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ORIGINAL PAPER

When the wind blows: agricultural fire exposure, parental investment, and long-term outcomes

Hai Hong[1] · Kevin Chen[1,2]

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Abstract
This paper examines the medium and long-term human capital consequences of in-utero exposure to agricultural fires in rural China. We exploit exogenous variations in birth month, fire intensity, and wind direction to identify the causal effect of fetal exposure to fire. Our findings suggest that in-utero exposure to agricultural fires significantly reduces individuals' health, cognitive, and non-cognitive performance in adolescence, with the effect primarily driven by the male sample. Tracking these cohorts into adulthood, we show that fire exposure decreases the number of years of education 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 *away* from exposed children. Using the rollout of China's New Cooperative Medical Scheme (NCMS) as a quasi-experiment, we present evidence that health insurance coverage can largely offset the 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 mitigating the adverse effects of pollution exposure.

Keywords Agricultural fire · In-utero exposure · Parental investment · Health insurance

JEL Classification Q51 · Q53 · D13 · I13 · I14

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✉ Kevin Chen
kzchen@zju.edu.cn

Hai Hong
haihong@zju.edu.cn

[1] School of Public Affairs, China Academy for Rural Development, Zhejiang University, Hangzhou, China

[2] International Food Policy Research Institute, Beijing, China

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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; He et al. 2020; Graff Zivin et al. 2020; Lai et al. 2022; Pullabhotla and Souza 2022; Ayesh 2023; Du et al. 2024; Garg et al. 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, 2014; Almond and Currie 2011; Almond et al. 2009), 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 2000 s, to estimate the long-term effects of fetal agricultural fire exposure for individuals born before the 2000 s, 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 (Rangel and Vogl 2019; He et al. 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

[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.

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 et al. 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 the burgeoning literature that examines the consequences of air pollution from agricultural fires (Rangel and Vogl 2019; He et al. 2020; Graff Zivin et al. 2020; Lai et al. 2022; Pullabhotla and Souza 2022; Ayesh 2023; Du et al. 2024; Garg et al. 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 to systematically investigate the long-term consequences of in-utero exposure to agricultural fires. One related paper is Carneiro et al. (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 sheds 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 et al. 2017; Ebenstein et al. 2017; Anderson 2020; Barreca et al. 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 (Bharadwaj et al. 2017; Isen et al. 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 et al. 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 NCMS in rural China (Lei and Lin 2009; Wagstaff et al. 2009; Chen and Jin 2012; Cheng et al. 2015; Gruber et al. 2023; Huang and Liu 2023; Wang et al. 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 et al. 2019). Our finding suggests that the provision of health insurance can increase parental 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),

[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 adverse 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 et al. (2018) find that parents make compensatory investments in their children's initial health. Leveraging a 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.

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 (He et al. 2020; Graff Zivin et al. 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 et al. 2020; Garg et al. 2024).[4] For example, He et al. (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) demonstrate that during the harvest season in agricultural production areas, the share of fine particulate matter emitted from agricultural fires exceeds 50% of the total regional emissions, and that pollutant emissions from burning significantly increase 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 et al. 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). A 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 (Chay and Greenstone 2003; Almond et al. 2009; Sanders 2012; Chen et al. 2013; Isen et al. 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

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

[4] Air pollution from agricultural burning is estimated to involve around 30 million people globally (Landrigan et al. 2018).

(Rangel and Vogl 2019). As numerous studies have indicated that even pollution well below the safety standards can have detrimental effects on human health (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 (Ebenstein 2012; Greenstone and Hanna 2014; Hanna and Oliva 2015; Bombardini and Li 2020; Anderson 2020; Barreca et al. 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 et al. (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 et al. (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 et al. (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 1 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, several studies 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 et al. (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

The introduction of the NCMS is a great progress in the health system in rural China (Wang et al. 2024). Before the introduction of NCMS in the 2000 s, the vast population in rural China had very limited access to health insurance (either private or public) and was vulnerable to health shocks (Yip and Hsiao 2008; Hu et al. 2008). Typically, more than 90% of rural residents had no health insurance throughout the 1990 s, 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 et al. 2023). Over time, additional counties were gradually incorporated to achieve 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 3 years of NCMS expansion (You and Kobayashi 2009). Within 6 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 et al. 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 (Huang and Liu 2023; Gruber et al. 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 (Wagstaff et al. 2009; Lei and Lin 2009; Gruber et al. 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

[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 the government financed 84%, 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 do not cover outpatient services at all.

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 et al. 2023; Huang and Liu 2023; Wang et al. 2024). For example, Chen and Jin (2012) show that the introduction of the NCMS program has significantly improved the school enrollment of 6-year-olds, while having a limited impact 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 et al. (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 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. To keep the paper concise, we mainly describe the CFPS dataset and our measure of agricultural fires and potential yield in this section, and leave detailed descriptions of auxiliary data (e.g., air pollution and meteorological data) in Appendix D.

3.1 The China Family Panel Studies

Our primary data source is from 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.[8]

To ensure that our results are not driven by the selection of different birth months, we visualize the distribution of birth months in Fig. 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.[9] 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 closely related to air pollution.[10] 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 et al. 2016; Hoynes et al. 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).

[8] 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 errors would only lead to an underestimation.

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

[10] We use the illness type classification provided in the CFPS to identify whether the adolescent has respiratory diseases. These include upper respiratory tract infections, pneumonia, chronic laryngitis, emphysema, other chronic obstructive pulmonary diseases (including chronic bronchitis), asthma, and other respiratory diseases.

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.[11] We then follow Grönqvist et al. (2020) and use the principal component analysis (PCA) to combine these sub-scores 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 g).

To investigate the channel of intra-household resource allocation, we use two additional measures of health expenditure and education expenses to proxy for the parental investment in adolescents' human capital, in response to the negative health shocks at birth.[12]

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 and 15 at the time of survey) to CFPS 2020 using the unique individual ID.[13] 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

[11] 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*".

[12] The corresponding questionnaires provided in the CFPS dataset are "*Last year, how much was spent in total due to the child's illness? (RMB)*" for health expenses and "*Last year, what's the total education expenses for the child? (RMB)*" for education expenses.

[13] The CFPS tracks the same households in each wave of the survey, allowing us to follow approximately 78% of the same individuals from 2010 to 2020. Therefore, sample attrition does not appear to be a major concern. We also provide empirical evidence that attrition is plausibly random and is not correlated with our measure of agricultural fire exposure, as shown in Appendix Table A18.

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 have been frequently used in recent studies on agricultural fires (Nian 2023; Cao and Ma 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-m 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 and 15 in 2010), this data limitation prevents us from directly estimating the effects of the number of fires on adolescent and adult outcomes.

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 is 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"). Figure 2 presents the distribution of fire months. Unlike the distribution of birth months, the distribution of fire months is uneven. We see 3 peak months in the figure: March (February), June, and October.[14] The change of fire months across different counties provides sufficient variation for our identification. 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.[15] The data used in this paper is

[14] The 3 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.

[15] 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.

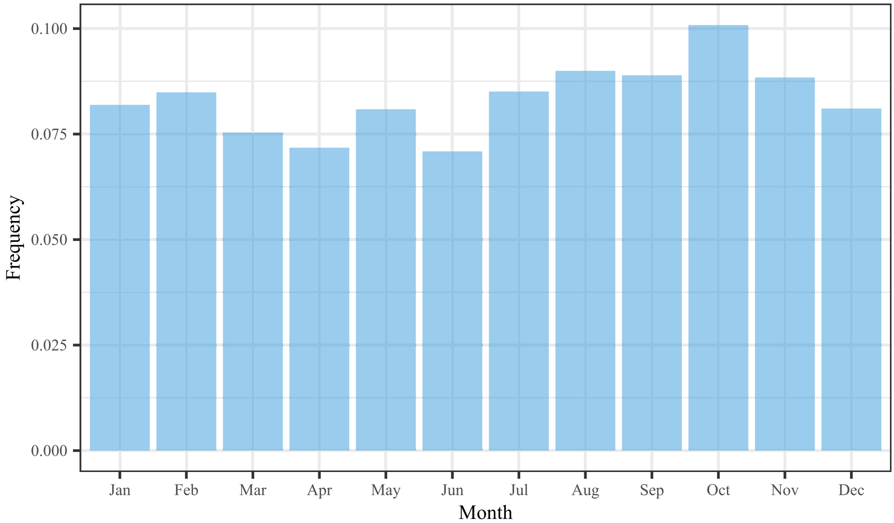


Fig. 1 The distribution of birth month. Notes: This figure presents the distribution of birth months of adolescents surveyed in CFPS 2010

from Liu et al. (2015), who constructed the potential yield raster for China at 1 km resolution using different crops.[16,17] The data is generated by combining *cell*-specific land quality attributes with established agronomic models for a given level of water supply and cultivation inputs. Potential yields summarize how detailed geographical attributes translate into productivity. 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. We first create a 1 km × 1 km grid covering the entire China's territory and map the grid with the potential yield raster as well as the county shapefile to determine the relative location of the potential yield grid to the county center. We then leverage the wind direction (described in Appendix D) during each county's fire month and determine whether a specific grid is located in the upwind or downwind direction of a county. In our baseline specification, we use a criterion of 45° to determine whether a grid is located in the upwind, downwind, or non-wind direction.[18] Appendix Figure A2 gives an illustration of how we define the upwind direction. For example, if the absolute difference between the angle of a specific grid to the county center and the wind direction is less than 45°, then the grid is classified as in 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

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

[17] Liu et al. (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.

[18] Alternative definitions of upwind direction are used as robustness checks.

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.

3.3 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.[19] 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 et al. 2022; Li and Xiao 2023).

4 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 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

[19] Since the timing of the NCMS rollout is plausibly not randomly assigned (Gruber et al. 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.

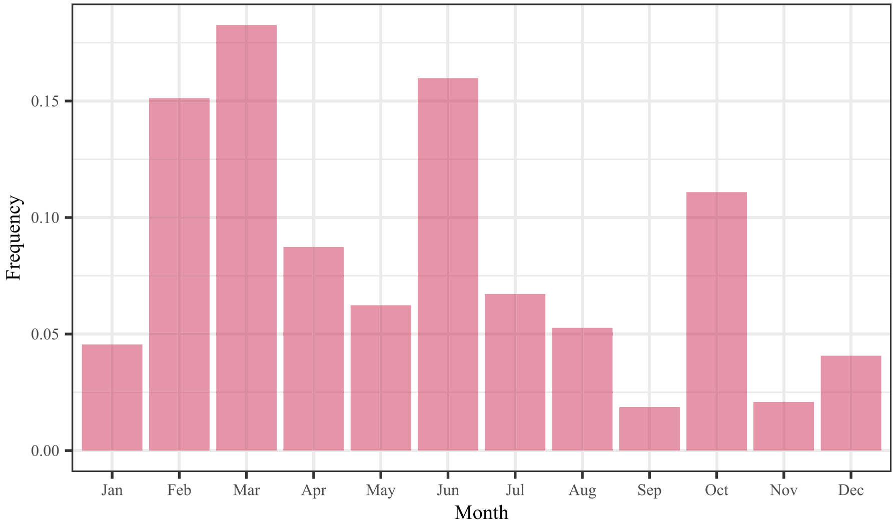


Fig. 2 The distribution of the fire month. Notes: This figure presents the distribution of fire months, which is defined as the month with the highest agricultural fire frequency

adolescents 10 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.

5 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, Fig. 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, Fig. 4 presents a binscatter plot showing the correlation between agricultural fires and potential yield. In addition to the spatial correlation documented in Fig. 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.

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

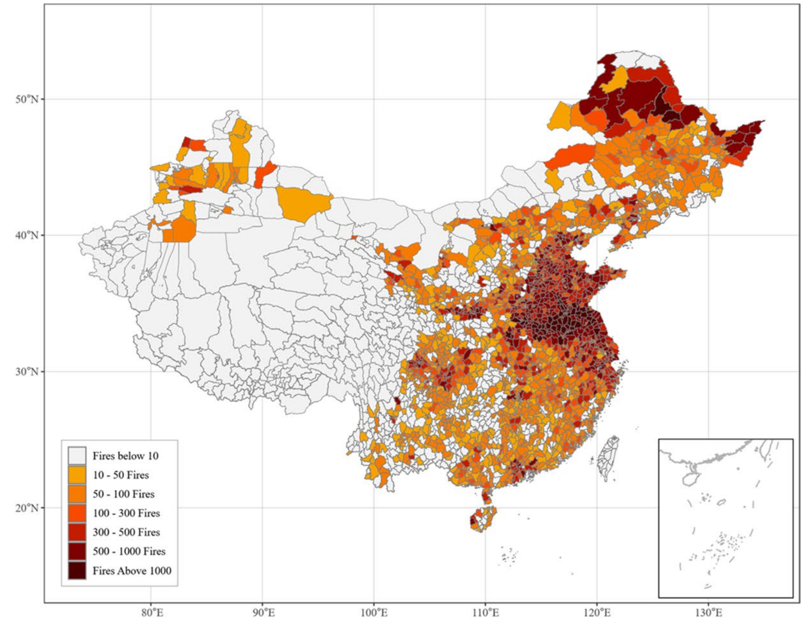
$$fire_{cpmt} = \beta_0 + \beta_1 APY_c + \Gamma \boldsymbol{W_{cpmt}} + \gamma_{pt} + \gamma_{pm} + \gamma_{mt} + \epsilon_{cpmt} \tag{1}$$

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 of 0 and a standard deviation of 1, so that the estimated coefficient, β_1, measures the effects of increasing the agricultural potential yield by 1 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.[20] We cluster the standard error at the prefecture level.

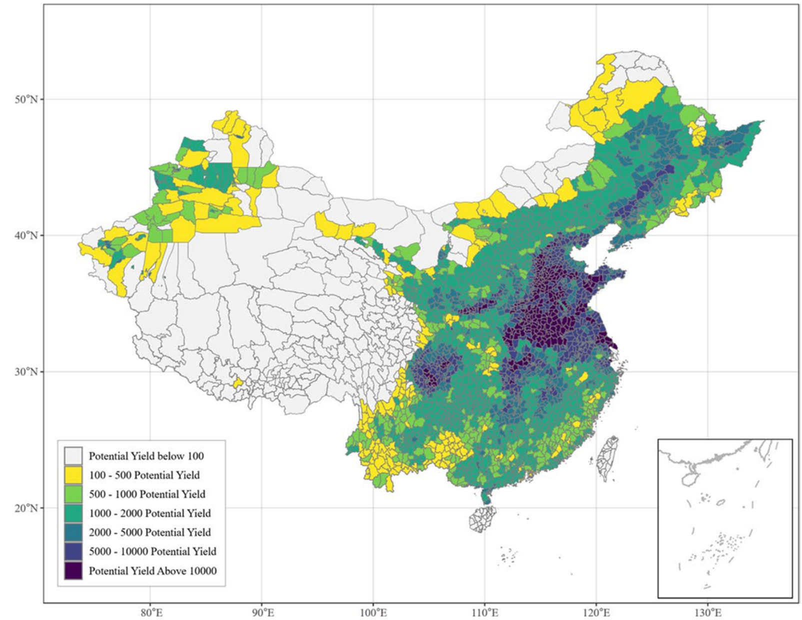
Table 1 reports the results estimated using Eq. (1). We estimate the equation using both least squares and the Poisson pseudo maximum likelihood (PPML) specification. The PPML specification performs well in cases where the dependent variable is non-negative and has possibly many zeros, which is exactly the case with the fire observations.[21] Specifically, the estimated coefficient from column (1) of Table 1 suggests that a 1 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

[20] 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.

[21] 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.



A Distribution of agricultural fires



B Distribution of potential yield (kg/ha)

Fig. 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

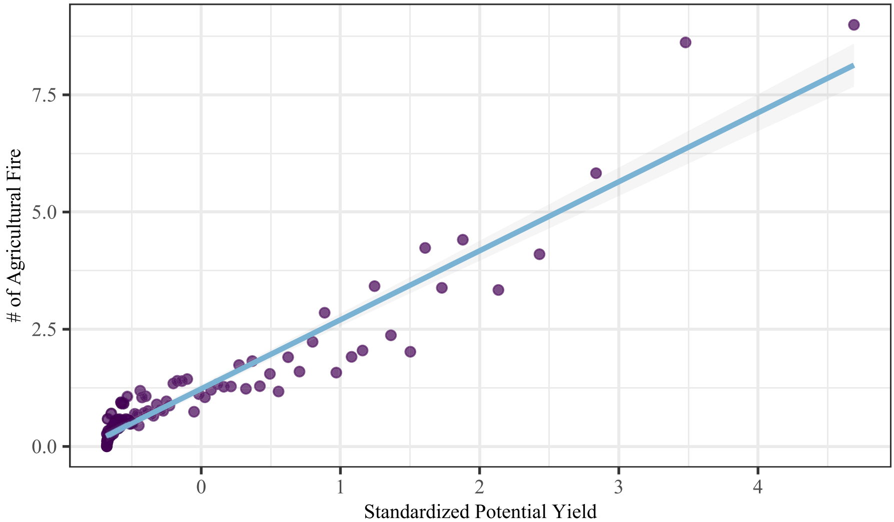


Fig. 4 Binscatter of agricultural fires versus potential yield. Notes: This figure presents the binscatter plot for agricultural fires versus potential yield, with a fitted line colored in blue. The shaded area is the 95% confidence interval. We standardize the potential yield to have a mean of 0 and a standard deviation of 1

Table 1 The effects of agricultural potential yield on agricultural fires

Dep. var. # Agri. fire	OLS		PPML	
	(1)	(2)	(3)	(4)
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

This table presents the estimated results of the effects of agricultural potential yield on agricultural fires. Observations are 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 errors are clustered at the prefecture level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

when including meteorological controls in column (2). Considering that on average a county experiences 1.18 monthly agricultural fires, our estimates imply that a 1 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 1 SD increase in potential yield is associated with an approximately 48.7% increase in agricultural fires.[22] In sum, the results from Table 1 confirm the significant and robust correlation between agricultural potential yield and agricultural fires.[23]

We then explore the relation between agricultural potential yield and air pollution. To do so, we modify our specification in Eq. (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 (Rangel and Vogl 2019; He et al. 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:

$$fire_{cpmt} = \beta_0 + \beta_1 UpwindAPY_c + \beta_2 DownwindAPY_c + \Gamma \boldsymbol{W}_{icmt} + \gamma_{pt} + \gamma_{pm} + \gamma_{mt} + \epsilon_{cpmt} \tag{2}$$

where $UpwindAPY_c$ and $DownwindAPY_c$ represent the average potential yield in the upwind and downwind regions of the county, respectively. We determine the upwind and downwind regions by leveraging the dominant wind direction during the fire month. 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 replace the dependent variable with the monthly $PM_{2.5}$ and find a strong correlation between agricultural potential yield and air pollution. 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 1 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 agricultural fires is associated with an increase of monthly $PM_{2.5}$ by 6.83 μg/m^3, which is very similar to the estimates from He et al. (2020).[24]

[22] 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.

[23] 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.

[24] 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.

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 unlikely to be correlated with agricultural fires. We then re-run both Eqs. (1) and (2) to examine whether they are correlated with potential yield. Columns (1) through (6) in Appendix Table A4 report the corresponding results. Consistently, we detect no significant effect for all three air pollutants. Another related concern is the potential effect of CO_2, as recent studies have pointed out that ambient CO_2 can affect agricultural yield (Liu 2025). But since our measurement is the maximum attainable agricultural yield within a specific cell, which is largely determined by soil quality, rainfall, and other natural conditions, changes in CO_2 should be less likely to impact the potential yield (though it affects the actual yield). We show in columns (7) and (8) of Table A4 that CO_2 emissions have no significant correlation with our potential yield measurement.

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 et al. 2020). We will illustrate this point in further detail in the next section.

6 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 abilities. Finally, we track these cohorts 10 years later and explore the effects on education and labor market outcomes.

6.1 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

Table 2 The effects of upwind/downwind potential yield on agricultural fires and $PM_{2.5}$

Dep. var	# Agri. fire		$PM_{2.5}$			
	(1)	(2)	(3)	(4)	(5)	(6)
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 $PM_{2.5}$. Observations are at the county-year-month level. The sample period for agricultural fires is from 2001 to 2019, whereas the sample period for $PM_{2.5}$ is from 1980 to 2019. Meteorological controls include dew point, sea level pressure, temperature, wind speed, and rainfall. Standard errors are clustered at the prefecture level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

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:

$$y_{icmt} = \alpha + \sum_{\tau=1}^{3} \beta_\tau^U UPwind\,APY_c \times 1\{Trimester_i = \tau\} + \sum_{\tau=1}^{3} \beta_\tau^D Downwind\,APY_c \times 1\{Trimester_i = \tau\} + \Lambda \boldsymbol{X}_{icmt} + \sum_{\tau=1}^{3} \Gamma_\tau \boldsymbol{W}_{cmt,\{Trimester_i=\tau\}} + \gamma_{mt} + \gamma_c + \epsilon_{icmt} \tag{3}$$

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 Eq. (2). $1\{\cdot\}$ is an indication function, which denotes during which trimester the individual is exposed to agricultural fire. The trimesters are determined by the relative distance between fire month and the birth month. For example, if an individual is born in December and the fire month in her county of residence is November, then we define that she is exposed to agricultural fire during the third trimester. In practice, we first identify the specific months corresponding to the three trimesters based on an individual's birth month, then determine which trimester the fire month falls within. 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 errors are clustered at the county level to account for any unobserved arbitrary correlations within the county.

The parameters of interest are β_τ^U s and β_τ^D s, 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 et al. 2020). To partial out such income effects, we exploit the fact that only the 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.[25] 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 Eq. (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).[26] Appendix Table A5 reports the results. We additionally report the estimated results for the differences between upwind and downwind 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 *ex-ante*. Such

[25] 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).

[26] The data is derived from County Statistical Yearbooks, 2000–2019.

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 Eq. (2).[27] 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 et al. (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 and fire month) for identification. Since straw burning is more of a seasonal activity, we believe that our measurement still captures important variations of fire intensity.[28] 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.

[27] 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 clusters the standard errors at the prefecture level.

[28] An alternative way to exploit yearly variations is to leverage monthly wind direction across different years. However, as we show in Appendix C.1 and C.6, the across-year wind direction variation is relatively small and our definition of upwind region can mostly account for such fluctuation.

6.2 The effects of fire exposure on adolescent outcomes

6.2.1 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 effects while 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 et al. 2005; Oster 2019).

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 periods (Glinianaia et al. 2004; Šrám et al. 2005; Currie and Neidell 2005; Kannan et al. 2006; Currie et al. 2014; Rangel and Vogl 2019).[29,30] Specifically, we estimate that a 1 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 1 SD increase in potential yield increases the unhealthiness index by 0.40 SD. Given that a 1 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.

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

[29] 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.

[30] 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.

Table 3 The effects of agricultural fires on adolescent health

Dep. var	Unhealthiness index				
	(1)	(2)	(3)	(4)	(5)
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	1567	1567	1567	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

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. Observations are 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 errors are clustered at the county level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

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.

Our estimates are quantitatively larger than previous findings for several possible reasons. First, since we are focusing on the rural population during an early period (most individuals in our sample were born between 1995 and 2000), the impact of prenatal exposure to air pollution may have been more severe due to insufficient awareness of the hazards of pollution exposure and limited access to adaptation measures. Second, agricultural fire is featured by great seasonality, which could generate substantial air pollution within a relatively short time window. Compared to sustained exposure, short-term acute exposure may have more detrimental effects on fetuses, which is reflected in their later-life health outcomes. Lastly, we note that our estimates are not a direct mapping from early-life exposure to later-life outcomes; instead, they also incorporate parental responses, which could potentially enlarge the damage of air pollution on individuals' health. This point will be discussed in further detail in the next section.

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 regions (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.[31] 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.

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 discernible effects of fire-induced pollution on any of the health components.

Heterogeneity Appendix Table A8 explores the potential heterogeneity of our baseline findings. In 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.[32] 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 contributor 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

[31] A recent study by Lee et al. (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 et al. 2020), it is thus plausible that fire-induced pollution has indistinguishable impacts on health outcomes of urban residents.

[32] This finding aligns with previous studies that show that air pollution affects vulnerable families disproportionally (Jans et al. 2018; Suarez Castillo et al. 2025).

and Noghanibehambari (2024) that these households live closer to the cropland and are more exposed to pollution when the agricultural fire occurs.

6.2.2 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, 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 more 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. This is in line with previous studies showing that males are more likely to be severely affected by air pollution exposure (Ebenstein et al. 2016). We also find consistent evidence that the effect is mainly concentrated in the first and third trimesters, aligning with previous findings. For example, using data from Brazil, Carneiro et al. (2024) show that prenatal exposure to agricultural fires, especially during the first and third trimesters, significantly lowers students' test scores, and the effects are more pronounced for 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.[33]

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, alternative clustering adjustment, and accounting for additional confounders and potential measurement errors. 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.

[33] 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.

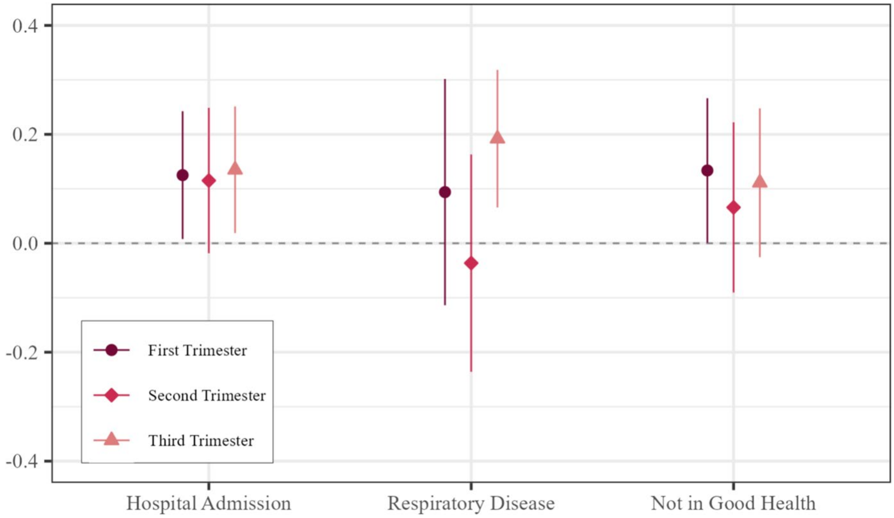


Fig. 5 The effects of agricultural fires on adolescent outcomes (health components). Notes: This figure visualizes the estimated coefficients of the effects of in-utero agricultural fire exposure during different trimesters on adolescent health outcomes, including hospital admission, respiratory disease, 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

6.3 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 A17 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.[34] It is therefore important to normalize the year of education by individuals' age, which allows us to compare individuals born

[34] Our sample size from Table A13 suggests that only half of the rural sample have completed their education and entered the labor market in 2020.

Table 4 The effects of agricultural fires on cognitive and non-cognitive ability

Panel A Cognitive ability	Standardized word test score			Standardized math test score		
	(1)	(2)	(3)	(4)	(5)	(6)
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	1384	659	701	1393	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	211	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

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. Observations are 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 errors are clustered at the county level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

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.[35,36] Taken 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 (Grönqvist et al. 2020), our empirical exercises thus far provide comprehensive evidence relating pollution exposure to human capital development across different stages.

7 Mechanisms

7.1 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), 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. One particular reason why male individuals are disproportionately affected by agricultural fire is that, biologically, male fetuses tend to be larger than female fetuses, which requires more supply of nutrients and makes them more fragile to prenatal negative shocks, and therefore have less innate health human capital at birth relative to females.

35 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.

36 In Appendix Table A18, we empirically investigate whether our results could be driven by sample selection by estimating the effect of agricultural fire exposure on a dummy variable indicating whether the individual can be tracked from CFPS 2010 to CFPS 2020. If sample attrition is plausibly random, then there should be no correlations between agricultural fire exposure and attrition probability. Reassuringly, we find no suggestive evidence that non-random sample attrition may affect our results. This further alleviates concerns that sample attrition may significantly affect our estimated effects.

Table 5 The effects of agricultural fires on early-life outcomes

Dep. var	# Illness at age 1			Gestation month			Birth weight		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
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	2308	1178	1114	2622	1331	1277	2661	1349	1298
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

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 g. Observations are 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 errors are clustered at the county level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Our results are also comparable to findings from existing studies. For instance, Rangel and Vogl (2019) suggest that doubling exposure to agricultural fire during the third trimester would decrease the gestation period by 4.6%, while our estimates suggest that the gestation month would be reduced by 5.9% for the male sample (column (5)). Similarly, their results imply that doubling the fire exposure would decrease birth weight by 18.8%, while our estimate suggests a corresponding reduction in birth weight by 22.2% (column (8)).

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.

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 A19 show that agricultural fire-induced air pollution has no significant effect on child mortality.[37] 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 A20, 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.

[37] 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.

7.2 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.

7.2.1 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.[38] 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).[39]

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 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.

Our exploration of the heterogeneity of mothers' education is inspired by the long strand of literature that investigates the effect of maternal education on children's human capital investment (Thomas et al. 1991; Desai and Alva 1998; Brown 2006; Leight and Liu 2020; Lavy et al. 2022). For example, Brown (2006) shows that while parents with higher education invest more in their children, the effect of

[38] 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 a 0.85 increase in the number of agricultural fires.

[39] Throughout our paper, both RMB and USD are measured on their 2010 monetary values.

Table 6 The effects of agricultural fires on health expenses

Dep. var	Log health expenses				
	(1)	(2)	(3)	(4)	(5)
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	1411	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

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. Observations are at the county-cohort level, with each cohort defined by its birth month. Low or high education corresponds to whether the mother has completed lower secondary education. Low or high income corresponds to whether the family income is below or above the median income. 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 errors are clustered at the county level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

mother's education is larger than that of father's education. This is in line with traditional Chinese family structure, where mothers exert more effort in raising the child, which makes their education more relevant when making the human capital investment decision.

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.

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.

7.2.2 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.

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 in 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 policies 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.

8 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 of these questions.

Table 7 The effects of agricultural fires on education expenses

Dep. var	Log education expenses				
	(1)	(2)	(3)	(4)	(5)
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	2049	1452	571	1105	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

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. Observations are at the county-cohort level, with each cohort defined by its birth month. Low or high education corresponds to whether the mother has completed lower secondary education. Low or high income corresponds to whether the family income is below or above the median income. 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 errors are clustered at the county level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

8.1 Response in 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).[40] 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), in columns (3) and (4), we additionally control for whether the

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

Table 8 The effects of early exposure to NCMS on adolescent outcomes

Dep. var.	Unhealthiness index			
	(1)	(2)	(3)	(4)
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	1233	327	1233
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

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. Observations are 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 errors are clustered at the county level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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.

8.2 Response in 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

Table 9 The effects of early exposure to NCMS on health expenses

Dep. var	Log health expenses					
	(1)	(2)	(3)	(4)	(5)	(6)
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 and low education	Non-exposure and low education	Exposure and 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 for children. Observations are at the county-cohort level, with each cohort defined by its birth month. Low or high education corresponds to whether the mother has completed lower secondary education. Low or high income corresponds to whether the family income is below or above the median income. 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 errors are clustered at the county level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 10 The effects of early exposure to NCMS on education expenses

Dep. var	Log education expenses					
	(1)	(2)	(3)	(4)	(5)	(6)
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	1151	550	842	490	725
Sample	Exposure	Non-exposure	Exposure and low education	Non-exposure and low education	Exposure and low income	Non-exposure and 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 for children. Observations are at the county-cohort level, with each cohort defined by its birth month. Low or high education corresponds to whether the mother has completed lower secondary education. Low or high income corresponds to whether the family income is below or above the median income. 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 errors are clustered at the county level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

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 one step further and examine whether the rollout of NCMS can mitigate the reduction in 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 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 incomes. 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.

In Table 10, 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.

8.3 Response in 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 A21, 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.

Although a comprehensive evaluation of the cost–benefit of NCMS is beyond the scope of the paper, we can nevertheless make some rough estimates based on our empirical results. To avoid exaggeration, we only consider the effect of agricultural fire exposure on individuals' earnings, which is monetized and more easily to compare. Our results in Appendix Table A17 imply that exposure to agricultural fires during the third trimester would reduce the wage income by 4.3%. Given the average annual wage of rural individuals in our sample is 72,316 RMB in 2020, our estimates suggest a 3110 RMB decline in annual earnings. Given that the estimated total cost of insurance coverage per child during early childhood is 2877 RMB in 2014 (Huang and Liu 2023), if we suppose that the NCMS coverage can fully offset the negative effect of agricultural fire exposure on earning, the estimated benefit, deflated to its 2014 value, is then 2762 RMB, which is of similar magnitude to the total cost of NCMS. Since our estimated benefits are likely to understate the overall impact of NCMS coverage (e.g., improved health status, reduced inpatient expenditure, and hospital costs), the overall benefits must exceed its total costs.

9 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 and 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 critical 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 sensitivity of pollution exposure 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 (dis-)investment, especially among low-income and low-education households, calls for the support of social protection programs. Strengthening the NCMS and embedding liquidity support measures (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 or subsidies for vulnerable populations.

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Data availability The primary data used in this study are from the China Family Panel Studies (CFPS). This is publicly available and can be applied through the following website: isss.pku.edu.cn/cfps/. However, the restricted-access dataset enabling matching between pseudocode county code and actual county code is protected under a confidentiality agreement with the Institute of Social Science Survey (ISSS) at Peking University and cannot be shared publicly. Relevant code for data processing and analysis is available upon request.

Declarations

Conflict of interest The authors declare no competing interests.

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