87,895	27,684	27,684	206,880	206,880

Note: The baseline is the jobs with no health insurance provided by an employer/union. The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 22. Heterogeneous Effects on Occupational Prestige Scores

	Less than bachelor's degree		Bachelor's degree or higher		White		Black		Asian		Other races	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
All women	-0.008***	-0.077***	-0.005***	-0.084***	-0.008***	-0.075***	-0.003*	-0.036	-0.017**	-0.184	-0.009***	-0.125***
	(0.001)	(0.010)	(0.001)	(0.015)	(0.001)	(0.010)	(0.001)	(0.046)	(0.005)	(0.097)	(0.001)	(0.025)
Observations	1,624,083	1,624,083	1,028,219	1,028,219	2,049,484	2,049,484	253,747	253,747	38,096	38,096	286,954	286,954
Married women	-0.008***	-0.082***	-0.006***	-0.062***	-0.008***	-0.065***	-0.001	-0.029	-0.020***	-0.186	-0.009***	-0.120***
	(0.001)	(0.011)	(0.001)	(0.013)	(0.001)	(0.010)	(0.002)	(0.052)	(0.005)	(0.098)	(0.001)	(0.032)
Observations	1,212,996	1,212,996	923,998	923,998	1,728,278	1,728,278	128,825	128,825	35,613	35,613	228,442	228,442
Married men	-0.000	-0.101***	-0.006*	-0.103***	-0.001	-0.108***	-0.002	0.049	-0.006	-0.008	-0.012***	-0.122**
	(0.002)	(0.019)	(0.003)	(0.021)	(0.002)	(0.018)	(0.003)	(0.088)	(0.006)	(0.073)	(0.002)	(0.036)
Observations	1,814,696	1,814,696	1,171,969	1,171,969	2,429,588	2,429,588	160,954	160,954	43,601	43,601	332,163	332,163

Note: The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

insurance benefits compared to fathers. Among Black women and women of other races with three or more children, there is a slight tendency to have jobs that provide employer-based health insurance. However, fathers from Black and other races are less likely to have a job with employer-based health insurance, which would explain the disparity for black mothers and women of other races to obtain employer-based health insurance. Unfortunately, unskilled and lower-paid jobs are less likely to provide affordable employer-provided health insurance, and ACA healthcare plans that are subsidized by the government are more attractive financial choices for health insurance for lower-income families eligible for subsidies.

Table 22 illustrates the impact on parents' occupational prestige scores. Parents with different education backgrounds experience similar magnitude declines in their occupational prestige scores. White parents' prestige scores significantly decrease by more than 6.5%, with a much higher decline (10.8%) among White fathers. Asian mothers' occupational prestige scores decrease by a statistically insignificant amount. In addition, Asian fathers' occupational prestige scores change the least among all fathers with a statistically insignificant amount. Asians in the US place a high social importance on the occupational prestige of their entire family including parents and children as a source of pride. Parents from other races choose much less prestigious jobs when having more children, with their prestige scores declining by more than 12%. The declines are not significantly different between mothers and fathers from other races.

3.6. Robustness Test

3.6.1. Flexibility by Occupational Categories

I use an alternative method to measure job flexibility. Following the approach taken Goldin (2014), I classify occupations into five categories and measure the occupational flexibility for each category based on the scores of the five job features I use in the main analysis. These categories include business, health, technology and science, law, and other occupations. I use multinomial logistic regression to see how they switch between occupation categories.

Table A14 presents the normalized weighted scores for each feature of occupation categories.

It is evident that the "Other" occupations category scores significantly lower than the other four categories across all five measures. This discrepancy indicates that, in contrast to the other four occupations, "Other" occupations exhibit greater time flexibility, fewer interactions with clients and colleagues, reduced emphasis on building and maintaining working relationships, higher levels of autonomy in task determination, and involvement in more specific projects with limited discretion. Following "Other" occupations, the technology and science sector demonstrates secondary flexibility. However, the relative ranking among business, health, and law categories remains less clear.

Table A15 illustrates the influence of the number of children on parental occupations. The baseline occupation category is “Other”, characterized by the highest flexibility among the five features outlined in Section 3.3. Across both specifications, nearly all estimates among the three groups are significantly negative, with 2SLS estimates showing larger magnitudes. This suggests that as the number of children increases, parents are more inclined to have occupations in the "Other" category rather than those in the remaining four occupation categories. Moreover, occupational choices differ between married women and married men. Married women are less likely to opt for jobs in the "Technology and Science" and "Law" categories compared to the "Other" category, and show a smaller propensity for jobs in the "Business" and "Health" categories. This indicates that married mothers are more likely to hold positions in "Business" and "Health" than in "Technology and Science" or "Law", whereas married fathers tend to exhibit the opposite pattern.

3.6.2. Twins as An Alternative IV

To address the endogeneity problem, some papers use whether the first birth are twins or not as an IV (e.g., Chen et al., 2021). I also use twins at the first birth as an alternative method to study the impact of family size on working parents’ occupational characteristics.

Table A16, A.17, and A.18 present the results of impacts on all the job characteristics in the main analysis. They indicate that with more children, parents tend to have jobs with more flexibility, employment-based health insurance, and lower occupational prestige scores.

3.7. Conclusion

This paper delves into how family size influences the labor market behavior and job characteristics of parents in the United States, employing an instrumental variable approach. I examine changes in parents' occupational characteristics, including job flexibility, access to employer-provided health insurance, and occupational prestige scores by using the exogenous variation in family size resulting from the sex composition of the first two children.

The findings reveal that parents with larger families tend to have occupations offering greater flexibility, with scores decreasing in all the five job features related to flexibility. Parents generally choose jobs that have employer/union-provided health insurance. Moreover, the analysis uncovers a noteworthy trend: each additional child corresponds to a decrease of 7.8% to 10.2% in the prestige scores of both mothers and fathers. This suggests a discernible movement towards occupations with lower prestige scores among parents as their family size increases.

These insights shed light on the intricate interplay between family dynamics and employment choices, underscoring the significance of accounting for familial factors in shaping labor market outcomes. However, a job cannot be generally defined as good or bad based on one or two dimensions. Parents make decisions based on all the aspects, and there are always pros and cons among jobs forcing parents to make trade-offs based on their priorities. For future studies, researchers can delve into finding a more holistic measure of job flexibility to study parents' occupational characteristics. In addition, researchers could study how parents weigh various job characteristics to make comprehensive employment decisions while isolating the labor market demand influences.

The research holds implications for crafting future policies that support working parents and fostering workplace environments conducive to family well-being. For example, one thing that policymakers could consider is the Federal implementation of paid family leave since the US is the only G20 country without it, which could benefit families and reduce the disparate impact on women's incomes from childbirth. Although the ACA has improved many employer-provided health plans, policymakers should consider the implementation of portability of employer subsidies for ACA marketplace plans, which could provide families with more continuity in healthcare and employee mobility.

Appendix A. Supplementary Materials

Table A1. Summary Statistics of the Variables in Norther Cities: Post-WCHP (2017-2021)

	Treat		difference in means	Control		difference in means
	Heating Period	Non-heating Period		Heating Period	Non-heating Period	
Dependent Variables (Annual: $\mu g/m^3$)						
$PM_{2.5}$	73.902	37.250	36.653	50.146	25.482	24.664
	(22.983)	(9.702)	(1.491)	(18.041)	(8.142)	(1.106)
PM_{10}	123.312	80.398	42.914	91.039	59.038	32.001
	(31.810)	(18.089)	(2.187)	(31.107)	(19.856)	(2.063)
AQI	107.661	69.156	38.505	79.247	52.764	26.483
	(26.012)	(12.150)	(1.716)	(21.707)	(13.178)	(1.420)
CO	1.284	0.818	0.465	0.914	0.619	0.296
	(0.410)	(0.253)	(0.029)	(0.260)	(0.187)	(0.018)
NO_2	45.102	31.539	13.562	31.464	21.698	9.766
	(10.386)	(7.641)	(0.771)	(9.092)	(6.323)	(0.619)
SO_2	26.545	12.827	13.718	20.884	10.458	10.427
	(20.513)	(5.790)	(1.274)	(12.875)	(5.365)	(0.780)
Weather Variables						
Temperature	12.110	194.177	-182.067	-21.586	183.237	-204.823
(0.1 °C)	(32.217)	(23.532)	(2.384)	(43.888)	(20.321)	(2.704)
Dew point	-89.912	104.155	-194.067	-113.577	94.644	-208.221
(0.1 °C)	(39.675)	(31.370)	(3.023)	(46.210)	(37.458)	(3.325)
Precipitation	0.520	2.839	-2.320	0.894	2.928	-2.034
(mm)	(0.487)	(0.725)	(0.052)	(1.022)	(1.096)	(0.084)
Wind Speed	26.385	26.181	0.204	27.686	27.611	0.075
(m/s)	(8.195)	(6.146)	(0.612)	(7.364)	(6.297)	(0.542)
City Characteristics						
GDP	376.366			176.876		
(Billion CNY)	(506.741)			(210.935)		
GDP Growth (%)	5.936			4.742		
	(2.689)			(3.014)		
Ratio of Secondary	43.070			36.525		
Industries (%)	(10.322)			(12.601)		
Observations	280	280		320	320	

Notes: In this table, all the observations are northern cities. Standard errors in parentheses.

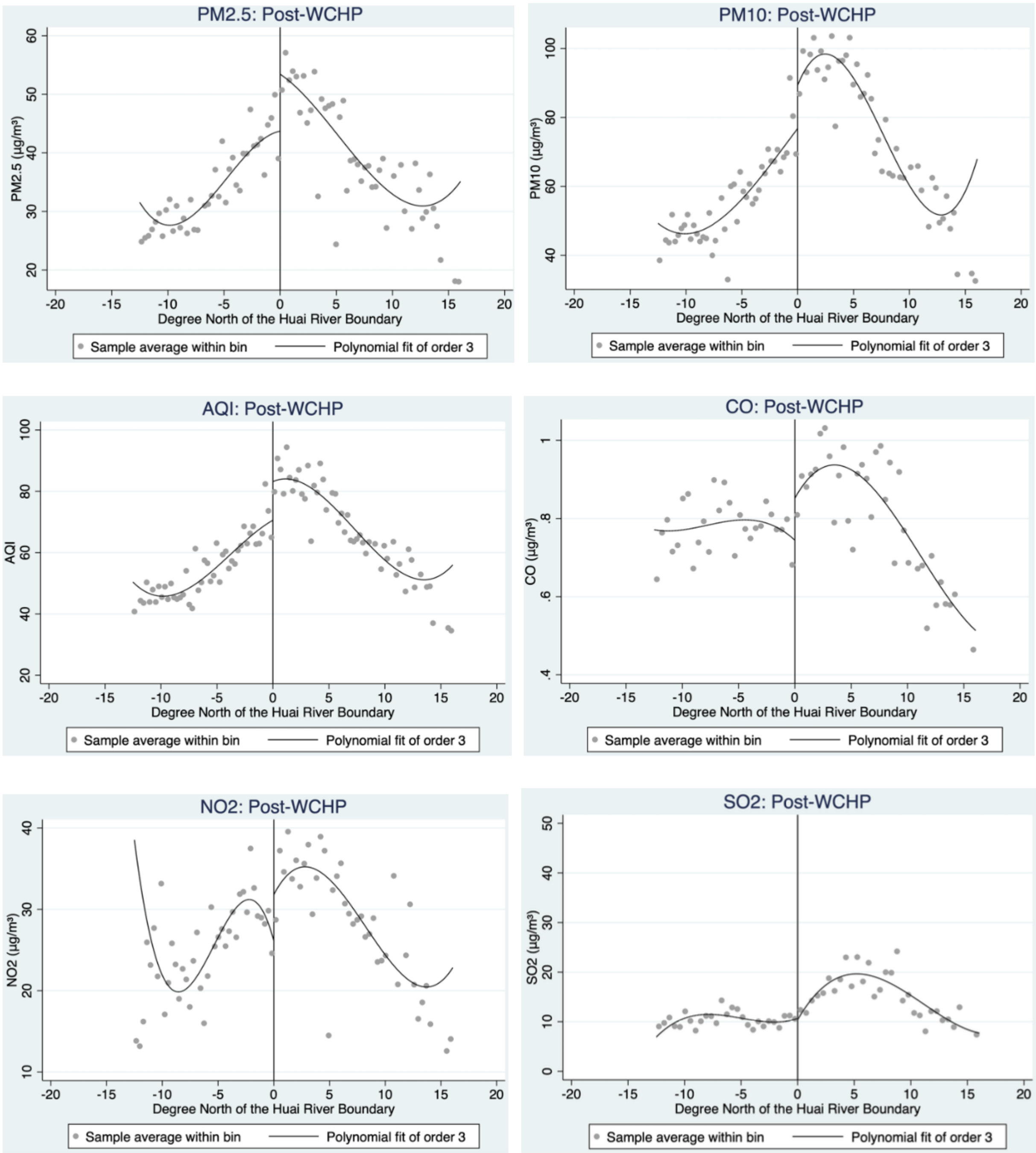

Figure A1. Fitted Values of Air Pollution Levels (Post-WCHP)

Notes: Fitted values obtained from a polynomial regression of air pollution exposure on distance from the Huai River estimated separately on each side of the river (Calonico et al., 2015a,b). Point 0 on the horizontal axis is the cut-off point, representing the latitude degrees of the Huai River line. The vertical axis represents the indicator values of air pollution levels.

Table A2. Exclusion of Adjacent Cities

	(1) $PM_{2.5}$	(2) PM_{10}	(3) AQI	(4) CO	(5) NO_2	(6) SO_2
	Panel 1: Staggered DID					
β^{ST}	-9.699***	-13.474***	-8.669***	-0.347***	-3.368**	-11.103***
	(2.026)	(3.334)	(2.537)	(0.027)	(1.045)	(2.834)
Observations	707	707	707	707	707	707
	Panel 2: Staggered DDD					
β^{STT}	-13.624***	-20.884***	-14.607***	-0.588***	-5.102***	-28.449***
	(2.383)	(3.225)	(2.332)	(0.052)	(1.064)	(5.848)
Observations	1414	1414	1414	1414	1414	1414

Notes: Air pollution data is annual level. Control variables include weather controls correlated with air pollution (temperature, precipitation, and dew point, etc.) and city characteristics (GDP, the GDP growth rate, and the ratio of secondary industries) in one city in year t. β^{ST} in panel 1 is the coefficient of $Treat_{it}$ (ATT) in equation (1.1). β^{STT} in panel 2 is the coefficient of interaction term $Heating_{it} \times Treat_{it}$ (ATT) in equation (1.3). I use the method in Borusyak et al. (2023). The Stata code is $did\_imputation$. Standard errors clustered by province in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A3. Effects on Air Pollution Levels in Northern China (Exclusion of Other Policies)

	(1) $PM_{2.5}$	(2) PM_{10}	(3) AQI	(4) CO	(5) NO_2	(6) SO_2
	Panel 1: Staggered DID					
β^{ST}	-7.212**	-10.406**	-5.535*	-0.370***	-2.520	-11.906**
	(2.216)	(3.947)	(2.717)	(0.025)	(1.345)	(3.803)
Observations	756	756	756	756	756	756
	Panel 2: Staggered DDD					
β^{STT}	-10.073***	-18.348***	-10.709***	-0.579***	-4.273**	-29.494***
	(2.075)	(4.551)	(2.475)	(0.053)	(1.564)	(7.789)
Observations	1512	1512	1512	1512	1512	1512

*Notes:*Air pollution data is annual level. Control variables include weather controls correlated with air pollution (temperature, precipitation, and dew point, etc.) and city characteristics (GDP, the GDP growth rate, and the ratio of secondary industries) in one city in year t. β^{ST} in panel 1 is the coefficient of $Treat_{it}$ (ATT) in equation (1.1). β^{STT} in panel 2 is the coefficient of interaction term $Heating_{it} \times Treat_{it}$ (ATT) in equation (1.3). I use the method in Borusyak et al. (2023). The Stata code is $did\_imputation$. Standard errors clustered by province in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A4. Effects on Disparities between Southern and Northern China (Exclusion of Other Policies)

		(1)	(2)	(3)
$PM_{2.5}$	*North*	17.367***	16.866***	22.643***
		(2.211)	(3.651)	(1.594)
	North $\times$ *Post*	-10.666***	-17.968***	-13.114***
		(2.068)	(2.971)	(1.273)
PM_{10}	*North*	32.554***	29.564***	35.018***
		(3.624)	(6.255)	(2.442)
	North $\times$ *Post*	-21.588***	-32.982***	-20.016***
		(3.353)	(4.774)	(2.013)
AQI	*North*	20.937***	20.732***	26.681***
		(2.685)	(4.643)	(1.924)
	North $\times$ *Post*	-10.627***	-20.586***	-12.648***
		(2.471)	(3.588)	(1.524)
CO	*North*	0.544***	0.410***	0.519***
		(0.053)	(0.081)	(0.034)
	North $\times$ *Post*	-0.556***	-0.600***	-0.504***
		(0.049)	(0.063)	(0.031)
NO_2	*North*	9.038***	11.304***	11.268***
		(1.226)	(2.175)	(1.089)
	North $\times$ *Post*	-4.881***	-11.804***	-4.454***
		(1.227)	(1.703)	(0.870)
SO_2	*North*	17.452***	7.397**	13.932***
		(1.914)	(2.327)	(1.217)
	North $\times$ *Post*	-25.592***	-16.396***	-22.311***
		(1.652)	(1.863)	(1.074)
RD Type		Polynomial	Polynomial	LLR
Polynomial Function		Cubic	Cubic	
Sample		Full	5°	

Notes: Air pollution data is annual level. Control variables include weather controls correlated with air pollution (temperature, precipitation, and dew point, etc.) and city characteristics (GDP, the GDP growth rate, and the ratio of secondary industries) in one city in year t. Estimates are α_1 and α_2, the coefficients of $North_i$ and $North_i \times Post_t$ in Equation (1.4) and (1.5). Column (1) reports OLS estimates in Equation (1.4) using the full sample (n=1830). Column (2) reports these estimates for the restricted sample (n=935) of cities within 5° of the Huai River. Column (3) presents estimates from local linear regression (LLR) in Equation (1.5), with triangular kernel and bandwidth selected by the method proposed by Calonico et al. (2015a) and Calonico et al. (2015b). Standard errors clustered in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A5. Effects on Air Pollution Levels in Northern China (Three-Year Duration)

	(1) $PM_{2.5}$	(2) PM_{10}	(3) AQI	(4) CO	(5) NO_2	(6) SO_2
			Panel 1: Staggered DID			
β^{ST}	-6.546***	-10.022***	-5.697**	-0.294***	-2.187*	-9.222***
	(1.753)	(2.916)	(2.141)	(0.026)	(1.001)	(2.707)
Observations	794	794	794	794	794	794
			Panel 2: Staggered DDD			
β^{STT}	-7.764***	-15.223***	-8.663***	-0.497***	-3.806***	-24.852***
	(2.075)	(4.551)	(2.475)	(0.053)	(1.564)	(7.789)
Observations	1588	1588	1588	1588	1588	1588

*Notes:*Air pollution data is annual level. Control variables include weather controls correlated with air pollution (temperature, precipitation, and dew point, etc.) and city characteristics (GDP, the GDP growth rate, and the ratio of secondary industries) in one city in year t. β^{ST} in panel 1 is the coefficient of $Treat_{it}$ (ATT) in equation (1.1). β^{STT} in panel 2 is the coefficient of interaction term $Heating_{it} \times Treat_{it}$ (ATT) in equation (1.3). I use the method in Borusyak et al. (2023). The Stata code is $did\_imputation$. Standard errors clustered by province in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A6. Effects on Disparities between Southern and Northern China (Three-Year Duration)

		(1)	(2)	(3)
$PM_{2.5}$	*North*	18.428***	16.865***	22.475***
		(2.197)	(3.594)	(1.640)
	North × *Post*	-12.788***	-17.150***	-13.654***
		(2.046)	(2.940)	(1.319)
PM_{10}	*North*	33.808***	29.196***	35.250***
		(3.619)	(6.203)	(2.333)
	North × *Post*	-23.762***	-31.873***	-21.086***
		(3.371)	(4.731)	(2.076)
AQI	*North*	21.976***	20.601***	26.533***
		(2.671)	(4.584)	(1.960)
	North × *Post*	-12.812***	-19.678***	-13.464***
		(2.456)	(3.559)	(1.568)
CO	*North*	0.554***	0.405***	0.514***
		(0.053)	(0.081)	(0.033)
	North × *Post*	-0.573***	-0.598***	-0.496***
		(0.048)	(0.062)	(0.031)
NO_2	*North*	9.619***	11.443***	11.006***
		(1.244)	(2.163)	(1.076)
	North × *Post*	-5.928***	-11.696***	-4.477***
		(1.267)	(1.681)	(0.913)
SO_2	*North*	17.867***	6.976**	13.566***
		(1.916)	(2.342)	(1.226)
	North × *Post*	-25.095***	-16.641***	-21.611***
		(1.633)	(1.858)	(1.077)
RD Type		Polynomial	Polynomial	LLR
Polynomial Function		Cubic	Cubic	
Sample		Full	5°	

Notes: Air pollution data is annual level. Control variables include weather controls correlated with air pollution (temperature, precipitation, and dew point, etc.) and city characteristics (GDP, the GDP growth rate, and the ratio of secondary industries) in one city in year t. Estimates are α_1 and α_2, the coefficients of $North_i$ and $North_i \times Post_t$ in Equation (1.4) and (1.5). Column (1) reports OLS estimates in Equation (1.4) using the full sample (n=1868). Column (2) reports these estimates for the restricted sample (n=926) of cities within 5° of the Huai River. Column (3) presents estimates from local linear regression (LLR) in Equation (1.5), with triangular kernel and bandwidth selected by the method proposed by Calonico et al. (2015a) and Calonico et al. (2015b). Standard errors clustered in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A7. Heterogeneous Effects by High/Low Manufacturing Energy Intensity

	(1)	(2)	(3)	(4)
	Panel 1: Owned-Occupied House Value (3,857,514 observations)			
Post × NBP × HighEnInt	0.079***	-0.587***	-0.045***	-0.026***
	(0.003)	(0.003)	(0.003)	(0.003)
Post × NBP	0.159***	0.496***	-0.047***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Post × HighEnInt	0.144***	0.479***	-0.063***	-0.080***
	(0.002)	(0.002)	(0.002)	(0.002)
	Panel 2: Monthly Gross Rent (1,944,329 observations)			
	(1)	(2)	(3)	(4)
Post × NBP × HighEnInt	0.024***	-0.270***	-0.019***	-0.013***
	(0.004)	(0.004)	(0.004)	(0.004)
Post × NBP	0.073***	0.274***	0.022***	0.040***
	(0.001)	(0.001)	(0.002)	(0.002)
Post × HighEnInt	0.164***	0.259***	0.008 ***	0.000***
	(0.002)	(0.002)	(0.002)	(0.002)
County Fixed Effects	Y	Y	Y	Y
Control	N	Y	Y	Y
Year Fixed Effects	N	N	Y	Y
County Trend	N	N	N	Y

Notes: The sample is 2000 Census data and 2005-2008 ACS data with county identifications. Logarithm of rent and house value are used. Standard errors in parentheses, clustered by county. * p<0.05, ** p<0.01, *** p<0.001

Table A8. Heterogeneous Effects by Manufacturing Intensity

	Panel 1: Owned-Occupied House Value (3,857,514 observations)			
	(1)	(2)	(3)	(4)
Post × NBP × ManInt	-2.519***	-3.076***	-0.541***	-0.470***
	(0.014)	(0.012)	(0.016)	(0.016)
Post × NBP	0.600***	0.616***	0.041***	0.073***
	(0.003)	(0.002)	(0.003)	(0.003)
Post × ManInt	1.765***	2.327***	-0.208***	-0.356***
	(0.006)	(0.004)	(0.012)	(0.012)
	Panel 2: Monthly Gross Rent (1,944,329 observations)			
	(1)	(2)	(3)	(4)
Post × NBP × ManInt	-1.272***	-1.226***	-0.191***	-0.163***
	(0.016)	(0.017)	(0.021)	(0.022)
Post × NBP	0.319***	0.287***	0.055***	0.067***
	(0.003)	(0.003)	(0.004)	(0.004)
Post × ManInt	1.027***	1.147***	0.112***	0.036*
	(0.005)	(0.004)	(0.014)	(0.014)
Control	Y	Y	Y	Y
County Fixed Effects	N	Y	Y	Y
Year Fixed Effects	N	N	Y	Y
County Trend	N	N	N	Y

Notes: The sample is 2000 Census data and 2005-2008 ACS data with county identifications. Logarithm of rent and house value are used. Standard errors in parentheses, clustered by county. * p<0.05, ** p<0.01, *** p<0.001

Table A9. Effects of the NBP: Exclude Rust Belt States

	Panel 1: Owned-Occupied House Value (3,095,583 observations)			
	(1)	(2)	(3)	(4)
Post × NBP × EnInt	-5.921***	-5.348***	-0.880***	-0.792***
	(0.028)	(0.029)	(0.038)	(0.038)
Post × NBP	0.660***	0.603***	0.053***	0.086***
	(0.003)	(0.003)	(0.004)	(0.004)
Post × EnInt	4.124***	4.667***	0.204***	-0.146***
	(0.011)	(0.008)	(0.025)	(0.025)
	Panel 2: Monthly Gross Rent (1,676,661 observations)			
	(1)	(2)	(3)	(4)
Post × NBP × EnInt	-4.085***	-2.942***	-0.594***	-0.484***
	(0.037)	(0.044)	(0.052)	(0.052)
Post × NBP	0.367***	0.345***	0.056***	0.072***
	(0.004)	(0.004)	(0.005)	(0.005)
Post × EnInt	2.597***	2.643***	0.297***	0.048
	(0.010)	(0.009)	(0.022)	(0.052)
Control	Y	Y	Y	Y
County Fixed Effects	N	Y	Y	Y
Year Fixed Effects	N	N	Y	Y
County Trend	N	N	N	Y

Notes: The sample is 2000 Census data and 2005-2008 ACS data with county identifications. Logarithm of rent and house value are used. Standard errors in parentheses, clustered by county. * p<0.05, ** p<0.01, *** p<0.001

Table A10. Heterogeneous Effects on Parents' Job Flexibility (Contact with Others)

	Less than bachelor's degree		Bachelor's degree or higher		White		Black		Asian		Other races	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
All women	-0.004***	-0.009	0.001**	0.008	-0.003***	-0.002	-0.001*	0.012	0.008***	-0.037	-0.003***	-0.016
	(0.000)	(0.006)	(0.000)	(0.006)	(0.000)	(0.005)	(0.001)	(0.014)	(0.002)	(0.027)	(0.001)	(0.011)
Observations	1,435,926	1,435,926	947,053	947,053	1,857,503	1,857,503	212,219	212,219	34,253	34,253	258,047	258,047
Married women	-0.004***	-0.020***	0.001**	0.008	-0.003***	-0.008	-0.001	-0.012	0.009***	-0.036	-0.003***	-0.005
	(0.000)	(0.005)	(0.000)	(0.005)	(0.000)	(0.004)	(0.001)	(0.016)	(0.002)	(0.028)	(0.001)	(0.011)
Observations	1,082,738	1,082,738	852,227	852,227	1,572,774	1,572,774	109,876	109,876	32,031	32,031	206,308	206,308
Married men	-0.002*	-0.026***	0.002***	-0.018**	-0.000	-0.021***	-0.001	-0.033*	0.009***	-0.030	-0.002***	-0.017
	(0.001)	(0.006)	(0.000)	(0.006)	(0.001)	(0.004)	(0.001)	(0.014)	(0.002)	(0.018)	(0.001)	(0.018)
Observations	1,688,385	1,688,385	1,060,815	1,060,815	2,245,527	2,245,527	143,573	143,573	38,387	38,387	302,863	302,863

Note: The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A11. Heterogeneous Effects on Parents' Job Flexibility (Interpersonal Relationships)

	Less than bachelor's degree		Bachelor's degree or higher		White		Black		Asian		Other races	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
All women	-0.001*	-0.041***	-0.000	-0.005	-0.001	-0.022***	-0.001	-0.003	0.000	-0.058	-0.002**	-0.068***
	(0.001)	(0.008)	(0.000)	(0.007)	(0.001)	(0.005)	(0.001)	(0.019)	(0.001)	(0.029)	(0.001)	(0.019)
Observations	1,435,926	1,435,926	947,053	947,053	1,857,503	1,857,503	212,219	212,219	34,253	34,253	258,047	258,047
Married women	-0.001	-0.043***	0.000	0.003	-0.000	-0.019***	-0.000	-0.027	-0.001	-0.055	-0.002*	-0.039
	(0.001)	(0.008)	(0.000)	(0.007)	(0.001)	(0.005)	(0.001)	(0.021)	(0.002)	(0.030)	(0.001)	(0.020)
Observations	1,082,738	1,082,738	852,227	852,227	1,572,774	1,572,774	109,876	109,876	32,031	32,031	206,308	206,308
Married men	-0.000	-0.044***	0.001*	-0.030***	0.001	-0.041***	-0.002*	-0.018	0.005**	-0.004	-0.004***	-0.028**
	(0.001)	(0.009)	(0.000)	(0.004)	(0.001)	(0.007)	(0.001)	(0.028)	(0.001)	(0.038)	(0.001)	(0.010)
Observations	1,688,385	1,688,385	1,060,815	1,060,815	2,245,527	2,245,527	143,573	143,573	38,387	38,387	302,863	302,863

Note: The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A12. Heterogeneous Effects on Parents' Job Flexibility (Structured vs. Unstructured)

	Less than bachelor's degree		Bachelor's degree or higher		White		Black		Asian		Other races	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
All women	-0.002***	-0.065***	0.000	-0.025***	-0.002**	-0.042***	-0.001*	-0.029	-0.000	-0.081**	-0.000	-0.076***
	(0.001)	(0.009)	(0.000)	(0.006)	(0.001)	(0.007)	(0.001)	(0.018)	(0.002)	(0.029)	(0.001)	(0.015)
Observations	1,435,926	1,435,926	947,053	947,053	1,857,503	1,857,503	212,219	212,219	34,253	34,253	258,047	258,047
Married women	-0.002***	-0.057***	0.001*	-0.019**	-0.001*	-0.033***	-0.002*	-0.032	-0.001	-0.101***	0.000	-0.060***
	(0.001)	(0.009)	(0.000)	(0.006)	(0.001)	(0.005)	(0.001)	(0.022)	(0.002)	(0.022)	(0.001)	(0.014)
Observations	1,082,738	1,082,738	852,227	852,227	1,572,774	1,572,774	109,876	109,876	32,031	32,031	206,308	206,308
Married men	-0.001	-0.017**	0.002***	-0.027***	0.001	-0.022***	-0.002**	-0.019	0.007***	-0.033	-0.003***	-0.011
	(0.001)	(0.006)	(0.000)	(0.005)	(0.001)	(0.004)	(0.001)	(0.015)	(0.002)	(0.027)	(0.000)	(0.013)
Observations	1,688,385	1,688,385	1,060,815	1,060,815	2,245,527	2,245,527	143,573	143,573	38,387	38,387	302,863	302,863

Note: The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A13. Heterogeneous Effects on Parents' Job Flexibility (Freedom to Make Decisions)

	Less than bachelor's degree		Bachelor's degree or higher		White		Black		Asian		Other races	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
All women	-0.001	-0.068***	-0.000	-0.042***	-0.001	-0.049***	-0.000	-0.034	-0.001	-0.081*	-0.002**	-0.108***
	(0.001)	(0.010)	(0.000)	(0.008)	(0.001)	(0.006)	(0.001)	(0.021)	(0.003)	(0.039)	(0.001)	(0.017)
Observations	1,435,926	1,435,926	947,053	947,053	1,857,503	1,857,503	212,219	212,219	34,253	34,253	258,047	258,047
Married women	-0.001	-0.057***	0.000	-0.032***	-0.000	-0.038***	-0.001	-0.038	-0.001	-0.082*	-0.002*	-0.079***
	(0.001)	(0.009)	(0.000)	(0.008)	(0.001)	(0.005)	(0.001)	(0.024)	(0.003)	(0.032)	(0.001)	(0.017)
Observations	1,082,738	1,082,738	852,227	852,227	1,572,774	1,572,774	109,876	109,876	32,031	32,031	206,308	206,308
Married men	-0.002	-0.023***	0.003***	-0.031***	0.000	-0.026***	-0.003***	-0.028	0.009***	-0.050*	-0.003***	-0.022
	(0.001)	(0.005)	(0.000)	(0.005)	(0.001)	(0.004)	(0.001)	(0.020)	(0.002)	(0.023)	(0.001)	(0.013)
Observations	1,688,385	1,688,385	1,060,815	1,060,815	2,245,527	2,245,527	143,573	143,573	38,387	38,387	302,863	302,863

Note: The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A14. O*NET Characteristics: Means (Normalized) by Occupational Group

O*Net Characteristics	Technology and science	Business	Health	Law	Other
1. Time pressure	-0.064	0.146	0.339	1.379	-0.298
2. Contact with others	0.235	0.332	1.035	0.518	-0.512
3. Establishing and maintaining interpersonal relationships	0.058	1.043	0.667	0.122	-0.227
4. Structured vs. unstructured work	0.060	0.595	0.258	1.463	-0.198
5. Freedom to make decisions	0.024	0.221	0.049	1.274	-0.442
Number of occupations	83	62	79	6	387

Notes: When there is more than one O*NET occupation for an ACS occupation, the characteristic is weighted by the number of workers in each of the O*NET occupations. Each of the O*Net characteristics has been normalized to have a mean of 0 and a standard deviation of 1.

Table A15. Effects on Parents' Occupation Categories

	All women		Married women		Married men	
	Mlogit	IV	Mlogit	IV	Mlogit	IV
Family size/same sex	-0.120***	-1.178***	-0.117***	-1.120***	-0.001	-1.337***
(Business)	(0.006)	(0.156)	(0.007)	(0.169)	(0.017)	(0.196)
Family size/same sex	0.025***	-0.185	0.028***	-0.347***	0.107***	-1.402***
(Health)	(0.006)	(0.147)	(0.007)	(0.153)	(0.010)	(0.306)
Family size/same sex	-0.253***	-1.656***	-0.262***	-1.548***	0.076***	-0.883***
(Tech and Science)	(0.017)	(0.316)	(0.019)	(0.315)	(0.014)	(0.227)
Family size/same sex	-0.150***	-2.784***	-0.143***	-3.288***	0.033***	-2.850***
(Law)	(0.016)	(0.454)	(0.018)	(0.501)	(0.014)	(0.457)
Observations	2,382,979	2,382,979	1,934,965	1,934,965	2,749,200	2,749,200

Note: The baseline is the "Other" occupation category. The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A16. Effects on Parents' Job Flexibility - Twins as An IV

	All women		Married women		Married men	
	Panel 1: More than two children					
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Twins (first stage)		0.089***		0.101***		0.090***
		(0.006)		(0.008)		(0.003)
	Panel 2: Five features of job flexibility					
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Time pressure	-0.005***	-0.026**	-0.006***	-0.036***	-0.001	-0.002
	(0.001)	(0.010)	(0.001)	(0.008)	(0.000)	(0.008)
Contact with others	-0.003***	-0.022***	-0.003***	-0.014*	-0.001	-0.032***
	(0.000)	(0.006)	(0.000	(0.005)	(0.001)	(0.008)
Interpersonal relationships	-0.002**	-0.053***	-0.001**	-0.043***	-0.000	-0.055***
	(0.000)	(0.009)	(0.000)	(0.008)	(0.001)	(0.010)
Structured vs. unstructured	-0.002***	-0.034***	-0.002***	-0.045***	-0.000	-0.047***
	(0.000)	(0.009)	(0.000)	(0.010)	(0.001)	(0.008)
Freedom to make decisions	-0.001*	-0.041***	-0.001	-0.049***	-0.001	-0.051***
	(0.001)	(0.011)	(0.000)	(0.012)	(0.001)	(0.009)
Observations	3,117,428	3,117,428	2,498,839	2,498,839	3,481,382	3,481,382

Note: The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A17. Effects on Jobs with Health Insurance from Employer/Union - Twins as An IV

	All women		Married women		Married men	
	Panel 1: More than two children					
	Logit	IV	Logit	Logit	Logit	Logit
Twins (first stage)		0.089***		0.101***		0.090***
		(0.006)		(0.008)		(0.003)
	Panel 2: Health Insurance from Employers/Unions					
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Family size/same sex	0.186***	1.236***	0.211***	1.184***	0.235***	1.665***
	(0.009)	(0.210)	(0.014)	(0.244)	(0.015)	(0.220)
Observations	2,038,551	2,038,551	1,610,324	1,610,324	2,170,721	2,170,721

Note: Information of health insurance is available since the year 2018. The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A18. Effects on Parents' Occupational Prestige Scores - Twins as An IV

	All women		Married women		Married men	
	Panel 1: More than two children					
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Twins (first stage)		0.089***		0.101***		0.090***
		(0.006)		(0.008)		(0.003)
	Panel 2: Prestige scores					
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Family size/Twins	-0.007***	-0.085***	-0.008***	-0.089***	-0.003	-0.152***
	(0.001)	(0.021)	(0.001)	(0.019)	(0.002)	(0.026)
Observations	3,480,139	3,480,139	2,767,575	2,767,575	3,771,586	3,771,586

Note: The sample only includes parents who are employed. Clustered by state. Standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

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Vita

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