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ISSN: 2365-9793

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ABSTRACT

Environmental Policy and Gender Health Gap*

Utilizing a nationally representative panel data of middle-aged and elder individuals from China, we assess the health impact of environmental policies, with special attention paid to gender disparities within their effects. This study utilizes thermal inversions to address the endogeneity of air pollution and constructs a fixed effects model. Our findings highlight that the negative impact of air pollution on female health is significant, particularly for females in the middle of the health distribution. Notably, the implementation of environmental policies leads to health improvements in females and plays a key role in bridging the health gap between genders. These findings provide compelling evidence of the importance of environmental policy in promoting health equity.

JEL Classification: C21, I14, J71, Q53, Q58

Keywords: environmental policy, gender health gap, China

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* We are very grateful for insights and suggestions from seminar participants at the Australian Gender Economics Workshop, Annual Conference of Chinese Economics Society Australia and Sydney Development Economics Group Workshop. Liwen Guo thanks for the financial support from UNSW and UNSW Canberra (Tuition Fee Scholarship (TFS) - fee component (RSRE7059), Tuition Fee Scholarship - stipend component (RSRE7080) and Development and Research Training Grant (RSTR9001)). Any remaining errors are ours.

1. Introduction

Research has indicated that air pollution has negative impacts on physical health (Chay and Greenstone, 2003; Deryugina et al., 2019), mental health (Buoli et al., 2018; Shuai Chen et al., 2018), cognition (Ebenstein et al., 2016), worker productivity (Chang et al., 2019; Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015), income and employment (Borgschulte et al., 2022), which can cause various socioeconomic issues both in the short- and long-term. Among them, particulate matter 2.5 (PM2.5) is recognized as a crucial risk factor for mortality and hospitalization resulting from respiratory and cardiovascular diseases (Brunekreef and Holgate, 2002). The air pollution issue is severe in developing countries, such as China (Xu et al., 2013). Outdoor air pollution, particularly PM2.5, exceeds the World Health Organization's recommended air quality levels of 10.0μg/m^3 by more than four times (WHO, 2018), and a number of studies have shown that outdoor air pollution has a notable impact on individual physical health. For instance, the winter heating system in areas north of the Huai River had a large negative impact on life expectancy (Ebenstein et al., 2017; Xu et al., 2013). A quarter of the premature deaths worldwide (i.e., approximately 1 million) due to outdoor air pollution in 2016 took place in China (WHO, 2018). Air pollution can exacerbate existing inequalities among people with different incomes and socioeconomic statuses. Those who have to live in polluted areas or lack environmental awareness may be particularly vulnerable to the health effects of air pollution, leading to a widening of the inequality gap.

To address the issue of widespread air pollution, the Chinese central government has implemented a range of environmental protection laws and regulations. Measuring the human capital benefits of these policies is essential for evaluating their effectiveness. Overestimating these benefits may lead to a lack of attention to air pollution issues, while underestimating them could result in excessive regulation. A vast amount of literature attempts to explain how air pollution brings negative impacts on individual, household-level and city-level decision-making and performance (Yang and Zhang, 2018; Zhang et al., 2018). For example, the increase in air pollution levels could prompt changes in human behavior, such as the increased purchase of masks, air purifiers and reduced purchase of houses (Chay and Greenstone, 2003; Ito and Zhang, 2020; Zhang and Mu, 2018). The objective of this study is to investigate an alternative explanation for the effect of air pollution by taking into account the consistent reduction in air pollution resulting from environmental policy. Considering the gender differences in genetic vulnerability to illness, reproductive and hormonal factors (Vlassoff, 2007), as well as possible different roles in society, we examine the effect of environmental policy on air pollution induced health status across gender and measure the gender physical health gap. We delved deeper into the reasons for the reduction in the gender health gap by examining the effects of air pollution that can be explained and those that cannot be explained. Our research differs from previous studies by examining the impact of environmental policy on physical health across different distribution points for gender, rather than just focusing on the average gender differential. We also use nationally representative individual microdata to strengthen the evidence in this area of literature.

More specifically, we employ high-resolution satellite data from the National Aeronautics and Space Administration (NASA) and a dataset of individual-level physical health with geocoding to explore the impact of environmental policy on the gender health gap. The selection of this data has several reasons. First, due to the possibility of data manipulation in Chinese local air pollution data (i.e., performance evaluations of local government officials are related to compliance with environmental standards), we choose NASA (i.e., an independent agency of the United States) satellite data of global air pollution. Second, physical health is one element of human capital and one of the central drivers for sustainable growth and poverty reduction of human beings (World Bank, 2020). An individual's physical health assets might be able to accumulate and have significant impacts on personal performance. Lastly, this individual-level dataset is focused on people who are aged equal to or above 45 years old. It is valuable to measure the outcomes of environmental policy on middle-aged and older adults as older adults tend to be more vulnerable to air pollution - a growing problem as the aging population has increased in many countries. If environmental policy benefits the aging population's physical health, their longevity becomes a valuable resource because healthy older people will keep contributing to society. Individuals in our sample do not migrate to new places in all survey years and hence the estimates are not biased by the migration tendency.

Our results show that females are more likely to be affected by air pollution before than after environmental policy, especially in the middle of the distribution. For females, a one standard deviation increase in air pollution leads to a 73.7% decrease in physical health before policy implementation, whereas it reduces by 35.6% in physical health after policy implementation. Moreover, females have a lower level of physical health compared to males. Except for females at the high end of the distribution, the gender health gap becomes smaller for the average population at the low end or middle of the distribution after the policy. The larger gender health gap at the high end of the distribution is caused by different increased rates of the negative impact of air pollution across gender. The increased rate of the negative impact of air pollution on physical health is relatively lower for females than males, especially in the high end of the distribution, but environmental policy will decrease the differences in increased rates. In addition, we investigate the impact of environmental policy on the gender health inequality gap. We also perform a number of robustness checks, which confirm that the results are consistent.

We divide the sample into the pre-policy cohort and post-policy cohort to compare the variations in physical health and gender health gap in response to air pollution. We follow the Recentered Influence Function (RIF) method and two-stage least squares (2SLS) regression analysis to generate unconditional quantile estimates and partial conditional quantile regressions. We apply Recentered Influence Function-Oaxaca-Blinder (RIF-OB) decomposition to decompose the gender health gap at different quantiles into explained and unexplained components, which in turn are decomposed into the contribution of explanatory variables (Firpo et al., 2018). The decomposition procedures contain the construction of counterfactual health distribution if females have received the same returns to personal characteristics as males and look at the explained and unexplained effects into the contribution of explanatory variables. We also adopt difference-in-differences (DID) estimation to quantify policy effects.

The predicted annual average PM2.5, based on the annual average of thermal inversion, wind speed and wind direction, is used as an instrumental variable for air pollution. In recent literature, the number of thermal inversion days (Arceo et al., 2016; Shuai Chen et al., 2018; Fu et al., 2021; Jans et al., 2018), thermal inversion values (Chen et al., 2022) and wind direction (Deryugina et al., 2019) are widely used to construct instrumental variables for air pollution. Some researchers utilize the predicted values based on both the number of thermal inversion days, thermal inversion values, wind direction and wind speed as instrumental variables for air pollution (He et al., 2019; Liu and Salvo, 2018; Qin et al., 2019). These studies show that a 10 $\mu g/m^3$ increase in PM2.5 reduces the daily output of workers by 1% (He et al., 2019), and children's school attendance (Liu and Salvo, 2018) and housing purchasing behaviors (Qin et al., 2019) will be negatively affected by severely polluted days. Average strengths of thermal inversions in the previous five years have also been used in research related to the net outmigration of counties (Chen et al., 2022). The research we conducted provides additional support for the correlation between air pollution and physical health and delves deeper into the effects of environmental policy and gender disparities in this connection.

Overall, the findings suggest that environmental policy has a positive impact on the health of individuals, especially for females in the low end or middle of the health distribution. Environmental policies can have a greater impact on human well-being than previously anticipated, as improved physical health can lead to better personal performance. The findings of this study contribute to the existing literature on the evaluation of environmental policies and highlight the importance of considering gender differences in the impact of such policies. This evidence can help formulating effective environmental policies that address the needs of vulnerable populations. Such policies are particularly necessary to protect females, who are more likely to be exposed to other types of air pollution, such as indoor air pollution.

The rest of the paper is arranged as follows. The second section describes the relevant background. The third section elaborates on the empirical strategy and describes the variables used in the study. The fourth section presents the results of the empirical analysis. The fifth section provides the results of robustness checks. The sixth section concludes.

2. Background

2.1. Environmental policies in China

The Chinese government formally participated in environmental protection in 1973 by promulgating "Several provisions on the protection and improvement of the environment". The government included environmental protection in the Constitution in 1982, and paying attention to the importance of environmental protection was also identified as a basic national policy in 1983. Nonetheless, some of these policies are not strict enough, and local governments and sectors may ignore the importance of environmental protection in the pursuit of economic benefits. In recent years, the Chinese central government has become more aware of the severity of air pollution issues and proposed more stringent environmental policies to address them.

In 2012, the Ambient Air Quality Standards was reviewed, and the scope of air quality monitoring started to include PM2.5. In September 2013, China's Air Pollution Action Plan (i.e., China's Clean Air Act) was released. It is the toughest-ever and most influential environmental policy. It set aside funding to reduce ambient air pollution and set concrete goals for the reduction of PM2.5 and PM10. Some regions with particularly severe air pollution problems have been allocated more resources and have higher targets for reducing air pollutants than other regions. In early 2014, the Chinese government announced a strong commitment to tackling air pollution. This announcement was followed by the amendment of the Environmental Protection Law, originally proposed in 1989, with the revised law scheduled to come into effect in the next year. The government's efforts to reduce pollution also included the gradual replacement of coal with clean energy in the winter heating system in northern China.

Overall, these measures reflect China has implemented considerable measures to combat the issue of air pollution since 2013, offering a rare opportunity to examine the impact of air quality interventions and make causal inferences after addressing any potential issues of residual confounding. As far as we know, there is limited research on the effects of air pollution policy. There is a related study in the United States that examines the link between long-term cumulative exposure to air pollution and the risk of developing Alzheimer's disease or related dementias (Bishop et al., 2018). The limitations of the study include the lack of consideration of time-varying variables that could potentially affect the results over the long study period, which could introduce bias. Additionally, a study conducted in China with a relatively shorter timeframe evaluated the impact of the Air Pollution Action Plan on the cognitive function of individuals aged 65 years and above, but it did not explore potential differences in effects across different population groups (Yao et al., 2022).

2.2. Environmental policy, physical health and gender differences

Air pollution poses a grave threat to human health and overall well-being, inducing harmful effects on various body organs and contributing to numerous diseases, ranging from respiratory conditions such as pneumonia, chronic obstructive pulmonary disease, and asthma, to metabolic diseases like diabetes (Fang et al., 2012; Gehring et al., 2013; Vella et al., 2015). Moreover, air pollution can also trigger hyperleptinemia, a condition associated with potential trajectories towards premature cardiovascular diseases, addictive behaviors, cognitive impairment, and Alzheimer's disease (Calderón-Garcidueñas et al., 2015). This detrimental relationship between air pollution and physical health has been corroborated in multiple studies, including research conducted in China (Chen et al., 2018; Qiu et al., 2019).

Personal behavioral modifications can help mitigate the harmful effects of air pollution. However, the efficacy of such changes often hinges on cost-effectiveness, limiting their utility (Janke, 2014). Consequently, environmental policies emerge as a powerful instrument in promoting physical health by regulating significant contributors to air pollution such as vehicles, cooking, and industrial processes. Evidence from research indicates that the promotion of clean energy and the adoption of improved biomass stoves can enhance the physical health of residents, with an apparent impact seen among Chinese populations (Mueller et al., 2013).

Despite the substantial body of research on the broad health implications of air pollution, studies exploring the confluence of gender differences and air pollution's health outcomes remain scant. This presents a significant knowledge gap, given the critical role gender plays in shaping the adverse outcomes of air pollution. A handful of studies have established the necessity of robust environmental policies to protect vulnerable groups like fetuses, children, pregnant women, and older adults from the harmful effects of air pollution. Specifically, air pollution has been associated with heightened infant mortality rates (Arceo et al., 2016), DNA damage in fetuses (Perera et al., 2005), brain damage in children (Brockmeyer and D'Angiulli, 2016; Rice and Barone Jr., 2000), mental health issues in pregnant women (Kanner et al., 2021) and older adults (WHO, 2017). Relative to other demographic cohorts, the elderly population may be at a heightened risk for serious mental health conditions due to immunosenescence, pre-existing medical conditions and stressful life events (WHO, 2017). This suggests that more comprehensive environmental policies are necessary, particularly in countries like China, where the aging population is growing rapidly (Yao et al., 2022).

Due to the inherent biological and social differences between genders, susceptibility, exposure, and responses to pollutants can vary, leading to dissimilar impacts of environmental policies on men and women. Studies have highlighted neurological differences between sexes, suggesting that women may be more susceptible to certain adverse effects of air pollution (Gallart-Palau et al., 2016). Thus, females tend to have a higher burden of disease compared to males (Nebel et al., 2018). Furthermore, occupational exposures, residential environments, and lifestyle factors might also influence the exposure to air pollution and subsequent health outcomes differently in men and women. Sociocultural norms in many developing countries can compound these effects, placing women in more vulnerable positions due to gender-prescribed roles (Clougherty, 2010).

While cognitive and educational gender disparities among younger Chinese cohorts are narrowing, significant differences persist among individuals aged 45 and above, particularly in traditional impoverished communities. Women in these communities often lack access to quality education and nutrition compared to men due to persisting son preference and the financial constraints associated with having more children (Lei et al., 2014; Zhang et al., 2015). Furthermore, older men tend to have more access to pension and medical benefits due to their historical advantage in education, income, and employment. In contrast, older women in China cannot claim pension or unemployment compensation based on their husbands' work histories, unlike their counterparts in the United States (Zhan, 2005). This disparity can lead to long-lasting health implications, with research suggesting that middle-aged and older women are more susceptible to several diseases including diabetes, heart disease, hypertension, disability in daily living activities, and depressive symptoms (Anson and Sun, 2002; Guo et al., 2021; Peng et al., 2021).

In conclusion, although the health impact of air pollution has been extensively studied, the literature lacks a comprehensive exploration of the health benefits resulting from improved air quality, particularly in relation to environmental policy implementation. Additionally, the current literature on environmental policy has generally not considered potential gender differences in outcomes. These limitations point towards the need for more gender-specific research on the health effects of air pollution and the impact of environmental policies on different genders. By understanding these disparities, policymakers can devise more equitable and effective environmental regulations.

3. Empirical strategy and data

3.1. Empirical strategy

We take three steps to measure the impact of environmental policy on the gender health gap. First, we estimate the effects of air pollution on physical health by gender across distributions before and after the policy. We use RIF unconditional quantile regressions to measure an increase in air pollution on unconditional statistics of physical health in different durations. This method allows us to obtain unconditional quantile partial effects.[1] It is analogous to the OLS regression, which assumes a linear correlation between the dependent variable and independent variable, but the coefficient represents the marginal effects of the independent variable on a quantile, i.e., how much the quantile of marginal dependent variable distribution is influenced by a shift to the right in the distribution of the independent variable. The results of RIF regressions with the mean statistic are identical to the results of ordinary least-squares (OLS) regression (Firpo et al., 2009). Second, we measure the variations in the gender health gap across distributions before and after the policy. We use partial conditional RIF regressions to check the changes in the gender health gap on quantiles. The coefficient of the condition, i.e., whether the individual is female, is used to estimate RIF and represents the physical health differences between females and males. This regression with binomial gender could be viewed as an OLS alternative to Oaxaca-Blinder (OB) decomposition. In the third step, we decompose the gender health gap across distributions into contributions of explanatory variables. The

[1] We adopt Gaussian kernel to smooth the data. Due to the possible lack of information on the conditional distribution of the transformed cut-points, we defined the low, medium, and high quantiles as the 10th, 50th, and 90th quantiles, respectively. We avoid using extreme quantiles such as the 1st and 99th due to the statistical uncertainty associated with them. In the robustness checks, we employ methods based on Bayesian quantile regression for ordinal outcomes to ensure the consistency of the results.

method is RIF-OB decompositions, which rely on the RIF regression estimates and OB decomposition (Jann, 2008). For the pre-policy and post-policy cohort, we estimate RIF unconditional quantile regressions for females, males and counterfactual health distributions (i.e., assume that for females, the returns of explanatory variables are the same as males). Then we could obtain the differences between males and females in the returns of explanatory variables. The differentials at each quantile include explained effect (i.e., namely composition effect or explained by discrimination, the gender health gap at a quantile is attributed to endowment differentials in explanatory variables, assuming the same returns for males and females) and unexplained effect (i.e., structure effect, the gender health gap at a quantile is due to different returns of explanatory variables for females and males) (Firpo et al., 2018). Furthermore, relevant work in China utilizes DID analysis to measure the impact of environmental policy on physical health. The DID estimator is based on the year dummy (2014 = 0, 2018 = 1) and locations with higher targets of Air Pollution Action Plan for local governments (provinces with 5% or below the target of PM2.5 reduction is viewed as a control group and others are intervention group) (Yao et al., 2022). Following this study, we utilize DID estimation to quantify policy effects for general population, females and males, respectively.

3.2. Data

The data utilized in this study is the China Health and Retirement Longitudinal Study (CHARLS), which is a nationally representative longitudinal survey of the population aged equal to or above 45 years of old in China. This survey collects health, economic and social information of these people and their spouses. The survey was conducted by Peking University in China in 2011, 2013, 2015 and 2018. This survey applies systematic probability proportional to size sampling method and uses implicit stratification by administrative boundary and socioeconomic status.

The detailed geographic location information of this data enables us to merge air pollution and other city-level attributes with it. Air pollution data comes from NASA Socioeconomic Data and Applications Center at Columbia University. [2] This data measures annual mean concentrations of ground-level PM2.5 (Hammer et al., 2021, 2022).

The dependent variable in the analysis is the self-rated health status. in the survey. We rescale the original variable and define an indicator for health that is the higher the score, the healthier (very poor=1, poor=2, fair=3, good=4, very good=5). We adopt air pollution as our independent variable in both pre-policy and post-policy regressions. Air pollution is measured by city-level annual mean PM2.5. Considering the possible endogenous problem of air pollution from sorting, pollution avoidance behaviors, and the correlation between air pollution and economic activities, we adopt predicted PM2.5 based on thermal inversions from 1000-975 and 975-950 hPa and wind speed at the ground level as an instrumental variable of PM2.5.[3] The construction of predicted PM2.5 is as follows:

$$PM\_fit_{2.5_{t,j}} = \sum_0^{t,j} \gamma_{1_{t,j}} InverValue_{t,j} + \sum_0^{t,j,l} \gamma_{2_{t,j,l}} WS_{t,j,l} + \sum_0^{t,j,l} \gamma_{3_{t,j,l}} InverDay_{t,j,l} + \varepsilon_{t,j,l} \quad (1)$$

where $PM\_fit_{2.5_{t,j}}$ represents the fitted value of PM2.5 at time t in city j. $InverValue_{t,j}$ is the value of thermal inversions at time t in city j. $WS_{t,j,l}$ and $InverDay_{t,j,l}$ indicate wind speed and the number of occurrences of thermal inversions at time t in city j at layer l, respectively.

[2] The air pollution data can be found at the website: https://beta.sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod-v4-gl-03.

[3] The data can be found at https://disc.sci.gsfc.nasa.gov/datasets/M2I6NPANA_5.12.4/summary?keywords=M2I6NPANA

With respect to covariates, we include a set of individual-level and city-level characteristics: age, marital status (never married=1, separated, divorced, widowed=2, married with spouse present, or married but not living with spouse temporarily for reasons such as work=3), number of living children, number of living parents, real gross domestic product per capita (thousand RMB), population density (per km^2), number of industrial firms per thousand people, ground-level temperature (°C), rainfall (10^6 kg/m^2*s), wind speed (m/s) and indicators for whether the individual is female (yes=1), has high school or above education (yes=1), migrated to other provinces (yes=1), has non-agricultural *hukou* (yes=1), has smoking behavior (yes=1), is included in the urban sample (yes=1) and lived in the city with high variance of PM2.5 within the city (yes=1).

Summary statistics of variables by gender and policy cohorts are reported in Table 1. Although males might be more likely to live in places with higher air pollution than females, males tend to have better health status than females. Gender differences in physical health decline after the implementation of environmental policy. Females have a lower level of education, are more likely to migrate to other provinces and need to take care of many living parents and children. Finally, females are less likely to have smoking behaviors and the proportion of individuals having smoking behaviors decreases after policy. Table 2 presents females' and males' mean physical health in pre-policy and post-policy cohorts. The ratio of females' physical health to males' physical health increased from 94.5% to 94.8%, suggesting a decrease in the gender physical health gap. Females with high school or above education tend to have a higher level of health compared to females with below high school education. Females living in big cities and female entrepreneurs also have a higher level of health status compared to those who live in non-big cities and non-entrepreneur females. Environmental policy will help to decrease the gender health gap for all populations but might not be able to decrease the inequality in females or in males. The descriptive results indicate that gender health disparity is larger for females with lower education and socioeconomic status, suggesting the existence of discrimination in obtaining good health. The environmental policy might be helpful for the reduction of the gender health gap but may not change the inequality level for each gender.

4. Empirical results

The coefficient estimates of RIF unconditional quantile regressions at mean without (or with) an instrumental variable are the same as the OLS (or 2SLS) estimates. Table 3 shows the OLS, 2SLS and ordered logistic estimates of the impact of air pollution on physical health. The OLS results show a negative but statistically insignificant effect of air pollution on physical health for the full sample. However, considering the biased results of the OLS model, we utilize an instrumental variable of air pollution in the regression. According to the 2SLS results, at the mean, a unit increase in air pollution will cause a 1.1% reduction in the physical health of females. In alternative words, a one standard deviation increase in air pollution will cause a 24.6% reduction in the physical health of females. The instrument's Kleibergen-Paap RK Wald F statistic is larger than ten and the t-statistic is larger than the threshold of 3.43 (Lee et al., 2022), suggesting no weak instrument variable issues. The estimates from the ordered logistic regression reveal similar findings. They are not reported because their parameter estimates are not directly comparable to linear models.

Panel A-D of Table 4 presents the estimates of separate RIF unconditional quantile regression estimates by gender at mean, low, medium and high quantiles for pre-policy (i.e., 2011, 2013) and post-policy cohorts (i.e., 2015, 2018). The coefficient estimates show that air pollution has different effects on females and males. The negative returns of air pollution are larger and more significant for females, whereas they are statistically insignificant for males. For instance, at the mean, before the issue of environmental policy, a unit increase in air pollution will lead to an 8.3% reduction in the physical health of females, whereas the effects become 7.7% after the policy implementation. In alternative words, a one standard deviation increase in air pollution will lead to a 204.0% reduction in the physical health scores of females, whereas the effects become 130.7% after the policy implementation. The effects are not significant for males. In 2011 and 2013, at the median, females who lived in places with one unit (or one standard deviation) increase of air pollution had 3.0% (or 73.7%) fewer physical health scores. In contrast, males do not experience negative and significant impacts from air pollution. In 2015 and 2018, at the median, females with one unit (or one standard deviation) increase of air pollution in their living places had 2.1% (or 35.6%) fewer physical health scores.

The results suggest that the negative impact is significant for the female sample, and that environmental policy brings health benefits for females since it reduces the negative returns of air pollution on their physical health. The results also suggest that environmental policy might help to reduce gender health differences in response to air pollution. We further check the effects of air pollution on the dispersion of physical health for the pre- and post-policy cohorts. These show that the increase in air pollution might lead to less dispersion of physical health for females, and that the introduction of environmental policy might eliminate this effect. It is likely that the increased rate of the negative impact of air pollution is relatively lower if females live in polluted areas. The immune responses stimulated by severe air pollution might generate a protective effect to help them survive in environmental adversity. Panel E and Panel F of Table 4 report the estimation results of partial conditional regressions on gender. These suggest that females have a lower level of physical health compared to males. Except for females at the high end of health distribution, the gender health gap becomes smaller for the average population in the low end or middle of distribution after the implementation of environmental policy. In terms of the dispersion of physical health, females tend to have less health inequality compared to males before the policy, and the health inequality of females is reduced more than males after the policy.

As is shown in Table 5, we decompose the differences between females and males across distributions into explained and unexplained components. For each cohort, we generate a counterfactual distribution of physical health if females have identical returns of explanatory variables as males. First, the coefficients of gender difference suggest that the gender health gap is smaller after policy. The results are consistent with the partial conditional regressions estimates on gender, which show that environmental policy brings more health benefits for females. Second, the significant coefficients of the unexplained component indicate that the gender health gap mainly comes from the unexplained part (i.e., the differences between the female's actual distribution and the female's counterfactual distribution), which decreases after the implementation of the policy. Thirdly, health return to air pollution is larger for females than for males (i.e., the increase rate of the negative impact of air pollution on health is lower for females than males), especially at the high end of the distribution. Yet, the environmental policy will reduce the differences in the increased rates of the negative impact of air pollution on health between females and males. Thus, the reduction in the differences of the increase rate might cause an identical and larger gender health gap at the high end of the distribution. We also check the variations of physical health inequality for females and males. The coefficients of gender difference are positive, suggesting that males tend to have larger health inequality than females. The increase in the coefficient of gender difference after the issue of policy represents the gender health inequality gap larger after the policy. The results are also confirmed by results of partial conditional regressions that environmental policy will help to reduce more health inequality among females than among males. The negative coefficient of unexplained air pollution shows that health inequality return to air pollution is larger for females than for males (i.e., the increase rate of the negative impact of air pollution on health dispersion is lower for females than males). Environmental policy will increase the differences in the increase rate of the negative impact of air pollution on health dispersion, which might provide an explanation for the occurrence of the larger gender health inequality gap.

Furthermore, we test the physical health benefits of environmental policy. The year dummy in our study is defined by whether the survey year belongs to the post-policy cohort (2011 or 2013 = 0, 2015 or 2018 = 1). The intervention group indicator is a categorial variable where provinces with 0%, 5% and above 5% target of PM2.5 reduction are equal to 0, 1 and 2, respectively. Table 6 displays the results and finds that after the implementation of environmental policy, high target PM2.5 reduction will lead to high physical health scores and this positive effect is significant for females rather than males.[4] Specifically, a one standard deviation increase in environmental policy stringency will increase health scores of the general population and females by 5.7% and 7.3%, respectively.

5. Robustness checks

Up to now, our sample has focused on differences between females and males. We next check the robustness of the results for specific groups of people. According to "the double burden hypothesis", the combination of being an employee and a parent will lead to high work strain and risks of absence and sickness (Floderus et al., 2008; Nilsen et al., 2017). People without children might have positive self-identities from the freedom of making their own life choices,

[4] We utilize the seemingly unrelated estimation to test whether or not the coefficients for females and males are equal. The results cannot be calculated in the pre-policy cohort and are not significant for the post-policy cohort. Then, we test the gender differences in the impact of air pollution on physical health and find that the differences are significant in the pre-policy cohort and not significant in the post-policy cohort. These findings are consistent with our previous results.

especially single women (Addie and Brownlow, 2014). Yet, people without children approaching middle age without age might have more physical health issues. For instance, the negative effect of having children for females will decrease for people after age 35 since the problems caused by having children will be modified by age (i.e., as mothers' ability to cope with parenthood by increasing age). Childlessness might also be associated with less support from family and social networks (Gironda et al., 1999; Graham, 2018). Having children for relatively older parents is more important in China due to the strong social norm of filial responsibility that adult children need to serve their parents well (Wang et al., 2021). We generate an interaction to measure whether environmental policy brings health benefits to populations without children. The interaction effects in Table A1 find that after the environmental policy, females without children still experienced the negative impacts of air pollution, whereas the impacts were not significant for males without children.

In the previous environmental performance, reduction in air pollution and stringent level of pollution control might be different in some areas. The Air Pollution Action Plan in 2013 emphasized the importance of reducing air pollution in three key regions (i.e., Beijing-Tianjin-Hebei, Yangtze River Delta and the Pearl River Delta) and planned to decrease PM2.5 concentrations by 25 percent, 20 percent and 15 percent in these regions, respectively. Beijing-Tianjin-Hebei region has the highest level of air pollution before and after the implementation of the environmental policy. The Pearl River Delta has the lowest air pollution level compared to the other two regions in almost all years. Table A2 report the estimation results for people living in these three key regions after environmental policy. In highly polluted areas such as cities in the Beijing-Tianjin-Hebei region, the negative impact of air pollution on males and females still exists after the implementation of environmental policy. Females living in the Yangtze River Delta also experienced adverse health outcomes from air pollution after environmental policy. Individuals, communities and governments need to make more effort to reduce air pollution in highly polluted areas and pay attention to the vulnerability of females to air pollution.

Environmental policies such as the Air Pollution Action Plan in 2013 might also bring benefits for climate change due to the actions of using clean energy to replace traditional energy. In order to examine the effect of greenhouse gas on the relationship between environmental policy and physical health, we use ozone as an independent variable in health regressions before and after environmental policy. The results in Table A3 show that greenhouse gas emissions harm the physical health of females before environmental policy and the negative impact is not significant after environmental policy, which is similar to our main results. The results also suggest that air pollution and climate change are linked issues and the environmental policy helps to avoid dangerous climate change when reducing air pollution exposure.

Considering that we assume conditional expectation is linear in the previous estimation, Table A4 adopts a logit re-weighting approach as in DiNardo et al. (1996) to estimate partial conditional regressions on gender and RIF-OB decomposition across policy cohorts. The advantage of applying reweighting method is that it is suitable for more general distributional statistics. The first step of reweighting procedure is to obtain inverse probability weights. We regress the gender variable on a set of control variables by using logit regression. The second step is to use weights in the estimation of average treatment effects and identification of the counterfactual distributions. Reweighting errors are small compared to total differences. They are nonsignificant in the pre-policy cohort but significant in the post-policy cohort (i.e., the regression might not be correctly reweighted, and reweighting has an undue effect on estimates in the post-policy cohort). In terms of explained and unexplained components, although the size and significance level of variables for the post-policy cohort alter in the weighted model, the significant impact of unexplained components and unexplained PM2.5 remain significant. Similar results prove the robustness of previous findings.

We adopt the Juhn-Murphy-Pierce (JMP) method to check the impact of environmental policy on the gender health gap and disentangle the unexplained effect into a residual portion and residual inequality.[5] (Juhn et al., 1991). Table A5 reports that the gender health gap decreased after the implementation of the environmental policy, and the impact is mainly from the residual gap rather than the predicted gap. The predicted gap is explained component of the differential and indicates there are differences in observed quantities (i.e., endowments) and observed prices (i.e., coefficients or returns). The residual gap is the unexplained part of the differential and suggests that there are differences in unobserved quantities and prices. From the results, we find the decrease in the gender health gap mainly due to the unexplained quantity effect (i.e., true female-specific effect). It represents that there are changes in the groups' differences in residual positions, such as changes in the group differences in unobserved quantities and discrimination. In alternative words, the environmental policy reduces the gender health gap because the percentile rankings of the females' residual health distribution changed when male residual health inequality remained the same.

To confirm the consistency of the role of air pollution in the relationship between environmental policy and the gender health gap, we adopt the model in long differences before and after environmental policy to look at historical trends and smooth measurement errors (Michaels et al., 2014). The two dependent variables, the independent variable and instrumental

[5] The RIF-OB method used in this paper does not identify the role of health structure on health gaps before and after environmental policy (i.e., changes in health inequality over time).

variable are the differences in physical health, gender health gap, air pollution and thermal inversion-induced air pollution before and after environmental policy, respectively.[6] The results in Table A6 show that the increase in air pollution will lead to lower female physical health and a larger gender health gap.

Following the Bayesian quantile regression for ordinal outcomes, we focus on the individuals might at the middle of the health distribution and utilize Bayesian estimation regression with Gibbs sampling and Metropolis-Hastings (MH) algorithm to confirm the consistency of results (Rahman, 2016). We drop the initial 2500 burn-in iterations and utilize the remaining 10000 Markov chain Monte Carlo (MCMC) iterations to generate the outcomes. Table A7 shows the posterior mean and standard deviation of the air pollution, and the sign and magnitude of the estimates are similar to that obtained from quantile regressions.

Considering the dependent variable in our study is based on self-reported physical health scores and might be highly skewed variables (e.g., people are more likely to report healthy), we check the distributions of the dependent variable in Figure A1. The figure indicates that the dependent variable is distributed relatively normally, with a significant peak at the mean of 3, i.e., most of the individuals in our sample have fair health scores for both pre-policy cohort (kernel = gaussian, bandwidth = 0.083) and post-policy cohort (kernel = gaussian, bandwidth = 0.111). It confirms that our results are not biased by the distribution of the dependent variable.

6. Conclusions

[6] The differences in 2011 are measured by the average differences between 2011 and 2015 as well as between 2011 and 2018, and the differences in 2013 are calculated by the average differences between 2013 and 2015 as well as between 2013 and 2018.

Utilizing a national representative sample of China in 2011, 2013, 2015 and 2018, we investigate the impact of environmental policy on the gender health gap. Our findings indicate that environmental policy implementation can help mitigate the adverse effects of air pollution, particularly for females in the middle of the health distribution. Although males generally have better physical health, environmental policy can still play a role in reducing gender-based health disparities, especially for individuals in the lower and middle segments of the health distribution. The unexplained effects of air pollution could potentially account for some of the observed reductions in the gender health gap. Furthermore, environmental policy is likely to have a more pronounced impact on reducing health inequalities among females compared to males.

Our findings hold relevant implications for explicating the drivers behind the amelioration of gender-based health inequities. In light of the varying rates at which air pollution detrimentally affects females and males, the aggregate gender health gap decreases for the broader populace. Our findings also suggest that environmental policy yields greater health benefits for females at the middle ends of the health distributions. However, further careful analysis is required to explore the relatively lower health benefits conferred by environmental policy at the higher end of the health distribution.

We acknowledge that our study has a primary limitation in that it solely examines the disparities between males and females in their reaction to air pollution and environmental policy, without exploring the potential pathways through which environmental policy impacts the gender-based health gap. It builds on prior research on physical health, in which we presume that both males and females are not independent of the influence of air pollution and environmental policy. Yet, our findings suggest that males in our sample may be less impacted by environmental policies, whereas females may be more susceptible to their influence. This discrepancy could potentially stem from differences in immune function, with males potentially exhibiting a superior ability to mitigate the negative impact of environmental pollutants. Consequently, by leveraging data from medical sciences, we may gain insights into how best to enhance the immune defense of females and promote gender parity in this regard. Another potential explanation for this disparity is the existence of differences in social norms, whereby females may experience more severe indoor air pollution due to traditional energy usage and exposure to secondhand smoke from their spouses. Additional investigation is imperative to scrutinize the precise mechanisms underlying these effects and how environmental policies are executed, especially in relation to industries and regions that have a higher concentration of female employees.

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Table 1
Descriptive Statistics.

Panel A: by gender	Full sample Mean	Full sample SD	Male Mean	Male SD	Female Mean	Female SD	Welch's t-statistic	Gender gap Value	Gender gap Ratio
Dependent variable									
Physical health	3.035	0.974	3.121	0.980	2.954	0.962	22.774***	0.167	5.7%
Independent variable									
PM2.5 (*μg/m*^{3})	52.773	22.373	52.953	22.407	52.603	22.340	2.073**	0.350	0.7%
Instrumental variable									
Predicted PM2.5 (*μg/m*^{3})	52.491	10.009	52.475	10.020	52.505	9.998	-0.401	-0.030	-0.1%
Control variables									
Age	60.042	9.775	60.339	9.670	59.765	9.865	7.783***	0.574	1.0%
Female (*yes=1*)	0.517	0.500	0.000	0.000	1.000	0.000	n.a.	n.a.	n.a.
High school of above (*yes=1*)	0.120	0.326	0.159	0.366	0.084	0.277	30.706***	0.075	89.3%
Migrated to other provinces (*yes=1*)	0.077	0.266	0.066	0.249	0.086	0.281	-9.958***	-0.020	-23.3%
Non-agricultural *hukou* (*yes=1*)	0.227	0.419	0.246	0.430	0.210	0.407	11.063***	0.036	17.1%
Marital status	2.984	0.124	2.982	0.134	2.987	0.113	-5.433***	-0.005	-0.2%
Smoking behavior (*yes=1*)	0.265	0.442	0.524	0.499	0.048	0.214	154.652***	0.476	991.7%
Number of living children	2.623	1.401	2.542	1.372	2.699	1.422	-14.923***	-0.157	-5.8%
Number of living parents	0.371	0.629	0.352	0.620	0.389	0.637	-7.960***	-0.037	-9.5%
Urban sample (*yes=1*)	0.399	0.490	0.392	0.488	0.407	0.491	-4.067***	-0.015	-3.7%
Real gross domestic product per capita (*thousand RMB*)	7.590	4.885	7.567	4.897	7.612	4.873	-1.238	-0.045	-0.6%
Population density (*per km*^{2})	469.936	312.629	470.313	313.193	469.563	312.100	0.318	0.750	0.2%
Number of industrial firms per thousand people	2.614	2.551	2.614	2.573	2.614	2.530	0.013	0.000	0.0%
Ground-level temperature (*°C*)	14.973	5.106	14.976	5.077	14.970	5.133	0.166	0.006	0.0%
Rainfall (10^6 *kg/m*^{2}**s*)	32.406	15.612	32.341	15.563	32.467	15.658	-1.072	-0.126	-0.4%
Wind speed (*m/s*)	2.994	2.379	2.985	2.382	3.001	2.376	-0.896	-0.016	-0.5%
High variance of PM2.5 within city (*yes=1*)	0.117	0.321	0.118	0.322	0.116	0.320	0.698	0.002	1.7%

Panel B: pre-policy cohort, by gender	Pre-policy cohort		Pre-policy cohort, male		Pre-policy cohort, female		Welch's t-statistic	Gender gap	
	Mean	SD	Mean	SD	Mean	SD		Value	Ratio
Dependent variable									
Physical Health	2.996	0.938	3.084	0.943	2.913	0.925	16.862***	0.171	5.9%
Independent variable									
PM2.5 ($\mu g/m^3$)	60.750	24.571	60.910	24.563	60.597	24.580	1.177	0.313	0.5%
Instrumental variable									
Predicted PM2.5 ($\mu g/m^3$)	52.549	10.038	52.520	10.051	52.577	10.025	-0.525	-0.057	-0.1%
Control variables									
Age	59.449	9.753	59.749	9.582	59.165	9.903	5.509***	0.584	1.0%
Female (*yes=1*)	0.514	0.500	0.000	0.000	1.000	0.000	n.a.	-1.000	-100.0%
High school or above (*yes=1*)	0.128	0.334	0.168	0.374	0.090	0.287	21.437***	0.078	86.7%
Migrated to other provinces (*yes=1*)	0.065	0.246	0.055	0.229	0.074	0.261	-6.884***	-0.019	-25.7%
Non-agricultural *hukou* (*yes=1*)	0.229	0.420	0.247	0.431	0.213	0.410	7.378***	0.034	16.0%
Marital status	2.985	0.120	2.983	0.130	2.988	0.108	-4.060***	-0.005	-0.2%
Smoking behavior (*yes=1*)	0.251	0.433	0.521	0.500	0.047	0.212	101.082***	0.474	1008.5%
Number of living children	2.641	1.440	2.557	1.409	2.721	1.465	-10.521***	-0.164	-6.0%
Number of living parents	0.404	0.648	0.381	0.637	0.426	0.658	-6.294***	-0.045	-10.6%
Urban sample (*yes=1*)	0.402	0.490	0.393	0.488	0.410	0.492	-3.254***	-0.017	-4.1%
Real gross domestic product per capita (*thousand RMB*)	6.859	5.108	6.836	5.142	6.880	5.076	-0.790	-0.044	-0.6%
Population density (*per km^2*)	468.171	309.371	468.719	308.815	467.609	309.893	0.330	1.110	0.2%
Number of industrial firms per thousand people	2.560	2.595	2.558	2.614	2.562	2.576	-0.162	-0.004	-0.2%
Ground-level temperature (*°C*)	14.481	5.179	14.496	5.158	14.467	5.199	0.506	0.029	0.2%
Rainfall (10^6 kg/m^2*s)	29.957	13.325	29.913	13.266	29.999	13.381	-0.592	-0.086	-0.3%
Wind speed (*m/s*)	3.064	2.432	3.051	2.436	3.076	2.428	-0.914	-0.025	-0.8%
High variance of PM2.5 within city (*yes=1*)	0.169	0.375	0.169	0.374	0.169	0.375	-0.057	0.000	0.0%

Panel C: post-policy cohort, by gender	Post-policy cohort		Post-policy cohort, male		Post-policy cohort, female		Welch's t-statistic	Gender gap	
	Mean	SD	Mean	SD	Mean	SD		Value	Ratio
Dependent variable									
Physical Health	3.071	1.006	3.156	1.012	2.992	0.993	15.554***	0.164	5.5%
Independent variable									
PM2.5 (*$\mu g/m^3$*)	45.326	17.010	45.448	17.047	45.212	16.976	1.325	0.236	0.5%
Instrumental variable									
Predicted PM2.5 (*$\mu g/m^3$*)	52.436	9.982	52.433	9.991	52.439	9.973	-0.059	-0.006	0.0%
Control variables									
Age	60.594	9.764	60.892	9.720	60.317	9.797	5.621***	0.575	1.0%
Female (*yes=1*)	0.519	0.500	0.000	0.000	1.000	0.000		-1.000	-100.0%
High school or above (*yes=1*)	0.113	0.317	0.151	0.358	0.078	0.268	21.961***	0.073	93.6%
Migrated to other provinces (*yes=1*)	0.088	0.283	0.077	0.266	0.098	0.297	-7.154***	-0.021	-21.4%
Non-agricultural *hukou* (*yes=1*)	0.224	0.417	0.244	0.430	0.206	0.405	8.262***	0.038	18.4%
Marital status	2.983	0.128	2.981	0.138	2.986	0.118	-3.668***	-0.005	-0.2%
Smoking behavior (*yes=1*)	0.278	0.448	0.525	0.499	0.049	0.215	116.851***	0.476	971.4%
Number of living children	2.607	1.362	2.528	1.337	2.679	1.382	-10.610***	-0.151	-5.6%
Number of living parents	0.340	0.609	0.324	0.602	0.356	0.615	-5.037***	-0.032	-9.0%
Urban sample (*yes=1*)	0.397	0.489	0.390	0.488	0.403	0.491	-2.518**	-0.013	-3.2%
Real gross domestic product per capita (*thousand RMB*)	8.272	4.562	8.255	4.549	8.288	4.575	-0.708	-0.033	-0.4%
Population density (*per km^2*)	471.576	315.622	471.809	317.250	471.361	314.115	0.136	0.448	0.1%
Number of industrial firms per thousand people	2.664	2.508	2.668	2.532	2.662	2.486	0.221	0.006	0.2%
Ground-level temperature (*°C*)	15.432	4.993	15.429	4.958	15.435	5.026	-0.098	-0.006	0.0%
Rainfall (*10^6 kg/m^2*s*)	34.693	17.167	34.631	17.144	34.750	17.189	-0.661	-0.119	-0.3%
Wind speed (*m/s*)	2.928	2.327	2.923	2.328	2.933	2.326	-0.405	-0.010	-0.3%
High variance of PM2.5 within city (*yes=1*)	0.068	0.252	0.070	0.255	0.067	0.250	0.957	0.003	4.5%

Notes: SD is the standard deviation. Welch's *t*-statistics are presented for the differences between male and female. Value and ratio of gender gap indicates male-female mean values gap and the ratio of male-female mean values gap to mean value of females, respectively.
∗ p <.10, ∗∗ p <.05, *** p <.01

Table 2
Descriptive Gender Physical Health Gap.

	Pre-policy cohort			Post-policy cohort		
	Male	Female	F/M	Male	Female	F/M
Mean physical health	3.084	2.913	0.945	3.156	2.992	0.948
Physical health by education level						
High school or above	3.285	3.208	0.977	3.302	3.249	0.984
Below high school	3.043	2.883	0.947	3.130	2.970	0.949
Physical health by city performance						
Big city	3.195	3.033	0.949	3.288	3.134	0.953
Non-big city	3.081	2.910	0.944	3.144	2.979	0.948
Physical health by occupation						
Agricultural work	3.103	2.935	0.946	3.120	2.991	0.959
Non-agricultural employed	3.432	3.243	0.945	3.422	3.280	0.959
Non-agricultural self-employed	3.349	3.181	0.950	3.430	3.292	0.960

Table 3
The Impact of Air Pollution on Physical Health.

	(1) Physical health		(2) Physical health		(3) Physical health	
PM2.5 ($\mu g/m^3$)	-0.000	(0.001)	-0.011**	(0.005)	-0.026***	(0.010)
Age	-0.041***	(0.007)	-0.040***	(0.007)	-0.081***	(0.014)
Age squared	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
Female (*yes=1*)	-0.159***	(0.013)	-0.157***	(0.013)	-0.335***	(0.026)
High school or above (*yes=1*)	0.111***	(0.018)	0.111***	(0.018)	0.247***	(0.036)
Migrated to other provinces (*yes=1*)	0.042*	(0.022)	0.042*	(0.023)	0.078*	(0.045)
Non-agricultural *hukou* (*yes=1*)	0.085***	(0.018)	0.083***	(0.018)	0.188***	(0.038)
Marital status	0.176***	(0.045)	0.179***	(0.045)	0.363***	(0.094)
Smoking behavior (*yes=1*)	0.051***	(0.014)	0.052***	(0.014)	0.107***	(0.029)
Number of living children	-0.004	(0.005)	-0.004	(0.006)	-0.013	(0.012)
Number of living parents	0.038***	(0.009)	0.038***	(0.009)	0.078***	(0.018)
Urban sample (*yes=1*)	0.065***	(0.018)	0.066***	(0.018)	0.147***	(0.037)
Real gross domestic product per capita (*thousand RMB*)	-0.005**	(0.002)	-0.009***	(0.003)	-0.020***	(0.006)
Population density (*per* km^2)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Number of industrial firms per thousand people	0.005	(0.012)	0.000	(0.012)	-0.004	(0.024)
Ground-level temperature (*°C*)	-0.001	(0.008)	0.001	(0.008)	-0.002	(0.016)
Rainfall ($10^3\ kg/m^2*s$)	-3.439***	(0.792)	-3.175***	(0.809)	-6.042***	(1.631)
Wind speed (*m/s*)	-0.003	(0.008)	0.005	(0.008)	0.020	(0.017)
High variance of PM2.5 within city (*yes=1*)	0.001	(0.019)	0.086**	(0.041)	0.204**	(0.083)
Constants	4.201***	(0.289)				
City fixed effect	Yes		Yes		Yes	
Month fixed effect	Yes		Yes		Yes	
Year fixed effect	Yes		Yes		Yes	
Observations	51708		51708		51708	
Clusters	10373		10373		10373	
Kleibergen-Paap rk Wald F statistic			569.009			
t statistic (instrument)			23.85		23.85	
Method	OLS		IV		Ologit-IV	

Notes: Robust standard errors are clustered by household and reported in parentheses. PM2.5 is the Particulate Matter 2.5.
∗ p <.10, ∗∗ p <.05, *** p <.01

Table 4
The Impact of Environmental Policy on Physical Health through Air Pollution by Gender.

Panel A: male, pre-policy cohort	(1) Physical health		(2) Physical health		(3) Physical health		(4) Physical health		(5) Physical health		(6) Physical health	
PM2.5	0.032	(0.053)	0.023	(0.024)	0.008	(0.015)	0.021	(0.044)	-0.002	(0.048)	-0.069	(0.080)
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	11052		11052		11052		11052		11052		11052	
Clusters	8112		8112		8112		8112		8112		8112	
Kleibergen-Paap rk Wald F statistic	22.438		22.438		22.438		22.438		22.438		22.438	
Sample mean RIF value	3.108		2.105		3.169		4.293		2.188		0.871	
Method	IV		IV		IV		IV		IV		IV	
Quantile	Mean		Low		Medium		High		High-Low		Variance	

Panel B: female, pre-policy cohort	(1) Physical health		(2) Physical health		(3) Physical health		(4) Physical health		(5) Physical health		(6) Physical health	
PM2.5	-0.083*	(0.047)	0.017	(0.018)	-0.030**	(0.015)	-0.063	(0.043)	-0.080*	(0.047)	-0.072	(0.069)
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	13589		13589		13589		13589		13589		13589	
Clusters	8259		8259		8259		8259		8259		8259	
Kleibergen-Paap rk Wald F statistic	28.951		28.951		28.951		28.951		28.951		28.951	
Sample mean RIF value	2.938		2.061		3.124		4.223		2.161		0.840	
Method	IV		IV		IV		IV		IV		IV	
Quantile	Mean		Low		Medium		High		High-Low		Variance	

Panel C: male, post-policy cohort	(1) Physical health		(2) Physical health		(3) Physical health		(4) Physical health		(5) Physical health		(6) Physical health	
PM2.5	-0.037	(0.035)	-0.014	(0.016)	0.001	(0.009)	-0.033	(0.028)	-0.019	(0.031)	-0.028	(0.055)
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	13610		13610		13610		13610		13610		13610	
Clusters	8061		8061		8061		8061		8061		8061	
Kleibergen-Paap rk Wald F statistic	79.192		79.192		79.192		79.192		79.192		79.192	
Sample mean RIF value	3.163		2.101		3.167		5.078		2.977		0.999	
Method	IV		IV		IV		IV		IV		IV	
Quantile	Mean		Low		Medium		High		High-Low		Variance	

Panel D: female, post-policy cohort	(1) Physical health		(2) Physical health		(3) Physical health		(4) Physical health		(5) Physical health		(6) Physical health	
PM2.5	-0.077**	(0.039)	-0.026	(0.017)	-0.021*	(0.011)	-0.009	(0.031)	0.017	(0.035)	0.064	(0.061)
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	13457		13457		13457		13457		13457		13457	
Clusters	8011		8011		8011		8011		8011		8011	
Kleibergen-Paap rk Wald F statistic	72.625		72.625		72.625		72.625		72.625		72.625	
Sample mean RIF value	3.006		2.064		3.134		5.019		2.955		0.965	
Method	IV		IV		IV		IV		IV		IV	
Quantile	Mean		Low		Medium		High		High-Low		Variance	

Panel E: partial conditional on gender, pre-policy cohort	(1) Physical health		(2) Physical health		(3) Physical health		(4) Physical health		(5) Physical health		(6) Physical health	
Female	-0.166***	(0.015)	-0.039***	(0.006)	-0.035***	(0.004)	-0.061***	(0.013)	-0.029**	(0.013)	-0.054***	(0.021)
PM2.5	-0.042	(0.035)	0.019	(0.015)	-0.014	(0.011)	-0.032	(0.032)	-0.050	(0.034)	-0.080	(0.054)
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	24641		24641		24641		24641		24641		24641	
Clusters	9076		9076		9076		9076		9076		9076	
Kleibergen-Paap rk Wald F statistic	30.967		30.967		30.967		30.967		30.967		30.967	
Sample mean RIF value	3.014		2.082		3.147		4.260		2.173		0.854	
Method	IV		IV		IV		IV		IV		IV	
Quantile	Mean		Low		Medium		High		High-Low		Variance	

Panel F: partial conditional on gender, post-policy cohort	(1) Physical health		(2) Physical health		(3) Physical health		(4) Physical health		(5) Physical health		(6) Physical health	
Female	-0.150***	(0.016)	-0.031***	(0.006)	-0.028***	(0.004)	-0.071***	(0.012)	-0.040***	(0.013)	-0.070***	(0.022)
PM2.5	-0.057**	(0.027)	-0.020*	(0.012)	-0.010	(0.007)	-0.021	(0.022)	-0.001	(0.024)	0.018	(0.042)
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	27067		27067		27067		27067		27067		27067	
Clusters	8922		8922		8922		8922		8922		8922	
Kleibergen-Paap rk Wald F statistic	80.951		80.951		80.951		80.951		80.951		80.951	
Sample mean RIF value	3.085		2.083		3.150		5.049		2.966		0.982	
Method	IV		IV		IV		IV		IV		IV	
Quantile	Mean		Low		Medium		High		High-Low		Variance	

Notes: Robust standard errors are clustered by household and reported in parentheses. PM2.5 is the Particulate Matter 2.5. All specifications control for covariates as in Table 3. Full results are available from the authors.
∗ p <.10, ∗∗ p <.05, *** p <.01

Table 5
The Impact of Environmental Policy on Gender Physical Health Gap.

Panel A: pre-policy cohort	(1) Physical health		(2) Physical health		(3) Physical health		(4) Physical health		(5) Physical health		(6) Physical health	
Gender difference	0.170***	(0.012)	0.040***	(0.004)	0.036***	(0.003)	0.064***	(0.010)	0.023**	(0.010)	0.030*	(0.016)
Explained	-0.021	(0.021)	-0.014**	(0.007)	-0.008	(0.006)	0.000	(0.017)	0.014	(0.018)	0.054*	(0.030)
Explained: PM2.5	-0.002	(0.003)	-0.000	(0.000)	-0.000	(0.000)	-0.002	(0.002)	-0.002	(0.002)	-0.003	(0.004)
Unexplained	0.192***	(0.024)	0.054***	(0.008)	0.044***	(0.007)	0.064***	(0.020)	0.009	(0.020)	-0.024	(0.034)
Unexplained: PM2.5	-0.382**	(0.172)	-0.039	(0.054)	-0.013	(0.047)	-0.360**	(0.149)	-0.324**	(0.154)	-0.557**	(0.250)
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Quantiles	Mean		Low		Medium		High		High-Low		Variance	

Panel B: post-policy cohort	(1) Physical health		(2) Physical health		(3) Physical health		(4) Physical health		(5) Physical health		(6) Physical health	
Gender difference	0.158***	(0.012)	0.037***	(0.004)	0.033***	(0.003)	0.060***	(0.010)	0.023**	(0.010)	0.033*	(0.017)
Explained	0.009	(0.021)	0.000	(0.007)	0.006	(0.005)	0.000	(0.019)	0.000	(0.019)	-0.011	(0.031)
Explained: PM2.5	-0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	-0.001	(0.002)	-0.001	(0.002)	-0.001	(0.003)
Unexplained	0.148***	(0.024)	0.037***	(0.008)	0.028***	(0.006)	0.059***	(0.021)	0.022	(0.022)	0.044	(0.035)
Unexplained: PM2.5	-0.002	(0.142)	0.060	(0.048)	0.021	(0.035)	-0.262**	(0.125)	-0.323**	(0.130)	-0.440**	(0.208)
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Quantiles	Mean		Low		Medium		High		High-Low		Variance	

Notes: Robust standard errors are clustered by household and reported in parentheses. PM2.5 is the Particulate Matter 2.5. All specifications control for covariates as in Table 3. Full results are available from the authors.

∗ *p* <.10, ∗∗ *p* <.05, *** *p* <.01

Table 6
The Impact of Environmental Policy on Physical Health using DID Estimation.

	(1) Physical health		(2) Physical health		(3) Physical health	
Post-policy cohort * target level	0.033**	(0.015)	0.042**	(0.020)	0.024	(0.020)
Control variables	Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes	
Observations	51708		27046		24662	
Clusters	10373		9505		9579	
Method	DID-OLS		DID-OLS		DID-OLS	
Sample	Full sample		Female		Male	

Notes: Robust standard errors are clustered by household and reported in parentheses. All specifications control for covariates as in Table 3. Full results are available from the authors.
* p <.10, ** p <.05, *** p <.01

Table A1
Robustness Checks: The Impact of Environmental Policy on Physical Health for Population without Children.

	(1) Physical health		(2) Physical health	
Population without children * Post-policy cohort	-0.027	(0.165)	-0.529***	(0.194)
PM2.5	-0.005	(0.007)	-0.015**	(0.006)
Control variables	Yes		Yes	
City, month and year fixed effects	Yes		Yes	
Observations	24662		27046	
Clusters	9579		9505	
Kleibergen-Paap rk Wald F statistic	516.178		528.303	
Sample mean RIF value	3.139		2.972	
Method	IV		IV	
Sample	Male		Female	

Notes: Robust standard errors are clustered by household and reported in parentheses. PM2.5 is the Particulate Matter 2.5. All specifications control for covariates as in Table 3. Full results are available from the authors.
$*$ p <.10, $**$ p <.05, *** p <.01

Table A2
Robustness Checks: The Impact of Environmental Policy on Physical Health for Key Regions.

	(1) Physical health		(2) Physical health		(3) Physical health		(4) Physical health		(5) Physical health		(6) Physical health	
Beijing-Tianjin-Hebei region * Post-policy cohort	-0.143**	(0.073)	-0.165**	(0.077)								
Yangtze River Delta region * Post-policy cohort					-0.037	(0.157)	-0.263**	(0.111)				
Pearl River Delta region * Post-policy cohort									-0.088	(0.070)	-0.070	(0.064)
PM2.5	-0.005	(0.007)	-0.016**	(0.007)	-0.005	(0.007)	-0.016**	(0.006)	-0.005	(0.007)	-0.016**	(0.006)
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	24662		27046		24662		27046		24662		27046	
Clusters	9579		9505		9579		9505		9579		9505	
Kleibergen-Paap rk Wald F statistic	535.306		527.768		513.873		525.820		514.193		526.415	
Sample mean RIF value	3.139		2.972		3.139		2.972		3.139		2.972	
Method	IV		IV		IV		IV		IV		IV	
Sample	Male		Female		Male		Female		Male		Female	

Notes: Robust standard errors are clustered by household and reported in parentheses. PM2.5 is the Particulate Matter 2.5. All specifications control for covariates as in Table 3. Full results are available from the authors.
* p <.10, ** p <.05, *** p <.01

Table A3
Robustness Checks: The Impact of Environmental Policy on Physical Health through Greenhouse Gas Emissions by Gender.

	(1)		(2)		(3)		(4)	
	Physical health		Physical health		Physical health		Physical health	
Ozone	-0.013	(0.018)	-0.026*	(0.015)	0.052	(0.032)	0.025	(0.034)
Control variables	Yes		Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes		Yes	
Observations	7328		9120		8946		8890	
Clusters	5478		5577		5406		5395	
Kleibergen-Paap rk Wald F statistic	2318.008		2989.398		18.288		13.905	
t statistic (instrument)	-48.15		-54.68		4.28		3.73	
Method	IV		IV		IV		IV	
Sample	Male, pre-policy		Female, pre-policy		Male, post-policy		Female, post-policy	

Notes: Robust standard errors are clustered by household and reported in parentheses. All specifications control for covariates as in Table 3. Full results are available from the authors.
∗ p <.10, ∗∗ p <.05, *** p <.01

Table A4
Robustness Checks: The Impact of Environmental Policy on Physical Health and Gender Physical Health Gap using Logit Reweighting.

Panel A: partial conditional on gender	(1) Physical health		(2) Physical health	
Female	-0.176***	(0.017)	-0.165***	(0.018)
PM2.5	-0.024	(0.038)	-0.083*	(0.045)
Control variables	Yes		Yes	
City, month and year fixed effects	Yes		Yes	
Observations	24641		27067	
Clusters	9076		8922	
Kleibergen-Paap rk Wald F statistic	36.453		42.639	
Sample mean RIF value	3.016		3.081	
Method	IV		IV	
Sample	Pre-policy		Post-policy	

Panel B: gender health gap	(1) Physical health		(2) Physical health	
Gender difference	0.170***	(0.012)	0.158***	(0.012)
Explained	-0.031**	(0.013)	-0.024*	(0.014)
Pure explained	-0.040*	(0.021)	-0.016	(0.021)
Specification errors	0.009	(0.023)	-0.008	(0.023)
Pure explained: PM2.5	-0.013*	(0.007)	-0.000	(0.002)
Specification errors: PM2.5	-0.371**	(0.162)	-0.002	(0.137)
Unexplained	0.201***	(0.014)	0.181***	(0.014)
Pure unexplained	0.192***	(0.012)	0.163***	(0.012)
Reweighting errors	0.010	(0.008)	0.018**	(0.008)
Pure unexplained: PM2.5	-0.447***	(0.169)	-0.113	(0.109)
Reweighting errors: PM2.5	0.013*	(0.007)	0.001	(0.002)
Control variables	Yes		Yes	
City, month and year fixed effects	Yes		Yes	
Sample	Pre-policy		Post-policy	

Notes: Robust standard errors are clustered by household and reported in parentheses. PM2.5 is the Particulate Matter 2.5. All specifications control for covariates as in Table 3. Full results are available from the authors.
$* p < .10$, $** p < .05$, $*** p < .01$

Table A5
Robustness Checks: The Impact of Environmental Policy on Gender Physical Health Gap using JMP Method.

	(1) Physical health
Difference in differentials	-0.013
Difference in predicted gap: total effect	0.020
Difference in predicted gap: quantity effect	0.020
Difference in predicted gap: price effect	0.000
Difference in residual gap: total effect	-0.033
Difference in residual gap: quantity effect	-0.033
Difference in residual gap: price effect	0.000
Control variables	Yes
City, month and year fixed effects	Yes

Notes: Robust standard errors are clustered by household and reported in parentheses. All specifications control for covariates as in Table 3. Full results are available from the authors.
∗ p <.10, ∗∗ p <.05, *** p <.01

Table A6
Robustness Checks: The Impact of Environmental Policy on Physical Health through Air Pollution using Long Difference Model.

	(1) ΔPhysical health		(2) ΔPhysical health		(3) ΔGender physical health gap	
ΔPM2.5	0.000	(0.054)	-0.128**	(0.061)	0.057***	(0.011)
Control variables	Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes	
Observations	7573		10037		24641	
Clusters	5393		5872		9076	
Kleibergen-Paap rk Wald F statistic	17.366		19.549		31.001	
t statistic (instrument)	4.17		4.42		5.57	
Method	IV		IV		IV	
Sample	Male		Female		Full sample	

Notes: Robust standard errors are clustered by household and reported in parentheses. PM2.5 is the Particulate Matter 2.5. All specifications control for covariates as in Table 3. Full results are available from the authors.
∗ *p* <.10, ∗∗ *p* <.05, *** *p* <.01

Table A7

Robustness Checks: The Impact of Environmental Policy on Physical Health through Air Pollution using Bayesian Regression.

	(1) Physical health		(2) Physical health		(3) Physical health		(4) Physical health	
PM2.5	0.029	(0.005)	-0.093	(0.005)	0.018	(0.009)	-0.033	(0.009)
Control variables	Yes		Yes		Yes		Yes	
City, month and year fixed effects	Yes		Yes		Yes		Yes	
Observations	9591		12008		11152		11289	
Method	IV		IV		IV		IV	
Sample	Male, pre-policy		Female, pre-policy		Male, post-policy		Female, post-policy	

Notes: We provide the results of posterior mean of variable from the complete MCMC run. Posterior standard deviation is clustered by individual and reported in parentheses. We narrow our focus on individuals with poor, fair and good health status (i.e., might in the middle of health distribution). PM2.5 is the Particulate Matter 2.5. All specifications control for covariates as in Table 3. Full results are available from the authors.

∗ p <.10, ∗∗ p <.05, *** p <.01

Figure A1
Kernel Density Estimate of Distribution of Physical Health Scores.