Do Wildfilres Harm Student Learning?

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Abstract

I evaluate the effect of wildfire smoke on primary and middle school students' English Language Arts (ELA) and math achievement across the United States. To estimate students' exposure to wildfires at the school district level, I merge satellite-based wildfire smoke plume boundaries and 1km-grid daily $PM_{2.5}$ values with school district locations, and weight the exposure by census tract population. I find that recent drifting wildfire smoke plumes significantly lower ELA and math test scores. When I proxy the wildfire intensity by $PM_{2.5}$, results suggest that severe wildfires generate lasting effects on young students in primary school. Effects are only transitory for students in middle school. Further analysis reveals that Black students in primary school and economically disadvantaged students are more negatively affected than others. Males are more affected by unhealthy air quality in elementary ELA and middle school math than female students. Overall, findings suggest that more environmental and educational policy responses are needed to protect students with the increase in wildfire occurrence and intensity.

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1 Introduction

The increasing number of wildfires and their destructive consequences have drawn much public attention in recent years. In 2017, over 71,000 wildfires burned 10 million acres of land (U.S. Congressional Research Service, 2020). Wildfires are known to generate direct effects on the ecosystem and wildlife with the burning of biomass, the changing of landcover, and the destruction of habitats (Wardle et al., 2003; Smith et al., 2021; Pausas & Keeley, 2019; Rollan & Real, 2011). Wildfire-generated smoke can spread miles away and the smoke is shown to affect public health (Liu et al., 2015; Heft-Neal et al., 2022; Johnston et al., 2012; Reid et al., 2016; Amjad et al., 2021; Mccoy & Zhao, 2021), migration (McConnell et al., 2021; Burke et al., 2022), and labor market outcomes (Borgschulte et al., 2022).

While much research has been done to explore the effect of wildfires, the evidence of the causal relationship between wildfires and cognitive abilities is limited, especially for young students. The goal of this study is to investigate the effect of wildfires on student learning, more specifically on students' English Language Arts (ELA) and math academic achievement. The key challenge to identifying the causal effects is to assess geographical variation in wildfire exposure. Simply using wildfire burning coordinates to determine exposure is inadequate because smoke plumes can travel great distances, and are affected by wind, wildfire intensity, and other meteorological factors. A drifting smoke plume generates exogenous variation in wildfire exposure. Therefore, I employ satellite-based data on wildfire plume boundaries and spatially join these smoke boundaries with school district maps to identify exposure areas.

However, smoke boundaries alone do not reveal the details of the pollution intensity. I follow Heft-Neal et al. (2022) to merge smoke boundaries with ensemble-based model predictions of high-resolution 1km-grid daily Particulate Matter 2.5 ($PM_{2.5}$) concentrations, which is widely known as one of the most important indicators of wildfire smoke pollution (United States Environmental Protection Agency, 2019). In addition, I add the census tract level population to the dataset by geometric locations. This allows me to estimate district-level exposure to wildfires by both wildfire smoke and the associated air pollution throughout the population of a given census tract. I link the exposure dataset to over 320 thousand student achievement records, including average English Language Arts (ELA) and math standardized test scores at the school district level throughout the United States, school years 2009-2010 through 2014-2015. This data offers a good representation of different ranges and variations of wildfires that affect primary and middle school students and thus allows my work to systematically study the wildfires' aftermath.

Findings show that having wildfire smoke plumes pass over a school district within 1 year prior to tests significantly reduces students' ELA and math scores in both primary school and middle school. In order to understand the effects of wildfires by severity, I follow U.S. Environmental Protection Agency (EPA) guidelines to construct a daily indicator of unhealthy air quality for sensitive groups using population-weighted $PM_{2.5}$ from wildfire smoke for each school district. I find that an increase in unhealthy air quality days 1 to 3 years prior to tests, with a $PM_{2.5}$ value greater or equal to $35.5ug/m^3$, deceases students' ELA and math scores. Magnitudes of effects are larger for math than ELA. Younger students in primary school are more affected by the lagged unhealthy air quality exposure, which generates a lasting effect. Middle school students are only responsive to recent exposure and the effects are transitory.

My empirical strategy relies on the assumption that wildfire breakouts are exogenous and unrelated to omitted factors affecting student achievement. These conclusions would suffer from endogeneity if students move in response to wildfires. To test for potential endogeneity associated with students or their families' mobility, I assess the effect of wildfires on the number of students in each demographic and socioeconomic group and conclude that the effect is limited.

This study contributes to the literature in the following ways: First, it provides critical implications for understanding the social costs of wildfires. A large number of studies address the effect of wildfire smoke on public health. Heft-Neal et al. (2022) show that additional exposure to wildfire smoke during pregnancy significantly increases the risk of preterm birth in California. Mccoy & Zhao (2021) identify a negative effect of wildfire smoke on infant birth weights. Liu et al. (2015), Emmanuel (2000), Mirabelli et al. (2009), and Reid et al. (2016) find an association between wildfires and respiratory disease. Exposure to wildfire smoke is also considered to be correlated with mortality (Johnston et al., 2012; Reid et al., 2016; Morgan et al., 2010; Neller & Arenberg, 2022). In addition, household migration is responsive to destructive wildfires (McConnell et al., 2021; Burke et al., 2022). More recent studies evaluate the impact on the labor market. Borgschulte et al. (2022) show that a nearly 2% reduction in labor income is attributed to wildfire exposure, and such effects are larger for the older workers. Neller & Arenberg (2022) find that wildfire exposure at an early age has long-lasting effects on lifetime earnings. If wildfire smoke affects health, productivity, and longevity, we might reasonably expect there also to be an effect of smoke on academic achievement. But only a few studies addressed this question in the literature, and this study seeks to fill the gap.

One study that also evaluates effects of wildfires from an environmental science viewpoint was recently published by Wen & Burke (2022) and they find that smoke-attributable $PM_{2.5}$ is an important factor in education. My study differs from Wen & Burke (2022) in a few important ways. First, I take a more granular approach to measuring wildfire exposure that offers more details on the variation of exposure within a school district. Specifically, I merge the census tract population, which is a smaller unit than the school district, with smoke plume and school district boundaries, and provide an estimation of the percentage of population that was exposed to smoke plume. Second, I contribute by introducing test time windows information in exposure measurement. This allows me to precisely measure the number of days that students were exposed to wildfires before tests. Third, my study evaluates the effect of smoke *per se* in addition to wildfire-generated $PM_{2.5}$ that was employed as the main treatment by (Wen & Burke, 2022). These estimates incorporate the potential psychological impact from wildfires nearby, even though the intensity is not heavy enough to generate negative health effects. Fourth, I separately report the estimates by primary and middle school, which reveal details of the heterogeneous effects across different levels of education. Overall, this study offers analysis from an economic perspective with finer measures of smoke exposure and additional tests for endogenous student mobility.

In addition, I add a technical aspect to the literature by interacting the wildfire smoke plume with $PM_{2.5}$ pollutants, school district boundaries, and census tract population to deliver additional evidence of the effect of wildfire-generated pollution on academic achievement. Although limited research has been done to evaluate wildfire-associated pollution on achievement, a growing literature has connected pollution more broadly to academic performance. Ebenstein et al. (2016) demonstrate the effect of transitory pollution on high-stakes exams in Israel. They find that transitory $PM_{2.5}$ leads to significant decline in test scores. Heissel et al. (2022) utilize wind direction variation to show that students who study in schools downwind of highways have worse academic performance due to the exposure to traffic pollution in Florida. Pollution from agricultural fires is also shown to result in weaker performance in National College Entrance Examination in China (Zivin et al., 2020). In addition, Gilraine & Zheng (2022) leverage the instrumental variables and show that the reduction in $PM_{2.5}$ significantly increases test scores. My conclusions are consistent with previous work, where wildfire and wildfire-generated pollution reduce students' academic performance in ELA and math, but for a less studied source of pollution and a wide range of grade levels across 50 states in the United States.

Furthermore, this paper identifies an additional environmental factor that could drive educational outcome disparities. Previous work has shown that family income (Dahl & Lochner, 2012), teacher quality (Marioni et al., 2020), and parental involvement (Houtenville

& Conway, 2008) are essential to education outcomes but access these resources is not equitable across student race, ethnicity, and location. In addition, external factors sometime have different effects on students with different backgrounds. Recent research investigates environmental influences. Park et al. (2020) demonstrate that higher temperature significantly lowers students' test scores overall, with more potent negative effects for Black, Hispanic, and lower-income students. My results add to this literature by exploring how effects vary by student genders, race/ethnicity, and economic disadvantage. I find that Black students in primary schools are most affected among the four racial/ethnic groups. White students receive the least impact of wildfire smoke but are heavily influenced by the lagged unhealthy air quality exposure with lasting effects. Asian students, although are not affected in math, get the largest negative impacts on ELA in middle school. A proportion of gender differences in educational achievement can be attributed to wildfires. The effect of unhealthy air quality exposure applies more to male students, especially for their primary school ELA achievement and middle school math achievement. Wildfires also widen the gap between economically disadvantaged students and students with higher-income families. These findings help explain part of racial/ethnic and income-associated achievement gaps.

Finally, the frequency and severity of wildfires have been increasing along with climate change and global warming (Westerling et al., 2006; Shi et al., 2021; Gillett et al., 2004; Balch et al., 2017; Schoennagel et al., 2017; Flannigan et al., 2013). My results suggest that a 10-day increase in wildfire smoke within 1 year prior to tests results in an average of 0.003 standard deviations reduction in ELA and 0.004 standard deviations reduction in math test scores. Quantifying the effect of wildfires on young students' cognitive abilities helps the public understand the importance of environmental governance.

2 Identification

I use the following specification to analyze changes in aggregate standardized test scores for each school district in response to the various levels of wildfire exposure:

$$Y_{git} = \alpha + \beta_{\kappa} * \sum_{\kappa=3}^{1} Exposure_{it-\kappa} + \theta X_{git} + \delta Z_{it} + \gamma C_{it} + \tau_i + \pi_t + \phi_g + \varepsilon_{it} \quad (1)$$

where Y_{git} represents standardized English Language Art (ELA) and math test scores for each grade g in Geographic School District (GSD) i during the school year t. $Exposure_{it-\kappa}$ denotes the typical number of days that 25%, 50%, or 75% of the population in school district i was exposed to wildfire smoke plumes over the κ^{th} year relative to district i tests in school year t, where I lag the exposure up to 3 years. The simple exposure to the drifting smoke plumes, however, does not reveal variation in the intensities of wildfires. Additionally, wildfire smoke plumes can travel up to thousands of miles from the actively burning spots. Students who live far from the wildfires may see smoke plumes overhead, while the pollution concentration was negligible. To evaluate if students who were close to severe wildfires were more affected than those who were not, $Exposure_{it-\kappa}$ alternatively counts the number of days, within the κ^{th} year before testing in school year t, that school district i had an unhealthy $PM_{2.5}$ level produced by wildfire smoke plumes, which is greater or equal to $35.5ug/m^3$ as defined by EPA.[1]

X_{git} is a vector of GSD level demographic and socioeconomic characteristics for students in each grade g, including the percentage of students of each race and ethnicity, the percentage of students who are economically disadvantaged, and the percentage of students who have free and reduced-price lunches. I also use vector Z_{it} to control for district-specific characteristics, including the location of GSD (urban, suburban, town, or rural), the percentage of English language learners, the percentage of students who

[1] $PM_{2.5}$ greater or equal to $3.5.5ug/m^3$ is defined by EPA as unhealthy air quality for sensitive groups, including children.

are in special education, the log of household median income, poverty rate, unemployment rate, SNAP receipt rate, single mother household rate, and the proportion of adults with a bachelor's degree or higher. C_{it} is a vector of meteorological control variables for each GSD: seasonal maximum, minimum, and average temperature, and seasonal average precipitation. I do not control for wind direction or wind speed in this model, as the satellite readings of smoke plumes have already incorporated the effect of wind.

τ_i is GSD fixed effect that absorbs time-invariant GSD-specific factors which could affect test scores. School year fixed effect π_t flexibly controls for time-varying shocks that could influence outcomes across all GSD. Time-invariant grade-specific terms that could differentially change academic performance are captured by grade fixed effect ϕ_g. ε_{it} represents an idiosyncratic error term. I cluster standard errors at the treatment level, which is the GSD in this context, as advised by Abadie et al. (2017). I follow Solon et al. (2015) and use a modified Breusch-Pagan test to confirm heteroskedasticity due to variation in cohort size across school districts. Therefore, I weight all estimates by the number of students in each GSD-grade cell.

β_κ is the parameter of interest for the effect of wildfires on student academic performance Y_{git}. To interpret β_κ as the causal effect of wildfires, I assume that students' exposure to wildfires is conditionally exogenous. One might argue that people who live in states which are known to be susceptible to wildfires, for example, California, may expect the presence of wildfire smoke each year. However, the exact number of days with smoke plumes passing over each school district varies, and the severity of fires is not predictable. Yet, estimates could still be biased if students or their families tended to move away from places with high wildfire smoke concentrations. McConnell et al. (2021) show that destructive wildfires lead to out-tract migration. The effect is more pronounced with severe wildfire smoke exposure (Burke et al., 2022). Besides, wildfire-generated poor air quality could also change migration behavior. Kim (2019) finds that more frequent air quality alerts had a negative effect on the migration of households in California. To examine if wildfire smoke would result in students' migration, which would potentially bias equation (1) estimates, I conduct a mobility analysis. I test if the total enrollment or demographic characteristics in a school district change over time in response to wildfire exposure, in terms of both the smoke plumes and the smoke-produced unhealthy air quality. Specifically, I re-estimate equation (1) with the outcome variable replaced by the number of students or standardized student counts for student subgroups at the GSD level.

3 Data

To investigate the effect of wildfires on education outcomes, I construct a sample combining school district level standardized test scores by grades, state test time window, meteorological conditions, daily wildfire smoke plume locations, daily gridded $PM_{2.5}$ concentrations, and American Community Survey (ACS) census tract level population.

3.1 Education Data

Stanford Education Data Archive (SEDA) V30 dataset contains academic achievement at the GSD level across the United States. SEDA harmonizes achievement measures from the assessment data in the EDFacts data system.[2] Specifically, I use Cohort Standardized (CS) English Language Arts (ELA) and math test scores from school years 2009-10 to 2014-15 in grades 3 to 8, which allows me to compare academic achievement across geographic locations, years, and education levels. For the consistency of the comparison, I only keep school districts and school years that report both ELA and math achievement for all grades. The year referred to in this paper indicates the spring semester of the school year, e.g., year 2009 represents the school year 2008-09.

In the SEDA dataset, the CS scale academic achievements are standardized relative to

[2] See Fahle et al. (2019) for details on the SEDA dataset construction

national reference cohorts. This baseline is created by taking the average of cohorts who were in 4th grade in 2009, 2011, and 2013. Standardized achievement is also reported separately by race/ethnicity, gender, and economically disadvantaged subgroups. This allows me to estimate heterogeneous effects of wildfires on different groups of students.

The covariates provided by the SEDA allow me to control for demographic and socioeconomic characteristics at the GSD level in the model. One group of variables is collected from the Common Core of Data (CCD) and EDFacts. These variables focus on the demographic characteristics of students and public schools: Urbanicity indicators are reported by GSD; the percentage of students of different race/ethnicity, the percentage of students who have free and reduced-price lunch, the percentage of students who are considered economically disadvantaged, and the number of students are reported for each grade-by-GSD; and the percentage of English language learners and students in special education are aggregated to the GSD level, regardless of grades. Another group of covariates is obtained from the American Community Survey (ACS). These covariates, including the log of median income, poverty rate, unemployment rate, SNAP receipt rate, the proportion of adults with a bachelor's degree or higher, and single mother household rate, describe the demographic and socioeconomic characteristics of the total population of residents for each GSD.

In addition to academic achievement, I collect the test time windows of each year from states' educational agencies. The test time windows vary across states and years, but are mostly concentrated in the spring. Each school would choose an exact date to administer the test within the time window. I assess GSD exposure by counting the number of days students are exposed to wildfires within the year before they started the test. Although the actual test date can be any day during the time frame, I conservatively use the first day of the state-determined test time window because any wildfires that break out after tests should not affect the current year's test scores. Aberrant time windows, with a test window that starts in October and ends in spring (19 out of 226 state-by-year test windows), are dropped from the sample.[3] For state-years with missing test time windows, I use the earliest test start time recorded for the state. For states with no available test time window, I use the first day of spring, March 1st.

3.2 Wildfire Smoke and Meteorological Data

Wildfire dates and locations describe the incidence of wildfires in the United States, but they lack information on how the surrounding areas are affected by each fire. To assess the effect of wildfires, I use spatial data describing wildfire smoke plumes. The wildfire smoke plume data is obtained from National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) Fire and Smoke Product, which produces daily fire smoke plume boundaries through satellite imagery across the United States. Since smoke boundaries are generated through more than one satellite instrument's information, one location may report multiple smoke plumes on the same day. As shown in Figure 1A, for example, there is more than one smoke plume layer across the same region in Colorado and New Mexico on July 15, 2011. However, HMS data does not allow me to distinguish the source of these multiple smoke layers. They can be generated from one satellite reading of multiple wildfires, multiple satellite readings of the same wildfire, or both. Directly using this information would artificially increase students' smoke exposure measurement. To avoid the double-counting error, I dissolve the interacted smoke plume and only keep the outermost boundary for each location (Figure 1B).

[Figure 1]

The smoke plume geometric locations allow me to overlap smoke with school districts. One limitation of HMS smoke data is that, when the ground is covered by snow or clouds, or when smoke only exists at night, smoke may not be detected from satellite imagery (Heft-Neal et al., 2022; Vargo, 2020; Ruminski et al., 2006). In my sample, there are 32 days (1.42% of the sample) with no smoke information. I assume there was no wildfire smoke

[3] See Appendix Table A1 for details.

on these days. Another limitation is that the smoke data does not include quantitative smoke density estimates. Even though it reports qualitative density descriptions, using thin, medium, and thick labels to distinguish the plumes, this measurement is not precise and 17.53% of the sample have missing density labels. The composition of wildfire smokes is complex, but $PM_{2.5}$ is considered as having high concentrations in the wildfire smoke and is harmful to public health (United States Environmental Protection Agency, 2019). Therefore, to differentiate students' exposure by wildfire intensity, I follow Heft-Neal et al. (2022) to merge the HMS smoke data with 1km-grid $PM_{2.5}$ concentrations that are collected from NASA Socioeconomic Data and Applications Center (SEDAC). The $PM_{2.5}$ values are estimated by an ensemble-based model, which integrated three machine learning algorithms along with a large number of predictor variables from monitor-based data, satellite aerosol optical depth (AOD) measurements, NOAA meteorological values, chemical transport model (CTM) simulations, land-use variables, etc. (Di et al., 2019, 2021). Compared with the station-monitored $PM_{2.5}$, the grided level pollutant estimates allow me to precisely fit these values into the irregular smoke plume shapes and school districts. I assume that the region's unhealthy air quality, as measured by $PM_{2.5}$, is produced by wildfire smoke if the region has smoke plumes pass over on a daily basis.

The meteorological control variables are obtained from NOAA National Centers for Environmental Information (NCEI) Global Summary of the Month (GSOM) dataset at the monitor station level. I spatially overlay the stations on the school district map, and aggregate the monthly maximum, minimum, and average temperature, and precipitation by season for each district.[4] These control variables are merged to education data by school year, where I follow the test time window and smoke exposure measurement to define school year t for the meteorological variables as March 1^{st} of year $t-1$ to February 28^{th} or 29^{th} of year t.

[4] I follow the meteorological season definition to aggregate March to May variables for spring, June to August for summer, September to November for fall, and December to February for Winter.

3.3 Wildfire Exposure Measurement

I spatially join smoke plume regions with school district areas each day to assess students' exposure to wildfires during the school year. I begin with measuring exposure by counting the number of days the school district had wildfire smoke plumes overhead within 365 days prior to the first day of the state test time window. However, simply counting the smoke days could misstate exposure if the smoke plume only covers a rural area where few people reside. As shown in Figure 2A, smoke plumes pass over part of the Mountain Valley School District RE-1 in Saguache County of Colorado on July 15$^{\text{th}}$, 2011. To reduce potential exposure measurement errors, I merge the 2007-2011 American Community Survey (ACS) 5-year estimates of census tract level population with school district boundaries and identify the population most directly affected by wildfire smoke. For example, as shown in Figure 2B, the Mountain Valley School District RE-1 region was divided by census tract #9776 and #9777. The interacted areas account for 45.66% and 35.84% of the two tracts' areas, respectively. The population in tract #9776 is 2864, and in tract #9777 is 3301. Therefore, the population of this school district is calculated as $(45.66\% * 2864) + (35.84\% * 3301) = 2491$. My key assumption here is that the population is uniformly distributed across each census tract. Figure 2C highlights the interacted area of the smoke plume with school district and tract #9776, which is 28.11% of the tract #9776 area. This indicates that 805 ($= 28.11\% * 2864$) people were exposed to wildfire smoke from this census tract. Figure 2D highlights the interacted area of the smoke plume with school district and tract #9777. This interacted region accounts for 35.84% of the tract, i.e. a population of 1183 ($= 35.84\% * 3301$) was exposed to the smoke. In total, 1988 out of 2491 people, which is 79.81%, in this school district were counted as exposed to wildfire smoke on July 15th, 2011. I did this calculation for each school district and each day, and then counted the number of days a school district had more than 25%, 50%, and 75% of the population exposed to wildfire smoke plumes each year.

[Figure 2]

When measuring wildfire smoke intensity, I plot daily 1km-grid $PM_{2.5}$ values on top of school districts, tracts, and smoke plumes. I first calculate a simple average $PM_{2.5}$ for each interacted area, as Figure 2C and Figure 2D show, and then compute school district level $PM_{2.5}$ using population-weighted averages. To access if more severe wildfires have more of an effect on students, I count the number of days 25%, 50%, and 75% of population exposed to smoke-produced $35.5ug/m^3$ or higher $PM_{2.5}$, which is defined as unhealthy air quality or worse by EPA, over the year prior to testing.

3.4 Summary Statistics

Table 1 reports summary statistics for the education data. The sample includes 6740 unique districts in the United States, reporting over 160 thousand ELA and math score records from grades 3 to 8, school years 2009-2010 to 2014-2015. Since scores are standardized across national reference cohorts using the full SEDA dataset, after constructing the sample to answer the specific research question in this paper, the mean values are close but not equal to zero, as shown in Panel A. On average, there are 436 students in each grade of a school district.

[Table 1]

Table 2 shows the summary statistics for seasonal meteorological conditions (Panel A) and wildfire exposure measurement (Panel B). Exposure to wildfire smoke is fairly common. On average, 75% of the population in a school district was exposed to 29 days of wildfire smoke per year. But in terms of the exposure to smoke produced unhealthy $PM_{2.5}$, the value is quite small, with a mean of near zero, and a maximum of 38 days. The "Smoke Exposure in Year" in Panel B reports means for an indicator equal to one if a school district ever had a wildfire smoke plume pass over in a given school year. From 2010 to 2015, almost all the school districts in this sample were exposed to at least one day of wildfire smoke, with mean values close to 1.

[Table 2]

4 Empirical Results

4.1 Main Results

Table 3 and Table 4 present the main results from estimations of equation (1) for ELA and math academic achievement. These two tables include the preferred measurement with at least 75% of the school district population being exposed to wildfires.[5] For presentation purposes, I scale exposure measurements by 10. Table 3 reports the effect of a 10-day increase in students' exposure to wildfire smoke, while Table 4 presents the estimates of a 10-day change in students' exposure to wildfire smoke-produced unhealthy air quality, which is approximated by the concentration of $PM_{2.5}$. I separately report the effect for all students in column 1, for primary schools only (grades 3-5) in column 2, and for middle schools only (grades 6-8) in column 3.

[Table 3] [Table 4]

In Table 3, Panel A shows that a 10-day increase in smoke exposure within 1 year prior to tests significantly decreases students' ELA test scores by 0.003 standard deviations, and such effect applies to both primary and secondary school students. In Panel B, the results show that within 1 year before tests, an additional 10 days of smoke exposure decreases math scores by 0.004 standard deviations. However, such effects are disproportionate for students in primary and middle school. Wildfire smoke only marginally decreases younger students' math study with magnitudes of 0.003 at a 10% significance level and has an effect of 0.005 standard deviations on students' math study in middle school at a 1% significance level. The 2-year and 3-year lagged smoke exposure does not negatively

[5] The estimates with at least 25%, 50%, and 75% of exposure population are presented in Appendix Table A2 and A3 for ELA performance, and Table A4 and A5 for math performance. In general, as I tighten the restriction of the exposure population from 25% to 75%, the magnitudes of effects become larger, and the significance level increases.

impact ELA or math studies. In Table 3, I also observe that the 2-year lagged smoke exposure has an unexpected positive estimated effect on middle school achievement. As shown in Appendix Table A2 and A4, both the positive coefficient for middle school and the significance level decline as the threshold for population exposure increases from 25% to 75%. Therefore, exposure measurement error may explain these counterintuitive positive coefficients. However, unobserved time-varying factors in middle grades may also play a role here. As discussed in section 4.4, middle grade achievement has a positive relationship with *future* wildfire smoke, a pattern that may conceal negative effects in the equation (1) model.

When considering variation in wildfire intensity, both students' ELA and math academic performances are responsive to 1-year and 3-year lagged unhealthy air quality, as presented in Table 4. In addition, lagged unhealthy air exposure has larger effects than recent exposure, and the magnitudes of the coefficients are larger compared to the magnitudes of simple smoke plumes measurement. In Panel A column 1, students' ELA test scores decrease by 0.026 standard deviations with an additional 10 unhealthy air quality days within 1 year prior to tests and decrease by 0.032 standard deviations with 3-year lagged exposure. Students' response varies by education level. Students in grades 3-5 are affected by 2-year and 3-year lagged unhealthy air quality, but students in grades 6-8 are only affected by recent exposure. The effects of wildfire-generated unhealthy air quality on math test scores in Panel B are similar to ELA. Math performance decreases by 0.03 and 0.04 the 10-day increases in unhealthy air quality days within 1-year and 3-year prior to tests, respectively. Primary school students are more affected by lagged exposure and middle school students are only responsive to the recent change in wildfire-associated air quality.

It should be mentioned that, although the coefficients in the unhealthy air quality estimates is about 10 times larger than the coefficients in smoke plume exposure estimates, the average number of days a school district has unhealthy $PM_{2.5}$ is close to zero, and the maximum is only 38. In this regard, a 10-day increase in unhealthy air quality days is a notable change.

Overall, wildfires are shown to significantly affect students' academic performance, but the extents vary across education levels, across years, and across measurement methods. Middle school students are affected by recent exposure in both measurement methods, while lower grade students are additionally affected by the earlier years' exposure when measuring exposure using unhealthy air quality. This applies to both ELA and math performance, although the magnitudes of effects are slightly larger for math. My findings indicate that the effects of smoke plume exposure tend to be transitory, while more intense wildfire smoke could generate lasting negative effects, especially for young students.

In the estimates for all students reported column 1 of Table 3 and 4, the effects range from 0.003 to 0.004, and from 0.026 to 0.040, respectively. These effects are not trivial. For comparison, Park et al. (2020) find that 1°F increase in the average maximum temperature lower PSAT achievement by 0.002 standard deviations; Persico & Venator (2021) find that pollution from Toxic Release Inventory (TRI) sites lower test scores by 0.024 standard deviations; Wen & Burke (2022) show that additional 10 ug/m^3 of wildfire smoke-associated $PM_{2.5}$ lower test scores by 0.029% of a standard deviation; and Ebenstein et al. (2016) conclude that 1 standard deviation increase in the $PM_{2.5}$ declines student performance by 0.039 standard deviations. A recent report by United Nations Environment Programme (UNEP) and GRID-Arendal Sullivan et al. (2022) shows that wildfires are projected to be more frequent and more destructive. Compared with 2010-2020, wildfire events are expected to increase by up to 33% in 2050 and 52% in 2100. Wildfire smoke exposure for a school district has a mean of 29 days and a maximum of 108 days from 2010 to 2015 in my sample. This means, as a back-of-the-envelope estimate, the exposure could increase up to 164 days in 2100, which translates into a 6.56 percent of a standard deviation decrease in academic achievement for vulnerable students.

[Table 3] [Table 4]

4.2 Mobility Tests

One potential threat to equation (1) identification is students' migration in response to wildfires. If students and their families realize the potential effect of wildfire smoke and smoke-produced unhealthy air quality on education and other aspects of their lives, and if they tend to move out of the most affected school districts, students who remain may be inherently different than movers. In this case, students that stay in school districts with high wildfire smoke risks are less likely to be responsive to wildfires. As a result of positive attrition, the effect of wildfire smoke and smoke-produced unhealthy air quality could be either not significant or significantly positive.

[Table 5] [Table 6]

Table 5 presents the results of the mobility tests with at least 75% of population exposure, where I replace the equation (1) dependent variable with the total number of students and the student counts in each demographic and socioeconomic group in the school district. The number of Asian, Black, Hispanic, white, and economically disadvantaged students does not significantly change with exposure of either wildfire-generated smoke or unhealthy air quality. Because of the right-skewed distribution of students in each group, the estimated coefficients and standard errors are very large.[6] I standardize the number of students and find consistent results as presented in Table 6.

4.3 Heterogeneous Effects

To test if the effect of wildfires varies across different groups of students, I estimate equation (1) by race, ethnicity, gender, and socioeconomics, and present the preferred

[6]The distribution of the number of students in each group is right-skewed with a long right tail. The median is smaller than the mean value. This is driven by the variation of school district size which ranges from 110 to 446674.

estimation results with 75% of population exposure.[7] The estimates are limited to school districts that separately report the test scores by these characteristics, therefore the number of observations is smaller than the full sample estimates.

[Table 7 - Table 10]

Analysis by race and ethnicity. In Table 7, Asian students' ELA scores are only affected by 1-year lagged wildfire smoke and 2-year lagged wildfire-generated unhealthy $PM_{2.5}$, and such effects only apply on middle school students. Students in primary school receive little impact. Asian students' math study is not influenced by wildfire exposure at either education level. Black students, as presented in Table 8, are affected in both ELA and math studies. Their academic performance is reduced with the increase in the 1-year lagged smoke plume exposure and the increase in 3-year lagged unhealthy air quality. Such effects are mostly concentrated on primary school students.

Table 9 presents the analysis for Hispanic students. In Panel A, when measuring wildfire exposure using smoke days, primary and middle school students' ELA and math performances decline with additional 2-year and 1-year lagged smoke exposure, respectively. In panel B, when I measure wildfire exposure by unhealthy $PM_{2.5}$, Hispanic students' ELA scores decrease as a result of more exposure within 1 year prior to test. When I disaggregate the effects by education level, coefficients only have a 10% significance level. Their math study is not affected. Table 10 shows estimates for white students. Smoke days have more negative effects on math, and unhealthy air quality days affect test scores in both subjects. In contrast with the estimates of Asian, Black, and Hispanic students, white students' ELA and math performances significantly decrease with both recent and lagged unhealthy $PM_{2.5}$ exposure.

Although the effect of wildfire varies across race and ethnicity, some consistent patterns are still noteworthy. Wildfire-generated smoke plume usually has short term effects so

[7] The estimations with 25% and 50% of population exposure are in Appendix Table A6 – A19.

that all four racial/ethnic groups of students in this analysis are negatively impacted by recent smoke exposures. Wildfire-generated unhealthy air quality, however, has mixed effects: Asian and Black students are more responsive to the earlier exposure, Hispanic students are only marginally affected, and white students are affected by both short-term and long-term exposure. Among the four racial/ethnic groups of students, Asian students in middle school received the largest size of impact on ELA study by wildfire-generated smoke and air pollution, although their math scores are not impacted at all. Primary school Black students are most vulnerable to wildfire in both subjects, and white students are heavily influenced by lagged unhealthy air quality.[8]

[Table 11] [Table 12]

Analysis by gender. Next, I examine the effects of wildfires by gender. Table 11 presents the effect on female students. In Panel A, smoke days only have short-term negative effects on both ELA and math study. Female students' test scores decrease by 0.004 standard deviations in ELA and 0.003 standard deviations in math due to an additional 10 smoke days. In Panel B, recent unhealthy air quality significantly decreases female students' ELA study, especially in middle school, and it has larger and lasting effects on math.[9] Comparing to female students, as presented in Table 12, male students are more affected by severe wildfire-produced pollution, especially for ELA study in primary school and math study in middle school. Moreover, unhealthy air quality exposure has more lasting effects on ELA test scores for males than females.

[Table 13]

Analysis for economically disadvantaged students. I further investigate the effects on academic achievement for economically disadvantaged students and present the esti-

[8] I also observe some positive coefficients for Hispanic and white students in the smoke days exposure measurement and they only apply to middle school. Part of it could be explained by the measurement error because as the exposure population thresholds tighten from 25% to 75%, some of positive coefficients are not statistically significant. I will also discuss it in the placebo test section.

[9] Again, the positive coefficients for female students will be discussed in the placebo test section.

mates in Table 13. The findings are consistent with the full sample analysis in Table 3 and 4 in general, but economically disadvantaged students receive a larger magnitude of effects from lagged smoke exposure and unhealthy air quality. This is especially true for students in primary school. These results indicate that younger economically disadvantaged students are more negatively impacted by wildfire smoke than their counterparts, and the effect could be lasting. This could widen the achievement gap between economically disadvantaged and other students.

[Table 14]

4.4 Placebo Tests

Finally, I examine placebo tests to determine if students' academic achievement responds to wildfire exposure in the future. Since the exact test time is unknown, to ensure students are matched to wildfires after testing in the spring, I measure future exposure by counting the number of smoke days or unhealthy air quality days starting in the summer, which ranges from July 1st of the school year t to June 30th of school year $t+1$.

Table 14 presents the results with 75% of the population exposure specification.[10] In both specifications presented in Panel A and B, middle school students' academic performances are shown to be positively related to future wildfires. This means that there may be dynamic and unobserved factors that lead middle school students to have higher than expected achievement in in areas with wildfire smoke exposure in the near future. This would work against the hypothesized negative effects and bias equation (1) estimated effects upward. The negative effect of wildfire smoke on students' achievement could have been larger if these factors for middle school were controlled. This may also help to explain counterintuitive positive lagged coefficients for middle schools in Table 3. My heterogeneity analysis reveals that such positive effects are mainly driven by Hispanic, white, and female students. This will be further examined in detail in my future studies.

[10]The estimations with 25% and 50% of population exposure are in Appendix Table A20 – A21.

5 Discussion

In this study, I estimate the effect of wildfire smoke and the associated pollution on primary and middle school students' ELA and math test scores across the United States. Results show that an increase of 10 wildfire smoke days within 1 year prior to tests significantly lowers students' ELA and math test scores by 0.003 and 0.004 standard deviations, respectively. Such effects are transitory as students are not negatively impacted by lagged exposure. However, more severe wildfires, which produce unhealthy air quality, tend to have lasting effects, and such effects mainly apply to students in primary school. My results also suggest that the effects of wildfire-produced unhealthy air quality on primary school students have larger magnitudes than that for students in middle school. These findings indicate that primary school students are more vulnerable to less frequent but more severe wildfires and the negative impacts could last for three years, while middle school students are only impacted by wildfire smoke in the short term.

In addition to the overall negative impact of wildfires on students' academic performance, this study also highlights how natural disasters contribute to educational outcome disparities across race/ethnicity, gender, and income. Asian students' math achievements are not significantly affected by wildfires, but their ELA study in middle school receives the largest impact by both smoke and unhealthy $PM_{2.5}$ among the four racial/ethnic groups. Black students in primary school are most vulnerable as their academic achievement in both subjects falls by a remarkable size with smoke exposure and unhealthy air quality exposure. And white students receive lasting negative effects on both subjects by the lagged unhealthy air quality exposure. When I compare the effects by gender, female students' ELA achievement is reduced by the recent exposure, while the effects of wildfire last longer for male students. When I examine the effect by income, primary school students who are economically disadvantaged are disproportionately harmed when exposed to additional unhealthy pollution by wildfire.

My results are consistent with findings in the medical and health literature. Mohai et al. (2011) show that high pollution concentration is associated with more test failures in higher grades than in lower grades. Environmental pollution is shown to harm children's central nervous system and cognitive ability (Suglia et al., 2008; Calderón-Garcidueñas et al., 2015, 2008). Wang et al. (2009) find that higher air pollution level is correlated with worse neurobehavioral performance for children. And Seifi et al. (2022) find that higher $PM_{2.5}$ and PM_{10} exposure is associated with lower IQ for children between age 6 and 8.

Overall, my results provide evidence from an educational aspect to call for more investment in environmental protection and wildfire prevention. In addition, more attention should be directed to Black students and economically disadvantaged students in primary school, who are more negatively impacted. Asian students in middle schools also are in need of additional help in the ELA study as they receive the largest size of effect among the racial/ethnic groups in this analysis. This study also reveals the details of gender differences in ELA and math studies with exposure to wildfires. Schools should provide more support to help eliminate gender gaps in the event of wildfires. Thanks to the large sample size of district-level education performance, and the precise estimation of the daily wildfire smoke plume and grided $PM_{2.5}$ values, this study offers systematic evaluations and insights on the causal relationship between wildfires and education across the United States. Due to the increasing number of wildfires worldwide induced by climate change, the knowledge offered in this study will be increasingly important.

However, my study is still limited in the following ways: first, my estimation only focuses on wildfire exposure from one to three years before the test window. Accumulative long-term effects are not identified. Also, students' air pollution tolerance is not considered in this study. It is possible that people who live in polluted regions respond differently to wildfire-related $PM_{2.5}$ compared to those who live in regions with good air quality.

Second, the exact test time in each school district is unknown and thus I can only collect test windows that are determined by the states' educational agencies. As a result, I conservatively use the first day of the test window as the test start time. In this regard, the effect of some wildfire exposure could be underestimated if it breaks out right before the exam starts but after the first day of the test time window.

Third, although in general, the two measures of wildfire exposure indicate negative effects on education, estimates of wildfire-produced unhealthy air quality do not align across education levels. Middle school students are only responsive to unhealthy air quality within 1 year prior to tests while primary school students are more influenced by the lagged exposure. It is likely that some unidentified factors would lead to such differences. Unfortunately, due to the limitation of the dataset, I am not able to investigate the underlying mechanism, including physiological factors and school activities, such as school closing due to smoke pollution, or moving outdoor activities indoors.

Fourth, the precision of smoke plume boundaries that are employed in this study suffers from inherent satellite data limitations. Smoke days may be underestimated if the ground is covered by snow or clouds (Heft-Neal et al., 2022; Vargo, 2020; Di et al., 2019). Night smoke is also unidentified from satellite imagery (Heft-Neal et al., 2022; Di et al., 2019). The height of the smoke plume to the ground is not observed from satellite imagery, nevertheless, this should not raise concerns in this study. A smoke plume that is closer to the ground is believed to generate higher pollution levels, and this is captured by the unhealthy air quality measurement where I utilize $PM_{2.5}$ to proxy the intensity.

Additionally, when matching the census tract level population to school districts and smoke plume boundaries, I assume the population is uniformly distributed across the tract. The within-tract population distribution information could possibly lead to a much more accurate estimation of students' wildfire exposure.

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Tables

Table 1: Descriptive Statistics for Students and GSDs

	Observations	Mean
Panel A: Academic Achievement *by GSD-Grade-School Year*		
English/Language Arts	160050	0.04
Math	160050	0.04
Panel B: Demographic Characteristic *by GSD-Grade-School Year*		
Asian	160050	0.02
Black	160050	0.09
Hispanic	160050	0.11
Native American	160050	0.02
White	160050	0.76
Economically Disadvantaged	160050	0.49
Free and Reduced-Priced Lunch	160050	0.49
Number of Students in Grade	160050	436
Panel C: Demographic Characteristic *by GSD-School Year*		
City/Urban Location	26675	0.08
Suburban Location	26675	0.20
Town Location	26675	0.27
Rural Location	26675	0.45
Log of Median Income	26675	10.80
Poverty Rate	26675	0.16
Unemployment Rate	26675	0.08
SNAP Receipt Rate	26675	0.11
Rate of Bachelor's Degree or Higher	26675	0.22
Single Mother Household Rate	26675	0.16
English language learners	26675	0.04
Special Education	26675	0.14
Number of Unique School Districts	6740	

Notes: The sample includes academic achievement, demographic and socioeconomic variables for students in Geographic School District (GSD) from grade 3 to 8 between school year 2009-10 and 2014-15. Academic achievement, race/ethnicity, economically disadvantage, free and reduced-price lunch, and the number of students in each grade are measured by each grade in GSD for each school year. The location of GSD, log of median income, poverty rate, unemployment rate, SNAP receipt rate, rate of Bachelor's degree or higher, single mother household rate, English language learners rate, and special education rate are measured at the GSD by school year level.

Table 2: Descriptive Statistics for Meteorological and Wildfire Smoke Data

	Observations	Mean	Min	Max
Panel A: Meteorology				
Avg. Temp Fall	26675	54.9	16.2	83.3
Avg. Temp Spring	26675	53.0	2.6	84.2
Avg. Temp Summer	26675	73.4	44.0	96.2
Avg. Temp Winter	26675	31.7	-15.7	73.2
Max Temp Fall	26675	66.1	21.1	97.8
Max Temp Spring	26675	64.4	9.0	96.8
Max Temp Summer	26675	84.5	50.2	111.1
Max Temp Winter	26675	41.1	-10.2	80.2
Min Temp Fall	26675	43.8	7.5	75.5
Min Temp Spring	26675	41.5	-3.8	74.3
Min Temp Summer	26675	62.2	37.9	84.0
Min Temp Winter	26675	22.3	-22.3	68.0
Precipitation Fall	26675	81.5	0.0	565.2
Precipitation Spring	26675	92.2	0.0	454.5
Precipitation Summer	26675	98.8	0.0	536.3
Precipitation Winter	26675	69.3	0.0	557.1
Panel B: Wildfire Exposure				
Days with Smoke, 25% Pop	26675	30.90	0	112
Days with Smoke, 50% Pop	26675	29.94	0	109
Days with Smoke, 75% Pop	26675	29.09	0	108
Days with Unhealthy PM2.5, 25% Pop	26675	0.06	0	38
Days with Unhealthy PM2.5, 50% Pop	26675	0.06	0	38
Days with Unhealthy PM2.5, 75% Pop	26675	0.06	0	38
Smoke Exposure in 2010	5104	0.99	0	1
Smoke Exposure in 2011	5507	1.00	0	1
Smoke Exposure in 2012	4934	1.00	0	1
Smoke Exposure in 2013	4521	1.00	0	1
Smoke Exposure in 2014	3374	1.00	1	1
Smoke Exposure in 2015	3235	1.00	0	1

Notes: The sample includes meteorological and wildfire smoke variables at Geographic School District (GSD) between school year 2009-10 and 2014-15. Temperatures are reported in Fahrenheit, and precipitation is reported in millimeters. The "days with fire smoke" measures the typical number of days at least 25%, 50%, and 75% of people in a GSD that are exposed to wildfire smoke over the year before the test start. The "days with unhealthy air quality" measures the typical number of days at least 25%, 50%, and 75% of people in each GSD have a PM2.5 level greater or equal to 35.5 ug/m^3 due to wildfire smoke, over the year before tests start.

Table 3: Estimated Effects of Wildfire Smoke Days (*10) on Academic Performance

	All (1)	Primary School (2)	Middle School (3)
Panel A: ELA Performance			
1 Year Prior	-0.003	-0.003	-0.003
	(0.001)***	(0.001)**	(0.001)***
2 Year Prior	0.001	-0.001	0.002
	(0.001)	(0.001)	(0.001)**
3 Year Prior	< 0.001	-0.002	0.001
	(0.001)	(0.001)	(0.001)
Panel B: Math Performance			
1 Year Prior	-0.004	-0.003	-0.005
	(0.001)***	(0.001)*	(0.001)***
2 Year Prior	0.001	-0.002	0.003
	(0.001)	(0.002)	(0.001)**
3 Year Prior	-0.001	-0.002	< 0.001
	(0.001)	(0.002)	(0.001)
Observations	160050	80025	80025

Notes: The dependent variables are standardized ELA test scores in Panel A and standardized math test scores in Panel B. Smoke days are measured with at least 75% of the population being exposed to wildfire smoke in the school district. The control variables include Asian, Black, Hispanic, and white student shares in each grade; the percentage of students who are economically disadvantaged, the percentage of students with free and reduced-price lunch at the grade level; the log of median income, poverty rate, unemployment rate, SNAP receipt rate, rate of bachelor's degree or higher, single mother household rate, school location, percentage of students in special education, and shares of English language learners at the GSD level; and the indicator of missing values of each control covariates. The missing values of control variables are imputed at the mean. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table 4: Estimated Effects of Unhealthy Air Quality Days (*10) on Academic Performance

	All (1)	Primary School (2)	Middle School (3)
Panel A: ELA Performance			
1 Year Prior	-0.026	-0.021	-0.032
	(0.011)**	(0.013)	(0.012)***
2 Year Prior	-0.014	-0.052	0.016
	(0.033)	(0.024)**	(0.051)
3 Year Prior	-0.032	-0.047	-0.020
	(0.013)**	(0.014)***	(0.015)
Panel B: Math Performance			
1 Year Prior	-0.030	-0.034	-0.030
	(0.013)**	(0.017)**	(0.014)**
2 Year Prior	-0.005	-0.020	-0.002
	(0.028)	(0.038)	(0.038)
3 Year Prior	-0.040	-0.057	-0.023
	(0.017)**	(0.020)***	(0.016)
Observations	160050	80025	80025

Notes: The dependent variables are standardized ELA test scores in Panel A and standardized math test scores in Panel B. Smoke days are measured with at least 75% of the population being exposed to wildfire smoke in the school district. The control variables include Asian, Black, Hispanic, and white student shares in each grade; the percentage of students who are economically disadvantaged, the percentage of students with free and reduced-price lunch at the grade level; the log of median income, poverty rate, unemployment rate, SNAP receipt rate, rate of bachelor's degree or higher, single mother household rate, school location, percentage of students in special education, and shares of English language learners at the GSD level; and the indicator of missing values of each control covariates. The missing values of control variables are imputed at the mean. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table 5: Estimated Effects of Wildfire on Total Enrollment

	All Students	Asian	Black	Hispanic	White	Econ. Disadvantaged
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Smoke Days (*10)						
1 Year Prior	-414.62	-40.37	-11.85	-283.14	-66.49	-438.59
	(358.46)	(41.89)	(70.36)	(176.38)	(75.21)	(349.03)
2 Year Prior	-226.03	-38.05	14.38	-132.27	-62.76	-186.39
	(158.63)	(20.42)*	(28.90)	(80.52)	(42.41)	(157.83)
3 Year Prior	183.82	32.06	63.51	1.46	80.25	90.24
	(244.03)	(22.78)	(69.99)	(119.52)	(43.48)*	(210.60)
Panel B: Unhealthy Air Quality Days (*10)						
1 Year Prior	-1339.36	-79.97	9.14	-1183.45	-52.55	-1866.42
	(1361.62)	(168.61)	(228.27)	(697.89)*	(301.42)	(1347.72)
2 Year Prior	-575.17	-283.78	92.07	-48.06	-315.17	-336.50
	(1305.78)	(203.00)	(543.86)	(604.55)	(534.78)	(1374.24)
3 Year Prior	4129.72	490.85	850.23	1669.49	975.24	3271.55
	(4391.54)	(428.82)	(1096.72)	(2135.92)	(722.33)	(3997.23)
Observations	25927	25927	25927	25927	25927	25927
Avg. Num. of Students in School District	2615	107	500	507	1468	1398

Notes: The dependent variables are the number of students in each group at the school district level. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table 6: Estimated Effects of Wildfire on Total Enrollment (Standardized)

	All Students	Asian	Black	Hispanic	White	Econ. Disadvantaged
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Smoke Days (*10)						
1 Year Prior	-0.05	-0.04	< -0.01	-0.08	-0.03	-0.07
	(0.04)	(0.04)	(0.02)	(0.05)	(0.03)	(0.06)
2 Year Prior	-0.03	-0.04	< 0.01	-0.04	-0.02	-0.03
	(0.02)	(0.02)*	(0.01)	(0.02)	(0.02)	(0.03)
3 Year Prior	0.02	0.03	0.02	< 0.01	0.03	0.01
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)*	(0.03)
Panel B: Unhealthy Air Quality Days (*10)						
1 Year Prior	-0.15	-0.08	< 0.01	-0.32	-0.02	-0.30
	(0.16)	(0.17)	(0.08)	(0.19)*	(0.11)	(0.21)
2 Year Prior	-0.07	-0.28	0.03	-0.01	-0.12	-0.05
	(0.15)	(0.20)	(0.19)	(0.16)	(0.20)	(0.22)
3 Year Prior	0.47	0.48	0.29	0.45	0.37	0.52
	(0.50)	(0.42)	(0.38)	(0.58)	(0.27)	(0.63)
Observations	25927	25927	25927	25927	25927	25927
Avg. std of Students in School District	0.00	-0.00	-0.00	0.00	-0.00	0.00

Notes: The dependent variables are the within-district standard deviation of the number of students in each group at the school district level. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table 7: Heterogeneous Effects Analysis for Asian Students - 75% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.008	-0.007	-0.012
	(0.004)**	(0.005)	(0.005)**
2 Year Prior	0.002	-0.004	0.003
	(0.003)	(0.004)	(0.004)
3 Year Prior	0.006	0.001	0.005
	(0.004)	(0.005)	(0.004)
Math			
1 Year Prior	0.003	0.005	0.001
	(0.004)	(0.004)	(0.004)
2 Year Prior	0.002	> -0.001	0.001
	(0.003)	(0.004)	(0.004)
3 Year Prior	0.006	0.007	0.002
	(0.004)	(0.005)	(0.005)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.024	-0.023	-0.046
	(0.072)	(0.094)	(0.084)
2 Year Prior	-0.096	0.004	-0.208
	(0.061)	(0.135)	(0.069)***
3 Year Prior	0.018	-0.003	0.050
	(0.047)	(0.050)	(0.056)
Math			
1 Year Prior	0.035	0.059	-0.021
	(0.097)	(0.116)	(0.118)
2 Year Prior	0.030	0.046	-0.009
	(0.066)	(0.149)	(0.109)
3 Year Prior	-0.052	-0.057	-0.038
	(0.061)	(0.069)	(0.082)
Observations	14052	7026	7026

Notes: The dependent variables are standardized ELA and math test scores of Asian students. Wildfire exposure is measured with at least 75% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table 8: Heterogeneous Effects Analysis for Black Students - 75% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.005	-0.005	-0.005
	(0.002)***	(0.002)**	(0.002)**
2 Year Prior	-0.003	-0.004	-0.001
	(0.002)	(0.003)	(0.002)
3 Year Prior	-0.001	-0.005	0.001
	(0.002)	(0.003)*	(0.002)
Math			
1 Year Prior	-0.006	-0.006	-0.005
	(0.003)**	(0.003)**	(0.003)*
2 Year Prior	0.003	0.004	0.002
	(0.003)	(0.004)	(0.002)
3 Year Prior	-0.001	-0.004	0.001
	(0.003)	(0.003)	(0.003)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.057	-0.003	-0.098
	(0.043)	(0.046)	(0.050)*
2 Year Prior	0.035	0.031	0.049
	(0.059)	(0.072)	(0.059)
3 Year Prior	-0.051	-0.075	-0.031
	(0.027)*	(0.029)***	(0.029)
Math			
1 Year Prior	0.024	-0.012	0.061
	(0.063)	(0.088)	(0.063)
2 Year Prior	0.062	0.071	0.045
	(0.068)	(0.097)	(0.064)
3 Year Prior	-0.061	-0.107	-0.021
	(0.035)*	(0.041)***	(0.033)
Observations	39108	19554	19554

Notes: The dependent variables are standardized ELA and math test scores of Black students. Wildfire exposure is measured with at least 75% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table 9: Heterogeneous Effects Analysis for Hispanic Students - 75% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.004	-0.002	-0.006
	(0.002)**	(0.002)	(0.002)***
2 Year Prior	-0.001	-0.004	0.003
	(0.001)	(0.002)**	(0.002)
3 Year Prior	0.004	0.001	0.006
	(0.002)**	(0.003)	(0.002)***
Math			
1 Year Prior	-0.002	-0.001	-0.004
	(0.002)	(0.003)	(0.002)**
2 Year Prior	-0.004	-0.007	-0.001
	(0.002)*	(0.002)***	(0.002)
3 Year Prior	> -0.001	-0.005	0.004
	(0.003)	(0.004)	(0.003)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.046	-0.041	-0.053
	(0.021)**	(0.025)*	(0.031)*
2 Year Prior	-0.037	-0.060	-0.009
	(0.068)	(0.044)	(0.101)
3 Year Prior	0.002	-0.032	0.026
	(0.027)	(0.033)	(0.027)
Math			
1 Year Prior	-0.016	-0.048	0.013
	(0.025)	(0.036)	(0.027)
2 Year Prior	-0.037	-0.021	-0.059
	(0.055)	(0.068)	(0.071)
3 Year Prior	-0.010	-0.044	0.020
	(0.039)	(0.047)	(0.043)
Observations	39480	19740	19740

Notes: The dependent variables are standardized ELA and math test scores of Hispanic students. Wildfire exposure is measured with at least 75% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table 10: Heterogeneous Effects Analysis for White Students - 75% Exposure

	All	Primary School	Middle School
	(1)	(2)	(3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.001	< 0.001	-0.002
	(0.001)	(0.001)	(0.001)*
2 Year Prior	0.002	-0.001	0.003
	(0.001)**	(0.001)	(0.001)***
3 Year Prior	< 0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)
Math			
1 Year Prior	-0.002	-0.001	-0.004
	(0.001)**	(0.001)	(0.001)***
2 Year Prior	0.002	> -0.001	0.003
	(0.001)*	(0.001)	(0.001)***
3 Year Prior	-0.001	> -0.001	-0.001
	(0.001)	(0.001)	(0.001)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.016	-0.017	-0.016
	(0.010)*	(0.013)	(0.012)
2 Year Prior	-0.034	-0.062	-0.019
	(0.025)	(0.026)**	(0.032)
3 Year Prior	-0.060	-0.062	-0.057
	(0.012)***	(0.014)***	(0.013)***
Math			
1 Year Prior	-0.035	-0.033	-0.040
	(0.012)***	(0.017)*	(0.013)***
2 Year Prior	-0.025	-0.049	-0.018
	(0.023)	(0.038)	(0.029)
3 Year Prior	-0.066	-0.070	-0.060
	(0.014)***	(0.017)***	(0.014)***
Observations	146298	73149	73149

Notes: The dependent variables are standardized ELA and math test scores of white students. Wildfire exposure is measured with at least 75% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table 11: Heterogeneous Effects Analysis for Female Students - 75% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.004	-0.003	-0.006
	(0.001)***	(0.001)**	(0.001)***
2 Year Prior	0.002	-0.001	0.004
	(0.001)*	(0.001)	(0.001)***
3 Year Prior	0.002	0.002	0.002
	(0.001)**	(0.001)	(0.001)
Math			
1 Year Prior	-0.003	-0.003	-0.004
	(0.001)***	(0.001)**	(0.001)***
2 Year Prior	0.001	-0.002	0.003
	(0.001)	(0.002)	(0.001)**
3 Year Prior	-0.001	-0.003	0.001
	(0.001)	(0.002)*	(0.002)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.042	-0.029	-0.055
	(0.013)***	(0.016)*	(0.016)***
2 Year Prior	-0.014	-0.043	0.005
	(0.035)	(0.025)*	(0.054)
3 Year Prior	0.003	-0.014	0.015
	(0.015)	(0.015)	(0.017)
Math			
1 Year Prior	-0.028	-0.040	-0.019
	(0.013)**	(0.018)**	(0.016)
2 Year Prior	-0.017	-0.036	-0.012
	(0.028)	(0.043)	(0.036)
3 Year Prior	-0.037	-0.058	-0.019
	(0.018)**	(0.021)***	(0.018)
Observations	132894	66447	66447

Notes:The dependent variables are standardized ELA and math test scores of female students. Wildfire exposure is measured with at least 75% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table 12: Heterogeneous Effects Analysis for Male Students - 75% Exposure

	All	Primary School	Middle School
	(1)	(2)	(3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.002	-0.003	-0.001
	(0.001)*	(0.001)***	(0.001)
2 Year Prior	> -0.001	-0.001	< 0.001
	(0.001)	(0.001)	(0.001)
3 Year Prior	-0.002	-0.005	< 0.001
	(0.001)**	(0.001)***	(0.001)
Math			
1 Year Prior	-0.003	-0.001	-0.006
	(0.001)***	(0.001)	(0.001)***
2 Year Prior	0.001	-0.001	0.003
	(0.001)	(0.002)	(0.001)*
3 Year Prior	> -0.001	0.001	-0.002
	(0.002)	(0.002)	(0.002)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.016	-0.020	-0.015
	(0.012)	(0.015)	(0.015)
2 Year Prior	-0.013	-0.053	0.018
	(0.035)	(0.029)*	(0.055)
3 Year Prior	-0.061	-0.079	-0.047
	(0.014)***	(0.015)***	(0.017)***
Math			
1 Year Prior	-0.035	-0.034	-0.041
	(0.015)**	(0.018)*	(0.018)**
2 Year Prior	0.004	-0.003	-0.002
	(0.031)	(0.040)	(0.043)
3 Year Prior	-0.035	-0.054	-0.019
	(0.018)**	(0.022)**	(0.017)
Observations	134274	67137	67137

Notes: The dependent variables are standardized ELA and math test scores of male students. Wildfire exposure is measured with at least 75% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table 13: Heterogeneous Effects Analysis for Econ. Disadvantaged Students - 75% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.003	-0.003	-0.003
	(0.001)***	(0.001)***	(0.001)**
2 Year Prior	-0.001	-0.003	< 0.001
	(0.001)	(0.001)**	(0.001)
3 Year Prior	-0.001	-0.003	0.001
	(0.001)	(0.001)**	(0.001)
Math			
1 Year Prior	-0.003	-0.002	-0.005
	(0.001)**	(0.001)	(0.001)***
2 Year Prior	> -0.001	-0.002	0.002
	(0.002)	(0.002)	(0.002)
3 Year Prior	-0.002	-0.003	-0.001
	(0.002)	(0.002)	(0.002)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.031	-0.022	-0.042
	(0.013)**	(0.015)	(0.017)**
2 Year Prior	-0.011	-0.050	0.027
	(0.048)	(0.036)	(0.074)
3 Year Prior	-0.037	-0.062	-0.019
	(0.016)**	(0.017)***	(0.018)
Math			
1 Year Prior	-0.020	-0.016	-0.027
	(0.015)	(0.019)	(0.017)
2 Year Prior	0.011	0.008	0.006
	(0.041)	(0.048)	(0.054)
3 Year Prior	-0.049	-0.077	-0.025
	(0.022)**	(0.026)***	(0.021)
Observations	123750	61875	61875

Notes: The dependent variables are standardized ELA and math test scores of Economically Disadvantaged students. Wildfire exposure is measured with at least 75% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

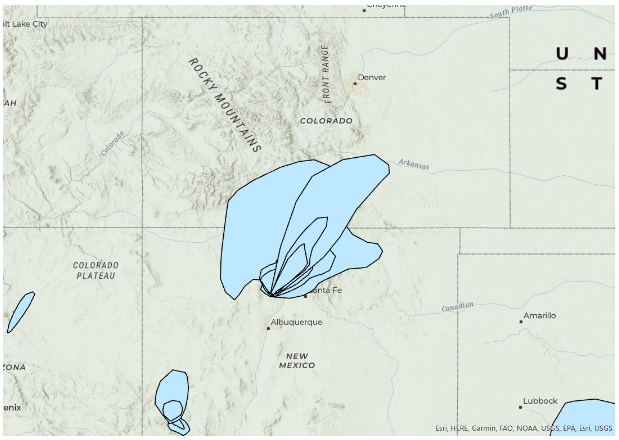
Table 14: Placebo Test: Future Wildfire Exposure - 75% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Future	0.001	< 0.001	0.002
	(0.001)	(0.001)	(0.002)
Math			
1 Year Future	0.001	-0.001	0.003
	(0.001)	(0.002)	(0.001)**
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Future	0.023	0.007	0.037
	(0.009)**	(0.010)	(0.012)***
Math			
1 Year Future	0.006	-0.020	0.031
	(0.013)	(0.016)	(0.013)**
Observations	160050	80025	80025

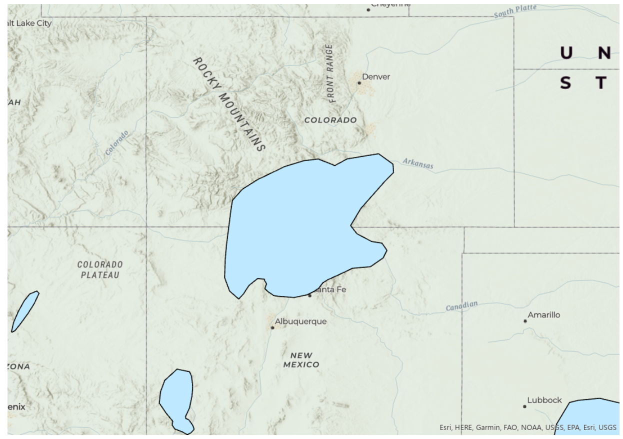
Notes: The dependent variables are standardized ELA and math test scores. Wildfire exposure is measured with at least 75% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Figures

Figure 1: Smoke Plumes across Colorado and New Mexico on July 15, 2011

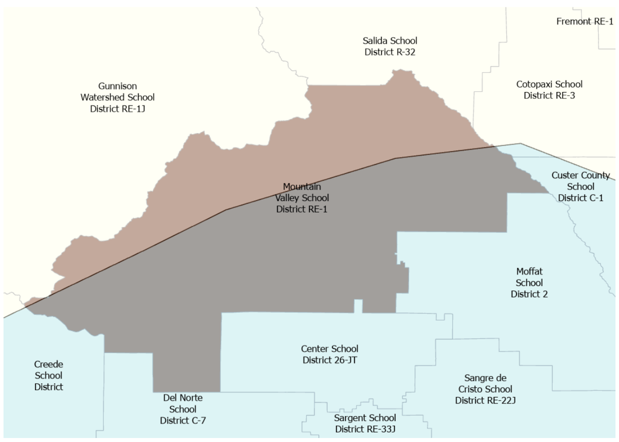


(a) Smoke Plumes

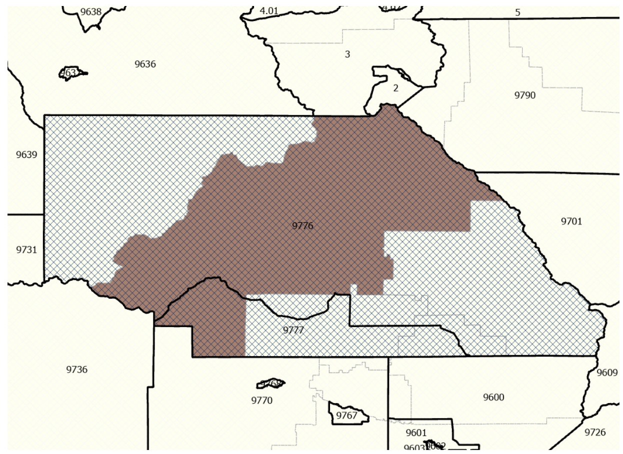


(b) Smoke Plumes Outermost Boundary After Dissolve

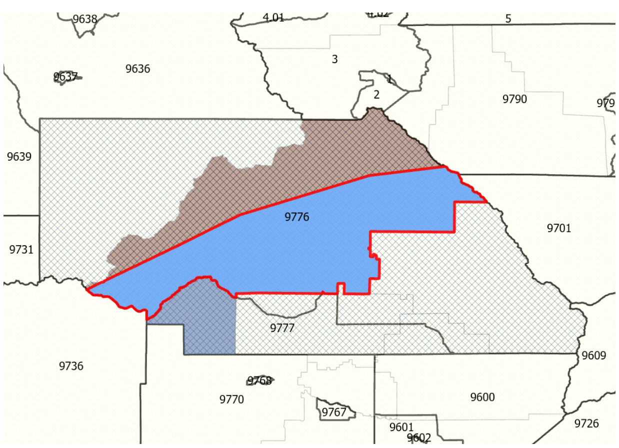
Figure 2: Smoke Exposure by Census Tract Population in School District



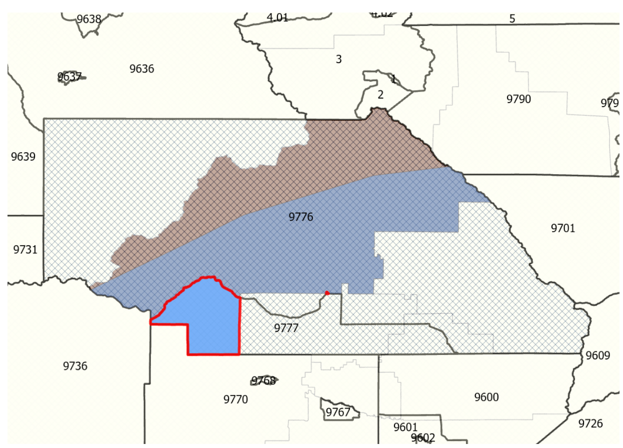
(a) smoke plumes over school district



(b) School District & Census Tracts



(c) Interacted Area of the Smoke Plume with School District and Tract #9776



(d) Interacted Area of the Smoke Plume with School District and Tract #9777

Appendix Tables

Table A1: States with Test Time Windows Started in October

State	Spring of the School Year
Hawaii	2011 - 2014
New Hampshire	2010 - 2014
North Dakota	2010 - 2014
Vermont	2010 - 2014

Notes: This table includes states with the test time window that started in October and are dropped in the analysis. I only include states that provided the exact test time window by the state educational agency. States without a test time window are assumed to start the test in the Spring.

Table A2: Estimated Effects of the Wildfire Smoke Days (*10) on ELA Performance

	All (1)	Primary School (2)	Middle School (3)
Panel A: 25% Exposure			
1 Year Prior	-0.001	-0.001	-0.002
	(0.001)**	(0.001)*	(0.001)*
2 Year Prior	0.002	> -0.001	0.004
	(0.001)**	(0.001)	(0.001)***
3 Year Prior	< 0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)
Panel B: 50% Exposure			
1 Year Prior	-0.003	-0.003	-0.003
	(0.001)**	(0.001)**	(0.001)**
2 Year Prior	0.001	-0.001	0.003
	(0.001)	(0.001)	(0.001)***
3 Year Prior	> -0.001	-0.002	0.001
	(0.001)	(0.001)*	(0.001)
Panel C: 75% Exposure			
1 Year Prior	-0.003	-0.003	-0.003
	(0.001)***	(0.001)**	(0.001)***
2 Year Prior	0.001	-0.001	0.002
	(0.001)	(0.001)	(0.001)**
3 Year Prior	< 0.001	-0.002	0.001
	(0.001)	(0.001)	(0.001)
Observations	160050	80025	80025

Notes: The dependent variables are standardized ELA test scores. The control variables include Asian, Black, Hispanic, and white student shares in each grade; the percentage of students who are economically disadvantaged, the percentage of students with free and reduced-price lunch at the grade level; the log of median income, poverty rate, unemployment rate, SNAP receipt rate, rate of bachelor's degree or higher, single mother household rate, school location, percentage of students in special education, and shares of English language learners at the GSD level; and the indicator of missing values of each control covariates. The missing values of control variables are imputed at the mean. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A3: Estimated Effects of the Unhealthy Air Quality Days (*10) on ELA Performance

	All (1)	Primary School (2)	Middle School (3)
Panel A: 25% Exposure			
1 Year Prior	-0.020	-0.022	-0.021
	(0.010)**	(0.013)	(0.012)*
2 Year Prior	0.056	0.024	0.081
	(0.058)	(0.055)	(0.069)
3 Year Prior	-0.026	-0.039	-0.018
	(0.014)*	(0.015)***	(0.015)
Panel B: 50% Exposure			
1 Year Prior	-0.025	-0.022	-0.030
	(0.011)**	(0.014)	(0.012)**
2 Year Prior	0.002	-0.039	0.035
	(0.036)	(0.025)	(0.055)
3 Year Prior	-0.030	-0.042	-0.022
	(0.013)**	(0.014)***	(0.014)
Panel C: 75% Exposure			
1 Year Prior	-0.026	-0.021	-0.032
	(0.011)**	(0.013)	(0.012)***
2 Year Prior	-0.014	-0.052	0.016
	(0.033)	(0.024)**	(0.051)
3 Year Prior	-0.032	-0.047	-0.020
	(0.013)**	(0.014)***	(0.015)
Observations	160050	80025	80025

Notes: The dependent variables are standardized ELA test scores. The control variables include Asian, Black, Hispanic, and white student shares in each grade; the percentage of students who are economically disadvantaged, the percentage of students with free and reduced-price lunch at the grade level; the log of median income, poverty rate, unemployment rate, SNAP receipt rate, rate of bachelor's degree or higher, single mother household rate, school location, percentage of students in special education, and shares of English language learners at the GSD level; and the indicator of missing values of each control covariates. The missing values of control variables are imputed at the mean. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A4: Estimated Effects of the Wildfire Smoke Days (*10) on Math Performance

	All (1)	Primary School (2)	Middle School (3)
Panel A: 25% Exposure			
1 Year Prior	-0.002	-0.002	-0.002
	(0.001)**	(0.001)*	(0.001)**
2 Year Prior	0.002	-0.001	0.004
	(0.001)	(0.001)	(0.001)***
3 Year Prior	> -0.001	-0.002	< 0.001
	(0.001)	(0.002)	(0.001)
Panel B: 50% Exposure			
1 Year Prior	-0.003	-0.002	-0.003
	(0.001)**	(0.001)*	(0.001)**
2 Year Prior	0.001	-0.001	0.004
	(0.001)	(0.001)	(0.001)***
3 Year Prior	-0.001	-0.002	> -0.001
	(0.001)	(0.002)	(0.001)
Panel C: 75% Exposure			
1 Year Prior	-0.004	-0.003	-0.005
	(0.001)***	(0.001)*	(0.001)***
2 Year Prior	0.001	-0.002	0.003
	(0.001)	(0.002)	(0.001)**
3 Year Prior	-0.001	-0.002	< 0.001
	(0.001)	(0.002)	(0.001)
Observations	160050	80025	80025

Notes: The dependent variables are standardized math test scores. The control variables include Asian, Black, Hispanic, and white student shares in each grade; the percentage of students who are economically disadvantaged, the percentage of students with free and reduced-price lunch at the grade level; the log of median income, poverty rate, unemployment rate, SNAP receipt rate, rate of bachelor's degree or higher, single mother household rate, school location, percentage of students in special education, and shares of English language learners at the GSD level; and the indicator of missing values of each control covariates. The missing values of control variables are imputed at the mean. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A5: Estimated Effects of the Unhealthy Air Quality Days (*10) on Math Performance

	All	Primary School	Middle School
	(1)	(2)	(3)
Panel A: 25% Exposure			
1 Year Prior	-0.026	-0.031	-0.024
	(0.013)**	(0.018)*	(0.014)*
2 Year Prior	0.047	0.040	0.041
	(0.038)	(0.046)	(0.046)
3 Year Prior	-0.030	-0.044	-0.019
	(0.016)*	(0.019)**	(0.015)
Panel B: 50% Exposure			
1 Year Prior	-0.031	-0.037	-0.028
	(0.013)**	(0.018)**	(0.014)*
2 Year Prior	0.019	0.009	0.016
	(0.033)	(0.044)	(0.041)
3 Year Prior	-0.034	-0.047	-0.023
	(0.015)**	(0.019)**	(0.015)
Panel C: 75% Exposure			
1 Year Prior	-0.030	-0.034	-0.030
	(0.013)**	(0.017)**	(0.014)**
2 Year Prior	-0.005	-0.020	-0.002
	(0.028)	(0.038)	(0.038)
3 Year Prior	-0.040	-0.057	-0.023
	(0.017)**	(0.020)***	(0.016)
Observations	160050	80025	80025

Notes: The dependent variables are standardized math test scores. The control variables include Asian, Black, Hispanic, and white student shares in each grade; the percentage of students who are economically disadvantaged, the percentage of students with free and reduced-price lunch at the grade level; the log of median income, poverty rate, unemployment rate, SNAP receipt rate, rate of bachelor's degree or higher, single mother household rate, school location, percentage of students in special education, and shares of English language learners at the GSD level; and the indicator of missing values of each control covariates. The missing values of control variables are imputed at the mean. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A6: Heterogeneous Effects Analysis for Asian Students - 25% Exposure

	All	Primary School	Middle School
	(1)	(2)	(3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	0.001	0.001	< 0.001
	(0.002)	(0.003)	(0.003)
2 Year Prior	0.006	< 0.001	0.010
	(0.003)**	(0.004)	(0.004)***
3 Year Prior	0.014	0.011	0.014
	(0.005)***	(0.005)**	(0.005)***
Math			
1 Year Prior	0.006	0.006	0.005
	(0.003)*	(0.004)*	(0.004)
2 Year Prior	0.004	0.001	0.005
	(0.003)	(0.004)	(0.004)
3 Year Prior	0.007	0.011	0.003
	(0.004)*	(0.005)**	(0.005)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	0.053	0.045	0.041
	(0.077)	(0.084)	(0.098)
2 Year Prior	0.279	0.389	0.213
	(0.169)*	(0.145)***	(0.252)
3 Year Prior	0.068	0.062	0.085
	(0.055)	(0.057)	(0.063)
Math			
1 Year Prior	0.145	0.129	0.121
	(0.074)*	(0.091)	(0.096)
2 Year Prior	0.177	0.281	0.066
	(0.089)**	(0.123)**	(0.122)
3 Year Prior	-0.017	0.006	-0.032
	(0.058)	(0.063)	(0.079)
Observations	14052	7026	7026

Notes: The dependent variables are standardized ELA and math test scores of Asian students. Wildfire exposure is measured with at least 25% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A7: Heterogeneous Effects Analysis for Asian Students - 50% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.009	-0.009	-0.011
	(0.004)**	(0.005)*	(0.006)*
2 Year Prior	0.002	-0.004	0.005
	(0.003)	(0.004)	(0.004)
3 Year Prior	0.007	0.001	0.006
	(0.004)*	(0.005)	(0.004)
Math			
1 Year Prior	0.002	0.002	0.003
	(0.003)	(0.004)	(0.004)
2 Year Prior	0.002	-0.001	0.003
	(0.003)	(0.004)	(0.004)
3 Year Prior	0.004	0.005	0.001
	(0.004)	(0.005)	(0.005)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.010	-0.009	-0.033
	(0.072)	(0.093)	(0.083)
2 Year Prior	-0.061	0.044	-0.184
	(0.056)	(0.118)	(0.072)**
3 Year Prior	0.039	0.034	0.046
	(0.051)	(0.052)	(0.059)
Math			
1 Year Prior	0.056	0.091	-0.009
	(0.090)	(0.106)	(0.115)
2 Year Prior	0.061	0.106	-0.010
	(0.063)	(0.136)	(0.105)
3 Year Prior	-0.027	-0.007	-0.041
	(0.059)	(0.065)	(0.081)
Observations	14052	7026	7026

Notes: The dependent variables are standardized ELA and math test scores of Asian students. Wildfire exposure is measured with at least 50% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A8: Heterogeneous Effects Analysis for Black Students - 25% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.003	-0.003	-0.003
	(0.002)**	(0.002)	(0.002)*
2 Year Prior	> -0.001	-0.002	0.001
	(0.002)	(0.002)	(0.002)
3 Year Prior	-0.001	-0.003	> -0.001
	(0.002)	(0.003)	(0.002)
Math			
1 Year Prior	-0.002	-0.005	> -0.001
	(0.002)	(0.003)*	(0.002)
2 Year Prior	0.006	0.006	0.005
	(0.002)**	(0.003)*	(0.002)***
3 Year Prior	< 0.001	-0.001	< 0.001
	(0.003)	(0.003)	(0.003)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	0.024	0.038	0.014
	(0.068)	(0.066)	(0.075)
2 Year Prior	0.161	0.160	0.164
	(0.082)**	(0.106)	(0.077)**
3 Year Prior	-0.034	-0.051	-0.021
	(0.026)	(0.031)	(0.028)
Math			
1 Year Prior	0.089	0.022	0.149
	(0.073)	(0.092)	(0.074)**
2 Year Prior	0.165	0.195	0.123
	(0.074)**	(0.105)*	(0.060)**
3 Year Prior	-0.042	-0.075	-0.016
	(0.027)	(0.035)**	(0.028)
Observations	39108	19554	19554

Notes: The dependent variables are standardized ELA and math test scores of Black students. Wildfire exposure is measured with at least 25% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A9: Heterogeneous Effects Analysis for Black Students - 50% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.005	-0.005	-0.005
	(0.002)**	(0.003)**	(0.002)**
2 Year Prior	-0.001	-0.003	0.001
	(0.002)	(0.003)	(0.002)
3 Year Prior	-0.001	-0.004	0.001
	(0.002)	(0.002)*	(0.002)
Math			
1 Year Prior	-0.003	-0.005	-0.001
	(0.002)	(0.003)*	(0.003)
2 Year Prior	0.005	0.005	0.004
	(0.003)*	(0.003)	(0.002)**
3 Year Prior	-0.002	-0.004	< 0.001
	(0.002)	(0.003)	(0.003)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.050	-0.013	-0.074
	(0.044)	(0.052)	(0.051)
2 Year Prior	0.075	0.032	0.127
	(0.061)	(0.066)	(0.077)
3 Year Prior	-0.041	-0.059	-0.027
	(0.025)	(0.030)*	(0.027)
Math			
1 Year Prior	0.024	-0.024	0.073
	(0.062)	(0.090)	(0.061)
2 Year Prior	0.106	0.116	0.089
	(0.071)	(0.102)	(0.061)
3 Year Prior	-0.048	-0.082	-0.021
	(0.027)*	(0.035)**	(0.028)
Observations	39108	19554	19554

Notes: The dependent variables are standardized ELA and math test scores of Black students. Wildfire exposure is measured with at least 50% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A10: Heterogeneous Effects Analysis for Hispanic Students - 25% Exposure

	All	Primary School	Middle School
	(1)	(2)	(3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.003	-0.001	-0.005
	(0.002)*	(0.002)	(0.002)***
2 Year Prior	0.001	-0.002	0.005
	(0.002)	(0.002)	(0.002)***
3 Year Prior	0.004	0.001	0.005
	(0.002)	(0.003)	(0.002)**
Math			
1 Year Prior	-0.001	-0.002	-0.001
	(0.002)	(0.003)	(0.002)
2 Year Prior	-0.001	-0.004	0.002
	(0.002)	(0.003)	(0.002)
3 Year Prior	< 0.001	-0.004	0.004
	(0.003)	(0.004)	(0.002)*
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.040	-0.057	-0.024
	(0.022)*	(0.027)**	(0.030)
2 Year Prior	0.052	0.038	0.070
	(0.091)	(0.075)	(0.114)
3 Year Prior	0.015	-0.017	0.036
	(0.028)	(0.033)	(0.029)
Math			
1 Year Prior	-0.018	-0.045	0.006
	(0.025)	(0.040)	(0.026)
2 Year Prior	0.012	0.033	-0.012
	(0.062)	(0.074)	(0.074)
3 Year Prior	0.008	-0.022	0.033
	(0.039)	(0.046)	(0.042)
Observations	39480	19740	19740

Notes: The dependent variables are standardized ELA and math test scores of Hispanic students. Wildfire exposure is measured with at least 25% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A11: Heterogeneous Effects Analysis for Hispanic Students - 50% Exposure

	All	Primary School	Middle School
	(1)	(2)	(3)
Panel A: ELA			
*Wildfire Smoke Days (*10)*			
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.005	-0.003	-0.007
	(0.002)**	(0.002)	(0.002)***
2 Year Prior	< 0.001	-0.003	0.004
	(0.002)	(0.002)	(0.002)*
3 Year Prior	0.002	-0.001	0.005
	(0.002)	(0.003)	(0.002)**
Math			
1 Year Prior	> -0.001	> -0.001	-0.001
	(0.002)	(0.003)	(0.002)
2 Year Prior	-0.002	-0.005	0.001
	(0.002)	(0.003)**	(0.002)
3 Year Prior	-0.001	-0.006	0.003
	(0.003)	(0.004)	(0.003)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.044	-0.043	-0.047
	(0.021)**	(0.026)*	(0.031)
2 Year Prior	-0.012	-0.036	0.016
	(0.074)	(0.051)	(0.105)
3 Year Prior	0.004	-0.026	0.022
	(0.027)	(0.033)	(0.026)
Math			
1 Year Prior	-0.021	-0.061	0.016
	(0.025)	(0.037)	(0.026)
2 Year Prior	-0.005	0.014	-0.032
	(0.065)	(0.078)	(0.076)
3 Year Prior	0.001	-0.028	0.025
	(0.040)	(0.048)	(0.042)
Observations	39480	19740	19740

Notes: The dependent variables are standardized ELA and math test scores of Hispanic students. Wildfire exposure is measured with at least 50% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A12: Heterogeneous Effects Analysis for White Students - 25% Exposure

	All	Primary School	Middle School
	(1)	(2)	(3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	< 0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)
2 Year Prior	0.002	-0.001	0.003
	(0.001)**	(0.001)	(0.001)***
3 Year Prior	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)
Math			
1 Year Prior	-0.002	< 0.001	-0.003
	(0.001)*	(0.001)	(0.001)***
2 Year Prior	0.001	> -0.001	0.002
	(0.001)	(0.001)	(0.001)**
3 Year Prior	> -0.001	< 0.001	-0.001
	(0.001)	(0.001)	(0.001)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.017	-0.018	-0.016
	(0.009)*	(0.013)	(0.011)
2 Year Prior	-0.009	-0.036	0.004
	(0.032)	(0.033)	(0.038)
3 Year Prior	-0.058	-0.060	-0.056
	(0.012)***	(0.014)***	(0.013)***
Math			
1 Year Prior	-0.036	-0.033	-0.040
	(0.012)***	(0.017)*	(0.013)***
2 Year Prior	-0.001	-0.022	0.003
	(0.027)	(0.038)	(0.034)
3 Year Prior	-0.063	-0.065	-0.058
	(0.014)***	(0.017)***	(0.014)***
Observations	146298	73149	73149

Notes: The dependent variables are standardized ELA and math test scores of white students. Wildfire exposure is measured with at least 25% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A13: Heterogeneous Effects Analysis for White Students - 50% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	> -0.001	< 0.001	-0.001
	(0.001)	(0.001)	(0.001)
2 Year Prior	0.001	-0.001	0.003
	(0.001)*	(0.001)	(0.001)***
3 Year Prior	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)
Math			
1 Year Prior	-0.002	> -0.001	-0.004
	(0.001)**	(0.001)	(0.001)***
2 Year Prior	0.002	> -0.001	0.003
	(0.001)	(0.001)	(0.001)**
3 Year Prior	-0.001	> -0.001	-0.002
	(0.001)	(0.001)	(0.001)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.017	-0.019	-0.016
	(0.010)*	(0.013)	(0.012)
2 Year Prior	-0.030	-0.059	-0.015
	(0.025)	(0.026)**	(0.032)
3 Year Prior	-0.060	-0.062	-0.058
	(0.012)***	(0.014)***	(0.013)***
Math			
1 Year Prior	-0.036	-0.035	-0.039
	(0.012)***	(0.018)**	(0.013)***
2 Year Prior	-0.019	-0.041	-0.014
	(0.023)	(0.037)	(0.029)
3 Year Prior	-0.065	-0.068	-0.060
	(0.014)***	(0.017)***	(0.014)***
Observations	146298	73149	73149

Notes: The dependent variables are standardized ELA and math test scores of white students. Wildfire exposure is measured with at least 50% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A14: Heterogeneous Effects Analysis for Female Students - 25% Exposure

	All	Primary School	Middle School
	(1)	(2)	(3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.003	-0.001	-0.004
	(0.001)***	(0.001)*	(0.001)***
2 Year Prior	0.002	-0.001	0.005
	(0.001)***	(0.001)	(0.001)***
3 Year Prior	0.002	0.002	0.001
	(0.001)*	(0.001)	(0.001)
Math			
1 Year Prior	-0.002	-0.003	-0.002
	(0.001)**	(0.001)**	(0.001)
2 Year Prior	0.002	-0.001	0.004
	(0.001)	(0.001)	(0.001)***
3 Year Prior	> -0.001	-0.002	0.001
	(0.001)	(0.002)	(0.002)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.032	-0.027	-0.039
	(0.013)**	(0.016)*	(0.017)**
2 Year Prior	0.053	0.038	0.059
	(0.058)	(0.059)	(0.066)
3 Year Prior	0.008	-0.005	0.016
	(0.016)	(0.017)	(0.017)
Math			
1 Year Prior	-0.025	-0.037	-0.016
	(0.014)*	(0.019)*	(0.016)
2 Year Prior	0.030	0.026	0.020
	(0.035)	(0.049)	(0.039)
3 Year Prior	-0.029	-0.045	-0.016
	(0.016)*	(0.019)**	(0.017)
Observations	132894	66447	66447

Notes:The dependent variables are standardized ELA and math test scores of female students. Wildfire exposure is measured with at least 25% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A15: Heterogeneous Effects Analysis for Female Students - 50% Exposure

	All	Primary School	Middle School
	(1)	(2)	(3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.004	-0.003	-0.006
	(0.001)***	(0.001)**	(0.001)***
2 Year Prior	0.002	-0.001	0.004
	(0.001)*	(0.001)	(0.001)***
3 Year Prior	0.002	0.001	0.002
	(0.001)*	(0.001)	(0.001)
Math			
1 Year Prior	-0.003	-0.003	-0.002
	(0.001)**	(0.001)**	(0.001)
2 Year Prior	0.001	-0.002	0.004
	(0.001)	(0.002)	(0.001)***
3 Year Prior	-0.001	-0.003	0.001
	(0.001)	(0.002)*	(0.001)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.041	-0.030	-0.053
	(0.013)***	(0.017)*	(0.016)***
2 Year Prior	0.002	-0.030	0.022
	(0.038)	(0.026)	(0.056)
3 Year Prior	0.005	-0.009	0.012
	(0.015)	(0.015)	(0.017)
Math			
1 Year Prior	-0.030	-0.044	-0.019
	(0.014)**	(0.019)**	(0.016)
2 Year Prior	0.007	-0.007	0.006
	(0.033)	(0.048)	(0.038)
3 Year Prior	-0.032	-0.048	-0.020
	(0.016)*	(0.020)**	(0.017)
Observations	132894	66447	66447

Notes:The dependent variables are standardized ELA and math test scores of female students. Wildfire exposure is measured with at least 50% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A16: Heterogeneous Effects Analysis for Male Students - 25% Exposure

	All	Primary School	Middle School
	(1)	(2)	(3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.001	-0.002	0.001
	(0.001)	(0.001)**	(0.001)
2 Year Prior	0.001	-0.001	0.002
	(0.001)	(0.001)	(0.001)*
3 Year Prior	-0.002	-0.005	< 0.001
	(0.001)*	(0.001)***	(0.001)
Math			
1 Year Prior	-0.002	-0.001	-0.003
	(0.001)	(0.001)	(0.001)**
2 Year Prior	0.002	> -0.001	0.003
	(0.001)*	(0.001)	(0.001)***
3 Year Prior	> -0.001	0.001	-0.001
	(0.001)	(0.002)	(0.001)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.011	-0.022	-0.002
	(0.012)	(0.015)	(0.015)
2 Year Prior	0.061	0.018	0.096
	(0.060)	(0.053)	(0.077)
3 Year Prior	-0.055	-0.071	-0.042
	(0.015)***	(0.016)***	(0.017)**
Math			
1 Year Prior	-0.027	-0.028	-0.030
	(0.016)*	(0.020)	(0.018)*
2 Year Prior	0.062	0.056	0.054
	(0.044)	(0.047)	(0.056)
3 Year Prior	-0.024	-0.038	-0.013
	(0.017)	(0.021)*	(0.016)
Observations	134274	67137	67137

Notes: The dependent variables are standardized ELA and math test scores of male students. Wildfire exposure is measured with at least 25% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A17: Heterogeneous Effects Analysis for Male Students - 50% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.002	-0.003	> -0.001
	(0.001)	(0.001)***	(0.001)
2 Year Prior	< 0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)
3 Year Prior	-0.002	-0.005	< 0.001
	(0.001)**	(0.001)***	(0.001)
Math			
1 Year Prior	-0.002	-0.001	-0.004
	(0.001)*	(0.001)	(0.001)**
2 Year Prior	0.002	-0.001	0.003
	(0.001)	(0.002)	(0.001)***
3 Year Prior	-0.001	< 0.001	-0.002
	(0.001)	(0.002)	(0.001)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.015	-0.022	-0.011
	(0.012)	(0.015)	(0.015)
2 Year Prior	0.003	-0.041	0.039
	(0.038)	(0.030)	(0.058)
3 Year Prior	-0.059	-0.075	-0.047
	(0.014)***	(0.015)***	(0.016)***
Math			
1 Year Prior	-0.035	-0.038	-0.036
	(0.015)**	(0.020)*	(0.018)**
2 Year Prior	0.027	0.022	0.019
	(0.036)	(0.044)	(0.047)
3 Year Prior	-0.028	-0.043	-0.017
	(0.017)*	(0.021)**	(0.016)
Observations	134274	67137	67137

Notes: The dependent variables are standardized ELA and math test scores of male students. Wildfire exposure is measured with at least 50% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A18: Heterogeneous Effects Analysis for Econ. Disadvantaged Students - 25% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.002	-0.003	-0.002
	(0.001)**	(0.001)**	(0.001)
2 Year Prior	> -0.001	-0.002	0.002
	(0.001)	(0.001)*	(0.001)
3 Year Prior	-0.001	-0.002	< 0.001
	(0.001)	(0.001)*	(0.001)
Math			
1 Year Prior	-0.002	-0.002	-0.003
	(0.001)*	(0.001)	(0.002)
2 Year Prior	0.001	-0.001	0.003
	(0.001)	(0.002)	(0.001)**
3 Year Prior	-0.002	-0.003	-0.001
	(0.002)	(0.002)	(0.001)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.022	-0.027	-0.020
	(0.013)*	(0.018)	(0.018)
2 Year Prior	0.068	0.036	0.096
	(0.065)	(0.058)	(0.082)
3 Year Prior	-0.028	-0.049	-0.016
	(0.015)*	(0.017)***	(0.017)
Math			
1 Year Prior	-0.014	-0.014	-0.018
	(0.017)	(0.024)	(0.017)
2 Year Prior	0.052	0.061	0.031
	(0.051)	(0.061)	(0.055)
3 Year Prior	-0.036	-0.057	-0.020
	(0.019)*	(0.023)**	(0.018)
Observations	123750	61875	61875

Notes: The dependent variables are standardized ELA and math test scores of Economically Disadvantaged students. Wildfire exposure is measured with at least 25% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A19: Heterogeneous Effects Analysis for Econ. Disadvantaged Students - 50% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Prior	-0.003	-0.004	-0.003
	(0.001)***	(0.001)***	(0.001)**
2 Year Prior	-0.001	-0.003	0.001
	(0.001)	(0.001)**	(0.001)
3 Year Prior	-0.001	-0.003	< 0.001
	(0.001)	(0.001)**	(0.001)
Math			
1 Year Prior	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.002)
2 Year Prior	0.001	-0.002	0.003
	(0.001)	(0.002)	(0.001)**
3 Year Prior	-0.003	-0.004	-0.002
	(0.002)*	(0.002)**	(0.002)
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Prior	-0.029	-0.024	-0.035
	(0.013)**	(0.017)	(0.016)**
2 Year Prior	0.019	-0.026	0.064
	(0.054)	(0.040)	(0.080)
3 Year Prior	-0.031	-0.052	-0.019
	(0.015)**	(0.017)***	(0.017)
Math			
1 Year Prior	-0.021	-0.023	-0.022
	(0.016)	(0.023)	(0.017)
2 Year Prior	0.052	0.055	0.040
	(0.054)	(0.064)	(0.060)
3 Year Prior	-0.038	-0.059	-0.022
	(0.019)**	(0.024)**	(0.018)
Observations	123750	61875	61875

Notes: The dependent variables are standardized ELA and math test scores of Economically Disadvantaged students. Wildfire exposure is measured with at least 50% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A20: Placebo Test: Future Wildfire Exposure - 25% Exposure

	All (1)	Primary School (2)	Middle School (3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Future	0.001	> -0.001	0.002
	(0.001)	(0.001)	(0.001)*
Math			
1 Year Future	0.001	-0.001	0.003
	(0.001)	(0.002)	(0.001)**
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Future	0.011	-0.003	0.023
	(0.012)	(0.013)	(0.016)
Math			
1 Year Future	0.007	-0.015	0.029
	(0.012)	(0.017)	(0.013)**
Observations	160050	80025	80025

Notes: The dependent variables are standardized ELA and math test scores. Wildfire exposure is measured with at least 25% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.

Table A21: Placebo Test: Future Wildfire Exposure - 50% Exposure

	All	Primary School	Middle School
	(1)	(2)	(3)
Panel A: Smoke Days (*10)			
ELA			
1 Year Future	0.002	0.001	0.003
	(0.001)	(0.001)	(0.001)*
Math			
1 Year Future	0.002	> -0.001	0.004
	(0.001)	(0.002)	(0.001)**
Panel B: Unhealthy Air Quality Days (*10)			
ELA			
1 Year Future	0.023	0.007	0.037
	(0.009)**	(0.010)	(0.012)***
Math			
1 Year Future	0.007	-0.019	0.032
	(0.013)	(0.016)	(0.013)**
Observations	160050	80025	80025

Notes: The dependent variables are standardized ELA and math test scores. Wildfire exposure is measured with at least 50% of the population being exposed to wildfire smoke in the school district. All estimates include the full panel of control variables. Standard errors are reported in parentheses and are clustered at the GSD level. Estimates are weighted by the grade size of each GSD. */**/*** denotes significance at the 10/5/1 percent level.