HUMAN CAPITAL ACCUMULATION IN A DEVELOPING-COUNTRY CONTEXT: GENDER DISPARITIES, CONCURRENT AND LAGGED EFFECTS OF AIR POLLUTION AND CLIMATE CHANGE

by

AYESHA KHALID

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Student: Ayesha Khalid

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This dissertation has been accepted and approved in partial fulfillment of the requirements for the Doctor of Philosophy degree in the Department of Economics by:

Trudy Ann Cameron	Chair
Alfredo Burlando	Core Member
Eric Zou	Core Member
Nicole Ngo	Institutional Representative

and

Kate Mondloch	Interim Vice Provost and Dean of the Graduate School

Original approval signatures are on file with the University of Oregon Graduate School.

Degree awarded June 2020

DISSERTATION ABSTRACT

Ayesha Khalid

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Department of Economics

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Title: Human Capital Accumulation in a Developing-country Context: Gender Disparities, Concurrent and Lagged Effects of Air Pollution and Climate Change

This research examines how air pollution and climate change influence human capital accumulation in a developing-country context and also studies the effects of policies targeted to keep children in school in face of whatever factors deter them from developing their human capital. Effective human capital accumulation enhances a society's potential for economic development and prosperity, and therefore is especially important for developing countries.

In Chapter II, I evaluate the effectiveness of an increase in the cash amount of a female-targeted conditional cash transfer on schooling outcomes for girls, using a novel monthly dataset on student enrollment and attendance at all public schools in Punjab, Pakistan. I find that the increase in the cash transfer increased female enrollment in 6^{th} grade and 9^{th} grade in treated districts. The increase in cash

transfer also had positive spillover effects on the enrollment of boys in middle and high schools in treated districts.

In Chapter III, I examine the causal effect of air pollution and temperature on student attendance and test scores using a satellite-based measure of daily pollution and a novel monthly dataset on school enrollment and test scores in Punjab, Pakistan. The instrumental variables estimation indicates that an exogenous increase in air pollution reduces student attendance, and has an adverse effect on test scores—specifically, math and Urdu scores. Estimates of the effects of different temperature levels show that high temperatures in the range 30-38°C (86-100.4°F) reduce test scores, especially math scores.

In Chapter IV, I investigate the effect of in-utero exposure to pollution and heatwaves on children's physical health and schooling status in Punjab, Pakistan. I find that an increase in air pollution during gestation and an additional heatwave day during gestation reduces height-for-age z-scores and weight-for-age z-scores. However, the negative effects of in-utero temperature shocks seem to decline with a child's age. Moreover, the results suggest in-utero pollution exposure decreases the probability of a school-age child being in school, whereas in-utero exposure to heatwaves lowers the current school-grade of a child, controlling for the child's age.

CURRICULUM VITAE

NAME OF AUTHOR: Ayesha Khalid

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:

University of Oregon, Eugene, OR
Portland State University, Portland, OR
Lahore University of Management Sciences, Pakistan

DEGREES AWARDED:

Doctor of Philosophy, Economics, 2020, University of Oregon
Master of Science, Economics, 2014, Portland State University
Master of Science, Economics, 2007, Lahore University of Management Sciences
Bachelor of Science, Economics, 2006, Lahore University of Management Sciences

AREAS OF SPECIAL INTEREST:

Applied Econometrics
Environmental Economics
Development Economics

GRANTS, AWARDS AND HONORS:

Gerlof Homan Research Scholarship, 2018, University of Oregon

Best Econometrics Performance Award, 2016, University of Oregon

Graduate Teaching Fellowship, 2015–2020, University of Oregon

Linda Hamilton Award (for highest GPA), 2014, Portland State University

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CHAPTER I

INTRODUCTION

A variety of climate change and pollution impacts have now been studied in advanced economies, but much less is known for the wide variety of developing countries. Effective policies to mitigate climate change and control pollution require estimation of the benefits of reductions in greenhouse gases and other types of air pollution. The potential adverse effects of both climate change and conventional pollutants on human capital accumulation are important considerations in the design of climate and environmental policies. Research in these areas is relatively scarce for developing countries due to the absence of comprehensive and reliable data. However, the impacts of climate change and air pollution are likely to be considerably greater for developing countries which have a lesser capacity to adapt to climate change or avoid pollution (Rylander et al., 2013; IPCC, 2014).

Careful efforts to quantify the causal relationship between climate change, growing industrial pollution, and economic outcomes will help answer open questions about the burden of these environmental threats in developing countries (Greenstone and Jack, 2015). A comprehensive understanding of the full scope of the benefits of reductions in climate change and air pollution is vital to policy decisions about the necessary stringency of environmental regulations in developing countries and globally (in case of carbon emissions).

This research aims to improve our understanding of the factors that affect human capital accumulation in a developing-country context. Chapter II acknowledges that many stressors contribute to low levels of educational attainment in developing countries. This chapter thus considers the effects of policies aimed at keeping children in school, in face of whatever factors deter them from developing their human capital. Chapters III and IV more specifically examine environmental shocks to human capital formation. The data for these analyses come from Pakistan.

Educational outcomes have traditionally been poor in Pakistan and can be worsened by pollution and climate change. There are almost 23 million children out of school in Pakistan, or about 44 percent of the total population of children between five and sixteen years of age (Academy of Educational Planning and Management, 2018). Investment in schooling is critical to the development process (Lucas, 1989; Galor and Weil, 2000), and human capital accumulation is an important driver of economic growth (Mankiw et al., 1992; Jones, 2011). Unfortunately, Pakistan also experiences some of the worst air pollution in the world and the mean annual temperature is predicted to rise substantially in the future due to climate change.

More specifically, in chapter II of the dissertation, I focus on the effect of an increase in the cash amount of a female-targeted conditional cash transfer program (CCT). Conditional cash transfer programs have been implemented in many developing countries to induce families to keep children in school and thus to improve human capital accumulation. Using novel monthly data on school enrollments and attendance in Punjab, the second-largest and most populous of the four provinces of Pakistan, I investigate the impact of an increased cash amount for the CCT on school enrollment and attendance of girls in middle and high schools.[1] In March 2017, the monthly cash transfer increased from \$1.31 to \$6.57. I find that this increase in the cash transfer increased female *enrollment* by 4.45 percent in 6^{th} grade, and by 3.86 percent in 9^{th} grade. However, there is no effect of the higher cash transfer on the *attendance* of girls in grades 6–10. The increased cash transfer also had positive spillover effects on the enrollment of boys in middle and high schools in treated districts.

In chapter III, I study the effects of short-term variations in air pollution and temperature on school attendance and learning, using the same source of monthly data on school enrollment and attendance of public schools in Punjab used in chapter II, but now augmented by data on test scores data available for third-grade students. The health effects of air pollution are well–established in

[1]The province of Punjab covers about 80,000 $miles^2$, which is roughly the same size as the U.S. states of Nebraska or Minnesota or Kansas. It has population of over 110 million in 2017, which is similar to the overall population of U.S. states of California, Texas, Florida and Ohio, put together.

other contexts in the economics literature. This analysis builds upon the emerging literature that connects air pollution to human capital accumulation. The school data run from September 2014 to March 2018, constituting an unbalanced panel for about 48,000 individual schools, with more than 1.5 million observations. There is no comprehensive ground-level air quality data available for Pakistan, so I use satellite data for air pollution across Punjab (specifically, a measure of AOD—aerosol optical depth) plus daily weather data that have been web–scraped from 38 weather stations across Punjab. Given that air pollution can be potentially endogenous, I exploit exogenous variation in air pollution due to dust coming from neighboring deserts. The results of instrumental variable estimation indicate that increases in air pollution reduce student attendance and lower test scores. Furthermore, temperatures higher than 16–18°C (60.8–64.4°F) reduce test scores.

In Chapter IV, I build upon the literature that examines the long-term effect of fetal and early life shocks. Using satellite measures of daily pollution and air temperature over the longer period of 2000–2011, and representative surveys of children, women and households, I examine the effect of imputed in-utero exposure to pollution and heatwaves on health and schooling outcomes of young children in Punjab, Pakistan. For this paper, I have assembled the most comprehensive daily pollution and weather data available for Punjab, Pakistan, over the period 2000–2011. The models control for sociodemographic characteristics and include birth-month, birth-year and jurisdiction-level fixed effects to control for unobserved spatial and temporal heterogeneity.

I find that an increase in pollution in the first and third trimester of gestation, and an additional heatwave day during the second and third trimesters, impedes physical growth of children under five. However, the effect of in-utero temperature shocks seems to decline gradually with age. Results also indicate that an increase in pollution during gestation decreases the probability of a school-aged child being in school and lowers the current school-grade of a child, controlling for age. However, heatwave days during trimesters have no effect on the probability of a school-age child being in school and the current school-grade of a child. I also compute the implied cumulative exposure to pollution and heatwave days for each child. I explore the effects of these cumulative exposures on physical health for children aged 0–59 months and find an adverse effect on both height-for-age and weight-for-age z-scores.

Collectively, the three studies that comprise this dissertation represent original contributions to our understanding of some of the potential future consequences, of both continued climate change and increasing pollution, for large numbers of some of the world's most vulnerable populations of children, and the effectiveness of policies aimed at keeping children in school.

Chapter V summarizes the findings and briefly discusses the policy implications from the findings in this dissertation.

CHAPTER II

CAN MORE MONEY GET GIRLS INTO SCHOOL AND KEEP THEM THERE? EFFECT OF CASH TRANSFER INCREASE ON FEMALE EDUCATION

"Why don't they let us study? They let the boys study, so they should let us study" — Bina, 15, forced to leave school after fifth grade, Karachi.

"Traveling to the nearest government middle school would cost Rs.3500 ($24.70) monthly." — Muskaan, left school during seventh grade, Lahore.

"My brothers don't work, so I started working at age 10. I work (embroidery) from morning until 2 p.m., then I do housework until 4, then embroidery again until 8 or 9 p.m" — Samika, 13, did not go to school, Lahore.[1]

Introduction

Education generates higher income levels and growth, both at the macro level (Lindahl and Krueger, 2001) and at the micro level (Angrist and Krueger, 1991; Duflo, 2001). Investment in schooling is critical to the development process (Lucas, 1989; Galor and Weil, 2000), and human capital accumulation is an important driver of economic growth (Mankiw et al., 1992; Jones, 2011). Educational outcomes have traditionally been poor in Pakistan. The adult literacy rate is only 58 percent, with 70 percent of men being literate compared to just 48 percent

[1] The interviews were conducted across Pakistan in 2017 by Human Rights Watch (reported in Human Rights Watch, 2018).

of women (Government of Pakistan, 2018). Public expenditure on education as a percentage of Gross Domestic Product (GDP) was merely 2.2 percent in 2017 (Government of Pakistan, 2018). In 2018, Pakistan ranked second lowest in the world in the global gender parity index. Specifically, the gender gap in educational attainment is about 20 percent in Pakistan, with only 10 of the 149 ranked countries having a larger gap in educational attainment (World Economic Forum, 2018).

The gender parity index for school enrollment in Pakistan is 0.78, which means that across grades on average, 78 girls are enrolled for every 100 boys (Academy of Educational Planning and Management, 2015). There are 22.84 million children out of school in Pakistan, which is 44 percent of the total population of children aged 5-16 years (Academy of Educational Planning and Management, 2018). 32 percent of school-age girls are out of school, whereas 21 percent of school-age boys are out of school (UNICEF, 2017). Currently, about five million children of primary-school age are out of school, and 62 percent of these are females. This gender disparity persists even among middle-school-aged children. In 2016, 59 percent of middle-school-aged girls were out of school, compared to 49 percent of boys, and by ninth grade only 13 percent of school-aged girls remain in school (Jamil, 2016).

In this paper, I study the impact of an increase in the cash amount of the female-targeted conditional cash transfer (CCT) program in the Punjab province in Pakistan on two important indicators of learning: enrollment and attendance.[2] The female-targeted CCT program was first implemented in Punjab in 2004. Specifically, I examine the effect of a monthly cash transfer increase, from \$1.31 to \$6.57 in 2017, on female school enrollment and attendance in middle school and high school (grades 6–10). The monthly cash transfer was increased to improve enrollment and retention among female students in middle school and high school. I use a novel monthly dataset on school enrollment and attendance, with more than one million observations, for all public schools in Punjab over the period September 2014 to April 2018.

I use a difference-in-difference and a triple-difference strategy, and also control for several possible confounding variables. For girls in middle school and high school, I find no effect of the increase in cash transfer on attendance but an increase in enrollment. The increase in the monthly cash transfer (to \$6.57) is conditional on maintaining an average attendance of at least 80%. However, the earlier cash transfer, just \$1.31 per month, was also conditional on maintaining an average attendance of at least 80%. Therefore, girls who were already getting the stipend must maintain that attendance of 80%, i.e. 80% was already binding, and remained binding.

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[2] Pakistan is the sixth most populous country in the world, and Punjab is the second–largest and most populous of the four provinces of Pakistan. Figure 16 in Appendix shows the province Punjab in Pakistan. The province of Punjab covers about 80,000 $miles^2$, which is roughly the same size as the U.S. states of Nebraska or Minnesota or Kansas. It has population of over 110 million in 2017, which is similar to the overall population of U.S. states of California, Texas, Florida and Ohio, put together.

The results indicate that the increase in the cash transfer increased enrollment by an average of 1.6 and 3.7 female students in 6^{th} grade and 9^{th} grade, respectively, per female middle school and high school in treated districts. This represents a 4.45 percent increase in female enrollment in 6^{th} grade and a 3.86 percent increase in 9^{th} grade, per month. Given that 6^{th} grade is a transition from primary to middle school and 9^{th} grade is a transition from middle to high school, the results suggest that the increase in the cash transfer provided incentive to roughly one additional female student to transition from primary to middle school, and about three additional female students to transition from middle to high school. The increased cash transfer also had positive spillover effects on the enrollment of boys in middle school and high schools in treated districts.

Rigorous evaluations of CCT programs have demonstrated their ability to improve schooling outcomes, such as increases in enrollment and attendance, and reductions in child work. Prior research on gender-targeted CCT programs in Bangladesh, Pakistan, Cambodia, and Malawi indicates that these CCT programs increased enrollment and attendance of girls (Khandker et al., 2003; Chaudhury and Parajuli, 2006; Filmer and Schady, 2008; Baird et al.; 2010; Hasan, 2010). Chaudhury and Parajuli (2006) find an annual increase in female enrollment of six students, in response to the original female-targeted CCT implemented in Punjab in 2004, which is a 9 percent annual increase in female enrollment in middle school (grades 6–8). Hasan (2010) finds that the CCT in 2004 led to an annual increase in female enrollment of about 1 to 4 students in grades 6–8, which is a 9–33 percent annual increase in female enrollment by grade. Alam et al. (2011) find that the CCT program increased annual female enrollment by 11–32 percent in the longer run, i.e. four years after the implementation in 2004. They also find the CCT increased the likelihood of girls transitioning into middle school and high school, by 3–6 percent and 4–6 percent, respectively.

Unlike earlier work, which evaluates the effectiveness of female-targeted CCT implemented in Punjab in 2004, I examine the incremental effect of the intervention in 2017 that increased the size of the cash transfer amount from $1.31 to $6.57. Prior research on the impact of the female-targeted CCT program in Punjab examines changes only in annual female enrollment. Given that my data have monthly records of enrollment, I can examine the impact of the increased cash transfer on monthly, rather than annual, enrollment. The data also have information on monthly attendance, which allows me to study the effect of the increase in the cash amount on attendance along with enrollment.

The remainder of the paper is organized as follows. Section 2.2 outlines the relevant background information concerning gender inequality and the CCT program in Punjab. Section 2.3 reviews the existing literature. The data are discussed in Section 2.4, and the empirical model is detailed in Section 2.5. Section 2.6 presents the estimation results, followed by concluding remarks in Section 2.7.

Background

Many children across Pakistan, especially girls, are locked out of education and into poverty. Girls, in particular, face many barriers and constraints that limit their access to education and the benefits they derive from education for various reasons. Public schools in Punjab are single-gendered. Many girls have no access to education at all due to a shortage of government schools especially for girls. Moreover, many girls are not allowed to attend school because they are employed as child laborers. Families also prioritize boys' education, sometimes encourage child marriage, and are concerned about sexual harassment on the way to school and terror attacks on girls' schools (Human Rights Watch, 2018). Barriers to education for girls are a reflection of the broader problem of gender inequality in Pakistan. According to the World Bank, Pakistan has the highest global rate of maternal mortality. Moreover, violence against women is prevalent—including domestic violence, forced marriages, child marriages, acid attacks and rape—and tends to precipitate no adequate government action in response. It is estimated that 21 percent of females are married under the age of 18, and 3 percent of females are married before 15 (Ijaz, 2017).

Though literacy rates are higher in Punjab compared to other provinces of Pakistan, gender differences in education persist. The adult literacy rate in Punjab is 77 percent for urban areas and 55 percent for rural areas (Government of Pakistan, 2018). In Punjab, 74 percent of men have ever attended school, compared to 56 percent of women. Similar gender disparities exist among those who have completed primary school (grades 1–5) in Punjab, with 61 percent of men completing primary school compared to 47 percent of women (Government of Pakistan Statistics Division, 2016).

The government of Punjab has undertaken several educational reform initiatives to improve education outcomes in the province. One such reform was the 2004 launch of a female-targeted conditional cash transfer (CCT) program, called the Female School Stipend Program (FSSP), to reduce the gender disparity in education. Under the FSSP, girls in middle school (grades 6–8) in 15 selected districts[3] received a monthly stipend of Rs. 200 ($1.31) conditional on maintaining an average attendance rate of at least 80%. The 15 (out of 36) districts selected for the intervention were those with literacy levels below 40 percent. In 2006, the FSSP was extended to include girls in 9th and 10th grades.

In March 2017, the government of Punjab replaced the existing FSSP by the Zewar-e-Taleem Programme. The monthly stipend for girls in secondary school was increased from Rs.200 ($1.31) to Rs.1000 ($6.57) in 16 districts[4]. Figure 17 in the Appendix shows the spatial locations of the districts in which the Zewar-e-Taleem Programme was implemented. The cost of this project was Rs.6 billion

[3]The districts were Bahawalnagar, Bahawalpur, Bhakkar, Dera Gazi Khan, Jhang, Kasur, Khanewal, Layyah, Lodhran, Muzaffargarh, Okara, Pakpattan, Rajanpur, Rahimyar Khan, and Vehari.

[4]The 15 districts were same as before. The new district is Chiniot, which became a separate district in 2009, whereas before it was merely a tehsil of Jhang district.

($42 million).[5] The stipend is paid on quarterly basis conditional on the student maintaining an attendance rate of at least 80 percent. Given that the minimum wage in Punjab is Rs.15,000 ($ 98.53) per month (Rahim, 2017), the new cash transfer amount is 6.67 percent of the monthly minimum wage, whereas the earlier stipend was only 1.33 percent of the monthly minimum wage.[6]

The purpose of introducing a higher stipend was to improve enrollment and retention among female students. Under the FSSP, the stipend was transferred through government postal service, whereas now the stipend is delivered through an ATM card to ensure efficient delivery and transparency. For households whose daughters are already going to secondary school, the conditional cash transfer functions simply as an income transfer, whereas it is an incentive payment for households who have daughters out of school.

Literature

Recent review studies of CCT evaluations (Fiszbein et al., 2009; Independent Evaluation Group, 2011) show that these programs improve schooling (increase enrollment and attendance, and decrease child work) and health outcomes (vaccinations, doctor visits). Due to a rigorous evaluation of the Mexican Oportunidades program, which has been operating since 1997, CCT programs have been implemented in Latin America and many other developing countries. There

[5] `https://nation.com.pk/16-Mar-2017/zewar-e-taleem-launched`

[6] `https://www.dawn.com/news/1358632`

were 29 countries that had some form of CCT program as of 2007 (Fiszbein et al., 2009).

CCT programs targeted to low-income households are becoming an important tool in developing countries as policies to increase human capital investments and to reduce poverty (de Janvry et al., 2006). These programs provide cash transfers to poor households, conditional on documentation of a pre-specified investment in the human capital of their children. The premise of these conditional cash transfers is that investment in human capital of children can break the inter-generational transmission of poverty by increasing the productivity of the affected children as adults.

A vast empirical literature has demonstrated the effectiveness of CCT programs in a variety of contexts, where the cash transfer is conditioned on school attendance. Many of these programs have improved schooling outcomes in developing countries (Schultz, 2004; de Janvry et al., 2006; Filmer and Schady, 2009). Rigorous evaluations of CCT programs in Mexico, Brazil, Honduras, Jamaica and Nicaragua have also demonstrated the ability of the programs to increase school enrollment rates (Rawlings and Rubio, 2005).

Young girls are an important demographic group to target in order to break the poverty cycle in developing countries (Levine et al., 2008). In many developing countries, households underinvest in female health and education, which necessitates gender-targeted interventions (Ezemenari et al., 2002).

Currently, there are a few CCT programs that target only girls, including programs in Bangladesh, Pakistan, Cambodia, and Malawi. Khandker et al. (2003) have studied the effect of the female secondary school stipend program (FSSP) introduced in rural Bangladesh in mid-1990s. They find that the program increased enrollment of girls in middle school by 8–12 percent. They did not find any spillover effect from girls' participation on the enrollment of boys. Sayeed (2016) finds that the FSSP in Bangladesh not only increased completed schooling by an average of 0.4 years, it also delayed the average age at first marriage by an average of 0.4 years, and the age at first birth by an average of 0.3 years.

Filmer and Schady (2008) examine the impact of the Japan Fund for Poverty Reduction program that provides scholarships to girls transitioning from primary school to secondary school in Cambodia. The scholarship program led to an increase in enrollment and attendance at program schools by 30–43 percent. Baird et al. (2010) study the effect of the CCT program in the Malawi—Zomba Cash Transfer Program, which targets girls who are both currently in school or recent dropouts. The CCT program, which offers \$10 per month and payment of secondary school fees, led to an increase in net enrollments by 35 percent.

Chaudhury and Parajuli (2006) use a provincial school census for 2003 and 2005 to evaluate the impact of the initial female secondary school stipend program (FSSP) in Punjab, Pakistan. They find a 9 percent increase in female enrollment in response to the FSSP. Hasan (2010) also examines the impact of the FSSP implemented in Punjab province of Pakistan in 2004. He finds that the FSSP not only increased the enrollment of girls in grades 6–8, but also had a positive spillover effect on boys' enrollment.

Alam et al.(2011) study the longer-run effects of the FSSP in Punjab. They find that the increase in enrollment of girls in middle school, due to the stipend, persists for five years into the program, and eligible girls are more likely to complete middle school. The results suggest that girls who are eligible for the stipend work less, delay their marriages, and have fewer births prior to 19 years of age. They also find that high-school-aged girls, who were eligible for the stipend in 2006 have a higher rate of enrolling and completing high school. The results provide evidence of spillover effects on male siblings. Specifically, families with daughters eligible for the stipend become more likely to enroll their sons in private schools in response to the stipend program.[7]

Descriptive Analysis

Data

The data on school attendance and test scores come from the Program Monitoring and Implementation Unit (PMIU) of the government of Punjab, a province covering about 80,000 *square miles* and a population of over 110 million

[7]Private schools are considered better than public schools in terms of educational quality.

in 2017.[8] The capital city alone (Lahore) has a population of over 11 million.[9] In 2014, PMIU initiated digital monthly monitoring all public schools in Punjab. The PMIU employs 950 field officers that randomly visit about 50,000 schools monthly in 36 districts of Punjab. They record student attendance, teacher attendance, and the condition of school facilities. They also administer a short test of English, Urdu and math to a sample of students in the third grade. The schools are not notified about the date of the monitoring visit. Moreover, PMIU shuffles the set of schools to be visited by different field officers each month.[10]

The school attendance data run from September 2014 to March 2018. The dataset has information on the district, tehsil, name of school, school ID, the gender served by the school, school level: primary (grades 1–5), middle (grades 6–8), and high (grades 9–10). Also included are the number of teachers currently employed, the number of teachers absent on the monitoring date, the number of students enrolled in each grade, and the number of students present in each grade on the monitoring date.[11]

The other school characteristics that I use in my analysis come from the annual school census for all public schools in Punjab. The census data include

[8] Punjab is roughly the same geographic size as the U.S. states of Nebraska or Minnesota or Kansas, and a total population similar to the total population of the U.S. states of California, Texas, Florida and Ohio, put together.

[9] This is roughly the combined populations of New York City and Chicago.

[10] The school attendance and test score data were acquired directly from the Database Administrator at PMIU by petition. The school attendance data are available on the PMIU website, but the data are not downloadable. The test score data are not publicly available.

[11] A tehsil is an administrative sub-division of a District.

information on many school characteristics. The characteristics that I use include the year the school was built, school size (ft^2), number of classrooms, number of open-air classrooms, the proportion of students and teachers who have furniture, and indicators for the presence of electricity, toilets, drinking water, whether the school has a fenced wall and a main gate.

During each monthly school visit, field officers record enrollment in each class. Though the school-year begins in April for public schools in Punjab, there is on-going enrollment throughout the year. In the data, enrollment levels recorded by field officers vary over the months. If a school does not have 80 percent attendance on the monitoring day, the school has to submit a formal report.

To ensure that the monthly enrollment records are not manipulated sometimes by field officers or school administrators to increase attendance above 80 percent, I compare percentage attendance as recorded by field officers with the percentage attendance computed using official start of school year (April) enrollment, considering 80 percent attendance as threshold. I find that for grades 1–5 grade, there are about 8 percent observations for which attendance rates based on enrollment at the start of the school year (April) is less than 80 percent, whereas the reported monthly enrollment is more than 80 percent. For grades 6–9, there are 3.3–5.7 percent of observations for which attendance based on April enrollment is less than 80 percent but attendance based on monthly enrollment is greater than 80 percent. For 10^{th} grade, about 19 percent of the observations for which attendance based on enrollment at the start of the school year is less than 80 percent, but attendance based on monthly enrollment is higher than 80 percent. Since the monthly enrollment records do not seem to be overwhelmingly manipulated to increase attendance above 80 percent, I use monthly enrollment for estimation.[12]

Summary statistics for the attendance and enrollment of girls in grades 6–10 are presented in Table 1 and Table 2. The column difference is the t-test to test for significant differences between the control and the treated group. Before the change in the payment, the mean female attendance for grades 6–8 is slightly higher in treated districts than in control districts. For grades 6–8, mean female attendance is about 92% in control districts and about 93% in treated districts. For grades 9–10, the mean attendance for females is about 91% in both treated and control districts. The mean enrollment of girls in middle school (grades 6–8) varies from about 47–49 girls in control districts, whereas it varies from about 32 - 36 girls in treated districts. For 9^{th} grade, the mean enrollment is about 104 and 95, in control and treated districts, respectively. The mean enrollment in 10^{th} grade is 93 girls in control districts and about 84 girls in treated districts.

[12] I have also estimated models with the start of the school year (April) enrollment. The results are not qualitatively different. These other results are available upon request.

TABLE 1.
Summary Statistics – Attendance (%)

	(1) Control	(2) Treated	(3) Difference
Grade 6	92.21	93.07	-0.859***
Grade 7	92.27	93.15	-0.879***
Grade 8	93.43	94.37	-0.944***
Grade 9	91.75	91.96	-0.209**
Grade 10	91.06	91.18	-0.119

Notes: The column difference is the t-test to test for significant differences between control and treated group
*** p<0.01, ** p<0.05, * p<0.1

TABLE 2.
Summary Statistics – Enrollment

	(1) Control	(2) Treated	(3) Difference
Grade 6	49.55	36.21	13.34***
Grade 7	49.09	34.25	14.84***
Grade 8	47.33	32.14	15.19***
Grade 9	104.16	95.87	8.29***
Grade 10	93.66	83.98	9.68***

Notes: The column difference is the t-test to test for significant differences between control and treated group
*** p<0.01, ** p<0.05, * p<0.1

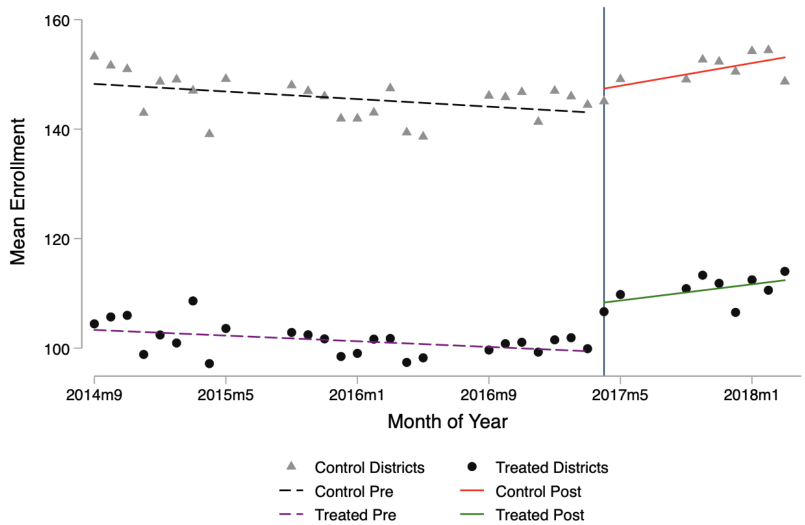
Trends in Enrollment

Figure 1 shows the mean enrollment of girls in middle and high school in treated and control districts pre– and post–treatment. The graphs suggest that the mean enrollment in both middle and high schools in treated districts increased post–treatment. The increase in mean enrollment post-treatment seems to be larger for high schools compared to middle schools in treated districts, but this could be due to noisier mean enrollment in high schools for both the treated and control districts.

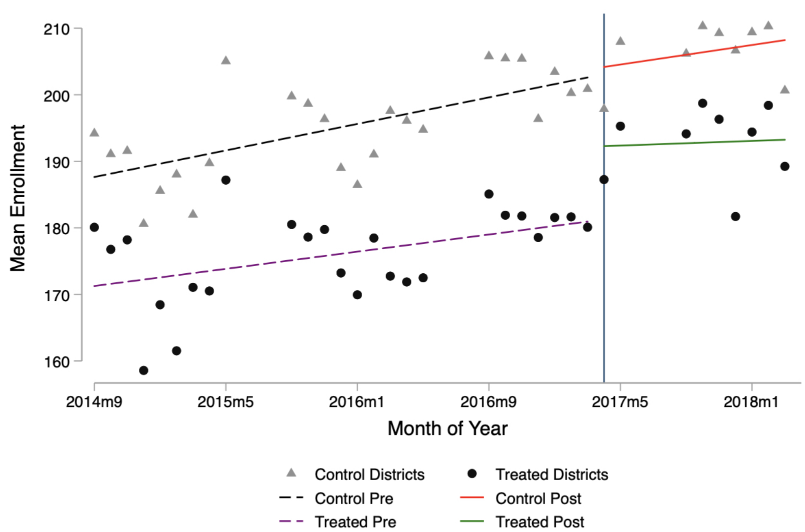
Methodology

I use a difference-in-difference (DD) and triple-difference (DDD) design to estimate the impact of the cash transfer increase intervention on enrollment and attendance of female students in middle and high school. The difference-in-difference model measures the effect of policy intervention on the outcome in the treated group (girls' schools in treated districts) relative to changes in the outcome in the control group (girls' schools in non-treated districts). This removes biases from comparisons over time in the treatment group that could be due to trends, as well as biases in post-intervention period comparisons between the treatment and control group that could be due to permanent differences between the groups. A potential problem with the difference-in-difference analysis is that other factors

FIGURE 1.
Enrollment of Girls: Pre– and Post–Intervention



(a) Middle school (grades 6–8)



(b) High school (grades 9–10)

unrelated to the new policy might effect the outcome of the treated group relative to the control group.

A more robust analysis makes use of a triple-difference strategy, where another control group (boys' schools in treated and untreated districts) is used to estimate the treatment effect of the policy change by comparing the double difference in the treated outcome with the double difference in the untreated outcome. This controls for more confounding factors that could potentially bias the average treatment effect.

The equations I estimate for DD and DDD analysis are of the following forms, respectively:

$$Y_{it} = \gamma_0 + \gamma_1 Post_t + \gamma_2 TreatDistr_i + \gamma_3 Post_t * TreatDistr_i + X_{it}\Pi + \gamma_{it} + \alpha_m + \delta_y + \mu_i + \epsilon_{it} \tag{2.1}$$

$$\begin{aligned} Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 TreatDistr_i + \beta_3 Female_i + \\ \beta_4 Post_t * TreatDistr_i + \beta_5 Post_t * Female_i + \beta_6 TreatDistr_i * Female_i + \\ \beta_7 Post_t * Female_i * TreatDistr_i + X_{it}\Pi + \gamma_{it} + \alpha_m + \delta_y + \mu_i + \epsilon_{it} \end{aligned} \tag{2.2}$$

where Y_i is either the percentage attendance or the enrollment level in school i on day t. $Post_t$ is an indicator which is 1 if the time t is after the intervention, and

0 before. $TreatDistr_i$ is an indicator that is 1 if school i is in a treated district and 0 if the school is in a non-treated district. $Female_i$ is an indicator, which is 1 if the school i is for girls, and 0 if it is for boys. To account for potential bias, I condition on X_{it}, which is a vector of observable school characteristics possibly related to attendance and enrollment, which includes teacher attendance, student–teacher ratio, school age, school size, number of classrooms, number of open-air classrooms, proportion of students and teachers who have furniture, and indicators for the presence of electricity, toilets, drinking water, a school fenced wall and a main gate.

To control for unobserved spatial and temporal heterogeneity, I also include fixed effects for the day of the week and the month, and school-year fixed effects, and school fixed effects in the estimation model, where the γ_{it} parameters are day of the week fixed effects, the α_m parameters are month fixed effects, the δ_y parameters are school-year fixed effects, and the μ_i parameters are fixed effect for schools.[13] Finally, ϵ_{it} is an idiosyncratic error term.

The identifying assumption is that there is no change in unobserved school characteristics when the new CCT is launched. I also control for several possible confounding variables so that, conditional on observables, the estimates should be unbiased. Thus, any estimated change in student enrollment and attendance is due to the increase in the amount of the cash transfer. For the DD estimate, the parameter of interest is γ_3, which represents changes in attendance or the

[13] The school–year is from April to March.

enrollment level in treated group relative to the control group. For the DDD estimate, the treatment group is girls in middle and high school in the CCT eligible districts, making β_7 as the parameter of interest.[14]

Results

Difference-in-Difference

The results for difference-in-difference estimation are presented in this section, to examine whether the increase in the size of the cash transfer had an effect on enrollment and attendance of girls in treated districts. Table 3 reports the percentage attendance results for girls in grades 6–10. The variable $TreatDistr$ drops out since school fixed effects are included. There is no effect of the increase in the size of the cash transfer on the attendance of girls in grades 6–10 in treated districts.

Table 4 presents the results for the enrollment of girls by grade. While there is no evidence for an increase in attendance, the increase in the size of the cash transfer increased the enrollment of girls by 3.44 students in 6^{th} grade per female middle school in treated districts. Using the mean female enrollment in treated districts in Table 2, this represents a 9.49 percent increase in female enrollment in 6^{th} grade. The higher cash amount increased 7^{th} grade enrollment by 1.58

[14] Earlier studies of female CCT have sometimes shown a spillover effect on boys' school enrollment. If the increase in the amount of cash transfer has a spillover effect on enrollment and attendance of boys' schools, the parameter estimates for β_7 in the DDD model would tend to be biased downwards.

TABLE 3.
Attendance: Effect of Cash Transfer Increase on Girls

	(1) Grade 6	(2) Grade 7	(3) Grade 8	(4) Grade 9	(5) Grade 10
$Post \times TreatDistr$	-0.165	-0.138	-0.0534	0.150	-0.360
	(0.187)	(0.185)	(0.176)	(0.225)	(0.286)
Day of the week FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓
School Controls	✓	✓	✓	✓	✓
Observations	202,577	201,986	195,164	79,153	77,780
R-squared	0.045	0.044	0.067	0.043	0.106
No. of schools	7,068	7,066	7,061	2,909	2,832

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

TABLE 4.
Enrollment: Effect of Cash Transfer Increase on Girls

	(1) Grade 6	(2) Grade 7	(3) Grade 8	(4) Grade 9	(5) Grade 10
$Post \times TreatDistr$	3.438***	1.582***	0.566	7.826***	1.001
	(0.433)	(0.359)	(0.392)	(1.136)	(1.026)
Day of the week FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓
School Controls	✓	✓	✓	✓	✓
Observations	204,352	203,743	200,272	80,352	79,592
R-squared	0.055	0.032	0.030	0.078	0.120
No. of schools	7,068	7,066	7,062	2,909	2,833

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

students, which is a 4.62 percent increase in female enrollment in 7^{th} grade. The enrollment in 9^{th} grade increased by 7.83 female students per female high school in treated districts, which is a 8.16 percent increase in female enrollment in 9^{th} grade.

I also investigate whether there are any spillover effects for boys schools in treated districts, by examining the effect of this policy intervention on the attendance and enrollment of boys using a difference-in-difference model. Table 5 reports the percentage attendance results for boys in grades 6–10. The increased cash transfer did not effect the attendance of boys, except in the 8^{th} grade. The attendance of boys decreased by 0.3 percent in the 8^{th} grade in treated districts. The unexpected sign on boys' attendance due to the female-targeted CCT program could be due to boys being substituted for girls' household labor by parents. This is because girls' school absence can lead to loss of the cash transfer, which is conditional on maintaining 80 percent attendance, whereas boys' school absence results in no income loss, assuming boys are not absent from school for paid outside work, or if they are, their income is less than the cash transfer.

Table 6 presents the enrollment results for boys. The higher cash transfer increased the enrollment of boys by 1.82, 2.04, 1.06 and 4.24 students in grades 6–9, respectively, per male middle and high school in treated districts. The increase in cash transfer increased male enrollment by 3.68 percent in 6^{th} grade, 4.28 percent in 7^{th} grade, 2.36 percent in 8^{th} and 4.32 percent in 9^{th} grade. This

TABLE 5.
Attendance: Effect of Cash Transfer Increase on Boys

	(1)	(2)	(3)	(4)	(5)
	Grade 6	Grade 7	Grade 8	Grade 9	Grade 10
$Post \times TreatDistr$	-0.132	-0.244	-0.302*	0.281	-0.268
	(0.186)	(0.192)	(0.163)	(0.208)	(0.276)
Day of the week FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓
School Controls	✓	✓	✓	✓	✓
Observations	190,871	190,345	184,338	96,858	95,344
R-squared	0.038	0.043	0.083	0.034	0.111
No. of schools	6,819	6,814	6,809	3,610	3,547

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

TABLE 6.
Enrollment: Effect of Cash Transfer Increase on Boys

	(1)	(2)	(3)	(4)	(5)
	Grade 6	Grade 7	Grade 8	Grade 9	Grade 10
$Post \times TreatDistr$	1.815***	2.036***	1.060**	4.239***	1.120
	(0.518)	(0.479)	(0.426)	(0.992)	(1.111)
Day of the week FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓
School Controls	✓	✓	✓	✓	✓
Observations	192,833	192,339	189,288	98,293	97,511
R-squared	0.062	0.025	0.012	0.139	0.146
No. of schools	6,824	6,819	6,813	3,612	3,548

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

suggests that the increased cash transfer had positive spillover effects on the enrollment of boys in both middle and high schools in treated districts.

Triple Difference

This section presents the results for triple difference estimation.[15] Table 7 reports the attendance (percentage) results by school level. The variables

TABLE 7.
Attendance: Effect of Cash Transfer Increase by School Level

	(1) Primary School	(2) Middle School	(3) High School
$Post \times TreatDistr$	-0.868***	-0.608***	-0.454*
	(0.295)	(0.223)	(0.237)
$Post \times Female$	0.276**	0.491***	0.551***
	(0.122)	(0.0892)	(0.121)
$Post \times TreatDistr \times Fem$	0.213	0.128	0.0395
	(0.195)	(0.160)	(0.218)
$Constant$	85.77***	82.57***	84.92***
	(0.804)	(1.996)	(3.192)
Month FE	✓	✓	✓
Year FE	✓	✓	✓
School FE	✓	✓	✓
School Controls	✓	✓	✓
Observations	1,328,690	394,441	176,242
R-squared	0.061	0.046	0.052
No. of schools	49,583	13,888	6,519

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

[15] I will be able to report the marginal effects for gender and treatment in triple difference specification.

$TreatDistr$, $Female$, $TreatDistrt \times Female$ drop out since school fixed effects are included. The majority of the public schools are primary level, which is why the sample sizes at the primary level are larger than at the middle school and high level school levels. The increase in the cash amount of the conditional cash transfer is intended to improve enrollment and attendance of girls in middle school and high school. However, the additional cash transfer does not appear to have been discernibly effective for increasing attendance rates for girls in middle school and high school in treated districts.

Table 8 reports the attendance results by grade level. Models 1–5 are results for middle and high school i.e. grades 6–10. The cash transfer is conditional on the student maintaining an average attendance of at least 80%. The new cash transfer (Rs. 1000) does not seem to influence the average attendance of girls in grades 6–10 in the treated districts. However, the earlier cash transfer (Rs. 200) was also conditional on maintaining average attendance of at least 80%. Therefore, girls who were already getting the stipend must already have been maintaining an attendance of 80%. If this attendance requirement was already binding, the new larger cash transfer may have had little additional effect on attendance, given enrollment.

Table 9 reports the enrollment results by middle school and high school levels. The estimates indicate that the increase in the cash amount by Rs. 800 ($5.25) did succeed in increasing the enrollment of girls in high school by about

TABLE 8.
Attendance: Effect of Cash Transfer Increase by Grade

	(1) Grade 6	(2) Grade 7	(3) Grade 8	(4) Grade 9	(5) Grade 10
$Post \times TreatDistr$	-0.150	-0.248	-0.309*	0.231	-0.323
	(0.185)	(0.191)	(0.162)	(0.207)	(0.277)
$Post \times Female$	0.305***	0.637***	0.602***	0.494***	0.750***
	(0.107)	(0.0999)	(0.0881)	(0.110)	(0.130)
$Post \times TreatDistr \times Fem$	-0.0169	0.103	0.248	-0.0577	-0.0104
	(0.177)	(0.195)	(0.152)	(0.225)	(0.275)
$Constant$	84.84***	83.47***	89.05***	84.42***	88.88***
	(2.573)	(2.339)	(1.588)	(2.937)	(4.476)
Day of the week FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓
School Controls	✓	✓	✓	✓	✓
Observations	393,448	392,331	379,502	176,011	173,124
R-squared	0.040	0.043	0.074	0.037	0.106
No. of schools	13,887	13,880	13,870	6,519	6,379

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

three students per female school in treated districts, but the change had no effect on the enrollment of girls in middle school. Table 10 presents the enrollment results by individual grade level. The results show that the increase in the size of the cash transfer increased enrollment of girls in 6^{th} grade by 1.6, and of those in 9^{th} grade by 3.7 students, per female middle and high school in treated districts. The higher cash amount does not seem to have had a statistically discernible effect on girls' enrollments in 7^{th}, 8^{th} and 10^{th} grades.

TABLE 9.
Enrollment: Effect of Cash Transfer Increase by School Level

	(1) Primary School	(2) Middle School	(3) High School
$Post \times TreatDistr$	7.394***	3.617***	1.578
	(1.267)	(0.952)	(1.578)
$Post \times Female$	4.300***	5.611***	2.616***
	(0.775)	(0.581)	(0.962)
$Post \times TreatDistr \times Fem$	-1.584	0.715	3.183**
	(1.147)	(1.045)	(1.580)
$Constant$	98.56***	103.7***	129.9***
	(1.533)	(4.123)	(8.493)
Month FE	✓	✓	✓
Year FE	✓	✓	✓
School FE	✓	✓	✓
School Controls	✓	✓	✓
Observations	1,332,803	396,384	178,292
R-squared	0.236	0.119	0.171
No. of schools	49,600	13,888	6,520

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

The total enrollment for smaller and larger schools is controlled for via school fixed effects. Using the mean female enrollment in treated districts in Table 2, the results indicate that the increased cash transfer led to a statistically significant increase in female enrollment of 4.45 percent in 6^{th} grade and 3.86 percent in 9^{th} grade, per month. Given that 6^{th} grade marks the transition from primary school to middle school and 9^{th} grade marks the transition from middle school to high school, these results suggest that the increase in the size of the cash transfer

TABLE 10.
Enrollment: Effect of Cash Transfer Increase by Grade Level

	(1) Grade 6	(2) Grade 7	(3) Grade 8	(4) Grade 9	(5) Grade 10
$Post \times TreatDistr$	1.805***	2.034***	1.050**	4.149***	1.122
	(0.518)	(0.479)	(0.426)	(0.995)	(1.101)
$Post \times Female$	2.377***	2.973***	2.138***	5.288***	1.629**
	(0.284)	(0.290)	(0.286)	(0.533)	(0.647)
$Post \times TreatDistr \times Fem$	1.613***	-0.451	-0.478	3.705***	-0.105
	(0.568)	(0.465)	(0.425)	(1.083)	(1.009)
$Constant$	45.23***	44.81***	42.39***	89.32***	97.44***
	(1.321)	(1.805)	(1.678)	(6.184)	(4.718)
Day of the week FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓
School Controls	✓	✓	✓	✓	✓
Observations	397,185	396,082	389,560	178,645	177,103
R-squared	0.054	0.027	0.019	0.105	0.130
No. of schools	13,892	13,885	13,875	6,521	6,381

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

provided a sufficient incentive for about one additional female student to transition from primary school to middle school, and for about three female students to transition from middle school to high school. The effectiveness of the CCT program when girls transition to the next level of schooling could reflect the greater commuting distance to a higher-level school, where additional compensation might affect the choices that households make. This is because the higher cash transfer could help cover the extra cost or time required to get girls to school, more than in the intervening years.

Conclusion

Gender inequality, in addition to income inequality, has been persistent in Pakistan. This research explores the effectiveness of a substantial increase in the cash amount of an existing female-targeted conditional cash transfer on schooling outcomes for girls. Specifically, I examine the impact of an increase in the monthly cash transfer from Rs.200 ($1.31) to Rs.1000 ($6.57) in 2017. The outcome variables of interest are enrollment and attendance in middle schools and high schools, and I make use of novel monthly data on student enrollment and attendance at all public schools in Punjab.

My research question has been whether the increase in the cash amount of the conditional cash transfer was successful in meeting its goal of improving enrollment and attendance of girls in middle school and high school. My empirical results suggest that the increase in the cash transfer increased female enrollment by an average of 1.6 female students in 6^{th} grade and 3.7 female students in 9^{th} grade, across girls' schools at the middle and high school levels in treated districts. This represents a 4.45 percent increase in female enrollment in the 6^{th} grade and a 3.86 percent increase in the 9^{th} grade. However, I find no discernable effects of the increased cash transfer on school attendance by girls in middle school and high school in the treated districts. However, the increase in the size of the cash transfer had positive spillover effects on the enrollment of boys in middle schools and high schools in treated districts.

Education is a critical component of human capital acquisition, and effective human capital accumulation is widely recognized as contributing to sustainable economic development and economic prosperity. In many developing countries, households underinvest in female education, often because they (1) prioritize boys' education, (2) depend upon the earnings from girls' labor, and (3) encourage child marriage. This gender differential argues for gender-targeted interventions. By improving educational outcomes, in particular by increasing school enrollment, attendance and retention, developing countries can contribute considerably to their future income growth.

CHAPTER III

HEAT, SOOT AND DUST: ENVIRONMENTAL FACTORS, SCHOOL ATTENDANCE AND TEST SCORES

Introduction

The social cost of poor environmental quality in developing countries is the most pressing and policy-relevant issue at the intersection of environment and development economics (Greenstone and Jack, 2015). About 98 percent of cities in low– to middle–income countries do not meet the air quality standards recommended by World Health Organization (WHO, 2016b). In many developing countries, levels of pollution are far higher than they have been in urban areas in the United States, even before the establishment of the U.S. Environmental Protection Agency and the passage of the Clean Air Act and its Amendments (Dominici et al., 2004).

Many of these countries have been reluctant to institute environmental regulations due to a concern that the economic benefits might be outweighed by the costs of regulation (Ebenstein et al., 2015). A variety of pollution impacts have now been studied in developed countries, but much less is known for developing countries. Research on the causal relationship between environmental quality and economic outcomes will help answer open questions about the burden of pollution in developing countries (Greenstone and Jack, 2015). A comprehensive understanding of the full scope of the benefits of reductions in air pollution is vital to policy decisions about the necessary stringency of environmental regulations in developing countries.

In this paper, I focus on the Pakistan, the sixth most populous country in the world. Pakistan has experienced rapid urbanization and industrialization, resulting in poor air quality. In Lahore, the capital of the province of Punjab in Pakistan, smog is considered as the "Fifth Season" (Zahra-Malik, 2017). According to the WHO (2016a), the annual median concentration of $PM_{2.5}$ was 68 μg/m^3 in the urban areas of Pakistan, and it was 60 μg/m^3 in the rural areas. Similar levels of pollution can be found in other high–population developing countries such as India and China.[1] In contrast, for the U.S., the annual $PM_{2.5}$ standard set by the Environmental Protection Agency (EPA) is only 15 μg/m^3. The total deaths attributed to air pollution in Pakistan in 2012 were about 33 per 100,000 population, whereas the comparable figure for the U.S. is only about 12 per 100,000 population (WHO, 2016a).

In Pakistan, rising temperatures are associated with climate change. Many studies have documented warming trends in Pakistan over the last few decades (Farooqi et al., 2005; Sheikh et al., 2009; Chaudhry et al., 2009; del Río et al., 2013). The temperature change in Pakistan over the period 1901–2000 was 0.11°F (0.06°C) per decade (Sheikh et al., 2009), whereas the mean temperature change

[1] In India, the annual median concentration of $PM_{2.5}$ was 66 μg/m^3 in urban areas, and 62 μg/m^3 in rural areas, whereas in China, the annual median concentration of $PM_{2.5}$ was 59 μg/m^3 in urban areas, and 54 μg/m^3 in rural areas (WHO, 2016a).

over the period 1960–2007 increased to 0.18°F (0.099°C) per decade in Pakistan (Chaudhry et al., 2009). The Turbat city in Baluchistan province of Pakistan, recorded the fourth-highest officially-recognized temperature (128.66°F) in the world on May 28, 2017 (World Meteorological Organization, 2019). The average annual temperature in Pakistan is projected to increase by 7.2°F (4°C) by the year 2100 (Haensler, 2013; Global Facility for Disaster Reduction and Recovery, 2014). A large epidemiological literature suggests that exposure to $PM_{2.5}$ (i.e. fine particles of soot) has harmful health effects in both rich and poor countries. In this paper, I build upon the emerging literature that examines the effect of pollution on labor productivity and human capital accumulation.[2]

Specifically, I examine the effects of short–term variation in air pollution and temperature on school attendance and learning, using data for Punjab, the second–largest and most populous of the four provinces of Pakistan.[3] I use a novel dataset on school attendance that includes scores on a short diagnostic test given to students in third grade for all public schools in Punjab, derived from monthly visits by school auditors. The data run from September 2014 to March 2018,

[2]For health effects, see Currie et al., 2009b; Currie and Walker, 2011; Currie et al., 2013; Barron and Torero, 2017; Jayachandran, 2009; Greenstone and Hanna, 2014; Arceo et al., 2016; Molina, 2018. For labor productivity, see Zivin and Neidell, 2012; Chang et al., 2016; Chang et al., 2019; Aragón et al., 2017; Fu et al., 2018. For human capital accumulation see Ham et al., 2014; Ebenstein et al., 2016; Bharadwaj et al., 2017; Aizer et al., 2018.

[3]The province of Punjab covers about 80,000 $miles^2$, which is roughly the same size as the U.S. states of Nebraska or Minnesota or Kansas. It has population of over 110 million in 2017, which is similar to the overall population of U.S. states of California, Texas, Florida and Ohio, put together.

constituting an unbalanced panel for about 48,000 individual schools, with more than 1.5 million observations.

For the research described in this paper, I have also assembled the most comprehensive daily pollution and weather data available for Punjab, Pakistan over the period 2014–2018. The daily detailed weather data have been web-scraped from 38 weather stations across Punjab. For better precision, I also extract daily (3–hourly) air temperature data for each school from the Global Land Data Assimilation System Version 2 (GLDAS-2.1) using Google's Earth Engine.[4] There exists no reliable panel of comprehensive ground–level monitoring of air quality in Pakistan, so there is only limited conventional administrative air quality data available for Punjab. Thus I use remotely sensed satellite data for air pollution across Punjab (specifically, AOD—aerosol optical depth). Satellite imagery allows researchers to overcome data–collection obstacles in developing countries, which is particularly important when ground–level air pollution data are scarce, intermittent and/or of questionable reliability (Chen et al., 2012).

I then regress school attendance on contemporaneous air pollution, air temperature, weather and school controls, time and school fixed effects. A concern is that periods of high economic activity, resulting in more air pollution, could be associated with higher demand for child labor or alternatively, lower demand for child labor if the income effect is positive. Thus, I use exogenous variation in

[4] https://developers.google.com/earth-engine/datasetscatalogNASA_GLDAS_V021_NOAH_G025_T3H

air quality over time, due to intermittent dust from neighboring deserts, to net out the confounding effects of economic activity. Given the hot and dry climatic conditions, a large amount of dust is generated from the arid lands within Pakistan (Hussain et al., 2005).

The results of instrumental variables estimation indicate significant negative effects of pollution on attendance and test scores. Specifically, I find that a one–standard–deviation increase in pollution (AOD) increases school absences by 6.83 percent of the sample mean. This is comparable to the 6.99 percent increase in the probability of student absence in China from a one–standard–deviation increase in AQI (Chen et al., 2018). A one–standard–deviation increase in AOD reduces total test scores by 10 percent of a standard deviation. For the separate subject scores, I find that a one–standard–deviation increase in AOD lowers the average Urdu (language) score by 17 percent of a standard deviation (std. dev.) and reduces the average math score by 8 percent of a standard deviation. These estimates are larger compared to prior studies in developed countries such as the U.S., Chile and Israel (Miller and Mauricio, 2013; Ham et al., 2014; Ebenstein et al., 2016).

I simultaneously consider variations in temperature as a second natural experiment influencing attendance and student performance on tests. Using a nonparametric specification for temperature with a series of indicator variables for 2°C bins for the temperature range in the data, I find that high temperatures have an adverse effect on test scores. For example, an increase in the outside temperature from 16–18°C (60.8–64.4°F) to 34–36°C (93.2–96.8°F) reduces a student's school's overall score by an average of 0.29 standard deviations, the average math score by 0.26 standard deviations, and the average Urdu and English scores by 0.2 standard deviations.

The contribution of this study is that it uses satellite measures of air pollution to examine the effect of air quality on human capital acquisition in a developing country where there are (a) no comprehensive ground–level air quality data, but (b) pollution levels that are similar to China and India. I have put together the most comprehensive daily pollution and weather data available for Pakistan over the period 2014–2018. This paper adds to the limited recent work (Liu and Salvo, 2018; Chen et al., 2018) linking air pollution to school attendance in developing countries. Both these other studies are based in China, where air pollution data are now available from local ground monitors and where schooling outcomes, in general, are much better than Pakistan.[5]

Another contribution of this paper is that there seems to have been no work done, to date, on the causal effect of pollution on test scores for developing countries. Outside the U.S., the limited existing literature studying the effect of air pollution on test scores is based largely on more–developed countries, such as the UK, Chile, and Israel (Miller and Mauricio, 2013; Ham et al., 2014; Ebenstein

[5]In China, the adult literacy rate is 96.36 percent, whereas it is only 58 percent in Pakistan. Similarly, the net enrollment rate in primary school is 100 percent in China, whereas it is only 68 percent in Pakistan (Xuepei et al., 2019).

et al., 2016; Roth, 2018; Heissel et al., 2019; Austin et al., 2019). With higher per-capita incomes, populations can be more resilient to environmental conditions.

A small literature has found evidence of an adverse effect of high temperatures on student test scores for developed countries (Park, 2017; Graff Zivin et al., 2018; Goodman et al., 2018) and in a developing-country context (Garg et al., 2017). However, the only paper that examines the effect of temperature on test scores in a developing country (Garg et al., 2017) does not control for air pollution, which is a potentially confounding factor. So it could be that they are measuring the impact of pollutants, as well as heat, since there tend to be more pollutants on hot days as a result of atmospheric chemistry. This paper contributes to the existing literature by examining the direct impact of temperature on test scores in a developing-country context while controlling for confounding factors including contemporaneous pollution exposure.

This paper highlights the importance of pollution and temperature control in classrooms, e.g. through the use of air conditioners. This is particularly relevant for Punjab, since most public schools in Punjab lack even basic infrastructure. None of the 48,000 schools in my sample have air purifiers or air–conditioning units. Some schools do not even have fans or windows that can be closed, and in some schools, classes are held outdoors, with students seated on the ground. The majority of students who attend public schools in Punjab are from households with low socioeconomic status. Wealthy families send their children to private schools.

School absences cause more harm to students who belong to socioeconomically disadvantaged households because these households are less able to compensate for the lost instructional time (Chang and Romero, 2008). Absenteeism can directly impact academic performance by affecting learning outcomes and probability of a student dropping out of school (Goodman, 2014; Gershenson et al., 2015; Aucejo and Romano, 2016). Human capital accumulation is critical for any country's sustained long-term growth, and therefore especially important in developing countries.

The remainder of the paper is organized as follows. Section 3.2 presents the background on sources of air pollution in Pakistan and reviews the physiological effects of poor air quality and elevated temperatures. Section 3.3 reviews the existing literature. The data are discussed in Section 3.4, and the empirical model is detailed in Section 3.5. Section 3.6 presents the estimation results, Section 3.7 discusses the heterogeneity analysis and Section 3.8 concludes.

Background

Physiological effects of Pollution and Temperature

Exposure to $PM_{2.5}$ (i.e. fine particles of soot) has harmful health effects, which include respiratory episodes, such as asthma attacks, and cardiovascular events, such as heart attacks. The less-extreme impacts of particulate matter include increased blood pressure, irritation of the nose, throat, ears and lungs, as well as mild headaches (Pope, 2000; Auchincloss et al., 2008). Even minor impairments of respiratory and cardiovascular functions can increase fatigue, reduce focus and impair cognition (Nelesen et al., 2008).

Fine particulate matter ($PM_{2.5}$) can remain suspended in the air for a long time period and can travel long distances. Unlike many other pollutants, it can easily penetrate buildings, especially buildings that are poorly insulated or poorly ventilated, with penetrations ranging from 70 to 100 percent (Thatcher and Layton, 1995; Vette et al., 2001).

The effects of heat exposure on cognitive function have been well-documented by the neurological literature. Extreme hot temperatures can increase blood viscosity and cholesterol levels, resulting in cardiovascular stress (Huynen et al., 2001). Moreover, when cognitive resources become overloaded by heat stress, individuals can have too few resources available for cognitive tasks, resulting in impairment of cognitive function (Hancock, 986b; Hocking et al., 2001).

Pollution in Pakistan

In Pakistan, air pollution has become an important environmental concern due to rapid urbanization and industrialization. The main environmental legislation in Pakistan is the Pakistan Environment Protection Act (PEPA) of 1997. There is a federal Environmental Protection Agency responsible for implementing the PEPA. However, ground-level monitoring of air quality in

Pakistan is scarce and intermittent. The data on pollution emissions from industries are provided through a voluntary program, under which industrial facilities self-report their emissions. In 2014, only 99 out of 6417 industrial units in Pakistan have systematically reported their emissions under the program (Sanchez-Triana et al., 2014). Moreover, violations of industrial emission standards are often ignored on the premise that the country cannot afford to hamper its economic growth. For example, in spite of their expected emissions, 13 coal-fired power plants are currently being built in Pakistan (Gilani, 2017).

The main sources of air pollution in Pakistan are industrial and vehicle emissions, biomass burning, and natural dust (Colbeck et al., 2009; Sanchez-Triana et al., 2014). The air pollutant considered in this study is particulate matter, measured by Aerosol Optical Depth (AOD). In general, particulate matter comes both from natural sources (such as volcanoes, wildfires and blowing dust) and from human activity (such as fossil fuel combustion, when heat and atmospheric chemistry cause gases from automobiles, power plants, and industries to interact to create particulate matter). The numerous sources of particulate matter air pollution in Pakistan include industry, power plants, vehicles and wind-blown dust (Stone et al., 2010). For example, in Lahore, it is estimated that dust accounts for about 41 percent of coarse particulate matter (PM_{10}) and 14 percent of fine particulate matter ($PM_{2.5}$) each month (von Schneidemesser et al., 2010).

Figure 18 in the Appendix depicts the average levels of air pollution across Pakistan for the period from September 2014 to March 2018 using the satellite measure of air pollution, AOD. The high AOD values across various regions of Pakistan during summers are typically associated with large amounts of dust aerosols (Khan et al., 2011). Ali et al. (2014) find that the high value of AOD in Lahore, an urban district in Punjab, is associated with high temperatures and intermittent dust storms. Similarly, in Multan and D.G. Khan, two other districts in Punjab, Alam et al., (2010) find the highest AOD values during summers, where these peaks are due to air masses coming from the Cholistan Desert in Pakistan and the Thar desert in India.

Literature Review

Air Pollution and Learning

Significant air pollution has a variety of social costs. The most obvious and severe are the costs to human health. The economics literature presents compelling evidence that pollution is harmful for human health, specifically birth outcomes, and infant health.[6] However, there are also less-lethal impacts of particulate matter that affect many healthy individuals on a daily basis but do not require formal health care encounters. The prevalence of these less-severe impacts has

[6]Currie et al., 2009b; Jayachandran, 2009; Currie and Walker, 2011; Currie et al., 2013; Greenstone and Hanna, 2014; Arceo et al., 2016; Barron and Torero, 2017; Molina, 2018

motivated recent economic research on labor productivity and human capital accumulation. This body of research demonstrates the adverse effects of pollution exposure on worker productivity and hours worked.[7]

A fairly new body of literature has begun to study the effects of exposure to pollutants on student learning. Miller and Mauricio (2013) find that a 10-unit increase in PM_{10} in Chile lowers average math and reading scores of children in the fourth, eighth and tenth grades by 2.6 and 2.3 percent of a standard deviation, respectively. Ham et al. (2014), using data for elementary school children in California, find that an increase in particulate matter, specifically PM_{10}, decreases math and reading scores on standardized tests. Ebenstein et al. (2016) presents empirical evidence that transitory exposure to $PM_{2.5}$ on exam days not only results in significant decline in the test performance of Israeli students, but is also negatively associated with postsecondary educational attainment and earnings. Roth (2018) shows that particulate matter (PM_{10}) has a significantly negative impact on test scores of university students in London.

Other studies have examined the impact of air pollution on absenteeism among school children. Ransom and Pope (1992) find that an increase in the 28-day moving average of PM_{10} (to 100 μg/m^3) in the Utah Valley during the time period 1985–1990 increased school absences by two percent. Gilliland et al. (2001) demonstrate that increase in pollution increase daily absences for 4th

[7]Zivin and Neidell, 2012; Chang et al., 2016; He et al., 2016; Aragón et al., 2017; Fu et al., 2018

grade students in California (due to respiratory illness). Currie et al. (2009a) find that high levels of CO, despite being still below the federal air quality standards, increase absences of students in elementary and middle schools in Texas. Liu and Salvo (2018) show that an increase in the preceding fortnight's $PM_{2.5}$ from 100 μg/m^3 to 200 μg/m^3 increases the probability of school absence by 1.9 percentage points, or 31 percent of the sample mean absence rate in China. Chen et al. (2018) find that a one-standard-deviation increase in AQI in China increases the likelihood of school absence by 6.99 percent.

Temperature and Learning

The small existing literature suggests that high temperatures have an adverse effect on student learning. Graff Zivin et al. (2018) present evidence that 5- to 14-year-old children in the U.S. perform worse on standardized math tests when the test is taken on warmer days above 26°C. Using data on high school exit exams from New York City public schools, Park (2017) finds that a temperature of 90°F on exam day lowers exam performance by 0.15 standard deviation compared to a temperature of 72°F on exam day. Garg et al. (2017) find that ten more days in a year with mean daily temperature higher than 29°C, relative to 15–17°C, lowers average math scores of primary and secondary school students in India by 0.03 standard deviations, and reading test performance by 0.02 standard deviations. Goodman et al. (2018) show that in the U.S., a 1°F increase in average school-year temperature prior to the PSAT exam lowers performance on the exam by 0.002 standard deviations, or about one percent of learning in a year.

Satellite Data

There are increasing numbers of papers in economics that rely on satellite imagery to measure pollution. Jayachandran (2009) uses aerosol optical depth (AOD) satellite data from the satellite to measure air pollution due to forest fires in Indonesia. Foster et al. (2009) explore the impact of air pollution, measured using satellite MODIS data, on infant mortality. Chen et al. (2013) and Bombardini and Li (2016), investigate the causes of air pollution in China, and compare satellite pollution data with pollution data from ground-based monitoring systems, in a context where pollution is a politically contentious issue. Voorheis (2017) combines satellite data on fine particulate matter with linked administrative and survey data to create a new dataset of individual pollution exposure each year in the U.S. between 2000 and 2014. Zou (2018) uses satellite measures of pollution (AOD) to compare pollution levels in the U.S. on monitored days and unmonitored days, to examine the consequences of federal Clean Air Act policy that requires monitoring sites to use a once-every-six-day air quality monitoring schedule.

Data

School Data

The school attendance and test-score data for this analysis are drawn from the Program Monitoring and Implementation Unit (PMIU) of the government of Punjab, one of the four provinces (i.e. states) in Pakistan, having a population of over 110 million in 2017. The capital city alone (Lahore) has a population of over 11 million. In 2014, the PMIU initiated digital monthly monitoring all public schools in Punjab. The PMIU employs 950 field officers who randomly visit about 48,000 schools each month in the 36 districts of Punjab. They record student attendance, teacher attendance, and the condition of school facilities. They also administer a short test to a sample of students in the third grade. The schools are not informed as to the date of the monitoring visit. Moreover, the PMIU re-assigns and shuffles schools to be visited by each field officer. The unique thing about this dataset is that it contains information on the exact date of each visit.[8]

The school attendance data run from September 2014 to March 2018. The dataset includes information on the district, the tehsil (i.e. sub-county), the name of each school, school ID, the gender studying in that school (since all schools are single-gender), the school level (primary, middle, high), the number of teachers hired, the number of teachers absent on the monitoring date, the number of

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[8]The school attendance and test score data were acquired directly from the Database Administrator at PMIU by petition. The school attendance data are available on the PMIU website but the data are not downloadable. The test score data are not publicly available.

students enrolled in each grade, and the number of students present in each grade on the monitoring date. The data on student test scores run from September 2015 to March 2018. These data include information on the grade of the student, questions asked, question subject (math, Urdu, English), the student answer, the correct answer, along with details of the district, the tehsil, the school name, and the school ID.

In each school, on average, either six or seven students in the third grade are randomly selected for testing during each monitoring visit. Each student (on average) answers seven questions, including at least two math questions, two English questions and three Urdu questions. In the test-score data, the individual students tested are arbitrarily numbered and there is no student ID or name provided for the individual students tested, so I am limited to computing a panel of test scores for the school, rather than following a panel of students. The other school characteristics used in the analysis come from the annual school census data for all public schools in Punjab. The census data include information on a variety of school characteristics.

The tests analyzed in other studies are standardized tests and/or high stakes test that are taken by all students. The tests studied in this research are taken by a selected sample of students from a question bank that is most likely limited and unchanging. But, the monitoring officers are randomly chosen and rotated for each monthly school visit and the students who take the test are randomly selected by the monitoring offers. However, it is possible that the monitoring officer is entertained with tea and snacks, while the headmaster selects the best students to take the test. So, the test scores might capture cognitive ability but also selection of students and testing conditions.

During each monthly school visit, field officers record enrollment in each class. The academic year begins in April for public schools in Punjab, but there is on-going enrollment through the year. In the data, the enrollment levels recorded by field officers vary over the months. If a school does not have at least 80 percent attendance on the monitoring day, the school has to submit a formal report. To ensure that the monthly enrollment records are not strategically manipulated by field officers or school administrators to increase attendance above 80 percent, I compare percentage attendance as recorded by field officers with the percentage attendance computed using official start-of-school-year (April) enrollment, considering 80 percent attendance as a threshold.

I find that for grades 1–5, about eight percent of school observations exhibit attendance based on enrollments at the start of the school year (April) that are less than 80 percent, whereas their (average) monthly attendance is more than 80 percent, making the latter figures perhaps suspect. For grades 6–9, the analogous fraction is 3.3–5.7 percent, whereas for tenth grade, it is 19 percent. Given that the monthly enrollment records do not seem to be widely manipulated to increase reported attendance rates, above 80 percent, I elect to use monthly enrollment for estimation.[9]

Pollution Data

There is limited administrative air-quality data available for Pakistan because there is no comprehensive ground-level monitoring of air quality in Pakistan. A variety of satellites, launched in the past two decades, have allowed for improved measurement of air quality from space. Moreover, remotely sensed data collected by satellites gives us access to information that is difficult to obtain in other ways. For example, in many parts of the world, especially in developing countries, ground-based pollution monitoring stations are extremely sparse, and may be subject to strategic government manipulation.[10]

For this study, it is important to measure day-to-day variation in pollution levels at a fine level of geographic specificity. Therefore, I use the aerosol optical depth (AOD) data directly, as has been done by Zou (2018). The daily air pollution (AOD) data for Punjab, for the period of September 2014 to March 2018, are obtained using the MODIS (Moderate Resolution Imaging Spectroradiometer) instrument on the Terra Satellite. I know the exact locations of each school, so

[9] I have also estimated models using attendance computed using enrollments reported at the start of the school year (i.e. in April). The results are not qualitatively different. These other results are available from the author.

[10] Donaldson and Storeygard (2016) provide an overview of the current state-of-the-art of satellite data that have been exploited in the economics literature and suggest future avenues for use of satellite data.

the daily AOD values that I associate with each school are the average of AOD values across all 10km x 10km cells that intersect a 1-km buffer around the specific school. The AOD value is missing for some school-days due to cloud coverage, so they are dropped from the sample. The AOD value ranges from -0.05 to 5, with higher value indicating more aerosols in the air.

Biomass burning (crop burning) is one significant source of air pollution in Pakistan. Crop burning is extensively used in many parts of the world, including Pakistan, to remove excess crop residue before sowing a new crop (Yevich and Logan, 2003). Burning cultivated fields is a quick and low-cost method to remove weeds, pests and diseases, to prepare fields for the next crop (McCarty et al., 2009). The timing of crop burning depends on the harvesting seasons for different crops. In Pakistan, Punjab is the main agricultural province, with two main crop growing seasons. The main Rabi (winter) crop is wheat, which is sown during October through December and harvested during March and April. The main Kharif (summer) crops are sugarcane, cotton, rice and maize. The sowing season starts in February for sugarcane, spans March–May for cotton, June–July for rice and July–August for maize. Most crops are harvested during October–December.

The fires used to prepare fields for the next crop produce smoke that affects air quality. The smoke contains particulate matter along with carbon monoxide and carbon dioxide. The fine particles of airborne crop residue are picked up by the wind and are carried over large distances resulting in higher AOD values in different locations as well (Badarinath et al., 2009; Ali et al., 2014). Moreover, the regions to the south of the Himalayas often have air inversions, where cold air is held fixed below a layer of warm air, trapping pollutants close to the ground, especially when smoke is present.[11] Figure 19 in the Appendix shows the number of fires in Pakistan on two different dates, using daily fire data retrieved from the Google Earth Engine. One date is before the sowing of the summer crop, and the other date is around the sowing of the winter crop. It is evident from the figures that a majority of the field-burning fires in Pakistan occur in the province of Punjab.

Economic Activity Data

Given that Punjab is the main agricultural province in Pakistan, I use monthly variation in the Normalized Vegetation Difference Index (NDVI), an indicator for live green vegetation, as a proxy for agricultural economic activity. The NDVI is a 16-day vegetation index, obtained from the MODIS TERRA satellite with 1-km spatial resolution. This index has been widely used as an indicator for vegetation presence over a range of geographic areas (Bégué et al., 2011; Pettorelli et al., 2005). Figure 20, 21 and 22 in the Appendix plot the NDVI parameter estimates for each month for all the districts in Punjab.[12] It is apparent from the figure that the NDVI decreases during March - April, which is around the

[11] https://modis.gsfc.nasa.gov/gallery/individual.php?db_date=2018-11-24

[12] I regress NDVI on monthly dummies for each district.

sowing season for summer crops and also the harvesting season for winter crops. NDVI also decreases during September through October, which is right before the sowing season for winter crops and is also the harvesting season for summer crops.

I also use the monthly survey of industrial production and employment in Punjab for the years 2014-2017 from the Bureau of Statistics of Punjab to control for variation in air pollution due to industrial activity.[13] These monthly surveys cover 46 important industries in Punjab, including more than 1700 industrial units across the province.[14]

Weather Data

The necessary 44 months of daily weather data from August 2014 to March 2018 (over 1,320 data points) have been web-scraped from 38 weather stations across Punjab. These observations include multiple daily observations on temperature, humidity, wind speed, and wind direction, along with descriptive information about key weather conditions, including the presence of smoke, dust storms, blowing dust, etc. For each school's weather data, I use the nearest (great-circle distance) weather station.

I also use weather data from the Global Land Data Assimilation System Version 2 (GLDAS-2.1) with a 0.25° spatial resolution. The GLDAS-2 has two components, the GLDAS-2.0 comes entirely from by the Princeton meteorological

[13] `http://bos.gop.pk/cisreports`

[14] The data was requested from the Bureau of statistics Punjab on petition.

data, and the GLDAS-2.1 comes from a combination of model and observation-based datasets. The Global Land Data Assimilation System (GLDAS) uses advance surface modeling and data assimilation techniques to process satellite and ground-based observational data products, to create optimal fields of land surface states and fluxes. The GLDAS is a unique land-surface modeling system which integrates large observation-based datasets, uses multiple models, runs globally at a high resolution of 0.25°, and generates near-real-time results (Rodell et al., 2004). Using Google's Earth Engine, I extract the daily (3-hourly) data for air temperature, precipitation, air pressure, and wind speed for each school location over the period August 2014 to March 2018.

Figure 23 in the Appendix depicts the mean, maximum and minimum daily temperature across the tehsils of Punjab over the period 2014–2018. The mean daily temperature ranges from 16°C (60.8°F) to 30°C (86°F), with more than half the tehsils having a mean daily temperature between 26°C (78.8°F) and 30°C (86°F). The maximum daily temperature varies from 30°C (86°F) to 44°C (111.2°F), with almost half the tehsils experiencing maximum daily temperatures as high as 42–44°C (107.6–111.2°F).

Summary Statistics

Table 11 presents summary statistics for AOD, the weather variables, and student and teacher attendance over the period September 2014–March 2018.

AOD levels in Punjab fall within a range between 0.001 and 4.95, with a mean of about 0.58. In contrast, for the United States, AOD ranges from 0 to 1, with an average of about 0.12 during the period 2001 through 2013 (Zou, 2018). Figure 24 in the Appendix depicts the mean AOD for each tehsil in Punjab across the period September 2014–March 2018. It is evident from the figure that there is significant spatial variation in mean AOD across the province.

TABLE 11.
Summary Statistics

	(1) Mean	(2) Std. Dev.	(3) Min	(4) Max
AOD	0.58	0.35	0.001	4.949
Temperature (°C)	23.99	7.59	1.874	42.647
Total attendance	90.31	11.49	0	100
Teacher attendance	93.23	13.95	0	100
Total questions asked	32.91	7.85	12	74
Urdu questions	12.89	4.35	3	31
Math questions	11.07	1.51	3	30
English questions	8.95	2.81	3	20
Total Score (all questions)	27.29	7.75	0	64
Urdu Score	10.84	4.21	0	26
Math Score	9.61	2.13	0	30
English Score	6.85	2.59	0	16
Maximum (Individual) Score	6.19	0.85	0	13
Minimum (Individual) Score	4.08	1.49	0	11

The daily temperature in Punjab varies from about 1.9°C (35.42°F) to 42.6°C (108.68°F), with an average temperature of 23.9°C (75.02°F). The average student attendance rate is 90.6 percent, whereas the average teacher attendance rate is 93 percent. The summary statistics in Table 11 report the percentage scores for each school (not for each individual student tested). However, the maximum and minimum scores represent the highest and lowest individual student (percentage) scores in a school during each monitoring visit.

Figure 2 presents a box plot of AOD and temperature on school-visit days, whereas Figure 3 depicts AOD as a function of temperature on school-visit days.[15] AOD seems to increase with temperature up to 40°C (104°F). It could be that AOD declines beyond 40°C because it is too hot to operate factories or burn the crop fields, which reduces output, and consequently, pollution.

Methodology

The equation I estimate is of the following form:

$$Y_{st} = \beta AOD_{st} + f(Temp_{st}) + X_{st}\Gamma + Z_{st}\Pi + \gamma_t + \alpha_m + \delta_y + \mu_s + \epsilon_{st} \tag{3.1}$$

where Y_{st} is the attendance or test scores for third grade students at school s on day of school-visit t. In the test-score data, there is no ID or name provided for

[15] Though each school is visited once a month, I have daily data for AOD and temperature. Figure 25 in Appendix shows the relation between daily AOD and daily temperature at tehsil (sub-county) level.

FIGURE 2.
Box plot of AOD and temperature

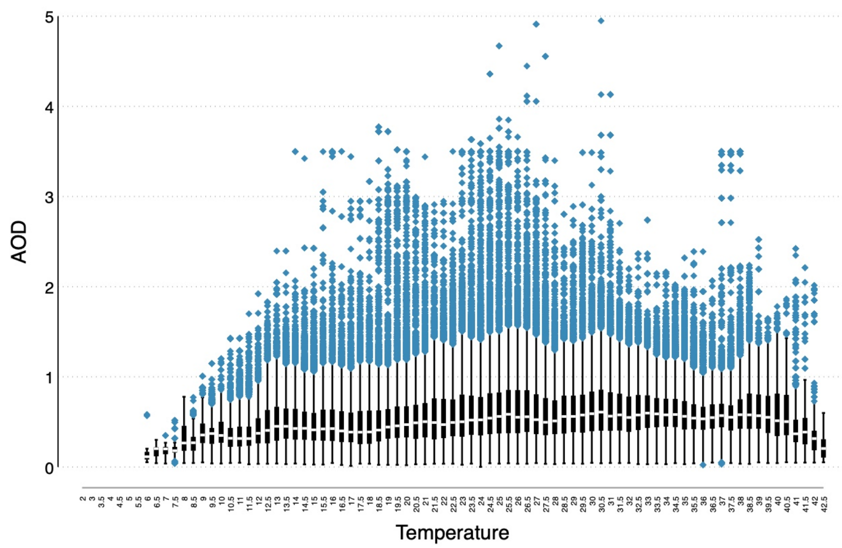
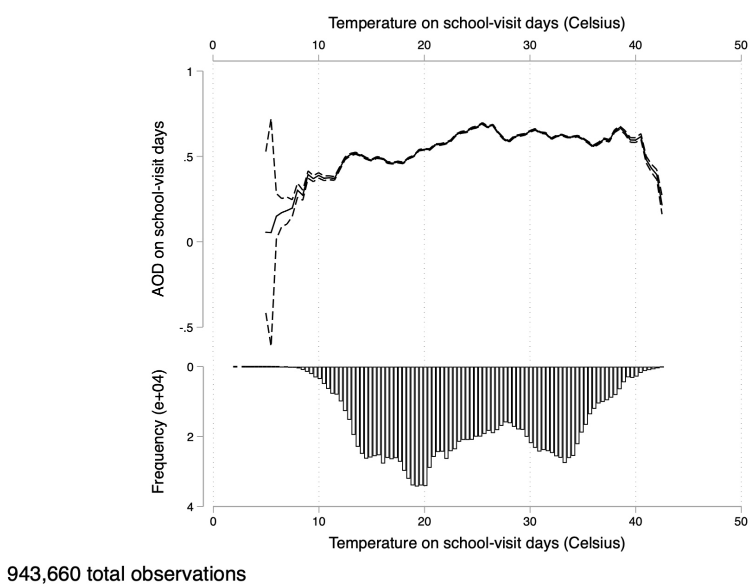


FIGURE 3.
AOD as a function of temperature on school-visit days



the individual students tested, so I compute the test score for each school. AOD_{st} is the measure of air pollution at school s at time t, which is measured by satellite-detected aerosol concentration. $Temp_{st}$ is the average temperature at school s on school-visit day t in degrees celsius. Specifically, I use 2-degree celsius temperature bins in the empirical analysis. X_{st} is a vector of weather controls at school s at time t, which includes mean humidity, mean precipitation, mean air pressure, and mean wind speed. To account for potential bias, I condition on Z_{st}, which is a vector of observable school characteristics potentially related to attendance and test scores, which include teacher attendance, student teacher ratio, school age, school size, number of classrooms, number of open-air classrooms, proportion of students and teachers who have furniture, plus indicators for the presence of electricity, toilets, drinking water, a walled school and main gate.

In the equations for test scores, Z_{st} also includes the size of the third grade class(es). To control for unobserved spatial and temporal heterogeneity, I also include day of the week, month, year and school fixed effects in the estimation model, where the γ_t parameters are day of the week fixed effects, the α_m parameters are calender month fixed effects, and the δ_y parameters are year fixed effects. The μ_s parameters are school fixed effects, and ϵ_{st} is an idiosyncratic error term. To consider variations in temperature as a simultaneous natural experiment influencing attendance and student performance on tests, I include a nonparametric specification for temperature with a series of indicator variables for 2°C (35.6°F) bins for the temperature range in the data, with 16–18°C (60.8–64.4°F) as the reference bin.[16]

For β to measure the causal relationship between air pollution and attendance, or air pollution and test scores, the unobserved determinants of student characteristics must be uncorrelated with pollution. One threat to identification could be the case where periods of high economic activity produce more air pollution and simultaneously lead some households to keep older children out of school, perhaps to care for the family's youngest children if both parents work. This could create omitted variable bias which exaggerates the extent to which higher pollution, itself, keeps children out of school. Alternatively, a period of greater economic activity, again resulting in more local air pollution, could actually induce more parents to send their children to school, since work opportunities take the parents away from home and younger school-aged children need the supervision provided by the school. This unobserved parental behavior would offset any negative effect of pollution on school attendance.

One possible strategy to control the potentially confounding effects of economic activity is to isolate the effects of exogenous variation in air quality using an instrument. In the context of Pakistan, an important exogenous determinant of pollution is dust driven from neighboring deserts. Dust storms are frequent in

[16]I choose 16–18°C (60.8–64.4°F) as the reference temperature bin because it seems to be optimal outside temperature for student performance on tests taken indoors. Perhaps a 65°F temperature outside produces a 20-22°C temperature indoors, with the free heat generated by bodies.

Pakistan. Given the hot and dry climatic conditions, dust from the arid lands within Pakistan and in neighboring countries can be driven by even a light wind (NASA, 2018). Frequent dust storms emanate from regional deserts (Thal, Cholistan, Kharan, Thar) in Pakistan, particularly during summers, and these contribute to deteriorating air quality in Punjab (Hussain et al., 2005).[17] Arid conditions and strong winds generate a large amount of dust in many parts of Punjab, elevating particulate matter (Sanchez-Triana et al., 2014). Transboundary transport of dust from India (Khanum et al., 2017) and the Arabian Peninsula (Stone et al., 2010; Shahid et al., 2016) also results in periodic increases in particulate matter in Punjab. Figure 27 in the Appendix shows some of the major dust storms that arose over Pakistan, specifically in June 2012, June 2017 and March 2018. To exploit exogenous variation in air pollution in Punjab due to dust, I use dust conditions specifically reported in the weather station data as instrumental variables, namely, the daily indicators for dust storm, wide-spread dust, or blowing dust.

I know the locations of the schools, so I can account for any time-invariant unobserved heterogeneity in schools with school fixed effects. Given that, there is potential unobserved heterogeneity from households with multiple children who may attend different schools within a tehsil (sub-county), so standard errors are

[17]Figure 26 in the Appendix shows the locations of the deserts in Pakistan.

clustered at the tehsil level for attendance estimation. The test scores are non-negative count data, so I use log-linear model.[18]

Results

Pollution

AOD is a dimensionless unit, with a value of less than 0.1 indicating a clean atmosphere, and a value of 1 indicating a very hazy conditions.[19]

Attendance

Table 12 reports estimation results for the effect of pollution (measured by AOD) and temperature on student attendance. In model 1, I report the fixed effects results with controls for only weather, including mean humidity, mean precipitation, mean air pressure, and mean wind speed. Model 2 also includes time fixed effects—namely day-of-the-week, month and year fixed effects. The coefficient estimate for AOD becomes much smaller now. In model 3, I also add school characteristics. Counter-intuitively, an increase in air pollution appears to increase student attendance in these specifications. Namely, a change in air quality from "clean" to "hazy" (an increase in AOD from 0 to 1) increases student attendance by about 0.2 percent. In models 4–6, I include school-month, district-year, and

[18] I have also estimated the test score model with Poisson estimation method but the Stata in-built Poisson instrumental variable algorithm does not allow for fixed effects.

[19] `https://earthobservatory.nasa.gov/global-maps/MODAL2_M_AER_OD`

tehsil-month fixed effects, respectively. The positive and statistically significant coefficient for AOD is robust across all these different fixed effects models.

TABLE 12.
Incremental effect of AOD on student attendance

	(1)	(2)	(3)	(4)	(5)	(6)
	Attend	Attend	Attend	Attend	Attend	Attend
AOD	0.645***	0.237***	0.196***	0.202**	0.192***	0.140**
	(0.0815)	(0.0592)	(0.0606)	(0.0792)	(0.0599)	(0.0612)
Time FE		✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓
School Controls			✓	✓	✓	✓
School-Month FE				✓		
District-Year FE					✓	
Tehsil-Month FE						✓
Observations	868,945	868,945	625,490	625,490	625,490	625,490
Number of schools	47,732	47,732	47,632	47,632	47,632	47,632

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Robust standard errors in parentheses

In Table 32 in the Appendix, I explore whether it is more appropriate to consider lagged effects of AOD on current-day attendance. I include mean AOD yesterday, in the past two days, and up to the past week, along with contemporaneous AOD. The sign and magnitude of the coefficient on contemporaneous AOD does not change qualitatively with the addition of successive lags of mean AOD during the past week. The estimated coefficient of AOD is positive, significant, and of similar magnitude in all specifications (except model 2, which has just contemporaneous AOD and mean AOD yesterday). There is a strong correlation between current and one-day-lagged AOD as depicted in Table 30 and Table 31 in the Appendix, so multicollinearity could obscure their distinct effects.

As discussed in the methodology section, a possible concern is that household behavior with respect to attendance is determined by some of the same processes that affect pollution levels. Periods of high agricultural or industrial activity could both (a) produce high pollution and (b) influence the decisions of households about whether to send younger school-aged children to school. Table 13 reports the results for models to explain AOD levels and attendance levels with controls for agricultural or industrial activity that would otherwise be omitted variables.

To control for agricultural activity, I add the level of NDVI and an indicator for a negative change in NDVI interacted with NDVI, to my model from Equation 3.1 to estimate model 2. For model 1, I regress AOD on NDVI and the indicator for a negative change in NDVI interacted with NDVI, including controls for weather and school, and time fixed effects. NDVI is included to capture crop biology, which could proxy for parents' agricultural (harvest) work. The results suggest that an increase in NDVI decreases AOD so that a decrease in NDVI, correlated with crop-harvesting or crop burning, *increases* both AOD and student attendance. For industrial activity, I use employment data from the monthly survey of industrial production and employment in Punjab that covers more than

TABLE 13.
The effects of variables previously omitted

	(1) AOD	(2) Attendance
Agricultural Activity		
NDVI (i.e. growing season)	-0.127***	0.719***
	(0.00460)	(0.100)
NDVI negative change	0.00535***	0.0926***
(i.e. harvest, or prolonged dry season)	(0.00109)	(0.0249)
Industrial Activity		
Employment (log)	0.00149***	0.342***
	(0.000463)	(0.0114)
Time FE	✓	✓
Weather Controls	✓	✓
School Controls	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

1700 industrial units and 46 important industries.[20] I find that an increase in industrial employment also *increases* both air pollution and student attendance.

Table 33 in the Appendix reports the results of the effect of pollution and temperature on student attendance by month, which shows that greater pollution is associated with higher attendance during harvest months.[21] When I exclude the crop-harvesting months from the sample, the results in Table 34 in the

[20] `http://bos.gop.pk/cisreports`

[21] Schools are closed from June-August, and there are no data for September.

Appendix show that an increase in AOD from 0 (clean atmosphere) to 1 (very hazy conditions) reduces student attendance by about 0.15 percent.

Given that pollution is potentially endogenous, I use instrumental variable estimation. Table 14 reports the first-stage results for the instrumental variables model. I use the dust condition indicator (dust storm, wide-spread dust, or blowing dust) from the nearest weather station data as instrument for AOD. The first stage model includes all exogenous variables in Equation 3.1. The instrument has a statistically significant effect on AOD as suggested by the large first-stage F statistics with a p value of 0.000.

Table 15 presents the instrumental variable (IV) estimation results.[22] School fixed effects are included in all models. Model 1 reports the fixed effects results with controls only for weather, Model 2 also includes time fixed effects, and Model 3 adds school controls. The results of Model 3 indicate that a change in atmospheric conditions from clean to very hazy (i.e. an increase in AOD from 0 to 1) decreases student attendance by 1.89 percent (0.16 std. dev.). Model 4 includes school-month fixed effects, whereas Model 5 and Model 6 have district-year, and tehsil-month fixed effects, respectively. The effect of AOD, instrumented by dust,on student attendance is robust across different fixed effect models (3–6), alleviating a potential concern that dust could be driven by local economic activity

[22] I use xtivreg in Stata.

that also affects attendance.[23]

TABLE 14.
Instrumental variable (IV): First stage

	(1)
	AOD
Dust	0.257***
	(0.0105)
Time FE	✓
Weather Controls	✓
School Controls	✓
Observations	625,490
No. of schools	47,632
F-statistics	7098.05

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

Test Scores

Table 16 reports the effect of AOD on total test scores with school fixed effects.[24] For the test scores data, not all students enrolled in third grade are

[23]For example, in the tehsil-month FE model, anything that is common across all schools in a specific tehsil in a specific month will be stripped away, leaving only the differences among schools within the tehsil in that month. If there is a concern that dust is driven by local conditions, such as drought, it will be shared by all schools in a tehsil, and therefore, will be absorbed by the tehsil-month fixed effects. The estimated differences in outcomes across schools in a tehsil-month, therefore, are due to differences in AOD and temperature across schools in a tehsil-month.

[24]The model includes temperature bins, and the temperature coefficients are reported in section 6.2.2.

TABLE 15.
IV: Incremental effect of AOD on student attendance

	(1)	(2)	(3)	(4)	(5)	(6)
	Attend	Attend	Attend	Attend	Attend	Attend
AOD	-0.419	-1.916***	-1.891***	-1.739**	-1.438**	-1.485**
	(0.557)	(0.578)	(0.648)	(0.838)	(0.624)	(0.643)
Time FE		✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓
School Controls			✓	✓	✓	✓
School-Month FE				✓		
District-Year FE					✓	
Tehsil-Month FE						✓
Observations	868,945	868,945	625,490	625,490	625,490	625,490
Number of schools	47,732	47,732	47,632	47,632	47,632	47,632

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Robust standard errors in parentheses

tested. As discussed in the data section, during each monitoring visit, an average of six or seven students in third grade in each school are randomly selected and tested. Only students who are present on the monitoring day can therefore be selected for testing. Among the models to explain test scores, Model 1 reports the fixed effects results with controls only for weather, Model 2 also includes time fixed effects, and Model 3 adds school controls. Model 4 includes school-month fixed effects, whereas Model 5 and Model 6 have district-year and tehsil-month fixed effects, respectively. The fixed effect (FE) estimates of the effect of AOD in Table 16 suggest that a change in atmospheric conditions from clean to very hazy (i.e. change in AOD from 0 to 1) increases total test scores. As discussed in previous

TABLE 16.
Incremental effect of AOD on test scores (log)

	(1)	(2)	(3)	(4)	(5)	(6)
	Scores	Scores	Scores	Scores	Scores	Scores
FE						
AOD	0.0119***	0.00460***	0.00242***	0.00523***	0.00156*	0.00355***
	(0.000755)	(0.000759)	(0.000887)	(0.00136)	(0.000887)	(0.000904)
IV						
AOD	-0.0200**	-0.0360***	-0.0421***	-0.0186	-0.0384***	-0.0237*
	(0.00835)	(0.00906)	(0.0113)	(0.0214)	(0.0114)	(0.0122)
Time FE		✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓
School Controls			✓	✓	✓	✓
School-Month FE				✓		
District-Year FE					✓	
Tehsil-Month FE						✓
Observations	561,516	561,516	381,741	381,741	381,741	381,741
Number of schools	43,026	43,026	40,068	40,068	40,068	40,068

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

subsection, the estimates of AOD are potentially distorted by omitted variable bias, as well as sample-selection bias, since they are conditional on attendance.

Table 16 also reports the effect of AOD on total test scores using the same dust-related instrument (IV) for AOD. The IV estimates of the AOD coefficient become consistently negative across different fixed effects (Models 3–6). For Model 3, the estimate implies that change in air conditions from clean to very hazy (i.e. change in AOD from 0 to 1) will lower total scores by about 4.2 percent. The estimate can be also interpreted as: the total score on a visit day with average pollution (AOD = 0.58) will be lower relative to the visit day with minimum pollution (AOD = 0.001) by 0.19 (= 4.21 x (0.58-0.001)/12.69) standard deviations. The result for distinct subject scores are presented in Table 17. For the subject scores, a change in air quality from clean to poor (change in AOD from 0 to 1) will reduce Urdu score by 8.4 percent (0.55 std. dev.), reduce math score by about 3.8 percent (0.26 std. dev.) but has no discernible effect on English scores.

Table 18 presents the effect of AOD on the distribution of scores, instrumenting for AOD. For test score analysis, I compute the test score for each school for each monitoring visit and use school fixed effects to control for any unobserved heterogeneity across schools. Given that I have test scores for each individual student tested, I can also examine the effects of AOD on maximum and minimum individual student scores in a school during each monitoring visit to analyze the effects of pollution and temperature on the distribution of test scores.

TABLE 17.
Incremental effect of AOD on subject scores (log)

	(1) Urdu	(2) Math	(3) English
AOD	-0.0841***	-0.0375**	0.00482
	(0.0150)	(0.0148)	(0.0168)
Instrument for AOD	✓	✓	✓
Time FE	✓	✓	✓
Weather Controls	✓	✓	✓
School Controls	✓	✓	✓
Observations	381,700	381,697	381,513
Number of schools	40,068	40,067	40,067

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

TABLE 18.
Incremental effect of AOD on maximum and minimum test scores

	(1) Maximum Score	(2) Minimum Score
AOD	-0.00594	-0.104***
	(0.00621)	(0.0259)
Instrument for AOD	✓	✓
Time FE	✓	✓
Weather Controls	✓	✓
School Controls	✓	✓
Observations	381,741	377,750
Number of schools	40,068	40,062

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

The estimates indicate that change in AOD has no effect on *maximum* individual scores, but a change from clean to very hazy air conditions (i.e. change in AOD from 0 to 1) will reduce the *minimum* score by an average of 10.4 percent (0.48 std. dev.), implying that weaker students have greater harm.

Had the average minimum score increased with poor air quality, we would expect that weaker students are more likely to be absent during periods of high pollution, which could account for them being weaker students in the first place. Of course, this selection effect could still be operating. If it were the case that some weaker students are actually staying home, the size of the negative effect of AOD on test scores would be underestimated.

Temperature

Attendance

Figure 4 shows the effects of temperature levels on student attendance with school fixed effects, without instrumenting for AOD (Model 3 in Table 12) and with instrumenting for AOD (Model 3 in Table 15). The estimates for the temperature bins indicate that an increase in mean air temperature from 16–18°C (60.8–64.4°F) to 34–36°C (93.2–96.8°F) reduces student attendance by 2.3 percent (0.2 std. dev.).[25] Similarly, an increase in mean air temperature from 16–18°C (60.8–64.4°F) to the highest temperature bin of 40–42°C (104–107.6°F) reduces

[25] 16–18°C (60.8–64.4°F) is the baseline temperature bin.

student attendance by 1.1 percent (0.1 std. dev.). On the other hand, a decrease in mean air temperature from 16–18°C (60.8–64.4°F) to 10–12°C (50–53.6°F) increases student attendance by about 0.7 percent.

With the instrument for AOD, temperature bin estimates show that an increase in mean daily air temperature from 16–18°C (60.8–64.4°F) to 34–36°C (93.2–96.8°F) reduces student attendance by about 1.2 percent (0.1 std. dev.), whereas an increase to 36–38°C (96.8–100.4°F) reduces student attendance by 1 percent (0.09 std. dev.). Temperature bins greater than 36–38°C (96.8–100.4°F) appear to have no effect on student attendance. However, some temperature bins lower than the omitted bin have a significant positive effect on attendance. For example, a decrease in mean air temperature from 16–18°C (60.8–64.4°F) to 12–14°C (53.6–57.2°F) increases student attendance by about 0.4 percent.

Test Scores

The effects of temperature levels on total scores for both the fixed effects and instrumental variables estimates (Model 3 in Table 16) are depicted in Figure 5.[26] For test-score analysis, I use bins to describe the mean temperature during the school day only. The estimates for the temperature bins indicate that air temperatures higher or lower than the reference bin (16–18°C) reduce test scores.

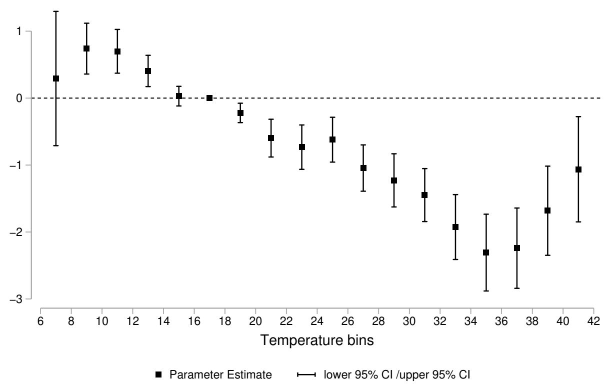
[26] I suppressed the coefficient for temperature bin of 8–10°C (46.4–50°F) in the test scores graphs due to the very small number of observations, and therefore, very large confidence intervals.

For example, an increase in outside temperature from 16–18°C (60.8–64.4°F) to 42–44°C (107.6–111.2°F) reduces total scores by an average of 5.97 percent (0.34 std. dev.). Similarly, a decrease in mean air temperature from 16–18°C (60.8–64.4°F) to 12–14°C (53.6–57.2°F) lowers total scores by an average of about 3 percent (0.17 std. dev.).

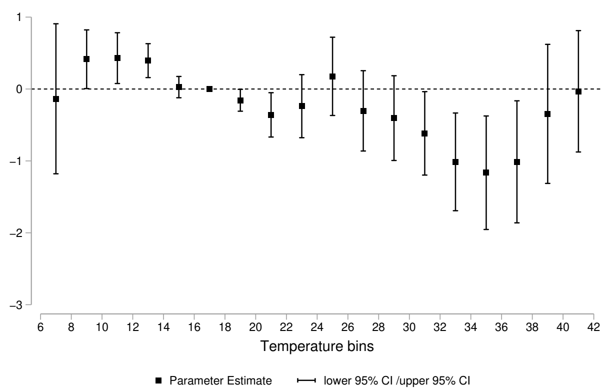
In a model that instruments for AOD, all temperatures relative to the reference bin (16–18°C) reduce total scores. An increase in outside temperature from 16–18°C (60.8–64.4°F) to 34–36°C (93.2–96.8°F) lowers total score by about 5.2 percent (0.29 std. dev.), whereas an increase to 42–44°C (107.6–111.2°F) reduces total score by 3.5 percent (0.2 std. dev.). Temperatures lower than the reference bin also reduce test scores. For example, a decrease in mean air temperature from 16–18°C (60.8–64.4°F) to 12–14°C (53.6–57.2°F), lowers average total scores by 3.89 percent (0.22 std. dev.).

The effects of temperature levels on specific subject scores, using the instrument for AOD, are depicted in Figure 6. The estimates for these temperature bins suggest that temperatures higher or lower than the omitted bin (16–18°C) are associated with lower subject scores. For example, an increase in outside temperature from 16–18°C to 34–36°C (93.2–96.8°F) reduces Urdu scores by 4.98 percent (0.23 std. dev.), math scores by 5.48 percent (0.26 std. dev.), and English scores by 6.14 percent (0.21 std. dev.). Moreover, an increase in outside

FIGURE 4.
Incremental effect of temperature on student attendance

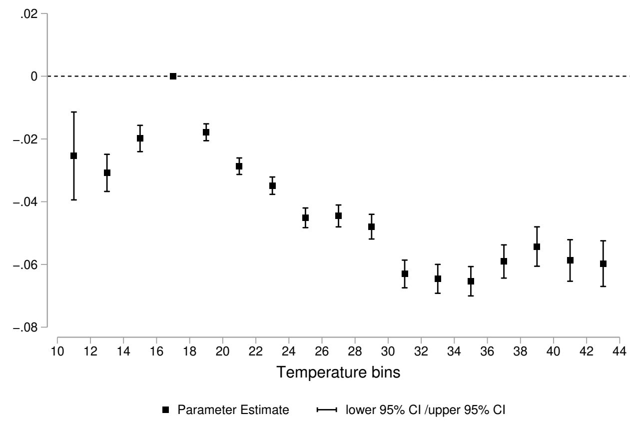


(a) FE only, no instrument

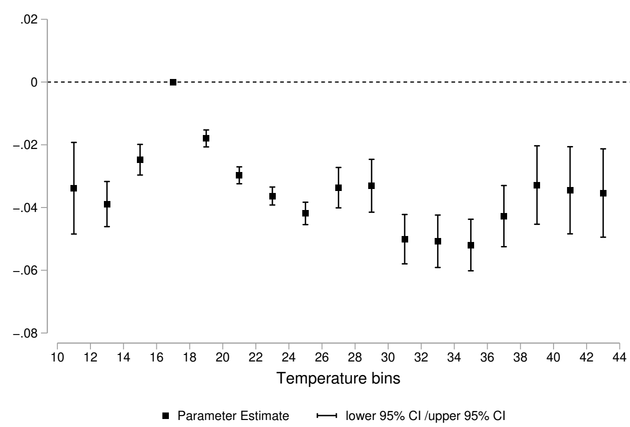


(b) FE plus IV for AOD

FIGURE 5.
Incremental effect of temperature on total scores (log)

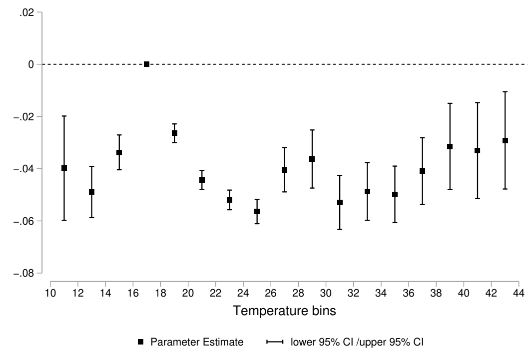


(a) FE only, no instrument

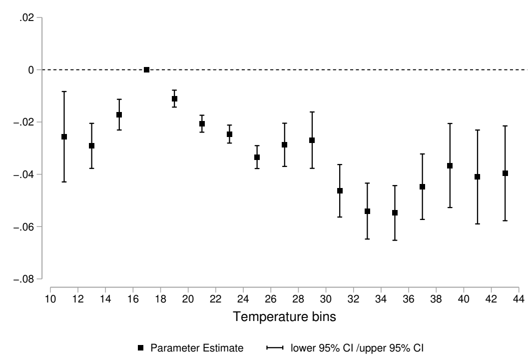


(b) FE plus IV for AOD

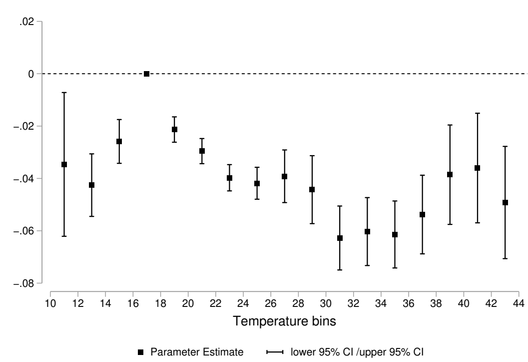
FIGURE 6.
Incremental effect of temperature on subject scores (log)
(FE plus IV for AOD)



(a) Urdu



(b) Math



(c) English

temperature from 16–18°C (60.8–64.4°F) to 42–44°C (107.6–111.2°F) lowers Urdu scores by 2.91 percent (0.13 std. dev.), math scores by 3.96 percent (0.19 std. dev.), and English scores by 4.92 percent (0.17 std. dev.). Even temperatures lower than the reference bin (16–18°C) reduce all subject scores. Specifically, a decrease in mean air temperature from 16–18°C (60.8–64.4°F) to 10–12°C (50–53.6°F), decreases Urdu scores by 3.98 percent (0.18 std. dev.), math scores by 2.56 percent (0.12 std. dev.), and English scores by 3.46 percent (0.12 std. dev.).

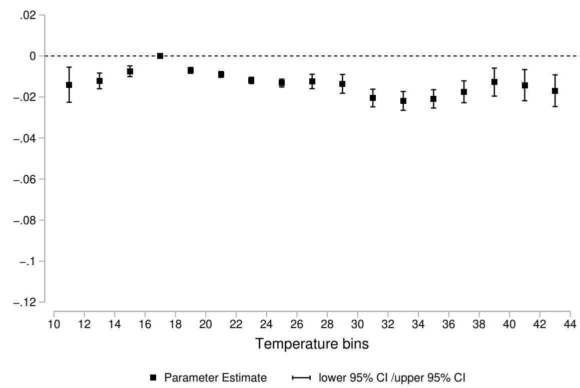
Figure 7 shows the effects of different temperature levels on the maximum and mininum scores, with an instrument for AOD. The estimates indicate that temperatures higher or lower than the 16–18°C reference bin reduce both maximum and minimum individual scores. The estimates can be interpreted as: an increase in outside temperature from 16–18°C (60.8–64.4°F) to 34–36°C (93.2-96.8°F) lowers the maximum individual score by 2.09 percent (0.22 std. dev.) and minimum individual score by 9.95 percent (0.24 std. dev.), whereas an increase to 42–44°C (107.6–111.2°F) reduces the maximum individual score by 1.69 percent (0.18 std. dev.) and minimum individual score by 6.44 percent (0.16 std. dev.)

Heterogeneity Analysis

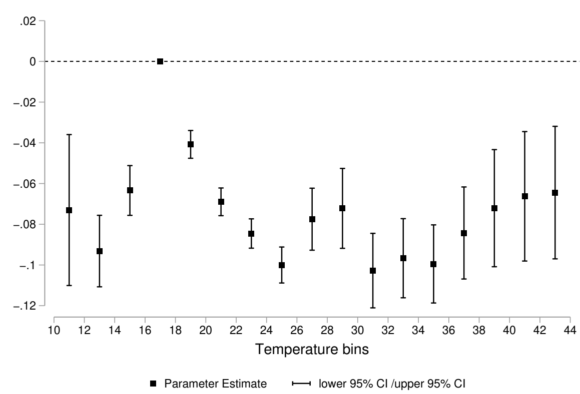
Pollution Effects by Gender

I examine the heterogeneity in the impact of AOD and temperature to

FIGURE 7.
Incremental effect of temperature on maximum and minimum test scores (IV for AOD)



(a) Maximum Score



(b) Minimum Score

identify whether any subgroups are more responsive to poor air quality or extreme temperatures. The gender-differentiated estimation results for pollution are reported in Table 19. These models show that pollution has a slightly larger negative effect on the attendance of boys compared to girls. Specifically, an increase in AOD from 0 to 1 decreases attendance of boys by 2 percent (0.18 std. dev.), whereas the same exposure reduces attendance of girls by 1.8 percent (0.15 std. dev.).

TABLE 19.
Attendance by gender

	(1)	(2)
	Male	Female
AOD	-2.021**	-1.814**
	(0.785)	(0.736)
Instrument for AOD	✓	✓
Time FE	✓	✓
Weather Controls	✓	✓
School Controls	✓	✓
Observations	290,745	334,745
No. of schools	22,400	25,232

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

In Table 20, I examine the differential effects of pollution and temperature levels on test scores for boys' and girls' schools, respectively. Test scores for boys' schools are affected more negatively by pollution than test scores for girls' schools, especially Urdu scores. Specifically, higher pollution (a change in AOD from 0 to 1) lowers total test scores at boys' schools by 4.64 percent (0.36 std. dev.) whereas the same change in AOD lowers test scores at girls' schools by 3.96 percent (0.32 std. dev.). Similarly, this change in air conditions from clean to very hazy lowers Urdu scores for boys' schools by 10.7 percent (0.68 std. dev.) and for girls' schools

TABLE 20.
Test scores (log) by gender

	(1)	(2)	(3)	(4)
	Total	Urdu	Math	English
Male				
AOD	-0.0464***	-0.107***	-0.0278	0.00392
	(0.0178)	(0.0245)	(0.0219)	(0.0267)
Female				
AOD	-0.0396***	-0.0663***	-0.0458**	0.00357
	(0.0146)	(0.0187)	(0.0201)	(0.0216)
Instrument for AOD	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓
School Controls	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

by 6.63 percent (0.45 std. dev.). Increases in pollution levels have no discernible effects on math scores at boys' schools, but this same pollution reduces math scores by 4.58 percent (0.31 std. dev.) at girls' schools.

Using the maximum and minimum individual student scores in a school during each monitoring visit, I examine the effects of pollution and temperature levels on boys' and girls' schools. The estimation results for the pollution effects are presented in Table 21. Pollution has no discernible effect on the maximum individual test score for both boys' and girls' schools. However, a change from clean to very hazy air conditions has a similar effect on the minimum scores at boys' and girls' schools, reducing minimum scores by 11 percent (0.5 std. dev.) for boys' schools, and by 10.1 percent (0.48 std. dev.) for girls' schools.

TABLE 21.
Maximum and minimum test scores by gender

	(1) log(Maximum Score)	(2) log(Minimum Score)
Male		
AOD	0.00305 (0.00956)	-0.110*** (0.0405)
Female		
AOD	-0.00871 (0.00817)	-0.101*** (0.0336)
Instrument for AOD	✓	✓
Time FE	✓	✓
Weather Controls	✓	✓
School Controls	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

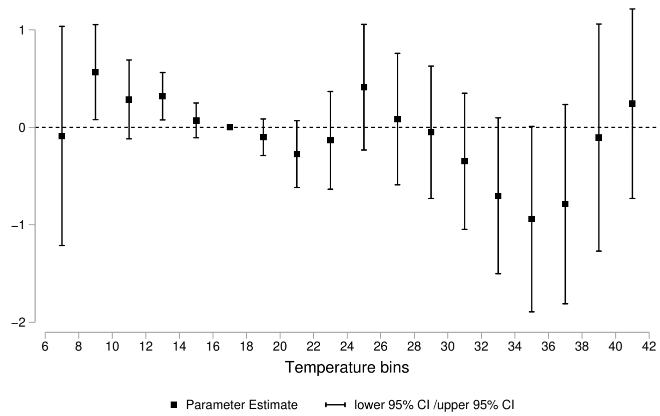
Temperature Effects by Gender

The temperature bin estimates for the two models in Table 19 are presented in Figure 8. Temperatures higher than 16–18°C (60.8–64.4°F) generally have no effect on the attendance of boys. However, for girls schools, an increase in mean air temperature from 16–18°C to 34–36°C (93.2–96.8°F) reduces attendance by 1.34 percent (0.12 std. dev.).

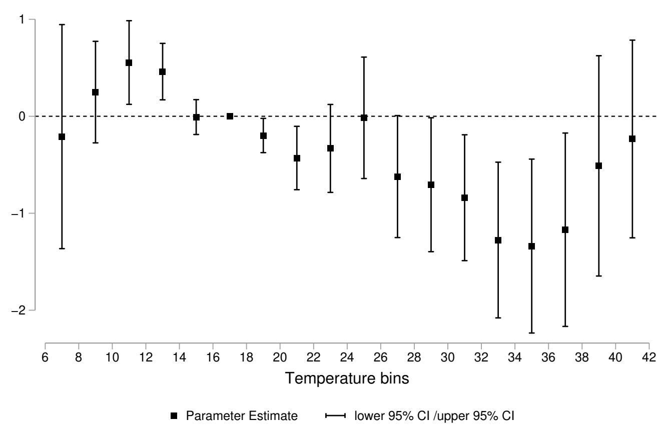
Figure 9 shows the effect of temperature levels on total scores (with the instrument for AOD) for boys' and girls' schools. Similarly, Figure 10 and Figure 11, show the effects of temperature levels on subject scores for boys' and girls' schools, respectively. It is evident from the figures that temperatures higher or lower than 16–18°C reduce test scores for both boys' and girls' schools. An increase in outside temperature from 16–18°C (60.8–64.4°F) to 34–36°C (93.2–96.8°F) reduces total test scores for girls' schools by 4.75 percent (0.27 std. dev.), and lowers total test scores for boys' school by 5.67 percent (0.3 std. dev.). Similarly, an increase in outside temperature from 16–18°C (60.8–64.4°F) to 42–44°C (107.6–111.2°F) reduces total test scores for girls' schools by 3.4 percent (0.19 std. dev.), and lowers total test scores for boys' school by 3.57 percent (0.19 std. dev.).

For subject scores, an increase in temperature from the reference bin (16–18°C) to 34–36°C (93.2–96.8°F) reduces Urdu scores by 5.32 percent (0.21 std.

FIGURE 8.
Effect of temperature on attendance by gender

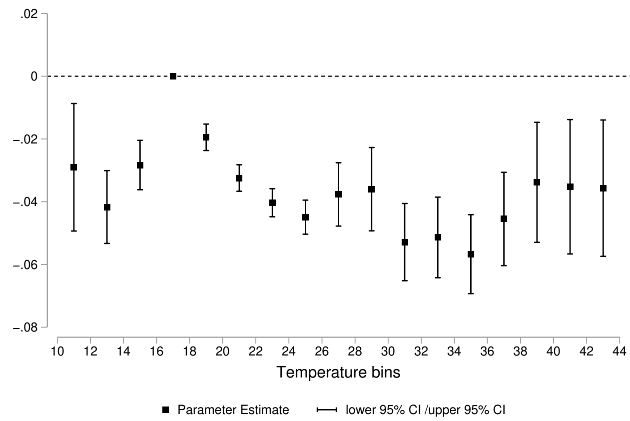


(a) Male

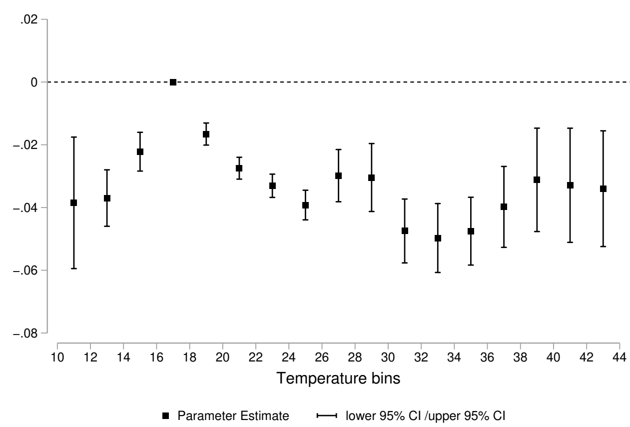


(b) Female

FIGURE 9.
Effect of temperature on total scores by gender

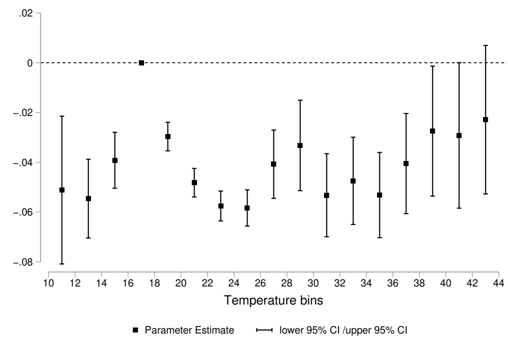


(a) Male

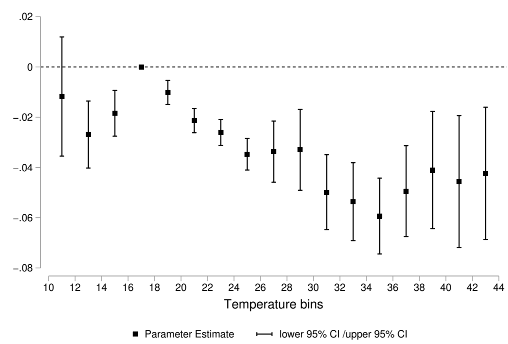


(b) Female

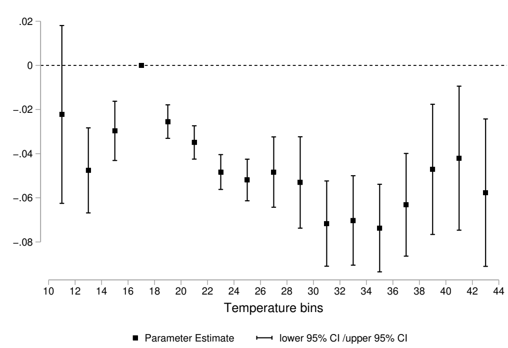
FIGURE 10.
Effect of temperature on subject scores: Male



(a) Urdu

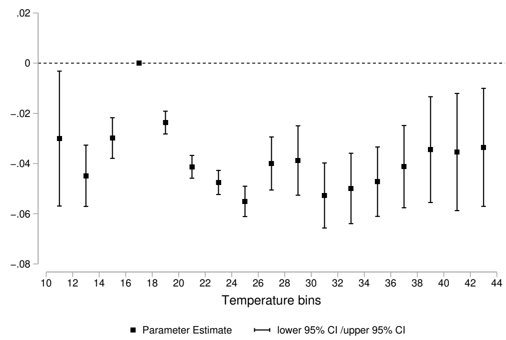


(b) Math

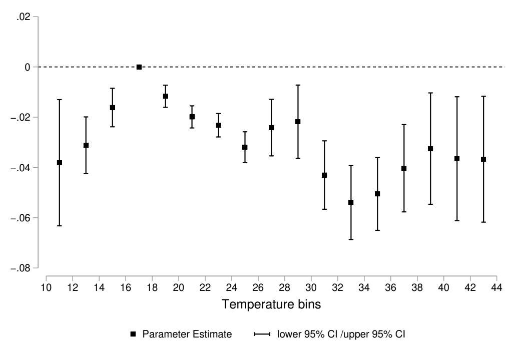


(c) English

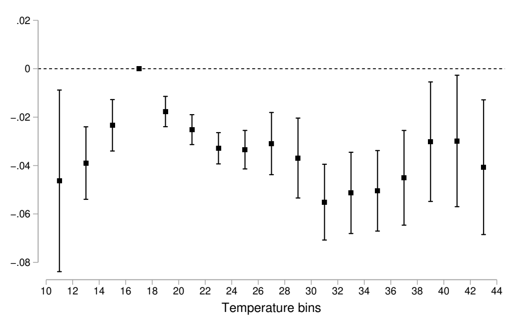
FIGURE 11.
Effect of temperature on subject scores: Female



(a) Urdu



(b) Math



(c) English

dev.) for boys' schools and by 4.72 percent (0.21 std. dev.) for girls' schools, reduces math scores by 5.93 percent (0.27 std. dev.) for boys' schools and by 5.1 percent (0.22 std. dev.) for girls' schools, whereas the English score is reduced by 7.37 percent (0.24 std. dev.) for boys' schools and by 5 percent (0.18 std. dev.) for girls' schools. Similarly, an increase in temperature from 16–18°C to 42–44°C (107.6–111.2°F) reduces Urdu scores by 3.35 percent (0.15 std. dev.) for girls' schools but has no effect on Urdu scores for boys' schools, reduces math scores by 3.67 percent (0.16 std. dev.) for girls' schools and by 4.23 percent (0.19 std. dev.) for boys' schools, whereas the English score is reduced by 4.1 percent (0.15 std. dev.) for girls' schools and by 5.77 percent (0.19 std. dev.) for boys' schools.

Temperatures lower than 16–18°C (60.8–64.4°F) also lower test scores for both boys' and girls' schools. For example, when mean air temperature decreases from 16–18°C (60.8–64.4°F) to 12–14°C (53.6–57.2°F), at boys' schools, there is a decrease in total scores by 4.17 percent (0.22 std. dev.), Urdu scores by 5.46 percent (0.22 std. dev.), math scores by 2.69 percent (0.12 std. dev.), and English scores by 4.76 percent (0.16 std. dev.), whereas at girls' schools, there is a decrease in total scores by 3.7 percent (0.21 std. dev.), Urdu scores by 4.49 percent (0.19 std. dev.), math scores by 3.11 percent (0.14 std. dev.), and English scores by 3.9 percent (0.14 std. dev.).

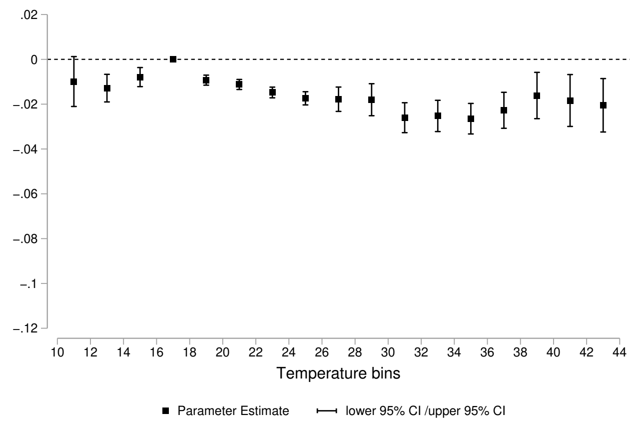
Figure 12 and Figure 13 presents the effects of different temperature levels (with the instrument for AOD) on maximum and minimum scores separately for boys' and girls' schools. Temperatures lower or higher than 16–18°C (60.8–64.4°F) reduce maximum and minimum individual scores of both boys' and girls' schools. For example, an increase in outside temperature from 16–18°C (60.8–64.4°F) to 34–36°C (93.2–96.8°F) lowers maximum individual score by 2.65 percent (0.26 std. dev.) at boys' schools and by 1.61 percent (0.17 std. dev.) at girls' schools, whereas the minimum individual score is reduced by 10.4 percent (0.25 std. dev.) at boys' schools and by 9.51 percent (0.23 std. dev.) at girls' schools.

Moreover, an increase in outside temperature from 16–18°C (60.8–64.4°F) to 42–44°C (107.6–111.2°F) lowers maximum individual score by 2.1 percent (0.2 std. dev.) at boys' schools and by 1.37 percent (0.14 std. dev.) at girls' schools, whereas the minimum individual score is reduced by 6.25 percent (0.15 std. dev.) at boys' schools and by 6.42 percent (0.16 std. dev.) at girls' schools. The maximum individual scores are reduced more by temperature for boys than for girls. Also, temperatures lower than 16–18°C (60.8–64.4°F) reduce maximum and minimum individual scores at both boys' and girls' schools.

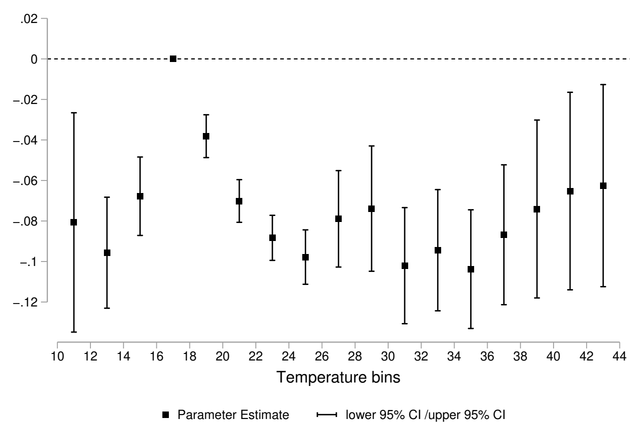
Conclusion

This paper investigates how short-run variations in air quality and temperature can affect children's opportunities to accumulate human capital in a developing country. Specifically, I have sought to estimate the causal effect of air pollution and temperature levels on student attendance and test scores using

FIGURE 12.
Effect of temperature on maximum and minimum scores: Male

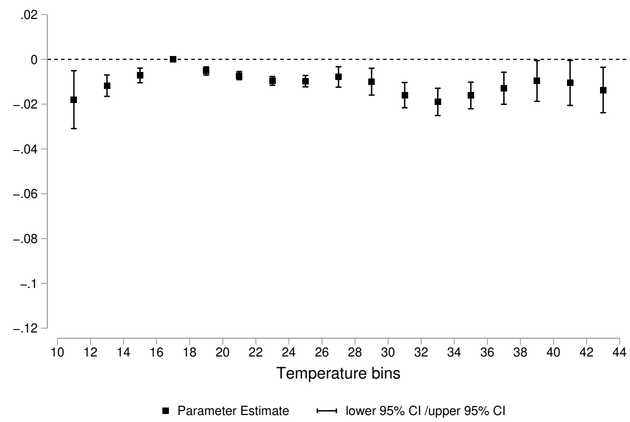


(a) Maximum Score

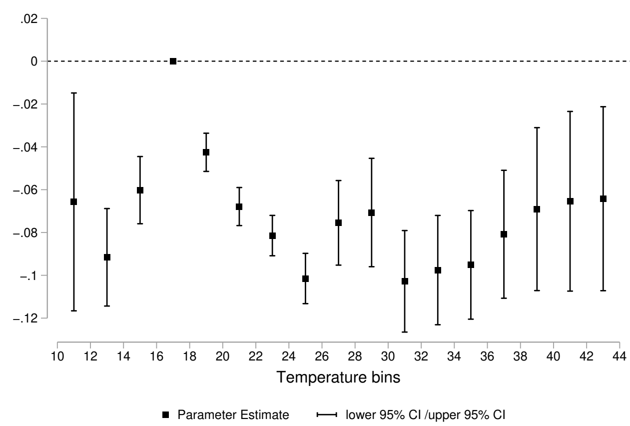


(b) Minimum Score

FIGURE 13.
Effect of temperature on maximum and minimum scores: Female



(a) Maximum Score



(b) Minimum Score

a satellite measure of daily pollution and a novel set of monthly data on school enrollment and test scores in Punjab, Pakistan. For my analysis, I have assembled the most comprehensive daily pollution and weather data available for Punjab over the period 2014–2018. Since air pollution is potentially endogenous, I use exogenous variation in air quality over time due to dust, typically arriving from the deserts within the country, as well as deserts in neighboring countries.

The results of the instrumental variables estimation indicate that an increase in air pollution reduces student attendance, and has an adverse effect on test scores—specifically, math and Urdu scores. Estimates of the effects of different temperature levels show that temperatures higher or lower than 16–18°C (60.8–64.4°F) reduce total test scores as well as subject scores. Temperatures higher than 16–18°C have a greater adverse effect on math scores compared to other subject scores. High temperatures seem to have similar adverse effects on the test scores for both boys and girls. The Urdu test scores are reduced more by pollution for boys than for girls. Increases in pollution seem to have no effect on the math scores for boys, but reduce math scores for girls.

The analysis highlights that the adverse effects of air pollution are not limited solely to health outcomes but can also affect educational outcomes. Moreover, climate change is likely to have not only environmental health effects, but also effects on school attendance and test scores. This is important, because education is a critical component of human capital acquisition, and effective human capital accumulation enhances the potential for sustainable economic development and economic prosperity. Education contributes significantly to higher income levels and economic growth, both at the macro level (Lindahl and Krueger, 2001) and at the micro level (Angrist and Krueger, 1991; Duflo, 2001). Adverse effects of pollution on human capital acquisition suggest that the benefits of regulating pollution are substantially underestimated by a narrow focus solely on environmental health effects.

CHAPTER IV

THE EFFECT OF EARLY-LIFE EXPOSURE TO POLLUTION AND HEATWAVES ON CHILD HEALTH AND SCHOOLING

Introduction

In many developing countries, levels of pollution are far higher than they have ever been in urban areas in the United States, even before the establishment of the U.S. Environmental Protection Agency and the passage of the Clean Air Act and its Amendments (Dominici et al., 2004). About 98 percent of cities in low- to middle-income countries do not meet the air quality standards recommended by World Health Organization (WHO, 2016b). A variety of pollution impacts have now been studied in developed countries, but much less is known for developing countries. A comprehensive understanding of the full scope of the benefits of reductions in air pollution is vital to policy decisions about the necessary stringency of environmental regulations in developing countries.

Increases in emissions of greenhouse gases over the past few decades have increased the frequency and intensity of extreme weather events (IPCC, 2014). There is a growing consensus that continued emissions will cause further warming and increases in precipitation levels and weather variability. These predicted increases in average global temperature and the frequency of extreme events can be expected to have an impact on human health. Effective policies to mitigate climate change require estimation of the benefits of reductions in greenhouse emissions. Research on the potential adverse effects of climate change on health and human capital accumulation is important for designing optimal climate change mitigation policies. Such research is lacking for developing countries because comprehensive and reliable data are unavailable, even though the impacts of climate change are expected to be greater for developing countries (Rylander et al., 2013; IPCC, 2014).

Fetal and early-life development is considered one of the most critical determinants of a child's later development. During the pre-natal period, the fetus is sensitive to external shocks, and adverse conditions in-utero can have substantial negative effects at birth or later in life. A large literature has demonstrated the causal effect on health of a variety of exogenous in-utero shocks, such as famine, war, epidemics, and terror attacks (Almond, 2006; Almond et al., 2007; Harville et al., 2010; Lee, 2014). The emerging literature shows that mild intra-uterine shocks, such as maternal stress, mild nutritional deprivation (during fasting), pollution and weather shocks can have a wide range of impacts on later-life outcomes, including health, educational attainment, test scores, income and crime (Almond and Currie, 2011; Currie and Almond, 2011; Almond et al., 2018).

Rather than focusing on the effects of in-utero shocks on birth or adult outcomes, this paper examines the impact of early-life exposure to mild and persistent shocks on child health and schooling outcomes in a developing country context. Specifically, this paper investigates the effect of in-utero exposure to pollution and heatwaves on physical health and schooling outcomes of young children in Punjab, Pakistan. In-utero exposure to pollution and heatwaves is a natural experiment since I use temporal variation in air pollution and heat waves are exogenous. This research uses satellite measure of pollution and air temperature over the period 2000-2011, and provincially representative surveys of children, women and households.

Concerning environmental quality, large literature suggests that exposure to pollution has harmful health effects in both rich and poor countries.[1] It has been established that in-utero exposure to pollution is associated with greater infant mortality (Glinianaia et al., 2004; Lacasana et al., 2005). The economics literature also provides compelling evidence that in-utero pollution exposure is harmful for birth outcomes, specifically infant mortality and birth weight (Greenstone and Chay, 2003; Currie and Neidell, 2005; Jayachandran, 2009; Currie et al., 2009b; Currie and Walker, 2011; Adhvaryu et al., 2016). Studies have shown that in-utero exposure to pollution also affects longer-term health outcomes, such as asthma, child stunting, and child weight (Clark et al., 2009; Goyal and Canning, 2018; Rosales-Rueda and Triyana, 2019; Spears et al., 2019; Singh et al., 2019).

The epidemiological literature suggests that early life exposure to pollution adversely affects neurological development and cognitive abilities (Perera et al.,

[1] Currie et al., 2009b; Currie and Walker, 2011; Currie et al., 2013; Barron and Torero, 2017; Jayachandran, 2009; Greenstone and Hanna, 2014; Arceo et al., 2016; Molina, 2018.

2008; Perera et al., 2009; Jedrychowski et al., 2014; Li et al., 2018). An emerging literature in economics indicates that in-utero pollution exposure has a negative effect on human capital accumulation, specifically cognition (Sanders, 2012; Bharadwaj et al., 2017; Molina, 2018; Peet, 2016 and labor market outcomes (Peet, 2016; Isen et al., 2017b; Molina, 2018). Similar adverse effects have been demonstrated for in-utero exposure to extreme temperatures.[2][3]

This paper contributes to the literature by addressing a research gap by focusing on early childhood health and schooling outcomes, given a large part of the existing literature that examines the impact of in-utero exposure to pollution or extreme temperature focuses on either birth outcomes or adult outcomes (Almond et al., 2018). To my knowledge, this is the first paper to estimate the effect of early-life exposure to air pollution and extreme temperature on children's physical health (as indicated by stunting and underweight status) and schooling outcomes in Pakistan.

Another contribution of this study is that I have assembled the most comprehensive daily pollution and weather data available for Punjab, Pakistan over the period 2000-2011. There is no reliable comprehensive ground-level

[2]On birth outcomes: Bhattacharya et al., 2003; Guryan and Deschenes, 2009; Cil and Cameron, 2017; Kim et al., 2019; Currie and Rossin-Slater, 2013; Grace et al., 2015; Andalón et al., 2016; Molina and Saldarriaga, 2017; Zhang et al., 2017; Banerjee and Maharaj, 2020; Chen et al., 2020

[3]On later-life outcomes: Child health and growth (Regmi et al., 2008; Wang et al., 2009; Skoufias and Vinha, 2012; Groppo and Kraehnert, 2016; Molina and Saldarriaga, 2018; Ogasawara and Yumitori, 2019; Bishwakarma, 2019), educational attainment and learning outcomes (Wilde et al., 2017; Barron et al., 2018; Zivin and Neidall, 2018; Hu and Li, 2019), and adult health and earnings (Agüero, 2014; Isen et al., 2017a; Mueller and Gray, 2018).

monitoring of air quality in Pakistan, so there is only very limited conventional administrative air quality data available for the country. Thus, I use remotely sensed satellite data for air pollution across Punjab (specifically, AOD—aerosol optical depth). The daily weather data (at three-hour intervals) is extracted from the Global Land Data Assimilation System Version 2 (GLDAS-2.1) using Earth Engine.[4]. Using the detailed daily satellite pollution and weather data, I also investigate the effects of cumulative exposure to pollution and heatwave days (from conception through the child's current age) on physical health outcomes for children aged 0–59 months. None of the existing studies on in-utero pollution and extreme temperature impacts examine the effects of *cumulative* exposures to pollution or extreme temperatures.

My results indicate that a one-standard-deviation increase in AOD exposure during the first trimester of gestation lowers height-for-age z-score by 0.068 standard deviations and the weight-for-age z-score by 0.065 standard deviations, whereas a one-standard-deviation increase in AOD exposure during the third trimester of gestation reduces height-for-age z-score by 0.057 standard deviations and the weight-for-age z-score by 0.06 standard deviations.[5] Other studies for Bangladesh (Goyal and Canning, 2018) and India (Singh et al., 2019, Spears et al.,

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[4] `https://developers.google.com/earth-engine/datasetscatalogNASA_GLDAS_V021_NOAH_G025_T3H`

[5] Negative height-for-age z-scores reflect long term deficiencies in nutrition and/or health, resulting in children not reaching their growth potential. Specifically, height-for-age z-scores of less than -2 are defined as stunting or growth retardation. Similarly, weight-for-age z-scores less than -2 define underweight children (World Health Organization, 1995b).

2019) find a larger effect of in-utero pollution exposure on the height-for-age z-score. This difference may stem from the fact that they measure pollution using satellite based $PM_{2.5}$.

I also find that an additional heatwave day during pregnancy reduces the height-for-age z-score by 0.008 standard deviations. In other words, a one-standard-deviation increase in heatwave days during pregnancy reduces the height-for-age z-score by 0.01 standard deviations. This finding is comparable to the 0.008-0.011 standard deviation reduction in the height-for-age z-score due to an additional high-temperature day during gestation in Nepal (Bishwakarma, 2019) and to the 0.09 standard deviation reduction in the height-for-age z-score from a one-standard-deviation increase in local mean temperature during pregnancy in Peru (Molina and Saldarriaga, 2018). The results also suggest that an additional heatwave day in the second trimester decreases the height-for-age z-score by 0.008 standard deviations. Similarly, an additional heatwave day in the third trimester lowers the height-for-age z-score by 0.012 standard deviations and the weight-for-age z-score by 0.009 standard deviations. Given that about 94 percent of households in the sample do not have air conditioning, there is little concern regarding the role of the mother's avoidance behavior (i.e. their ability to avoid heat).

To investigate whether exposure to such adverse events in-utero has long-lasting effects, I divide the sample of children aged 0–59 months into four subgroups according to their ages: children younger than 16 months, children between 16 and 30 months, children between 31 and 45 months, and children older than 45 months.[6] I find that in-utero exposure to heatwave days has a discernible adverse effect on height-for-age z-scores of children younger than 46 months but seems to have no effect on children between 46–59 months, suggesting that the effects of temperature shocks in-utero decline with age. For Nepal, Bishwakarma (2019) also finds a significant effect of high temperature days in-utero on the height-for-age z-score for children younger than 30 months but no such effect for children between 31–59 months.

The results for the effects of cumulative exposure (conception until current age) to pollution and heatwave days on health outcomes for children aged 0–59 months suggests an adverse effect of pollution on both the height-for-age z-score and the weight-for-age z-score, but an adverse effect of heatwave days on only the height-for-age z-scores. I also find that an increase in pollution in the first trimester decreases the probability of a school-age child being in school and the current grade of the child, controlling for age, whereas poor air quality in the second trimester lowers the propensity of a school-age child to be in school. However, heatwave days during trimesters have no effect on the probability of a school-age child being in school and the current grade of the child.

[6] The sample of children under five is divided into four sub-samples so that sample size of each sub-sample remains relatively large.

The remainder of the paper is organized as follows. Section 4.2 presents the background on the health indicators used in the paper. Section 4.3 discusses data, and the empirical model is detailed in Section 4.4. Section 4.5 presents the estimation results, and robustness checks are discussed in 4.6, followed by concluding remarks in Section 4.7.

Background

Child growth is considered an important indicator of nutritional status and health (World Health Organization, 1995b). Across the world, there are 165 million malnourished children under five years of age (Black et al., 2013). Childhood malnourishment, including conditions of underweight, stunting and wasting, is prevalent in developing countries and accounts for at least half of deaths among children under five years old (Meshram et al., 2012; Demissie and Worku, 2013; Liu et al., 2015).[7] Stunting is the most common form of malnutrition, and one of the most important policy issues in developing countries (Oruamabo, 2015; de Onis and Branca, 2016).[8] Growth faltering usually begins in-utero and goes on for at least the first two years of life (de Onis and Branca, 2016).

[7]Underweight children can reflect wasting, stunting or both. Stunting, on the other hand, reflects cumulative effects of undernutrition, therefore, reflects long-term changes in malnutrition.

[8]Stunting is one of the six global nutrition targets adopted by World Health Assembly for 2025 (World Health Organization, 2012).

Pakistan has one of the highest prevalences of malnourished children in comparison to other developing countries (Di Cesare et al., 2015). In 2012, 45 percent of children under five in Pakistan had stunting, whereas the world average rate of stunting for children under five was 24.9 percent.[9]. Similarly, 31.6 percent of children under five were underweight in Pakistan in 2012, whereas the world average was 15.4 percent.[10]. Being underweight increases mortality risks in children and inhibits their cognitive development. Malnourished women are more likely to have low-birth-weight babies, therefore perpetuating malnourishment across generations (World Health Organization, 1995a). Stunting is also associated with higher mortality, reduced long-term health, poor school performance, reduced cognitive ability, decreased adult labor productivity and income, and lower offspring birth weight (Strauss and Thomas, 2008; Victora et al., 2008; Kelly, 2011; Vogl, 2014; McGovern et al., 2017; Rosales-Rueda and Triyana, 2019).

Data

Data on Children

The data on physical health and schooling outcomes for children are drawn from two rounds of the Punjab Multiple Indicator Cluster Survey (MICS), during

[9] https://data.worldbank.org/indicator/SH.STA.STNT.ZS

[10] https://data.worldbank.org/indicator/SH.STA.MALN.ZS

2007-2008 and 2011.[11] The Punjab MICS is a provincially representative survey of children, women and households. The smallest geographical unit in these surveys is the tehsil (sub-county) for the household.[12] Figure 28 in Appendix depicts the tehsils in Punjab. The Punjab MICS uses a two-stage stratified cluster sample selection technique and has comprehensive information on the children, including early childhood development and schooling outcomes.[13] Specifically, the Punjab MICS has detailed information on the heights and weights of children aged 0-59 months. For school-aged children (5–14 years), there is information on whether a child attends school, the current grade of the child and the type of school the child attends. The Punjab MICS also has information about the birth history of women aged 15 to 49, maternal background and household characteristics. The 2007-2008 Punjab MICS has a sample size of 91,280 households with information on 74,830 children, whereas the 2011 Punjab MICS has a sample size of 102,545 households, with information on 161,061 children.[14]

[11] The Multiple Indicator Cluster Survey is conducted by the Bureau of Statistics, Government of Punjab in collaboration with United Nation Children Fund (UNICEF) and United Nation Development Program (UNDP).

[12] The more recent Punjab MICS, for 2014 and 2017-2018, are at the district (county) level.

[13] In the first stage, enumeration areas (enumeration blocks in urban areas or villages/mouzas/dehs in rural areas) were selected in the 273/287 sampling domains, with probability proportional to population size. In the second stage, in each enumeration area, a systematic sample of 12 households in urban areas and 16 households in rural areas was randomly drawn.

[14] For children under 5 years of age, about 23 percent of the sample size is dropped due to missing data for birth year or birth month, having a birth year prior to 2000 (because the satellite AOD and weather data starts from 2000), and, when a child appears to be a significant outlier in terms of their height-for-age or weight-for-age z-scores.

This paper focuses on in-utero exposure to pollution and heatwaves for which I need the geographic location of the birth to match the pollution and temperature data for the child's trimesters of gestation. The trimesters of pregnancies are computed relative to the birth month. The third trimester of pregnancies is imputed as the three-month period prior to birth. Similarly, the second trimester is the fourth through six months prior to the birth month, and the first trimester is the six through nine months prior to the birth month. I make the assumption that the residence of the mother during gestation is the same as the current residence of a child since no more-detailed residential location information is available.

The outcome variables for child health used in this paper consist of anthropometric measures: height-for-age and weight-for-age z-scores, calculated using the World Health Organization standards for children aged 0–59 months. The mean height-for-age z-score in the sample is -1.42 and the mean weight-for-age z-score is -1.49. Negative height-for-age z-scores reflect long-term deficiencies in nutrition and/or health, resulting in children not reaching their growth potential. Specifically, height-for-age z-scores of less than -2 are defined as stunting or growth retardation. Similarly, weight-for-age z-scores less than -2 define underweight children (World Health Organization, 1995b). However, underweight is a composite indicator, which can reflect stunting and/or wasting (acute weight loss), making it difficult to interpret. Figure 29 and Figure 30 in Appendix show the distribution of height-for-age and weight-for-age z-scores in the sample. About 34 percent of these children are stunted, and about 33 percent of these children are underweight. The schooling outcome variables used in this paper are (a) whether a school-aged child (aged 5–14) is in school, and (b) the current grade of a school-aged child.

Pollution Data

There is limited administrative air-quality data available for Pakistan since the country does no comprehensive ground-level monitoring of air quality. A variety of satellites, launched in the past two decades, have allowed for improved measurement of air quality from space. Moreover, remotely sensed data collected by satellites gives us access to information that is difficult to obtain in other ways. For example, in many parts of the world, especially in developing countries, ground-based pollution monitoring stations are not only extremely sparse, they may also be subject to strategic government manipulation.[15]

This paper focuses on in-utero exposure, so it is important to measure daily or monthly pollution levels at a fine level of geographic specificity. Therefore, I use the aerosol optical depth (AOD) data. The daily air pollution (AOD) data for Punjab are obtained using the MODIS (Moderate Resolution Imaging Spectroradiometer) instrument on the Terra Satellite over the period 2000-2011. Observed daily AOD values in the data ranges from -0.05 to 5, with higher values

[15] Donaldson and Storeygard (2016) provide an overview of the current state-of-the-art of satellite data that have been exploited in the economics literature and suggest future avenues for use of satellite data.

indicating more aerosols in the air and thus poorer air quality.[16] I know the location (tehsil) of current residence of each child, so the daily AOD values that I associate with each child's in-utero and early life exposure are the average AOD values across all 10km x 10km cells within 1-km of the specific tehsil. Using the daily AOD values, I compute average pollution levels during each trimester of each child's gestation period.

There are increasing numbers of papers in economics that rely on satellite imagery to measure pollution. Jayachandran (2009) uses aerosol optical depth (AOD) data from the satellite to measure air pollution due to the forest fires in Indonesia. Foster et al. (2009) explore the impact of air pollution, measured using satellite MODIS data, on infant mortality. Chen et al. (2013) and Bombardini and Li (2016), investigate the causes of air pollution in China. They also compare satellite pollution data with pollution data from ground-based monitoring systems, in a context where pollution is a politically contentious issue. Voorheis (2017) combines satellite data on fine particulate matter with linked administrative and survey data to create a new dataset of individual pollution exposure each year in the U.S. between 2000 and 2014. Zou (2018) uses satellite measures of pollution (AOD) to compare pollution levels in the U.S. on monitored days and unmonitored days, to examine the consequences of federal Clean Air Act policy that requires monitoring sites to use a once-every-six-days air quality monitoring schedule.

[16]The AOD value is missing for some tehsil-days due to cloud coverage.

Weather Data

My analysis uses weather data from the Global Land Data Assimilation System Version 2 (GLDAS-2.1) with a 0.25° spatial resolution.[17] The Global Land Data Assimilation System (GLDAS) uses advanced surface modeling and data assimilation techniques to process satellite and ground-based observational data products, to create optimal fields of land surface states and fluxes. The GLDAS is a unique land-surface modeling system which (1) integrates large observation-based datasets, (2) uses multiple models, (3) runs globally at a high resolution of 0.25°, and (4) generates near-real-time results (Rodell et al., 2004). The GLDAS-2 has two components, the GLDAS-2.0 dataset comes entirely from the Princeton meteorological data, and the GLDAS-2.1 dataset comes from a combination of model and observation-based datasets. Using Google's Earth Engine, I extract daily data (at three-hour intervals) for air temperature, precipitation, humidity, and wind speed for each tehsil in Punjab over the period 2000–2011. Using these daily temperature data, I construct a measure for heatwave days in each child's tehsil of birth/residence as follows:

[17] There are about 38 ground weather stations distributed unevenly across Punjab, but the daily weather data from these monitors does not go back as far as 2000 for any of these weather stations.

$$heatwave_{jm\tau} = \begin{cases} 1, & \text{if} \quad temp_{jm\tau} > \overline{temp_{jm\tau}} + 1.5 * \sigma_{jm\tau} \quad \& \quad temp_{jm\tau} >= 32°C \\ \\ 0, & \text{otherwise} \end{cases} \tag{4.1}$$

The variable $temp_{jm\tau}$ is the mean temperature on calendar day τ in month m in tehsil j, $\overline{temp_{jm\tau}}$ is the tehsil's temperature mean for calendar day τ in month m over the entire study period e.g. 2000–2011, and $\sigma_{jm\tau}$ is the temperature standard deviation of tehsil j for calendar day τ in month m over the same time period. In other words, a day is defined as a heatwave day if the mean temperature on that day is at least 1.5 standard deviations greater than the tehsil's temperature mean over the entire time period and the mean temperature on that day is greater than 32°C (89.6°F).[18] [19] [20] [21]

[18]It may have been preferable to use historical temperature data, but the GLDAS data do not extend prior to 2000.

[19]Molina and Saldarriaga (2017) and Barron et al. (2018) define temperature shock during gestation period as one standard deviation above district's historical mean. Kim et al. (2019) considers extreme heat exposure during gestation as three standard deviations above county-month's average.

[20]I have also done the analysis with heatwaves defined as temperature that is one and two standard deviation above tehsil's historical mean. The results are not very different qualitatively.

[21]The mean temperature on a particular day being at least 1.5 standard deviations greater than the tehsil's temperature mean over the period 2000–2011 will only likely be a problem if the mean temperature on the day is also high, such as above 90°F. For example, if temperature on a day in winter is at least 1.5 standard deviations greater than the tehsil's mean temperature, temperatures will be unseasonably high, but in an absolute sense they might be quite pleasant, rather than uncomfortably cold.

Table 22 presents summary statistics for average monthly AOD and the count of heatwave days in a month in Punjab over the period 2000–2011. The monthly AOD ranges between 0.05 and 3.5, with a mean of about 0.62. In contrast, for the United States, AOD ranges from 0 to 1, with an average of about 0.12 during the period 2001 through 2013 (Zou, 2018). AOD is a dimensionless unit, with a value of less than 0.1 indicating a "clean" atmosphere, whereas a value of 1 or more indicating very hazy conditions.[22]. Figure 31 in the Appendix depicts the average AOD for the different tehsils of Punjab across the entire period of 2000–2011.

Over time, however, the mean annual temperature in Punjab has increased from 24.9°C (76.8°F) in 2000 to 25.8°C (78.5°F) in 2011. Figure 32 in the Appendix depicts mean annual temperatures across all tehsils of Punjab in 2000 versus 2011. The maximum annual temperature has increased from 27.8°C (82.0°F) in 2000 to 28.7°C (83.7°F) in 2011. Across all tehsils and all months, the average number of heatwave days in a month in a tehsil is about 1 day (but ranges from 0 to 25).

The average age of children in the sample is about 7 years, and on average there are 1.5 siblings in each child's family.[23] The mean school grade of current students is 4^{th} grade. The mean age of the mother at birth is about 28 years and mothers have about 3 years of schooling on average. Given that 94 percent of

[22] `https://earthobservatory.nasa.gov/global-maps/MODAL2_M_AER_OD`

[23] This includes all children aged 0–14 years in the sample.

households in the data do not have air conditioning, there is little concern about each mother's avoidance behavior (i.e. their ability to avoid heat through the unobserved availability of air conditioning in the home).

TABLE 22.
Summary Statistics

	(1) Mean	(2) Std. Dev.	(3) Min	(4) Max
AOD	0.66	0.31	0.07	3.5
Heatwave days	0.48	1.42	0	16
Height-for-age z-score	-1.44	1.64	-6	5.99
Weight-for-age z-score	-1.49	1.21	-6	5.98
1(Attends school)	0.80			
Current grade	3.92	2.39	1	14
Age	6.87	4.29	0	14
1(Male)	0.52			
No. of siblings	1.57	1.32	0	8
Mother's age at birth	27.76	5.84	16	49
Mother's education	3.67	4.55	0	17
1(Urban tehsil)	0.29			

Notes: The variables Attends school, Male, and Urban tehsil are indicator variables.

Empirical Model

The main equations I estimate take the following form:

$$Y_{ijym} = \alpha_0 + \beta AOD_{ijym} + \gamma T_{ijym} + W_{ijym}\Theta + X_i\Pi_i + \alpha_m + \delta_y + \mu_j + \epsilon_{ijym} \quad (4.2)$$

where Y_{ijym} is some health or schooling outcome variable for child i, assumed to have been born in tehsil j, in year y and month m. AOD_{ijym} is the average air pollution in child i's tehsil of birth, j, during his or her gestation. T_{ijym} is the number of heatwave days in child i's tehsil of birth during gestation. W_{ijym} is a vector of additional weather controls in child i's tehsil of birth, also in month m, which includes mean humidity, mean precipitation, and mean wind speed.

It has been established empirically in the previous literature in other contexts that health and schooling outcomes can be associated with sociodemographic characteristics of the child, mother and the household. Failure to account for these sociodemographic characteristics in the estimation model for health and schooling outcomes would potentially allow the sociodemographic characteristics to confound the estimates of the effects of pollution and heatwaves on these outcomes of interest. I define X_i as a vector of child, mother and household characteristics that can also affect child health and schooling outcomes. These child characteristics include age, gender, and number of siblings, whereas the mother characteristics include age at child's birth, education and marital status. Additional household characteristics include whether the household dwells in an urban area (as opposed to a rural area), and the household's wealth score relative to the a distribution of wealth scores across the survey sample.[24]

[24] The wealth scores are computed by the Bureau of Statistics, Government of Punjab, using information on household goods and assets. These include number of rooms; material used for roof, floor, and dwelling wall; type of cooking fuel; gas; electricity; radio; television; cable television; mobile phone; computer; internet access; refrigerator; washing machine; air conditioner; cooler; microwave; sewing machine; iron; watch; car or truck; motorcycle; bicycle;

To minimize any heterogeneity bias from unobserved factors, I also use birth-month (seasonal) fixed effects, α_m, birth-year fixed effects, δ_y, and tehsil fixed effects, μ_j, in the estimation model. These fixed effects control for seasonality in birth outcomes, and any common systematic changes in birth or schooling outcomes over the years, and time-invariant tehsil characteristics. Finally, ϵ_{ijym} is an idiosyncratic error term. To account for likely spatial correlations, the robust standard errors are clustered at the tehsil level.

To examine whether the effects of pollution and heatwave days vary by trimester, I modify Equation 4.2 by including AOD, heatwave days, and weather controls separately for each trimester. According to the medical literature, the first trimester is the period of fetal body development. In the second trimester, vital organs develop. The third trimester is characterized by fetal growth in size and weight.

$$Y_{ijym} = \alpha_0 + \sum_{k=1}^{3} \beta_k AOD_{ijymk} + \sum_{k=1}^{3} \gamma_k T_{ijymk} + \sum_{k=1}^{3} W_{ijymk}\Theta_k + X_i\Pi_i + \alpha_m + \delta_y + \mu_j + \epsilon_{ijym} \tag{4.3}$$

where AOD_{ijym1}, AOD_{ijym2} and AOD_{ijym3} measure mean pollution in the first, second and third trimesters, respectively, of child i, born in tehsil j, in year y and calendar month m. Similarly, T_{ijym1}, T_{ijym2} and T_{ijym3} are the numbers

animal-drawn cart; water filter; motor pump; drinking water source and type of sanitation facility. Each household is weighted by the number of household members.

of heatwave days in the first, second and third trimesters, respectively. The differences in the health and schooling outcome variables attributable to pollution and heatwave days during different pregnancy trimesters are given by β and γ, respectively.

Results

Height for age. Table 23 reports the effect of AOD and heatwave days on height-for-age z-scores. Model 1 reports the results with controls only for weather. Model 2 includes child characteristics, and Model 3 adds mother characteristics. Model 4 further includes other household characteristics. All models include birth-month, birth-year and tehsil fixed effects. The results in the full Model (4) suggest that a change in atmospheric conditions from clean to very hazy (i.e. change in mean AOD from 0 to 1) during gestation lowers height-for-age z-scores by 0.372, whereas an additional heatwave day during gestation reduces height-for-age z-scores by 0.0129.[25]

Weight for age. Table 24 reports the effects of AOD and heatwave days on weight-for-age z-scores. As in Table 23, Model 1 reports the results with controls only for weather, whereas Model 2 also includes child characteristics. Model 3 adds

[25] Results of Model (4) with all the controls are provided in Table 36 in the Appendix. Mother's education has a positive and statistically effect on child's height-for-age z-score. Having more siblings lowers a child's height-for-age z-score, and children in households with a higher wealth score have larger height-for-age z-scores.

TABLE 23.
Effect of AOD & Heatwaves on Height-for-Age z-scores

	Height-for-Age			
	(1)	(2)	(3)	(4)
AOD	-0.241	-0.562***	-0.565***	-0.372**
	(0.151)	(0.151)	(0.152)	(0.167)
Heatwaves	-0.0132***	-0.0117***	-0.0122***	-0.0129***
	(0.00213)	(0.00212)	(0.00212)	(0.00223)
Weather Controls	✓	✓	✓	✓
Child Controls		✓	✓	✓
Mother Controls			✓	✓
HH Controls				✓
Birth-month FE	✓	✓	✓	✓
Birth-year FE	✓	✓	✓	✓
Tehsil FE	✓	✓	✓	✓
Observations	116,881	116,881	114,767	97,468
R-squared	0.068	0.072	0.083	0.095

Notes: The weather controls include mean humidity, mean precipitation and mean wind speed. The child controls include age, gender and number of siblings, whereas mother controls include age at birth, education and marital status. The household controls include whether the household dwells in an urban area, and the household's wealth score. Robust standard errors are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

mother characteristics and Model 4 also includes household characteristics. All models include fixed effects for birth-month, birth-year and tehsil. The results in the full Model (4) suggest that a change in atmospheric conditions from clean to very hazy (i.e. change in mean AOD from 0 to 1) during gestation reduces weight-for-age z-scores by 0.4, whereas an additional heatwave day during gestation reduces weight-for-age z-scores by 0.00496.[26]

TABLE 24.
Effect of AOD & Heatwaves on Weight-for-Age z-scores

	Weight-for-Age			
	(1)	(2)	(3)	(4)
AOD	-0.582***	-0.529***	-0.537***	-0.400***
	(0.121)	(0.121)	(0.121)	(0.138)
Heatwaves	-0.00399**	-0.00425**	-0.00458***	-0.00496***
	(0.00175)	(0.00175)	(0.00175)	(0.00187)
Weather Controls	✓	✓	✓	✓
Child Controls		✓	✓	✓
Mother Controls			✓	✓
HH Controls				✓
Birth-month FE	✓	✓	✓	✓
Birth-year FE	✓	✓	✓	✓
Tehsil FE	✓	✓	✓	✓
Observations	116,879	116,879	114,765	97,458
R-squared	0.037	0.038	0.048	0.054

Notes: The weather controls include mean humidity, mean precipitation and mean wind speed. The child controls include age, gender and number of siblings, whereas mother controls include age at birth, education and marital status. The household controls include whether the household dwells in an urban area, and the household's wealth score. Robust standard errors are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

[26] Results of Model (4) with all the controls are depicted in Table 37 in the Appendix. Higher mother's education increases child's weight-for-age z-score. Having more siblings lowers a child's weight-for-age z-score, and children in households with a higher wealth score have larger weight-for-age z-scores.

Differentiating effects by trimester. Table 25 presents the results of the effect of AOD and heatwave days by trimesters. The results indicate that an increase in mean AOD in the first and third trimester reduces both height-for-age z-scores and weight for age z-scores. Specifically, a change in air condition from clean to very hazy (i.e. change in mean AOD from 0 to 1) in the first trimester, lowers height-for-age z-scores by 0.358 and weight-for-age z-scores by 0.253. Similarly, a change in atmospheric conditions from clean to very hazy (i.e. change in mean AOD from 0 to 1) in the third trimester reduces height-for-age z-scores by 0.303 and weight-for-age z-scores by 0.234. However, an increase in AOD during the second trimester increases height-for-age z-scores, which seems counter-intuitive and puzzling.

Concerning the effects of heatwaves by trimester, an additional heatwave day during the second trimester reduces height-for-age z-scores by 0.013. Similarly, an additional heatwave day in the third trimester lowers average height-for-age z-scores by 0.0192 and average weight-for-age z-scores by 0.011.

Schooling outcomes. Table 26 reports the results of the effect of AOD and heatwave days in-utero, by trimester, on whether a school-aged (5-14) child is in school and on the current school-grade of the child, controlling for their age. Whether or not a school-aged child is in school is an indicator variable, so I estimate Model 1 using a binary logit specification. As current grade is a discrete

TABLE 25.
Effect of AOD & Heatwaves by Trimesters

	(1) Height-for-age z-score	(2) Weight-for-age z-score
AOD		
Trimester 1	-0.358***	-0.253***
	(0.0847)	(0.0721)
Trimester 2	0.166**	0.0187
	(0.0842)	(0.0699)
Trimester 3	-0.303***	-0.234***
	(0.0993)	(0.0829)
Heatwaves		
Trimester 1	0.000190	0.00124
	(0.00340)	(0.00290)
Trimester 2	-0.0130***	0.000474
	(0.00351)	(0.00293)
Trimester 3	-0.0192***	-0.0111***
	(0.00292)	(0.00250)
Controls	✓	✓
Birth-month FE	✓	✓
Birth-year FE	✓	✓
Tehsil FE	✓	✓
Observations	97,468	97,458
R-squared	0.096	0.054

Notes: The controls include weather, child, mother and household characteristics. The weather characteristics include mean humidity, mean precipitation and mean wind speed. The child characteristics include age, gender and number of siblings, whereas mother controls include age at birth, education and marital status. The household controls include whether the household dwells in an urban area, and the household's wealth score. Robust standard errors are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

TABLE 26.
Effect of AOD & Heatwaves on Schooling Status

	(1) In School	(2) Current Grade
AOD		
Trimester 1	-0.238**	-0.0843***
	(0.112)	(0.0300)
Trimester 2	-0.509***	-0.0211
	(0.115)	(0.0308)
Trimester 3	0.0191	0.0357
	(0.134)	(0.0357)
Heatwaves		
Trimester 1	-0.00226	-0.000198
	(0.00756)	(0.00141)
Trimester 2	-0.00393	-0.00105
	(0.00666)	(0.00147)
Trimester 3	0.00947	0.000518
	(0.00644)	(0.00159)
Controls	✓	✓
Birth-month FE	✓	✓
Birth-year FE	✓	✓
Tehsil FE	✓	✓
Observations	72,352	43,223

Notes: See Table 25 notes for controls included.
Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

variable with a minimum value of one, I estimate Model 2 using a truncated Poisson. The results indicate that an increase in mean AOD in the first trimester decreases the probability of a school-age child to be in school and reduces the current grade of the child, controlling for age, whereas an increase in mean AOD in the second trimester decreases the propensity for a school-age child to be in school. Heatwave days during trimesters have no effect on the probability of a school-age child being in school and the current school-grade of a child.[27]

Declining effects by age. Exposure to adverse events in-utero can have long-lasting effects (Almond & Currie, 2011; Almond et al., 2017). To investigate whether the in-utero effects of mean pollution exposure and heatwaves are persistent as a child gets older, I divide the sample of children under the age of five (60 months) into four groups: children younger than 16 months, children between 16 and 30 months, children between 31 and 45 months, and children older than 45 months. Using the baseline specification in Equation 4.2, I estimate the in-utero effect of mean AOD and heatwave days on height-for-age z-scores and weight-for-age z-scores for each group. The coefficient estimates are plotted in Figure 14 and Figure 15.[28]

The coefficient estimates of AOD are statistically insignificant for many groups, for both the height-for-age z-scores and the weight-for-age z-scores. However, in-utero exposure to AOD reduces height-for-age z-scores for the oldest group, and surprisingly, increases height-for-age and weight-for-age z-scores for the

[27] In Table 38 in the Appendix, Model 1 is estimated using a probit specification and Model 2 is estimated using a Poisson specification.

[28] The sample of children under five is divided into four sub-samples so that sample size of each sub-sample remains relatively large.

youngest group. It might be that AOD is correlated with exposure to other things for older children.

The coefficient estimates for in-utero exposure to heatwave days on height-for-age z-scores and weight-for-age z-scores are negative and statistically significant for most of the age groups. For height-for-age z-scores, the coefficient estimate is statistically insignificant tor the oldest group, suggesting that the effect of in-utero exposure to heatwaves declines with age.

Cumulative Exposure. I also examine the impact of cumulative lifetime exposure to pollution and heatwave days on height-for-age z-scores and weight-for-age z-scores for children under five.[29] The results are reported in Table 27. The results indicate that cumulative exposure to AOD has an adverse effect on both the height for age z-scores and the weight for age z-scores for children under five. However, cumulative exposure to heatwave days reduces only height for age z-scores.

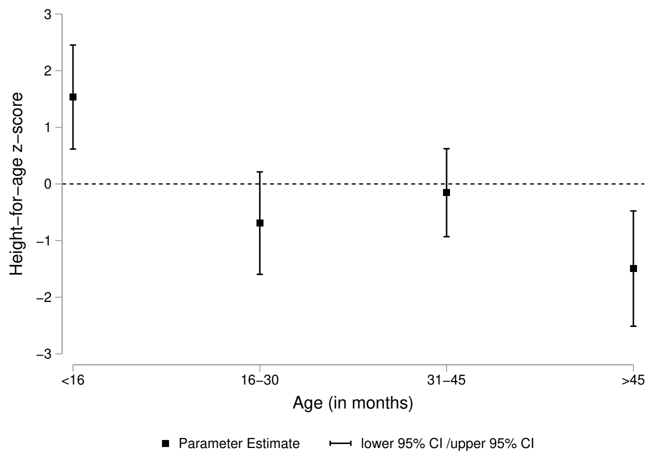
Robustness Test

As a robustness check, I modify Equation 4.3 to include mean AOD, heatwave days, and other weather controls in the pre-conception trimester.[30] The results are reported in Table 28. The results suggest that in-utero exposure to

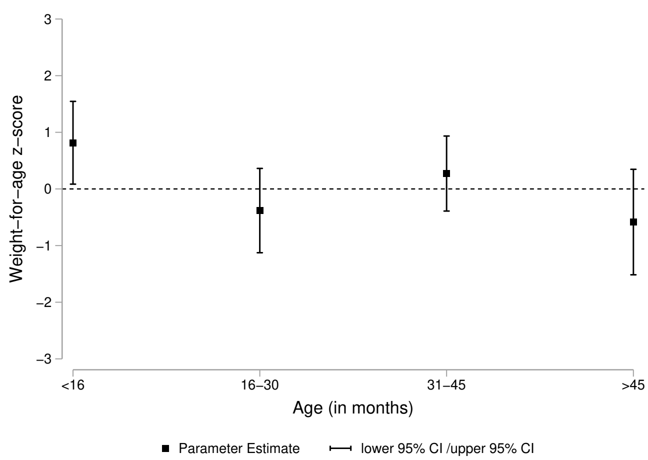
[29] Lifetime exposure is the exposure from conception until the current age of the child.

[30] I define the pre-conception trimester as the three months prior to first month of pregnancy.

FIGURE 14.
Effects by Age: AOD

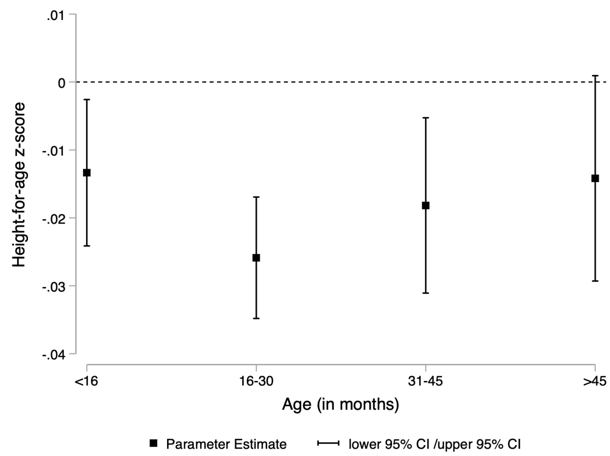


(a) Height-for-age z-score

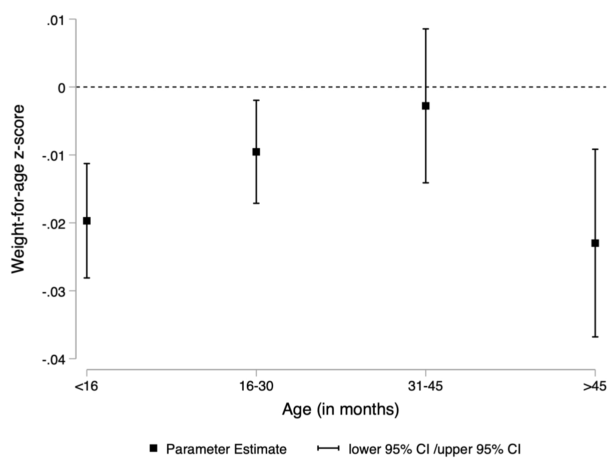


(b) Weight-for-age z-score

FIGURE 15.
Effects by Age: Heatwaves



(a) Height-for-age z-score



(b) Weight-for-age z-score

TABLE 27.
Cumulative Effects of AOD & Heatwaves

	(1)	(2)
	Height-for-age z-score	Weight-for-age z-score
AOD		
Cumulative exposure	-0.000997***	-0.00104***
	(0.000160)	(0.000151)
Heatwaves		
Cumulative exposure	-0.00865***	-0.00242
	(0.00153)	(0.00149)
Controls	✓	✓
Birth-month FE	✓	✓
Birth-year FE	✓	✓
Tehsil FE	✓	✓
Observations	92,135	92,124
R-squared	0.098	0.057

Notes: See Table 25 notes for controls included. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

AOD in the first and third trimester reduces height-for-age z-scores and weight-for-age z-scores. Moreover, an additional heatwave day in the second trimester lowers height-for-age z-scores, whereas an additional heatwave day in the third trimester reduces both height-for-age z-scores and weight-for-age z-scores. The results for each trimester of gestation in Table 25 seem robust to inclusion of exposure for the mother in the pre-conception trimester.

TABLE 28.
Effect of AOD & Heatwaves: Falsification

	(1)	(2)
	Height-for-age z-score	Weight-for-age z-score
AOD		
Preconception trimester	0.0238	-0.00291
	(0.0818)	(0.0690)
Trimester 1	-0.216**	-0.171**
	(0.0885)	(0.0749)
Trimester 2	0.255***	0.0795
	(0.0876)	(0.0730)
Trimester 3	-0.183*	-0.169*
	(0.103)	(0.0861)
Heatwaves		
Preconception trimester	0.00369	-0.00241
	(0.00328)	(0.00288)
Trimester 1	0.00404	0.00231
	(0.00359)	(0.00306)
Trimester 2	-0.0129***	-0.000390
	(0.00362)	(0.00303)
Trimester 3	-0.0144***	-0.00857***
	(0.00303)	(0.00259)
Controls	✓	✓
Birth-month FE	✓	✓
Birth-year FE	✓	✓
Tehsil FE	✓	✓
Observations	97,468	97,458
R-squared	0.096	0.055

Notes: See Table 25 notes for controls included. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Following Buckles and Price (2013), I test for selection into conception by examining the effect of pollution and heatwaves on mother and household observable characteristics.[31] Specifically, using Equation 4.3, I regress mother's age at birth, mother's education and household wealth score on pollution and heatwave days during each trimester, including weather controls, whether a household dwells in an urban area, birth-month, birth-year and tehsil fixed effects. Controlling for time fixed effects, we generally expect the amount of pollution and the number of heatwaves to be random, so the observable mother and household characteristics should not vary with pollution and heatwaves.

The results presented in Table 29 show that higher AOD during pregnancy reduces wealth score, and more heatwaves during pregnancy are associated with lower mother's age at birth, suggesting that there is selection in trimesters where AOD and heatwaves have an effect on mother's and household's observed characteristics. Thus, the regression results in Table 25 may overstate the true effects of pollution and heatwaves during pregnancy.

[31] I also estimated Equation 4.3 using family fixed effects, as an alternative specification, to account for unobserved characteristics of the family. The results are presented in Table 39 in the Appendix. The results are not consistent with Table 25 (no statistically significant effect of AOD or heatwave days). This could be due to 1) selection effects i.e. children of poor mothers are conceived during periods of more pollution and/or heatwaves, or 2) skewed sample, i.e. fixed effects model is estimated using only a small sample of children having siblings under the age of five.

TABLE 29.
Effect of AOD & Heatwaves: Selection Test

	(1)	(2)	(3)
	Mother age	Mother education	Wealth score
AOD			
Trimester 1	-0.0976	0.114	-0.00310
	(0.205)	(0.128)	(0.0227)
Trimester 2	-0.336	0.192	-0.0531**
	(0.210)	(0.128)	(0.0229)
Trimester 3	0.0491	0.244	-0.0320
	(0.247)	(0.155)	(0.0275)
Heatwaves			
Trimester 1	-0.0167**	-0.000642	-0.000107
	(0.00803)	(0.00563)	(0.000927)
Trimester 2	-0.000783	0.00843	0.000787
	(0.00835)	(0.00573)	(0.000954)
Trimester 3	0.000322	0.00550	0.000406
	(0.00693)	(0.00489)	(0.000792)
Controls	✓	✓	✓
Birth-month FE	✓	✓	✓
Birth-year FE	✓	✓	✓
Tehsil FE	✓	✓	✓
Observations	98,745	98,731	100,578
R-squared	0.008	0.212	0.472

Notes: The controls include mean humidity, mean precipitation, mean wind speed and whether the household dwells in an urban area. Robust standard errors are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Conclusion

Motivated by concerns about the multi-faceted impacts of air pollution and climate change on some of the world's most vulnerable populations, I examine the effect of in-utero exposure to pollution and heatwaves on child health and schooling status in a developing-country context. Pakistan experiences some of the worst air pollution in the world and is one of the most vulnerable countries when it comes to climate change. Moreover, Pakistan has a very high prevalence of malnourished children (i.e. suffering from underweight, stunting and wasting) in comparison to other developing countries. Also, its education system has profound problems that may be worsened by pollution and climate change.

My sample contains information on children born between 2000-2011 in Punjab, Pakistan, providing a rich set of data that permits me to analyze the effects of pollution and heatwaves on child's physical health, specifically height and weight, and their probability of being in school and their current school-grade-for-age level. I have assembled the most comprehensive daily pollution and weather data available for Punjab, Pakistan over the period 2000-2011. There is no reliable comprehensive ground–level monitoring of air quality in Pakistan, so there is only very limited conventional administrative air-quality data available for Pakistan. Thus, I use remotely sensed satellite data to measure air pollution across Punjab at a high level of spatial granularity.

The results indicate that higher levels of air pollution in the first and third trimester lower both the height-for-age z-scores and the weight-for-age z-scores among young children in Punjab. I also find that an additional heatwave day during gestation reduces height-for-age z-scores and weight-for-age z-scores. The sensitivity of height-for-age z-scores and weight-for-age z-scores to temperature shocks is concentrated largely in the second and third trimesters of pregnancy. The results also reveal that in-utero exposure to heatwave days has a discernible adverse effect on height-for-age z-scores of children younger than 46 months but seems to have no effect on children between 46–59 months, suggesting that the effects of temperature shocks in-utero decline with age.

The effects of cumulative exposure to air pollution and heatwave days on health outcomes for children aged 0–59 months indicate an adverse effect of pollution on both the height-for-age z-scores and weight-for-age z-scores, but an adverse effect of heatwave days on only the height for age z-scores. I also find that poor air quality in the first trimester decreases the probability of a school-age child being in school and the current grade of the child, controlling for age, whereas an increase in pollution in the second trimester decreases the propensity for a school-age child to be in school. However, heatwave days during trimesters have no effect on the probability of a school-age child being in school and the current school-grade of a child.

Of course, this analysis does not identify the mechanism by which pollution or heatwave exposure in-utero impacts child physical health and schooling outcomes. Mitigation efforts for climate change are costly, given that they involve investments in clean technology. In developing countries, industrial emission standards are often disregarded by industry and not enforced by government agencies, on the premise that the country cannot afford to allow such regulations to hamper economic growth. Therefore, it is important to measure the different costs from both pollution and climate change to determine optimal mitigation policies, especially in developing countries. Research on the causal relationship between climate change and economic outcomes will help answer open questions about the burden of pollution and climate change borne by developing countries (Greenstone and Jack, 2015).

CHAPTER V

CONCLUSION

This dissertation examines how air pollution and climate change influence human capital accumulation in a developing-country context and also studies the effects of policies intended to keep children in school in the face of whatever factors deter them from developing their human capital. Children's health and education are critical components of human capital, and effective human capital accumulation enhances a society's potential for economic development and economic prosperity. Human capital accumulation is important for any country's sustained long-term growth, and therefore especially important in developing countries.

In Chapter II, I study the effectiveness of an increase in the cash amount of the female-targeted conditional cash transfer on schooling outcomes for girls. Specifically, I examine the impact of an increase in the monthly cash transfer from Rs.200 (\$1.31) to Rs.1000 (\$6.57) in 2017, using a novel monthly dataset on student enrollment and attendance at all public schools in Punjab, Pakistan. Unlike earlier work, which evaluates the effectiveness of female-targeted CCT implemented in Punjab in 2004, I examine the effect of the later intervention in 2017 that increased the cash transfer amount from \$1.31 to \$6.57.

The increase in the cash amount of the conditional cash transfer was targeted specifically to improve enrollment and attendance by girls in middle school and high school. In many developing countries, households underinvest in female education, often because they (a) prioritize boys' education, (b) depend upon the earnings from child labor, and (c) encourage child marriage. This gender differential argues for gender-targeted interventions. I find that the increase in the cash transfer increased female enrollment in 6^{th} grade and 9^{th} grade in treated districts. However, I find no effect of the increased cash transfer on the attendance of girls in middle and high school in the treated districts. The increase in cash transfer also had positive spillover effects on the enrollment of boys in middle and high schools in treated districts.

In Chapter III, I examine the causal effect of air pollution and temperature levels on student attendance and test scores using a satellite-based measure of daily pollution and a novel set of monthly data on school enrollment and test scores in Punjab, Pakistan. Pakistan experiences some of the worst air pollution in the world and is one of the most vulnerable countries when it comes to climate change. There seems to have been no research done, to date, on the causal effect of pollution on test scores specifically for developing countries. Outside the U.S., the limited existing literature studying the effect of air pollution on test scores is based largely on more–developed countries. With higher per-capita incomes, populations can be more resilient to environmental conditions. Also, unlike the existing literature for developing countries, this paper examines the direct impact of temperature on test scores in a developing–country context while controlling for confounding factors including contemporaneous pollution exposure.

Since air pollution is potentially endogenous, I use exogenous variation in air quality, over time, due to wind-driven dust from deserts within the country, as well as deserts in neighboring countries. The results of the instrumental variables estimation indicate that an exogenous increase in air pollution reduces student attendance, and has an adverse effect on test scores—specifically, math and Urdu scores. Estimates of the effects of different temperature levels show that temperatures higher or lower than 16–18°C (60.8–64.4°F) reduce total test scores as well as subject scores. Temperatures higher than 16–18°C have a greater adverse effect on math scores compared to other subject scores. High temperatures seem to have similar adverse effects on the test scores for both boys and girls. The Urdu test scores are reduced more by pollution for boys than for girls. Increases in pollution seem to have no effect on the math scores for boys, but reduce math scores for girls.

In Chapter IV, I investigate the effect of in-utero exposure to pollution and heatwaves on children's physical health and schooling status in a developing-country context. A large part of the existing literature that examines the impact of in-utero exposure to pollution or extreme temperature has focused on either birth outcomes or adult outcomes. This paper addresses a research gap by focusing on early childhood health and schooling outcomes. The results indicate that an increase in air pollution in the first and third trimester lowers height-for-age z-scores and weight-for-age z-scores, and an additional heatwave day during gestation reduces height-for-age z-scores and weight-for-age z-scores. The sensitivity of height-for-age z-scores and weight-for-age z-scores to temperature shocks is concentrated almost completely in the second and third trimesters of pregnancy.

I also find that an increase in pollution during gestation decreases the probability of a school-aged child being in school and lowers the current school-grade of a child, controlling for age. However, heatwave days during trimesters have no effect on the probability of a school-age child being in school and the current school-grade of a child. The results also reveal that in-utero exposure to heatwave days has a discernible adverse effect on height-for-age z-scores and weight-for-age z-scores for children younger than 46 months but seems to have no effect on children between 46–59 months, suggesting that the negative effects of in-utero temperature shocks decline with a child's age. I find that *cumulative* exposure to air pollution and heatwave days adversely affects health outcomes for children aged 0–59 months, leading to both lower height-for-age z-scores and lower weight-for-age z-scores. None of the existing studies concerning in-utero pollution and extreme temperature exposures has examined the effects of cumulative, rather than acute, exposures to pollution or extreme temperatures.

In Chapter III and IV, I have assembled the most comprehensive daily pollution and weather data available for Punjab, the second largest and most populated province in Pakistan, over the periods 2000–2011 and 2014–2018. These data can be used for future research on the effects of pollution and climate change on other economic variables. The research documented in this dissertation represents original contributions to our understanding of some of the potential future consequences of climate change and pollution, for some of the world's most vulnerable populations of children. My findings highlight that the adverse effects of air pollution are not limited solely to health outcomes but can also affect educational outcomes, and suggest that the benefits of regulating pollution are substantially underestimated by a narrow focus solely on environmental health effects. More generally, climate change is likely to affect not only environmental health, but also human capital accumulation. The analysis described in this dissertation can help determine optimal mitigation policies for pollution and climate change in developing countries, and also inform policymakers on the effectiveness of policies targeted to keep children in school.

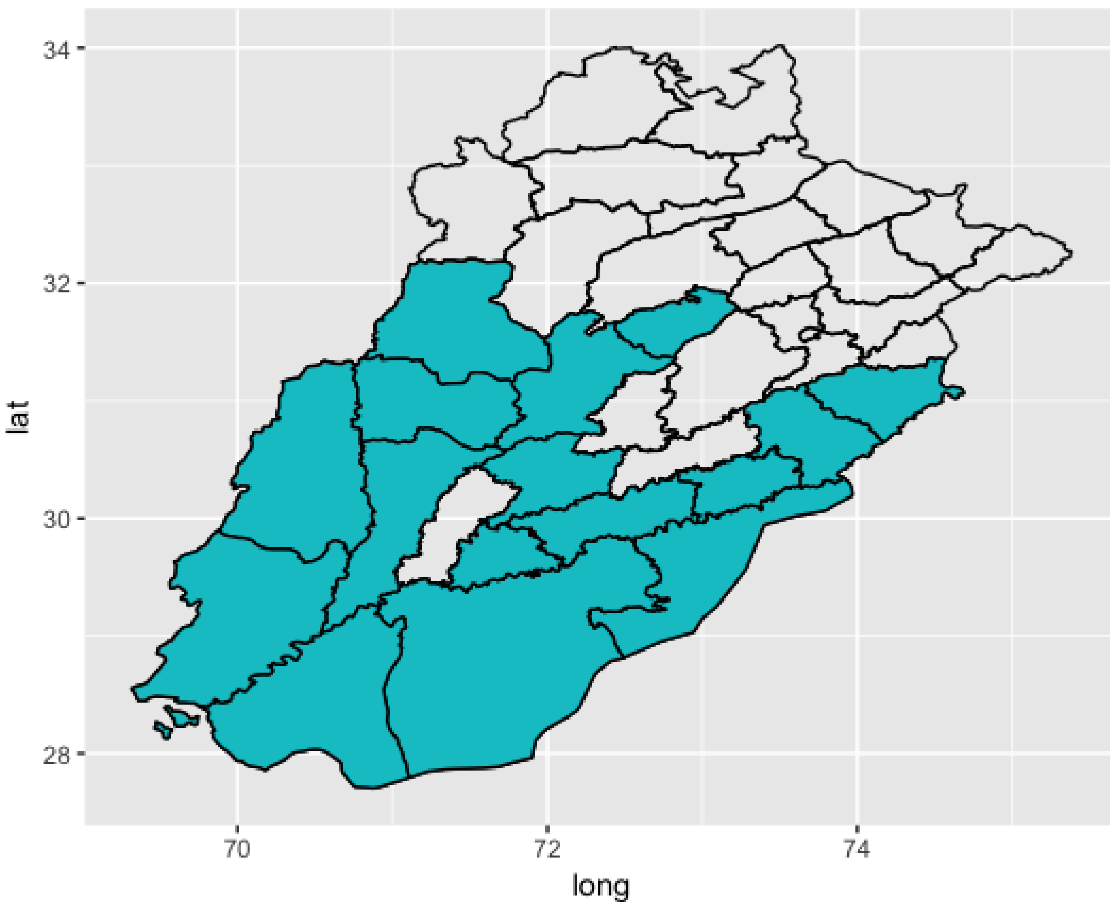
APPENDIX

ADDITIONAL TABLES AND FIGURES

Chapter II Miscellaneous Tables and Figures

FIGURE 16.
Pakistan

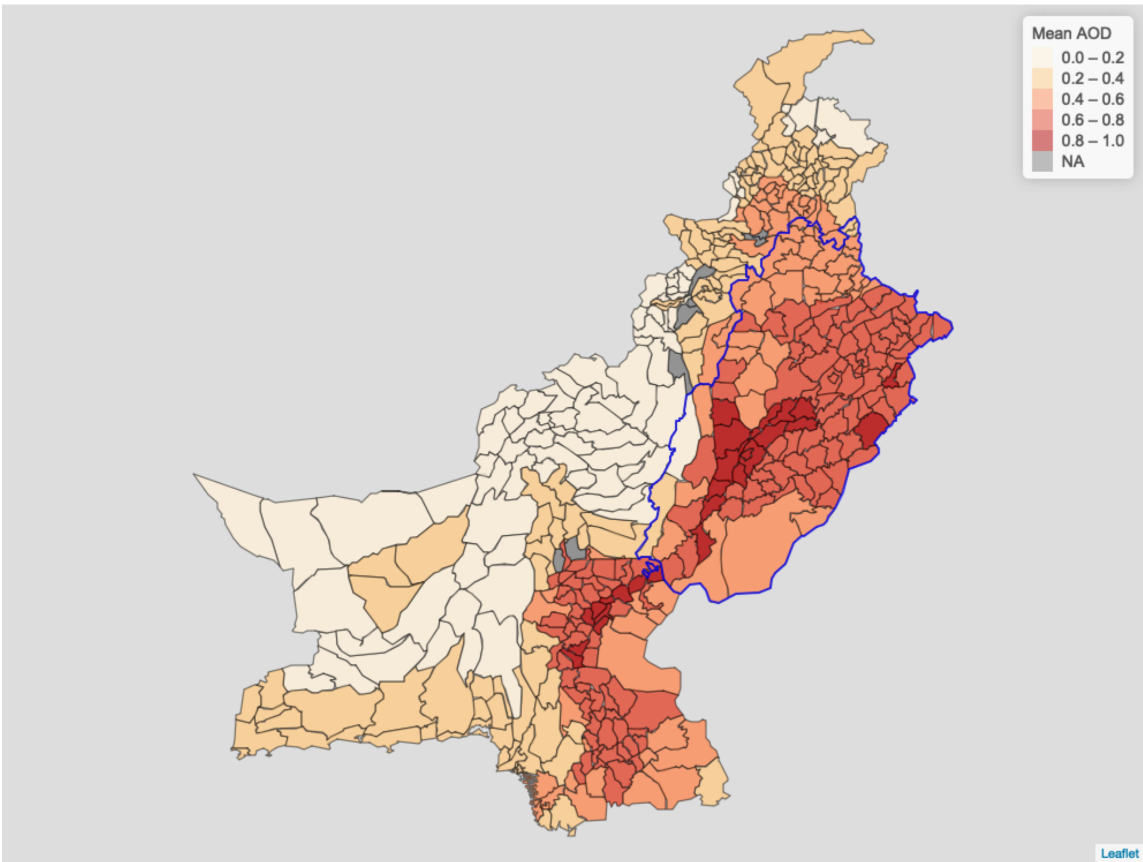
FIGURE 17.
Districts in Punjab with CCT



Notes: The CCT program is implemented in the colored districts. These include the districts of Bahawalnagar, Bahawalpur, Bhakkar, Chiniot, Dera Gazi Khan, Jhang, Kasur, Khanewal, Layyah, Lodhran, Muzaffargarh, Okara, Pakpattan, Rajanpur, Rahimyar Khan, and Vehari.

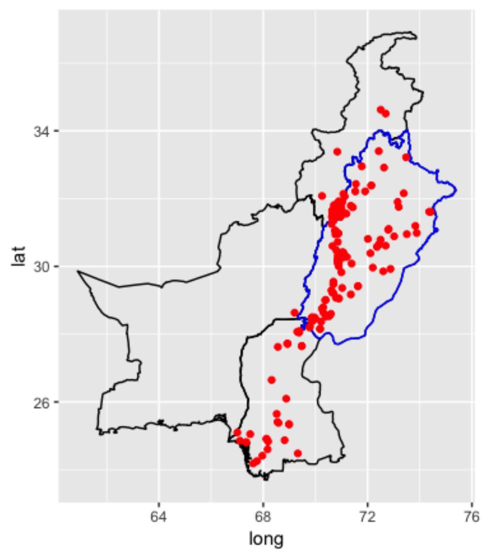
Chapter III Miscellaneous Tables and Figures

FIGURE 18.
Mean Aerosal Optical Depth (AOD) in Pakistan (by Tehsil)

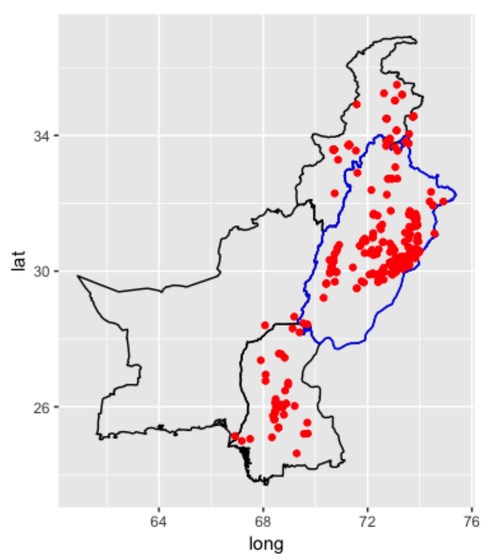


Notes: This map depicts the mean AOD during the period September 2014 - March 2018 for all tehsils in Pakistan. The region bounded by blue line is Punjab. The darker colors indicate more aerosals (air pollution).

FIGURE 19.
Fires during agricultural burning season

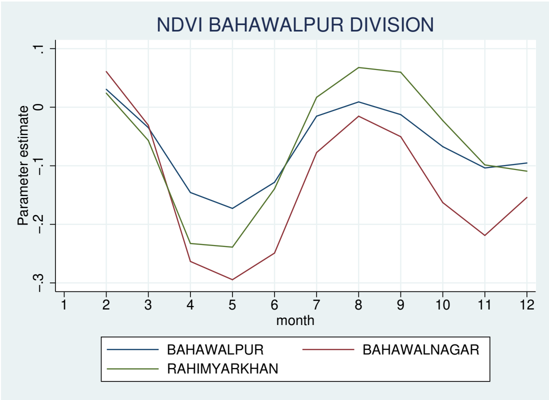


(a) March 10 2015

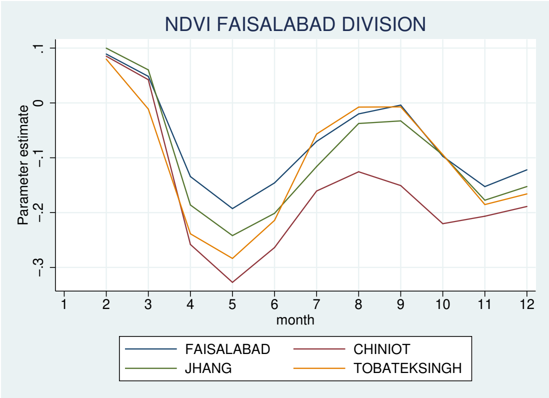


(b) October 29 2017

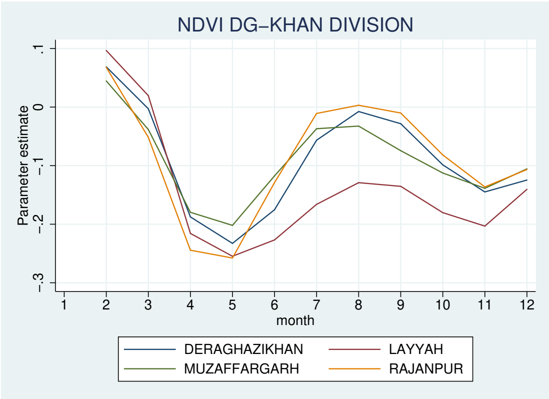
FIGURE 20.
NDVI Parameter Estimates by Division



(a) Bahawalpur

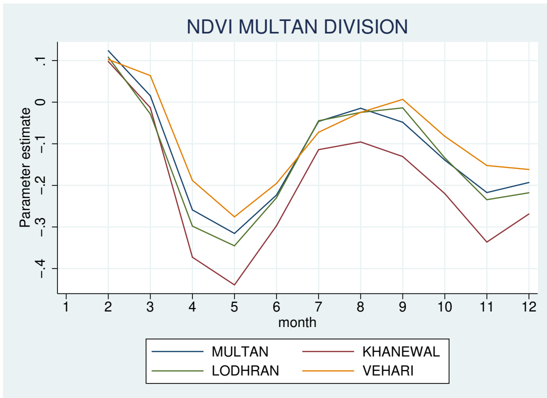


(b) Faisalabad

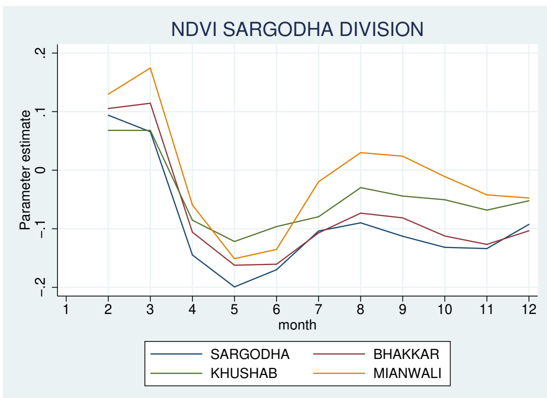


(c) DGKhan

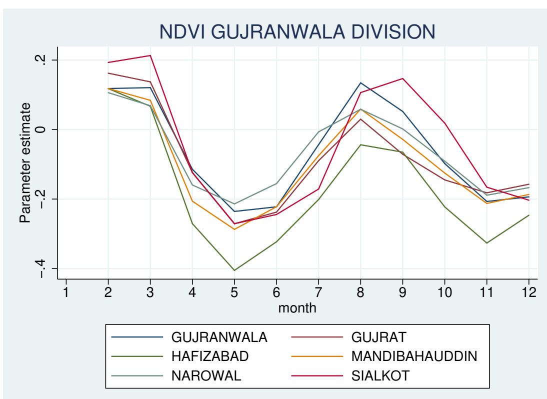
FIGURE 21.
NDVI Parameter Estimates by Division



(a) Multan

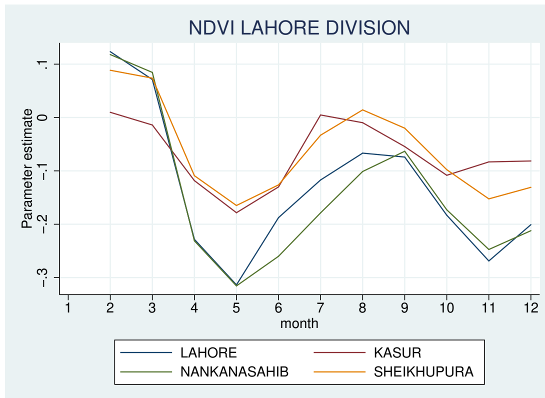


(b) Sargodha

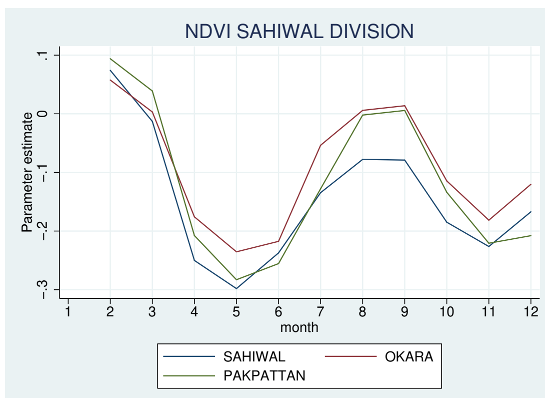


(c) Gujranwala

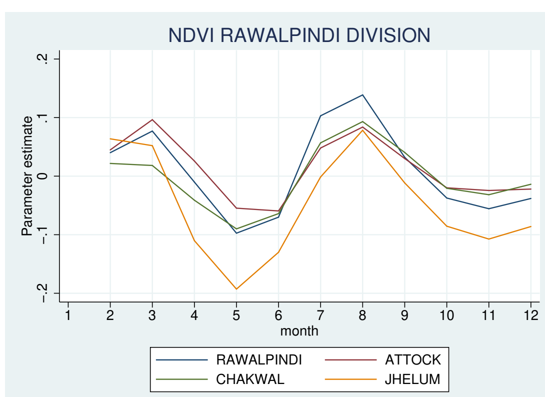
FIGURE 22.
NDVI Parameter Estimates by Division



(a) Lahore

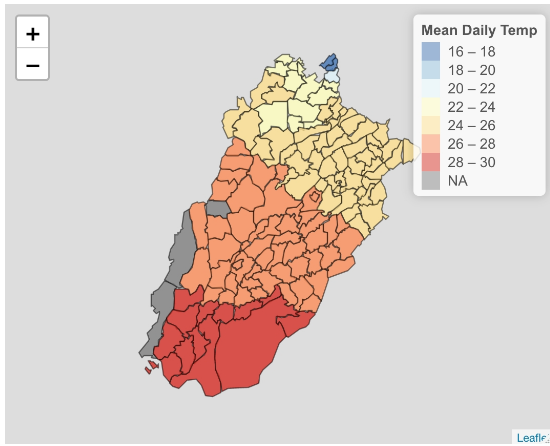


(b) Sahiwal

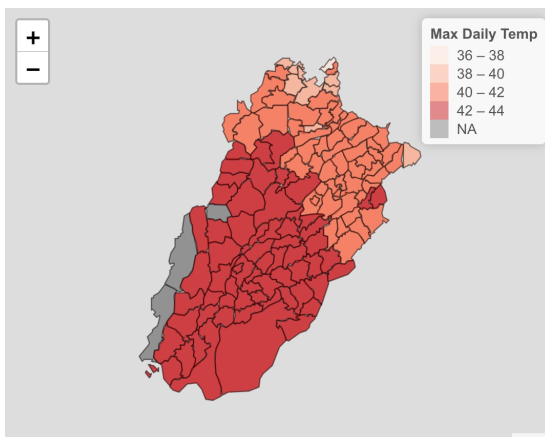


(c) Rawalpindi

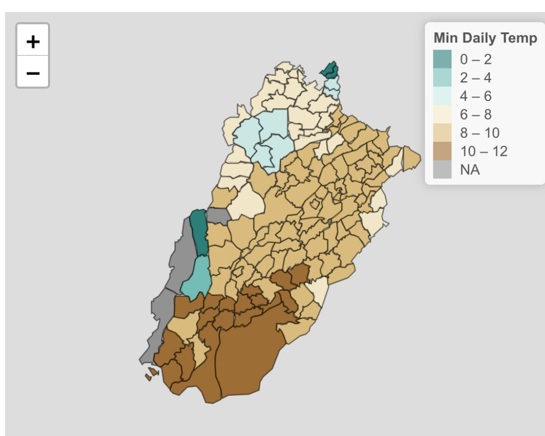
FIGURE 23.
Daily Temperature: 2014–2018



(a) Mean

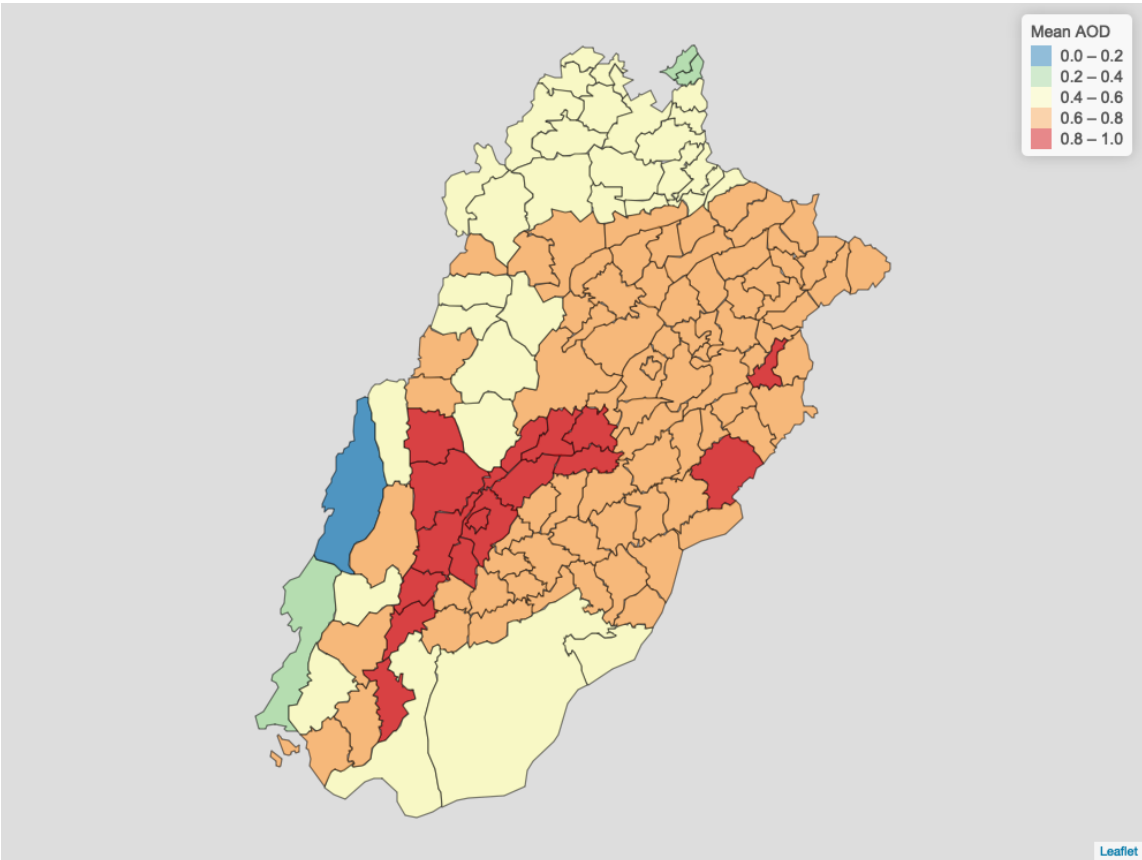


(b) Maximum



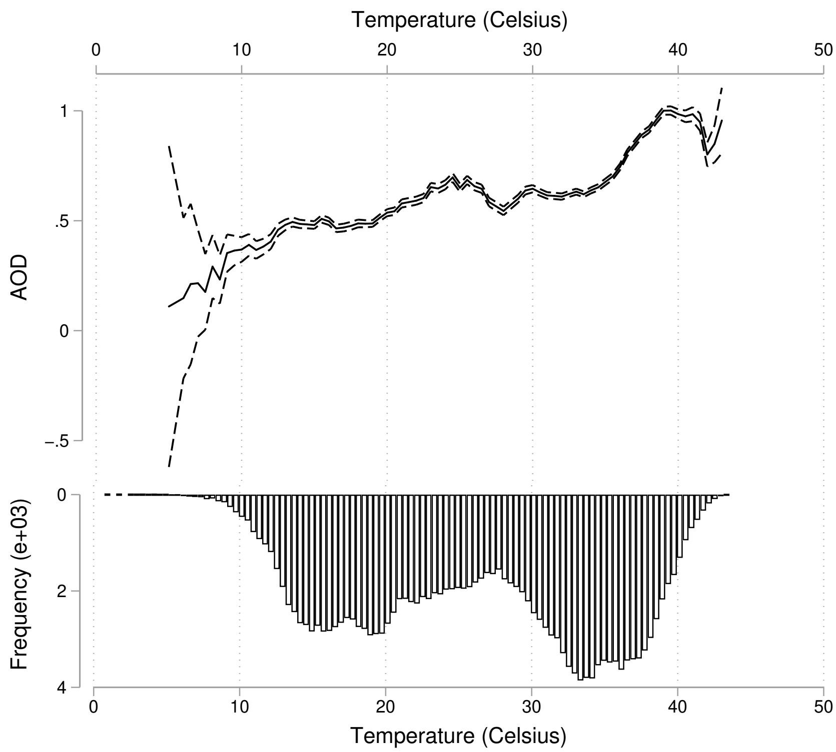
(c) Minimum

FIGURE 24.
Mean Aerosal Optical Depth (AOD) in Punjab



Notes: This map depicts the mean AOD across all tehsils in Punjab during the period September 2014 - March 2018. The darker colors indicate more aerosals (air pollution).

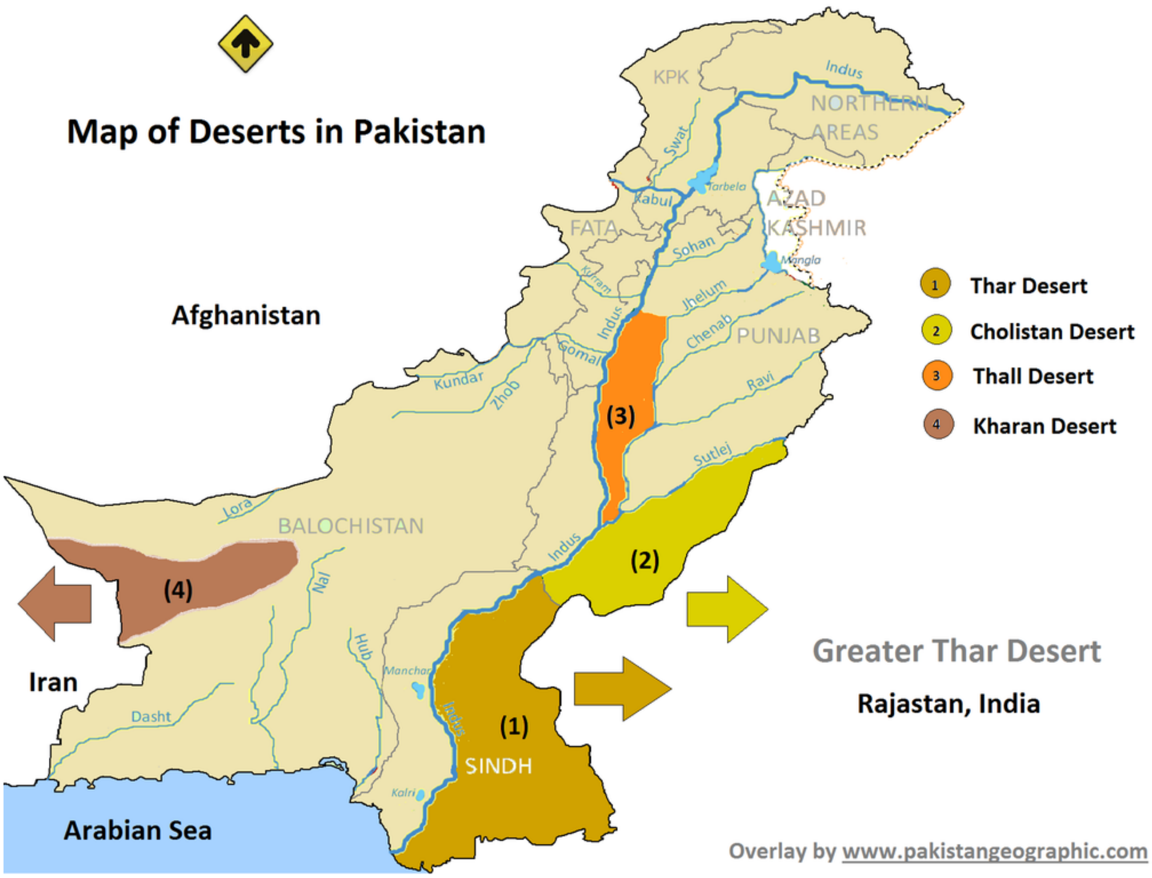
FIGURE 25.
AOD as a function of temperature



107,885 total observations

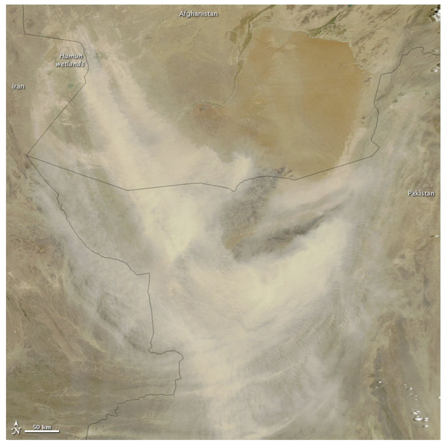
Notes: This graph depicts the relation between daily AOD and daily temperature at tehsil level for the time period September 2014–March 2018.

FIGURE 26.
Deserts in Pakistan

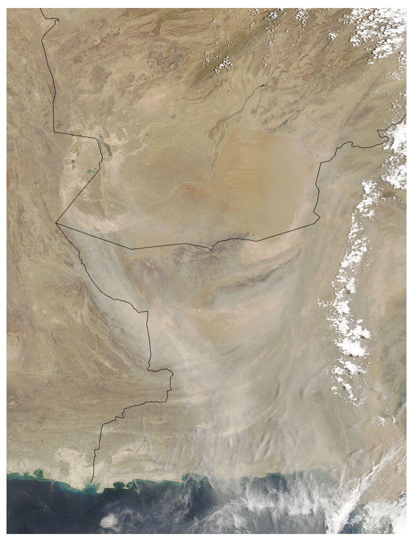


Notes: This map shows the location of the four deserts within Pakistan.

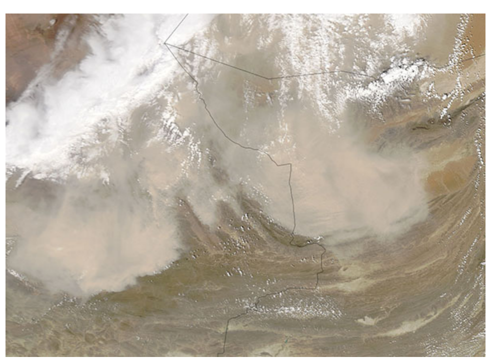
FIGURE 27.
Dust Storms over Pakistan



(a) June 4 2012



(b) June 27 2017



(c) March 21 2018

Notes: The images for June 4 2012 and June 27 2017 are taken by NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua satellite. The Image for March 21 2018 is taken by the Terra satellite.

TABLE 30.
Correlation of AOD with its lagged values

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AOD	AOD_{-1}	AOD_{-2}	AOD_{-3}	AOD_{-4}	AOD_{-5}	AOD_{-6}	AOD_{-7}
AOD	1.0000							
AOD_{-1}	0.5859	1.0000						
AOD_{-2}	0.4639	0.5803	1.0000					
AOD_{-3}	0.3500	0.4725	0.5863	1.0000				
AOD_{-4}	0.2929	0.3625	0.4800	0.6089	1.0000			
AOD_{-5}	0.2397	0.2804	0.3428	0.4803	0.5911	1.0000		
AOD_{-6}	0.1672	0.2659	0.2978	0.3555	0.4879	0.5716	1.0000	
AOD_{-7}	0.1845	0.1495	0.2438	0.2821	0.3451	0.4641	0.562	1.0000

TABLE 31.
Effect of lags of AOD & temperature on contemporaneous values

	(1)	(2)
	AOD	Temperature
AOD_{-1}	0.502***	
	(0.00226)	
AOD_{-2}	0.177***	
	(0.00259)	
AOD_{-3}	-0.00741***	
	(0.00265)	
AOD_{-4}	0.0376***	
	(0.00274)	
AOD_{-5}	0.0493***	
	(0.00260)	
AOD_{-6}	-0.120***	
	(0.00264)	
AOD_{-7}	0.110***	
	(0.00230)	
$Temperature_{-1}$		1.128***
		(0.000791)
$Temperature_{-2}$		-0.222***
		(0.00120)
$Temperature_{-3}$		0.0318***
		(0.00122)
$Temperature_{-4}$		-0.0132***
		(0.00122)
$Temperature_{-5}$		0.0714***
		(0.00119)
$Temperature_{-6}$		-0.0136***
		(0.00117)
$Temperature_{-7}$		0.00848***
		(0.000786)
$Constant$	0.179***	0.223***
	(0.00171)	(0.00316)
Observations	209,977	1,508,870
R^2	0.378	0.978

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

TABLE 32.
Student attendance = f(AOD, temperature, mean lag AOD)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Attend	Attend	Attend	Attend	Attend	Attend	Attend
AOD	0.196***	0.0606	0.149**	0.222***	0.240***	0.265***	0.271***
	(0.0606)	(0.0685)	(0.0607)	(0.0590)	(0.0591)	(0.0589)	(0.0590)
$\overline{AOD}_{-1}$		0.138**					
		(0.0691)					
$\overline{AOD}_{-2}$			-0.0642				
			(0.0722)				
$\overline{AOD}_{-3}$				-0.174**			
				(0.0732)			
$\overline{AOD}_{-4}$					-0.244***		
					(0.0819)		
$\overline{AOD}_{-5}$						-0.284***	
						(0.0775)	
$\overline{AOD}_{-6}$							-0.377***
							(0.0826)
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Obs	625,490	452,268	539,463	576,174	593,850	605,901	611,899
R^2	0.051	0.054	0.053	0.052	0.052	0.051	0.051
Schools	47,632	47,540	47,609	47,624	47,631	47,632	47,632

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

TABLE 33.
Student attendance by month

	(1) Attend	(2) Attend	(3) Attend	(4) Attend	(5) Attend	(6) Attend	(7) Attend	(8) Attend
AOD	-0.266	0.197	1.540***	-0.804**	-0.0578	0.394***	0.124	-0.511**
	(0.232)	(0.183)	(0.467)	(0.400)	(0.191)	(0.131)	(0.109)	(0.216)
Month	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Oct**	**Nov**	**Dec**
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
School Controls	✓	✓	✓	✓	✓	✓	✓	✓
Obs	55,696	61,012	61,702	81,918	80,107	123,494	86,655	74,906
Schools	35,423	36,274	36,296	43,339	42,592	46,334	43,094	40,502

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

TABLE 34.
Student Attendance: non-harvesting months

	(1)
	Attendance
AOD	-0.153**
	(0.0668)
Time FE	✓
Weather Controls	✓
School Controls	✓
Observations	440,294
No. of Schools	47,601

Notes: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

TABLE 35.
Correlation of temperature with its lagged values

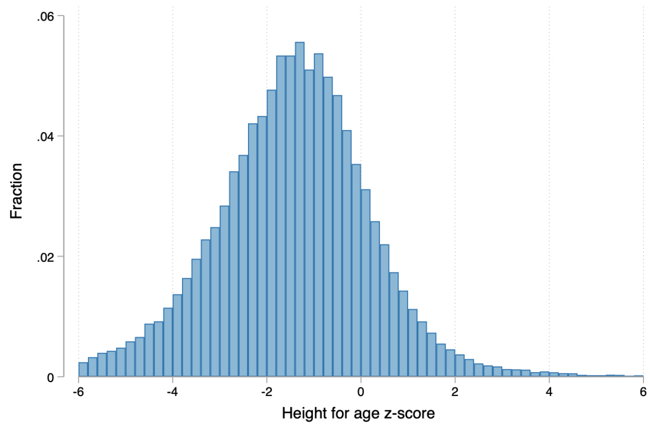
VARIABLES	(1) Temp	(2) $Temp_{-1}$	(3) $Temp_{-2}$	(4) $Temp_{-3}$	(5) $Temp_{-4}$	(6) $Temp_{-5}$	(7) $Temp_{-6}$	(8) $Temp_{-7}$
$Temp$	1.0000							
$Temp_{-1}$	0.9884	1.0000						
$Temp_{-2}$	0.9728	0.9876	1.0000					
$Temp_{-3}$	0.9586	0.9716	0.9877	1.0000				
$Temp_{-4}$	0.9472	0.9581	0.9724	0.9880	1.0000			
$Temp_{-5}$	0.9380	0.9469	0.9586	0.9726	0.9877	1.0000		
$Temp_{-6}$	0.9302	0.9389	0.9485	0.9601	0.9734	0.9878	1.0000	
$Temp_{-7}$	0.9217	0.9306	0.9401	0.9497	0.9605	0.9728	0.9870	1.0000

Chapter IV Miscellaneous Tables and Figures

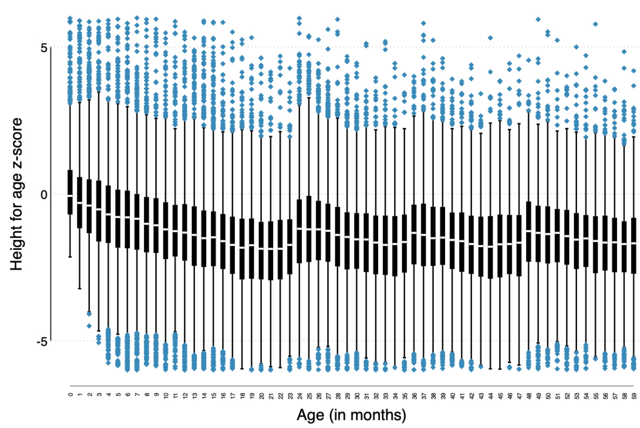
FIGURE 28.
Tehsils in Punjab

Notes: The figure shows the tehsils in Punjab. A tehsil is an administrative subdivision of a district.

FIGURE 29.
Histogram and Box Plot for Height for Age z-scores

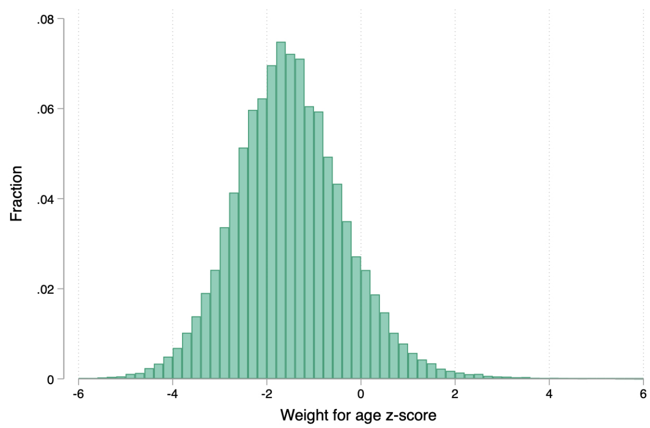


(a) Histogram



(b) Box Plot

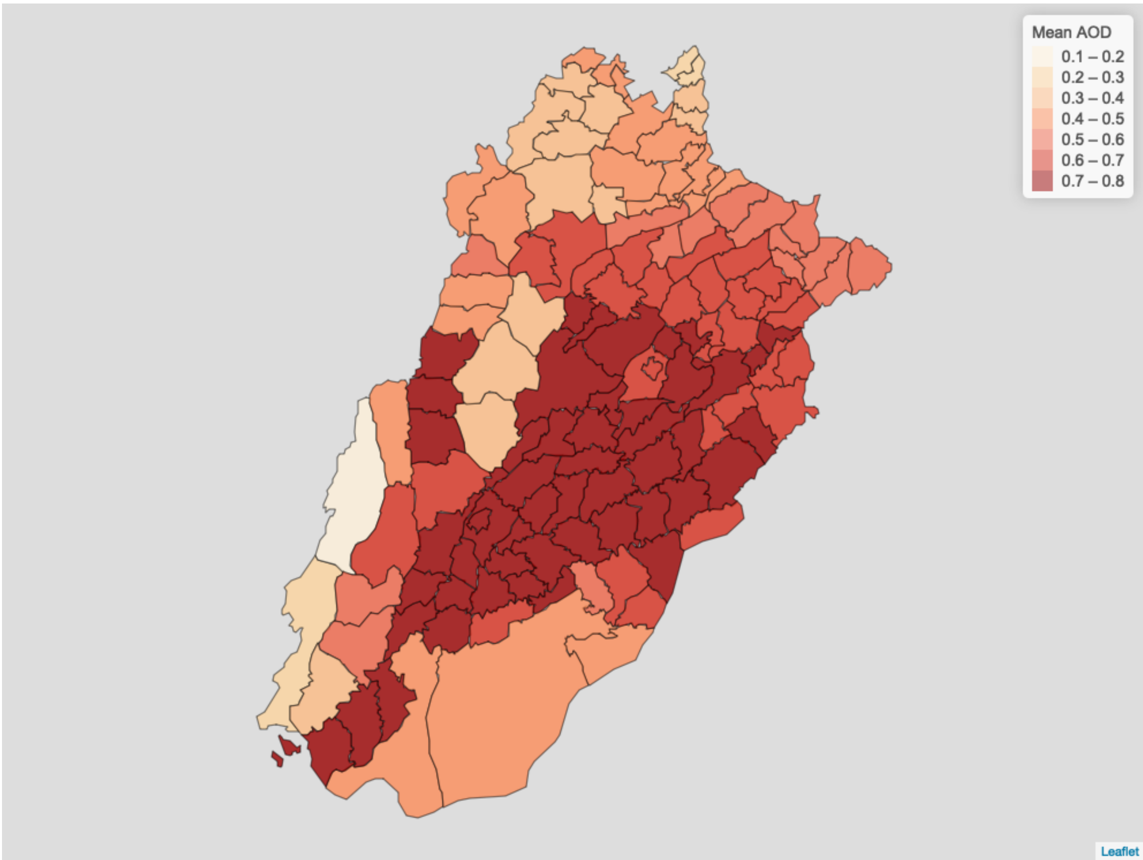
FIGURE 30.
Histogram and Box Plot for Weight for Age z-scores



(a) Histogram

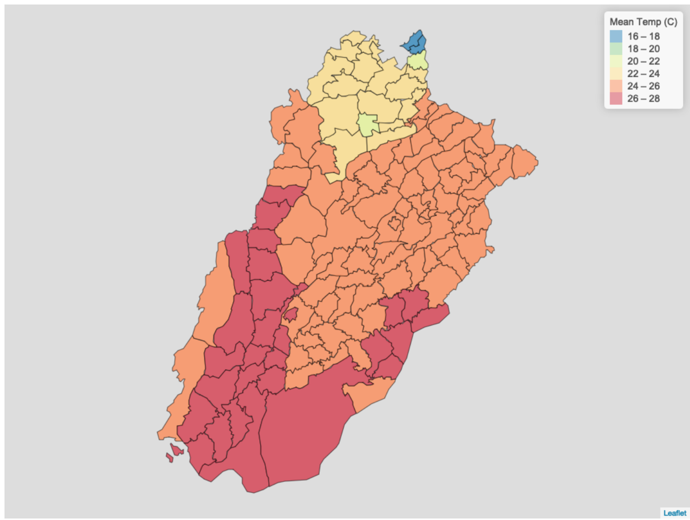
(b) Box Plot

FIGURE 31.
Mean Aerosal Optical Depth (AOD) in Punjab (by Tehsil)

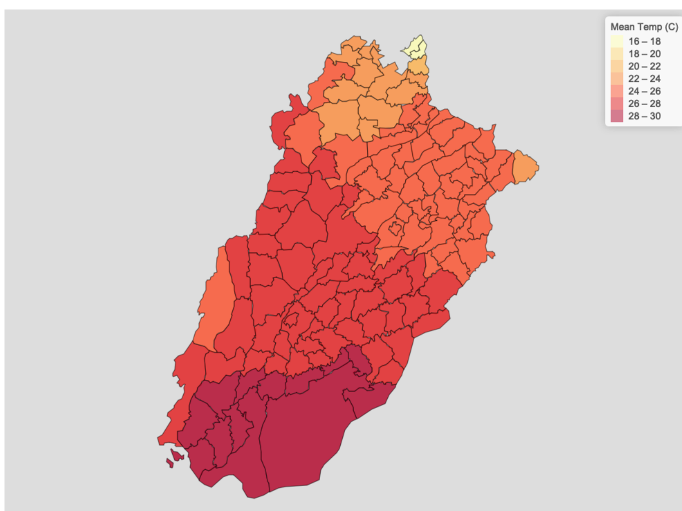


Notes: This map depicts the mean AOD during the period 2000–2011 for all tehsils in Punjab. The darker colors indicate more aerosals (air pollution).

FIGURE 32.
Mean Annual Temperature (°C)



(a) 2000



(b) 2011

TABLE 36.
Effect of AOD & Heatwaves on Height-for-Age z-score

	(1)
	Height-for-age z-score
AOD	-0.372**
	(0.167)
Heatwaves	-0.0129***
	(0.00223)
Humidity	-0.121
	(22.10)
Precipitation	1,738
	(2,799)
Wind speed	-0.0521
	(0.0670)
Age (months)	0.0142***
	(0.000807)
Male	-0.0118
	(0.0159)
Mother age at birth	-0.00680
	(0.0113)
Mother age at birth^2	0.000177
	(0.000188)
Mother education	0.0358***
	(0.00237)
Mother married	0.0439
	(0.0731)
No. of siblings	-0.0406***
	(0.00749)
Urban	-0.196***
	(0.0258)
Wealth score	0.315***
	(0.0139)
Birth-month FE	✓
Birth-year FE	✓
Tehsil FE	✓
Observations	97,468
R-squared	0.095

Notes: Robust standard errors are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

TABLE 37.
Effect of AOD & Heatwaves on Weight-for-Age z-score

	(1)
	Weight-for-age z-score
AOD	-0.400***
	(0.138)
Heatwaves	-0.00496***
	(0.00187)
Humidity	56.05***
	(18.68)
Precipitation	-9,335***
	(2,416)
Wind speed	-0.159***
	(0.0568)
Age (months)	0.000782
	(0.000669)
Male	-0.0160
	(0.0135)
Mother age at birth	-0.0158*
	(0.00952)
Mother age at birth^2	0.000286*
	(0.000159)
Mother education	0.0287***
	(0.00206)
Mother married	0.114*
	(0.0622)
No. of siblings	-0.0468***
	(0.00651)
Urban	-0.182***
	(0.0233)
Wealth score	0.233***
	(0.0117)
Birth-month FE	✓
Birth-year FE	✓
Tehsil FE	✓
Observations 97,458	
R-squared	0.054

Notes: Robust standard errors are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

TABLE 38.
Effect of AOD & Heatwaves on Schooling Status

	(1) In School	(2) Current Grade
AOD		
Trimester 1	-0.122*	-0.0484**
	(0.0630)	(0.0208)
Trimester 2	-0.300***	-0.00847
	(0.0646)	(0.0213)
Trimester 3	-0.0104	0.0291
	(0.0756)	(0.0251)
Heatwaves		
Trimester 1	-0.000765	-0.00103
	(0.00420)	(0.00113)
Trimester 2	-0.00135	-0.00139
	(0.00373)	(0.00116)
Trimester 3	0.00628*	-0.000465
	(0.00358)	(0.00117)
Controls	✓	✓
Birth-month FE	✓	✓
Birth-year FE	✓	✓
Tehsil FE	✓	✓
Observations	72,352	43,223

Notes: See Table 25 notes for controls included. Model 1 is estimated using a Logit specification and Model 2 using a Poisson specification. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

TABLE 39.
Effect of AOD & Heatwaves: Family Fixed Effects Models

	(1) Height-for-age z-score	(2) Weight-for-age z-score
AOD		
Trimester 1	0.0827	-0.0471
	(0.164)	(0.140)
Trimester 2	0.116	-0.0164
	(0.138)	(0.108)
Trimester 3	0.128	0.108
	(0.179)	(0.138)
Heatwaves		
Trimester 1	0.00338	-0.000125
	(0.00544)	(0.00502)
Trimester 2	0.0159***	0.0182***
	(0.00576)	(0.00492)
Trimester 3	-0.00719	-0.00407
	(0.00519)	(0.00408)
Controls	✓	✓
Birth-month FE	✓	✓
Birth-year FE	✓	✓
Tehsil FE	✓	✓
Observations	97,439	97,439
R-squared	0.054	0.061
Number of HH	65,411	65,411

Notes: See Table 25 notes for controls included.
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

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