Fogging the mind, sweating the brain: environmental factors, school attendance and learning*

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ABSTRACT

This paper examines the effects of air pollution and temperature on human capital accumulation in a developing-country context. Specifically, I investigate the causal effects of air quality and temperature on student attendance and test scores, using a satellite measure of daily pollution and a novel monthly dataset on school attendance and test scores. The effect of air pollution on health is well-established in other contexts in the economics literature. This analysis builds upon the emerging literature that connects air pollution to human capital accumulation. 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, high temperatures between 30–38°C (86–100.4°F) lower test scores, especially math scores.

Keywords: air quality; temperature; education; human capital accumulation; development

JEL Codes: Q53, I25, O15

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1. 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 the 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 at-

[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).

tributed 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 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 mean annual temperature in Pakistan is projected to increase to 38.84°F (3.8°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.[2] In this paper, I build upon the emerging literature that examines the effect of pollution on labor productivity[3] and human capital accumulation[4]. Specifically, I examine the effects of short-term variation in air pollution and temperature on school attendance and learning, in Punjab, the second-largest and most populous of the four provinces of Pakistan.[5] I use a novel data set on school attendance and 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, constituting an unbalanced panel for about 48,000 individual schools, with more than 1.5 million observations.

In this paper, I have assembled the most comprehensive daily pollution and weather

[2]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).

[3]Zivin and Neidell (2012), Chang et al. (2016), Chang et al. (2019), Aragón et al. (2017), Fu et al. (2018).

[4]Ham et al. (2014), Ebenstein et al. (2016), Bharadwaj et al. (2017), Aizer et al. (2018).

[5]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.

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 Earth Engine.[6] There is no reliable comprehensive ground-level monitoring of air quality in Pakistan, so there is only limited conventional administrative air quality data available for Pakistan. 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 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

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

the average math score by 8 percent of a standard deviation. These estimates are larger compared to prior studies in developed countries such as U.S., Chile and Israel (Ebenstein et al., 2016; Ham et al., 2014; Miller and Mauricio, 2013)

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 temperaturse have an adverse effect on test scores. For example, an increase in outside temperature from 20–22°C (68–71.6°F) to 34–36°C (93.2–96.8°F) reduces total score by 0.16 of a standard deviation, and the average math and English scores by 0.2 of a standard deviation.

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 no comprehensive ground-level air quality data and pollution levels 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 is available from local ground monitors and schooling outcomes are much better than Pakistan.[7]

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 UK, Chile, and Israel (Miller and Mauricio, 2013; Ham et al., 2014; Ebenstein et al., 2016; Roth, 2018). 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 stu-

[7]In China, 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 68 in Pakistan (Xuepei et al., 2019).

dent test scores for developed countries (Zivin et al., 2015; Jisung, 2017; 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 potentially a confounding factor. So it could be that they are measuring the impact of pollutants instead of 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 household 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 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 reviews existing literature. The data are discussed in Section 4, and the empirical model is detailed in Section 5. Section 6 presents the estimation results, Section 7 discusses the heterogeneity analysis and Section 8 concludes.

2. Background

2.1 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 poorly insulated and ventilated buildings, with penetration 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 the cognitive resources become overloaded by heat stress, an insufficient amount of cognitive resources are available for cognitive tasks, resulting in impairments of cognitive function (Hancock, 986b; Hocking et al., 2001).

2.2 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, air quality ground-level monitoring 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, 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 Aerosal Optical Depth (AOD). In general, particulate matter comes 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 12 depicts the average 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, Khan et al., (2010) find the highest AOD values during summers, which is due to air masses coming from the Cholistan Desert in Pakistan and the Thar desert in India.

3. Literature Review

3.1 Air Pollution and Learning

Significant air pollution has a variety of 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.[8] 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 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.[9]

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 a decrease in particulate matter, specifically PM_{10}, increases 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 earning. 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 of 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 absence by 2 percent. Gilliland et al. (2001) demonstrate that increases in pollution increased

[8] 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

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

daily absences, due to respiratory illness, for 4th grade students in California. 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 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.

3.2 Temperature and Learning

The small existing literature suggests that high temperatures have an adverse effect on student learning. Zivin et al. (2015) 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 beyond 26°C. Using high school exit exam data from New York City public schools, Jisung (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.

4. Data

4.1 School Data

The school attendance and test-score data come 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 it contains information on the exact date of each visit.[10]

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, the school level (primary, middle, high), the number of teachers hired, 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. 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 (English, Urdu, Math), 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 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.

[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.

4.2 Pollution Data

There is limited administrative air-quality data available for Pakistan since 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.[11]

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

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, 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

[11] 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.

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.

Biomass burning (crop burning) is one main 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 economical method to remove weeds, pests and diseases, to prepare fields for the next crop (McCarty et al., 2009). Crop burning depends on the harvesting season of 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, 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 high-speed winds 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.[12] Figure 13 in 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 summer crop, and the other around the sowing of winter crop. It is evident from the figures that a majority of the field-burning fires in Pakistan occur in the province of Punjab.

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

Since, Punjab is the main agricultural province, 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, which is 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 14 and Figure 15 in appendix plot the parameter estimates for each month for all the districts in Punjab.[13] It is apparent from the figure that the NDVI decreases during March - April, which is around the 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 monthly survey of industrial production and employment in Punjab for the years 2014-2017 from the Bureau of Statistics of Punjab to gauge variation in air pollution due to industrial activity.[14] These monthly surveys cover 46 important industries in Punjab, including more than 1700 industrial units across the province.[15]

4.3 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

[13] I regress NDVI on monthly dummies for each district.
[14] `http://bos.gop.pk/cisreports`
[15] The data was requested from the Bureau of statistics Punjab on petition.

GLDAS-2.0 comes entirely from by the Princeton meteorological 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 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 11 in 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 temperature as high as 42–44°C (107.6–111.2°F).

Table 1 presents summary statistics for AOD, the weather variables, and student and teacher attendance for over the period September 2014–March 2018. The AOD in Punjab falls 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 16 in the Appendix depicts the mean AOD across all tehsils of Punjab for the period September 2014–March 2018. It is evident from the figure that there is significant spatial variation in mean AOD across the province.

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 is 93 percent. The summary statistics 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.

Table 1: Summary Statistics

VARIABLES	(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	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	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

Figure 1 presents a box plot of AOD and temperature on school-visit days, whereas Figure 2 depicts AOD as a function of temperature on school-visit days.[16] 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.

[16]Though each school is visited once a month, I have daily data for AOD and temperature. Figure 17 in appendix shows the relation between daily AOD and daily temperature at tehsil (sub-county) level

Figure 1: Box plot of AOD and temperature

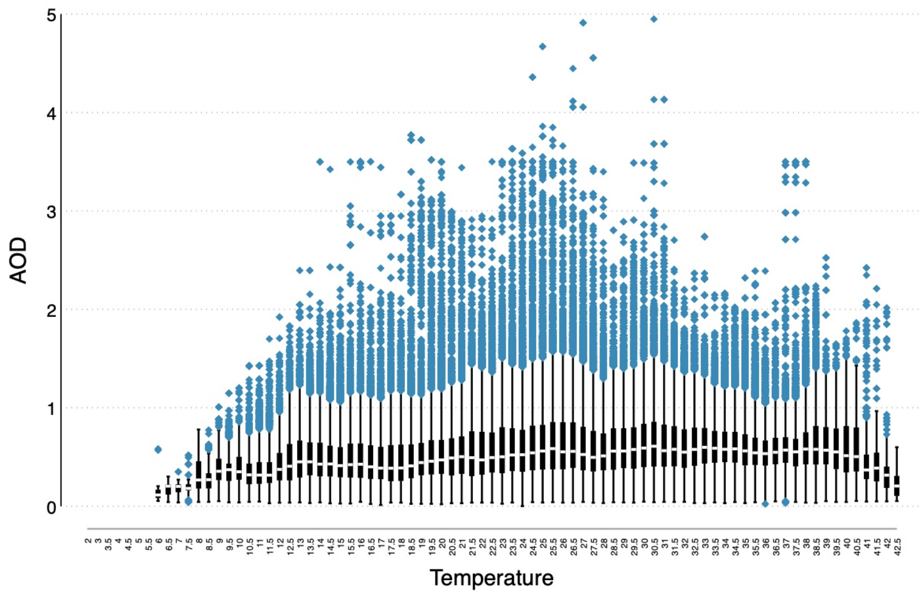
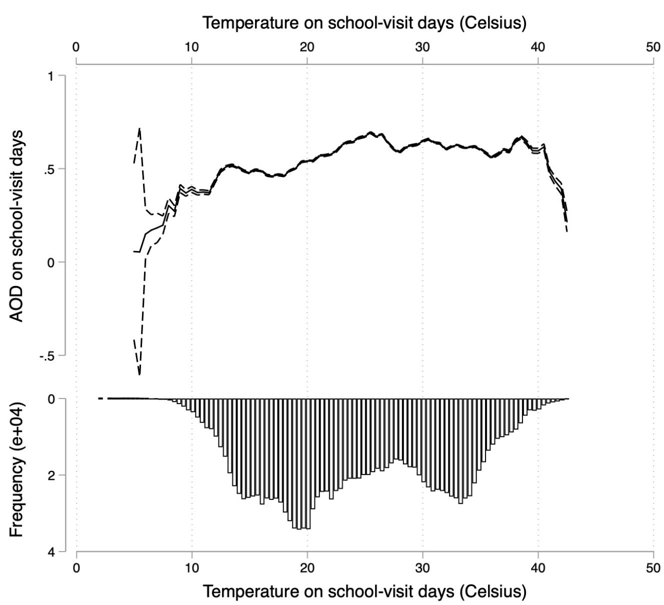


Figure 2: AOD as a function of temperature on school-visit days



943,660 total observations

5. Methodology

The equation I estimate is of the following form

$$Y_{st} = \beta AOD_{st} + f(Temp_{st}) + X_{st}\Gamma + Z_{st}\Pi + DOW_t + \alpha_m + \delta_y + \mu_s + \epsilon_{st} \tag{1}$$

where Y_{st} is the attendance or test scores for third grade students at school s at time t. In the test-score data, there is no ID or name provided for 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 at time 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. Z_{st} 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, X_{st} also includes the size of the third grade class(es). DOW_t, α_m, and δ_y are day of the week, month and year fixed effects, respectively. The μ_s parameters are school fixed effect, 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 20–22°C (68–71.6°F) as the reference bin.

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 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 19 shows some of the major dust storms that arose over Pakistan, specifically in June 2012, June 2017 and March 2018. To exploit the 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.

During each monthly school visit, field officers record enrollment in each class. The aca-

[17]Figure 18 shows the location of the deserts in Pakistan.

demic 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 threshold.

I find that for grades 1–5, about 8 percent of school observations exhibit attendance based on enrollments at the start of the school year (April) that are less than 80 percent, their (average) monthly attendance is more than 80 percent. For grades 6–9, the analogous fraction is 3.3–5.7 percent whereas for tenth grade, it is 19 percent. Since the monthly enrollment records do not seem to be manipulated systematically to increase attendance above 80 percent, I use monthly enrollment for estimation.[18]

I know the location 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 clustered at the tehsil level for attendance estimation. The test scores are count data, so I use log-linear model.[19]

6. Results

6.1 Pollution

AOD is a dimensionless unit, with a value of less than 0.1 indicating a clean atmosphere, whereas a value of 1 indicating a very hazy condition.[20]

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

[19] 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. Results for a Poisson specification without fixed effects are reported in Appendix.

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

6.1.1 Attendance

Table 2 reports the results of the effect of pollution (measured by AOD) and temperature on student attendance. The temperature estimates will be presented in section 6.2. 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 increases student attendance. Specifically, a change in atmosphere 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 tehsil-month fixed effects, respectively. The positive and statistically significant coefficient for AOD is robust across all these different fixed effects models.

Table 2: Incremental effect of AOD on student attendance

VARIABLES	(1) Attend	(2) Attend	(3) Attend	(4) Attend	(5) Attend	(6) 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 17 in 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 with just contemporaneous AOD and mean AOD yesterday). There is a strong correlation between current and one-day-lagged AOD as depicted in Table 12 in 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 produce high pollution and influence the decisions of households about whether to send younger school-aged children to school. Table 3 reports the results with controls for agricultural or industrial activity that would otherwise be omitted variables.

Table 3: Omitted Variable

	(1)	(2)
VARIABLES	AOD	Attendance
Agricultural Activity		
NDVI	-0.127***	0.719***
	(0.00460)	(0.100)
NDVI negative change	0.00535***	0.0926***
	(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

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 1. 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 1700 industrial units and 46 important industries.[21] I find that an increase in industrial employment also *increases* both air pollution and student attendance.

Table 15 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.[22] When I exclude the crop-harvesting months from the sample, the results in Table 16 in the Appendix show that an increase in AOD from 0 (clean atmosphere) to 1 (very hazy conditions) reduces student attendance by about 0.15 percent.

Due to pollution being potentially endogenous, I use instrumental variable estimation. Table 4 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 weather station data as instrument for AOD. 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 5 presents the instrumental variable (IV) estimation results.[23] 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

[21] `http://bos.gop.pk/cisreports`
[22] Schools are closed from June-August, and there were no attendance data for September.
[23] I use xtivreg in Stata.

Table 4: Instrumental variable (IV): First stage

VARIABLES	(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

Table 5: IV: Incremental effect of AOD on student attendance

VARIABLES	(1) Attend	(2) Attend	(3) Attend	(4) Attend	(5) Attend	(6) 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

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 conditions.[24]

[24]For example, in the tehsil-month FE model, anything that is common across all schools in a specific tehsil

6.1.2 Test Scores

Table 6 reports the effect of AOD on total test scores with school fixed effects.[25] For the test scores data, not all students enrolled in third grade are tested. As discussed in the data section, during each monitoring visit, an average of six or seven students in third grade are randomly selected and tested in each school. 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 AOD in Table 6 indicate 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 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 6 also reports the effect of AOD on total test scores with instrument (IV) for AOD. The IV estimates of the AOD coefficient are 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 7. 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 effect on English

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.

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

scores.

Table 6: Incremental effect of AOD on test scores (log)

VARIABLES	(1) Scores	(2) Scores	(3) Scores	(4) Scores	(5) Scores	(6) 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

Table 7: Incremental effect of AOD on subject scores (log)

VARIABLES	(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 8 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 also use maximum and minimum individual student scores in a school during each monitoring visit to analyze the effect of pollution and temperature on the distribution of test scores. 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 *minimum* score by an average of 10.4 percent (0.48 std. dev.).

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.

Table 8: Incremental effect of AOD on maximum and minimum test scores

	(1)	(2)
VARIABLES	Maximum Score	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

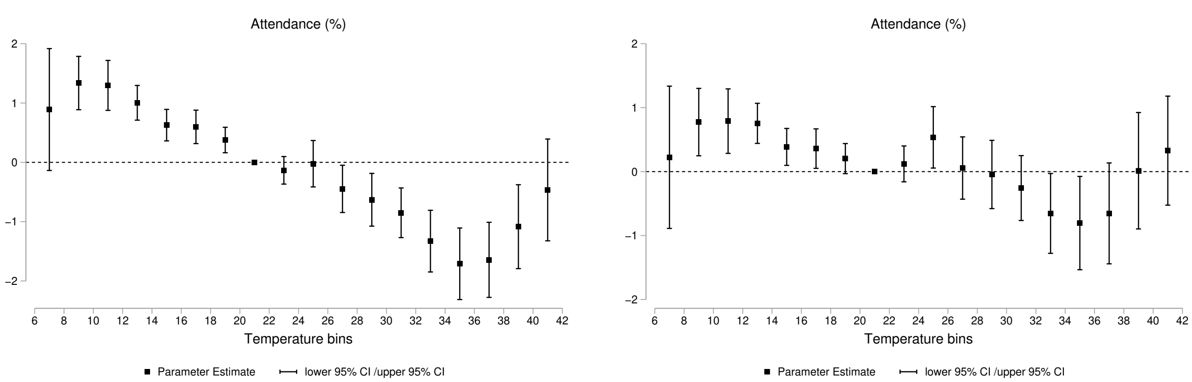
Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Robust standard errors in parentheses

6.2 Temperature

6.2.1 Attendance

The effects of temperature levels on student attendance with school fixed effects, without instrumenting for AOD (Model 3 in Table 2) and with instrument for AOD (Model 3 in Table 5) are depicted in Figure 3. The estimates for the temperature bins indicate that an increase in mean air temperature from 20–22°C (68–71.6°F) to 34–36°C (93.2–96.8°F) reduces student attendance by 1.71 percent (0.15 std. dev.). Similarly, an increase in mean air temperature from 20–22°C (68–71.6°F) to 38–40°C (100.4–104°F) reduces student attendance by 1.1 percent (0.1 std. dev.). The highest temperature bin of 40–42°C (104–107.6°F) occurs rarely in the data (Figure 2), and appears to have no effect on student attendance. On the other hand, a decrease in mean air temperature from 20–22°C (68–71.6°F) to 10–12°C (50–53.6°F) increases student attendance by about 1.3 percent.

Figure 3: Incremental effect of temperature on student attendance



(a) FE only, no instrument

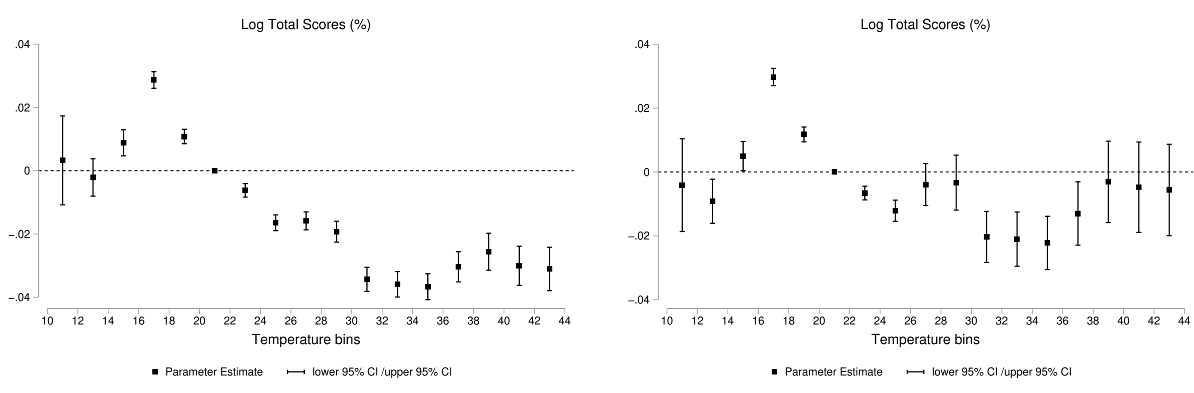
(b) FE plus IV for AOD

With instrument for AOD, temperature bin estimates show that an increase in mean daily air temperature from 20–22°C (68–71.6°F) to 32–34°C (89.6–93.2°F) reduces student attendance by 0.65 percent, whereas an increase to 34–36°C (93.2–96.8°F) reduces student attendance by 0.8 percent (0.07 std. dev.). No other temperature bin greater than 20–22°C (68–71.6°F) appears to have an effect on student attendance. However, most of the temperature bins lower than the omitted bin still have a significant effect on attendance. For example, a decrease in mean air temperature from 20–22°C (68–71.6°F) to 12–14°C (53.6–57.2°F) increases student attendance by 0.75 percent.

6.2.2 Test Scores

The effects of temperature levels on total scores for both the fixed effects and instrumental variables estimation (Model 3 in Table 6) are depicted in Figure 4.[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 than the reference bin (20–22°C) reduce test scores. For example, an increase in outside temperature from 20–22°C (68–71.6°F) to 42–44°C (107.6–111.2°F) reduces total scores by an average of 3.11 percent (0.25 std. dev.).

Figure 4: Incremental effect of temperature on total scores (log)



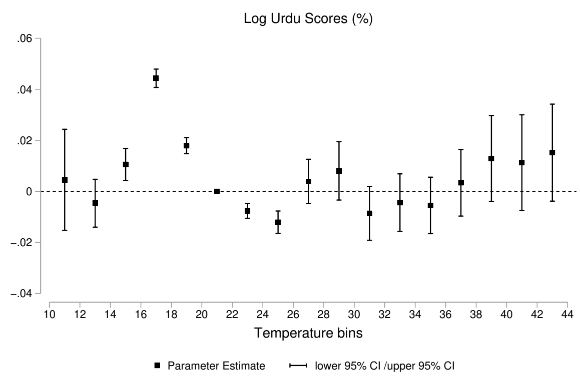
(a) FE only, no instrument

(b) FE plus IV for AOD

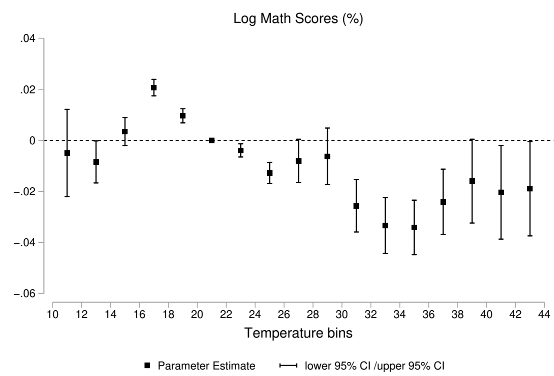
[26]I suppressed the coefficient for temperature bin of 8–10°C (46.4–50°F) in the test scores graphs due to the very small number of observations, and therefore, very large confidence intervals.

Temperatures lower than the reference bin seem to increase test scores, especially the temperature bin 16–18°C (60.8–64.4°F). Specifically, a decrease in mean air temperature from 20–22°C (68–71.6°F) to 16–18°C (60.8–64.4°F) increases total scores by an average of 2.87 percent (0.23 std. dev.). In a model that instruments for AOD, temperatures between 30–38°C (86–100.4°F) lower total scores. For example, an increase in outside temperature from 20–22°C (68–71.6°F) to 34–36°C (93.2–96.8°F) reduces total score by 2.22 percent (0.17 std. dev.). Lower temperatures, between 16°C (60.8°F) and 20°C (64.4°F), increase test scores. Specifically, a decrease in mean air temperature from 20–22°C (68–71.6°F) to 16–18°C (60.8–64.4°F), increases average total scores by 2.97 percent (0.23 std. dev.).

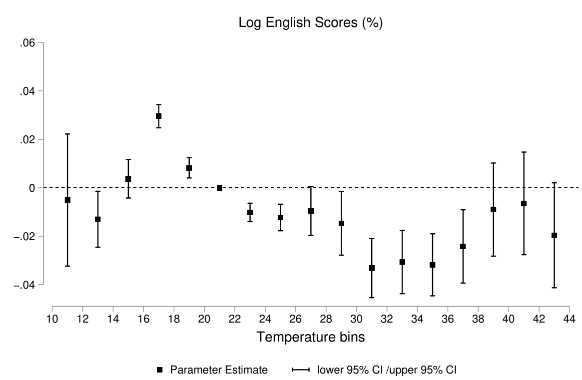
Figure 5: Incremental effect of temperature on subject scores (log) (FE plus IV for AOD)



(a) Urdu



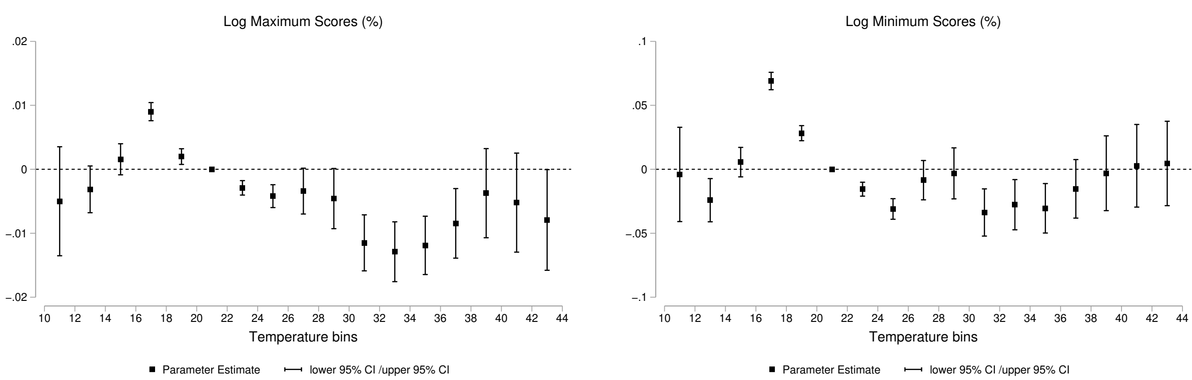
(b) Math



(c) English

The effects of temperature levels on subject scores, using the instrument for AOD, are depicted in Figure 5. The estimates for these temperature bins suggest that temperatures higher than the omitted bin (20–22°C), particularly between 30–38°C (86–100.4°F), are associated with lower math and English scores. For example, an increase in outside temperature from 20–22°C to 34–36°C (93.2–96.8°F) reduces math scores by 3.41 percent (0.23 std. dev.), and English scores by 3.18 percent (0.17 std. dev.). Temperatures higher than 38°C lower only math scores. An increase in outside temperature from 20–22°C (68–71.6°F) to 40–42°C (104–107.6°F) reduces math scores by 2.04 percent (0.14 std. dev.). Temperatures between 16–20°C (60.8–68°F) seem to increase test scores. Specifically, a decrease in mean air temperature from 20–22°C (68–71.6°F) to 16–18°C (60.8–64.4°F), increases Urdu scores by 4.43 percent (0.29 std. dev.), math scores by 2.07 percent (0.14 std. dev.), and English scores by 2.96 percent (0.16 std. dev.).

Figure 6: Incremental effect of temperature on maximum and minimum test scores (IV for AOD)



(a) Maximum Score

(b) Minimum Score

Figure 6 shows the effects of different temperature levels on the maximum and mininum scores, with an instrument for AOD. The estimates indicate that some temperatures higher than the reference bin (20–22°C)—specifically temperatures between 30–38°C (86–100.4°F)—

reduce both maximum and minimum individual scores. The estimates can be interpreted as: an increase in outside temperature from 20–22°C (68–71.6°F) to 34–36°C (93.2-96.8°F) lowers the maximum individual score by 1.19 percent (0.15 std. dev.) and minimum individual score by 3.05 percent (0.14 std. dev.). For the maximum score, temperature effect is not insignificant compared to effect of AOD, whereas for the minimum score, the temperature effect is much smaller than the effect of AOD. Temperatures higher than 38°C appear to have no statistically discernible effect on either maximum and minimum individual scores, whereas temperatures between 16–20°C 60.8–68°F) increase both maximum and minimum individual scores.

7. Heterogeneity Analysis

7.1 Pollution Effects by Gender

I examine the heterogeneity in the impact of AOD and temperature to 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 9. 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.).

In Table 10 , 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 score 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 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.

Table 9: Attendance by gender

VARIABLES	(1) Male	(2) 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

Table 10: Test scores (log) by gender

VARIABLES	(1) Total	(2) Urdu	(3) Math	(4) 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

Table 11: Maximum and minimum test scores by gender

VARIABLES	(1) log(Maximum Score)	(2) log(Minimum Score)
Male		
AOD	0.00305	-0.110***
	(0.00956)	(0.0405)
Female		
AOD	-0.00871	-0.101***
	(0.00817)	(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

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 pollution are presented in Table 11. 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.

7.2 Temperature Effects by Gender

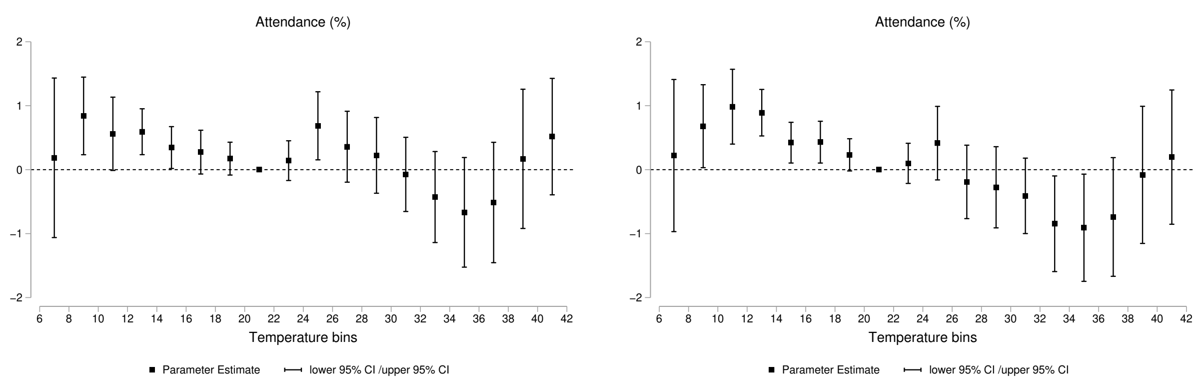
The temperature bin estimates for the two models in Table 9 are presented in Figure 7. Temperatures higher than 20–22°C (68–71.6°F) generally have no effect on the attendance of boys. However, for girls schools, an increase in mean air temperature from 20–22°C to 34–36°C (93.2–96.8°F) reduces attendance by 0.9 percent (0.08 std. dev.).

Figure 8 and Figure 9, correspondingly show the effects of temperature levels on total and subject scores (with the instrument for AOD) for boys' and girls' schools, respectively.

Temperatures between 30–38°C (86–100.4°F) reduce test scores for both boys' and girls' schools, except Urdu scores, whereas temperatures higher than 38°C (100.4°F) have no effect on test scores for either type of school. An increase in outside temperature from 20–22°C (68–71.6°F) to 34–36°C (93.2–96.8°F) reduces total test scores for girls' schools by 2 percent (0.16 std. dev.), and lowers total test scores for boys' school by 2.4 percent (0.19 std. dev.).

For subject scores, an increase in temperature from the reference bin (20–22°C) to 34–36°C (93.2–96.8°F) reduces math scores by 3.8 percent (0.26 std. dev.) for boys' schools and by 3.1 percent (0.21 std. dev.) for girls' schools, whereas the English score is reduced by 3.9 percent (0.2 std. dev.) for boys' schools and by 2.5 percent (0.14 std. dev.) for girls' schools. Moreover, an increase in temperature from 20–22°C to 36–38°C (96.8–100.4°F) reduces math scores for boys' school by 2.8 percent (0.19 std. dev.) and for girls' schools by 2 percent (0.14 std. dev.).

Figure 7: Effect of temperature on attendance by gender

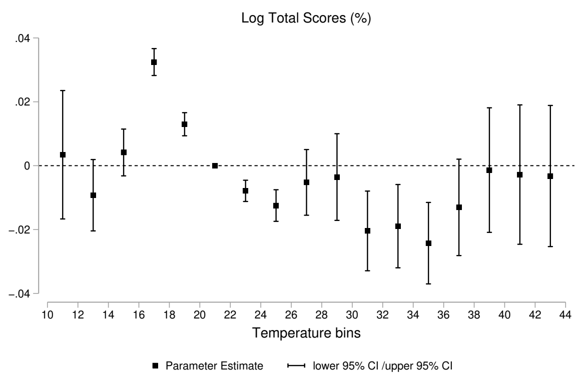


(a) Male (b) Female

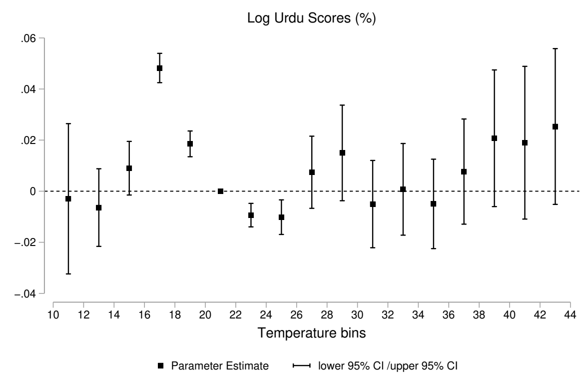
Temperatures between 16–20°C (60.8–68°F) increase test scores for both boys' and girls' schools. For example, when mean air temperature decreases from 20–22°C (68–71.6°F) to 16–18°C (60.8–64.4°F), at boys' schools, there is an increase in total scores by 3.2 percent

(0.25 std. dev.), Urdu scores by 4.8 percent (0.3 std. dev.), math scores by 2.1 percent (0.15 std. dev.), and English scores by 3.5 percent (0.18 std. dev.), whereas at girls' schools, there is an increase in total scores by 2.8 percent (0.22 std. dev.), Urdu scores by 4.1 percent (0.28 std. dev.), math scores by 1.9 percent (0.13 std. dev.), and English scores by 2.5 percent (0.14 std. dev.).

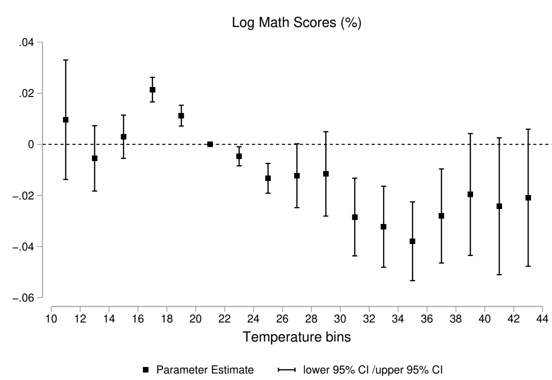
Figure 8: Effect of temperature on scores: Male



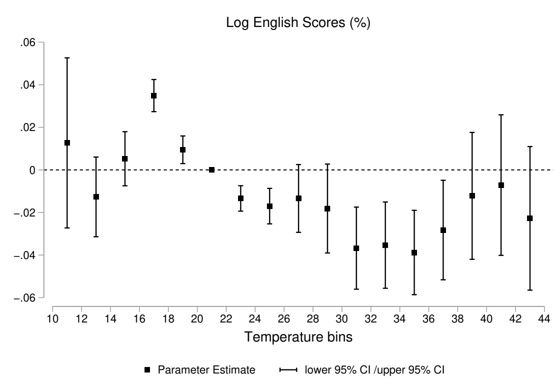
(a) Total



(b) Urdu

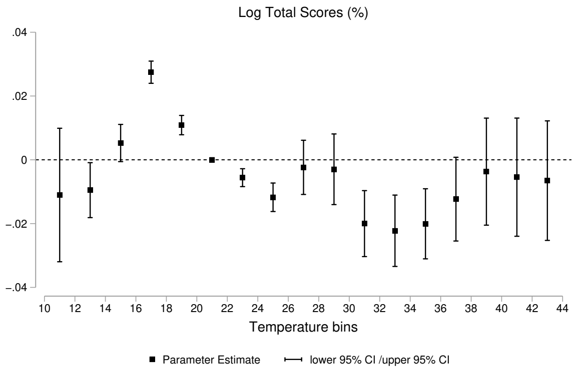


(c) Math

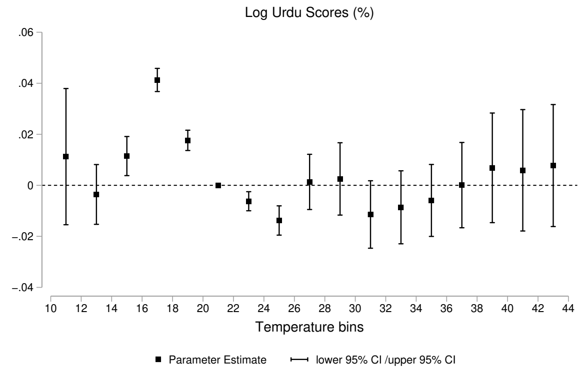


(d) English

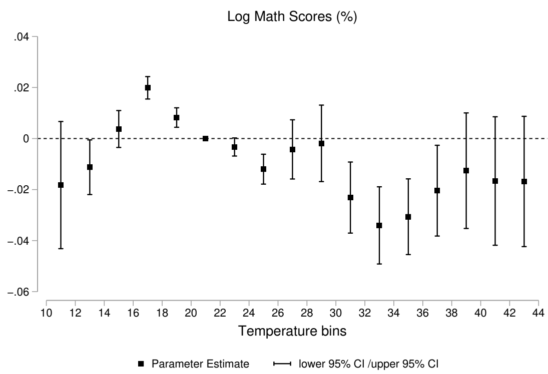
Figure 9: Effect of temperature on scores: Female



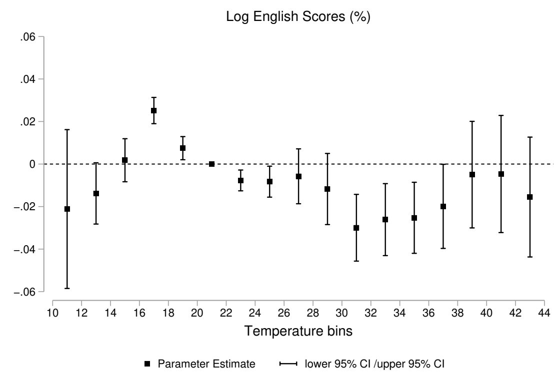
(a) Total



(b) Urdu



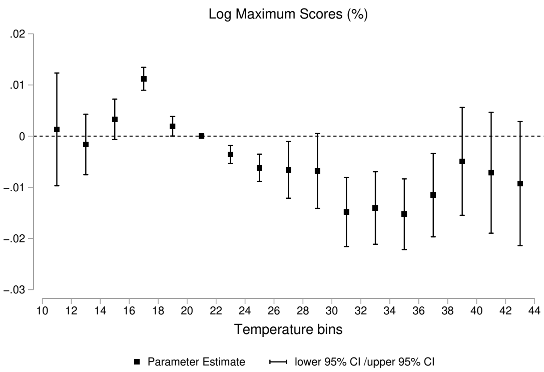
(c) Math



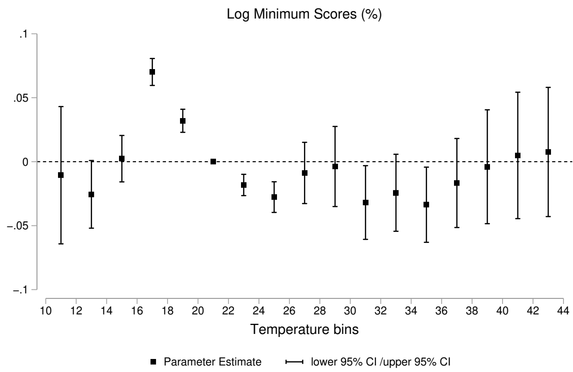
(d) English

Figure 10 presents the effects of different temperature levels (with the instrument for AOD) on maximum and minimum scores seperately for boys' and girls' schools. Temperatures between 30–38°C (86–100.4°F) reduces maximum individual scores of both boys' and girls' schools. For example, an increase in outside temperature from 20–22°C (68–71.6°F) to 34–36°C (93.2–96.8°F) lowers maximum individual score by 1.5 percent (0.19 std. dev.) at boys's schools and by 0.9 percent (0.12 std. dev.) at girls' schools. For boys' school, there is no effect of high temperatures on minimum individual scores. However, for girls' school, temperatures between 30–36°C (86–96.8°F) lower the minimum individual scores. Moreover, temperatures between 16–20°C (60.8–68°F) increase maximum and minimum individual scores at boys' and girls' schools.

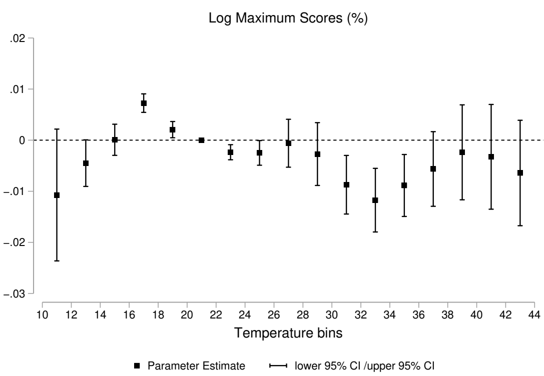
Figure 10: Effect of temperature on maximum and minimum test scores by gender



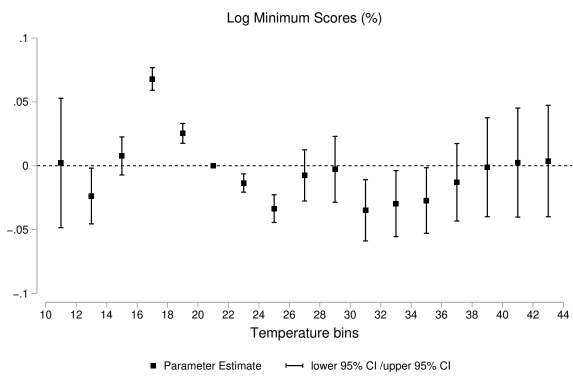
(a) Male: Maximum Score



(b) Male: Minimum Score



(c) Female: Maximum Score



(d) Female: Minimum Score

8. 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 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 driven 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 high temperatures in the range 30-38°C (86-100.4°F) reduce test scores, especially math scores. The total and 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. Similarly, high temperatures have a larger adverse effect on the test scores of boys compared to 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 (Krueger and Lindahl, 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.

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Appendix

Table 12: Correlation of AOD with its lagged values

VARIABLES	(1) AOD	(2) AOD_{-1}	(3) AOD_{-2}	(4) AOD_{-3}	(5) AOD_{-4}	(6) AOD_{-5}	(7) AOD_{-6}	(8) 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 13: Correlation of temperature with its lagged values

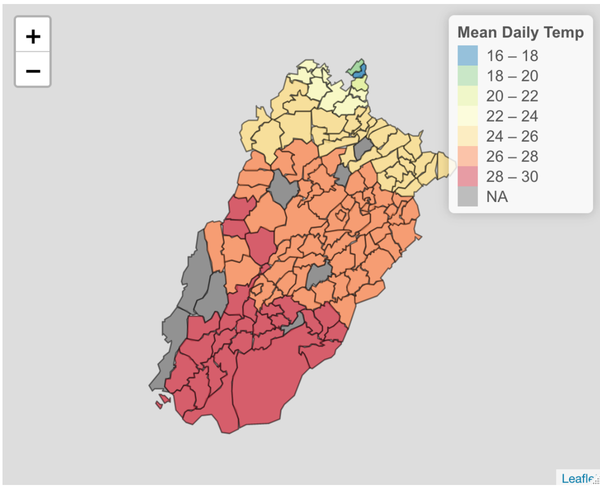
VARIABLES	(1) Temp	(2) $Temp_{-1}$	(3) $Temp_{-2}$	(4) $Temp_{-3}$	(5) $Temp_{-4}$	(6) $Temp_{-5}$	(7) $Temp_{-6}$	(8) $Temp_{-7}$
$Temp$	1.0000							
$Temp_{-1}$	0.9884	1.0000						
$Temp_{-2}$	0.9728	0.9876	1.0000					
$Temp_{-3}$	0.9586	0.9716	0.9877	1.0000				
$Temp_{-4}$	0.9472	0.9581	0.9724	0.9880	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

Table 14: Effect of lags of AOD and temperature on contemporaneous values

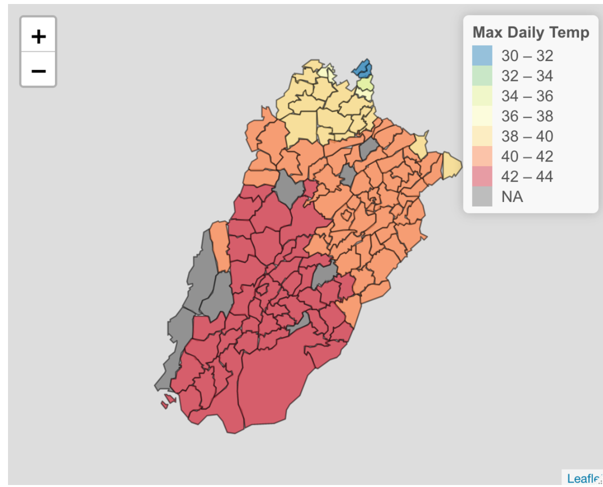
VARIABLES	(1) AOD	(2) Temperature
AOD_{-1}	0.502***	
	(0.00226)	
AOD_{-2}	0.177***	
	(0.00259)	
AOD_{-3}	-0.00741***	
	(0.00265)	
AOD_{-4}	0.0376***	
	(0.00274)	
AOD_{-5}	0.0493***	
	(0.00260)	
AOD_{-6}	-0.120***	
	(0.00264)	
AOD_{-7}	0.110***	
	(0.00230)	
$Temperature_{-1}$		1.128***
		(0.000791)
$Temperature_{-2}$		-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

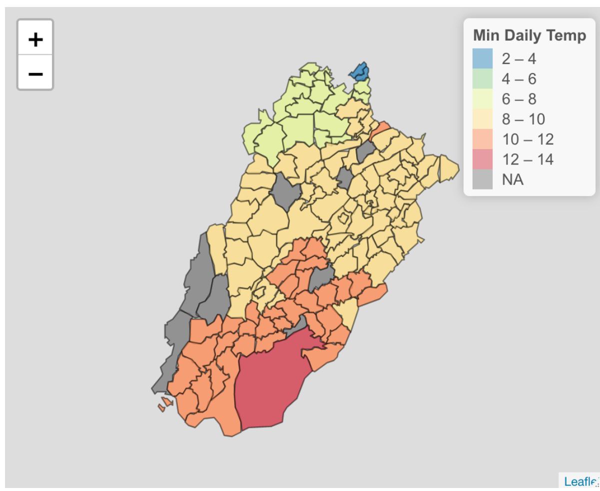
Figure 11: **Daily Temperature: 2014–2018**



(a) Mean

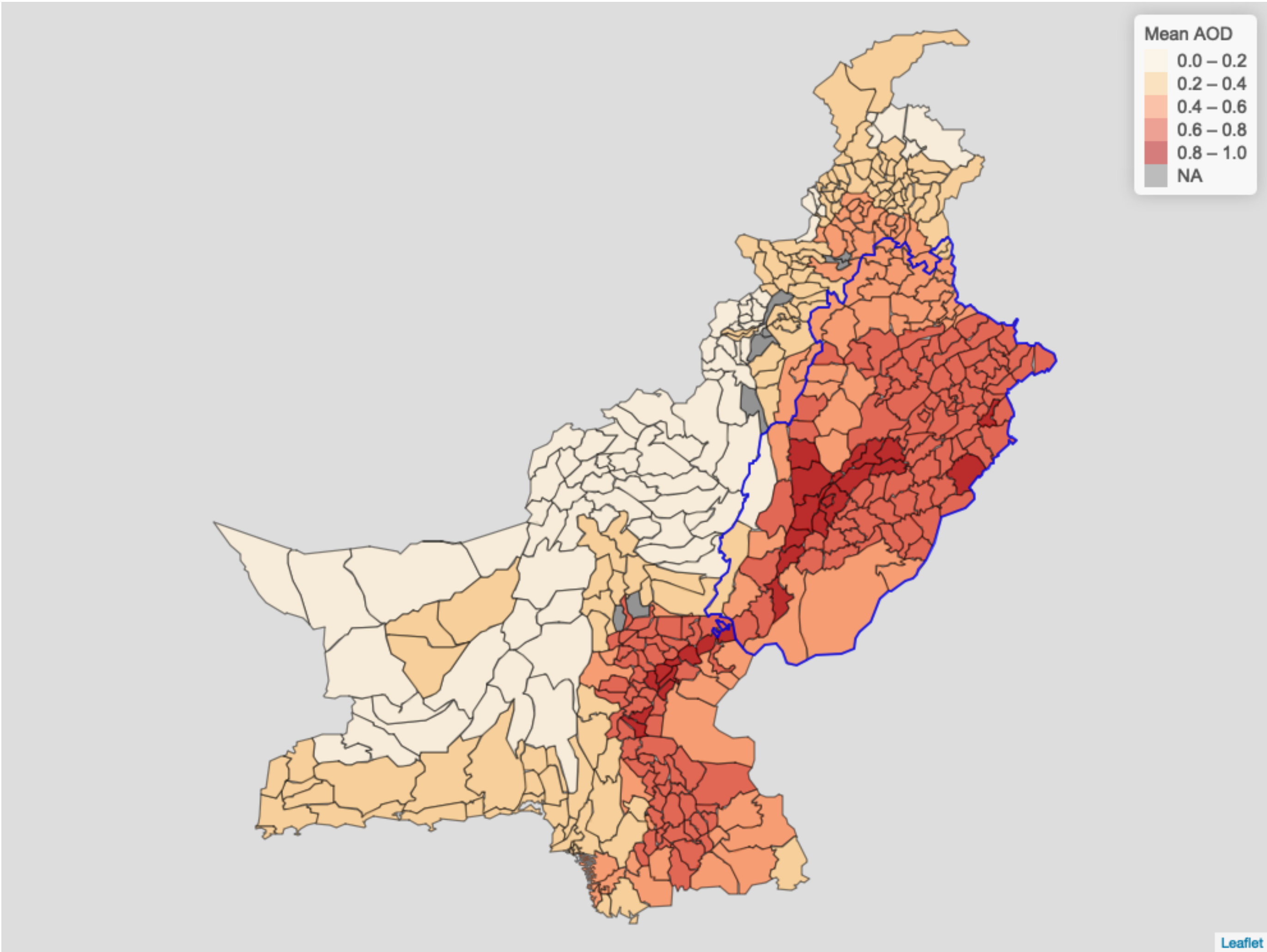


(b) Maximum



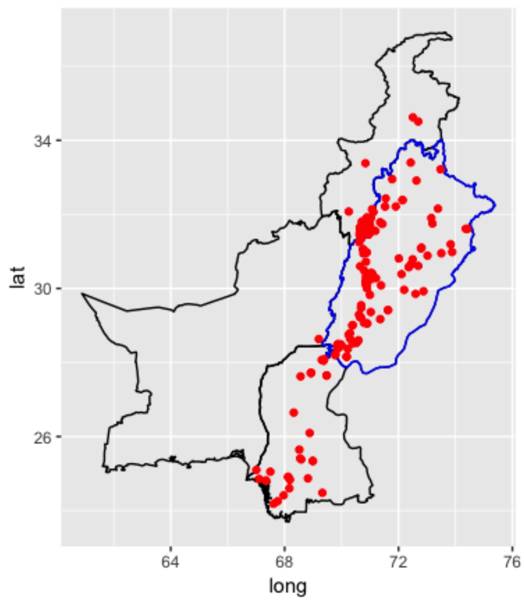
(c) Minimum

Figure 12: Mean Aerosal Optical Depth (AOD) in Pakistan (by Tehsil)

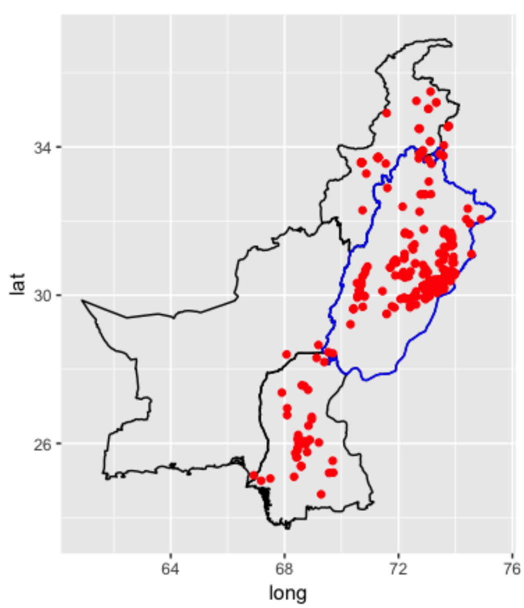


Notes: This map depicts the mean AOD during the period September 2014 - March 2018 for all tehsils in Pakistan. The region bounded by blue line is Punjab. The darker colors indicate more aerosals (air pollution).

Figure 13: Fires during agricultural burning season

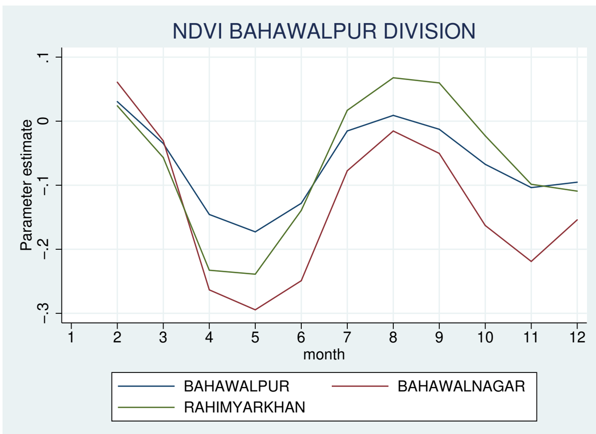


(a) March 10 2015

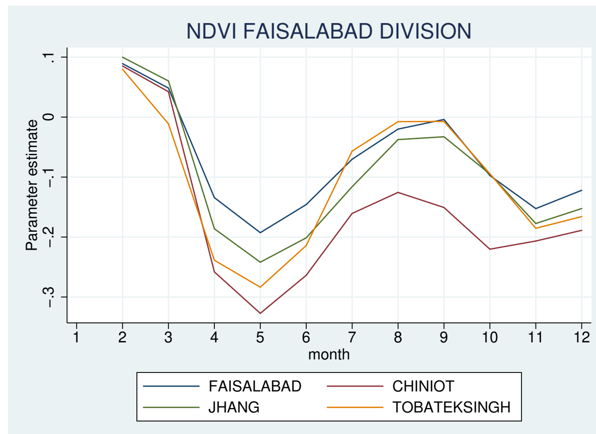


(b) October 29 2017

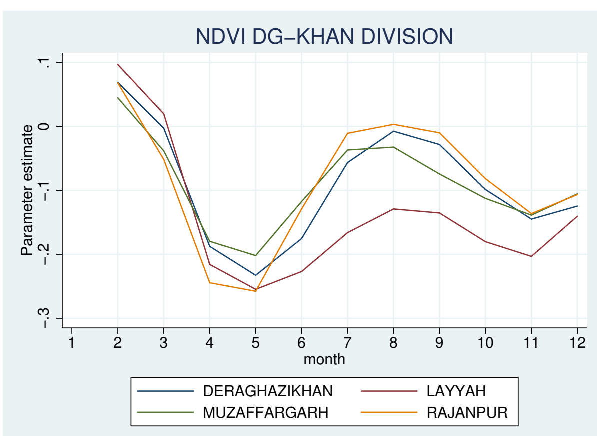
Figure 14: NDVI Parameter Estimates by Division



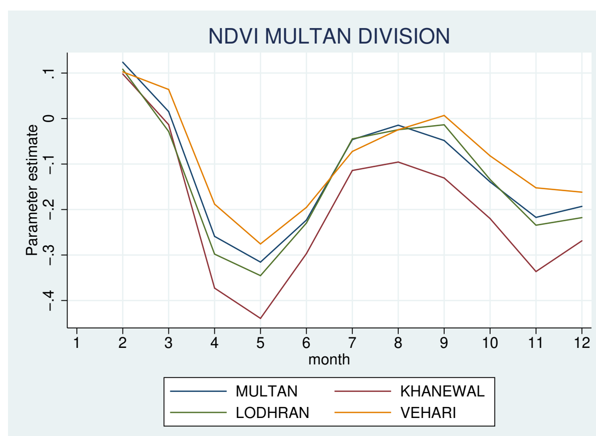
(a) BAHAWALPUR



(b) FAISALABAD

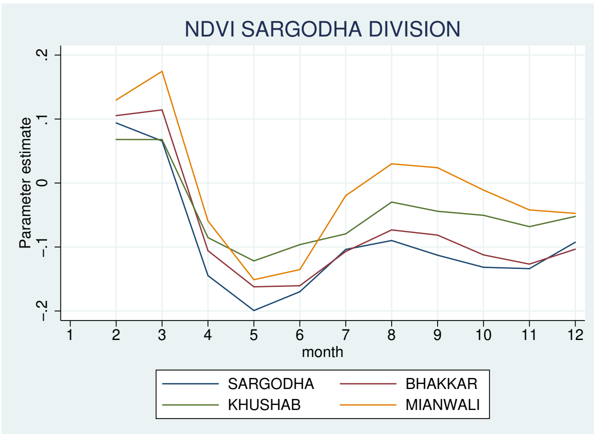


(c) DGKHAN

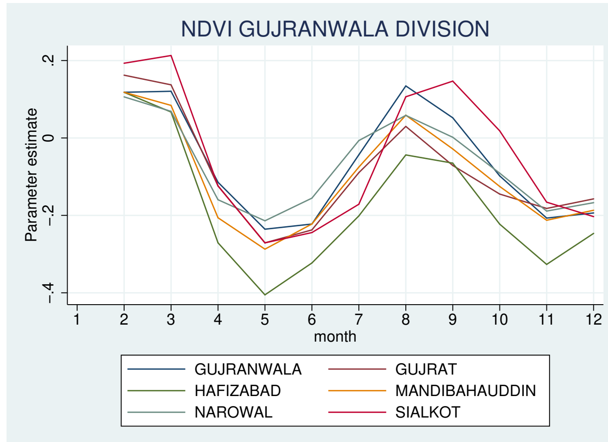


(d) MULTAN

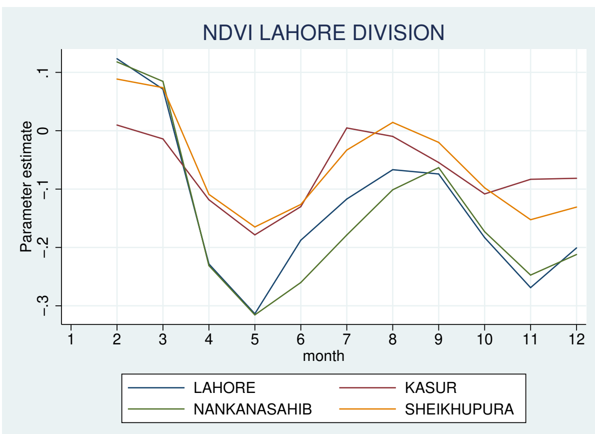
Figure 15: NDVI Parameter Estimates by Division



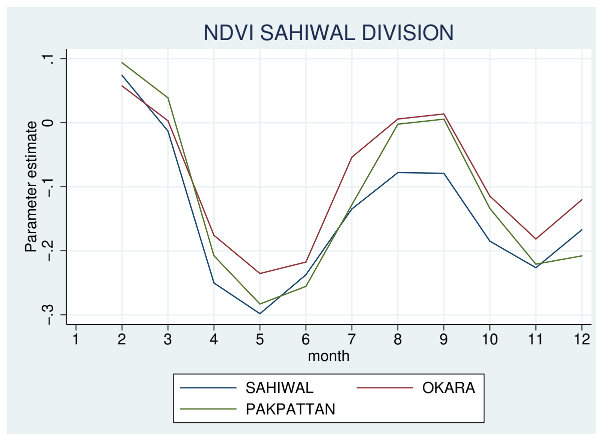
(a) SARGODHA



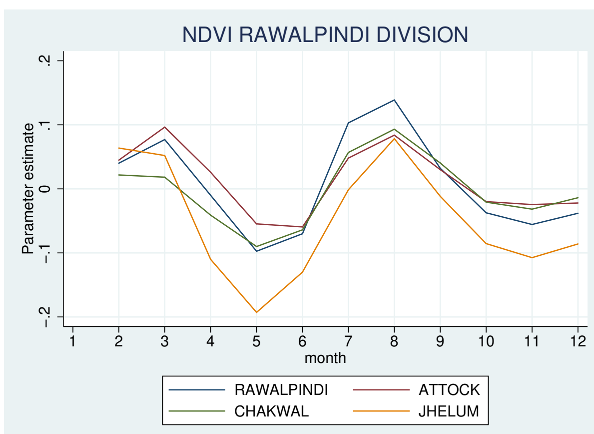
(b) GUJRANWALA



(c) LAHORE

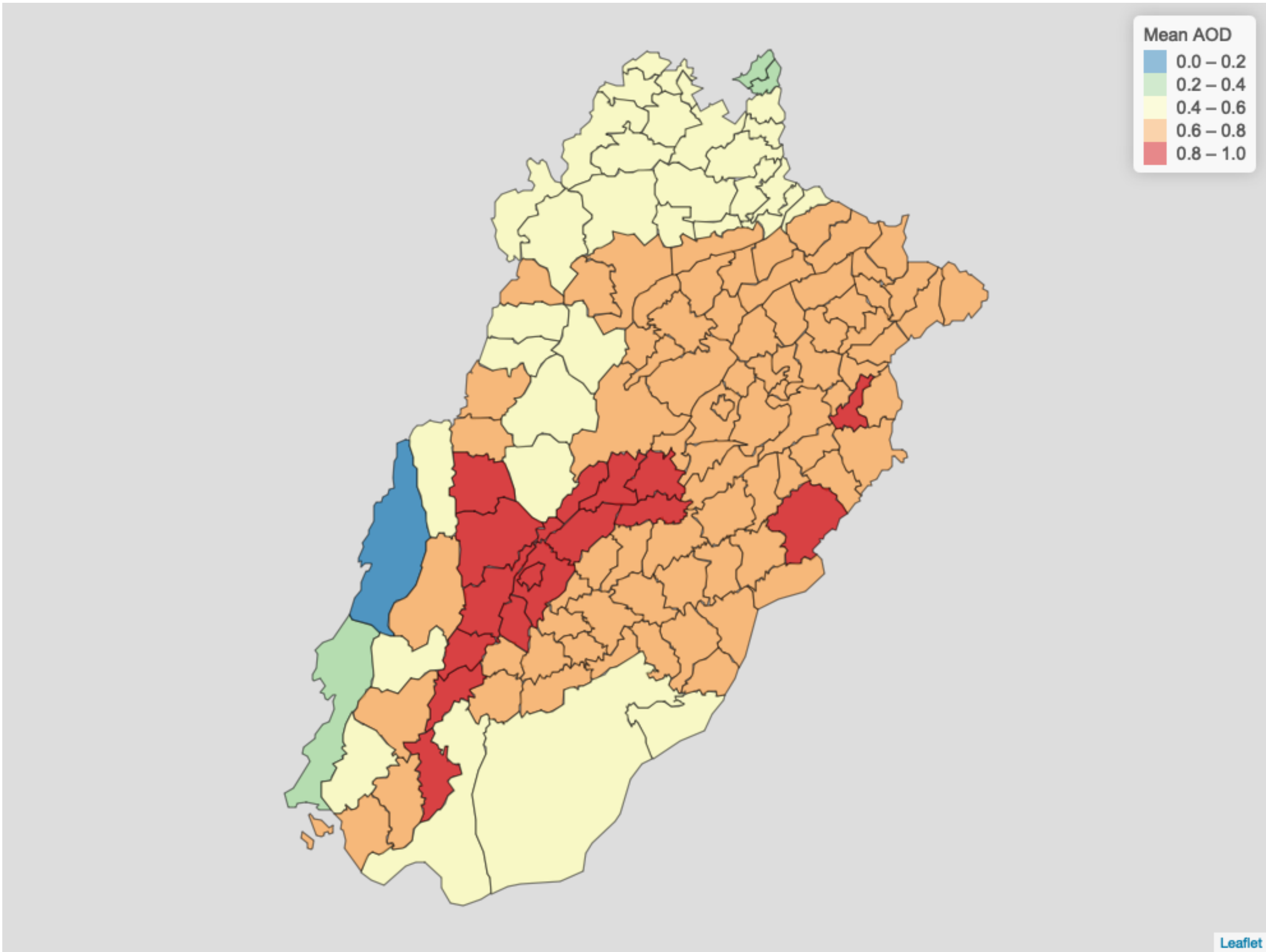


(d) SAHIWAL



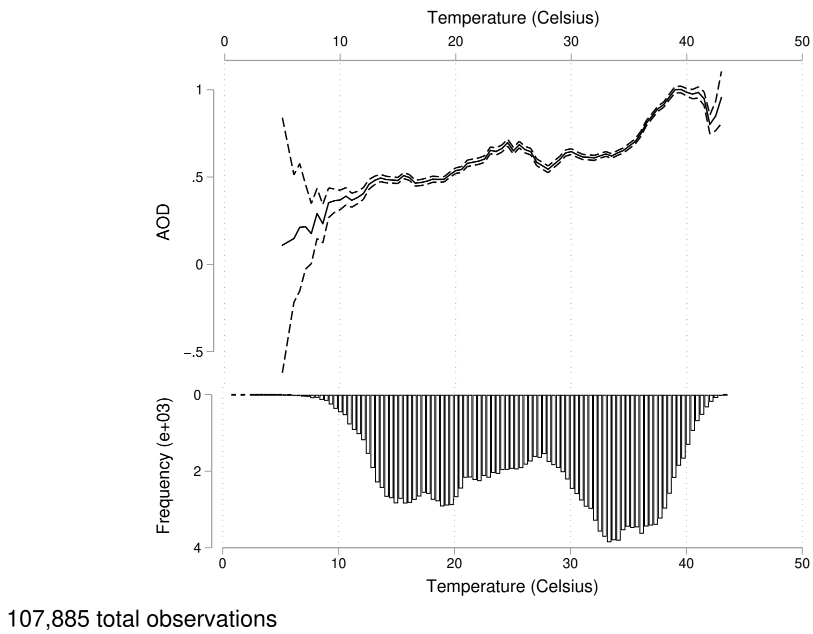
(e) RAWALPINDI

Figure 16: Mean Aerosal Optical Depth (AOD) in Punjab



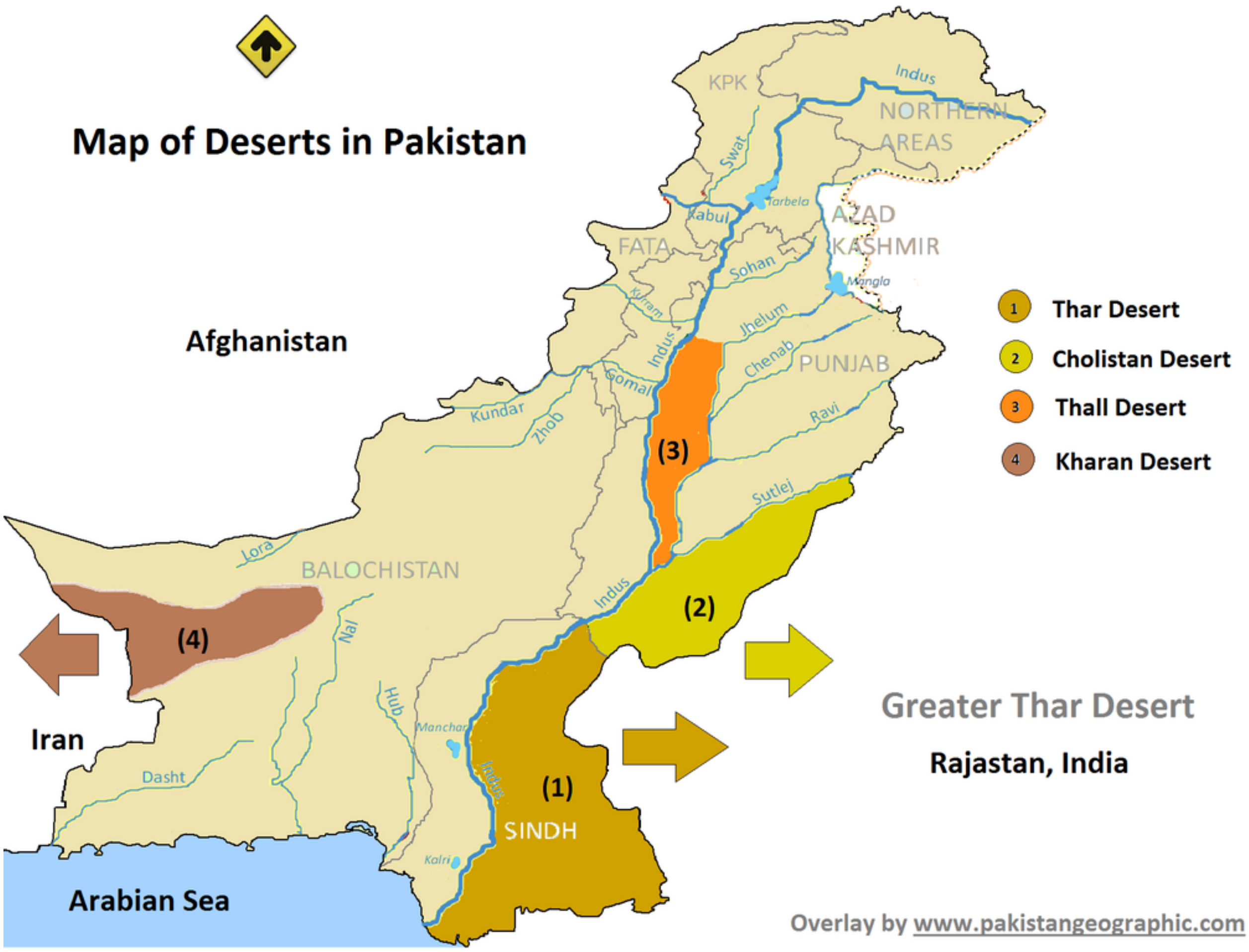
Notes: This map depicts the mean AOD across all tehsils in Punjab during the period September 2014 - March 2018. The darker colors indicate more aerosals (air pollution).

Figure 17: AOD as a function of temperature



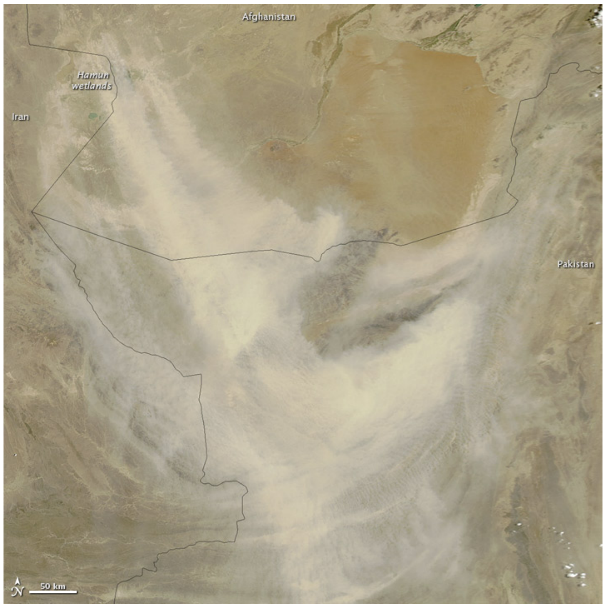
Notes: This graph depicts the relation between daily AOD and daily temperature at tehsil level for the time period September 2014–March 2018.

Figure 18: Deserts in Pakistan

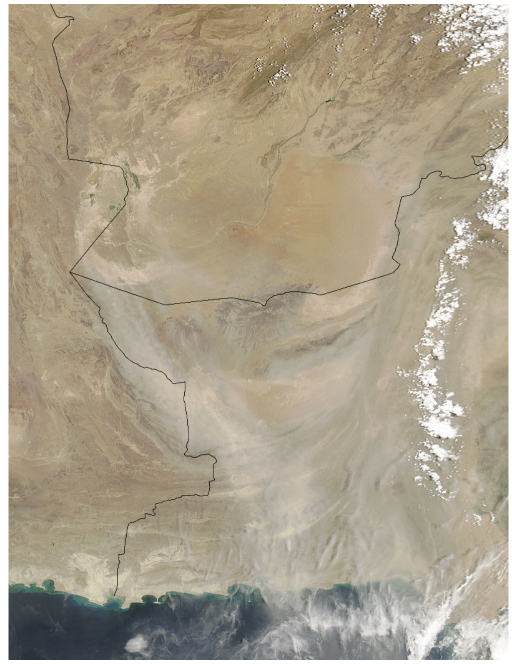


Notes: This map shows the location of the four deserts within Pakistan.

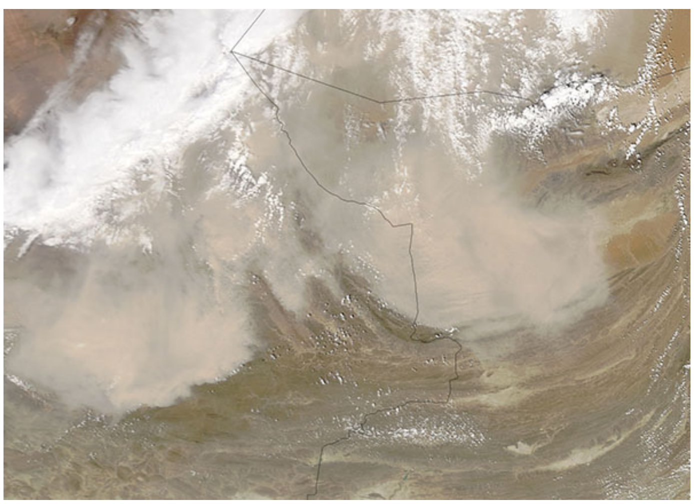
Figure 19: Dust Storms over Pakistan



(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 15: Student attendance by month

VARIABLES	(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	✓	✓	✓	✓	✓	✓	✓	✓
Observations	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 16: Student Attendance: non-harvesting months

VARIABLES	(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 17: Student attendance = f(AOD, temperature, mean lag AOD)

VARIABLES	(1) Attend	(2) Attend	(3) Attend	(4) Attend	(5) Attend	(6) Attend	(7) Attend	(8) Attend
AOD	0.196***	0.0606	0.149**	0.222***	0.240***	0.265***	0.271***	0.287***
	(0.0606)	(0.0685)	(0.0607)	(0.0590)	(0.0591)	(0.0589)	(0.0590)	(0.0596)
$\overline{AOD}_{-1}$		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)	
$\overline{AOD}_{-7}$								-0.491***
								(0.0992)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
School Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	625,490	452,268	539,463	576,174	593,850	605,901	611,899	616,994
R^2	0.051	0.054	0.053	0.052	0.052	0.051	0.051	0.051
Schools	47,632	47,540	47,609	47,624	47,631	47,632	47,632	47,632

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