When the Wind Blows: Agricultural Fire Exposure, Parental Investment, and Long-term Outcomes

Hai Hong; Kevin Chen[§]

Abstract:

This paper examines the medium and long-term human capital consequences of in-utero exposure to agricultural fires in rural China. Leveraging data from a nationally representative household sample, we exploit exogenous variations in birth month, fire intensity, and wind direction to identify the causal effect of fetal exposure to fire. We show that in-utero exposure to agricultural fires significantly reduces individuals' health, cognitive, and non-cognitive performance in adolescence. Tracking these cohorts into their adulthood, we find that fire exposure decreases education years and earnings. Besides the transmission of adverse conditions in early life, a key mechanism driving the persistent effect of fetal exposure is that liquidity-constrained households reinforce the negative impacts by reallocating resources (e.g., health and education investment) *away* from exposed children. Using the phased rollout of China's New Cooperative Medical Scheme (NCMS) as a quasi-experiment, we find that health insurance coverage can largely offset the deleterious effects of agricultural fire exposure by easing financial constraints and promoting parental investments. Our findings underscore the disproportionate cost of pollution on vulnerable rural families and have significant policy implications for how to mitigate the adverse effects of pollution exposure.

Key Words: Agricultural Fire; In-utero Exposure; Parental Investment; Health Insurance.
JEL Codes: Q51; Q53; D13; I13; I14.

[§] Hong: China Academy for Rural Development, School of Public Affairs, Zhejiang University (email address: haihong@zju.edu.cn). Chen: China Academy for Rural Development, School of Public Affairs, Zhejiang University; International Food Policy Research Institute (email address: kzchen@zju.edu.cn). Kevin Chen is the correspondent author.

1. Introduction

Agricultural fire is a prevalent practice in developing countries for disposing of crop residues after harvest. While it benefits agricultural production by reducing the cost of residue disposal and eliminating potential pests and diseases, it also contributes significantly to seasonal air pollution, leading to severe health and cognitive consequences (Rangel and Vogl 2019; Graff Zivin et al. 2020; He, Liu, and Zhou 2020; Lai et al. 2022; Pullabhotla and Souza 2022; Ayesh 2023; Du et al. 2024; Garg, Jagnani, and Pullabhotla 2024). This issue is particularly salient for infants, who are more vulnerable and susceptible to environmental pollutants (Currie and Neidell 2005; Currie et al. 2009; Almond and Currie 2011; Almond, Edlund, and Palme 2009; Currie et al. 2014), and the potential costs of pollution exposure (e.g., cognitive deficits, chronic diseases) may not become apparent until years after birth, leading policymakers to underestimate their long-term effects. Moreover, due to lower income and weaker health infrastructure in the rural counterparts of developing countries, fetal exposure to agricultural fires may further affect the decision of intra-household resource reallocation (Yi et al. 2015), which could even exacerbate the potential costs of pollution exposure.

In this paper, we examine the long-term effects of in-utero exposure to agricultural fires on adolescent and adult outcomes in rural China and explore potential mechanisms. To carry out the empirical analysis, we face two empirical challenges. First, since valid measures of agricultural fires (e.g., satellite observations) are only available after the 2000s, to estimate the long-term effects of fetal agricultural fire exposure for individuals born before the 2000s, we need effective proxy measures for agricultural fires. Second, to shed light on the long-term effects of pollution exposure, as well as potential mechanisms (e.g., intra-household resource allocation), we need detailed data that records individuals' health and non-health outcomes (e.g., cognitive and labor market performance) and parental investment.

To address the first challenge, we resort to exogenous agricultural potential yield and borrow insights from previous studies to construct measures for upwind/downwind potential yield (e.g., Rangel and Vogl 2019; He, Liu, and Zhou 2020; Lai et al. 2022). We provide a set of verification tests in Section 4 to show that the upwind/downwind potential yield measures are valid proxies for agricultural fire intensity and air pollution (e.g., $PM_{2.5}$) across different counties. To address the second challenge, we exploit a nationally representative household dataset, the China Family Panel Studies (CFPS), which records detailed health and (non-)cognitive measures for adolescents and the corresponding parental investment (e.g., health and education expenditure). The CFPS also tracks adolescents into adulthood, allowing for an examination of the labor market impacts of in-utero agricultural fire exposure. In addition, CFPS records retrospective questions on early-life conditions (e.g., health at birth and age 1), which enables us to investigate how in-utero agricultural fire exposure affects early-life outcomes.

We begin by estimating the effects of in-utero agricultural fire exposure on the health, cognitive, and non-cognitive outcomes of adolescents. Our identification hinges on three sources of plausibly exogenous variations. The first is variations in individuals' birth month, which we exploit to determine during which trimester the individual is exposed to agricultural fires. The second is variations in fire intensity across different counties, proxied by agricultural potential yields. We augment our identification by including a third variation in wind direction, which allows us to implement an upwind-downwind specification that eliminates potential income effects that may confound our identification. Our results suggest that in-utero agricultural fire exposure can have significant deleterious effects on adolescent development. Specifically, we find that agricultural fire exposure leads to worsened health outcomes (measured by a composite index combining information on self-reported health, hospitalization, and chronic respiratory disease), cognitive outcomes (measured by standardized word test scores), and non-cognitive outcomes. Additionally, we show that the estimated effects are more pronounced if individuals are exposed to agricultural fires during the first and third trimesters, which is in line with previous literature in economics and epidemiology (Glinianaia et al. 2004; Šrám et al. 2005; Currie and Neidell 2005; Kannan et al. 2006; Currie et al. 2014; Rangel and Vogl 2019). The effects are stronger for boys than girls, possibly because male fetuses are more susceptible to in-utero pollution exposure. We find no effects on urban adolescents.

Due to the panel structure of the CFPS, we are able to track the same adolescents into their adulthood, which allows us to explore the effects of in-utero agricultural fire exposure on educational and labor market outcomes. Our findings reveal that fire exposure can significantly lower the number of years of education. Conditional on entering the labor market, we show that exposed cohorts earn lower annual wages and are more likely to work in the agricultural sector.

We then proceed to explore the potential mechanisms through which in-utero exposure to agricultural fires leads to persistent effects. As suggested by Currie et al. (2014), there are at least two channels through which early-life exposure to air pollution translates into long-term consequences. The first is the direct channel through the transmission of adverse early life outcomes, and the second is the indirect channel through intra-household resource reallocation, i.e., parental investment. While the sign of the first channel is theoretically unambiguous, parental investment in responding to the adverse health shocks could be either reinforcing or compensating.[1] To shed light on these potential mechanisms, we first examine how agricultural fire exposure worsens early-life health conditions. We find consistent evidence that in-utero agricultural fire exposure increases the number of illnesses at age 1, and leads to shortened gestation months and lower birth weight.

Next, we investigate how parents respond to negative health shocks induced by agricultural fire exposure. We show that parents reduce both health and education investment in children who are exposed to agricultural fires, consistent with reinforcement behavior. Exploring the potential heterogeneity, we find that the reduction in parental investments is primarily driven by mothers with lower education levels and households with lower income. This suggests that liquidity constraints may be an important driver that explains why rural households reduce their investment in exposed children. Moreover, our results also imply that the consequences of agricultural fire exposure are unevenly distributed across rural households, with more disadvantaged households being more severely affected.

Given that agricultural fires can have significant adverse long-term effects on rural adolescents and that parental responses could even reinforce such negative impacts, a critical policy question is what measures can be taken to mitigate the adverse pollution effects. In the last part of our empirics, we investigate the effects of the provision of public health insurance on mitigating the effects of agricultural fire exposure. To this end, we leverage the sequential rollout of the New Cooperative Medical Scheme (NCMS) in rural China (see Section 2.3 for a more detailed description of the program), which is the largest insurance program in history (Gruber, Lin, and Yi 2023). The NCMS program is financed by low individual contributions and high government payments and offers generous subsidies for inpatient expenses. We follow Huang and Liu (2023) and denote individuals who were less than 5 years old when the NCMS program was implemented as those exposed to the policy. We find that, for individuals who are exposed to the NCMS program, in-utero exposure to agricultural fires has no significant effect on adolescent outcomes, which suggests a mitigating role of public health insurance coverage. Moreover, we provide evidence that the mitigating role of the NCMS program is mainly through increasing parental investments, especially for those more disadvantaged households, and find no evidence that NCMS exposure can mitigate adverse health outcomes at birth.

This paper speaks to three strands of literature in environmental and health economics. First, we add to

[1] The compensatory channel suggests that family would invest more on children who are more exposed to pollution, while the reinforcing channel suggests that family would invest more on children who are less exposed to pollution, as the return to human capital is higher.

the burgeoning literature that examines the consequences of air pollution from agricultural fires (Rangel and Vogl 2019; Graff Zivin et al. 2020; He, Liu, and Zhou 2020; Lai et al. 2022; Pullabhotla and Souza 2022; Ayesh 2023; Du et al. 2024; Garg, Jagnani, and Pullabhotla 2024). While much of the existing research focuses on the contemporaneous effects of exposure to agricultural fires and a wide range of health and behavioral outcomes (see more detailed discussion in Section 2.2), our paper is among the first that systematically investigate the long-term consequences of in-utero exposure to agricultural fires. One related paper is Carneiro, Cole, and Strobl (2024), which examines the effects of in-utero exposure to agricultural fires on students' test scores. Our paper differs in providing more comprehensive evidence on how in-utero agricultural fire exposure leads to health and (non-)cognitive consequences in adolescence and labor market outcomes in adulthood, and shedding light on the potential mechanisms. More broadly, we contribute to the literature that estimates the long-term effects of early-life pollution exposure (Chen et al. 2013; Isen, Rossin-Slater, and Walker 2017; Ebenstein et al. 2017; Anderson 2020; Barreca, Neidell, and Sanders 2021). While most of the existing studies focus on the effects of air pollution on urban residents, there is a lack of research that estimates the long-term consequences of pollution exposure for the rural sample, who are more vulnerable to pollution exposure due to income volatility and limited access to health facilities.

Second, we contribute to the literature by empirically examining the mechanisms through which in-utero exposure to air pollution can have long-term consequences (Currie et al. 2014). While there is a vast strand of literature that estimates the long-term consequences of early-life/prenatal pollution exposure (e.g., Bharadwaj et al. 2017; Isen, Rossin-Slater, and Walker 2017; Black et al. 2019; Rosales-Rueda and Triyana 2019; Von Hinke and Sørensen 2023; Ferro et al. 2024; Chen 2025), surprisingly, only a scant amount of literature investigates the potential mechanisms. We add to this broad literature by providing the first empirical evidence on how prenatal exposure to air pollution affects the human capital investment in rural China. Our finding reveals that rural households make reinforcing investments in their children, which suggests an amplification of the effects of in-utero exposure to air pollution. In doing so, we also echo the emerging literature on how early life shocks affect intra-household human capital investment and formation (Yi et al. 2015; Adhvaryu and Nyshadham 2016; Bharadwaj, Eberhard, and Neilson 2018). While the empirical evidence is mixed on how families make compensatory or reinforcing investments in response to early life shocks, our finding suggests that the liquidity constraints and limited access to health insurance may be the reasons that explain why rural households make reinforcing investments in children exposed to prenatal air pollution.[2]

Lastly, we contribute to the literature that investigates the impacts of public health insurance, more specifically, the provision of the New Cooperative Medical Scheme (NCMS) in rural China (Lei and Lin 2009; Wagstaff et al. 2009; Chen and Jin 2012; Cheng et al. 2015; Gruber, Lin, and Yi 2023; Huang and Liu 2023; Wang, Wu, and Yuan 2024). While the majority of the literature investigates the potential benefits of health insurance coverage (e.g., increased consumption, education, and reduced mortality), our paper highlights additional benefits of how the coverage of health insurance can mitigate the adverse effects of in-utero air pollution exposure. In doing so, we add to the recent literature that examines how later intervention can mitigate the negative effects of early life shocks (Billings and Schnepel 2018; Duque, Rosales-Rueda, and Sanchez Torres 2019). Our finding suggests that the provision of health insurance can increase parental

[2] Focusing on China, Yi et al. (2015) show that parents act as a net equalizer in which they increase health investment and reduce education investment to children who suffer from negative early health shocks, while our finding implies that for children who exposed to prenatal air pollution, family reduces both health and education investment, possibly because fatal pollution exposure can have both health and cognitive consequences. Using data from Chile, Bharadwaj, Eberhard, and Neilson (2018) find that parents make compensatory investment regarding initial health. Leveraging large-scale iodine supplementation program in Tanzania, Adhvaryu and Nyshadham (2016) indicate that children with higher program exposure receive more parental investment, which favors the compensatory mechanism.

investment, which largely mitigates the deleterious effects of in-utero pollution exposure.

2. Background and Literature

2.1 Agricultural fires and air pollution

In rural China, fire has long been a widely used technology for clearing the fields since ancient times. The earliest written record of the use of agricultural fires, found in the "Fundamental Arts for the People's Welfare" (QIMIN Yaoshu in Chinese), dates back to the North Wei dynasty (386-534 AD). It is also commonly believed that the ashes from burning the crop residues can fertilize the soil (Hays et al. 2005), while the heat generated during the burning process can eliminate the hidden pests (Graff Zivin et al. 2020; He, Liu, and Zhou 2020; Nian 2023). Following the abolition of the People's Commune in the 1980s, grain production in China increased rapidly (Lin 1992), and the country has since become the largest producer of both grain and straw globally. Wheat, maize, and rice are the primary sources of straw, contributing to over 80% of the total straw production in China.[3]

The rapid increase in grain production has, however, created significant challenges in the disposal and management of crop residues. Due to the benefits of crop burning for agricultural cultivation and production, approximately 31% of crop residues are burned *in situ* (Graff Zivin et al. 2020). However, the burning of these residues generates considerable particulate matter, particularly $PM_{2.5}$, contributing to elevated air pollution (Rangel and Vogl 2019; He, Liu, and Zhou 2020; Garg, Jagnani, and Pullabhotla 2024).[4] For example, He, Liu, and Zhou (2020) document that 10 additional agricultural fires will lead to a 4.79 $\mu g/m^3$ increase in monthly $PM_{2.5}$. Shi et al. (2014) show that in agricultural production areas during the harvest season, the share of fine particulate matter emitted from agricultural fires exceeds more than 50% of the total regional emissions and that pollutant emissions from burning significantly increased the occurrence of regional haze. Despite regulations on crop burning being introduced as early as the 1990s, their enforcement has remained ineffective due to the high costs of monitoring and enforcement (Nian 2023). It was not until 2013 that the Chinese government launched a new round of campaign-style regulation that aimed to comprehensively reduce the number of agricultural fires (Wang, Wang, and Yin 2022; Cao and Ma 2023).

Besides China, the burning of agricultural biomass is a common phenomenon in other developing countries, especially those growing staple foods (e.g., India, Thailand, Vietnam, and the Philippines). It is estimated that every year, after the rice harvest, about 2.5 million farmers in northwestern India burn the remaining straw *in situ* (Keil et al. 2021). And study by Kim Oanh et al. (2018) indicates that the air pollution caused by agricultural fires in Vietnam and the Philippines has already exceeded the pollution caused by forest fires.

Several attributes of agricultural fires make them an intriguing source of air pollution and have drawn growing attention in the literature. First, unlike previous studies that exploit either natural or quasi-experiments as the source of variation to examine the effects of air pollution (e.g., Chay and Greenstone 2003; Almond, Edlund, and Palme 2009; Sanders 2012; Chen et al. 2013; Isen, Rossin-Slater, and Walker 2017; Gong et al. 2023), the burning of agricultural biomass is a seasonal and regular activity amid the production of agricultural goods (e.g., wheat, maize, and rice). Moreover, the pollution generated from agricultural fires is relatively lower than traditional sources of industrial pollution (Rangel and Vogl 2019). As numerous

[3] According to the World Bank data, China's agricultural value added accounted for 31.1 percent of the world's total agricultural value added in 2021. See https://www.gov.cn/xinwen/2022-11/02/content_5723319.htm.

[4] It is estimated that air pollution from agricultural burning involves around 30 million people globally (Landrigan et al. 2018).

studies have indicated that even pollution well below the safety standards can have detrimental effects on human health (Janet Currie et al. 2009; Aizer et al. 2018), it is thus important to understand the effects and magnitudes of such seasonal and (relatively) low-level pollution. Second, while the literature provides significant insights into the adverse effects of industrial air pollution (e.g., Ebenstein 2012; Greenstone and Hanna 2014; Hanna and Oliva 2015; Anderson 2020; Bombardini and Li 2020; Barreca, Neidell, and Sanders 2021), much less is known about the potential costs of agricultural air pollution. This is, nevertheless an important issue given that rural populations, often facing pervasive poverty and limited access to public health insurance, may be more vulnerable to the deleterious effects of pollution.

2.2 Fire-induced pollution and related consequences

There is now a burgeoning strand of literature that investigates the broad impacts of fire-induced pollution. Rangel and Vogl (2019) is the first paper in economics that studies the effects of agricultural fires and shows that in-utero exposure to agricultural fires increases infant mortality in Brazil. Carneiro, Cole, and Strobl (2024) extend the results from Rangel and Vogl (2019) and show that in-utero exposure to agricultural fires reduces adolescents' cognitive ability. Focusing on China, He, Liu, and Zhou (2020) investigate the impacts of short-term exposure to agricultural fires and elderly mortality, while Lai et al. (2022) find that air pollution from straw burning significantly decreases the cognitive function of the elderly. Graff Zivin et al. (2020) studied the effects of agricultural fires that occurred during high-stakes exams on students' performance and find that temporary exposure to agricultural fires significantly decreases students' scores. Using exogenous variation from the construction of rural roads in India, Garg, Jagnani, and Pullabhotla (2024) find that rural roads increase labor exit and result in more crop fires, which in turn lead to an increase in infant mortality in the downwind region. Using detailed data from blood pressure testing, Pullabhotla and Souza (2022) find that the number of upwind fires observed one day before blood pressure testing significantly increases the risk of hypertension. Ayesh (2023) studies the impacts of burning agricultural biomass on crime activities and finds that it increases all types of crimes, particularly violent crimes.

Besides agricultural fires, there are several studies that investigate the impacts of other types of fires (e.g., forest fires). To name a few, Jayachandran (2009) studies the short-term impacts of exposure to Indonesia's forest fires and finds that prenatal exposure to air pollution caused by wildfires increases child mortality. Rosales-Rueda and Triyana (2019) investigate the persistent consequences of the 1997 Indonesian forest fire and find that it leads to significant increases in the presence of stunts and decreases in lung capacity. Borgschulte, Molitor, and Zou (2024) and Coulombe and Rao (2025) investigate the impacts of wildfires on labor market outcomes and find that exposure to wildfires decreases local employment growth and reduces quarterly earnings. Du et al. (2024) study the effects of transboundary vegetation fire in Southeast Asian countries on expressed sentiment and find that increases in upwind fire decrease sentiment scores.

2.3 The New Cooperative Medical Scheme (NCMS)

The introduction of the New Cooperative Medical Scheme (NCMS) is a great progress of the health system in rural China (Wang, Wu, and Yuan 2024). Before the introduction of NCMS in the 2000s, the vast population in rural China had very limited access to health insurance (either private or public), and was vulnerable to health shocks (Hu et al. 2008; Yip and Hsiao 2008). Typically, more than 90 percent of rural residents had no health insurance throughout the 1990s, with a significant number of households being pushed back into poverty due to unaffordable out-of-pocket payments for health care (Huang and Liu 2023).

The NCMS program was introduced in 2003 and progressively rolled out at the county level. Following guidelines set by the central government, each province is required to select at least two to three pilot counties in the first year of NCMS introduction (Gruber, Lin, and Yi 2023). Over time, additional counties were gradually incorporated, with the goal of achieving nationwide coverage by 2010. In Appendix Figure A1, we show the geographic distribution of the timing of NCMS adoption across different counties. It is evident that, following the vast expansion between 2003 and 2008, nearly all counties have adopted the NCMS. The enrollment rate amounted to 78.6% during the first three years of NCMS expansion (You and Kobayashi 2009). Within six years after its initial launch, the NCMS had expanded to cover over 800 million rural residents, making it the largest health insurance program in modern history (Gruber, Lin, and Yi 2023).

The NCMS program is eligible for only households with local agricultural *Hukou*.[5] Though voluntary, the enrollment rate is particularly high since it is financed by low individual contributions and high government payments, which are shared between local and central governments (Gruber, Lin, and Yi 2023; Huang and Liu 2023).[6] Though being a national policy, the design and implementation of the NCMS program are characterized by great discretion at the local county level. In particular, while all NCMS programs cover inpatient medical care, enrolled counties differ in their coverage for outpatient care. For example, while all counties that adopt the NCMS program offer a 50% subsidy for inpatient expenses, only approximately 80% of counties cover both inpatient and outpatient expenses (Lei and Lin 2009; Wagstaff et al. 2009; Gruber, Lin, and Yi 2023).[7] In addition, the coverage of outpatient care is also heterogeneous across counties. Specifically, within counties that cover outpatient expenses, 25% of counties provide direct payment for outpatient care, while the remaining 75% of counties set up mandatory medical saving accounts that would be used to pay for outpatient care (Burns and Liu 2017). The mandatory saving account is contributed to by both individuals and the government, with the sharing rule determined by local governments (Milcent 2018). Since 2007, more counties have started to incorporate outpatient expenses into the program (Huang and Liu 2023).

There is a modest but emerging strand of literature that investigates the broad impact of the NCMS program (Lei and Lin 2009; Wagstaff et al. 2009; Chen and Jin 2012; Cheng et al. 2015; Gruber, Lin, and Yi 2023; Huang and Liu 2023; Wang, Wu, and Yuan 2024). For example, Chen and Jin (2012) show that the introduction of the NCMS program has significantly improved the school enrollment of six-year-olds, while having limited impacts on child and maternal mortality. Exploiting a cohort difference-in-difference design, Huang and Liu (2023) document that early-life exposure to NCMS has significantly improved both the health and cognitive outcomes of rural adolescents. Focusing on the elderly, Cheng et al. (2015) find that the NCMS improved daily living activities and cognitive functions, while Gruber, Lin, and Yi (2023) indicate a substantial reduction in elderly mortality. We link the adoption of NCMS with air pollution from agricultural fires and investigate whether the introduction of health insurance can alleviate the long-term effects of pollution exposure.

3. Data

To estimate the effects of agricultural fires on long-term outcomes, we assemble data from multiple

[5] The *Hukou* system, introduced after the founding of the People's Republic of China, is a household registration system that classifies citizens into two categories: agricultural and non-agricultural *Hukou* holders. This classification plays a crucial role in determining an individual's eligibility for social services and welfare, which are tied to their place of registration. *Hukou* status is inherited from one's parents and is subject to strict government controls, making changes to *Hukou* type or registered location highly restricted.

[6] For instance, the average payment of the NCMS was 246 RMB in 2011 (approximately 35 USD), of which 84 percent was financed by the government, and households were only required to contribute 39 RMB annually per person.

[7] The remaining 20% counties only cover outpatient services for catastrophic diseases or did not cover outpatient services at all.

sources, including individual surveys that document adolescent outcomes and track cohorts into their adulthood, satellite-derived measures of agricultural potential yield, agricultural fires, air pollution, and other meteorological variables. Additionally, to investigate the mitigating role of rural health insurance, we also collect the timing of NCMS implementation across counties. In what follows, we introduce these data in turn, illustrate how we merge across different datasets, and present summary statistics.

3.1 The China Family Panel Studies (CFPS)

Our primary data source is from China Family Panel Studies (CFPS), a nationwide survey data implemented by the China Social Science Survey Center of Peking University, which has been conducted biennially as a tracking survey since 2010. It covers 162 counties in 25 provinces in China, representing 94.5% of the country's total population (Xie 2012). The survey is conducted on a household basis for each member of the household, and baseline households are continuously tracked in subsequent surveys.

We rely on CFPS 2010 to explore the effects of in-utero exposure to agricultural fires on adolescent outcomes and provide supplemental evidence on adult outcomes using CFPS 2020. We include only the sample that had a local *Hukou* and were born and resided in the county at age 3 and at the time of the survey, so that the sample would be most likely to be measured with correct exposure intensity and suffer less concerns of endogenous migration. We primarily focus on the effects on the rural sample where the agricultural fire occurs, but for the following empirical exercises, we will also present the corresponding results for the urban sample for either comparison or falsification tests.

Besides birth year, CFPS 2010 additionally provides the birth month of each individual, which we exploit as a source of variation to distinguish the effects of exposure to agricultural fires during different trimesters. Specifically, we denote the last 3 months prior to the birth month as the third trimester, the 3-6 months before birth as the second trimester, and the 6-9 months before birth as the first trimester. Since we do not have data on the exact birth date, this definition of trimesters may be measured with error. Nevertheless, as long as the date of birth is randomly distributed, such measurement error would only lead to an underestimation.

To ensure that our results are not driven by the selection of different birth months, we visualize the distribution of birth months in Figure 1. Though not perfectly balanced, the distribution of birth months is relatively flat and we observe no significant spikes at first glance. This alleviates the potential concerns that parents may strategically choose the timing of birth to avoid pollution exposure.[8] We provide more solid statistical evidence in our subsequent empirical analysis to show that the birth month is not correlated with potential exposure to agricultural fires.

We measure the health and cognitive outcomes of adolescents using the CFPS 2010. Specifically, we measure the health outcomes of adolescents using three variables. The first variable is a categorical measure of general health status, which is self-rated and ranges from 1 to 5 (1 = very good, 2 = good, 3 = fair, 4 = poor, 5 = very poor). We define a dummy variable for not-in-good health, which takes the value of 1 if the self-rated health status is greater than 3 (i.e., poor or very poor), and 0 otherwise. The second variable is a dummy variable indicating whether the adolescent was hospitalized due to illness in the previous year. The third variable measures the occurrence of respiratory diseases, which are more closely related to air pollution. Specifically, we use the illness type classification provided in the CFPS to identify whether the adolescent

[8] Since most of our sampled individuals born during the 1990s, we believe that the selection of birth month due to air pollution is less plausible. First, the information on air quality is relatively scarce back in that time, and the construction of air quality monitoring stations does not begin until 2000s, which are measured with great error due to local discretion (Greenstone et al. 2022). Second, the public awareness on the detrimental effects of air pollution is relatively low (Xie, Yuan, and Zhang 2023; Barwick et al. 2024).

has respiratory diseases.[9] To avoid issues with multiple hypothesis testing, we create an unhealthiness index by first standardizing the three health variables, and then calculating the simple average of their standardized z-scores (Boudreaux, Golberstein, and McAlpine 2016; Hoynes, Schanzenbach, and Almond 2016). We measure the cognitive abilities of adolescents using two test scores, i.e., a word test score and a math test score. To ensure comparability across different age cohorts, we calculate the age-specific standardized z-scores for both test scores (Huang and Liu 2023).

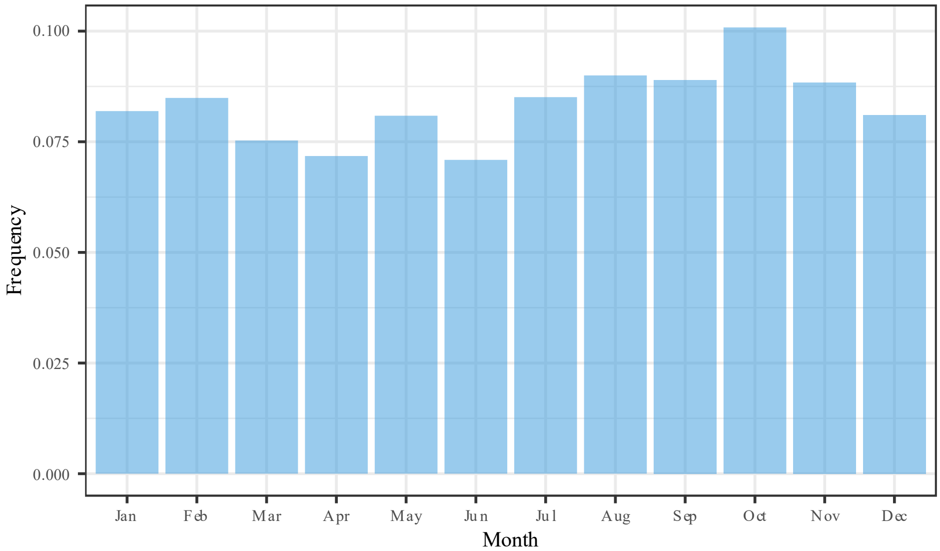

Figure 1 The Distribution of Birth Month

Notes: This figure presents the distribution of birth months of adolescents surveyed in CFPS 2010.

In addition, CFPS 2010 asks adolescents about their attitudes toward a range of statements (e.g., "I decide my own life goals" or "Some children are born lucky"), which we exploit to reflect the personal traits of the respondents. Individuals respond with their level of agreement on each statement, which we re-coded as categorical variables ranging from 1 to 5, with greater values representing a higher degree of agreement. We divide these statements into two broad categories reflecting positive and negative attitudes.[10] We then follow Grönqvist, Nilsson, and Robling (2020) and use the principal component analysis (PCA) to combine these subscores into two general measures of noncognitive ability (reflecting positive and negative attitudes toward life).

Besides current outcomes, CFPS 2010 also provides retrospective data on birth conditions, which enables an investigation of the effect of in-utero exposure to agricultural fires on health outcomes at birth. This serves as a potential channel for the long-term effects of fire-induced air pollution. Specifically, we measure health at birth with three outcome variables. The first is the number of illnesses at age 1. The second is the length of the gestation period (measured in months). The third is the birth weight (measured in 500 grams).

To investigate the channel of intra-household resource allocation, we use two additional measures of

[9] These include upper respiratory tract infections, pneumonia, chronic laryngitis, emphysema, other chronic obstructive pulmonary diseases (including chronic bronchitis), asthma, and other respiratory diseases.

[10] Specifically, statements that reflect positive attitudes include (1) "I pursue my own values instead of following others", (2) "I decide my own life goals", (3) "Once I start something, I have to finish it no matter what", and (4) "I am the kind of person who believes that planning ahead will make things better". Whereas statements that reflect negative attitudes include (1) "Some children are born lucky", (2) "Don't spend too much time trying, because it will never prove to be useful", (3) "Once you make a mistake, it's almost impossible to correct it", (4) "The best way to deal with problems is not to think about them", and (5) "When bad things are about to happen, they are going to happen no matter how hard you try to stop them".

health expenditure and education expenses to proxy for the parental investment in adolescents' human capital.

We include several control variables to mitigate concerns of omitted variable bias. Specifically, we control for the age and gender of adolescents, parental age, birth month, and education. We also include controls for family income, family size, and number of siblings.

To estimate the effects of in-utero exposure to agricultural fires on adulthood outcomes, we track adolescents in CFPS 2010 (aged between 10-15 at the time of survey) to CFPS 2020 using the unique individual ID. We measure the effects of fire exposure on educational attainment and labor market outcomes using three variables. The first variable is the number of years of schooling completed. Since some individuals may not have finished their education by the time of the survey, we normalize this by age to calculate age-specific years of schooling. The second measure is the annual wage. Given that some individuals may not be participating in the labor market, we restrict our sample to those with non-zero earnings. The third measure is a dummy variable indicating whether the individual works in the agricultural sector, which generally requires lower skills compared to work in the manufacturing sector. Panel A of Table A1 provides summary statistics for the above variables.

3.2 Agricultural fires and potential yield

The agricultural fire data used in our paper is sourced from NASA's MODIS aboard the Terra and Aqua satellites, which has been frequently used in recent studies on agricultural fires (Cao and Ma 2023; Nian 2023). These satellites pass over China twice daily, typically occurring between 10 am and 3 pm, and between 9 pm and 2 am China Standard Time. We identify agricultural fires by leveraging land cover data from the China Land Cover Dataset (CLCD), a remotely sensed product providing nationwide land type classifications at 30-meter resolution from 1990 to 2020 (Yang and Huang 2021). We match the fire point data to the land cover raster and define fires as agricultural fires if they occur within cropland pixels. The satellites started to record fire points in November 2000, and we have no available data on fire records prior to this time point. Since the majority of our sampled individuals were born before 2000 (aged between 10-15 in 2010), this data limitation prevents us from directly estimating the effects of the number of fires on adolescent and adult outcomes.

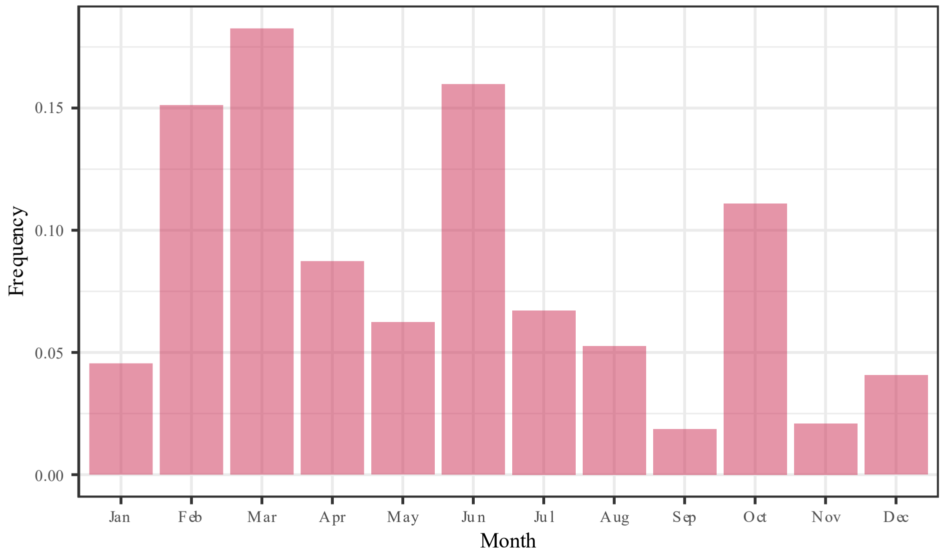

Figure 2 The Distribution of the Fire Month

Notes: This figure presents the distribution of fire months, which is defined as the month with the highest agricultural fire frequency.

That said, the occurrence of agricultural fire still provides useful information for our research design. Since we identify the effects of fire exposure primarily using variations in the birth month (and thus exposure to fires during different trimesters), it's essential to pin down the month with the highest frequency of agricultural fires. To do so, we calculate the total number of agricultural fires within each county-month cell from 2001 to 2019, and determine the month with the highest frequency of fires for each county (hereafter referred to as "fire month"). To reduce measurement error, we omit counties with fewer than 100 fire points and assign a month as a fire month only if the fire frequency is at least 30% of the total frequency. Figure 2 presents the distribution of fire months. Unlike the distribution of birth months, the distribution of fire months is uneven. We see three peak months in the figure: March (February), June, and October. The three months correspond to the spring peak of straw burning activities in the northeastern region, the summer and autumn peaks in the central and southern regions. The change of fire months across different counties provides sufficient variation for our identification. Specifically, by comparing the fire month with the birth month of each individual, we are able to pin down the trimester during which the individual is exposed to agricultural fires.

Since data on agricultural fires is not available for our sampled cohorts, we need a valid proxy to produce convincing estimates. To this end, we use the agricultural potential yield calculated using the Global Agro-Ecological Zones (GAEZ) model as a proxy for the occurrence of agricultural fires.[11] The data used in this paper is from Liu, Xu, and Chen (2015), who constructed the potential yield raster for China at 1km resolution using different crops.[12,13] For instance, the top three crops used for data construction are wheat, maize, and rice, which are the main contributors to crop residues.

Formally, for the potential yield to be a valid proxy for agricultural fire and air pollution, we processed the data with the following steps. In the first step, we create grid-level data covering the entire China's territory and map the potential yield raster with the grid. In the second step, we match this grid with the county shapefile and determine the relative location of the grid to the county center based on longitude and latitude. In the third step, we leverage the wind direction (described in the next subsection) for each county's fire month and determine whether a specific grid is located in the upwind or downwind direction of a county.[14] Appendix Figure A2 gives an illustration of how we define the upwind direction. Finally, we calculate the county-level average potential yield for both upwind grids and non-upwind grids. If the potential yield is indeed a valid proxy for agricultural fires and air pollution, we should find strong evidence that the potential yield is positively correlated with both the number of agricultural fires and air pollution. Moreover, we should observe that, while both upwind and non-upwind potential yield correlate with agricultural fire occurrence, only upwind potential yield should have statistically significant predictive power on air pollution. We empirically provide valid support for these hypotheses in the next section.

[11] The GAEZ model first estimates the light-temperature production potential for a crop based on temperature and solar radiation, then combines water availability, soil properties, and topography to estimate the light-temperature-water production potential. It simulates the climatic production potential under ideal conditions and, considering factors like agricultural technology and arable land distribution, calculates the food production potential of each raster using a step-by-step limiting method.

[12] For more details on the data description, see https://www.resdc.cn/DOI/doi.aspx?DOIid=43.

[13] Liu, Xu, and Chen (2015) construct the potential yield data from 1970 to 2010 (in 10-year intervals). To avoid potential endogeneity, we use the potential yield data measured in 1990 and use data measured in alternative years as robustness checks.

[14] In our baseline specification, we use a criterion of 45 degree to determine whether a grid is located in the upwind, downwind, or non-wind direction. Alternative definitions of upwind direction are used as robustness checks.

3.3 Air pollution and other meteorological data

We measure air pollution using $PM_{2.5}$, the major pollutant emitted from agricultural fires. We obtain ground-level PM2.5 data from the NASA Socioeconomic Data and Applications Center (SEDAC).[15] The dataset combines AOD retrievals from multiple satellite algorithms and exploits the GEOS-Chem chemical transport model to relate the total column measure of aerosol to near-surface PM2.5 concentration. Calibration is performed using Geographically Weighted Regression (GWR) to produce the final products. We aggregate the raw raster data of PM2.5 concentrations, originally captured at a 1km resolution, to the county level and compute the year-month average of PM2.5 concentration for each county.

We obtain meteorological data from the fifth-generation European Center for Medium-Range Weather Forecasts reanalysis dataset (ECMWF ERA-5). The ERA-5 dataset provides hourly, daily, and monthly atmospheric conditions at a resolution of 0.1 degrees (which is approximately 11km). We download a sequence of monthly weather conditions, including temperature, precipitation, humidity, sea level pressure, and wind speed. We collapse the weather data to the county-year-month level.

The weather data serves two purposes. On the one hand, it allows for a more precise estimation of the effects of agricultural fires, as well as the potential yield on air pollution. More importantly, it allows us to control for the confounding effects of other in-utero weather conditions. For instance, a large strand of literature has shown that in-utero or early-life exposure to exogenous weather shocks (e.g., extreme heat, rainfall, drought, flood, etc.) could have both short-term impacts on birth outcomes and enduring effects on individuals' life trajectories (Maccini and Yang 2009; Shah and Steinberg 2017; Wilde, Apouey, and Jung 2017; Rosales-Rueda 2018). To account for the confounding effects of these weather conditions, we control for the in-utero exposure to weather shocks by calculating the weather conditions experienced during each trimester.

3.4 NCMS rollout

We manually collect the data on the implementation timing of NCMS across counties from multiple sources, including news and media coverage, government announcements, and other documents. Appendix Figure A1 provides the geographic distribution of the rollout timing of the NCMS policy. To define whether the individual is exposed to the NCMS policy, we follow Huang and Liu (2023) and denote individuals who were less than 5 years old when the NCMS policy was implemented as those exposed to the policy. Appendix Table A2 provides summary statistics and balance tests between cohorts exposed and not exposed to the NCMS policy, finding limited evidence that exposure to the NCMS is based on the selection of individual covariates.[16] To control for other concurrent early-life exposures that may confound the effects of NCMS exposure, we also control for some village-specific characteristics (e.g., accessibility to infrastructure, education, and health facilities) and other village-cohort confounders, e.g., early-life exposure to tap water (Chen, Li, and Xiao 2022; Li and Xiao 2023).

3.5 Summary statistics

Appendix Table A1 presents the summary statistics for the main variables used in our empirical analysis. Panel A provides summary statistics for individual variables, separately for rural and urban samples. As shown in the table, rural adolescents are generally more disadvantaged in terms of health and cognitive

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[15] The data is from (Hammer et al. 2020; 2022). See more details from https://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod-v4-gl-03.

[16] Since the timing of the NCMS rollout is plausibly not randomly assigned (Gruber, Lin, and Yi 2023), we also report the results of the balance tests conditional on a set of county characteristics. Conditional on these additional characteristics does not alter our results. See Appendix A for more details.

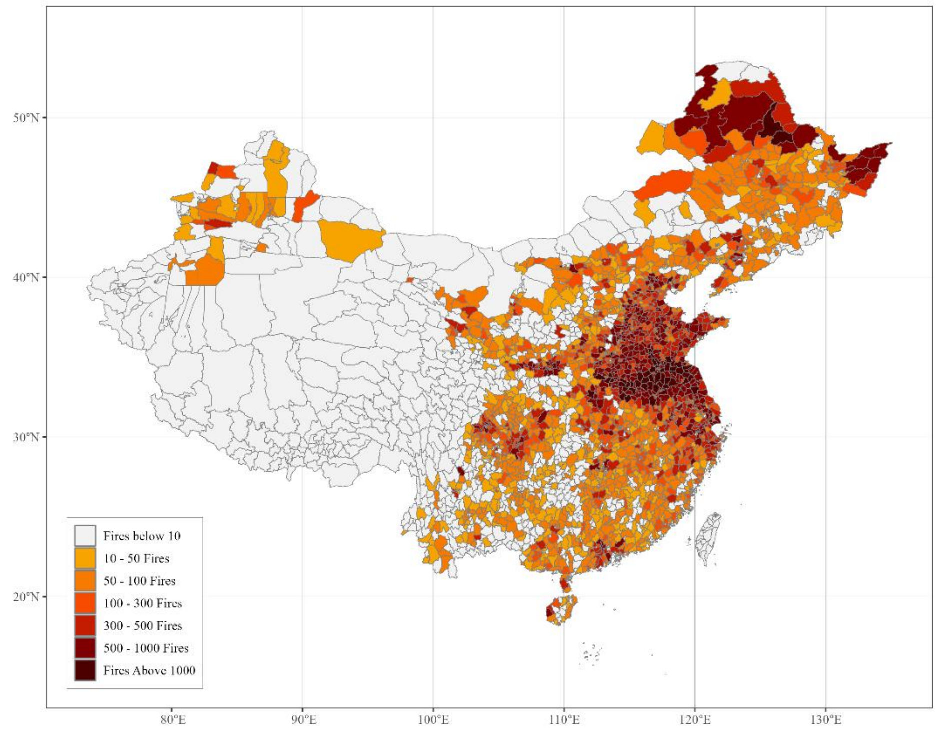
outcomes compared with urban adolescents. We see that rural adolescents report that they are more likely to feel in bad health (twice as the urban sample), while reporting (slightly) fewer hospital admissions than the urban adolescents. This may be the result of inadequate access to health facilities. In general, rural adolescents are less likely to have respiratory disease than urban adolescents. This is plausible given that the air quality in urban regions is worse than that in rural areas. We also note that urban adolescents, on average, have better cognitive performance than rural adolescents. Tracking these adolescents ten years later, we find that rural individuals are more likely to complete less education and are more likely to enter the labor market: more than half of the rural sample have already started to work in 2020, while only a quarter of the urban sample have. Finally, the rural sample is more likely to stay in the agricultural sector.

We also find that there is a relative balance in which trimesters individuals were exposed to agricultural fires. Ideally, the probability that an individual was exposed to agricultural fires at a specific trimester is 0.25 if both fire month and birth month are randomly distributed. The summarized mean is close to this probability, and we observe no significant difference between the rural and the urban sample, both of which suggest that the selection of birth month is less likely to occur.

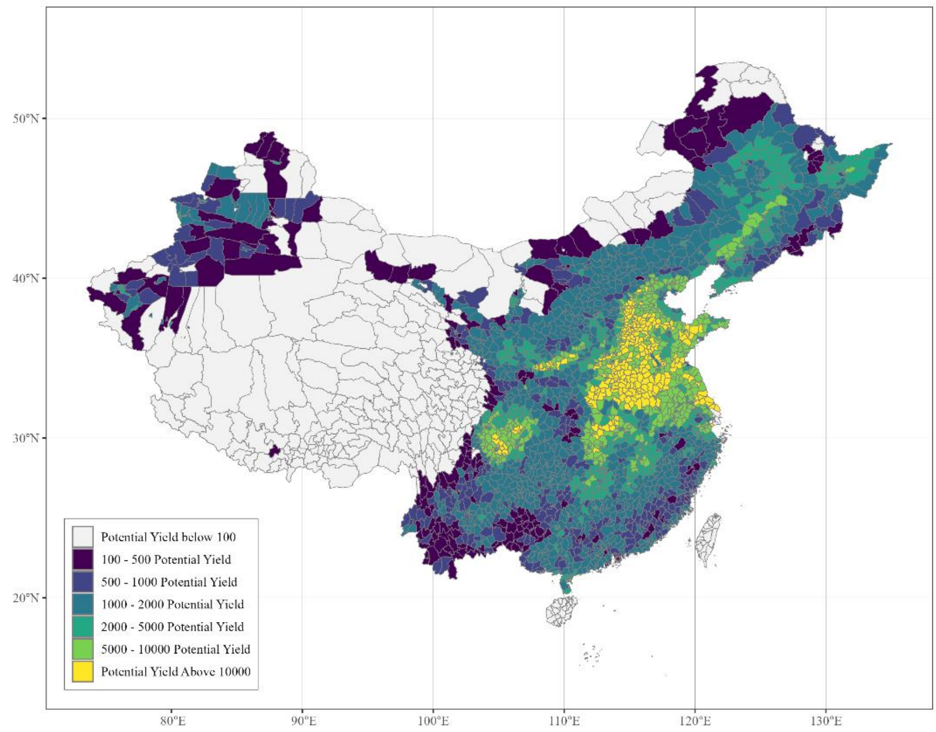
We present summary statistics for county variables in Panel B of Table A1. Except for potential yield variables, all variables are defined at the county-year-month level. Data on agricultural fires is only available from 2001 onward, while data on $PM_{2.5}$ and other meteorological variables are available from 1990 onward. For agricultural potential yield, we report both the upwind and downwind potential yield. Not surprisingly, the two variables are nearly identical regarding the mean and the standard deviation, as the wind direction at the fire month should be (and indeed is) orthogonal to the distribution of potential yield within the county.

4. Validation of Fire Measures

This section provides evidence that the agricultural potential yield is a valid proxy for agricultural fire as well as fire-induced air pollution. To start with, Figure 3 displays the geographic distribution of agricultural fires (Panel A) and potential yield (Panel B). We observe a high correlation between the two variables. This is especially evident in the central region, where most counties are highly suitable for agricultural production and have more burning activities. To lend further support, Figure 4 presents a binscatter plot showing the correlation between agricultural fires and potential yield. In addition to the spatial correlation documented in Figure 3, we also find strong evidence for a linear relationship between the two variables. Taken together, the above graphical evidence provides preliminary yet persuasive support for the strong correlation between agricultural fire and potential yield.



Panel A Distribution of agricultural fires



Panel B Distribution of potential yield (kg/ha)

Figure 3 Geographic Distribution of Agricultural Fires and Potential Yield

Notes: This figure presents the geographic distribution of agricultural fires (Panel A) and potential yield (Panel B). Darker colors in Panel A correspond to more agricultural fires while lighter colors in Panel B correspond to higher potential yield.

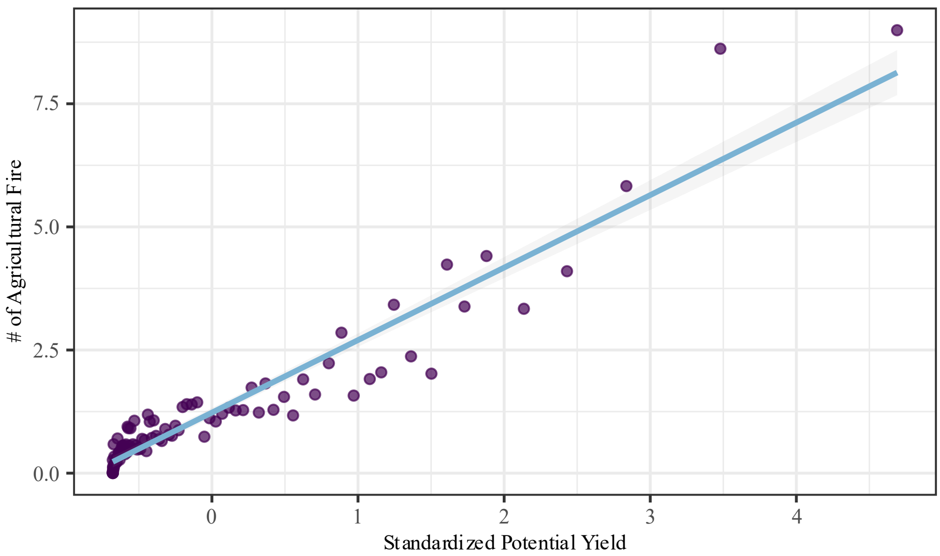


Figure 4 Binscatter of Agricultural Fires versus Potential Yield

Notes: This figure presents the binscatter plot for agricultural fires versus potential yield, with a fitted line colored in blue. The shaded Area is the 95% confidence interval. We standardize the potential yield to have a mean of 0 and a standard deviation of 1.

Formally, we carry out the following regression specification to examine the correlation between agricultural fires and potential yield:

$$y_{cpmt} = \beta_0 + \beta_1 APY_c + \Gamma \boldsymbol{W_{cpmt}} + \gamma_{pt} + \gamma_{pm} + \gamma_{mt} + \epsilon_{cpmt} \quad (1)$$

Where y_{icmt} is the number of agricultural fires in county c and prefecture p that are observed in month m and year t. APY_c is the agricultural potential yield in county c, which is time-invariant. We standardize the variable to have a mean 0 and a standard deviation of 1, so that the estimated coefficient, β_1, measures the effects of increasing the agricultural potential yield by one SD on the number of agricultural fires. We control for a set of time-varying meteorological covariates, $\boldsymbol{W_{icmt}}$, which include dew point, sea level pressure, wind speed, temperature, and rainfall. To net out potential confounders and obtain a more precise estimate, we include a detailed set of fixed effects. Specifically, we control for the prefecture-year fixed effects, γ_{pt}, the prefecture-month fixed effects, γ_{pm}, and the prefecture-year fixed effects, γ_{mt}. The inclusion of these fixed effects absorbs substantial time-varying variations at the prefecture level, and allows us to only use within-prefecture variation to identify the effects of agricultural potential yield on the number of agricultural fires.[17] We cluster the standard error at the prefecture level.

Table 1 reports the results estimated using equation (1). We estimate the equation using both least squares and the Poisson Pseudo Maximum Likelihood (PPML) specification. The PPML specification performs well in cases where the dependent variable is non-negative and has possibly many zeros, which is exactly the case with the fire observations.[18] Specifically, the estimated coefficient from column (1) of Table 1 suggests that a one SD increase in potential yield (corresponding to an increase in potential grain output by 2864 kg/ha) is associated with an additional 1.71 agricultural fires per month. This result remains largely unchanged when including meteorological controls in column (2). Considering that on average a county

[17] Due to the time-invariant nature of agricultural potential yield, we cannot control for any county-level fixed effects. We base our fixed effects at the city level as it is the immediate upper administrative division of the county.

[18] In the presence of potential zero values, log-like transformations may not be suitable as the logarithm of zero is undefined, and adding arbitrary constants to address this issue could introduce additional bias (Chen and Roth 2023). The PPML estimation avoids such concerns by directly modeling the non-negative dependent variable in levels, while still allowing for an interpretation in terms of proportional or percentage changes.

experiences 1.18 monthly agricultural fires, our estimates imply that a one SD increase in potential yield would nearly double the number of agricultural fires, representing an increase of approximately 145%. Turning to the results from PPML in columns (3) and (4), we find that a one SD increase in potential yield is associated with an approximately 48.7% increase in agricultural fires.[19] In sum, the results from Table 1 confirm the significant and robust correlation between agricultural potential yield and agricultural fires.[20]

Table 1 The Effects of Agricultural Potential Yield on Agricultural Fires

Dep. Var. # Agri. Fire	(1)	(2)	(3)	(4)
	OLS		PPML	
APY	1.711***	1.722***	0.473***	0.487***
	(0.263)	(0.267)	(0.048)	(0.047)
Observations	660,972	660,972	603,024	603,024
Prefecture-Year FE	Yes	Yes	Yes	Yes
Prefecture-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Weather Controls	No	Yes	No	Yes
Dep. Var. Mean	1.181	1.181	1.181	1.181
Adjusted/Pseudo R-squared	0.196	0.199	0.620	0.633

Notes: This table presents the estimated results of the effects of agricultural potential yield on agricultural fires. The observation is at the county-year-month level. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. Standard error is clustered at the prefecture level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

We then explore the relation between agricultural potential yield and air pollution. To do so, we modify our specification in equation (1) to allow for the differential effects of upwind and downwind potential yield. The idea is motivated by previous studies that identify the effects of agricultural fires on air pollution (e.g., Rangel and Vogl 2019; He, Liu, and Zhou 2020). Since pollution within a county is more likely to be caused by upwind fires, we should find strong correlations between upwind potential yield and air pollution, while observing weak correlations between downwind potential yield and air pollution. Specifically, we estimate the following specification:

$$y_{cpmt} = \beta_0 + \beta_1 UpwindAPY_c + \beta_2 DownwindAPY_c + \Gamma \boldsymbol{W_{icmt}} + \gamma_{pt} + \gamma_{pm} + \gamma_{mt} + \epsilon_{cpmt} \qquad (2)$$

Where $UpwindAPY_c$ and $DownwindAPY_c$ represent the average potential yield in the upwind and downwind region of the county, respectively. If the potential yield is indeed a valid measure, then we should estimate a significant result for β_1 and an insignificant result for β_2.

Table 2 presents the corresponding results. In columns (1) and (2), we first confirm that both upwind and downwind potential yield have significant predictive power on the number of agricultural fires. We also show that the coefficients are quantitatively analogous, which suggests that the two variables are balanced in terms of the effects on agricultural fires. Next, in columns (3) and (4), we regress the monthly $PM_{2.5}$ on agricultural potential yield, and find a strong correlation between the two variables. This is not surprising given the significant effects of agricultural fires on $PM_{2.5}$. Finally, in columns (5) and (6), we regress the monthly $PM_{2.5}$ on both upwind and downwind potential yield. Aligning with our expectation, we show that only upwind potential yield has significant predictive power on air pollution, while finding an exactly null effect of downwind potential yield on air pollution. Specifically, the estimated coefficients in Table 2 suggest that a one SD increase in upwind potential yield is associated with a 0.82 increase in monthly agricultural fire and a 0.56 μg/m^3 increase in monthly $PM_{2.5}$. Put differently, we find that a per 10 points increase in

[19] Note that the coefficients from OLS are not directly comparable to those from PPML as β_{ols} reflects the absolute change while β_{ppml} only reflects changes relative to the conditional mean of the dependent variable.

[20] To mitigate concerns of omitted variable bias and spurious correlation, in Appendix Table A3, we use non-agricultural fires as a placebo test. Reassuringly, we find no evidence that agricultural potential yield is associated with non-agricultural fires, the estimated coefficients are small in magnitude and insignificant.

agricultural fires is associated with an increase of monthly $PM_{2.5}$ by 6.83 μg/m^3, which is very similar to the results from He, Liu, and Zhou (2020).[21]

To ensure that our estimated relationship between upwind/downwind potential yield is indeed driven by the occurrence of agricultural fires, we examine the effects of potential yield on other pollutants. If there are unobservables that drive the correlation between agricultural potential yield and air pollution, then we should find similar effects on other pollutants. But if the correlation is solely driven by the occurrence of agricultural fires, then we should expect to find no effects on other air pollutants. From County Statistical Yearbooks, we derive three common air pollutants (i.e., NO_x, SO_2, and Dust) that are less correlated with agricultural fires. We then re-run both equations (1) and (2) to examine whether they are correlated with potential yield. Appendix Table A4 reports the corresponding results. Consistently, we detect no statistically significant effect for all three air pollutants.

Table 2 The Effects of Upwind/Downwind Potential Yield on Agricultural Fires and $PM_{2.5}$

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	# Agri. Fire		PM2.5			
Upwind APY	0.822***	0.817***			0.667***	0.564***
	(0.306)	(0.307)			(0.150)	(0.148)
Downwind APY	0.943***	0.959***			-0.015	-0.008
	(0.328)	(0.330)			(0.169)	(0.167)
APY			0.762***	0.630***		
			(0.089)	(0.093)		
Observations	660,972	660,972	1,018,800	1,018,800	1,018,800	1,018,800
Prefecture by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture by Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	No	Yes	No	Yes	No	Yes
Dep. Var. Mean	1.181	1.181	63.81	63.81	63.81	63.81
Adjusted R-squared	0.196	0.199	0.846	0.847	0.846	0.847

Notes: This table presents the estimated results of the effects of upwind/downwind agricultural potential yield on agricultural fires and $PM_{2.5}$. The observation is at the county-year-month level. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. Standard error is clustered at the prefecture level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Taken together, the above analyses offer valid support that the upwind and downwind agricultural potential yields are able to provide valid and exogenous variation to identify the effects of fire-induced pollution on adolescent outcomes. Moreover, the difference in upwind-downwind coefficients allows us to effectively rule out the potential income effects associated with agricultural fires (Rangel and Vogl 2019; He, Liu, and Zhou 2020). We will illustrate this point in further detail in the next section.

5. The Impacts of Agricultural Fires

This section outlines our empirical strategy, presents our main findings and robustness, and discusses several heterogeneity results. Specifically, we introduce how we build on our previous findings in Section 4 to construct a valid exogenous variation. We then rely on the empirical framework to identify the health effects of in-utero exposure to agricultural fires and explore the robustness and heterogeneity of our findings. Despite health consequences, we also shed light on other outcomes, for instance, the development of cognitive and non-cognitive ability. Finally, we track these cohorts ten years later and explore the effects on education and labor market outcomes.

[21] Typically, using monthly data in the summer season, they show that per 10 points increase in agricultural fires increases the monthly $PM_{2.5}$ by 4.43-5.03 μg/m^3.

5.1 Empirical specification

Our empirical strategy exploits three sources of variation. The first is the difference between the fire month and the birth month, which we leverage to identify during which trimester the individual is exposed to agricultural fires. The second is cross-sectional variations from the differences in agricultural potential yield across counties, which we exploit to proxy for fire intensity. The third variation comes from changes in wind direction during the fire month, which we use to conduct upwind-downwind comparison that avoids any confounding factors that are systematically correlated with agricultural production. Specifically, we use the following specification:

$$y_{icmt} = \alpha + \sum_{\tau=1}^{3} \beta_\tau^U UPwindAPY_c \times \mathbb{I}\{Trimester_i = \tau\} + \sum_{\tau=1}^{3} \beta_\tau^D DownwindAPY_c \times \mathbb{I}\{Trimester_i = \tau\}$$
$$+ \Lambda \boldsymbol{X}_{icmt} + \sum_{\tau=1}^{3} \Gamma_\tau \boldsymbol{W}_{cmt,\{Trimester_i=\tau\}} + \gamma_{mt} + \gamma_c + \epsilon_{icmt} \quad (3)$$

Where y_{icmt} denotes the outcome of individual i living in county c that was born in month m and year t. $UPwindAPY_c$ and $DownwindAPY_c$ are similarly defined as in equation (2). $\mathbb{I}\{\cdot\}$ is an indication function, which denotes during which trimester the individual is exposed to agricultural fire. Individuals not exposed to agricultural fires during their whole gestation period are left as the comparison group. $\boldsymbol{X}_{icmt}$ denotes a set of individual covariates, which include gender, age, father's and mother's age, education, family income, family size, and number of siblings. $\boldsymbol{W}_{cmt,\{Trimester_i=\tau\}}$ is individual-birth year-trimester specific controls that account for the confounding effects of weather conditions. Typically, it includes a set of meteorological controls (i.e., temperature, rainfall, humidity, sea level pressure, and dew point), which we average to county-trimester-year level and then match with each individual based on their birth month, birth year, and county of birth. γ_{mt} and γ_c are birth year-month and county fixed effects, respectively. Finally, the standard error is clustered at the county level to account for any unobserved arbitrary correlations within the county.

The parameters of interest are β_τ^Us and β_τ^Ds, which capture the effects of upwind and downwind potential yield (and hence agricultural fires). However, neither of the coefficients has a causal interpretation. Since agricultural fires typically occur shortly after harvesting, this, in turn, could generate substantial income effects that confound the true effects of prenatal agricultural fire exposure (Rangel and Vogl 2019; He, Liu, and Zhou 2020). To partial out such income effects, we exploit the fact that only upwind agricultural potential yield is correlated with air pollution and that the wind direction is plausibly uncorrelated with agricultural production. Therefore, although both β_τ^U and β_τ^D are confounded by income effects, the magnitudes of such effects should be quantitatively the same, and hence a difference between the two coefficients should efficiently remove the confounding income effects.[22] To this end, we focus on the estimation of parameter θ_τ, which is defined as:

$$\theta_\tau = \beta_\tau^U - \beta_\tau^D.$$

Valid identification of θ_τ requires two additional assumptions. The first assumption is that wind direction is orthogonal to potential income effects. To support this assumption, we re-estimate equation (2), with the dependent variable replaced by a set of outcomes that are correlated with agricultural production (e.g., grain output, rural income, agricultural employment, and agricultural GDP).[23] Appendix Table A5 reports the results. We additionally report the estimated results for the differences between upwind and downwind

[22] For this reason, in our subsequent analyses, we only report the estimated results for the differences between β_τ^U and β_τ^D, a la Rangel and Vogl (2019).

[23] The data is derived from County Statistical Yearbooks, 2000-2019.

coefficients to examine whether the effects of potential yield are statistically different with respect to wind direction. While we find that both upwind and downwind agricultural potential yields are significantly correlated with all four measures of agricultural production, the estimated coefficients for their differences are small in magnitude and statistically insignificant. This piece of evidence provides support that the upwind-downwind comparison can indeed effectively partial out the confounding income effects.

The second assumption is that there is no selection into the birth month. If households are aware of the negative impacts of fire exposure, then parents may reschedule their timing of reproduction to avoid in-utero pollution exposure in *ex-ante*. Such endogenous selections may bias our results by overestimating the true effects of agricultural fire exposure. To ensure that this is not the case, we examine whether agricultural fire impacts the decision on the birth month. To do so, we regress three dummies indicating during which trimesters individuals are exposed to agricultural fires on upwind and downwind potential yields. If households are indeed responding to fire-induced air pollution, then we should find significantly negative correlations in these regressions. Appendix Table A6 reports the corresponding results, based on the regression specification in equation (2).[24] Reassuringly, we find no evidence supporting the presence of birth month selection, with all coefficients being insignificant. In Appendix Table A7, we further examine the effects of agricultural fire intensity on fertility decisions. A recent study by Gao, Song, and Timmins (2024) finds that pollution exposure may distort the fertility decision, therefore, another related concern is the potential fertility selection. We show that this is not the case in the rural sample. Typically, results from column (1) of Table A7 suggest that there are no significant correlations between upwind/downwind agricultural potential yield and the number of children. In columns (2) and (3), we focus on the number of boys and girls. Though there are significantly negative correlations between upwind potential yield and the number of girls, the effects vanished after accounting for the potential income effects. Taken together, the above exercises provide valid support for our identification strategy.

Before we proceed to present our baseline results, several caveats of our research design should be borne in mind. First, the potential yield only varies cross-sectionally but has no variation in the time-series dimension. Thus, it only measures the average intensity of agricultural fires across different counties but cannot account for the variability of fire occurrence across different years. While this limitation prevents us from precisely identifying the treatment effects for cohorts born in different years, it does not essentially affect the estimation for cohorts born in different months, since we mainly exploit the within-year variation (i.e., differences in birth month) for identification. Second, our indirect measure of agricultural fires only allows us to identify the concurrent effects of in-utero exposure to fire-induced pollution, i.e., pollution that occurred during fire month. Ideally, to fully characterize the effects of in-utero pollution exposure, it would be better to use cumulative pollution or fire exposure. However, this is infeasible in our econometric framework, and our empirical identification only partially captures such effects. Therefore, our estimated effects are better interpreted as a lower bound of the true effects.

5.2 The effects of fire exposure on adolescent outcomes

5.2.1 Health outcomes

Unhealthiness index. Table 3 presents our baseline estimates on the effects of in-utero agricultural fire exposure on adolescent health. The dependent variable is a normalized health index with a greater value representing worse health conditions (see Section 3.1 for variable construction). Column (1) reports the parsimonious specification where we include birth year, birth month, and county of birth fixed effect while

[24] As agricultural potential yield is time-invariant at the county level, our regression only controls for birth year by birth month fixed effects and prefecture fixed effects, and cluster the standard errors at the prefecture level.

controlling for individual characteristics. To control for the confounding effects of prenatal weather conditions, in column (2), we include a set of meteorological controls. Column (3) augments the identification by further controlling for the birth year by month fixed effects. This allows us to effectively partial out any within-year seasonal activity and unobserved time trends. Across different specifications, the estimated coefficients are relatively stable, suggesting less concern about the selection on unobservables (Altonji, Elder, and Taber 2005; Oster 2019).

Table 3 The Effects of Agricultural Fires on Adolescent Health

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	Unhealthiness Index				
Diff. Upwind-Downwind Trimester 1	1.428***	1.454***	1.433***	2.378***	0.778
	(0.397)	(0.428)	(0.462)	(0.668)	(0.822)
Diff. Upwind-Downwind Trimester 2	0.846**	0.832**	0.813**	1.436**	0.479
	(0.384)	(0.381)	(0.401)	(0.610)	(0.796)
Diff. Upwind-Downwind Trimester 3	1.563***	1.567***	1.524***	2.174***	1.540**
	(0.332)	(0.363)	(0.385)	(0.566)	(0.649)
Observations	1,567	1,567	1,567	746	799
Sample	Full	Full	Full	Boy	Girl
Birth Year FE	Yes	Yes	No	No	No
Birth Month FE	Yes	Yes	No	No	No
Birth Year by Birth Month FE	No	No	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	No	Yes	Yes	Yes	Yes
Dep. Var. SD	2.011	2.011	2.011	2.011	2.011
Adjusted R-squared	0.0304	0.0284	0.0194	0.0538	0.0156

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on adolescent health, using the rural sample. The dependent variable is a normalized health index with a greater value representing worse health conditions. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Regarding coefficients, we find that the effects are more pronounced when individuals are exposed to agricultural fires during the first and third trimesters, which is in line with findings from epidemiological and economic literature that the effects of pollution are more deleterious in the early and later gestation period (Glinianaia et al. 2004; Šrám et al. 2005; Currie and Neidell 2005; Kannan et al. 2006; Currie et al. 2014; Rangel and Vogl 2019).[25,26] Specifically, we estimate that a one SD increase in agricultural potential yield during the first and third trimesters (which approximately corresponds to a 0.8-0.9 unit increase in monthly agricultural fires) is associated with a 1.43 and 1.52 unit increase in the unhealthiness index, respectively. Given that the SD of the outcome is 2.01, this is equivalent to an increase of 0.71 and 0.76 SD. The effects of exposure during the second trimester are smaller in magnitude, which suggests that a one SD increase in potential yield increases the unhealthiness index by 0.40 SD. Given that a one SD increase in potential yield is associated with an increase of $PM_{2.5}$ by 0.76 μg/m^3, our results imply that even a small amount of pollution exposure during the gestation period can lead to substantial long-term consequences.

[25] In the first trimester, rapid organogenesis and placental development make the fetus highly vulnerable to structural abnormalities, epigenetic changes, and impaired growth caused by pollution. During the third trimester, rapid fetal growth, brain development, and immune system maturation increase susceptibility to oxidative stress, low birth weight, and preterm birth. The second trimester is relatively less affected as it is a more stable developmental phase. Thus, pollution exposure during the first and third trimesters poses greater risks to fetal health and long-term outcomes.

[26] This evidence also suggests that the persistence of early life exposure is an important channel through which in-utero fire exposure impacts adolescent health outcomes. We discuss this mechanism later in the section.

In columns (4) and (5), we explore the gender heterogeneity in pollution exposure. We find that the effects are mostly concentrated on boys. This also aligns with previous epidemiological literature that male fetuses grow faster and have higher metabolic demands, making them more susceptible and vulnerable to oxidative stress and nutrient deprivation caused by air pollution. Typically, our estimates suggest that the effects of the same amount of agricultural fire exposure can worsen the health outcome of boys by more than 40% compared to girls.

In Appendix Table B1, we replicate our baseline results on the urban sample. In contrast to the significant effects we find for the rural sample, we estimate insignificant impacts of agricultural fire exposure on the urban sample. Given that $PM_{2.5}$ generated from straw burning can travel from rural to urban (Guo 2021), there are at least two reasons for the insignificant effects on urban adolescents. First, air pollution from agricultural fires has less negative impact on urban residents because (1) the pollution concentration decays as it travels from rural to urban, and (2) the pollution from agricultural fires is less deleterious than industrial air pollution.[27] Second, urban residents have better access to health facilities and can mitigate the negative effects of pollution exposure. Our later investigation suggests that the former seems to be the primary reason.

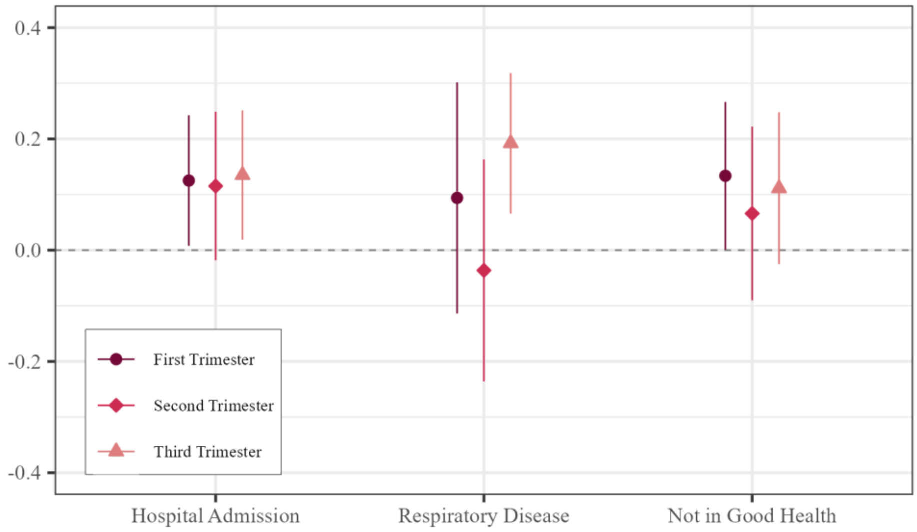


Figure 5 The Effects of Agricultural Fires on Adolescence Outcomes (Health Components)

Notes: This figure visualizes the estimated coefficients of the effects of in-utero agricultural fire exposure during different trimesters on adolescent health outcomes, including hospital admission, respiratory disease, and self-rated status, using the rural sample. All regressions include individual and weather controls. Point estimates and the corresponding 95% confidence intervals are jointly presented.

Health components. Figure 5 visualizes the estimated results for the three health components that we used to construct the unhealthiness index, i.e., hospital admission, respiratory disease, and self-rated health status. We find that exposure to agricultural fires in the first trimester increases the probability of hospital admission and feelings of bad health, while exposure during the third trimester significantly increases the probability of having respiratory disease and hospital admission. In Appendix Figure B1, we plot the effects of fire exposure on health components for the urban sample. Again, we find no statistically disenable effects of fire-induced pollution on any of the health components.

Heterogeneity. Appendix Table A8 explores the potential heterogeneity of our baseline findings. In

[27] A recent study by Lee, Wilson, and Hsiang (2025) reveals that pollution from different sources can have different health impacts. Since industrial production is mainly concentrated in the urban sector, and emissions from industrial sources contribute more to air pollution than emissions from agricultural sources (He, Liu, and Zhou 2020), it is thus plausible that fire-induced pollution has indistinguishable impacts on health outcomes of urban residents.

columns (1) and (2), we divide our sample by whether the mother has completed middle school education. We show that our estimated effects are mostly driven by individuals whose mothers have lower education levels. In columns (3) and (4), we divide our sample by family income and find that the detrimental effects of pollution exposure are more pronounced for families with lower income. Together, this evidence suggests that agricultural fires have disproportionally stronger effects on more disadvantaged families, and the liquidity constraints seem to be a potential driver of the observed negative outcomes.[28] We will discuss this issue in further detail in the next section when we shed light on the role of parental investment. Finally, in columns (5) and (6), we divide the sample by whether the family is engaged in grain production, which is the major agricultural productivity that contributes to agricultural fires. We show that the effects are more significant for individuals from households engaged in grain production, which is in line with findings from Fletcher and Noghanibehambari (2024) that these households live closer to the cropland and are more exposed to pollution when the agricultural fire occurs.

Table 4 The Effects of Agricultural Fires on Cognitive and Non-cognitive Ability

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A Cognitive Ability	Standardized Word Test Score			Standardized Math Test Score		
Diff. Upwind-Downwind Trimester 1	-0.598*	-1.711***	0.557	0.139	-0.185	0.665
	(0.329)	(0.514)	(0.681)	(0.476)	(0.601)	(0.879)
Diff. Upwind-Downwind Trimester 2	-0.0148	-0.722	0.569	0.355	0.697	0.402
	(0.299)	(0.632)	(0.625)	(0.499)	(0.765)	(0.724)
Diff. Upwind-Downwind Trimester 3	-0.256	-1.375***	0.463	0.324	0.372	0.398
	(0.308)	(0.515)	(0.659)	(0.444)	(0.622)	(0.715)
Observations	1,384	659	701	1,393	667	702
Sample	Full	Boy	Girl	Full	Boy	Girl
Adjusted R-squared	0.239	0.222	0.227	0.141	0.052	0.165
Panel B Non-Cognitive Ability	Positive Attitudes			Negative Attitudes		
Diff. Upwind-Downwind Trimester 1	-0.817*	-1.289*	-0.252	1.447**	3.467***	0.617
	(0.538)	(0.735)	(0.939)	(0.559)	(0.910)	(1.122)
Diff. Upwind-Downwind Trimester 2	-0.571	0.362	-0.707	0.0656	2.359**	0.677
	(0.558)	(0.989)	(0.906)	(0.711)	(1.188)	(1.061)
Diff. Upwind-Downwind Trimester 3	-0.844*	-1.204*	-0.150	0.476	2.349**	0.770
	(0.495)	(0.679)	(0.950)	(0.674)	(1.036)	(1.057)
Observations	450	238	239	448	212	236
Sample	Full	Boy	Girl	Full	Boy	Girl
Adjusted R-squared	0.236	0.297	0.169	0.109	0.162	0.128
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on adolescent cognitive and non-cognitive ability, using the rural sample. The dependent variables in Panel A are age-specific standardized word test scores and math test scores. The dependent variables in Panel B are two measures that gauge the positive and negative attitudes of respondents. The observation is at the county-cohort level, with each cohort defined by its birth month. All regressions include both individual and weather controls. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

5.2.2 Cognitive and non-cognitive outcomes

We then proceed to explore the cognitive and non-cognitive impacts of agricultural fire exposure. Table 4 reports the corresponding results, with Panel A presenting the estimated coefficients for cognitive ability

[28] This finding aligns with previous studies which show that air pollution affect vulnerable families disproportionally (Jans, Johansson, and Nilsson 2018; Suarez Castillo, Benatia, and Thi 2025).

while Panel B presents the estimates for non-cognitive ability. In columns (1) and (4), we estimate the effects using a full sample, whereas in columns (2) and (3), as well as in columns (5) and (6), we estimate the gender heterogeneity in pollution exposure. Focusing on the cognitive outcomes, we show that in-utero exposure to agricultural fires significantly reduces word test scores but has an insignificant impact on math test scores. In line with findings from Table 3, we show that the negative effects on word test scores are solely driven by boys, and are pronounced if the exposure to agricultural fires occurs during the first and third trimesters.

We also document a strong negative impact of agricultural fires on non-cognitive abilities. Specifically, we show that in-utero fire exposure during the first and third trimesters significantly decreases individuals' positive attitudes toward life and increases their negative attitudes in the meantime. Again, these effects are found in the male sample. Taken together, our estimates from Table 4 reveal that in-utero exposure to fire-induced air pollution has strong detrimental effects on the development of cognitive and non-cognitive abilities among male adolescents.[29]

To streamline our empirics, we refer interested readers to Appendix C for additional evidence that supports the validity and robustness of our baseline findings. Specifically, we show that our results are robust to alternative definitions of the upwind direction, using alternative and more granular fixed effects, and accounting for additional confounders. We also perform a randomized inference to ensure that our results are not driven by variations that may potentially correlate with our fire intensity measure.

5.3 The effects of fire exposure on adult outcomes

After showing that in-utero fire exposure can lead to worsened health and (non-)cognitive outcomes in adolescence, this subsection proceeds to present more evidence on whether these negative effects penetrate into adulthood and their potential impacts on educational attainment and labor market outcomes. Tracking the cohort in CFPS 2010 to CFPS 2020, Table A12 presents the estimated coefficients on the effects of in-utero agricultural fire exposure on adulthood outcomes. We focus on three outcome variables measured in CFPS 2020: (1) the completed number of years of education, normalized by individuals' age; (2) annual wage, conditioning on entering the labor market; and (3) a dummy variable that denotes whether the individual is employed in the agricultural sector.

Our findings indicate that in-utero fire exposure during the first trimester leads to a significantly shortened year of education completed. The estimated coefficient suggests that first-trimester exposure to agricultural fires is associated with a 0.075 decrease in the completed year of education, and the effects are larger for males and insignificant for females. It is worth noting that, by the time of 2020, not all individuals had completed their education.[30] It is therefore important to normalize the year of education by individuals' age, which allows us to compare individuals born in the same year but in different months. We also show that first- and third-trimester exposure to agricultural fires leads to worsened labor market outcomes. Take the coefficients estimated from third-trimester exposure as an example, our estimates suggest that it would lower the annual wage by 4.3% and increase the probability of being employed in the agricultural sector by more than 34% for the male sample. Again, no significant impacts are detected for the female sample.[31] Taken

[29] We present the estimated results of in-utero fire exposure on cognitive outcomes for the urban sample in Appendix Table B2, and again find no suggestive evidence that agricultural fires can affect the cognitive performance of urban adolescents. We cannot replicate this exercise for non-cognitive performance as the sample size is too small to run the regression specification.

[30] Our sample size from Table A12 suggests that only half of the rural sample have completed their education and entered the labor market in 2020.

[31] Appendix Table B3 replicates the results of agricultural fire exposure on education attainment in the urban sample, again finding no significant impacts. Unfortunately, due to the small sample size, we cannot recover the effects on labor market outcomes.

together, our findings suggest that the effects of in-utero exposure to agricultural fires can have persistent deleterious long-term effects. Given the abundant studies that link the development of health, cognitive, and non-cognitive abilities to labor market outcomes (e.g., Grönqvist, Nilsson, and Robling 2020), our empirical exercises thus far provide comprehensive evidence relating pollution exposure to human capital development across different stages.

6. Mechanisms

6.1 Early-life outcomes

To shed light on the mechanisms of long-term consequences of agricultural fire exposure, this subsection examines the effects of in-utero exposure on early-life outcomes. As previously documented by Rangel and Vogl (2019) that in-utero exposure to sugarcane fires can increase prenatal mortality and negatively affect health at birth. If our estimated long-term effects are indeed caused by exposure to fire-induced air pollution, then we should find strong negative correlations between in-utero fire exposure and early life outcomes. Table 5 presents the estimated results. Specifically, our evidence suggests that in-utero exposure to agricultural fires is positively correlated with the number of illnesses at age 1, and is negatively associated with gestation month and birth weight, indicating worsened health at birth and in early life. Moreover, the worsened early-life outcomes are exclusively concentrated in the male sample, which (partly) explains why the long-term effects of agricultural fire exposure are primarily driven by males.

There are two natural concerns pertaining to our findings in Table 5. The first is to what extent survival to birth affects our main estimates, and the second is potential measurement errors in our independent variables due to reduced gestation periods. Theoretically, fetuses with higher health capital are more likely to survive when exposed to air pollution, and therefore the estimated effects are biased downward due to selection into survival. Similarly, as measurement error is more likely to occur when individuals are more susceptible to pollution exposure, the estimated effects are also downwardly biased.

Table 5 The Effects of Agricultural Fires on Early Life Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.	# Illness at Age 1			Gestation Month			Birth Weight		
Diff. Upwind-Downwind Trimester 1	0.227	0.409*	0.139	-0.327**	-0.672***	-0.151	-0.736*	-1.859***	-0.116
	(0.138)	(0.232)	(0.195)	(0.131)	(0.184)	(0.175)	(0.413)	(0.615)	(0.636)
Diff. Upwind-Downwind Trimester 2	0.130	0.590*	-0.201	-0.245	-0.367*	-0.051	-0.242	-0.326	-0.150
	(0.147)	(0.305)	(0.341)	(0.167)	(0.213)	(0.215)	(0.481)	(0.586)	(0.738)
Diff. Upwind-Downwind Trimester 3	0.191**	0.236	0.245	-0.210	-0.530**	0.106	-0.253	-0.765	0.470
	(0.096)	(0.152)	(0.158)	(0.196)	(0.219)	(0.211)	(0.410)	(0.617)	(0.669)
Observations	2,308	1,178	1,114	2,622	1,331	1,277	2,661	1,349	1,298
Sample	Full	Boy	Girl	Full	Boy	Girl	Full	Boy	Girl
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.142	0.155	0.136	0.216	0.207	0.249	0.137	0.089	0.174

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on early-life outcomes, using the rural sample. In columns (1) to (3), the dependent variable is the number of illnesses at age 1. In columns (4) to (6), the dependent variable is the length of the gestation period, measured in months. In columns (7) to (9), the dependent variable is the individual's birth weight, measured in 500 grams. The observation is at the county-cohort level, with each cohort defined by its birth month. All regressions include both individual and weather controls. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

To explore whether exposure to agricultural fires increases infant mortality, we first calculate the number of children who did not survive to the survey year and the mortality rate within the household, where the latter is calculated by dividing the number of children that died by the number of children that survived to the survey year. Our results from Appendix Table A13 show that agricultural fire-induced air pollution has no significant effect on child mortality.[32] However, this result does not preclude the confounding effect of potential unobservables, as we only exploit cross-sectional variation for identification. Thus, the results should be interpreted with great caution. We then examine whether the potential selection affects our main estimates. In Appendix Table A14, we replicate our estimated effects for the unhealthiness index, cognitive, and non-cognitive abilities by additionally controlling for child mortality and gestation length. The results are largely unaffected, suggesting less concern about selection.

Taken together, the results in this section suggest that in-utero exposure to agricultural fires can have persistent detrimental effects on human capital formation and development. Specifically, it negatively affects health outcomes in early life, and leads to worsened health and (non-)cognitive outcomes in adolescence, which further translates into worsened educational attainment and labor market outcomes in adulthood. Undoubtedly, an important mechanism for these outcomes is the transmission of reduced prenatal health capital into later life. However, a largely unexplored mechanism is how pollution triggers intra-household responses and resource allocations (e.g., parental investment), and how these responses contribute to the observed outcomes. The next subsection discusses how parental investment responds to pollution exposure.

6.2 Parental Investment

In this subsection, we examine how parental investments of rural households respond to in-utero exposure to agricultural fires. Theoretically, parents could either make compensatory or reinforcing investments. The compensating investment suggests that parents would devote more resources to their children who are *more* exposed to agricultural fire-induced air pollution, whereas the reinforcing investment suggests that parents would devote more resources to children who are *less* exposed to pollution, as the human capital return of investing in these children is higher. This section brings the theoretical ambiguity to our data and empirically investigates whether rural households make compensatory or reinforcing investments. Specifically, we investigate how parental investments in health and education respond to in-utero pollution exposure.

6.2.1 Health investment

We first examine how families adjust their health investment in response to in-utero pollution exposure. We measure the health investment by the health expenditures on children. Column (1) of Table 6 reports the estimated effects. We find that parents significantly reduced their investment in children's health. Specifically, a one unit increase in fire exposure during the first trimester corresponds to approximately a 15.8% decrease in health expenses.[33] Given that the mean value of health expenses of children in the rural area is 401 RMB (approximately 61.7 USD), our estimates suggest that in-utero exposure to agricultural fires during the first trimester reduces parental health expenses by 63 RMB (corresponding to 9.75 USD).

In columns (2) to (5), we investigate the potential heterogeneity of our results. Specifically, in columns (2) and (3), we divide the sample according to whether the mother has completed at least lower secondary

[32] Since CFPS 2010 only asks whether the child is alive and does not record in which year the child has passed away, the age of death is thus unknown, so as to whether it is prenatal death or postnatal death. Therefore, our estimated effects are a composite of both the effects on prenatal death and postnatal death.

[33] The magnitude is calculated by (exp(0.126)-1)/0.85, where we divide the coefficient by 0.85 since a one standard deviation increase in potential yield approximately corresponds to 0.85 increases in the number of agricultural fires.

education (corresponding to the low and high education groups). We find that the effects of investment reduction come mainly from households where the mother has lower education. Our estimates suggest that for mothers with lower education, in-utero exposure to agricultural fires reduces health expenses by 119.6 RMB (equivalent to 18.4 USD). This is in line with our results from Appendix Table A8, where we show that the effects of in-utero agricultural fire exposure on adolescent health are more pronounced if the mother has a lower level of education. In columns (4) and (5), we divide the sample according to the median value of family income (corresponding to the low and high income groups). We show that the effects are primarily driven by households with lower income, and the magnitude estimated from column (4) is comparable to the coefficients from column (2). Again, this result aligns with estimates from Table A8, where the effects of fire exposure on health are more significant for households with lower income. These heterogeneities in treatment effects seem to suggest that resource constraint is a plausible driver of the observed outcomes.

Table 6 The Effects of Agricultural Fires on Health Expenses

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	Log Health Expenses				
Diff. Upwind-Downwind Trimester 1	-0.126**	-0.226**	-0.162	-0.257*	-0.004
	(0.074)	(0.098)	(0.169)	(0.133)	(0.082)
Diff. Upwind-Downwind Trimester 2	-0.119	-0.191*	-0.071	-0.058	-0.128
	(0.083)	(0.110)	(0.144)	(0.114)	(0.102)
Diff. Upwind-Downwind Trimester 3	-0.057	-0.076	-0.195	-0.215*	0.015
	(0.061)	(0.105)	(0.138)	(0.115)	(0.084)
Observations	1,411	966	391	632	733
Sample	Full	Low Education	High Education	Low Income	High Income
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.144	0.128	0.180	0.175	0.135

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on families' health expenses, using the rural sample. The dependent variable is the logged value of health expenses on children. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

In Appendix Table B4, we investigate the effects on health expenses for the urban sample. As urban residents are less exposed to agricultural fires, they serve as an ideal placebo to examine whether our estimated effects of health expenses reduction are indeed driven by in-utero agricultural fire exposure. Reassuringly, we find neither effects nor heterogeneity of in-utero fire exposure on health expenses for the urban sample.

6.2.2 Education investment

We then examine how parental education investments respond to in-utero agricultural fire exposure. Similarly, we measure the education investments by parents' education expenses on their children. Column (1) of Table 7 reports the estimated coefficients. We find that, in response to in-utero agricultural fire exposure, parents significantly reduced educational investment in their children, and the effects are mostly pronounced for individuals exposed during the third trimester. Specifically, the estimated coefficients suggest that a one unit increase in agricultural fire exposure during the third trimester is associated with an 8.7% decrease in parental education expenses for their children. Given that the mean value of education expenditure is 629 RMB (approximately 96.8 USD), our estimates imply a reduction in education expenditure by 54.7 RMB (corresponding to 8.4 USD).

In columns (2) to (5), we perform the same heterogeneous exercises as in Table 6. We find similar patterns that the reduction in education expenses is more significant for mothers with lower education and families with lower income. Analogously, in Appendix Table B5, we examine the effects of in-utero agricultural fire exposure on education expenditure for the urban sample. Again, no significant effects are found.

Table 7 The Effects of Agricultural Fires on Education Expenses

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	Log Education Expenses				
Diff. Upwind-Downwind Trimester 1	-0.030	-0.039	-0.008	-0.047	-0.032
	(0.020)	(0.022)	(0.057)	(0.029)	(0.042)
Diff. Upwind-Downwind Trimester 2	-0.003	-0.001	-0.015	-0.040	0.046
	(0.032)	(0.036)	(0.049)	(0.034)	(0.068)
Diff. Upwind-Downwind Trimester 3	-0.071***	-0.066**	-0.058	-0.078***	-0.011
	(0.021)	(0.025)	(0.047)	(0.027)	(0.057)
Observations	2,049	1,452	571	1,105	881
Sample	Full	Low Education	High Education	Low Income	High Income
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	No	Yes	Yes	Yes	Yes
Adjusted R-squared	0.338	0.331	0.347	0.368	0.310

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on families' education expenses, using the rural sample. The dependent variable is the logged value of education expenses on children. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Taken together, our results in this section suggest that in response to negative early life shocks induced by in-utero exposure to agricultural fires, rural households reduce both health and education investment on their affected children. This aligns with the Reinforcement channel in which parents, constrained by limited resources, will invest less in children who have a lower return to human capital investment. More importantly, our results highlight salient unequal effects of early life pollution exposure, even in low-income settings like rural China. These results call for polices that aim to mitigate the negative effects of pollution exposure, especially policies that directly target rural households. In what follows, we examine the mitigating role of an important health insurance coverage in rural China, i.e., the rollout of the New Cooperative Medical Scheme.

7. The Role of Health Insurance

In the last part of our empirical investigation, we examine the role of health insurance in mitigating the adverse effects of pollution exposure during gestation on long-term outcomes. Given that parents reduce their human capital investment in response to in-utero exposure to agricultural fires, a related question is whether the coverage of health insurance can offset such reinforcing mechanisms. Besides, as the long-term persistence of early-life outcomes is another important channel, it is also of great importance to examine whether health insurance coverage can moderate the deleterious effects of pollution exposure on early outcomes. We now present the formal analyses to these questions.

7.1 Adolescent outcomes

We first examine the role of health insurance in mitigating the effects of in-utero agricultural fire exposure on adolescent outcomes. Columns (1) and (2) of Table 8 report the estimated results on the unhealthiness index, where we divide our sample by whether the individual is exposed to NCMS before age 5, following Huang and Liu (2023).[34] We show that the adverse health effects of in-utero fire exposure are primarily driven by individuals who are not exposed to NCMS. For individuals who are exposed to NCMS, the estimated coefficients are small in magnitude and are insignificant. To ensure that our results are not driven by other concurrent exposure (e.g., exposure to tap water, electricity, etc.), in columns (3) and (4), we additionally control for whether the individual is exposed to electricity, tap water, road, railway, and natural gas before age 5. Our results remain unaffected after the inclusion of these additional controls. In Appendix Table B6, we re-estimate our regression for the urban sample. As the NCMS only covers rural residents, we should find no mitigating effects for the urban sample. Not surprisingly, we reveal no effect of NCMS exposure on the urban sample.

Table 8 The Effects of Early Exposure to NCMS on Adolescent Outcomes

	(1)	(2)	(3)	(4)
Dep. Var.	Unhealthiness Index			
Diff. Upwind-Downwind Trimester 1	0.714	1.516***	0.434	1.566***
	(1.680)	(0.432)	(1.524)	(0.458)
Diff. Upwind-Downwind Trimester 2	0.0784	1.014**	0.249	1.063**
	(0.882)	(0.448)	(1.074)	(0.444)
Diff. Upwind-Downwind Trimester 3	0.812	1.429***	0.393	1.420***
	(1.505)	(0.396)	(1.396)	(0.389)
Observations	327	1,233	327	1,233
Sample	Exposure to NCMS	Non-Exposure to NCMS	Exposure to NCMS	Non-Exposure to NCMS
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Other Exposure	No	No	Yes	Yes
Adjusted R-squared	0.132	0.036	0.137	0.041

Notes: This table presents the estimated results of the role of NCMS coverage in mitigating the effects of in-utero agricultural fire exposure on adolescent health using the rural sample. The dependent variable is a normalized health index with a greater value representing worse health conditions. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Other exposures include controls on whether the individual is exposed to electricity, tap water, road, railway, and natural gas before age 5. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

7.2 Parental investment

We then investigate whether the coverage of health insurance can mitigate the negative impacts of in-utero pollution exposure on parental investment. Columns (1) and (2) of Table 9 examine the moderating effects of NCMS on health expenses. We find that for individuals who are exposed to the NCMS, in-utero exposure to agricultural fires does not significantly reduce parental health investment. For individuals who are not exposed to NCMS, fire exposure significantly reduces households' health expenses for their children. As we show in Table 6 that the effects of in-utero fire exposure on health expenditure are mostly driven by mothers with lower education and households with lower income, in columns (3) to (6), we take a one step further and examine whether the rollout of NCMS can mitigate the reduction on health investment for these vulnerable subgroups. Our results confirm this hypothesis and reveal that, compared with individuals whose mother has a lower level of education and was not exposed to NCMS before age 5, individuals exposed to

[34] Unfortunately, due to our relatively small sample size, we cannot perform estimation for other cognitive and non-cognitive outcomes.

NCMS receive relatively higher health investment, even if their mother has the same lower level of education. The same results hold for individuals who are from households with lower income. Moreover, we also notice that the coefficients in columns (3) and (5) are basically positive, though insignificant due to large standard errors. This provides suggestive evidence that the rollout of NCMS may increase parental health investment for individuals who are exposed to agricultural fires, and may turn the reinforcing behavior into compensatory behavior.

Table 9 The Effects of Early Exposure to NCMS on Health Expenses

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Log Health Expenses					
Diff. Upwind-Downwind Trimester 1	-0.068	-0.202*	-0.129	-0.234**	0.095	-0.442***
	(0.088)	(0.115)	(0.245)	(0.118)	(0.215)	(0.150)
Diff. Upwind-Downwind Trimester 2	-0.074	-0.130	0.247	-0.251	0.290	-0.095
	(0.091)	(0.158)	(0.356)	(0.169)	(0.314)	(0.188)
Diff. Upwind-Downwind Trimester 3	-0.099	-0.087	0.109	-0.056	0.189	-0.264
	(0.124)	(0.161)	(0.261)	(0.184)	(0.272)	(0.206)
Observations	636	797	357	568	348	481
Sample	Exposure	Non-Exposure	Exposure & Low Education	Non-Exposure & Low Education	Exposure & Low Income	Non-Exposure & Low Income
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other Exposure	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.176	0.098	0.087	0.064	0.169	0.102

Notes: This table presents the estimated results of the role of NCMS coverage in mitigating the effects of in-utero agricultural fire exposure on parental health investment using the rural sample. The dependent variable is the logged value of health expenses on children. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Other exposures include controls on whether the individual is exposed to electricity, tap water, road, railway, and natural gas before age 5. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

In Appendix Table A15, we provide the same estimate for the mitigating effects of NCMS on parental education expenditure. Again, similar patterns emerge. We find that parental education investment does not respond to in-utero agricultural fire exposure for individuals who were exposed to NCMS, and that the mitigating role of NCMS exposure is more pronounced for individuals whose mother has lower education and individuals who are from households with lower income.

7.3 Early-life outcomes

We have shown that NCMS exposure can dampen the adverse effects of in-utero agricultural fire exposure on adolescent health outcomes, and one potential mechanism is increased parental investment. A remaining question is whether early life outcomes are also improved due to the rollout of the NCMS. We empirically examine this issue in Table A16, where we compare the estimated coefficients on early-life outcomes for individuals who are exposed and not exposed to NCMS. In contrast to previous findings, we find no discernible differences in treatment effects heterogeneity regarding whether the individual is exposed to the NCMS. This suggests that the rollout of NCMS may not mitigate the adverse effects of agricultural fires on individuals' health at birth. One potential reason for this outcome may be that rural families may not be (sufficiently) aware of the negative effects of agricultural fire exposure during fetal life, so even with health insurance coverage, health outcomes early in life remain unimproved. This calls for further policy improvement to enhance the awareness and dissemination of the harmful effects of potential sources of pollution in rural areas.

8. Conclusion

This paper studies the long-term effects of in-utero exposure to agricultural fires. Using a nationally representative household dataset on rural China, we show that in-utero exposure to agricultural fires significantly decreases health outcomes, cognitive and non-cognitive performance in adolescence. The effects are mostly driven by exposure during the first and third trimesters, and are found to be larger in the male sample. Tracking these cohorts into their adulthood, we show that agricultural fire exposure during gestation leads to lower years of education and lower earnings, while increasing the probability of individuals working in low-skill sectors (e.g., agriculture).

Exploring the potential mechanisms, we find that in-utero exposure to agricultural fires significantly worsens early-life health conditions (i.e., more illnesses at age 1, shorter gestation period, and lower birth weight). More importantly, we show that parental investment is another driver of the observed effects. Specifically, our evidence suggests that parents reduce their health and education investment in exposed children. The reduction effects are stronger for individuals whose mother has a lower education level and individuals from families with lower income, which suggests that the liquidity constraints may be a potential explanation. Finally, we investigate how the provision of public health insurance can mitigate the adverse effects of pollution exposure. Exploiting the exogenous variation in the implementation of the NCMS program, we show that early-life exposure to NCMS can largely offset the negative effects of agricultural fire exposure. We further show that such mitigation is mainly through improvements in health and education investment, and is more pronounced for more disadvantaged households.

Our findings underscore the critical need for policy interventions to mitigate the lifelong consequences of in-utero environmental shocks. First, given the heightened sensitivity during the first and third trimesters, region-specific regulations on agricultural burning should prioritize seasonal restrictions aligned with cropping cycles, particularly in areas with high fire density. Complementary measures, such as real-time air quality monitoring and targeted advisories for pregnant women, could reduce fetal exposure during these vulnerable windows. Second, the evidence on parental disinvestment, especially among low-income and low-education households, calls for integrated social protection programs. Strengthening the New Cooperative Medical Scheme (NCMS) and embedding liquidity support mechanisms (e.g., conditional cash transfers tied to health and education expenditures) could alleviate financial constraints that perpetuate underinvestment. Importantly, the mitigating role of NCMS highlights the potential for scaling up health insurance to cover pollution-related developmental risks, potentially through pollution-specific insurance riders or subsidies for high-risk populations.

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Conflict of Interest

The authors declare no competing interests.

Data Availability

The primary data used in this study are publicly available from the China Family Panel Studies (CFPS). However, the restricted-access dataset enabling pseudocode county code-to-actual county name matching is protected under a confidentiality agreement with the China Social Science Research Center at Peking University and cannot be shared publicly.

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Appendix A: Additional Tables and Figures

Additional Tables

Table A1 Summary Statistics

	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Panel A: Individual variables		Rural Sample			Urban Sample	
Adolescent outcomes						
Unhealthiness index	1846	0.009	2.011	1182	0.006	1.639
Not in good health = 1	1846	0.030	0.172	1182	0.014	0.119
Hospital admission = 1	1846	0.019	0.136	1182	0.022	0.146
Respiratory disease = 1	1846	0.102	0.303	1182	0.173	0.379
Word test score	1762	20.61	7.289	1162	23.36	6.318
Math test score	1773	10.67	4.532	1165	11.91	4.226
Health at birth						
# illness (age 1)	2691	3.058	5.145	2268	3.069	4.569
Gestation month	3065	9.274	0.573	2607	9.363	0.583
Birth weight (500g)	3128	7.105	1.654	2624	6.696	1.201
Adulthood outcomes (CFPS 2020)						
Education year	1504	10.30	2.930	1218	10.40	2.896
Annual wage (per thousand RMB)	830	72.32	34.54	329	36.23	34.99
Work in agricultural = 1	830	0.122	0.327	329	0.083	0.276
Agricultural fire exposure						
Exposed during the first trimester	3128	0.241	0.428	2624	0.229	0.421
Exposed during the second trimester	3128	0.236	0.424	2624	0.220	0.414
Exposed during the third trimester	3128	0.291	0.454	2624	0.312	0.463
Covariates						
Age	3128	10.27	3.414	2624	8.994	3.519
Gender	3128	0.513	0.500	2624	0.530	0.499
Father's age	3118	38.49	6.028	2605	37.09	5.627
Father completed middle school	3128	0.434	0.496	2624	0.755	0.430
Mother's age	3081	36.42	5.703	2590	35.37	5.380
Mother completed middle school	3128	0.295	0.456	2624	0.663	0.473
Family income (per thousand RMB)	2988	25.27	46.58	2489	40.28	57.66
Family size	3128	5.318	1.720	2624	4.672	1.696
# of siblings	3110	2.343	1.291	2615	1.838	1.074
Parental investment						
Health expense (per thousand RMB)	1815	0.401	0.962	1841	0.694	1.449
Education expense (per thousand RMB)	3098	0.629	0.910	2598	1.583	2.109
NCMS exposure						
Exposed to NCMS during 0-5	3128	0.429	0.495	2624	0.406	0.491

Panel B: County variables	Obs	Mean	Std. Dev.
# of agricultural fires	660,972	1.181	10.42
# of non-agricultural fires	660,972	1.460	10.74
Potential yield (kg/ha)	1,046,539	3052	2865
Upwind potential yield (kg/ha)	1,046,539	2957	3013
Downwind potential yield (kg/ha)	1,046,539	2968	3037
PM2.5 (μg/m3)	1,046,539	63.81	84.30
Dew point	1,046,539	6.672	11.88
Sea level pressure	1,046,539	1016	8.630
Temperature	1,046,539	13.73	10.51
Wind speed	1,046,539	2.333	0.798
Rainfall	1,046,539	2.811	3.068

Notes: This table presents the summary statistics for the main variables that are used in the empirical analysis. Panel A provides summary statistics for the individual sample from CFPS 2010 and CFPS 2020. Variables are separately summarized for both the rural and urban samples. Panel B provides summary statistics for county-level variables. Except for potential yield variables, all variables are defined at the county-year-month level.

Table A2 Balance Test between NCMS-exposed and Non-exposed Sample

	NCMS-exposed		NCMS-non-exposed		Mean Diff.	
Variables	Obs	Mean	Obs	Mean	Unconditional	Conditional
Age	1517	13.07	349	11.16	1.904***	0.846***
Gender	1517	0.506	349	0.461	0.044	0.073*
Father's age	1513	40.54	348	40.15	0.392	0.0288
Father completed middle school	1517	0.436	349	0.393	0.043	-0.001
Mother's age	1495	38.60	347	37.89	0.715*	0.377
Mother completed middle school	1517	0.281	349	0.272	0.009	-0.008
Family income (per thousand RMB)	1463	24.18	327	24.12	0.056	0.606
Family size	1517	5.115	349	5.372	-0.258	0.144
# of siblings	1510	2.239	346	2.494	-0.255*	0.008

Notes: This table presents the results of summary statistics and balance tests between NCMS-exposed and non-exposed samples. The Unconditional differences perform a simple t-test between exposed and non-exposed individuals. Only the age variable is strongly significant, as we use age and NCMS implementation timing to distinguish whether the individual is exposed to the policy. The conditional differences perform an OLS regression analysis by running each of the individual covariates on the NCMS exposure dummy while conditioning on a set of county-level characteristics, which includes counties' grain output, rural income, agricultural employment, and agricultural GDP.

Table A3 The Effects of Agricultural Potential Yield on Non-agricultural Fires

Dep. Var. # Non-agri. Fire	(1)	(2)	(3)	(4)
	OLS		PPML	
APY	-0.117	-0.099	-0.135	-0.127
	(0.085)	(0.085)	(0.093)	(0.093)
Observations	660,972	660,972	634,613	634,613
Prefecture-Year FE	Yes	Yes	Yes	Yes
Prefecture-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Weather Controls	No	Yes	No	Yes
Dep. Var. Mean	1.460	1.460	1.460	1.460
Adjusted/Pseudo R-squared	0.159	0.161	0.518	0.530

Notes: This table presents the estimated results of the effects of agricultural potential yield on non-agricultural fires. The observation is at the county-year-month level. The sample period is from 2001 to 2019. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. Standard error is clustered at the prefecture level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table A4 The Effects of Potential Yield on Agricultural Fires and Other Pollutants

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	NOx		SO2		Dust	
Upwind APY		-0.513		0.063		0.108
		(0.494)		(0.302)		(0.142)
Downwind APY		0.168		-0.011		0.050
		(0.154)		(0.221)		(0.309)
APY	-0.440		-0.015		-0.004	
	(0.438)		(0.401)		(0.404)	
Observations	53,920	53,920	53,920	53,920	53,920	53,920
Prefecture by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.101	0.101	4.617	4.617	2.570	2.570
Adjusted R-squared	0.0747	0.0748	0.122	0.122	0.120	0.120

Notes: This table presents the estimated results of the effects of upwind/downwind agricultural potential yield on agricultural fires and air pollutants (NO_x, SO_2, and Dust). The observation is at the county-year level. The sample period is from 2000 to 2019. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. Standard error is clustered at the prefecture level.

Table A5 The Differential Effects of Upwind/Downwind Potential Yield on Agricultural Production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Grain Output		Rural Income		Agri. Employment		Agri. GDP	
Upwind APY		54.891***		0.359***		12.218***		21.237***
		(7.887)		(0.117)		(2.412)		(3.135)
Downwind APY		51.840***		0.377***		11.499***		19.585***
		(8.444)		(0.140)		(2.534)		(3.020)
APY	110.852***		0.889***		22.800***		43.098***	
	(11.984)		(0.127)		(2.949)		(4.031)	
Diff. Upwind-Downwind		3.051		-0.018		0.719		1.652
		(11.397)		(0.221)		(4.038)		(4.774)
Observations	53,920	53,920	53,920	53,920	53,920	53,920	53,920	53,920
Prefecture by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	224.3	224.3	7.530	7.530	112.9	112.9	113.9	113.9
Adjusted R-squared	0.386	0.387	0.807	0.806	0.490	0.493	0.528	0.527

Notes: This table presents the estimated results of the effects of upwind/downwind agricultural potential yield on a set of variables that are related to agricultural production to examine the income effects. The observation is at the county-year level. The sample period is from 2000 to 2019. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. Standard error is clustered at the prefecture level.

Table A6 Birth Month Selection

	(1)	(2)	(3)
Dep. Var.	Exposed in the 1st Trimester	Exposed in the 2nd Trimester	Exposed in the 3rd Trimester
Upwind APY	-0.006	-0.005	0.003
	(0.040)	(0.056)	(0.042)
Downwind APY	0.117	-0.128	0.028
	(0.083)	(0.094)	(0.051)
Diff. Upwind-Downwind	-0.123	0.123	-0.025
	(0.093)	(0.126)	(0.069)
Observations	1,460	1,460	1,460
Birth Year by Birth Month FE	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Adjusted R-squared	0.188	0.137	0.205

Notes: This table presents the estimated results of the effects of upwind/downwind agricultural potential yield on the birth month selection. The dependent variables are three dummies indicating during which trimester the individual is exposed to agricultural fires. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the prefecture level.

Table A7 Fertility Selection

	(1)	(2)	(3)
Dep. Var.	# of Children	# of Boys	# of Girls
Upwind APY	-0.452	0.021	-0.473**
	(0.304)	(0.088)	(0.236)
Downwind APY	0.778	0.078	0.700
	(0.778)	(0.246)	(0.564)
Diff. Upwind-Downwind	-1.230	-0.057	-1.173
	(1.018)	(0.316)	(0.749)
Observations	1,452	1,452	1,452
Birth Year by Birth Month FE	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Adjusted R-squared	0.138	0.148	0.187

Notes: This table presents the estimated results of the effects of upwind/downwind agricultural potential yield on fertility selection. The dependent variable in column (1) is the number of children, whereas in columns (2) and (3), the dependent variables are the number of boys and girls, respectively. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include the father's education and age, the mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. Standard error is clustered at the prefecture level.

Table A8 The Heterogeneous Effects of Agricultural Fires on Health

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Unhealthiness Index					
Diff. Upwind-Downwind Trimester 1	1.137**	0.728	1.896***	4.316	1.757***	0.795
	(0.518)	(1.276)	(0.635)	(2.886)	(0.532)	(1.208)
Diff. Upwind-Downwind Trimester 2	0.516	0.633	1.115	0.402	0.960**	0.188
	(0.418)	(1.308)	(1.081)	(1.637)	(0.428)	(1.387)
Diff. Upwind-Downwind Trimester 3	1.555***	0.366	1.850**	1.517	1.692***	-0.0191
	(0.493)	(1.206)	(0.855)	(1.765)	(0.437)	(1.159)
Observations	1,384	659	701	640	667	702
Sample	Low Education	High Education	Low Income	High Income	Grain Production	Non-grain Production
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0383	0.0837	0.0673	0.0174	0.0522	0.0381

Notes: This table presents the heterogeneity of our baseline results, using the rural sample. We consider the heterogeneous effects regarding three variables: mother's education level (whether completed middle school), family income level (whether the family income is above the median value), and whether the family is engaged in grain production. The dependent variable is a normalized health index with a greater value representing worse health conditions. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table A9 Robustness: Controlling for Additional Time Trends and Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Unhealthiness Index		Word Test Score		Positive Attitudes		Negative Attitudes	
Diff. Upwind-Downwind Trimester 1	2.452***	2.358***	-0.918*	-1.179*	-1.317*	-1.321*	3.044***	3.078***
	(0.824)	(0.843)	(0.560)	(0.612)	(0.771)	(0.791)	(0.873)	(0.916)
Diff. Upwind-Downwind Trimester 2	1.002	0.987	-0.204	-0.292	0.537	0.549	0.773	0.756
	(0.728)	(0.756)	(0.616)	(0.700)	(1.117)	(1.164)	(1.343)	(1.411)
Diff. Upwind-Downwind Trimester 3	2.057***	2.111***	-0.580	-0.587	-1.254	-1.254	1.511	1.496
	(0.713)	(0.768)	(0.539)	(0.608)	(0.783)	(0.824)	(1.261)	(1.317)
Observations	746	712	741	712	238	235	212	208
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province by Birth Year Trends	Yes	No	Yes	No	Yes	No	Yes	No
Province by Birth Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.257	0.321	0.222	0.175	0.241	0.134	0.110	0.088

Notes: This table presents the estimated results for including additional birth-year trends and birth-year fixed effects, using the rural sample. The dependent variable in columns (1) and (2) is the unhealthiness index, in columns (3) and (4), it's the standardized word test score, in columns (5) and (6), it's the positive measure of non-cognitive ability, while in columns (7) and (8), it's the negative measure of non-cognitive ability. The observation is at the county-cohort level, with each cohort defined by its birth month. All regressions include both individual and weather controls. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table A10 Robustness: Controlling for Additional Pollution Sources

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Unhealthiness Index		Word Test Score		Positive Attitudes		Negative Attitudes	
Diff. Upwind-Downwind Trimester 1	2.714***	2.714***	-1.278***	-1.263***	-1.336*	-1.348*	3.515***	3.396***
	(0.835	(0.837)	(0.486)	(0.483)	(0.743)	(0.765)	(1.051)	(1.038)
Diff. Upwind-Downwind Trimester 2	1.290*	1.290*	-0.545	-0.538	0.332	0.333	2.555*	2.825**
	(0.699)	(0.697)	(0.593)	(0.596)	(0.984)	(0.981)	(1.287)	(1.252)
Diff. Upwind-Downwind Trimester 3	2.364***	2.364***	-0.781	-0.777	-1.221*	-1.207*	2.664**	2.930***
	(0.712)	(0.720)	(0.482)	(0.480)	(0.687)	(0.676)	(1.010)	(1.004)
Observations	737	737	737	737	235	235	210	210
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indoor Air Pollution	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Water Pollution	No	Yes	No	Yes	No	Yes	No	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.120	0.113	0.239	0.237	0.280	0.274	0.176	0.186

Notes: This table presents the estimated results for including additional birth-year trends and birth-year fixed effects, using the rural sample. In odd columns, we include controls for whether households use straws as their primary source of fuel. While in even columns, we additionally control for the fertilizer expenses as a proxy for potential exposure to water pollution. The dependent variable in columns (1) and (2) is the unhealthiness index, in columns (3) and (4), it's the standardized word test score, in columns (5) and (6), it's the positive measure of non-cognitive ability, while in columns (7) and (8), it's the negative measure of non-cognitive ability. The observation is at the county-cohort level, with each cohort defined by its birth month. All regressions include both individual and weather controls. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table A11 Robustness: Controlling for Additional Infrastructure and Facility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Unhealthiness Index		Word Test Score		Positive Attitudes		Negative Attitudes	
Diff. Upwind-Downwind Trimester 1	2.612***	2.675***	-1.067**	-1.109**	-1.493**	-1.689**	3.912***	4.234***
	(0.841)	(0.888)	(0.506)	(0.506)	(0.688)	(0.670)	(1.113)	(1.243)
Diff. Upwind-Downwind Trimester 2	1.177*	1.157*	-0.389	-0.469	0.248	0.313	3.073**	3.393**
	(0.682)	(0.686)	(0.585)	(0.584)	(1.026)	(0.999)	(1.488)	(1.446)
Diff. Upwind-Downwind Trimester 3	2.277***	2.287***	-0.601	-0.643	-1.390**	-1.416*	3.308***	3.550***
	(0.724)	(0.744)	(0.490)	(0.508)	(0.679)	(0.762)	(1.198)	(1.165)
Observations	731	731	731	731	234	234	209	209
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Health and Educational Facilities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infrastructure Controls	No	Yes	No	Yes	No	Yes	No	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0741	0.0653	0.253	0.255	0.283	0.269	0.0943	0.0519

Notes: This table presents the estimated results for including additional birth-year trends and birth-year fixed effects, using the rural sample. In odd columns, we include controls for health and educational facilities (i.e., number of kindergartens and primary schools, and number of hospitals and pharmacies). While in even columns, we additionally control for the infrastructure construction at the village level (i.e., access to electricity, road, and railway). The dependent variable in columns (1) and (2) is the unhealthiness index, in columns (3) and (4), it's the standardized word test score, in columns (5) and (6), it's the positive measure of non-cognitive ability, while in columns (7) and (8), it's the negative measure of non-cognitive ability. The observation is at the county-cohort level, with each cohort defined by its birth month. All regressions include both individual and weather controls. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table A12 The Effects of Agricultural Fires on Adulthood Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.	Education Year			Log Wage			Work in Agriculture		
Diff. Upwind-Downwind Trimester 1	-0.075**	-0.133*	-0.032	-0.029**	-0.019	-0.024	0.297**	0.416**	0.373
	(0.036)	(0.076)	(0.054)	(0.014)	(0.083)	(0.028)	(0.128)	(0.208)	(0.226)
Diff. Upwind-Downwind Trimester 2	-0.0200	-0.058	0.019	-0.028**	-0.041**	-0.021	0.337**	0.231	0.207
	(0.041)	(0.079)	(0.070)	(0.014)	(0.017)	(0.032)	(0.162)	(0.190)	(0.192)
Diff. Upwind-Downwind Trimester 3	-0.033	-0.019	-0.067	-0.023*	-0.043**	-0.025	0.217*	0.346*	0.340
	(0.035)	(0.083)	(0.049)	(0.013)	(0.019)	(0.030)	(0.120)	(0.193)	(0.220)
Observations	1,228	614	561	657	323	297	657	323	297
Sample	Full	Boy	Girl	Full	Boy	Girl	Full	Boy	Girl
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.180	0.208	0.145	0.030	0.033	0.198	0.059	0.102	0.040

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on adulthood outcomes, using the rural sample. In columns (1) to (3), the dependent variable is the number of education years completed, normalized by the individual's age. In columns (4) to (6), the dependent variable is the logged value of annual wage, conditioning on whether the individual enters the labor market. In columns (7) to (9), the dependent variable is a dummy that indicates whether the individual works in the agriculture sector. The observation is at the county-cohort level, with each cohort defined by its birth month. All regressions include both individual and weather controls. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table A13 The Effects of Agricultural Fire-Induced Air Pollution on Child Mortality

	(1)	(2)
Dep. Var.	# of Deaths	mortality
Upwind APY	-0.018	-0.006
	(0.033)	(0.011)
Downwind APY	-0.115*	-0.037*
	(0.060)	(0.021)
Diff. Upwind-Downwind	0.097	0.031
	(0.066)	(0.023)
Observations	1,452	1,322
Birth Year by Birth Month FE	Yes	Yes
Prefecture by Birth Year FE	Yes	Yes
Prefecture by Birth Month FE	Yes	Yes
Individual Controls	Yes	Yes
Weather Controls	Yes	Yes
Adjusted R-squared	0.0202	0.0594

Notes: This table presents the estimated results of the effects of upwind/downwind agricultural potential yield on child mortality. The dependent variable in column (1) is the number of deaths, and the dependent variable in column (2) is the mortality rate calculated by dividing the number of deaths by the number of surviving children. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include the father's education and age, the mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. Standard error is clustered at the prefecture level.

Table A14 Main Estimates after Control for Potential Selection

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Unhealthiness Index			Standardized Word Test Score		
Diff. Upwind-Downwind Trimester 1	1.781**	2.781***	-0.289	-0.768*	-1.988***	0.564
	(0.875)	(0.875)	(1.395)	(0.400)	(0.551)	(0.818)
Diff. Upwind-Downwind Trimester 2	0.856	1.256*	-0.509	-0.048	-0.784	0.478
	(0.692)	(0.692)	(1.455)	(0.363)	(0.665)	(0.733)
Diff. Upwind-Downwind Trimester 3	1.328***	2.328***	0.868	-0.352	-1.502**	0.512
	(0.350)	(0.750)	(1.227)	(0.376)	(0.518)	(0.750)
Observations	1,561	755	784	1,385	671	690
Sample	Full	Boy	Girl	Full	Boy	Girl
Adjusted R-squared	0.0534	0.0234	0.0517	0.238	0.239	0.200
	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Var.	Non-cognitive Ability (Positive)			Non-cognitive Ability (Negative)		
Diff. Upwind-Downwind Trimester 1	-0.674	-1.319*	-0.052	1.375**	3.244***	0.582
	(0.526)	(0.728)	(0.931)	(0.561)	(1.026)	(0.955)
Diff. Upwind-Downwind Trimester 2	-0.613	0.0097	-0.318	-0.014	2.420*	0.522
	(0.529)	(0.972)	(0.912)	(0.698)	(1.280)	(1.024)
Diff. Upwind-Downwind Trimester 3	-0.798*	-1.323*	-0.382	0.474	2.309**	0.814
	(0.471)	(0.634)	(0.875)	(0.680)	(1.098)	(1.053)
Observations	443	232	232	441	209	229
Sample	Full	Boy	Girl	Full	Boy	Girl
Adjusted R-squared	0.247	0.301	0.187	0.111	0.137	0.165
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on adolescent health, cognitive, and non-cognitive ability by additionally controlling for selection, using the rural sample. The dependent variables are the unhealthiness index in columns (1) to (3), age-specific standardized word test scores in columns (4) to (6), positive measure of cognitive ability in columns (7) to (9), and negative measure of cognitive ability in columns (10) to (12). The observation is at the county-cohort level, with each cohort defined by its birth month. All regressions include both individual and weather controls. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table A15 The Effects of Early Exposure to NCMS on Education Expenses

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Log Education Expenses					
Diff. Upwind-Downwind Trimester 1	0.016	-0.022	0.137	-0.051	0.022	-0.099**
	(0.049)	(0.035)	(0.155)	(0.035	(0.063)	(0.031
Diff. Upwind-Downwind Trimester 2	-0.023	0.057	0.002	0.029	0.017	0.026
	(0.053)	(0.050)	(0.136)	(0.054)	(0.077	(0.076)
Diff. Upwind-Downwind Trimester 3	-0.048	-0.070*	-0.004	-0.110*	-0.044	-0.149***
	(0.049)	(0.040)	(0.147)	(0.031	(0.066)	(0.038
Observations	846	1,151	550	842	490	725
Sample	Exposure	Non-Exposure	Exposure & Low Education	Non-Exposure & Low Education	Exposure & Low Income	Non-Exposure & Low Income
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other Exposure	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.294	0.408	0.254	0.367	0.322	0.350

Notes: This table presents the estimated results of the role of NCMS coverage on mitigating the effects of in-utero agricultural fire exposure on parental education investment, using the rural sample. The dependent variable is the logged value of education expenses on children. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Other exposures include controls on whether the individual is exposed to electricity, tap water, road, railway, and natural gas before age 5. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table A16 The Effects of Early Exposure to NCMS on Early-life Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	# Illness at Age 1		Gestation Month		Birth Weight	
Diff. Upwind-Downwind Trimester 1	0.157	0.666**	-0.510**	-0.361*	-0.226	-0.967
	(0.209)	(0.266)	(0.228)	(0.194)	(0.617)	(0.641)
Diff. Upwind-Downwind Trimester 2	0.289	0.267	-0.299	-0.273	0.247	-0.099
	(0.344)	(0.341)	(0.245)	(0.201)	(0.646)	(0.776)
Diff. Upwind-Downwind Trimester 3	0.572***	0.302	-0.122	-0.372*	-0.059	-0.284
	(0.199)	(0.208)	(0.332)	(0.201)	(0.628)	(0.632)
Observations	963	1,087	1,089	1,246	1,103	1,262
Sample	Exposure	Non-Exposure	Exposure	Non-Exposure	Exposure	Non-Exposure
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other Exposure	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.173	0.175	0.225	0.249	0.112	0.116

Notes: This table presents the estimated results of the role of NCMS coverage on mitigating the effects of in-utero agricultural fire exposure on early-life outcomes, using the rural sample. In columns (1) and (2), the dependent variable is the number of illnesses at age 1. In columns (3) and (4), the dependent variable is the length of the gestation period, measured in months. In columns (5) and (6), the dependent variable is the individual's birth weight, measured in 500 grams. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Other exposures include controls on whether the individual is exposed to electricity, tap water, road, railway, and natural gas before age 5. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Additional Figures

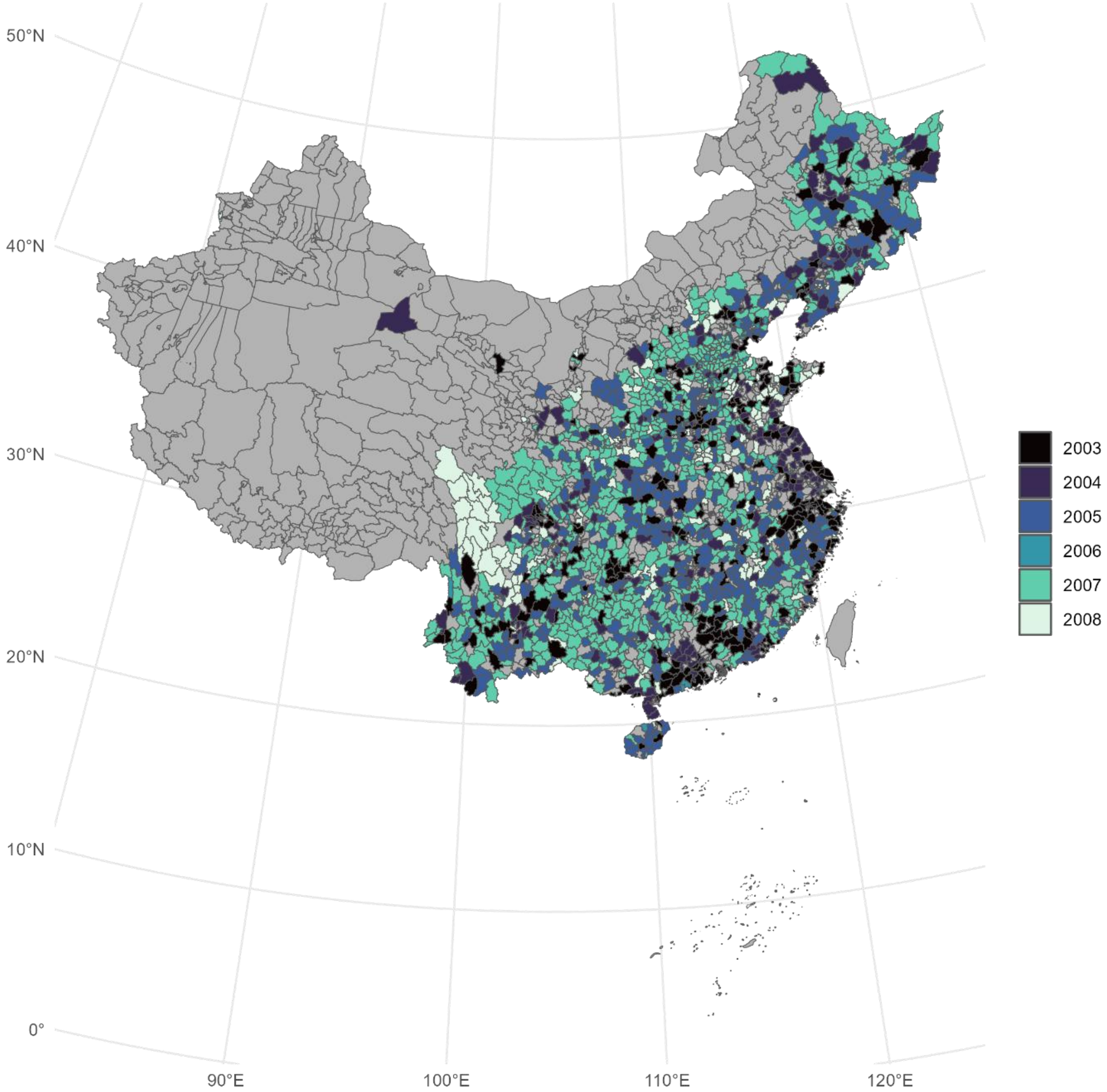


Figure A1 The Geographic Distribution of NCMS Rollout Timing

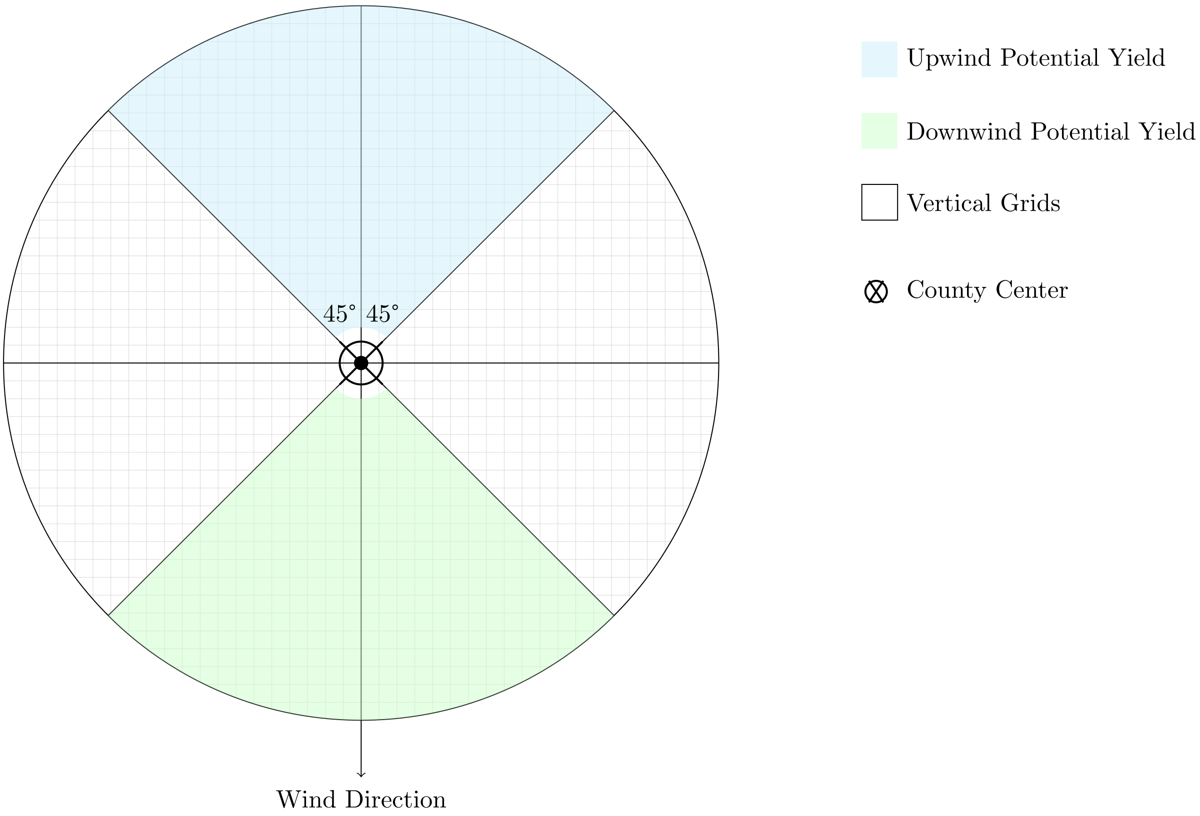


Figure A2 An Illustration on Determining the Upwind Region

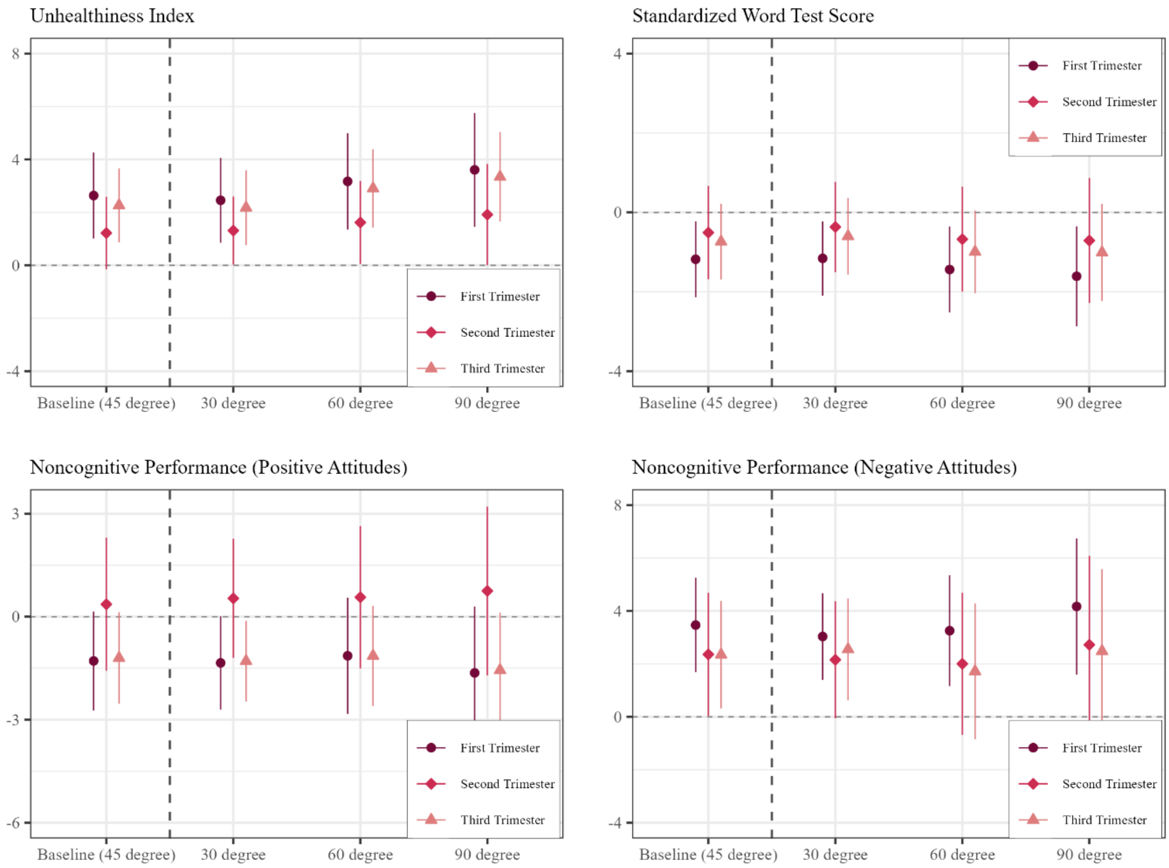


Figure A3 Robustness: Altering the Definition of Upwind Direction

Notes: This figure presents the estimated robustness results of altering the definition of upwind direction. Our baseline results adopt a definition of 45 degrees, and we check for the robustness of our results by using 30, 60, and 90 degrees. The figure is comprised of 4 subplots. The upper left panel depicts the corresponding effects on the unhealthiness index, the upper right panel depicts the effects on the standardized word test score, the lower left panel depicts the effects on the positive non-cognitive performance, and the lower right panel depicts the effects on the negative non-cognitive performance. We focus on the sample of rural male adolescents. Point estimates and the corresponding 95% confidence intervals are jointly presented.

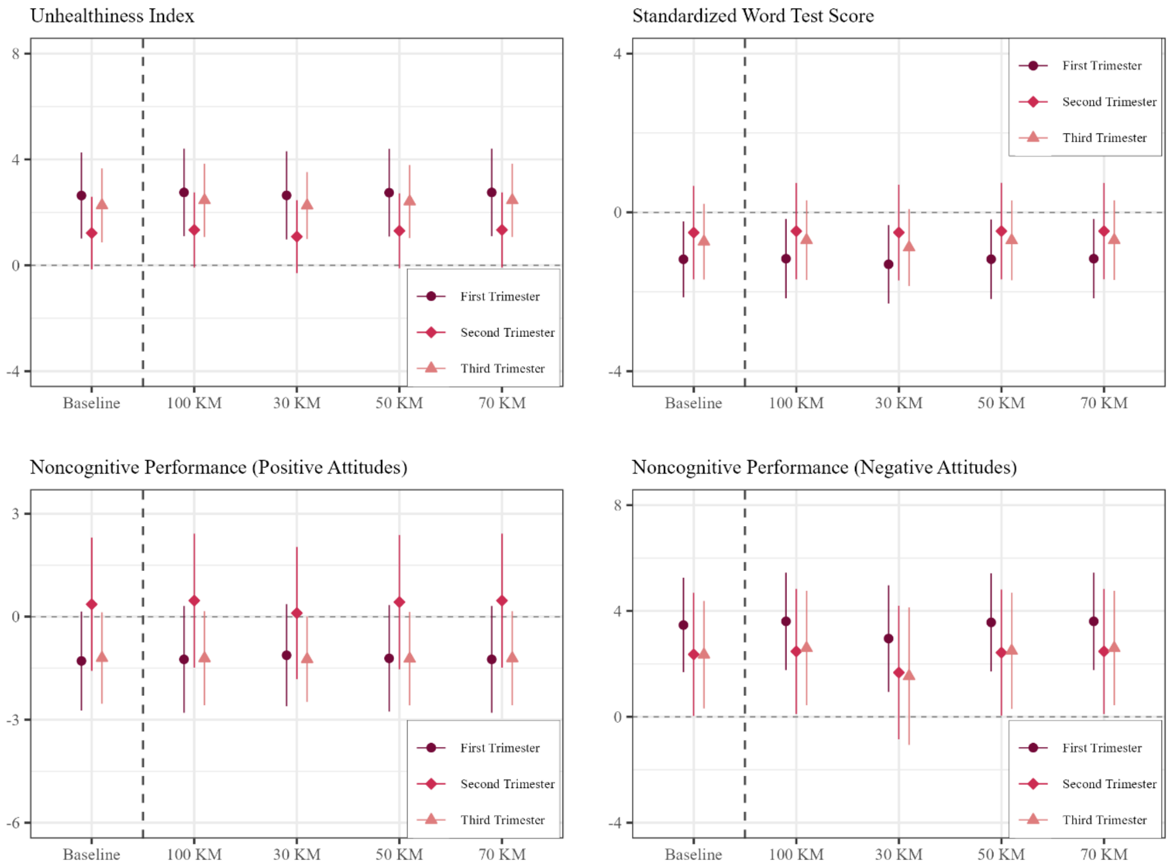
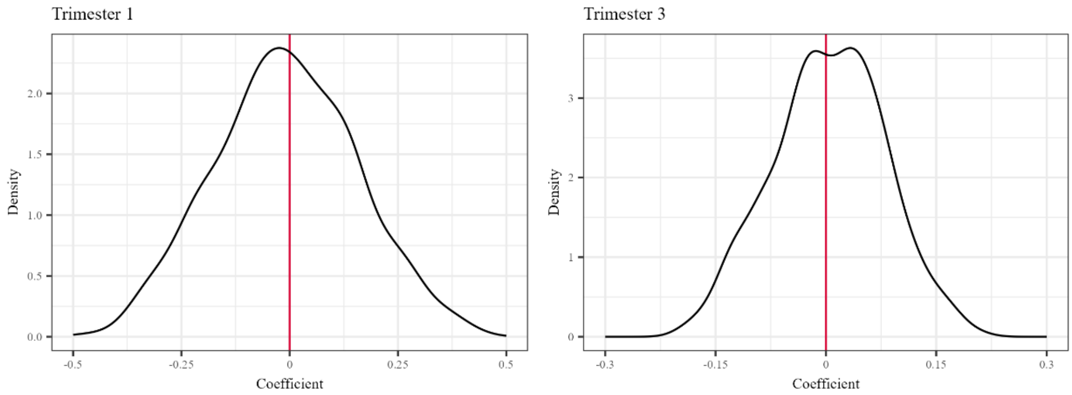
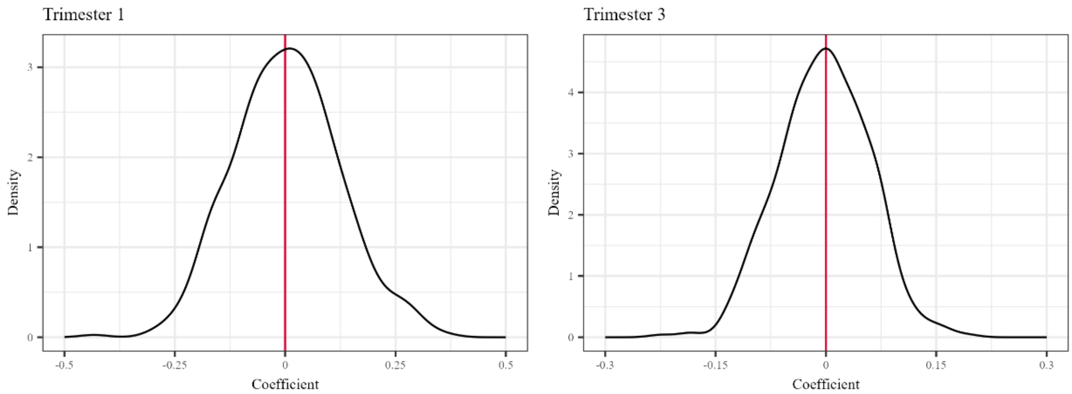


Figure A4 Robustness: Different Choices of Potential Yield Coverage

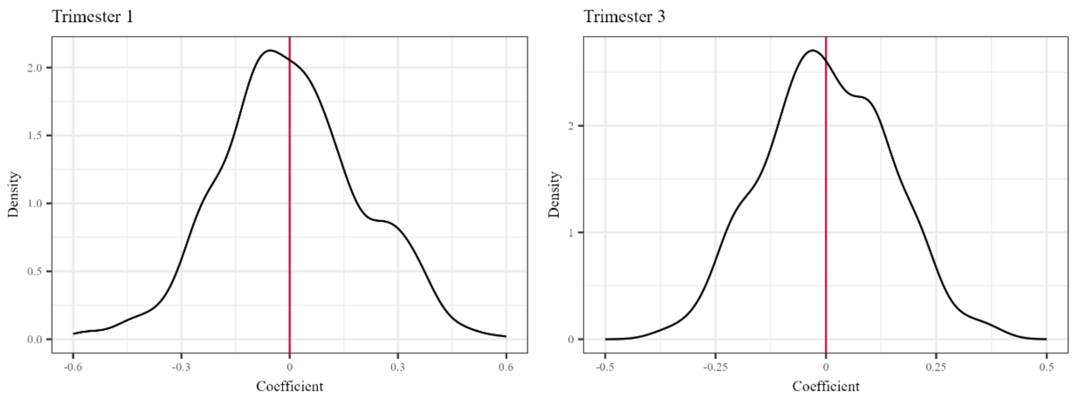
Notes: This figure presents the estimated robustness results of changing the coverage radii of agricultural potential yield. Our baseline results calculate the upwind/downwind potential yield covering the entire county, and we use potential yield grids with radii of 100 KM, 70 KM, 50 KM, and 30 KM to the county center to test the robustness of the results. The figure is comprised of 4 subplots. The upper left panel depicts the corresponding effects on the unhealthiness index, the upper right panel depicts the effects on the standardized word test score, the lower left panel depicts the effects on the positive non-cognitive performance, and the lower right panel depicts the effects on the negative non-cognitive performance. We focus on the sample of rural male adolescents. Point estimates and the corresponding 95% confidence intervals are jointly presented.



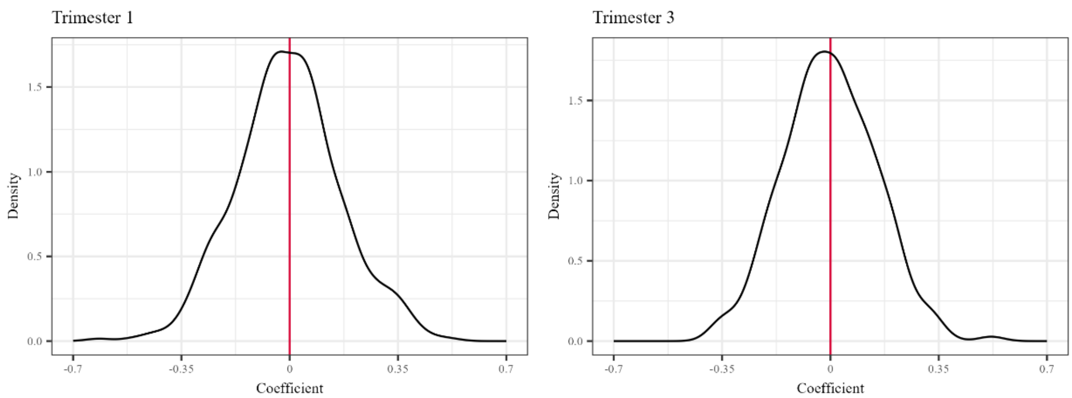
Panel A: Unhealthiness Index



Panel B: Standardized Word Test Score



Panel C: Positive Non-cognitive Performance



Panel D: Negative Non-cognitive Performance

Figure A5 Robustness: The Distribution of Placebo Coefficients

Notes: This figure presents the distribution of placebo coefficients on four of our main outcome variables, focusing on the effects of fire exposure during the first and third trimesters. In Panel A, we plot the distribution of coefficients from regressing the unhealthiness index on placebo upwind/downwind potential yield. Whereas in Panels B, C, and D, the dependent variables are the standardized word test score, the positive non-cognitive performance, and the negative non-cognitive performance. The sample is comprised of rural male adolescents.

Appendix B: Additional Results on the Urban Sample

Table B1 The Effects of Agricultural Fires on Adolescents' Health (Urban Sample)

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	Unhealthiness Index				
Diff. Upwind-Downwind Trimester 1	-0.344	-0.305	-0.355	-0.170	-0.929
	(0.347)	(0.362)	(0.409)	(0.709)	(0.576)
Diff. Upwind-Downwind Trimester 2	-0.0521	-0.0341	-0.0870	0.0452	-0.435
	(0.356)	(0.363)	(0.387)	(0.782)	(0.681)
Diff. Upwind-Downwind Trimester 3	0.264	0.255	0.141	0.0504	0.290
	(0.329)	(0.336)	(0.375)	(0.688)	(0.676)
Observations	1,837	1,837	1,834	1,096	945
Sample	Full	Full	Full	Boy	Girl
Birth Year FE	Yes	Yes	No	No	No
Birth Month FE	Yes	Yes	No	No	No
Birth Year by Birth Month FE	No	No	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	No	Yes	Yes	Yes	Yes
Dep. Var. SD	1.638	1.638	1.638	1.638	1.638
Adjusted R-squared	0.440	0.441	0.440	0.432	0.449

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on adolescent health, using the urban sample. The dependent variable is a normalized health index with a greater value representing worse health conditions. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B2 The Effects of Agricultural Fires on Cognitive Test Scores (Urban Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Standardized Word Test Score			Standardized Math Test Score		
Diff. Upwind-Downwind Trimester 1	-0.417*	-0.473	-0.298	0.00588	0.0688	0.0799
	(0.246)	(0.711)	(0.274)	(0.248)	(0.520)	(0.326)
Diff. Upwind-Downwind Trimester 2	-0.488	-0.599	-0.509	-0.491	-0.943	-0.222
	(0.309)	(0.812)	(0.348)	(0.310)	(0.688)	(0.371)
Diff. Upwind-Downwind Trimester 3	-0.139	-0.0927	0.467	-0.236	-0.113	-0.182
	(0.237)	(0.780)	(0.320)	(0.254)	(0.543)	(0.423)
Observations	816	408	368	818	409	369
Sample	Full	Boy	Girl	Full	Boy	Girl
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.232	0.217	0.228	0.202	0.157	0.232

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on adolescent cognitive ability, using the urban sample. The dependent variables are age-specific standardized word test scores and math test scores. The observation is at the county-cohort level, with each cohort defined by its birth month. All regressions include both individual and weather controls. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B3 The Effects of Agricultural Fires on Adulthood Outcomes (Urban Sample)

	(1)	(2)	(3)
Dep. Var.	Education Year		
Diff. Upwind-Downwind Trimester 1	-0.0207	0.0246	0.0219
	(0.0332)	(0.0527)	(0.0377)
Diff. Upwind-Downwind Trimester 2	-0.0116	0.0546	-0.0247
	(0.0287)	(0.0537)	(0.0335)
Diff. Upwind-Downwind Trimester 3	0.00531	0.0493	0.00612
	(0.0311)	(0.0499)	(0.0281)
Observations	994	470	472
Sample	Full	Boy	Girl
Birth Year by Birth Month FE	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Adjusted R-squared	0.377	0.367	0.479

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on adulthood outcomes, using the urban sample. The dependent variable is the number of education years completed, normalized by the individual's age. The observation is at the county-cohort level, with each cohort defined by its birth month. All regressions include both individual and weather controls. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B4 The Effects of Agricultural Fires on Health Expenses (Urban Sample)

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	Log Health Expenses				
Diff. Upwind-Downwind Trimester 1	0.008	0.032	-0.049	0.043	0.068
	(0.008)	(0.026)	(0.092)	(0.104)	(0.141)
Diff. Upwind-Downwind Trimester 2	0.006	0.035	-0.015	-0.034	0.085
	(0.008)	(0.023)	(0.080)	(0.123)	(0.116)
Diff. Upwind-Downwind Trimester 3	0.008	0.018	-0.050	0.065	0.088
	(0.008)	(0.024)	(0.077)	(0.131)	(0.121)
Observations	1,834	623	1,185	928	885
Sample	Full	Low Education	High Education	Low Income	High Income
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.140	0.087	0.175	0.211	0.125

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on families' health expenses, using the urban sample. The dependent variable is the logged value of health expenses on children. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B5 The Effects of Agricultural Fires on Education Expenses (Urban Sample)

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	Log Education Expenses				
Diff. Upwind-Downwind Trimester 1	-0.030	0.013	-0.043	0.006	-0.024
	(0.032)	(0.075)	(0.038)	(0.060)	(0.048)
Diff. Upwind-Downwind Trimester 2	-0.023	0.037	-0.037	-0.063	0.040
	(0.033)	(0.067)	(0.040)	(0.057)	(0.044)
Diff. Upwind-Downwind Trimester 3	-0.008	0.025	-0.019	-0.027	0.021
	(0.028)	(0.072)	(0.038)	(0.052)	(0.041)
Observations	1,662	538	1,092	823	811
Sample	Full	Low Education	High Education	Low Income	High Income
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	No	Yes	Yes	Yes	Yes
Adjusted R-squared	0.402	0.342	0.357	0.368	0.336

Notes: This table presents the estimated results of the effects of in-utero agricultural fire exposure on families' education expenses, using the urban sample. The dependent variable is the logged value of education expenses on children. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B6 The Effects of Early Exposure to NCMS on Adolescent Outcomes (Urban Sample)

	(1)	(2)	(3)	(4)
Dep. Var.	Unhealthiness Index			
Diff. Upwind-Downwind Trimester 1	-0.618	-0.114	-0.668	-0.213
	(0.728)	(0.526)	(0.740)	(0.549)
Diff. Upwind-Downwind Trimester 2	-0.573	0.546	-0.615	0.498
	(0.566)	(0.612)	(0.553)	(0.607)
Diff. Upwind-Downwind Trimester 3	-0.229	0.329	-0.273	0.286
	(0.735)	(0.478)	(0.734)	(0.492)
Observations	828	985	828	985
Sample	Exposure to NCMS	Non-Exposure to NCMS	Exposure to NCMS	Non-Exposure to NCMS
Birth Year by Birth Month FE	Yes	Yes	Yes	Yes
County of Birth FE	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Other Exposure	No	No	Yes	Yes
Adjusted R-squared	0.321	0.448	0.321	0.449

Notes: This table presents the estimated results of the role of NCMS coverage on mitigating the effects of in-utero agricultural fire exposure on adolescent health, using the urban sample. The dependent variable is a normalized health index with a greater value representing worse health conditions. The observation is at the county-cohort level, with each cohort defined by its birth month. Individual controls include gender, age, father's education and age, mother's education and age, family income, family size, and number of siblings. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. All weather controls are constructed by averaging the weather conditions during different trimesters. Other exposures include controls on whether the individual is exposed to electricity, tap water, road, railway, and natural gas before age 5. Standard error is clustered at the county level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

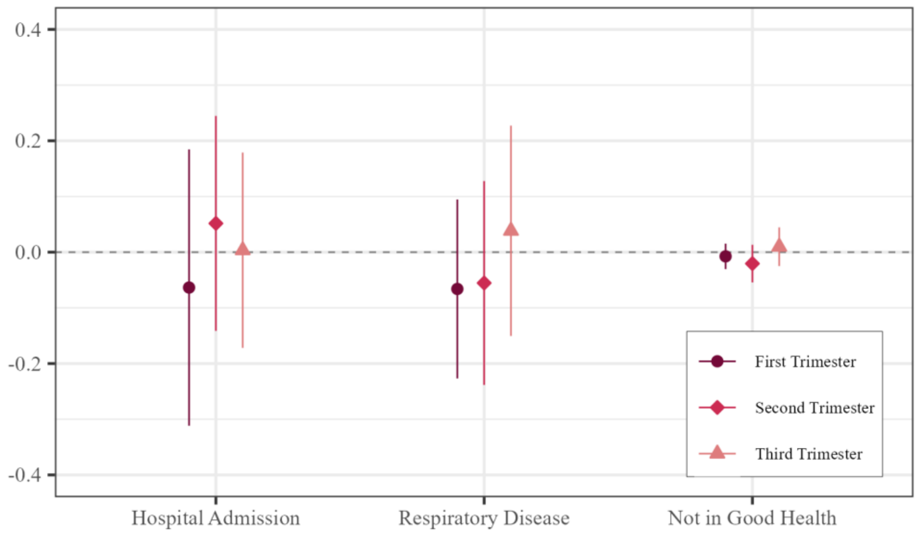


Figure B1 The Effects of Agricultural Fires on Adolescence Health Components (Urban Sample)

Notes: This figure visualizes the estimated coefficients of the effects of in-utero agricultural fire exposure during different trimesters on adolescent health outcomes, including hospital admission, respiratory disease, and self-rated status, using the urban sample. Point estimates and the corresponding 95% confidence intervals are jointly presented.

Appendix C: Robustness Checks

This section briefly discusses the robustness of our baseline estimates. Since our main analyses above suggest that the effects are primarily driven by the male sample, we focus on the male sample for our following robustness checks to avoid redundancy.

C.1 Alternative definition of upwind direction and potential yield coverage

In the baseline regressions, we use the 45-degree criterion to define upwind agricultural potential yields, i.e., whether the angle between the direction of the prevailing wind and the direction of the particular potential yield grid to the county center is less than 45 degrees. To mitigate concerns that our results are driven by the specific choice of wind direction. In Appendix Figure A3, we re-estimate the baseline effects of agricultural fire exposure on health and (non-)cognitive outcomes by changing the definition of upwind direction. Specifically, we consider alternative definitions of 30, 60, and 90 degrees. The estimated results in Figure A3 suggest that our results are robust to alternative definitions of upwind directions.

We then examine whether our estimated results are sensitive to different choices of potential yield coverage radii. In our baseline construction, we calculate the upwind/downwind potential yield covering the entire county. To avoid potential measurement error and examine the sensitivity of our results to different choices of potential yield coverage, we choose alternative radii of 100KM, 70KM, 50KM, and 30KM of coverage. Appendix Figure A4 presents the corresponding results for these alternative specifications. Again, we find that our estimates are stable across different choices of potential yield coverage.

C.2 Controlling for additional trends and fixed effects

Our baseline specification includes birth year by birth month fixed effects to account for the confounding effect of unobserved aggregate time-varying shocks specific to individuals born in different years. However, these unobserved shocks (e.g., shocks to agricultural productivity, natural disasters, or extreme temperatures) may also vary across regions, resulting in the observed association between agricultural fire exposure and adolescent outcomes. To address such concerns, in Appendix Table A9, we re-estimate our baseline results by additionally including the province-by-birth-year trends and province-by-birth-year fixed effects. The inclusion of these additional regional-specific time trends and fixed effects lends us additional credit that our estimated effects are not driven by unobserved shocks. Reassuringly, the estimated coefficients of fire exposure on health and (non-)cognitive measures remain significant, and the magnitudes are similar to our baseline results.

C.3 Accounting for additional confounders

Our baseline estimates reveal a significant correlation between in-utero agricultural fire exposure and adolescent outcomes. However, the presence of several potential confounders may prevent us from convincingly establishing the causal relationship. Specifically, there are two main challenges to our identification. First, despite air pollution from agricultural fires, the potential yield may correlate with other sources of rural pollution. Apart from *in situ* burning, another use of straw residues is for household fuel, which is associated with indoor air pollution. Besides, since higher potential yield is correlated with higher grain output, which may be associated with the intensive use of fertilizer and pesticide, leading to potential water pollution. Second, the agricultural potential yield may be correlated with other factors that simultaneously affect adolescent outcomes. For example, higher potential yield may be correlated with higher agricultural income, which in turn may result in differential access to infrastructure and other facilities.

First, to ensure that our results are not driven by pollution from other sources (e.g., indoor air pollution or fertilizer-induced water pollution), in Appendix Table A10, we include additional controls on whether households use straws as their primary fuel source and the household expenses on fertilizer. The former accounts for the potential channel of indoor air pollution, while the latter accounts for the potential confounding of water pollution. We find that the inclusion of these additional controls for pollution exposure merely affects our estimated effects, suggesting that we can be less concerned that our potential yield measures may be correlated with other sources of rural pollution.

Next, we examine whether our estimated effects are driven by the differential access to infrastructures and other facilities. Specifically, we consider facilities that are related to education and health (e.g., number of kindergartens, number of primary schools, number of hospitals and pharmacies in the village). We also include controls on whether villages have access to electricity, roads, and railways, to serve as proxies for Infrastructure construction. The corresponding results are reported in Appendix Table A11. We show that the estimated coefficients are stable in both magnitude and significance level after the inclusion of these additional controls. Taken together, the above exercises suggest that our results are less likely to be driven by omitted variables, which again provides support to the validity of our research design that leverages exogenous sources from wind directions for identification.

C.4 Randomized inference

As a further validation, we provide the randomized inference to show that our estimated effects are not the result of any arbitrary idiosyncratic variations. To do so, we first simulate placebo upwind/downwind agricultural potential yield, which are drawn from the same distribution and have the same mean and standard deviation as the original data. We then follow equation (3) and interact the placebo upwind/downwind potential yield with dummies indicating during which trimester the individual is exposed to agricultural fires. For each random draw of potential yield, we re-estimate equation (3) and record the corresponding coefficients. The process is repeated 500 times. As the effect of in-utero agricultural fire exposure on adolescent outcomes is primarily driven by exposure during the first and third trimesters, we mainly focus on examining the extent to which the placebo coefficients for fire exposure in these two trimesters can replicate our baseline estimates. Appendix Figure A5 plots the corresponding distribution of placebo coefficients on four of our main outcome variables. We find that the placebo coefficients are centered around zero and are small in magnitude, and are far away from the true coefficients. This piece of evidence suggests that our estimated effects are plausibly unlikely to be accounted for by arbitrary idiosyncratic variations.