

Discussion Paper Series

IZA DP No. 18977

September 2026

When the Fields Burn: The Hidden Costs of Agricultural Fires on Children's Education

Lihini de Silva

Monash University

Rafat Mahmood

Monash University
and IZA@LISER

Sundar Ponnusamy

Deakin University

The IZA Discussion Paper Series (ISSN: 2365-9793) ("Series") is the primary platform for disseminating research produced within the framework of the IZA@LISER Network, an unincorporated international network of labour economists coordinated by the Luxembourg Institute of Socio-Economic Research (LISER). The Series is operated by LISER, a Luxembourg public establishment (établissement public) registered with the Luxembourg Business Registers under number J57, with its registered office at 11, Porte des Sciences, 4366 Esch-sur-Alzette, Grand Duchy of Luxembourg.

Any opinions expressed in this Series are solely those of the author(s). LISER accepts no responsibility or liability for the content of the contributions published herein. LISER adheres to the European Code of Conduct for Research Integrity. Contributions published in this Series present preliminary work intended to foster academic debate. They may be revised, are not definitive, and should be cited accordingly. Copyright remains with the author(s) unless otherwise indicated.

When the Fields Burn: The Hidden Costs of Agricultural Fires on Children's Education^{*}

Abstract

Agricultural residue burning releases pollutants that prevailing winds carry across administrative boundaries. We study the effects of fire-driven pollution on the cognitive development and educational trajectories of around 700,000 children aged 5–16 in Pakistan, combining satellite-derived burned area data, wind direction, and nationally representative learning assessments. Our treatment measure captures fires within 15 kilometers of a child's district that burn upwind; comparable downwind fires, which reflect the same agricultural activity but carry smoke away from the child, serve as a placebo. A one standard deviation increase in upwind fire exposure reduces test scores in mathematics, reading, and English by roughly 0.02 standard deviations; downwind fires have no effect. Impacts are concentrated in the school term, with no effect from summer-holiday fires. Boys and girls suffer similar cognitive losses, but over time older girls face higher dropout, consistent with lower perceived returns to female education in a patrilocal society, and child labor rises. The results survive extensive robustness checks. Agricultural burning is thus a constraint on human capital development, not only a public health issue.

JEL classification

Q53, Q54, I25, J13, O12

Keywords

agricultural fires, air pollution, cognitive development, child labor

Corresponding author

Rafat Mahmood

rafatmahmood214@gmail.com

^{*} We thank Umair Khalil, Hemant Pullabhotla, and Erica Myers for their valuable feedback. We are also grateful to Muhammad Sarfaraz (Pakistan Bureau of Statistics) and Sehar Saeed (Annual Status of Education Report) for providing access to the PSLM and ASER datasets, respectively. The authors declare no conflicts of interest. All errors are our own. Rafat Mahmood is grateful to the ARC Centre of Excellence for the Elimination of Violence against Women for their support. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

1 Introduction

Air pollution ranks among the world’s leading environmental health threats, killing an estimated seven million people annually, with South Asia accounting for nearly 2.6 million deaths in 2021 alone ([World Health Organization, 2026](#); [State of Global Air, 2025](#)). Beyond its immediate health consequences ([Deryugina et al., 2019](#); [Heft-Neal et al., 2020](#); [Pullabhotla et al., 2023](#)), pollution undermines long-term economic development by impairing human capital formation. Emerging evidence links exposure to reduced worker productivity ([Zivin and Neidell, 2012](#)), lower test scores among children exposed prenatally ([Sanders, 2012](#)), and diminished cognitive performance on high-stakes examinations with lasting effects on educational attainment ([Ebenstein et al., 2016](#)). This aligns with World Bank estimates that air pollution imposes economic costs equivalent to nearly five percent of global GDP, a burden concentrated in low- and middle-income countries where both exposure and vulnerability are greatest ([World Bank, 2025a](#)).

A substantial portion of ambient pollution in these regions stems from human-driven landscape fires. Satellite-based assessments put the global area burned each year at roughly four million square kilometers, a figure that probably understates the true extent because coarse-resolution sensors fail to capture many small agricultural fires ([Chuvieco et al., 2019](#)). Most of this burning occurs in landscapes shaped by farming, grazing, and land-management choices ([Lauk and Erb, 2009](#); [Giglio et al., 2013](#); [Chuvieco et al., 2021](#)). Open burning of crop residues, a cheap and widespread way to dispose of the biomass left after harvest, releases fine particulate matter (PM_{2.5}), black carbon, and other pollutants ([Akagi et al., 2011](#)) linked to a range of adverse health effects ([Roberts and Wooster, 2021](#)). In South Asia, agricultural intensification has raised crop-residue volumes, while the short interval between harvest and replanting and the cost of machinery leave burning the default way to clear fields ([Lin and Begho, 2022](#); [Lan et al., 2022](#)). This seasonal burning produces recurrent pollution episodes in which particulate concentrations can reach many times the levels recommended by the World Health Organization ([Bikkina et al., 2019](#); [Lan et al., 2022](#); [Dipoppa and Gulzar, 2024](#)). Because the smoke is carried far downwind, elevated pollution during the weeks-long burning season reaches both the rural areas where fires are set and distant urban centers ([Mhawish et al., 2022](#); [World Bank, 2025b](#)). While the health consequences of these pollution spikes are increasingly documented, their effects on cognitive development and educational outcomes remain poorly understood: the existing evidence on smoke and cognition comes mainly from wildfires in high-income settings or from adult populations ([Wen and Burke, 2022](#); [Cleland et al., 2022](#); [Lai et al., 2022](#)), leaving the school-age children of developing countries, where agricultural burning recurs every year, largely unstudied. This gap is consequential: education is a central determinant of long-run welfare and intergenerational mobility, and without credible estimates of the educational costs of agricultural burning, the full social cost of the practice is unknown.

Pakistan provides a particularly informative setting in which to study these dynamics. Be-

tween 3.6 and 5.0 million tonnes of rice residue are burned annually in Pakistan’s rice-wheat belt (IGC, 2022; Zaheed and Salik, 2024), producing emissions that degrade air quality for millions (Azhar et al., 2019). Regulatory bans and awareness campaigns have had limited impact, in part because mechanized alternatives are costly and the interval between harvest and replanting is short (Dialogue Earth, 2019; Zaheed and Salik, 2024). At the same time, 35% of children aged 5–16 are out of school (UNICEF, 2026), and learning poverty is widespread: roughly 77% of children cannot read and understand a simple text by age 10 (World Bank, 2022). These conditions suggest that children may be especially vulnerable to environmental shocks that disrupt learning. Yet quantifying the effect of agricultural fire pollution on cognitive development poses distinct empirical challenges. Burning generates a heterogeneous bundle of pollutants (Chen et al., 2017; Samburova et al., 2016) with potentially cumulative effects, and exposures are measured with substantial error (Pan et al., 2020; Johnson et al., 2020). Moreover, fire activity is closely linked to agricultural cycles and local economic conditions that independently shape educational investments, complicating causal inference.

To quantify the impact of crop residue burning on children’s cognitive development and labor outcomes, we combine high-resolution satellite data on agricultural fires with nationally representative educational assessment data from the Annual Status of Education Report (ASER) in Pakistan, covering roughly 700,000 children aged 5–16 across 2012–2016. Cognitive outcomes include test scores in mathematics, local-language reading, and English, together with a normalized learning index, and an indicator for having dropped out of school. ASER assessments are conducted between September and December. Our baseline specification measures fire exposure over the 12 months preceding the start of the survey period, from September of the previous year to August of the survey year. Our primary exposure variable measures the area of agricultural land burned in the upwind direction within 15 km of a district boundary, serving as a proxy for pollutants transported into the district by prevailing winds.¹

A key identifying assumption is that variation in upwind fire exposure is plausibly exogenous to local determinants of child outcomes. While agricultural burning reflects farming practices in neighboring districts, the direction and intensity with which the resulting pollution is transported across district boundaries is driven by short-term meteorological conditions, particularly wind direction, which are orthogonal to socioeconomic conditions and education-related investments within the receiving district. To the extent that wind patterns persist over long horizons, a district’s windward orientation could in principle be correlated with its long-run socioeconomic conditions; all our specifications therefore include district fixed effects, so that identification relies on within-district changes in upwind exposure over time rather than on

¹The choice of 15 km builds on approaches used in comparable studies. For example, Pullabhotla et al. (2023) use a 30 km radius from the birth location, leveraging precise geocoded data. In our setting, the exact location of children is not available, so we use 15 km from the district boundary as a plausibly close approximation. We also report results using 10, 20, 30, 40, and 50 km thresholds (Table 1). The estimated effects remain consistent in direction across specifications, although precision declines as the threshold expands, with estimates at larger distances becoming noisier and often losing statistical significance.

comparisons between windward and leeward districts. By focusing on fires that occur upwind relative to a district in a given period, we exploit variation in pollution exposure that is governed by wind direction, a meteorological factor beyond the influence of households, schools, or local policy, rather than by burning activity within the child’s own district. As a further validation, we construct a placebo measure based on downwind fires, whose emissions are transported away from the district. Because upwind fires transport pollution toward the district while downwind fires carry it away, comparing the two differences out confounding factors correlated with regional burning intensity, such as crop cycles or broader economic conditions, thereby isolating the causal effect of pollution transport. This identification strategy builds on [Deryugina et al. \(2019\)](#) and [Pullabhotla et al. \(2023\)](#), who use wind direction to isolate pollution exposure from confounding factors. To examine child labor outcomes, we link fire exposure to the Pakistan Social and Living Standards Measurement (PSLM) survey, which records whether children have worked in the month preceding the survey. We explore heterogeneity by age, gender, and timing relative to the school calendar, and assess multiple temporal windows, including contemporaneous exposure and up to three-year lags, to capture both immediate and persistent effects on cognitive development, schooling, and labor participation.

Our main findings show that exposure to upwind fires within 15 km of a district’s boundary has significant adverse effects on children’s cognitive performance, whereas downwind fires have no measurable impact. A one standard deviation increase in upwind burned area reduces arithmetic test scores by approximately 0.03 points, corresponding to a 1.5% decline relative to the mean; the proportional effects are similar for reading (1.6%) and English (1.7%). In standardized terms, this is a reduction of roughly 0.02 standard deviations of the outcome distribution, consistent with a recent meta-analysis of the causal evidence on pollution and learning ([Nguyen, 2026](#)) and comparable to estimates from prenatal and ambient pollution exposure ([Sanders, 2012](#); [Gilraine and Zheng, 2022](#)) and from rainfall shocks ([Shah and Steinberg, 2017](#)). Estimates for downwind fires are small and statistically indistinguishable from zero, supporting a causal interpretation.

Fires during the active school term, particularly the exam period and the trimester preceding it, are the most detrimental, while fires during summer holidays have no measurable impact. Cognitive scores decline similarly for boys and girls in the short run, but the behavioral responses differ. In the longer run, older girls (aged 11–16) are the most likely to leave school in response to repeated exposure, with cumulative upwind exposure over the year of exposure and the two subsequent years raising their dropout probability by about 2.2 percentage points, or roughly 12% of their mean dropout rate of 17.8%. Child labor also rises for both genders, with effects that build over time and peak two years after exposure; the gender contrast lies in schooling, as boys remain enrolled while taking on work. These findings are robust to alternative exposure radii, district-specific time trends, province-by-year fixed effects, and additional controls for weather, wind speed, and local economic activity.

This paper contributes to four strands of the literature. First, it connects to a large body of

work on air pollution and human capital outcomes. Foundational studies establish that air pollution harms infant health and raises child mortality (Chay and Greenstone, 2003; Currie and Neidell, 2005; Deryugina et al., 2019; Heft-Neal et al., 2020). A subsequent strand documents effects on cognitive performance and educational attainment: Ebenstein et al. (2016) show that pollution spikes on the days of high-stakes national examinations in Israel lower scores and reduce long-run attainment; Sanders (2012) finds that prenatal particulate exposure reduces test scores in the United States; and Zivin and Neidell (2012) document output losses among agricultural workers exposed to ambient ozone. We contribute evidence from a developing-country setting where ambient pollution levels are substantially higher, institutional capacity to respond is limited, and the affected population spans a broad cohort of school-age children. Our closest antecedents within this literature study other fire sources or other populations. Wildfire smoke lowers test scores among schoolchildren in the United States (Wen and Burke, 2022) and impairs adults' cognitive performance (Cleland et al., 2022). Closest to our design, Lai et al. (2022) use upwind and downwind crop-residue fires in China and find that smoke temporarily lowers the cognitive test performance of adults aged 55 and above, while Chen (2025) links early-life exposure to industrial pollution to lower long-run educational attainment. We differ from these studies in three respects: we study school-age children rather than adults; we examine a developing-country setting where burning recurs with the harvest calendar rather than striking episodically; and we follow the shock beyond test scores into schooling and labor market trajectories, showing that a transitory cognitive loss hardens into persistent dropout and child labor responses. Our identification strategy, which exploits wind-driven variation in fire smoke transported across district boundaries, complements designs based on traffic or industrial emission sources and broadens the evidence on which types of pollution impair learning.

Second, the paper contributes to an emerging literature on the externalities of open agricultural burning. This literature has linked fire activity to infant mortality (Pullabhotla et al., 2023), adult mortality (Roberts and Wooster, 2021), ambient particulate matter concentrations (Bikina et al., 2019; Lan et al., 2022), and crime (Ayesh, 2023). Dipoppa and Gulzar (2024) show that stronger bureaucratic incentives reduce crop burning and its associated mortality costs in South Asia, providing evidence on the available policy levers. We extend this literature by documenting that the cognitive development and schooling trajectories of school-age children in receiving districts are also materially harmed. Test scores and dropout rates capture the average effect on human capital accumulation for an entire cohort, rather than the tail outcomes captured by mortality or crime. Our estimates imply that conventional social cost calculations for crop residue burning, which have focused primarily on health and mortality, substantially understate the true cost by omitting the educational channel.

Third, the paper speaks to the literature on gender disparities in education in developing countries. A well-established body of research documents that girls in South Asia face lower parental investment in schooling relative to boys, driven by son preference, differential returns to education across genders, and the structure of marriage markets (Jayachandran, 2015; Du-

flo, 2012). In patrilocal societies, where women join the husband’s household after marriage, parents may perceive the returns to daughters’ education as accruing to the marital rather than the natal family, weakening the incentive to sustain girls’ schooling when household conditions deteriorate (Khalil and Mookerjee, 2019). Environmental and income shocks have been shown to produce gendered educational responses: rainfall shocks that raise the opportunity cost of schooling pull older children out of school and reduce attainment in South Asia (Shah and Steinberg, 2017), with long-run effects that are especially pronounced among girls (Pon-nusamy, 2025). We show that an air-quality shock, operating through a channel distinct from agricultural income, generates an analogous and persistent gendered response. The multi-year persistence of dropout effects for older girls, with no corresponding effect for boys, is consistent with a parental-investment model in which perceived academic deterioration leads households to disengage from daughters’ education first.

Finally, the paper contributes to the literature on child labor and environmental shocks. Classical models predict that child labor and schooling are substitutes and that negative shocks induce households to shift children from education to work (Basu and Van, 1998; Edmonds, 2007). Environmental shocks have been shown to operate through this mechanism: Maccini and Yang (2009) document that early-life rainfall deficits reduce long-run educational attainment and adult health in Indonesia, with effects concentrated among women. We show that air pollution from agricultural fires generates a similar substitution, increasing the probability of child labor for children aged 10–17, with effects that build over time and remain detectable two years after exposure. The persistence of these labor effects, together with the dropout evidence, suggests that even moderate pollution episodes can set children on persistently lower human capital trajectories, reinforcing intergenerational poverty.

The remainder of the paper is organized as follows. Section 2 provides background on education and agricultural burning in Pakistan. Section 3 describes the data. Section 4 outlines the estimation strategy. Section 5 presents the results. Section 6 concludes.

2 Background

2.1 The Status of Education in Pakistan

Pakistan, the world’s fifth most populous nation, has a predominantly young demographic, with nearly two-thirds of its citizens below the age of 24. The country’s education system comprises both public and private institutions, with the state serving as the main provider of schooling services (Halai and Durrani, 2021).² Private schools, however, play a substantial role at the secondary level, accounting for around 66% of middle schools and 58% of high schools, and enrolling roughly 38% and 32% of students at these respective levels (NEMIS–AEPAM, 2018).

²A smaller third stream of education consists of Madrassas, which operate under a separate governance structure and follow distinct curricula (Halai and Durrani, 2021).

Despite this expansion of private education, public schools continue to educate most students across the country but face significant resource constraints, including shortages in teaching staff, with only about 49% of Pakistan's teachers employed in the public sector. In 2010, the Eighteenth Constitutional Amendment introduced Article 25-A, which guarantees free and compulsory education for children aged 5 to 16, formally establishing the Right to Education in law.

Yet Pakistan continues to face a severe educational access crisis. An estimated 25.1 million children between the ages of 5 and 16, equivalent to 35% of this age group, remain out of school, the world's second-highest number (UNICEF, 2026). Gender inequality compounds the problem. In 2013, the gross primary enrollment ratio stood at 74.2% for boys but only 63.2% for girls; the gap persisted at the secondary level (36.4% for boys versus 26.4% for girls), and just 8.7% of women were enrolled in tertiary education (World Bank, 2024).

Learning outcomes also remain poor. Roughly 77% of Pakistani children are unable to read and understand a simple text by age 10 (World Bank, 2022). Literacy rates mirror these disparities, with about 71% of men but only 47% of women able to read and write (World Bank, 2024). Reflecting these challenges, Pakistan ranked 164th out of 193 countries in the 2023–24 Human Development Report, placing it in the low human development category (UNDP, 2024). Academic performance in mathematics and science is also concerning: when Pakistan participated for the first time in the Trends in International Mathematics and Science Study (TIMSS) in 2019, it ranked among the lowest of the 58 participating countries (Mullis et al., 2020).

Given that nearly half of Pakistan's population is under the age of 20, the scale of these challenges is especially pressing. Addressing them will require sustained investment in education and employment opportunities to harness the country's demographic potential and avoid long-term social and economic stagnation.

2.2 Stubble Burning in Pakistan

Crop residue burning, commonly known as stubble burning, is a widespread agricultural practice in Pakistan that poses significant environmental and public health challenges. Following the rice harvest, typically in October and November, farmers across Punjab and Sindh burn the remaining straw in the fields to clear the land rapidly before the wheat planting season. Pakistan burns between 3.6 and 5.0 million tonnes of rice residue annually, making this one of the largest sources of seasonal air pollution in South Asia (IGC, 2022; Azhar et al., 2019; Zaheed and Salik, 2024). The short window between rice harvest and wheat sowing, often as little as two to three weeks, creates strong economic incentives to burn rather than incorporate or remove residues through slower mechanical means.

The government of Pakistan has introduced regulatory measures to restrict open burning, including provincial bans and awareness campaigns (Zaheed and Salik, 2024). However, en-

forcement has been limited and compliance remains low. Mechanized alternatives, such as happy seeders and combine harvesters equipped with straw-management attachments, can reduce residue burning but require upfront capital investment that is prohibitive for smallholder farmers ([Dialogue Earth, 2019](#)). In the absence of affordable substitutes or sufficient subsidy support, open burning continues to be the dominant practice. The resulting smoke events generate dense smog that can persist for days to weeks and is transported by prevailing winds across district boundaries, exposing millions of children and adults to elevated concentrations of PM_{2.5} and other harmful pollutants.

3 Data

This study draws on multiple data sources to examine how exposure to agricultural fires affects human capital formation in Pakistan. The primary data on children’s cognitive development come from the Annual Status of Education Report (ASER) surveys ([Annual Status of Education Report, Pakistan, 2017](#)), which cover roughly 700,000 children aged 5–16 from rural districts across the four provinces of Pakistan between 2012 and 2016.³ ASER assessments are conducted annually between September and December and test three core learning domains for each child: reading ability in the local language (hereafter, reading), English proficiency (hereafter, English), and arithmetic skills (hereafter, math).⁴

Each domain comprises four progressively difficult tasks. For instance, in the reading assessment, children are tested on whether they can recognize letters, read words, sentences, and stories. Each task is coded as one if completed successfully and zero otherwise. Following [Shah and Steinberg \(2017\)](#), we construct a cumulative score by summing the correct responses across the four tasks. For example, a child who can read letters, words, and sentences but not a story receives a reading score of three. The same scoring approach is applied to the English and math assessments, resulting in domain-specific scores ranging from 0 to 4, where higher values reflect better performance. To capture overall learning performance, we also construct a normalized learning index by combining the standardized scores for reading, English, and math. In addition to test scores, the ASER dataset records school enrollment, from which we construct a binary indicator, “dropout,” equal to one if a child is not enrolled in school and zero otherwise.

Data on children’s participation in the labor market are obtained from the Pakistan Social and Living Standards Measurement (PSLM) Survey ([Pakistan Bureau of Statistics, 2020](#)). [Table A1](#) presents summary statistics for the key variables used in the analysis. The average test score across subjects is approximately 2 on the 0–4 scale, and 7.1% of children have dropped

³Detailed information on ASER’s sampling framework and survey instruments is available in [Annual Status of Education Report, Pakistan \(2017\)](#).

⁴The local language refers to the primary language spoken in the household, most commonly Urdu, Hindi, or Pashto ([Annual Status of Education Report, Pakistan, 2017](#)).

out of school. Among children aged 10–17, approximately 12% worked during the month preceding the survey.⁵

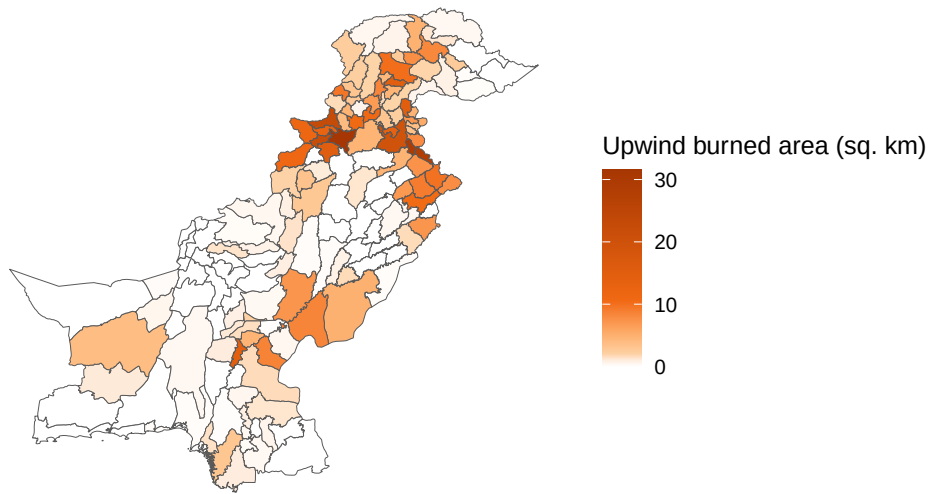
Our key explanatory variable, exposure to upwind fires, measures the total area of agricultural land burned (in square kilometers) within a 15-kilometer buffer of a district boundary, where the burned areas lie in the upwind direction relative to the district, as determined by prevailing wind patterns. Fire activity data are drawn from the European Space Agency’s Climate Change Initiative FireCCI_L1 product, which provides globally consistent monthly estimates of burned area at a $0.05^\circ \times 0.05^\circ$ pixel resolution (Chuvieco et al., 2019). Monthly wind direction at the district level is obtained from the ERA5 atmospheric reanalysis (Copernicus Climate Change Service), which provides hourly gridded data on the u (eastward) and v (northward) wind components at $0.25^\circ \times 0.25^\circ$ resolution; we compute monthly average wind direction for each district by converting the u and v components into directional bearings. For each district-year observation, we compute upwind burned area as the total burned area within the buffer that lies in the upwind direction, and downwind burned area as the burned area in the complementary downwind arc. Figure 1A maps the resulting district-level distribution of upwind burned area, which is concentrated in the agricultural heartland of Punjab as well as parts of Khyber Pakhtunkhwa and Sindh, while Figure 1B illustrates the upwind/downwind classification. Based on Panel B of Table A1, a child is exposed on average to 2.34 sq. km of upwind burned area and 3.27 sq. km of downwind burned area. The upwind burned area is particularly relevant, as wind direction carries pollutant particles from these fires into the child’s district of residence.

To assess whether our measures of upwind and downwind fires meaningfully capture variation in air pollution, we examine their relationship with district-level particulate matter concentrations, using yearly district-level $PM_{2.5}$ estimates from van Donkelaar et al. (2021). As robustness checks, we control for several potential confounders, including weather conditions proxied by the Standardized Precipitation-Evapotranspiration Index (SPEI), a multi-scalar drought indicator that captures moisture deficit as the standardized difference between precipitation and potential evapotranspiration (Vicente-Serrano et al., 2010). Additional controls include average wind speed, district-level $PM_{2.5}$ concentration, and local economic activity proxied by nighttime light intensity (Li et al., 2025). All these variables are constructed at the district-year level.

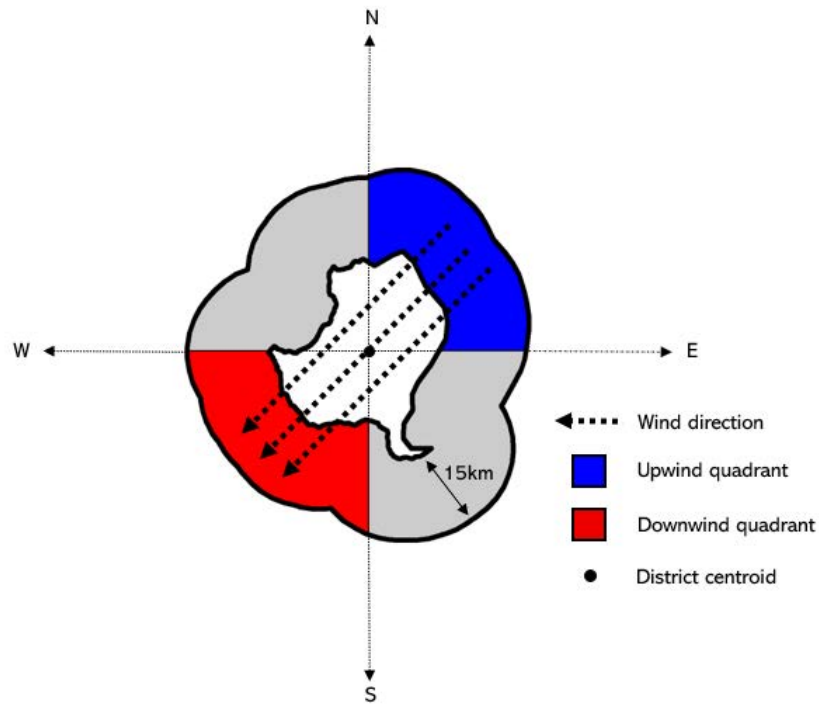
4 Estimation Method

To estimate the impact of exposure to agricultural fires on human capital outcomes, we use the following multiple fixed-effects specification:

⁵The variable equals one if the child is reported to have worked at any time during the month preceding the survey, and zero otherwise.



(A) Burned area, 2012–2016



(B) Upwind/downwind classification

Figure 1: Agricultural fire exposure across Pakistani districts. (A) District-level average upwind burned area (km^2), 2012–2016; darker shading indicates higher exposure, concentrated in the agricultural heartland of Punjab as well as parts of Khyber Pakhtunkhwa and Sindh. (B) Schematic of the upwind/downwind classification: fires in the ring surrounding a district are assigned to the upwind or downwind quadrant according to the prevailing monthly wind direction relative to the district centroid.

$$Y_{ids} = \beta_1 UW_{ds} + \beta_2 DW_{ds} + \mathbf{X}'_{ids} \boldsymbol{\lambda} + \delta_d + \delta_t + \delta_s + \eta_{ids}, \quad (1)$$

where Y_{ids} denotes the educational outcome of child i residing in district d , born in year t , and surveyed in year s . The outcomes of interest are math, reading, and English test scores, the normalized learning index, and an indicator for having dropped out of school. The key explanatory variable, UW_{ds} (*Upwind Fires*), measures exposure to upwind fires in square kilometers: the total area burned within a 15 km buffer of a district boundary where wind direction carries pollutant particles into the focal district. Consequently, UW_{ds} provides plausibly exogenous variation in exposure to smoke for children living in district d , enabling identification of the causal relationship between agricultural fire exposure and child outcomes. The coefficient of interest, β_1 , is expected to be negative, as greater exposure to fire pollution is anticipated to harm human capital formation.

The specification includes DW_{ds} (*Downwind Fires*), defined as the area burned within the 15 km buffer where, due to wind direction, the resulting pollution is carried away from the focal district. The downwind term serves as a built-in placebo within the same regression: if the observed relationship between fire exposure and human capital is truly causal, only upwind fires should exhibit detrimental effects, whereas if the results merely capture a broader regional association, downwind fires would also be expected to matter. $\mathbf{X}'_{ids}$ denotes a vector of control variables, including parental education, parental age, and household wealth indicators such as home ownership, electricity and television access, and mobile phone ownership.⁶ The specification also includes district fixed effects (δ_d), age fixed effects (δ_t), and survey-year fixed effects (δ_s). Accordingly, the estimated treatment effect reflects the impact of within-district variation in exposure to pollution from upwind agricultural fires on human capital development over time. Standard errors are clustered at the district level, and η_{ids} represents time-varying unobservable shocks to the outcome variable.

In our main specifications, we adopt a parsimonious set of controls that include parental characteristics and household wealth indicators. To verify that the estimated effects are not confounded by omitted factors, we further incorporate additional controls such as weather conditions (SPEI), wind speed, and local economic activity (nighttime light intensity). For the timing analysis, upwind fires are decomposed into four quarterly windows relative to the school calendar; for the long-run analysis, we include up to three annual lags of fire exposure. For child labor, we estimate analogous specifications using PSLM data.

4.1 Threats to Identification

The principal threat to identification is that fire activity near a district may be correlated with unobserved shocks that independently affect children's outcomes. We address this concern in

⁶To address missing data, parental education and age values are coded as 99, with additional dummy variables included to indicate missing observations.

layers. First, the most natural confounder, a regional agricultural or economic shock that drives both burning and household decisions, is differenced out by construction (Pullabhotla et al., 2023; Lai et al., 2022): because the same fire counts as upwind for the districts its smoke blows toward and downwind for the districts its smoke blows away from, the two measures describe the same fires and the same regional agricultural activity; they differ only in whether the smoke reaches the district (mean downwind exposure, 3.27 km², in fact exceeds mean upwind exposure, 2.34 km²). Agricultural income and labor market linkages between a district and its neighbors do not depend on the direction of the wind, so a confounding shock of this kind should load on both measures. As we show in Section 5, the estimated downwind coefficients are consistently null (Figure 2, Panel C, and Appendix Table A4).

Second, the estimated effect could in principle reflect shocks common to a broader area rather than pollution received by the district itself. To address this, we control directly for the average upwind exposure of neighboring districts, a proxy for region-wide burning intensity; as we show in Section 5.7, the estimates are unaffected (Appendix Table A5).

Third, wind direction is determined by meteorology and follows predetermined climatological patterns; it cannot respond to socioeconomic conditions or schooling investments in the receiving district, and reverse causality is ruled out because fires are set by farmers outside the district on their own harvest schedule. A related potential concern is that, to the extent that wind patterns persist over long horizons, a district’s windward orientation could be correlated with its long-run socioeconomic character. Our design, however, never compares windward districts to leeward ones. District fixed effects absorb all time-invariant differences across districts, including any long-run socioeconomic or developmental consequences of local wind patterns, baseline poverty, and baseline cognitive performance. As Section 4 makes explicit, identification comes from within-district variation over time: we compare children in the same district surveyed in years with more versus less upwind burning, so that stable features of windward locations cannot drive the estimates.

Fourth, remaining confounders would have to be time-varying, upwind-specific, and unrelated to burning itself; our specifications absorb these margins through province-by-year fixed effects, which absorb any shock common to a province in a given year, district-specific linear trends, and controls for fires within the own district, weather (SPEI), wind speed, and local economic activity (nighttime lights), and the estimates remain stable across all of these specifications (Section 5.7, Table 2). We therefore interpret the upwind coefficients as the causal effect of fire-driven pollution exposure.

5 Results

5.1 Validation: Upwind Fires and Pollution

Before turning to the main analysis, we verify that our exogenous measure of burned area is meaningfully associated with district-level pollution. Since the upwind burned area represents fires whose emissions are carried into the focal district by prevailing winds, we expect only upwind fires to increase $\text{PM}_{2.5}$ concentrations, whereas downwind fires should show no significant association. Figure 2 (Panel A) reports coefficients from regressions of district-level $\text{PM}_{2.5}$ on upwind and downwind fires, controlling for district and year fixed effects and district-specific linear time trends; the corresponding estimates are reported in Appendix Table A2. The coefficient on upwind fires is 0.035 ($p < 0.01$): a one standard deviation increase in upwind burned area raises district-level $\text{PM}_{2.5}$ by $0.22 \mu\text{g}/\text{m}^3$, or about 0.4% of the sample mean of $51.5 \mu\text{g}/\text{m}^3$. The coefficient on downwind fires is statistically insignificant. The per- km^2 effect is smaller than the $0.49 \mu\text{g}/\text{m}^3$ reported by Pullabhotla et al. (2023) using ground-station monitors, although differences in measurement technology and spatial resolution make direct comparison difficult: ground monitors capture highly localized concentrations near emission sources, whereas satellite-based estimates smooth local variation across grid cells (Diao et al., 2019). Nonetheless, the result confirms that the upwind measure captures meaningful variation in pollution exposure.

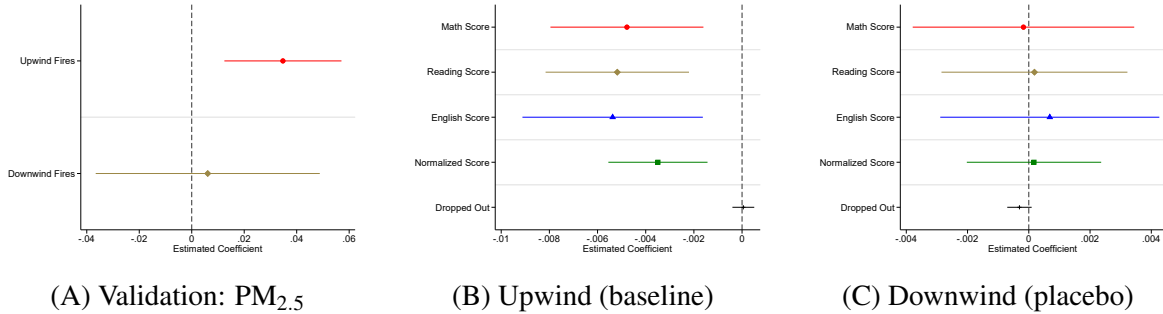


Figure 2: **Agricultural fires, pollution, and cognitive development.** (A) Coefficients from regressions of district-level $\text{PM}_{2.5}$ on upwind and downwind burned area, with district and year fixed effects and district-specific linear time trends (Appendix Table A2). (B) Coefficients of upwind burned area on test scores (mathematics, reading, English, and the normalized learning index) and school dropout, from the conditional baseline specification with district, survey-year, and age fixed effects and child and household controls (Appendix Tables A3–A4). (C) Corresponding coefficients of downwind burned area (placebo). Bars indicate 95% confidence intervals. $N \approx 689,000$.

5.2 Agricultural Fires and Human Capital Development

Having established the link between agricultural fires and pollution, we turn to the main analysis. Figure 2 (Panels B and C) summarizes the baseline estimates from the conditional spec-

ification, which includes district, survey-year, and age fixed effects together with child and household controls (gender, parental education and age, home ownership, and household assets). The full estimates, including the unconditional specification and the placebo test, are reported in Appendix Tables A3 and A4.

Exposure to upwind fires significantly reduces children’s cognitive performance across all test domains. While the marginal effect per square kilometer is small, exposure is highly skewed: nearly two-thirds of district-year observations experience no burning, while a subset is exposed to substantially higher levels (mean = 2.34, SD = 6.22 km²). A one standard deviation increase in upwind burned area reduces arithmetic test scores by approximately 0.03 points, a 1.5% decline relative to the mean; the proportional effects are similar for reading (1.6%) and English (1.7%). In standardized terms, a one standard deviation increase in fire exposure reduces test scores by approximately 0.02 standard deviations. This magnitude is consistent with a recent meta-analysis of causal studies, which reports average pollution effects on learning outcomes in the range of 0.02–0.04 standard deviations (Nguyen, 2026); it is also comparable to the effects of prenatal pollution (Sanders, 2012) and satellite-based air pollution (Gilraïne and Zheng, 2022) on test scores, and falls within the 2–5% of a standard deviation range of rainfall-shock effects on math scores reported by Shah and Steinberg (2017). All test-score estimates are significant at the 1% level. The estimated effect on dropout is close to zero and statistically insignificant, indicating that contemporaneous fire exposure does not immediately alter enrollment decisions. As shown in Appendix Table A3, the coefficients are virtually identical across the unconditional and conditional specifications, indicating that the estimates are not driven by household socioeconomic characteristics or parental background and reinforcing a causal interpretation.

Estimates for downwind fires are small and statistically indistinguishable from zero across all outcomes (Figure 2, Panel C; Appendix Table A4). The finding that only upwind fires, which transport smoke toward the district, reduce cognitive scores, while downwind fires have no impact, provides strong evidence that the observed effects operate through pollution exposure rather than through other channels associated with fire activity itself. While previous studies have primarily examined pollution generated within a district, our results show that pollution originating in neighboring districts can also adversely affect learning when carried into a child’s district by prevailing winds (Mhawish et al., 2022).

5.3 Heterogeneity by Age and Gender

Gender disparities are pervasive in Pakistan, especially in education. To assess whether the effects of exposure vary by age and gender, we divide children into four groups: younger girls, older girls, younger boys, and older boys. We define the younger cohort as children aged 5–10 and the older cohort as those aged 11–16, which broadly corresponds to the transition from primary to secondary education, in line with Shah and Steinberg (2017). Figure 3 presents the

estimates, with the full results in Appendix Table A6.

Both boys and girls appear to be affected in a similar manner relative to their respective outcome means. For instance, a one standard deviation increase in upwind burned area reduces arithmetic scores by 1.4% for younger girls, 1.7% for older girls, 1.8% for younger boys, and 1.3% for older boys, relative to their respective means. In absolute magnitude, the point estimates are largest for older girls, although in proportional terms the four groups are broadly comparable. Similar patterns are observed for reading, English, and the overall learning index. The lack of gender differences in the short-run test-score effects may reflect the limited temporal window: since we focus on contemporaneous exposure, the duration may be too short for parents to perceive any deterioration in their children’s cognitive performance and respond through changes in educational investment or attendance. This gender similarity applies to test scores; gendered differences instead appear in how families respond to that decline through schooling and labor decisions, which we examine below.

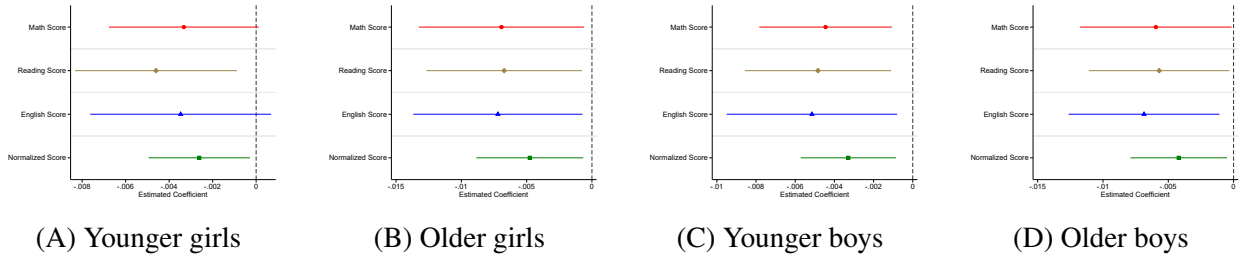


Figure 3: Heterogeneity by age and gender. Coefficients of upwind burned area on test scores (mathematics, reading, English, and the normalized learning index), estimated separately for four age–gender subgroups: (A) younger girls (5–10), (B) older girls (11–16), (C) younger boys (5–10), and (D) older boys (11–16). All specifications include district, survey-year, and age fixed effects and child and household controls. Bars indicate 95% confidence intervals. Full estimates in Appendix Table A6.

5.4 Timing of Exposure

The 12-month exposure window in the baseline specification may mask differential effects depending on when fires occur relative to the school calendar. In Pakistan, the academic year begins in April, with summer vacations from June to mid-August and final examinations in March. We disaggregate fire exposure into four quarterly windows relative to the September–December ASER assessment period: the last three months (June–August, summer break), three to six months (March–May, exam period and start of the new grade), six to nine months (December–February), and ten to twelve months (the previous September–November). In the rice-wheat calendar, wheat residue burning is concentrated in April–May following harvest, while rice residue burning occurs in October–November (Zahid et al., 2020). Figure 4 reports the estimates, with the full results in Appendix Table A7.

Two findings emerge. First, fires during the active school term have the strongest negative

effects on test scores, concentrated in the March–May window, which spans final examinations and the transition into the new grade and coincides with the wheat-residue burning season; the effect is present across all four subgroups. Older boys additionally show large effects from fires in the September–November window, which coincides with the rice-residue burning season. Second, fires during the summer holidays (June–August) have negligible effects, consistent with disruption to instructional time driving the cognitive consequences: during vacations children are not engaged in formal learning, so smoke exposure has little immediate effect on academic performance, whereas during the school term even short-term exposure can impair attention, memory, and cognitive functioning.

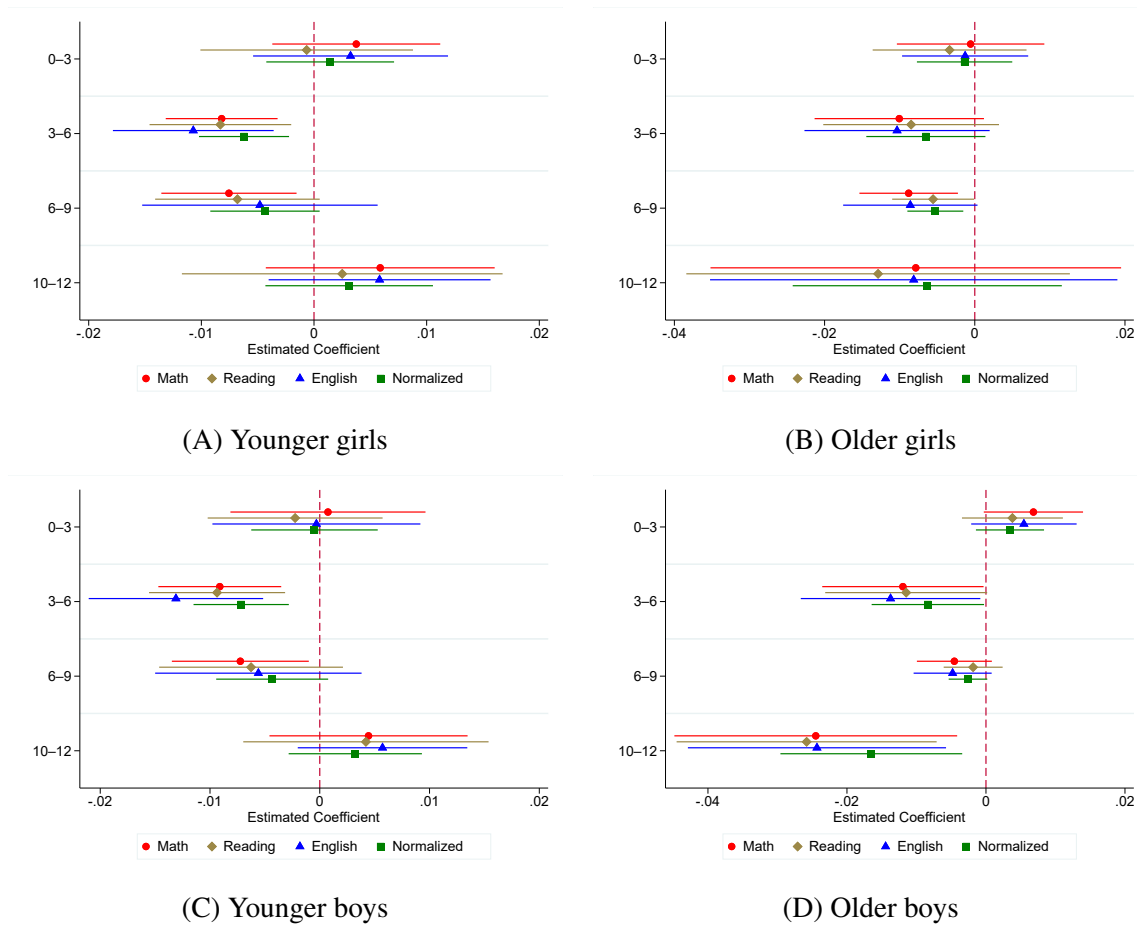


Figure 4: **Timing of fire exposure.** Coefficients of upwind burned area on test scores, by quarter of the 12-month window preceding the survey, defined relative to the September start of the ASER assessment. From most to least recent: 0–3 months (June–August, summer holidays), 3–6 months (March–May, final exams and start of the new grade), 6–9 months (December–February), and 10–12 months (the previous September–November). Points denote mathematics, reading, English, and the normalized learning index. Bars indicate 95% confidence intervals. Full estimates in Appendix Table A7.

5.5 Long-Run Impacts on Cognitive Performance

The impacts of fire exposure may persist beyond the year of occurrence, and focusing only on contemporaneous effects could mask the overall impact. We therefore estimate current and lagged effects of upwind exposure, including up to three annual lags, disaggregated by age cohort and gender. Figure 5 reports the results for test scores.

Across all four subgroups, the contemporaneous effect of upwind fire exposure on the normalized learning index is negative and statistically significant: a one standard deviation increase in upwind burned area reduces the index by 0.018 SD for younger girls, 0.029 SD for older girls, 0.022 SD for younger boys, and 0.024 SD for older boys. The lagged coefficients are generally small and statistically insignificant, indicating that the cognitive effects of fire exposure do not accumulate over time and that test scores recover within a year. The pattern is similar across individual subjects: contemporaneous coefficients on mathematics, reading, and English are uniformly negative, while lagged coefficients cluster around zero. As the next section shows, however, the schooling and labor responses to this transitory cognitive shock are neither transitory nor gender-neutral.

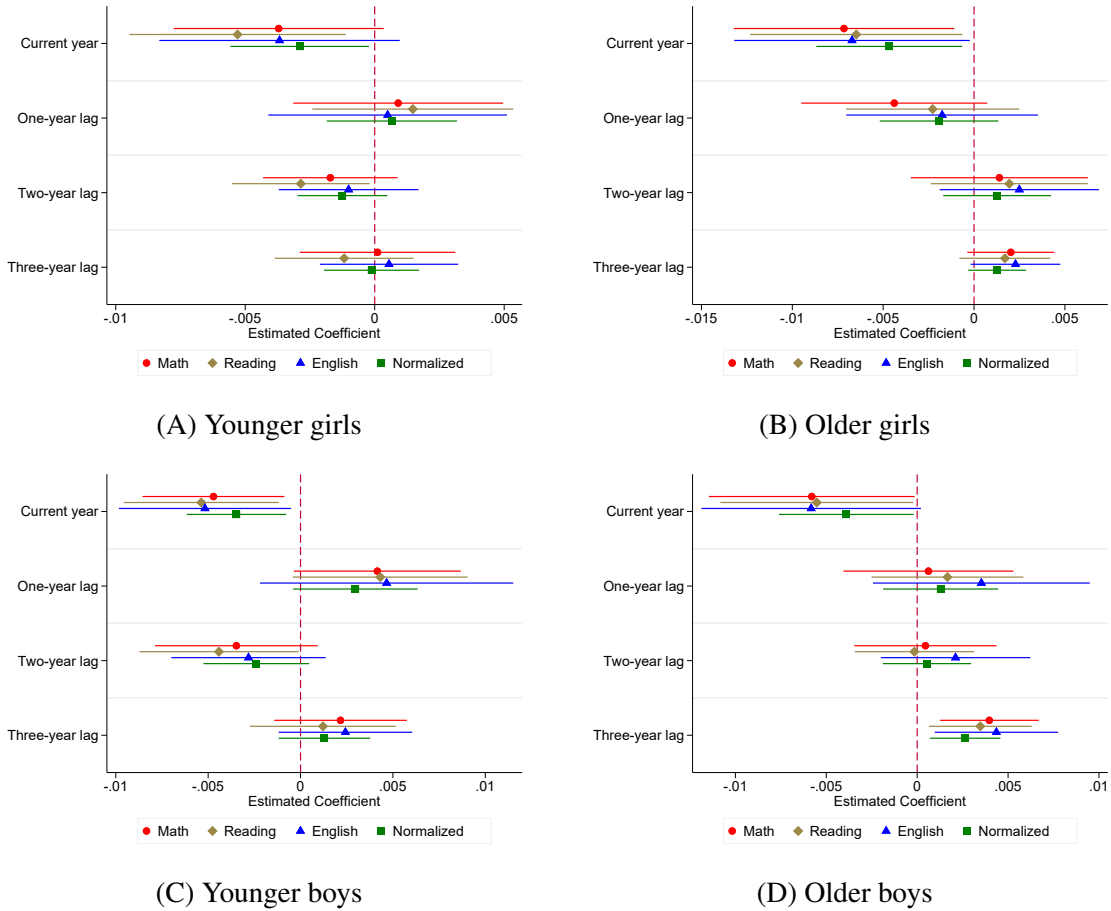


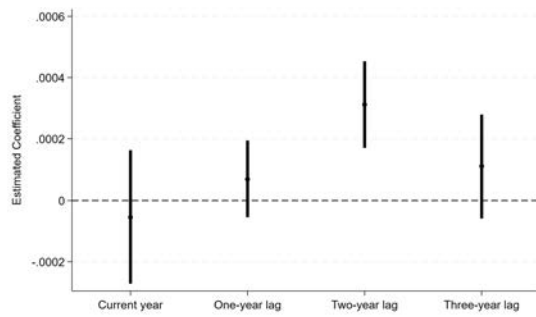
Figure 5: **Long-run impacts on test scores.** Contemporaneous and lagged (up to three years) coefficients of upwind burned area on test scores (mathematics, reading, English, and the normalized learning index) for (A) younger girls, (B) older girls, (C) younger boys, and (D) older boys. Bars indicate 95% confidence intervals.

5.6 School Dropout and Child Labor

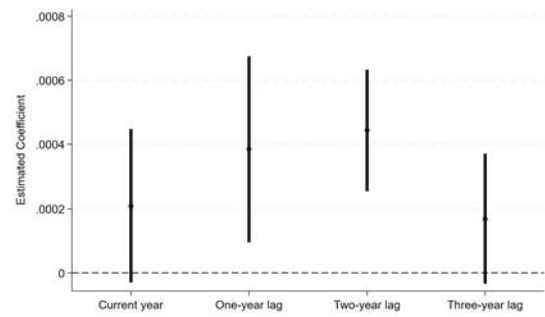
While the cognitive effects fade within a year, the behavioral responses to repeated exposure are persistent and differ sharply by gender. Figure 6 reports the effects of contemporaneous and lagged upwind exposure on child labor (Panels A and B; children aged 10–17 in the PSLM) and on school dropout (Panels C and D; ASER). The corresponding estimates are reported in Appendix Tables A8 (dropout) and A9 (child labor).

Turning first to child labor, the point estimates for girls are positive at lags one through three but reach statistical significance only at the two-year lag (Figure 6, Panel A; Appendix Table A9). For boys, upwind fires also increase the likelihood of engaging in child labor. The contemporaneous effect is marginally significant at the 10% level, while the effects at the first and second lags are statistically significant. The effect then diminishes and becomes statistically insignificant by the third lag (Panel B). In terms of magnitude, a one standard deviation increase in upwind exposure (6.22 km^2) at the two-year lag raises the probability of work by approximately 0.27 percentage points for boys (1.5% of their mean rate of 17.9%) and 0.19 percentage points for girls (3.2% of their mean of 6.0%); in proportional terms, the delayed response is thus larger for girls. Together, these patterns indicate that fire exposure raises children's engagement in work, with effects that build over time, consistent with a reallocation of time from schooling toward labor (Basu and Van, 1998; Edmonds, 2007).

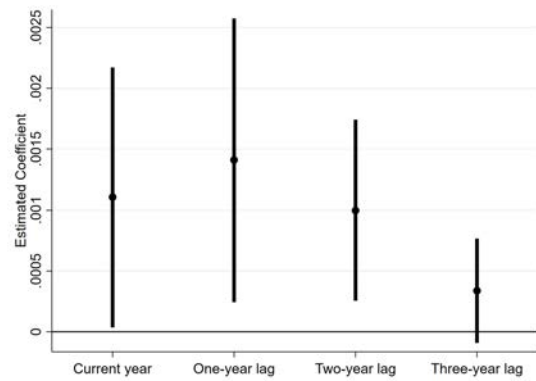
The schooling response is sharply gendered. Among secondary-school-aged children, girls become significantly more likely to drop out following upwind exposure, both in the current year and for up to two subsequent years (Figure 6, Panel C; Appendix Table A8). A one standard deviation increase in upwind exposure raises older girls' dropout probability by roughly 0.7, 0.9, and 0.6 percentage points in the year of exposure and the following two years; cumulated over these three years, the effect is about 2.2 percentage points, or approximately 12% of their mean dropout rate of 17.8%. Boys, by contrast, remain enrolled despite their greater engagement in work and their diminished cognitive performance (Panel D). This asymmetry is consistent with gendered parental investment. Pakistan is a patrilocal society in which daughters typically join the husband's household after marriage (Khalil and Mookerjee, 2019), which lowers parents' perceived returns to investing in girls' education (Jayachandran, 2015). When parents observe a decline in a daughter's performance, they may be more inclined to withdraw her from school or redirect her toward domestic responsibilities, whereas sons are kept in school even as they take on work. Taken together, the labor and dropout responses suggest that fire exposure can set in motion self-reinforcing cycles in which pollution depresses human capital, which in turn deepens reliance on child labor and, for girls in particular, reinforces the intergenerational transmission of educational disadvantage.



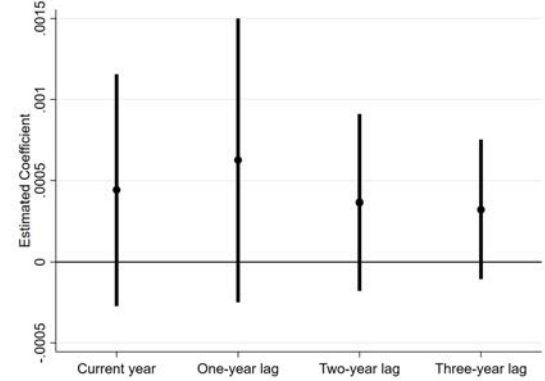
(A) Child labor (girls)



(B) Child labor (boys)



(C) Dropout (girls)



(D) Dropout (boys)

Figure 6: **Child labor and dropout by gender.** Coefficients of upwind fires on child labor (A, B; worked in the month preceding the survey, ages 10–17, PSLM) and school dropout (C, D; ASER), for the current year and up to three annual lags, estimated separately for girls and boys. Bars indicate 95% confidence intervals. Full estimates in Appendix Tables A8 and A9.

5.7 Robustness

We subject the baseline results to a battery of robustness exercises, reported in Tables 1 and 2. First, we vary the exposure radius. Using radii of 10, 20, 30, 40, and 50 km (Table 1), the detrimental effects of upwind fires are strongest closest to the district boundary and attenuate monotonically with distance, becoming statistically insignificant at 40 km and beyond, consistent with the physical dispersion of pollutants. Downwind fires show no discernible effect at any radius.

Second, we probe sensitivity to sample composition and specification (Table 2). The results are robust to (i) excluding the top five percentile of high-exposure districts, which if anything strengthens the estimated effects; (ii) including district-specific linear time trends; (iii) replacing year fixed effects with province-year fixed effects; (iv) excluding children who were never enrolled or had already dropped out; and (v) controlling for agricultural fires within the focal (source) district together with average wind speed, district-level pollution, weather (SPEI), and local economic activity (nighttime lights). Across all of these exercises, the coefficients on upwind fires remain negative, statistically significant, and close to the baseline in magnitude, reinforcing the interpretation of the estimated effects as the causal impact of pollution exposure.

Third, we control for the average upwind exposure of neighboring districts, a proxy for region-wide burning intensity (Appendix Table A5). The own-district coefficients are essentially unchanged, while neighboring exposure is small and statistically insignificant, implying that outcomes respond to the pollution a district directly receives rather than to conditions in the surrounding region.

Table 1: Agricultural Fires and Cognitive Development: Different Radii

Dependent Variable	Math Score	Reading Score	English Score	Normalized Score	Dropped Out
	(1)	(2)	(3)	(4)	(5)
Panel A: 10 KM Radius					
Upwind Fires _t	-0.0056*** (0.0021)	-0.0069*** (0.0020)	-0.0076*** (0.0023)	-0.0046*** (0.0014)	0.0001 (0.0003)
Downwind Fires _t	0.0008 (0.0026)	0.0014 (0.0021)	0.0022 (0.0024)	0.0010 (0.0015)	-0.0004 (0.0003)
Panel B: 20 KM Radius					
Upwind Fires _t	-0.0029** (0.0014)	-0.0033*** (0.0013)	-0.0036** (0.0016)	-0.0022** (0.0009)	0.0001 (0.0002)
Downwind Fires _t	-0.0005 (0.0013)	-0.0001 (0.0011)	0.0002 (0.0014)	-0.0001 (0.0008)	-0.0002 (0.0001)
Panel C: 30 KM Radius					
Upwind Fires _t	-0.0015 (0.0012)	-0.0021* (0.0011)	-0.0025* (0.0013)	-0.0014* (0.0008)	-0.0001 (0.0001)
Downwind Fires _t	-0.0006 (0.0010)	-0.0002 (0.0009)	-0.0001 (0.0011)	-0.0002 (0.0007)	-0.0001 (0.0001)
Panel D: 40 KM Radius					
Upwind Fires _t	-0.0008 (0.0009)	-0.0012 (0.0008)	-0.0015 (0.0009)	-0.0008 (0.0006)	-0.0001 (0.0001)
Downwind Fires _t	-0.0008 (0.0009)	-0.0003 (0.0008)	-0.0004 (0.0009)	-0.0003 (0.0006)	-0.0001 (0.0001)
Panel E: 50 KM Radius					
Upwind Fires _t	-0.0007 (0.0007)	-0.0009 (0.0007)	-0.0012 (0.0008)	-0.0006 (0.0005)	-0.0001 (0.0001)
Downwind Fires _t	-0.0007 (0.0008)	-0.0001 (0.0007)	-0.0004 (0.0008)	-0.0002 (0.0005)	-0.0001 (0.0001)

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All specifications include fixed effects for the child's age, district, and survey year, as well as the full set of child and household controls. Standard errors clustered at the district level are reported in parentheses.

Table 2: Agricultural Fires and Cognitive Development: Robustness Exercises

Dependent Variable	Math Score	Reading Score	English Score	Normalized Score	Dropped Out
	(1)	(2)	(3)	(4)	(5)
Panel A: Excluding High-Exposure Regions					
Upwind Fires _t	-0.0087** (0.0037)	-0.0095** (0.0037)	-0.0091** (0.0042)	-0.0062** (0.0026)	0.0002 (0.0004)
Panel B: Controlling for District-Specific Time Trends					
Upwind Fires _t	-0.0050*** (0.0016)	-0.0055*** (0.0015)	-0.0057*** (0.0018)	-0.0037*** (0.0010)	0.0001 (0.0002)
Panel C: Province-Year Fixed Effects					
Upwind Fires _t	-0.0039** (0.0017)	-0.0046*** (0.0017)	-0.0039* (0.0020)	-0.0028** (0.0012)	0.0001 (0.0002)
Panel D: Excluding Never Enrolled and Dropped Out Children					
Upwind Fires _t	-0.0044*** (0.0015)	-0.0047*** (0.0015)	-0.0051*** (0.0019)	-0.0032*** (0.0010)	- -
Panel E: Additional Controls (Source Fires, Weather, Wind Speed, Nightlights)					
Upwind Fires _t	-0.0051*** (0.0018)	-0.0048*** (0.0018)	-0.0051** (0.0021)	-0.0034*** (0.0012)	0.0001 (0.0003)

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Panel A excludes the top five percentile of high-exposure districts (conditional on experiencing fires); Panel D drops children who were never enrolled or had already dropped out; Panel E adds controls for fires in the source district, SPEI, wind speed, district-level PM_{2.5}, and nighttime lights. All specifications include the baseline fixed effects and controls. Standard errors clustered at the district level are reported in parentheses.

6 Conclusion

Agricultural land clearing through open burning is a major challenge in many developing countries and is associated with severe environmental and health consequences. This study investigates the impact of exposure to agricultural fires on the cognitive development of children aged 5–16 in Pakistan. Leveraging variation in wind direction, we construct a treatment measure that captures exposure to pollution from upwind fires, which transport fine particulate matter into a child’s district of residence. As a placebo test, we examine downwind fires, which reflect the same burned area but, due to wind direction, disperse pollution away from the child’s location.

Our findings show that exposure to upwind fires within 15 km of a district’s boundary has significant adverse effects on children’s cognitive performance, whereas downwind fires have no measurable impact. These results are robust to alternative exposure radii and to controls for local weather, economic activity, and other potential confounders. The effects are similar for boys and girls in the short run, and fires occurring during the school term are particularly detrimental while exposure during holidays is inconsequential. In the longer run, older girls (aged 11–16) become more likely to drop out of school, consistent with parents withdrawing girls from schooling because of lower perceived returns to female education in a patrilocal society, while child labor rises for both boys and girls in the years following exposure. Pollution exposure thus disrupts both cognitive development and educational trajectories and triggers compensatory labor responses within households, with consequences that persist for several years.

Several limitations temper these conclusions. First, although the upwind–downwind comparison addresses many identification concerns, we cannot entirely rule out that wind direction is correlated with unobserved determinants of child outcomes; the stability of the estimates across the robustness exercises in Section 5.7, including district-specific trends, province-year fixed effects, and controls for source-district fires and local economic activity, mitigates this concern. Second, satellite fire products likely under-detect the true extent of burning because of cloud cover, atmospheric conditions, and the timing of satellite overpasses. Since such under-detection introduces classical measurement error into the exposure variable, our estimates most plausibly represent a lower bound, with the true effects potentially larger. Third, agricultural fires emit a complex mixture of pollutants, so while we identify the effect of fire-driven pollution as a whole, we cannot isolate the specific compounds, such as fine particulate matter or black carbon, responsible for the cognitive and behavioral responses we document.

The findings carry direct policy implications. Because the harms of agricultural burning extend beyond health to children’s learning and schooling, the case for curbing it is stronger than health-focused assessments alone would suggest. Agricultural residue burning in Pakistan is driven by the low cost of open burning relative to mechanized alternatives and the narrow window between harvest and replanting; subsidies or credit schemes for mechanized harvesting equipment could reduce burning incentives while maintaining agricultural productivity. At

the regulatory level, since fires during the academic months have the most pronounced effects while those during summer holidays are largely inconsequential, targeted enforcement of existing burning bans during the school year, or strengthened bureaucratic incentives to enforce them ([Dipoppa and Gulzar, 2024](#)), may generate the greatest educational benefits. School-level interventions, such as air filtration in classrooms or adjustments to the exam calendar to avoid peak burning periods, offer lower-cost alternatives. The persistent dropout effects for older girls also point to the value of conditional cash transfers or other gender-targeted programs that sustain parental investment in girls' education in the aftermath of environmental shocks.

Title: Declaration of generative AI and AI-assisted technologies in the manuscript preparation process.

Statement: During the preparation of this work, the authors used ChatGPT to check grammar, spelling, and readability. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the published article.

References

- Akagi, S., R. J. Yokelson, C. Wiedinmyer, M. J. Alvarado, J. S. Reid, T. Karl, J. D. Crounse, and P. O. Wennberg (2011). Emission factors for open and domestic biomass burning for use in atmospheric models. *Atmospheric Chemistry and Physics* 11(9), 4039–4072.
- Annual Status of Education Report, Pakistan (2017). Aser pakistan. <http://aserpakistan.org/index.php>.
- Ayesh, A. (2023). Burned agricultural biomass, air pollution and crime. *Journal of Environmental Economics and Management* 122, 102887.
- Azhar, R., M. Zeeshan, and K. Fatima (2019). Crop residue open field burning in Pakistan: Multi-year high spatial resolution emission inventory for 2000–2014. *Atmospheric Environment* 208, 20–33.
- Basu, K. and P. H. Van (1998). The economics of child labor. *American Economic Review* 88(3), 412–427.
- Bikkina, S., A. Andersson, E. N. Kirillova, H. Holmstrand, S. Tiwari, A. K. Srivastava, D. S. Bisht, and Ö. Gustafsson (2019). Air quality in megacity Delhi affected by countryside biomass burning. *Nature Sustainability* 2(3), 200–205.
- Chay, K. Y. and M. Greenstone (2003). The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession. *Quarterly Journal of Economics* 118(3), 1121–1167.
- Chen, J., C. Li, Z. Ristovski, A. Milic, Y. Gu, M. S. Islam, S. Wang, J. Hao, H. Zhang, C. He, et al. (2017). A review of biomass burning: Emissions and impacts on air quality, health and climate in China. *Science of the Total Environment* 579, 1000–1034.
- Chen, P. (2025). Industrialization and pollution: The long-term impact of early-life exposure on human capital formation. *Journal of Public Economics* 241, 105270.
- Chuvieco, E., F. Mouillot, G. R. Van der Werf, J. San Miguel, M. Tanase, N. Koutsias, M. García, M. Yebra, M. Padilla, I. Gitas, et al. (2019). Historical background and current developments for mapping burned area from satellite Earth observation. *Remote Sensing of Environment* 225, 45–64.
- Chuvieco, E., M. L. Pettinari, N. Koutsias, M. Forkel, S. Hantson, and M. Turco (2021). Human and climate drivers of global biomass burning variability. *Science of the Total Environment* 779, 146361.

- Cleland, S. E., L. H. Wyatt, L. Wei, N. Paul, M. L. Serre, J. J. West, S. B. Henderson, and A. G. Rappold (2022). Short-term exposure to wildfire smoke and pm2. 5 and cognitive performance in a brain-training game: a longitudinal study of us adults. *Environmental health perspectives* 130(6), 067005.
- Currie, J. and M. Neidell (2005). Air pollution and infant health: What can we learn from California's recent experience? *Quarterly Journal of Economics* 120(3), 1003–1030.
- Deryugina, T., G. Heutel, N. H. Miller, D. Molitor, and J. Reif (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review* 109(12), 4178–4219.
- Dialogue Earth (2019). Pakistan threatens farmers with jail over stubble burning. <https://dialogue.earth/en/pollution/pakistan-threatens-farmers-with-jail-over-stubble-burning/>.
- Diao, M., T. Holloway, S. Choi, S. M. O'Neill, M. Z. Al-Hamdan, A. Van Donkelaar, R. V. Martin, X. Jin, A. M. Fiore, D. K. Henze, et al. (2019). Methods, availability, and applications of PM2. 5 exposure estimates derived from ground measurements, satellite, and atmospheric models. *Journal of the Air & Waste Management Association* 69(12), 1391–1414.
- Dipoppa, G. and S. Gulzar (2024). Bureaucrat incentives reduce crop burning and child mortality in South Asia. *Nature* 634(8036), 1125–1131.
- Duflo, E. (2012). Women empowerment and economic development. *Journal of Economic Literature* 50(4), 1051–1079.
- Ebenstein, A., V. Lavy, and S. Roth (2016). The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution. *American Economic Journal: Applied Economics* 8(4), 36–65.
- Edmonds, E. V. (2007). Child labor. In T. P. Schultz and J. A. Strauss (Eds.), *Handbook of Development Economics*, Volume 4, pp. 3607–3709. Elsevier.
- Giglio, L., J. T. Randerson, and G. R. Van Der Werf (2013). Analysis of daily, monthly, and annual burned area using the fourth-generation global fire emissions database (GFED4). *Journal of Geophysical Research: Biogeosciences* 118(1), 317–328.
- Gilraine, M. and A. Zheng (2022). Air pollution and student performance in the us. Technical report, National Bureau of Economic Research.
- Halai, A. and N. Durrani (2021). School education system in Pakistan: Expansion, access, and equity. In *Handbook of Education Systems in South Asia*, pp. 665–693. Springer.

- Heft-Neal, S., J. Burney, E. Bendavid, K. K. Voss, and M. Burke (2020). Dust pollution from the Sahara and African infant mortality. *Nature Sustainability* 3(10), 863–871.
- IGC (2022). Stubble burning in Pakistan: Why it continues and how can it be curtailed. <https://www.theigc.org/blogs/climate-priorities-developing-countries/stubble-burning-pakistan-why-it-continues-and-how-can>.
- Jayachandran, S. (2015). The roots of gender inequality in developing countries. *Annual Review of Economics* 7, 63–88.
- Johnson, A. L., M. J. Abramson, M. Dennekamp, G. J. Williamson, and Y. Guo (2020). Particulate matter modelling techniques for epidemiological studies of open biomass fire smoke exposure: A review. *Air Quality, Atmosphere & Health* 13(1), 35–75.
- Khalil, U. and S. Mookerjee (2019). Patrilocal residence and women’s social status: Evidence from South Asia. *Economic Development and Cultural Change* 67(2), 401–438.
- Lai, W., S. Li, Y. Li, and X. Tian (2022). Air pollution and cognitive functions: evidence from straw burning in china. *American Journal of Agricultural Economics* 104(1), 190–208.
- Lan, R., S. D. Eastham, T. Liu, L. K. Norford, and S. R. Barrett (2022). Air quality impacts of crop residue burning in India and mitigation alternatives. *Nature Communications* 13(1), 6537.
- Lauk, C. and K.-H. Erb (2009). Biomass consumed in anthropogenic vegetation fires: Global patterns and processes. *Ecological Economics* 69(2), 301–309.
- Li, X., Y. Zhou, M. Zhao, and X. Zhao (2025). Harmonization of DMSP and VIIRS nighttime light data from 1992–2024 at the global scale. <https://doi.org/10.6084/m9.figshare.9828827>.
- Lin, M. and T. Begho (2022). Crop residue burning in South Asia: A review of the scale, effect, and solutions with a focus on reducing reactive nitrogen losses. *Journal of Environmental Management* 314, 115104.
- Maccini, S. and D. Yang (2009). Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review* 99(3), 1006–1026.
- Mhawish, A., C. Sarangi, P. Babu, M. Kumar, M. Bilal, and Z. Qiu (2022). Observational evidence of elevated smoke layers during crop residue burning season over Delhi: Potential implications on associated heterogeneous PM_{2.5} enhancements. *Remote Sensing of Environment* 280, 113167.

- Mullis, I. V., M. O. Martin, P. Foy, D. L. Kelly, and B. Fishbein (2020). TIMSS 2019 international results in mathematics and science. <https://timss2019.org/reports/>.
- NEMIS–AEPAM (2018). Pakistan education statistics 2016–17. <http://library.aepam.edu.pk/Books/Pakistan%20Education%20Statistics%202016-17.pdf>.
- Nguyen, T. D. (2026, 1). The effect of air pollution on student achievement: A systematic review and meta-analysis of the causal evidence. EdWorkingPaper ai26-1381, Annenberg Institute at Brown University.
- Pakistan Bureau of Statistics (2020). Pakistan social and living standards measurement survey. <https://www.pbs.gov.pk/>.
- Pan, X., C. Ichoku, M. Chin, H. Bian, A. Darmanov, P. Colarco, L. Ellison, T. Kucsera, A. da Silva, J. Wang, et al. (2020). Six global biomass burning emission datasets: Intercomparison and application in one global aerosol model. *Atmospheric Chemistry and Physics* 20(2), 969–994.
- Ponnusamy, S. (2025). The impact of rainfall shocks in childhood and adolescence on human capital development. *American Journal of Agricultural Economics*.
- Pullabhotla, H. K., M. Zahid, S. Heft-Neal, V. Rathi, and M. Burke (2023). Global biomass fires and infant mortality. *Proceedings of the National Academy of Sciences* 120(23), e2218210120.
- Roberts, G. and M. Wooster (2021). Global impact of landscape fire emissions on surface level pm2.5 concentrations, air quality exposure and population mortality. *Atmospheric Environment* 252, 118210.
- Samburova, V., J. Connolly, M. Gyawali, R. L. Yatawelli, A. C. Watts, R. K. Chakrabarty, B. Zielinska, H. Moosmüller, and A. Khlystov (2016). Polycyclic aromatic hydrocarbons in biomass-burning emissions and their contribution to light absorption and aerosol toxicity. *Science of the Total Environment* 568, 391–401.
- Sanders, N. J. (2012). What doesn’t kill you makes you weaker: Prenatal pollution exposure and educational outcomes. *Journal of Human Resources* 47(3), 826–850.
- Shah, M. and B. Steinberg (2017). Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy* 125(1), 45–82.
- State of Global Air (2025). Air pollution and health impacts in Central, Southeast, and South asia.

UNDP (2024). Human development report 2023/24: Breaking the gridlock: Reimagining cooperation in a polarized world. United Nations Development Programme, New York.

UNICEF (2026). Education. <https://www.unicef.org/pakistan/education>. Accessed August 2026.

van Donkelaar, A., M. S. Hammer, L. Bindle, M. Brauer, J. R. Brook, M. J. Garay, N. C. Hsu, O. V. Kalashnikova, R. A. Kahn, C. Lee, R. C. Levy, A. Lyapustin, A. M. Sayer, and R. V. Martin (2021). Monthly global estimates of fine particulate matter and their uncertainty. *Environmental Science & Technology* 55(22), 15287–15300.

Vicente-Serrano, S. M., S. Beguéría, and J. I. López-Moreno (2010). A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of Climate* 23(7), 1696–1718.

Wen, J. and M. Burke (2022). Lower test scores from wildfire smoke exposure. *Nature Sustainability* 5(11), 947–955.

World Bank (2022). Pakistan – learning poverty brief. <https://documents1.worldbank.org/curated/en/099812207212211713/pdf/IDU0e0c38ddc0f77b04fda0a7ad0e2f4235d517a.pdf>.

World Bank (2024). World development indicators. World Bank, Washington, DC. Gross school enrollment (SE.PRM.ENRR, SE.SEC.ENRR, SE.TER.ENRR) and adult literacy (SE.ADT.LITR) indicators, by sex.

World Bank (2025a). Accelerating access to clean air for a livable planet.

World Bank (2025b). Clean-air solutions can improve lives of nearly one billion people across South Asia. <https://www.worldbank.org/en/news/press-release/2025/12/15/clean-air-solutions-can-improve-lives-of-nearly-one-billion-people-across-south-asia>

World Health Organization (2026). Air pollution.

Zaheed, J. and K. M. Salik (2024). Restricting crop residue burning practices in Punjab, Pakistan: What needs to be done? <https://sdpi.org/assets/lib/uploads/Enforcing%20Change.pdf>.

Zahid, A., S. Ali, M. Ahmed, and N. Iqbal (2020). Improvement of soil health through residue management and conservation tillage in rice-wheat cropping system of Punjab, Pakistan. *Agronomy* 10(12), 1844.

Zivin, J. G. and M. Neidell (2012). The impact of pollution on worker productivity. *American Economic Review* 102(7), 3652–3673.

ONLINE APPENDIX (NOT FOR PUBLICATION)

WHEN THE FIELDS BURN: THE HIDDEN COSTS OF AGRICULTURAL FIRES
ON CHILDREN'S EDUCATION

A1 Additional Tables and Figures

Table A1: Summary Statistics

Variable	Mean	Standard Deviation	Min	Max	Source
Panel A: Main Outcome Variables					
Math Score	2.000	1.494	0	4	ASER
Reading Score	2.028	1.534	0	4	ASER
English Score	1.944	1.566	0	4	ASER
Normalized Score	0.000	1.000	-1.399	1.395	ASER
Dropped Out	0.071	0.256	0	1	ASER
Child Labor	0.124	0.329	0	1	PSLM
Panel B: Explanatory Variables of Interest					
Upwind Fires	2.340	6.221	0	66.71	ESA
Downwind Fires	3.271	8.059	0	68.03	ESA

Note: The table provides summary statistics for the key variables used in the analysis.

Table A2: Agricultural Fires and Pollution: Validation Exercise

	Dependent Variable = PM2.5 Particulate Matter		
	(1)	(2)	(3)
Upwind Fires _t	0.036*** (0.010)		0.035*** (0.011)
Downwind Fires _t		0.016 (0.021)	0.006 (0.022)
Mean Outcomes	51.523	51.523	51.523
Observations	670	670	670

Note: *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. All specifications include district and year fixed effects, controls for weather (SPEI) and average wind speed, and district-specific linear time trends. Standard errors are clustered at the district level. The sample covers the district-year panel common to the fire and pollution data, 2005–2016.

Table A3: Agricultural Fires and Cognitive Development: Baseline Results

Dependent Variable	Math Score	Reading Score	English Score	Normalized Score	Dropped Out
	(1)	(2)	(3)	(4)	(5)
Panel A: Unconditional Specifications					
Upwind Fires _t	-0.0049*** (0.0018)	-0.0052*** (0.0015)	-0.0054*** (0.0019)	-0.0035*** (0.0011)	0.0001 (0.0002)
Mean Outcomes	2.000	2.028	1.944	0.000	0.071
Observations	712285	713706	711497	719010	713622
Panel B: Conditional Specifications					
Upwind Fires _t	-0.0048*** (0.0016)	-0.0052*** (0.0015)	-0.0054*** (0.0019)	-0.0035*** (0.0010)	0.0001 (0.0002)
Mean Outcomes	1.999	2.026	1.942	-0.001	0.071
Observations	688813	690128	688073	695182	689460

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All specifications include fixed effects for the child's age, district, and survey year. In Panel B, additional controls include the child's gender, parental education and age, home ownership status, and household assets such as access to television, electricity, and mobile phone connection. Standard errors clustered at the district level are reported in parentheses.

Table A4: Agricultural Fires and Cognitive Development: Placebo (UW and DW Fires)

Dependent Variable	Math Score	Reading Score	English Score	Normalized Score	Dropped Out
	(1)	(2)	(3)	(4)	(5)
Upwind Fires _t	-0.0048*** (0.0016)	-0.0053*** (0.0015)	-0.0056*** (0.0019)	-0.0036*** (0.0010)	0.0001 (0.0002)
Downwind Fires _t	0.0003 (0.0018)	0.0008 (0.0015)	0.0013 (0.0018)	0.0006 (0.0011)	-0.0003 (0.0002)
Mean Outcomes	1.999	2.026	1.942	-0.001	0.071
Observations	688813	690128	688073	695182	689460

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All specifications include fixed effects for the child's age, district, and survey year, as well as controls for the child's gender, parental education and age, home ownership status, and household assets. Standard errors clustered at the district level are reported in parentheses.

Table A5: Agricultural Fires and Cognitive Development: Regional Spillovers

Dependent Variable	Math Score	Reading Score	English Score	Normalized Score	Dropped Out
	(1)	(2)	(3)	(4)	(5)
Upwind Fires _t	-0.0045*** (0.0017)	-0.0051*** (0.0015)	-0.0054*** (0.0020)	-0.0034*** (0.0011)	0.0001 (0.0002)
Downwind Fires _t	0.0008 (0.0020)	0.0011 (0.0017)	0.0016 (0.0020)	0.0008 (0.0012)	-0.0004 (0.0002)
Neighboring UW Fires _t	-0.0008 (0.0009)	-0.0006 (0.0008)	-0.0006 (0.0009)	-0.0005 (0.0006)	0.0001 (0.0001)
Mean Outcomes	1.999	2.026	1.942	-0.001	0.071
Observations	688813	690128	688073	695182	689460

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All specifications include fixed effects for the child's age, district, and survey year, as well as controls for the child's gender, parental education and age, home ownership status, and household assets. Standard errors clustered at the district level are reported in parentheses.

Table A6: Agricultural Fires and Cognitive Development: Heterogeneity by Age and Gender

Dependent Variable	Math Score	Reading Score	English Score	Normalized Score
	(1)	(2)	(3)	(4)
Panel A: Younger Girls (Age 5-10)				
Upwind Fires _t	-0.0033* (0.0017)	-0.0046** (0.0019)	-0.0035 (0.0021)	-0.0026** (0.0012)
Mean Outcomes	1.416	1.429	1.366	-0.399
Observations	174986	175343	174699	176510
Panel B: Older Girls (Age 11-16)				
Upwind Fires _t	-0.0069** (0.0032)	-0.0067** (0.0030)	-0.0072** (0.0033)	-0.0048** (0.0021)
Mean Outcomes	2.546	2.623	2.515	0.389
Observations	88664	88704	88540	89553
Panel C: Younger Boys (Age 5-10)				
Upwind Fires _t	-0.0045** (0.0017)	-0.0048** (0.0019)	-0.0051** (0.0022)	-0.0033*** (0.0012)
Mean Outcomes	1.597	1.594	1.519	-0.287
Observations	258336	259014	258098	260676
Panel D: Older Boys (Age 11-16)				
Upwind Fires _t	-0.0060** (0.0029)	-0.0057** (0.0027)	-0.0069** (0.0029)	-0.0042** (0.0019)
Mean Outcomes	2.944	3.006	2.897	0.652
Observations	166827	167067	166736	168443

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All specifications include fixed effects for the child's age, district, and survey year and the full set of child and household controls. Standard errors clustered at the district level are reported in parentheses.

Table A7: Agricultural Fires and Cognitive Development: Temporal Window Within One Year

Dependent Variable	Math Score	Reading Score	English Score	Normalized Score	Dropped Out
	(1)	(2)	(3)	(4)	(5)
Panel A: Younger Girls (Age 5-10)					
Upwind Fires (Last Three Months) _t	0.0038 (0.0038)	-0.0006 (0.0048)	0.0032 (0.0044)	0.0014 (0.0029)	-0.0001 (0.0002)
Upwind Fires (Three to Six Months) _t	-0.0082*** (0.0025)	-0.0083*** (0.0032)	-0.0107*** (0.0036)	-0.0062*** (0.0020)	0.0002 (0.0002)
Upwind Fires (Six to Nine Months) _t	-0.0076** (0.0030)	-0.0068* (0.0037)	-0.0048 (0.0053)	-0.0044* (0.0025)	0.0003 (0.0002)
Upwind Fires (Ten to Twelve Months) _t	0.0059 (0.0051)	0.0025 (0.0072)	0.0058 (0.0050)	0.0031 (0.0038)	-0.0000 (0.0007)
Mean Outcomes	1.416	1.429	1.366	-0.399	0.033
Observations	174986	175343	174699	176510	159000
Panel B: Older Girls (Age 11-16)					
Upwind Fires (Last Three Months) _t	-0.0006 (0.0050)	-0.0034 (0.0052)	-0.0013 (0.0042)	-0.0014 (0.0032)	-0.0001 (0.0009)
Upwind Fires (Three to Six Months) _t	-0.0101* (0.0057)	-0.0085 (0.0059)	-0.0103* (0.0062)	-0.0065 (0.0040)	0.0005 (0.0008)
Upwind Fires (Six to Nine Months) _t	-0.0088*** (0.0033)	-0.0056** (0.0028)	-0.0086* (0.0045)	-0.0053*** (0.0019)	0.0012 (0.0018)
Upwind Fires (Ten to Twelve Months) _t	-0.0079 (0.0138)	-0.0129 (0.0129)	-0.0081 (0.0137)	-0.0063 (0.0091)	-0.0003 (0.0020)
Mean Outcomes	2.546	2.623	2.515	0.389	0.182
Observations	88664	88704	88540	89553	94414
Panel C: Younger Boys (Age 5-10)					
Upwind Fires (Last Three Months) _t	0.0007 (0.0045)	-0.0022 (0.0040)	-0.0003 (0.0048)	-0.0005 (0.0029)	-0.0000 (0.0002)
Upwind Fires (Three to Six Months) _t	-0.0091*** (0.0028)	-0.0094*** (0.0031)	-0.0131*** (0.0040)	-0.0072*** (0.0022)	0.0002 (0.0002)
Upwind Fires (Six to Nine Months) _t	-0.0072** (0.0032)	-0.0063 (0.0042)	-0.0056 (0.0048)	-0.0043* (0.0026)	0.0001 (0.0002)
Upwind Fires (Ten to Twelve Months) _t	0.0044 (0.0046)	0.0042 (0.0056)	0.0057 (0.0039)	0.0032 (0.0031)	0.0001 (0.0003)
Mean Outcomes	1.597	1.594	1.519	-0.287	0.025
Observations	258336	259014	258098	260676	253380
Panel D: Older Boys (Age 11-16)					
Upwind Fires (Last Three Months) _t	0.0068* (0.0036)	0.0038 (0.0037)	0.0055 (0.0038)	0.0035 (0.0025)	0.0001 (0.0006)
Upwind Fires (Three to Six Months) _t	-0.0120** (0.0059)	-0.0115* (0.0059)	-0.0137** (0.0065)	-0.0084** (0.0041)	0.0004 (0.0007)
Upwind Fires (Six to Nine Months) _t	-0.0045* (0.0027)	-0.0018 (0.0021)	-0.0048* (0.0028)	-0.0026* (0.0014)	0.0002 (0.0005)
Upwind Fires (Ten to Twelve Months) _t	-0.0245** (0.0103)	-0.0258*** (0.0095)	-0.0243** (0.0094)	-0.0165** (0.0066)	-0.0005 (0.0020)
Mean Outcomes	2.944	3.006	2.897	0.652	0.112
Observations	166827	167067	166736	168443	182666

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Fire exposure is decomposed into four quarterly windows relative to the September start of the ASER assessment. All specifications include the full set of fixed effects and controls. Standard errors clustered at the district level are reported in parentheses.

Table A8: Long-Run Effects on School Dropout, by Age and Gender

Dependent Variable: Dropped Out	Younger Girls	Older Girls	Younger Boys	Older Boys
	(1)	(2)	(3)	(4)
Upwind Fires _t	0.0002 (0.0001)	0.0011** (0.0005)	0.0001 (0.0001)	0.0004 (0.0004)
Upwind Fires _{t-1}	0.0003* (0.0002)	0.0014** (0.0006)	0.0001 (0.0001)	0.0006 (0.0004)
Upwind Fires _{t-2}	0.0002 (0.0001)	0.0010*** (0.0004)	0.0002** (0.0001)	0.0004 (0.0003)
Upwind Fires _{t-3}	0.0000 (0.0001)	0.0003 (0.0002)	0.0000 (0.0001)	0.0003 (0.0002)
Mean Outcomes	0.032	0.178	0.024	0.114
Observations	142210	85530	224838	163501

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The dependent variable equals one if the child has dropped out of school. Each column reports contemporaneous and lagged (up to three years) coefficients of upwind burned area for the indicated age–gender subgroup. All specifications include the full set of fixed effects and controls. Standard errors clustered at the district level are reported in parentheses.

Table A9: Agricultural Fires and Child Labor

Dependent Variable	Worked (Girls)	Worked (Boys)
	(1)	(2)
Upwind Fires _t	-0.00005 (0.00011)	0.00021* (0.00012)
Upwind Fires _{t-1}	0.00007 (0.00006)	0.00039*** (0.00015)
Upwind Fires _{t-2}	0.00031*** (0.00007)	0.00044*** (0.00010)
Upwind Fires _{t-3}	0.00011 (0.00009)	0.00017 (0.00010)
Mean Outcomes	0.060	0.179
Observations	233413	272850

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample comprises children aged 10–17 from the PSLM. The dependent variable equals one if the child worked at any time during the month preceding the survey. Each column reports contemporaneous and lagged (up to three years) coefficients of upwind burned area. All specifications include the full set of fixed effects and controls. Standard errors clustered at the district level are reported in parentheses.