Wildfire Exposure and Learning Loss: Evidence from California*

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*We are deeply grateful to Alex Eble's support throughout this project. This paper would not have been possible without the helpful suggestions of Peter Bergman, Sarah Cohodes, Jordan Matsudaira, Kirsten Slungaard Mumma, Sebastián Otero, R. Jisung Park, Douglas Ready, Sean Reardon, Randall Reback, Jonah Rockoff, Judith Scott-Clayton, and Pietro Tebaldi. We also thank participants at the Russell Sage Foundation & William T. Grant Foundation Conference and Columbia University Economics of Education seminars for their helpful suggestions. Funding for this project was generously provided by the Russell Sage Foundation and William T. Grant Foundation. Yifeng Luo thanks the National Natural Science Foundation of China (No. 72074004) for their financial support. All errors are our own.

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Abstract

Wildfires have grown larger, more frequent, and more geographically widespread in the past decade, disrupting schooling and student learning. This paper links California student assessment data to detailed information on wildfires, school closures, wildfire smoke, and weather conditions to examine the causal effects of wildfire exposure on student academic achievement and the mechanisms through which these effects operate. Leveraging exogenous variation in wildfire shocks across time, geography, and intensity across schools and cohorts, we find that exposure to wildfires decreases Math and ELA scores by about 0.028 and 0.020 standard deviations, with larger effects among students with lower socioeconomic backgrounds. We also exploit quasi-random variation in wind direction and wildfire characteristics as instruments for school closures and smoke exposure to explore potential mechanisms. Our estimates identify both wildfire-induced school closures and smoke-related air pollution as important mechanisms: benchmark calculations suggest that closures account for roughly 15–20% of the observed learning losses, while smoke exposure accounts for an additional 33% of the decline in math achievement and 5% of the decline in ELA achievement.

Keywords: Wildfire; School closure; Air pollution; Test score

JEL Codes: I21, Q54

1. Introduction

Human capital accumulation is central to economic growth and individual well-being, yet it can be disrupted by adverse shocks such as natural disasters, which are becoming more frequent and severe with climate change. Among these shocks, wildfires have drawn increasing attention in recent decades as they have become larger, more frequent, and more geographically widespread (Burke et al., 2021). Recent events illustrate the growing scale and severity of wildfire-related disruptions. The January 2025 Southern California wildfires, for example, forced more than 200,000 people to evacuate and destroyed over 18,000 homes and structures, while the 2023 Canadian wildfires burned a larger area than any previous wildfire season in the country's recorded history. Despite the increasing prevalence of wildfires and their potential to disrupt schooling and learning environments, there is limited empirical evidence on how unexpected wildfire exposure affects human capital development. This paper addresses this gap by exploiting variation in the timing of wildfire exposure across schools within a staggered difference-in-differences framework to estimate the causal effects of sudden wildfire exposure on student achievement.

Moreover, the literature rarely presents evidence on the mechanisms behind the observed effects of natural disasters on human capital development. This paper contributes by unpacking the channels through which wildfire shocks affect student achievement. In addition to the direct physical damage and economic losses, wildfires can affect learning through two main pathways: school closures implemented for safety reasons and exposure to wildfire smoke, which can persist for days and spread far beyond fire-affected areas. This paper therefore focuses on these two key mechanisms: school closures and wildfire smoke exposure. Understanding these mechanisms is also important for policy. During wildfire events, policymakers and school administrators face a trade-off between reducing students' exposure to health risks and maintaining instructional time. School closures may mitigate exposure to hazardous smoke and immediate safety threats, but

they also reduce time spent in class and may disrupt learning. Quantifying the relative importance of these channels provides evidence to inform decisions about whether and how long to close schools in response to increasingly frequent wildfire shocks.

This study examines wildfires in California during the 2009–10 to 2018–19 academic years. California provides an ideal empirical setting, as it is particularly affected by wildfires. In 2017 alone, wildfires disrupted schooling for more than 867,000 students, and the number of California schools impacted by wildfires rose sharply over the past decade. During the 2017–2018 academic year, wildfire-related closures accounted for 91 percent of all school closure days statewide. We combine multiple administrative datasets from California and link detailed wildfire exposure measures to school-level test score data.

The empirical strategy exploits plausibly exogenous variation in wildfire shocks across time and geographic areas to identify the causal effects of wildfire exposure on student achievement. Compared to commonly studied shocks such as extreme winter weather (Goodman, 2014; Marcotte and Hemelt, 2008), wildfires are less predictable and exhibit substantial spatial and temporal variation, making them less likely to be anticipated or incorporated into instructional planning. This unpredictability generates quasi-random variation in exposure across schools and cohorts, strengthening causal identification.

To isolate the mechanisms of school closures and wildfire smoke exposure, we first restrict the sample by excluding schools located in close proximity to wildfire events, thereby minimizing the influence of direct economic damage and psychological trauma. A key feature of wildfires that supports this identification strategy is the sharp spatial decay of their direct impacts: economic damages and acute psychological trauma are highly concentrated in areas immediately adjacent to fire perimeters and decline rapidly with distance, unlike many other natural disasters whose effects are more spatially diffuse. We leverage this feature to strengthen the exclusion restriction by excluding schools located in close proximity to wildfire events.

Within this restricted sample, we isolate the mechanisms of school closures and wild-

fire smoke exposure using two complementary strategies. To estimate the impact of school closures, we exploit variation in wildfire intensity and proximity as instruments for closure decisions. We also exclude schools located downwind of wildfires to minimize the influence of smoke. To identify the effect of smoke exposure, we leverage exogenous variation in air pollution driven by changes in wind direction. Both strategies rely on sources of variation that plausibly affect school closures or smoke exposure while being orthogonal to other determinants of student achievement, allowing us to isolate the respective causal channels.

We first estimate the overall impact of wildfire exposures on students' academic performance. This analysis captures the combined influence of multiple channels, including air pollution, school closures, economic disruptions, and psychological stress associated with wildfires. The results reveal that wildfire exposures have a negative impact on test scores in both English language arts (ELA) and math. Our preferred specification shows that on average, exposure to wildfires decreases Math scores by 0.025-0.030 standard deviations (SD) and ELA scores by 0.018-0.023 SD relative to the scores of the national reference cohort in the same grade. Such a magnitude is equivalent to at least 4.5% of the total yearly learning according to the estimates of Betthäuser et al. (2023), or approximately 20 percent of the effect of a 1-SD change in teacher quality, which can translate into a 1.12% change in lifetime earnings according to the estimates of Chetty et al. (2014a,b).[1]

Next, we explore heterogeneity in the effects of wildfire exposures on student achievement by socioeconomic status (SES). We find that learning loss is greater among students from low-SES schools than among those from high-SES schools, which is consistent with related work (Goodman, 2014; Groppo and Kraehnert, 2017). This heterogeneity indicates that wildfire shocks exacerbate educational inequality. Accordingly, policymakers

[1] Betthäuser et al. (2023) summarizes that students generally improve their performance by around 0.4 standard deviations per school year. Therefore, our estimate of 0.018 - 0.030 SD learning loss corresponds to 4.5% - 7.5% annual learning. Chetty et al. (2014a) suggest that a 1 standard deviation (SD) improvement in teacher quality raises test scores by 0.14 SD in math and 0.1 SD in English, so our estimates are approximately 20% of these magnitudes.

allocating resources in the aftermath of such events should consider targeting low-income students.

We then explore two important mechanisms driving these learning losses: school closures and air pollution. School closures can lead to both less time for instruction and out-of-school environment. The results show that on average, one closure day due to wildfires decreases math scores by 0.0076 SD and ELA scores by 0.0071 SD. This suggests that school closure is an important channel through which wildfires harmed student learning and has policy implications for alleviating learning loss during unexpected school closures.

We also explore whether air pollution caused by wildfires underlies the link between wildfire exposures and learning loss. Estimating the causal effect of air pollution on student test scores is complicated by potential omitted variable bias (e.g., student sorting into residential districts partly based on environmental quality) and measurement error. We overcome these challenges by combining an instrumental variables (IV) approach exploiting variation in air pollution attributable to changes in wind direction, and using Childs et al. (2022) wildfire smoke data that specifically measures wildfire-driven PM2.5. Our IV estimates show that an increase of 1 microgram per cubic meter $(\mu g/m^3)$ in the cumulative concentration of PM 2.5 wildfire smoke (particulate matter 2.5 microns in diameter or smaller) decreases math scores by 0.051% of a SD and ELA scores by 0.006% of a SD, suggesting that air pollution serves as another important channel through which wildfires lead to learning loss.

We conduct a series of robustness analyses to assess the validity of our identification strategy and to rule out confounding from unobserved school characteristics. First, using an event-study design, we show that student achievement exhibits no differential pre-trends prior to wildfire exposure. Second, we demonstrate that future wildfire exposure does not predict past student achievement, alleviating concerns related to anticipatory effects or spurious correlations. In addition, we examine whether student mobility re-

sponses drive our estimates. We find that wildfire exposure does not affect overall enrollment and has only small effects on the racial and ethnic composition of students. These compositional changes account for a negligible share of the estimated impact of wildfire exposures on test scores. Finally, we find no evidence that wildfire-related school closure days influence the incidence of other school closures within the same academic year, alleviating concerns about jointly determined closure decisions and suggesting that unobserved closures are unlikely to drive the observed learning loss.

Our study contributes to several streams of literature. First, it adds to the body of research examining the effects of severe natural disasters on human capital development. We extend this literature by providing the first, to the best of our knowledge, well-identified evidence on the impact of wildfire exposures—an increasingly common phenomenon in recent years—on student test scores and inequality in academic achievement. We also link data from multiple sources to uncover the mechanisms driving this relationship, with results highlighting school closures and exposure to air pollution as key factors. Only a few papers have touched upon the mechanisms behind the impact of natural disasters, mostly attributing the observed correlation to the financial loss of lower-income families(Groppo and Kraehnert, 2017). Our study identifies mechanisms beyond financial loss, offering new evidence on the pathways through which natural disasters affect student learning. Prior studies on the impacts of natural disasters on human capital development have mainly focused on the impact of typhoons, earthquakes, or heavy snow in developing countries (Deuchert and Felfe, 2015; Herrera-Almanza and Cas, 2020; Paudel and Ryu, 2018). Our findings emphasize the importance of extending this line of research to developed countries.[2] This is particularly critical given the increasing global

[2]A few studies have explored this topic in the context of developed countries. Sacerdote (2012), for example, finds that Hurricanes Katrina and Rita negatively affected New Orleans students' test scores in the first year following the storms. These two hurricanes, however, almost completely destroyed the entire public school system—more frequent but less disastrous events may have different effects. In addition, the Covid-19 pandemic prompted studies on the impact of the pandemic on college graduation rates and job placement (Aucejo et al., 2020), student math progress on an online platform (Chetty et al., 2020), and predicted learning loss (Kuhfeld et al., 2020).

impact of climate change and infectious diseases on educational systems.

Our research also adds to a growing body of literature on the impact of air pollution on human well-being. Research has shown that air pollution is associated with many significant outcomes in life (Aguilar-Gomez et al., 2022).[3] We exploit plausibly exogenous variation in wind direction to provide one of the first pieces of quasi-experimental evidence that wildfire smoke harms student test scores, complementing studies exploring whether interventions that improve air quality increase test scores (Ebenstein et al., 2016; Gilraine, 2020; Roth, 2016). Further, we use wildfire smoke data from Childs et al. (2022) rather than the conventional overall PM 2.5 concentration data to measure wildfire-driven air pollution. This improvement in data quality greatly strengthens the identification of causal effects of wildfire-driven air pollution on student achievement. Our estimates also suggest that the endogeneity problem can lead to an underestimation of the negative impact of air pollution, which is consistent with Deryugina et al. (2019).

Our findings also contribute to the small but growing literature on the economic and social costs of wildfires. Research has documented the correlation between wildfires and air quality that translates into health deterioration (Burke et al., 2023), house price declines, credit card and mortgage defaults (An et al., 2023), and lower earnings (Borgschulte et al., 2022). Our findings that wildfires negatively affect student test scores, especially those with lower socio-economic status, have important implications for the evaluation of the social cost of wildfire-related disasters.

Finally, this paper contributes to the literature on the effects of instructional time on student achievement. A large and well-identified body of work examines variation in scheduled instructional time (Carlsson et al., 2015; Lavy, 2015; Rivkin and Schiman, 2015), while other studies exploit unexpected disruptions to instructional time, particularly school closures due to extreme weather such as snow days (Fuller, 2013; Good-

[3]Studies have shown the relationship between air pollution and health outcomes, (Deryugina et al., 2019; He et al., 2020; Pullabhotla and Souza, 2022), productivity (Adhvaryu et al., 2022; He et al., 2019), cognitive performance (Ebenstein et al., 2016; La Nauze and Severnini, 2021), and violent crimes (Burkhardt et al., 2019).

man, 2014; Hansen, 2011; Marcotte, 2007; Marcotte and Hemelt, 2008). We extend this literature by examining school closures induced by wildfires, a form of disruption that is highly unpredictable and varies substantially across both time and space, facilitating causal identification. Importantly, we isolate the effect of instructional time loss by focusing on precautionary closures, thereby minimizing confounding channels such as psychological trauma or local economic disruption. In addition, our measure of instructional time loss is specific to wildfire-related closures, rather than total closure days as is common in the prior literature. This approach allows us to more closely align the instrument with the underlying source of variation in instructional time and strengthens the first stage. The richness of the school closure data further enables us to control for other types of closures, helping to mitigate concerns that correlated disruptions across closure types confound the estimates.

The rest of the paper is organized as follows. Section 2 reviews the study's background and data. Section 3 describes the empirical strategy and the results of the overall effects of wildfire exposures. Section 4 presents the main results of two important mechanisms through which wildfire exposures affect student learning: school closures and air pollution. Section 5 concludes.

2. Background and Data

2.1. Wildfires, Smoke, and School Closures

Over the past few decades, wildfires have become more frequent, larger in scale, and more damaging in terms of economic and social losses. In the United States, the 2024 wildfire season alone recorded nearly 65,000 fires that burned more than 8.9 million acres and destroyed thousands of structures nationwide. Globally, wildfire activity has also intensified, with an estimated 390 million hectares burned in 2025 (UNDRR, 2025), an area roughly equivalent to 92% of the European Union's land area.

Recent events also highlight how wildfire damages are increasingly concentrated in densely populated and economically important regions. For instance, the January 2025 Southern California wildfires, comprising 14 destructive fires across the Los Angeles metropolitan area and San Diego County, resulted in at least 31 fatalities, forced more than 200,000 residents to evacuate, destroyed over 18,000 homes and other structures, and burned approximately 57,529 acres. These fires were the costliest disaster of the year, with estimated damages exceeding USD 53 billion (UNDRR, 2025).

Unexpected wildfires affect a large number of students in the United States each year. In California, for example, wildfires affected more than 867,000 students in 2017; further, the number of California schools affected by wildfires increased dramatically over the past decade (see Figure 1). Figure 2 illustrates the geographic distribution of California wildfires between 2007 and 2019, showing that many public schools across a widespread geographical area are located in close proximity to wildfire events.

Beyond the direct threat from active fires, wildfires also produce large amounts of smoke that can linger for days or even weeks and travel hundreds or thousands of miles. For example, in June 2023, smoke and particulate emissions from severe Canadian wildfires affected an estimated 122 million people across the Northeast and North Central United States, leading to some of the worst air quality levels on record (Aguilar-Gomez et al., 2022). In 2020, U.S. counties experienced wildfire smoke coverage for an average of 20.2 days per year, and 64 days per year in California (An et al., 2023). As a result, students may be exposed to poor air quality even when fires are geographically distant or already contained. What's worse, wildfire smoke is becoming an even larger threat to schools. Figure 3 illustrates regional and time patterns in wildfire smoke exposure from 2011-2019. Darker red areas represent higher levels of wildfire smoke exposure, and black dots represent schools. It is clear that most schools are exposed to some degree of wildfire smoke, with significantly higher pollution levels in later years. Large wildfire smoke plumes can contribute to a range of adverse health (Deryugina et al., 2019) and

non-health outcomes (He et al., 2019). The fine particulate matter in wildfire smoke is particularly harmful to human health and is more toxic than pollution from typical urban sources such as vehicle emissions (Aguilar-Gomez et al., 2022).

Moreover, wildfire events force schools to close to ensure public safety, thus disrupting students' education. In California, wildfire school closures predominantly occur during the Fall semester. For instance, within our sample, 92% of such closures happened between August and December, as shown in Figure 4. Considering that California's statewide assessment of student performance is conducted from January to early July, the majority of wildfire school closures in our sample occurred prior to these assessment dates. The decision to shut down schools during wildfire emergencies typically arises from a collaborative process involving district-level decision-making and guidance from local and state government authorities.

Unfortunately, schools do not always make up for closure days. In the United States, states have varying requirements regarding the number of instructional days and hours in an academic year. The majority of states set the school year at 180 days. However, when extreme situations prevent schools from having enough school days, states may not require schools to make up all missed school days. In California, for example, Education Code § 41422 provides that in extreme circumstances, if a school district can show, to the satisfaction of the superintendent, that specific reasons prevented the school from holding classes for at least 175 school days during a fiscal year it can still "receive the same apportionment from the State School Fund as it would have received." Therefore, schools in California may not have enough incentive to make up for unexpected closure days. Consequently, school closures caused by unexpected disastrous events can potentially lead to unfinished teaching plans.

Further, researchers have predicted that climate change will generate more frequent extreme weather events, such as heatwaves, heavy precipitation, and droughts, in at least some regions of the world (Seneviratne et al., 2012). These trends imply that unexpected

wildfires, along with the resulting smoke exposure and school closures, will increasingly affect students, making it important to quantify their impacts on educational outcomes.

2.2. Data

2.2.1. Test score and school characteristics

We combine multiple data sources to assess the effects of wildfire exposure on student achievement. First, we use school-grade-level test score data from the California Department of Education (CDE) for the 2009-10 through 2018-19 AYs. These test score data are not directly comparable before and after 2014 because the state changed its assessment in 2014[4]. We follow the procedures developed by Reardon et al. (2017) to re-scale these school-grade-level test scores.[5] Specifically, we link reliability-adjusted California school test score scales to the NAEP scales for ELA and math using the following equation:

$$\hat{\mu}^{n\hat{a}ep}_{sygb} = \hat{\mu}^{naep}_{cygb} + \frac{\hat{\mu}^{state}_{sygb}}{\sqrt{\hat{\rho}^{state}_{cygb}}} * \hat{\sigma}^{naep}_{cygb}$$

where $\hat{\mu}^{n\hat{a}ep}_{sygb}$ is the estimated test score for school **s**, in year **y**, grade **g**, and subject **b** $\in \{ELA, math\}$, on the NAEP scale. $\hat{\mu}^{naep}_{cygb}$ and $\hat{\sigma}^{naep}_{cygb}$ are the NAEP test score means and standard deviations of year **y**, grade **g**, and subject **b** in California. $\hat{\mu}^{state}_{sygb}$ and $\hat{\rho}^{state}_{cygb}$ represent the original school-grade-level test score and the reliability of the state test. To ease interpretation, we then standardize the re-scaled scores using the cohort standardization technique recommended in Reardon et al. (2017). For the resulting scores, 1 unit refers to 1 grade-specific standard deviation above the average test score of the California reference group, which consists of five cohorts of California students who were in 4th

[4]Test score data for 2013–2014 AY are missing due to the assessment change.

[5]Reardon et al. (2017) developed a method to link test score data from states to NAEP data, which provides comparable state-level scores in reading and math for students in grades 4 and 8 in odd years. Reardon et al. (2017) use this linking method to estimate test scores that are comparable across years and states.

grade in 2007, 2009, 2011, 2013, and 2015. These standardized school-grade-level scores are comparable across schools and years but not across grades. We also obtained information on several school-level characteristics from the CDE. We use data on school location, grade-level enrollment, gender, and racial/ethnic composition of the student body, and percentage of students eligible for free/reduced-price lunch.

2.2.2. Wildfires

We use data from the California Department of Forestry and Fire Protection to obtain information on the timing and geographical coverage of all wildfire events in California during the focal period. The department maintains a GIS dataset that allows us to match each school to all adjacent wildfires. We use this dataset to calculate the distance from each school to each wildfire edge and determine whether a school is exposed to wildfires at each point in time.

2.2.3. Smoke, school closure, and climate data

To examine the mechanisms by which wildfire exposure affects test scores, we analyze data on school closures, air pollution, and weather conditions. School closure data are drawn from the California Public School Closure Database, which has information on the number of school closure days for each school by cause, including natural disasters and weather, wildfires, and student safety, over the 2002-03 to 2018-19 academic years. Figure 6 shows that the number of closure days caused by wildfires is highly variable across years.

The wildfire smoke data derive from Childs et al. (2022), which generates daily estimates of wildfire-driven PM2.5 across the contiguous US from 2006 to 2020 based on

ground, satellite, and reanalysis data sources.[6] We construct school-level measures of cumulative wildfire-driven PM2.5 by aggregating daily smoke data to the academic-year level and linking smoke data to schools via ZIP codes[7].

We also use hourly wind direction from the California Air Resources Board to determine whether a school-year cell is in the downwind area of a wildfire. A school is defined as being downwind of a fire if it is located in the direction that smoke would plausibly travel given the prevailing wind direction during the wildfire month. Specifically, the dominant wind direction (i.e. where the wind is coming from) is converted into the direction the wind is blowing toward. From the fire's location, a downwind area is constructed that spans a certain angle (e.g., 60 degrees) centered on this downwind direction. A school is classified as downwind if it falls within this area.

2.3. Descriptive statistics

Table 1 presents summary statistics of test scores, demographics, and wildfire-related characteristics, and Table 2 compares mean values of these statistics between the unexposed and exposed samples, defined as school-grade-year cells that are within 10 km of the edge of the wildfires. About 59% of students in the analytic sample are eligible for free or reduced-price lunch. About half of the sample members are Hispanic, while 26% are White, 8% are Asian, and 4% are Black. Panel A of Table 2 shows that students in the exposure sample score higher. This may be related to the demographics in Panel B, which shows that the exposure sample has a smaller proportion of students eligible for free/reduced price lunch. Students in the exposure sample are also slightly more likely

[6]We follow Burke et al. (2022) to calculate smoke-attributable PM2.5 as the deviation from location-specific median PM2.5 on non-smoke days in the same month, with the median calculated over a 3-year window centered on the current year. This anomaly value is assigned to the smoke PM2.5 variable on smoke days and set to zero for non-smoke days. Smoke days with negative anomaly values are also set to zero. The resulting measure captures variation in PM2.5 attributable to wildfire smoke, under the assumption that other PM2.5 sources are not systematically elevated on smoke days.

[7]We first merge the wildfire smoke PM2.5 data to schools based on the 5-digit zipcodes. For schools that cannot be matched to the smoke data (approximately 17% of school–year observations), we rely on 4-digit and 3-digit ZIP codes to match them to the smoke data.

to be White and less likely to be Asian, Black, or Hispanic.

Our analytic sample includes about 220,000 school-grade-year cells. Among them, about 9.27% are exposed to wildfires located within 10 km of the wildfire edges. Panel C of Table 1 presents summary statistics on wildfire smoke and school closures due to wildfires. On average, our analytic sample experiences 0.09 days of school closures due to wildfires. These closures are mostly concentrated in the exposure sample, which, on average, experiences 0.47 days of such closures. Wildfire smoke is more severe in the exposure sample, as expected.

Table A.I presents the average within- and between-school-grade variation in four wildfire-related variables, which we use as instruments in regressions. We observe considerable variation both across school-grades and over time within school-grades, indicating that there is substantial variation that can be used for our identification strategy. Students of different cohorts within the same school and same grade can be differently exposed to wildfires in terms of frequency, wildfire size, and distance to the closest wildfires due to exogenous wildfire events. This pattern thereby generates plausibly random variation in smoke exposure and school closures.

3. The Overall Impact of Wildfire Exposure

We first estimate the overall effect of wildfire exposure on student test scores. This analysis captures the combined influence of multiple channels, including air pollution, school closures, economic disruptions, and psychological stress associated with wildfires. We then decompose this total effect by estimating the contribution of specific channels, focusing in particular on wildfire smoke exposure and school closures.

3.1. Empirical Strategy

A key identification challenge in estimating the effects of wildfire exposure is that exposed schools may differ systematically from unexposed schools along both observed and unobserved dimensions. To address this concern, we exploit variation in the timing of wildfire exposure across schools in a staggered difference-in-differences framework, comparing outcomes within the same school–grade before and after exposure.

Our specification includes school–grade fixed effects, which absorb all time-invariant differences across school–grade cells, such as geographic characteristics, as well as year fixed effects to account for common shocks affecting students statewide. Identification relies on the assumption that, absent wildfire exposure, outcomes in treated and untreated schools would have evolved in parallel. Specifically, we estimate the causal effects of wildfire exposures using the following equation:

$$\begin{aligned} Score_{sgt} =& \alpha + \beta Exposure_{sgt} + \\ & \gamma X_{sg(t-1)} + \mu_{sg} + \phi_{t-g} + \lambda_t + post14 \cdot \omega_c + \epsilon_{sgt} \end{aligned} \tag{1}$$

where $Score_{sgt}$ denotes the mean standardized test scores in math or ELA for school s, grade g, and year t. $Exposure_{sgt}$ is an indicator of whether school s in year t is exposed to wildfires. We define wildfire exposure using multiple distance thresholds. Specifically, for each school–grade–year cell, we match wildfires that burned more than 100 acres and occurred within 50 km of the school, where distance is calculated as the minimum distance between the school and the fire perimeter. We then construct indicator variables capturing whether a school is located within 1, 2, 3, 4, 5, or 10 km of a wildfire perimeter, which we use as measures of wildfire exposure in our empirical analysis. β is the coefficient of interest, which measures the impact of exposure on test scores in the current (academic) year. μ_{sg} denotes the school-by-grade fixed effects. λ_t denotes the year fixed effects.

Although school-by-grade fixed effects address endogeneity caused by time-invariant

confounders, omitting time-variant variables may still bias the estimates. To address this problem, we control for lagged school-grade-year measures of the gender and racial/ethnic composition of the student body as well as the proportion of students eligible for free/reduced-price lunch (X_{dgt}). Cohort fixed effects (ϕ_{t-g}) are also included to control for cohort-specific shocks. To account for level shifts in achievement associated with the transition from the STAR program to the California Assessment of Student Performance and Progress (CAASPP) system in 2014, we include county-by-post-2014 fixed effects ($post14 \cdot \omega_c$). We also include weather controls, including temperature, precipitation, and wind speed at the school level.[8] We weight observations using the test-taking population at the school-grade-year-subject level, a conventional weighting scheme.

A potential concern is that the estimated effects of wildfire exposure may be confounded by differential pre-trends in student achievement between exposed and unexposed schools. To assess this possibility, we implement an event study specification that estimates dynamic treatment effects relative to the timing of wildfire exposure:

$$\begin{aligned} Score_{sgt} =& \alpha + \Sigma_{t=-5}^{5} \beta_t Exposure1_{sgt} + \\ & \gamma X_{sg(t-1)} + \mu_{sg} + \phi_{t-g} + \lambda_t + post14 \cdot \omega_c + \epsilon_{sgt} \end{aligned} \tag{2}$$

All variables are defined in the same way as in Equation 1, except that $Exposure1_{sgt}$ is a dummy that switches on after the first exposure to wildfires. We let t index the academic year(s) relative to the academic year in which fire exposure first occurred. Figure 5 shows that there is no clear trend before exposure to wildfires. At first glance, the figure shows sharp decreases in both math and ELA scores immediately following wildfire exposures.

[8] We include yearly maximum and minimum temperatures as temperature controls, represented by indicators for deciles of maximum and minimum temperatures at the 5-digit zip-code level. We do the same for precipitation and wind speed.

3.2. Results

Table 3 reports the estimated effects of wildfire exposures on Math (Panel A) and ELA (Panel B), respectively. As described above, we define wildfire exposure using alternative distance thresholds from the wildfire perimeter, with results reported across columns. Across nearly all specifications, the estimated effects are negative and statistically significant, consistent with expectations.

In Columns (1) and (2), exposure is defined as school–year cells located within 1 km and 2 km of wildfire perimeters, respectively. While the estimated effect sizes are similar to those obtained under broader distance thresholds, they are generally not statistically significant. This is likely driven by the smaller number of treated observations under these more restrictive definitions, resulting in lower statistical power and larger standard errors.

When we define exposure as school-year cells located within 3, 4, or 5km of the wildfire edges, the estimates are all negative and statistically significant. These are also our preferred specifications, which show that exposure to wildfires decreases math scores by 0.025-0.030 SD and ELA scores by 0.018-0.023 SD. In Column (6), the estimated effects are smaller in magnitude, suggesting that the impact attenuates with distance from wildfires.

Heterogeneity. We examine heterogeneity by socio-economic status. We calculate the average proportion of free/reduced-price lunch students in school s between 2009 and 2017; divide the distribution of average proportions into terciles; and categorize schools in the analytic sample as having low, medium, or high SES. We estimate equation 1, replacing $Exposure_{sgt}$ with three interaction terms between $exposure$ and indicators of whether school s belongs to each of the three SES groups (i.e., low SES x$exposure$, medium SES x $exposure$, high SES x $exposure$).

Table 4 reports the estimated coefficients on these interaction terms. We use the three preferred thresholds to define exposure (within 3, 4, or 5 km of the edges of the wildfire). The negative effects of exposure on test scores are clearly concentrated among schools

with a high proportion of free/reduced-price lunch students. On average, wildfire exposure decreases math scores by 0.07 - 0.09 SD and decreases ELA scores by 0.03 - 0.05 SD for students in schools with lower socio-economic status. For students in schools with middle socio-economic status, the negative impacts of exposure range from 0.02 to 0.04 SD and are smaller in magnitude, and the estimates are mostly statistically insignificant. Students in schools with high socio-economic status still suffer from wildfire exposures, but the estimates have relatively small magnitudes and are statistically insignificant.

Robustness. We perform several robustness analyzes to check (1) whether student migration after wildfires pollutes our estimates, (2) whether the possibility that tests may be taken before the occurrence of wildfires within an academic year affects our results, and (3) whether our estimates suffer from a negative weighting problem in the presence of staggered adoption and heterogeneous treatment effects.

We first explore whether wildfire exposures are associated with changes in enrollment and student composition. Table A.II shows that the association between wildfire exposures and enrollment is negative, as expected. The estimate is small in magnitude and statistically insignificant: on average, wildfire exposure decreases the school-grade level enrollment by only 0.43-0.46 students (the average enrollment in the sample is over 100). This implies that wildfire exposures have a limited impact on enrollment and are unlikely to drive the learning loss detected after wildfire exposure.

We also examine whether wildfire exposures are associated with changes in the racial composition of focal schools. The results in Table A.III show that although wildfire exposures are associated with changes in student body racial/ethnic composition, the magnitudes of these shifts are small: on average, wildfire exposure is associated with a 0.021 - 0.083 percentage point change in the proportion of each of the four largest racial groups (Asian, Black, Hispanic, and White).

Another potential concern is that some assessments may have been administered prior to the occurrence of wildfires. In such cases, measured exposure would be mechanically

unrelated to test performance, potentially contaminating our estimates. To address this concern, we implement a placebo test that examines whether wildfires occurring after the administration of California's statewide assessments affect test scores. Because future wildfire exposure cannot influence contemporaneous academic outcomes, any estimated effect would reflect anticipatory behavior, spurious correlation, or unobserved confounding.

We implement this test by restricting the sample to school–year observations that are either not exposed to wildfires or are exposed only in June or July, after testing has concluded. Table A.IV reports the results. As expected, the estimated effects are statistically insignificant in 11 out of 12 specifications, providing no evidence that post-assessment wildfire exposure affects test scores.

Studies have shown that treatment effect estimates from two-way fixed effects models can be biased due to negative weights assigned to groups and periods when the treatment is implemented at different times and the treatment effect is heterogeneous (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Callaway et al., 2021; Sun and Abraham, 2021). Because wildfire exposure occurred in different years across schools, we perform robustness analyses to check if our estimated effects of wildfire exposure suffer bias from the negative weights.

Following De Chaisemartin and d'Haultfoeuille (2020), we calculate the weights attached to the regressions with the *twowayfeweights* Stata package. We find that less than 0.3% of the weights are negative and the sum of the negative weights is -0.0001. Meanwhile, in our sample, about 1% - 3% of observations in the sample are ever exposed to wildfires, depending on the definition of "exposure". Therefore, there are a large number of "never-treated" and no "always-treated" units, alleviating the weighting problem. In addition, we follow Lazuka (2023) to estimate equation 1 using subsamples to evaluate

the robustness.[9] Table A.V shows the estimates from the "treated sample", which are similar to those in Table 3. This evidence points to the absence of a negative weighting bias and heterogeneous treatment effects.

4. Mechanisms: The Role of School Closures and Air Pollution

4.1. The Impact of Wildfire-Induced School Closures

This section examines the impact of school closures due to wildfires on test scores. On the one hand, the decision to close schools can protect students from exposure to wildfires, especially when commute routes are directly influenced by wildfires or when wildfire smoke becomes a severe problem. On the other hand, these closures lead to loss of school environment and instructional time, which are important determinants of academic success (Chabrier et al., 2016). Therefore, whether the decision to close schools in response to wildfires adversely affects test scores becomes an empirical question that has important policy implications.

4.1.1. Empirical Strategy

To identify the effect of wildfire-induced school closures, we exclude school–year cells that are either located downwind of wildfires or within 5 km of a fire perimeter. This sample restriction helps isolate the closure channel by excluding schools that are more likely to be directly affected by wildfire smoke or to experience psychological distress or economic disruptions due to proximity to wildfires. This leaves two groups of school-year cells: (1) those that did not suffer from school closures, and (2) those that experienced

[9] Lazuka (2023) compares results when controls include only "treated," "always-treated," or "never-treated". In our setting, there are no "always-treated" units. Therefore, we compare estimates from the full sample, which includes both "never-treated" and "treated" units, with estimates from the subsample consisting only of "treated" units.

preemptive or precautionary school closures but did not encounter severe air pollution, financial losses, or psychological trauma. In other words, this restricted sample allows us to identify the impact of precautionary school closures on test scores.

We estimate the following equation:

$$\begin{aligned} Score_{sgt} =& \alpha + \beta Closure_days_{sgt} + \\ & \gamma X_{sg(t-1)} + \mu_{dg} + \phi_{t-g} + \lambda_t + post14 \cdot \omega_c + \epsilon_{sgt} \end{aligned} \tag{3}$$

where all variables are defined in the same way as in Equation 1, except that $Closure_days_{sgt}$ denotes the number of closure days due to wildfires.

In addition, we employ an instrumental variables approach to address potential endogeneity in school closure decisions. We use three instruments that exploit variation in wildfire proximity and intensity: (i) an indicator for exposure to wildfires within 10 km in the month of school closure, as defined in Section 3; (ii) the proximity-weighted size of the largest matched wildfire occurring in the same month as the school closure and within 10 km of the school; and (iii) the inverse of the distance from the school to the largest matched wildfire.

The validity of the instrumental variables strategy relies on two conditions: (i) the instruments must be sufficiently predictive of school closure days (relevance), and (ii) they must affect student test scores only through their impact on school closures (exclusion restriction). Panel A of Table 5 presents the first-stage estimates, which assess instrument relevance. Exposure to a wildfire within 10 km, the size of the largest matched wildfire, and proximity to the largest matched wildfire all increase the number of wildfire-induced school closure days, and their impacts are all statistically significant. Although the exclusion restriction cannot be tested directly, our sample restrictions mitigate concerns about alternative channels through which wildfire exposure may affect student achievement. In particular, the restricted sample excludes schools located downwind of wildfires and those in close proximity to wildfire perimeters. As a result, it is less likely that wildfire ex-

posure affects test scores through air pollution, psychological trauma, or local economic disruption, supporting the validity of the exclusion restriction.

4.1.2. Results

Panels B and C of Table 5 report the result. Panel B shows the ordinary least squares (OLS) estimates of the relationship between the number of closure days due to wildfires and test scores, suggesting that these closures are negatively associated with both ELA and math test scores. However, the OLS results may be subject to omitted-variable bias due to endogeneity in school closure decisions. Thus, Panel C presents the corresponding IV estimates of the causal effects of school closures due to wildfires on test scores. These estimates indicate that, on average, one closure day due to wildfires decreases math scores by 0.0076 SD and ELA scores by 0.0071 SD.

One potential concern of our empirical strategy is that the number of wildfire school closure days may affect the number of other types of school closures. Schools that experienced wildfire school closures in year t may be less likely to close for other reasons, either to meet the minimum number of required school days or to avoid further student learning loss. We apply two methods to address this issue. First, we estimate the model controlling for the number of closure days caused by other factors, such as violence, heavy rain, snow, impassable roads, and broken/damaged infrastructure. Columns (3) and (4) of Table 5 report the results, which confirm the robustness of our main estimates to the inclusion of other types of school closures. Second, we test the potential impact of school closures from wildfires on other school closures by regressing the total number of other types of school closures on the number of school closure days due to wildfires using the following model:

$$\begin{aligned} Days_Closure_other_{st} =& \alpha_0 + \beta_k Days_Closure_Fire_{st} + \\ & \mu_s + \lambda_t + \epsilon_{st} \end{aligned} \tag{4}$$

Table A.VI reports the results. The impacts of wildfire school closure days on other types of school closure days are statistically insignificant and small in magnitude. Therefore, we do not find evidence that the number of wildfire school closure days in our sample influences other types of school closure days.

In this analysis, we exclude schools located within 5 km of a wildfire perimeter to mitigate channels operating through psychological distress or economic disruption associated with close proximity to fires. To assess the sensitivity of our results to this distance threshold, we further restrict the sample by excluding additional school–year observations with moderate exposure to wildfires. Specifically, we exclude observations located within 6 km, 7 km, and 8 km of a wildfire perimeter. Table A.VII reports the results. All estimates have the expected signs and are similar in magnitude to those reported in Table 5. This suggests that our findings are robust to the choice of sample restriction.

4.2. The Impact of Wildfire Smoke

Another possible channel through which wildfire exposure may affect student learning is wildfire smoke. A substantial literature documents the correlation between air pollution and human capital outcomes. Building on this evidence, we investigate whether wildfire-induced smoke adversely affects learning.

4.2.1. Empirical Strategy

To identify the effect of wildfire smoke, we restrict the sample by excluding school-year cells located within 5 km of wildfire perimeters or those that experienced wildfire-induced school closures. This restriction reduces the likelihood that student outcomes are affected by channels of psychological distress, economic disruption, or school closures

themselves. We estimate the following equation to identify the effect of wildfire smoke:

$$\begin{aligned} Score_{sgt} =& \alpha_0 + \theta Smoke_{st} \\ &+ \gamma X_{sgt} + \mu_{sg} + \phi_{t-g} + \lambda_t + post14 \cdot \omega_c + \epsilon_{sgt} \end{aligned} \tag{5}$$

where all variables are defined in the same way as in Equation 1, except for an additional term $Smoke_{st}$, the measure of wildfire smoke exposure for school s in year t. During a school year, 84% of the wildfires occur between August and March, and CA statewide assessments were mostly administered from late March to May. Therefore, we calculate $Smoke_{st}$ using cumulative smoke from August to March in the school year t. As introduced in Section 2, the wildfire smoke data developed by Childs et al. (2022) directly measure smoke transmitted from wildfires. The availability of this measure facilitates the identification of the impacts on test scores that are attributable to air pollution caused by wildfires. θ is the coefficient of interest that shows the impact of smoke exposure on test scores.

To address potential endogeneity arising from families' self-selection into areas with differing levels of air pollution, we implement an instrumental variables strategy. Specifically, we use two instruments: (i) an indicator for whether a school is located downwind of a wildfire during the August–March period, and (ii) the size of the largest wildfire in the upwind area. These instruments exploit variation in smoke exposure driven by wind patterns and wildfire intensity.[10] The validity of the instrumental variables strategy relies on two assumptions: relevance and the exclusion restriction. Relevance requires that the instruments be strongly predictive of wildfire smoke exposure. Panel A of Table 6 reports the first-stage results, which provide evidence in support of this assumption. Both being located downwind of wildfires and the size of the largest wildfire in the upwind area are positively associated with smoke exposure.

[10]We construct a downwind area from the fire's location that spans ±30 degrees (60 degrees in total) centered along the downwind direction.

The validity of the exclusion restriction is supported by several considerations. First, whether a school is located downwind of a wildfire is plausibly exogenous: the timing and location of wildfires are largely unpredictable, and prevailing wind directions vary substantially over time. Second, our sample restrictions substantially limit alternative channels through which wildfire characteristics could directly affect test scores. In particular, schools in the restricted sample do not experience wildfire-induced school closures and are not in close proximity to fire perimeters. Under these restrictions, it is reasonable to assume that being located downwind of a wildfire and variation in wildfire size affect test scores only through wildfire smoke exposure.

4.2.2. Results

Table 6 reports the results. Panel B shows the ordinary least squares (OLS) estimates of the relationship between smoke exposure and test scores, suggesting air pollution from wildfires is negatively associated with both ELA and math test scores. These estimates suggest that, on average, a 1-$\mu g/m^3$ increase in cumulated smoke is associated with a 0.004% of a SD decrease in both math and ELA scores. These magnitudes are highly consistent with Wen and Burke (2022), in which the authors find that each $\mu g/m^3$ increase in wildfire smoke exposure is associated with a 0.0043% of a SD decrease in both math and ELA scores using 2009-16 academic years of nearly 11,700 school districts across the U.S.

However, the OLS results may be subject to the omitted variable bias issue. Thus, Panel C presents the corresponding IV estimates of the causal effects of smoke exposure on test scores. The IV estimates show that the effect of wildfire smoke on math test scores is larger than that from OLS regressions. On average, a 1-$\mu g/m^3$ increase in smoke exposure results in a 0.051% of a SD decrease in math scores and a 0.006% of a SD decrease in ELA scores. The median cumulative smoke exposure at the school-year level is 40.67 $\mu g/m^3$. This translates to a 0.027 SD decrease in math test scores and a 0.003 SD decrease

in ELA test scores.

We further assess the robustness of our IV results to the definition of the "downwind area". Specifically, instead of defining the downwind sector as spanning ± 30 degrees around the prevailing wind direction, we construct alternative measures using wider sectors of ± 35 and ± 40 degrees. Results are shown in Table A.VIII. The results are highly consistent with those in Table 6, suggesting that our findings are robust to alternative definitions of "downwind area".

4.3. Discussion

This section discusses the magnitude of our estimated effects of wildfire exposure, school closures, and wildfire smoke, and situates them within the existing literature and their policy implications. While relatively few studies examine the overall impact of wildfires on student achievement, our estimates can be compared to evidence from the broader literature on natural disasters. We also benchmark the magnitudes of the two mechanisms we study against related strands of research. In particular, studies on student absenteeism and instructional time are relevant for interpreting the effects of school closures, while research on air pollution and test scores provides a useful comparison for the effects of wildfire smoke.

Literature on the effects of natural disasters. Deuchert and Felfe (2015) find that Philippine children who suffered from housing damages in typhoon Mike lagged on average 0.13 years behind in school. Sacerdote (2012) analyzes the impact of Hurricane Katrina and Rita in Orleans and finds an initial decline of 0.10 standard deviations in test scores immediately following the hurricane. Our estimated effects of wildfire exposure are smaller in magnitude than these studies. This likely reflects the fact that exposure to wildfires is generally less severe than extreme events such as typhoons or hurricanes, and that these two studies focus on more disadvantaged students.

Literature on the effects of instructional time. A large body of literature has docu-

mented the positive correlation between instructional time and test scores. Using PISA 2006 data, Lavy (2015) finds that an additional hour of weekly instruction in math, science, or language increases test scores in the corresponding subject by 0.15 of a standard deviation. Assuming a 40-week academic year and five hours of instruction per day, this corresponds to an increase of approximately 0.02 standard deviations per additional instructional day. Using U.S. data, Hansen (2011) finds that one additional instructional day raises student achievement by roughly 0.01–0.04 standard deviations. However, Aucejo and Romano (2016) finds a much smaller impact: one additional instructional day raises math scores by 0.17% and reading scores by 0.08% of a standard deviation. These estimates are closer to Betthäuser et al. (2023)'s argument that students generally improve their performance by around 0.4 standard deviations per school year.

In contrast, the literature generally finds larger per-day effects of student absenteeism. For studies in the U.S., Goodman (2014) finds that each additional day of absence induced by bad weather reduces math achievement by 0.05 standard deviations, and Aucejo and Romano (2016) find a similar impact of 0.055 SD on math and 0.029 SD on reading. Swiderski et al. (2025) find that during the pandemic, each additional day of absence is associated with a 0.0057 standard deviation decline in math test scores.

Our results indicate that each additional day of wildfire school closure reduces math scores by 0.0075 standard deviations and ELA scores by 0.0071 standard deviations. The magnitudes of our estimates are larger than the effect of losing one instructional day but smaller than the effect of student absenteeism. This pattern is consistent with the notion that school closures disrupt students' study routines and planned instruction, making them more disruptive than a marginal reduction in instructional time by a single day. At the same time, because closures affect all students simultaneously, they do not generate within-class disparities in missed instruction and are therefore less disruptive than individual absenteeism. This interpretation is consistent with the congestion model of classroom learning presented in Lazear (2001). As mentioned in Goodman (2014), schools

tend to adapt more effectively to coordinated disruptions, such as snow days, than to uncoordinated disruptions like student absences that occur at different times.

Literature on the effects of air pollution. Studies have consistently found a negative correlation between air pollution and test scores, and the impact of a 1-$\mu g/m^3$ increase in PM 2.5 (or PM 10) on test scores ranges from 0 .1% to 3% of a SD. Ebenstein et al. (2016), for example, finds that in Israel, an increase of 1 $\mu g/m^3$ in air pollution on the test date decreases test scores by about 0.6% SD; and Gilraine (2020) finds that air filters can improve math and ELA scores by 3% of a SD (per 1 $\mu g/m^3$ decrease in pollution) using data from Los Angeles Unified School District. Using data from China, Zhang et al. (2018) finds that an increase in the 7-day mean Air Pollution Index by 1 SD lowers verbal test scores by 0.026 SD, while a 1 SD increase in average Air Pollution Index over 3 years is associated with a 0.108 SD drop in verbal test scores. This translates into a 0.12% SD decrease in test score per 1 $\mu g/m^3$ transitory pollution exposure, and a 0.8% SD decrease per 1 $\mu g/m^3$ cumulative average pollution exposure.

As noted above, one of the most closely related studies is Wen and Burke (2022). Their estimated correlation between wildfire smoke exposure and test scores is similar to our OLS results (0.004%), which is substantially smaller than the above-mentioned studies. However, our IV estimate suggests that the impact of wildfire smoke can be underestimated due to omitted variable bias. Our IV estimate shows that a 1 $\mu g/m^3$ increase in cumulative smoke leads to 0.051% SD decrease in math scores and 0.006% SD decrease in ELA scores. These magnitudes are largely in line with the existing literature.

We also decompose the overall effects of wildfire exposure into their underlying mechanisms. In Section 3, we find that exposure to wildfires decreases math scores by 0.025-0.030 SD and ELA scores by 0.018-0.023 SD. The effects of wildfire exposure may operate through several channels, among which school closures and wildfire smoke are likely key mechanisms driving the observed learning losses. Our results show that each additional day of wildfire-induced school closure decreases math scores by 0.0075 SD and

ELA scores by 0.0071 SD. On average, school-grades exposed to wildfires experience 0.525 more closure days than unexposed schools.[11] This translates into a reduction of 0.004 SD in both math and ELA scores. In addition, we find that a 1-$\mu g/m^3$ increase in smoke exposure results in a 0.051% SD decrease in math scores and a 0.006% SD decrease in ELA scores. School-grades exposed to wildfires experience, on average, 18.15 $\mu g/m^3$ more smoke exposure than unexposed schools.[12] This translates into a 0.009 SD decrease in math scores and a 0.001 SD decrease in ELA scores. Therefore, school closures account for about 14.5% of the learning loss in math and 19.5% of the learning loss in ELA. Wildfire smoke exposure may account for another 32.7% of the learning loss in math and 4.9% of the learning loss in ELA.

Our results have implications for policies aimed at mitigating the educational impacts of wildfires. We find that both school closures and wildfire smoke exposure can lead to learning losses, suggesting that interventions to improve indoor air quality in schools, as well as programs that compensate for lost instructional time, are important. While our mechanism estimates are derived from subsamples and therefore do not provide an exact decomposition of the total effect, they offer informative insights into the relative importance of these channels. Our findings also inform policy decisions regarding school closures during wildfire events. In particular, the decision to close schools involves a trade-off between reducing students' exposure to wildfire smoke and the loss of instructional time. Quantifying the magnitude of these two channels provides policymakers with a useful benchmark for evaluating the costs and benefits of school closures under different wildfire conditions.

[11] The average number of wildfire school closure days is 0.577 for the exposure sample and 0.052 for the non-exposure sample.

[12] The median level of smoke exposure is 59.29 for the exposed sample and 41.14 for the non-exposed sample. We use the median rather than the average value because the distribution of smoke exposure is highly right-skewed.

5. Conclusion

Wildfires have attracted increasing attention from the media, researchers, and policymakers. Given their growing frequency, size, and severity in recent decades and the large number of schools and students affected, it is increasingly important to understand how unexpected wildfire exposure influences student learning, particularly among disadvantaged students. Using administrative data from multiple sources in California, this paper investigates the causal effects of wildfire exposure on student achievement and examines the mechanisms through which these effects operate.

We find that exposure to wildfires significantly reduces student achievement. Specifically, wildfire exposure lowers Math scores by 0.025–0.030 standard deviations and ELA scores by 0.018–0.023 standard deviations. These learning losses are substantially larger for students in low–socioeconomic status schools than for those in high-SES schools.

We next examine two key mechanisms underlying these effects: school closures and air pollution. We find that each additional day of wildfire-induced school closure reduces math scores by 0.0076 standard deviations and ELA scores by 0.0071 standard deviations. These results imply that wildfire-induced school closures account for about 14.5% of the learning loss in math and 19.5% of the learning loss in ELA. Therefore, school closures are an important channel through which wildfires harm student learning, with direct implications for policies aimed at mitigating learning loss during unexpected school disruptions.

Wildfire-related air pollution also contributes meaningfully to learning losses. A one microgram per cubic meter ($\mu g/m^3$) increase in cumulative $PM_{2.5}$ concentration from wildfire smoke reduces Math scores by 0.051% of a standard deviation and ELA scores by 0.006% of a standard deviation. This suggests that wildfire smoke accounts for another 32.7% of the learning loss in math and 4.9% of the learning loss in ELA. Therefore, wildfires adversely affect student achievement not only through school closures but also through degraded air quality, highlighting the potential benefits of interventions that im-

prove indoor air quality during wildfire seasons. These findings complement existing evidence on the importance of air quality in educational settings (Gilraine, 2020).

These findings highlight the need for policymakers to develop and implement strategies to mitigate learning loss in the aftermath of disasters and to ameliorate the resulting increases in inequality. The findings complement existing policy efforts, including the climate action plan released by the U.S. Department of Education in 2021, which focused on preparing the country to confront the rapidly changing climate and its impacts, as well as the work of Park et al. (2020), which suggested that extreme weather disproportionately affects students of color, leading to increases in inequality in the United States. Thus, the current findings can inform the design of remediation policies. By identifying the effects of wildfires, the mechanisms underlying these effects, and their distributional consequences, this study has implications for the development of more targeted and effective interventions.

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TABLE 1
Summary Statistics

	Mean	SD	Min	Max
Panel A: Test Scores				
Math score	0.09	1.03	-4.85	4.56
ELA score	0.09	1.03	-4.85	6.04
Panel B: Demographics				
Free/reduced-price lunch	0.59	0.29	0	1
Female	0.49	0.59	0	1
Asian	0.08	0.14	0	1
Black	0.06	0.08	0	1
Hispanic	0.53	0.29	0	1
White	0.26	0.24	0	1
Panel C: Wildfire Exposure				
% Exposed to wildfires $\leq$ 1 km	0.34			
% Exposed to wildfires $\leq$ 2 km	0.80			
% Exposed to wildfires $\leq$ 3 km	1.35			
% Exposed to wildfires $\leq$ 4 km	2.11			
% Exposed to wildfires $\leq$ 5 km	3.05			
% Exposed to wildfires $\leq$ 10 km	9.27			
Panel D: Closures and Air Pollution				
Wildfire closure days	0.09	0.68	0	17
Wildfire smoke	116.61	257.07	0	3033.24
Obs. (school–grade–year in Math)		216,522		
Obs. (school–grade–year in ELA)		226,308		

Notes: This table presents summary statistics for test scores, student demographics, and wildfire-related characteristics in the full analysis sample. Columns (1)–(4) report the mean, standard deviation, minimum, and maximum, respectively. Panel A reports standardized test scores; details on the construction of these measures are provided in Section 2. Panel B reports student demographic characteristics, including the fraction eligible for free or reduced-price lunch and the racial composition of students. Panel C reports the percentage of school–grade–year observations located within 1, 2, 3, 4, 5, and 10 km of a wildfire perimeter. Panel D reports wildfire-related school closure days and cumulative wildfire-induced $PM_{2.5}$ exposure during the academic year.

TABLE 2
Comparison of Exposure and Non-Exposure Samples

	(1) Non-Exposure Sample	(2) Exposure Sample	(3) Difference (2) − (1)
Panel A: Test Scores			
Math score	0.079	0.141	0.062^{***}
ELA score	0.081	0.177	0.097^{***}
Panel B: Demographics			
Free/Reduced price lunch	0.593	0.548	-0.046^{***}
Asian	0.089	0.074	-0.014^{***}
Black	0.059	0.048	-0.012^{***}
Hispanic	0.529	0.498	-0.031^{***}
White	0.251	0.306	0.055^{***}
Panel C: Closures & Air Pollution			
Closure days	0.049	0.471	0.422^{***}
Wildfire Smoke ($\mu g/m^3$)	113.25	145.92	32.67^{***}
Obs. (School-grade-year in Math)	195,137	21,385	
Obs. (School-grade-year in ELA)	204,080	22,228	

Notes: Column (1) reports means for the non-exposure sample and column (2) reports means for the exposure sample, defined as school-grade-year cells that are within 10 km of the edge of the wildfires. Column (3) reports the difference between the exposure and non-exposure samples. Means are weighted by school-grade enrollment. Math scores and variables in Panel B use the Math estimation sample, while ELA scores use the ELA estimation sample. Test scores in Panel A are standardized. Values in Panel B represent proportions. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 3
Exposure to Wildfires and Test Scores

	Panel A: Math Scores					
	(1)	(2)	(3)	(4)	(5)	(6)
	$< 1km$	$< 2km$	$< 3km$	$< 4km$	$< 5km$	$< 10km$
Exposure	-0.028	-0.028*	-0.030***	-0.029***	-0.025***	-0.015***
	(0.020)	(0.016)	(0.011)	(0.009)	(0.007)	(0.004)
Observations	216,522	216,522	216,522	216,522	216,522	216,522
	Panel B: ELA Scores					
	(1)	(2)	(3)	(4)	(5)	
	$< 1km$	$< 2km$	$< 3km$	$< 4km$	$< 5km$	$< 10km$
Exposure	0.003	-0.017	-0.023**	-0.020**	-0.018***	-0.013***
	(0.018)	(0.014)	(0.010)	(0.008)	(0.006)	(0.004)
Observations	226,308	226,308	226,308	226,308	226,308	226,308

Notes: This table reports the effect of exposure to wildfires on test scores. All regressions include cohort fixed effects, year fixed effects, school-x-grade fixed effects, controls for lagged school level student race and gender composition, the percentage of students eligible for free/reduced price lunch, and post-2014 dummies for each county. Estimates are weighted by school-year-grade enrollments. Robust standard errors clustered at the school level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 4
Impact of Exposure by
Proportion of Free/Reduced-price Lunch (FRPL) Students

		$< 3km$		$< 4km$		$< 5km$	
		(1) Math	(2) ELA	(3) Math	(4) ELA	(5) Math	(6) ELA
Exposure	* High FRPL	-0.069***	-0.030**	-0.076***	-0.039**	-0.091***	-0.050**
		(0.013)	(0.014)	(0.017)	(0.016)	(0.021)	(0.021)
	* Medium FRPL	-0.016	-0.018	-0.025	-0.020	-0.043**	-0.036**
		(0.013)	(0.013)	(0.016)	(0.015)	(0.020)	(0.018)
	* Low FRPL	-0.009	-0.013	-0.009	-0.011	0.005	-0.002
		(0.011)	(0.009)	(0.014)	(0.011)	(0.016)	(0.013)
Observations		216,522	226,308	216,522	226,308	216,522	226,308

Notes: This table reports the effect of wildfire exposure on student achievement by the proportion of students eligible for free/reduced-price lunch at districts/schools. All regressions include cohort fixed effects, year fixed effects, school-x-grade fixed effects, controls for lagged school level student race and gender composition, and post-2014 dummies for each county. Estimates are weighted by school-year-grade enrollments. Robust standard errors clustered at the school level are reported in parentheses.

TABLE 5
Impact of Wildfire School Closures on Test Scores

	(1) Math	(2) ELA	(3) Math	(4) ELA
Panel A: First Stage (Dept. Var.: *closuredays*)				
$Exposure(<10km)$	0.092***	0.082***	0.096***	0.086***
	(0.004)	(0.004)	(0.004)	(0.004)
Largest FireSize	0.136***	0.126***	0.130***	0.119***
	(0.002)	(0.002)	(0.002)	(0.002)
InvDistFire	26.452***	26.397***	27.525***	27.465***
	(1.474)	(1.418)	(1.451)	(1.398)
p-value on joint F test	0.000	0.000	0.000	0.000
Observations	209,275	218,813	209,275	218,813
Panel B: OLS				
Closure days	-0.0117***	-0.0074***	-0.0126***	-0.0072***
	(0.0019)	(0.0017)	(0.0020)	(0.0017)
Observations	209,275	218,813	209,275	218,813
Panel C: IV Estimates				
Closure days	-0.0076**	-0.0071**	-0.0084**	-0.0080***
	(0.0032)	(0.0029)	(0.0034)	(0.0030)
Controls for Other Closures	NO	NO	YES	YES
Cragg-Donald Wald F-statistic	31690.348	33194.225	31911.810	33423.984
Observations	209,275	218,813	209,275	218,813

Notes: This table reports first-stage, OLS, and IV estimates of the effect of school closures caused by wildfires on student achievement. *InvDistFire* is defined as $\frac{1}{DistFire+1}$, where *DistFire* is the distance to the nearest wildfire. All regressions control for cohort fixed effects, year fixed effects, school-x-grade fixed effects, lagged school level race and gender composition, lagged percentage of students eligible for free/reduced price lunch, and dummies for post-2014 for each county. Columns (3) and (4) control for closure days due to reasons other than wildfires. Estimates are weighted by school-year-grade enrollments. Robust standard errors clustered at school level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1

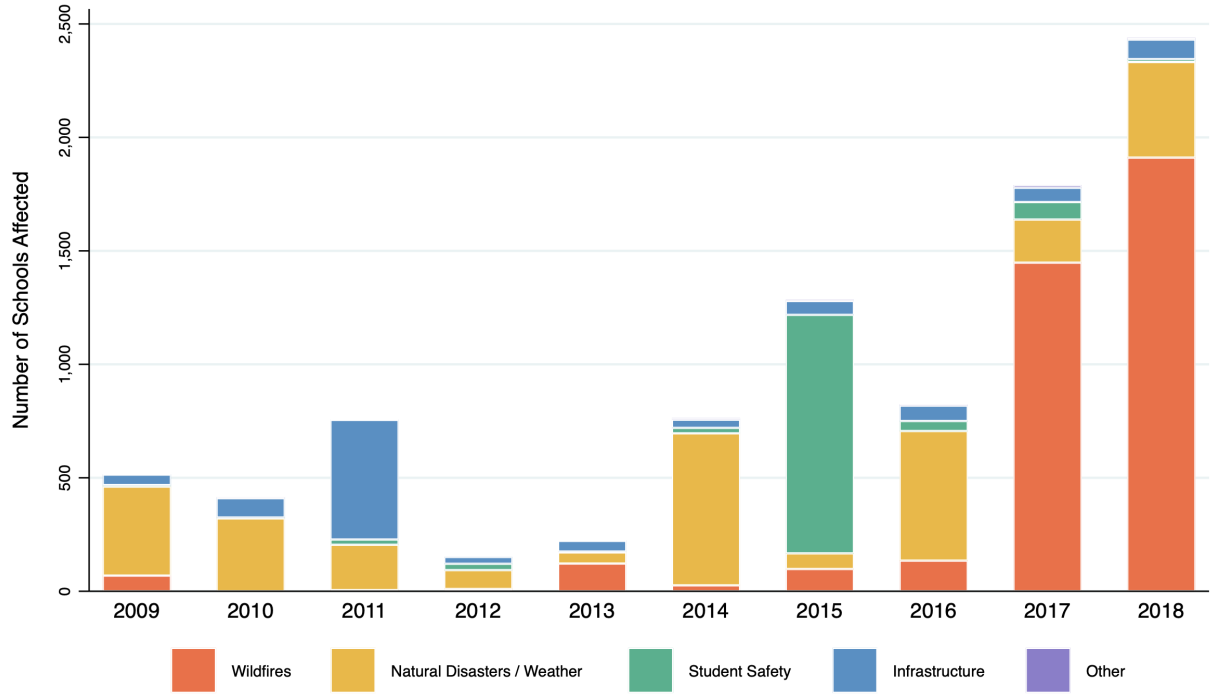
TABLE 6
Impact of Air Pollution Caused by Wildfires on Test Scores

	(1) Math	(2) ELA
Panel A: First Stage (Dept. Var.: *Cumulated smoke*)		
Downwind	0.02650	0.21578
	(1.3956)	(1.3158)
Largest Firesize	0.00347***	0.00331***
$*$*Downwind*	(0.00035)	(0.00032)
p-value on joint F test	0.000	0.000
Observations	201,429	210,898
Panel B: OLS		
Cumulated smoke	-0.00004***	-0.00004***
	(0.00001)	(0.00001)
Observations	201,429	210,898
Panel C: IV Estimates		
Cumulated smoke	-0.00051**	-0.00006
	(0.00023)	(0.00019)
Cragg-Donald Wald F-statistic	96.71640	108.06233
Observations	201,429	210,898

Notes: This table reports first-stage, OLS, and IV estimates of the effect of smoke exposure on student achievement. All regressions include cohort fixed effects, year fixed effects, school-x-grade fixed effects, controls for lagged school level student race and gender composition, the percentage of students eligible for free/reduced price lunch, and post-2014 dummies for each county. Estimates are weighted by school-year-grade enrollments. Robust standard errors clustered at the school level are reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

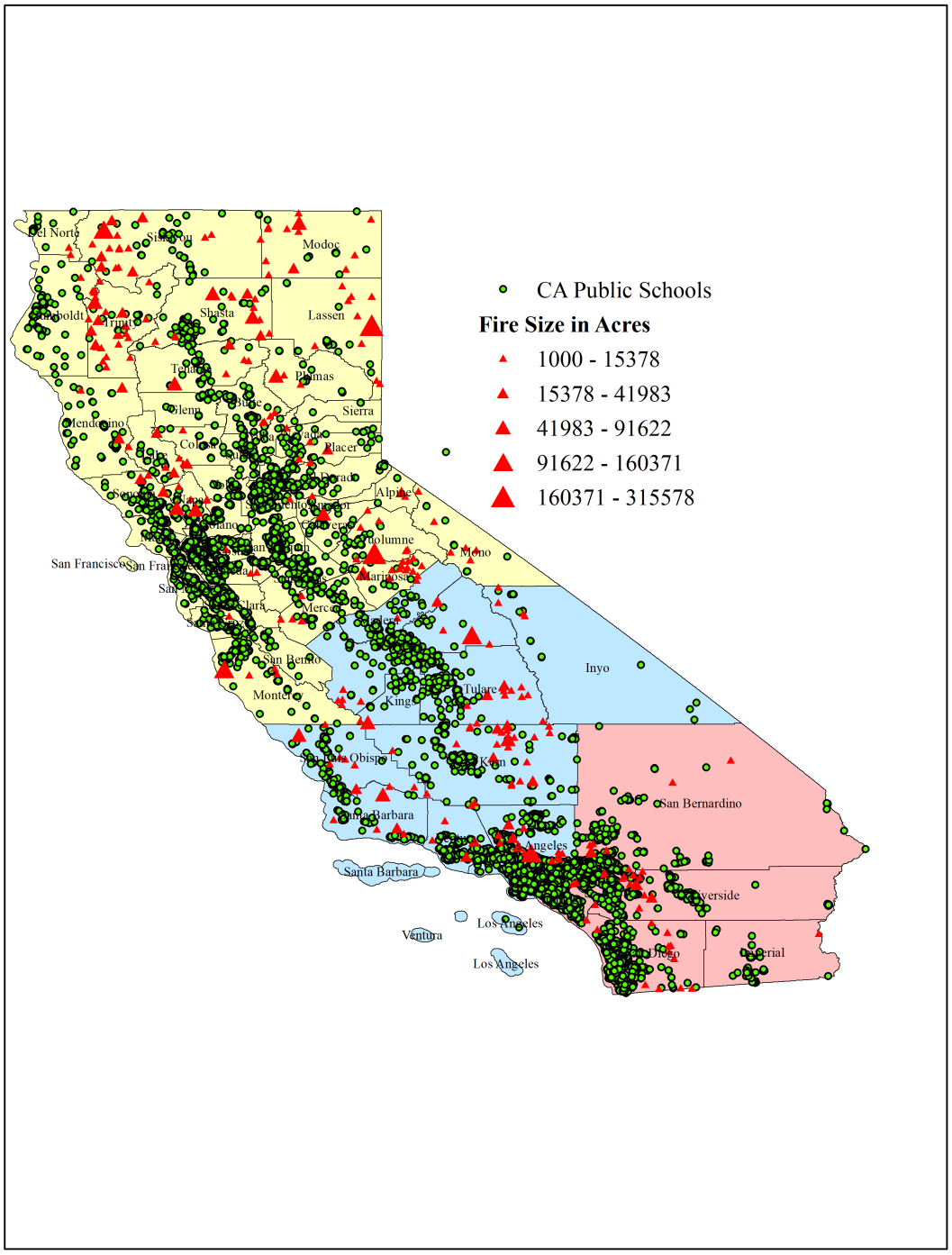
Figures

FIGURE 1
Number of schools impacted by school closures due to listed causes in California



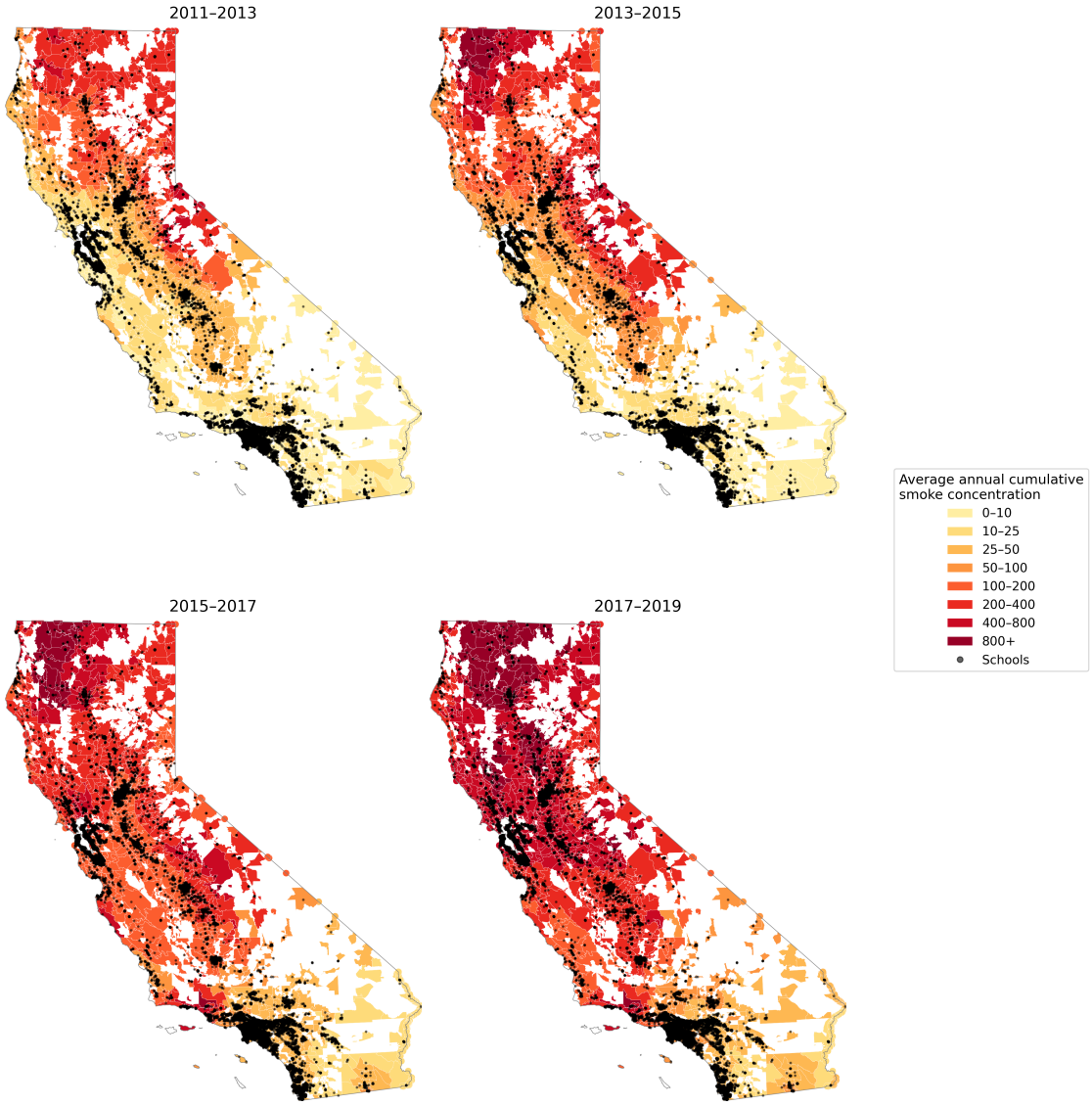
Notes: This figure shows the number of schools affected by wildfires, natural disasters & weather, student safety reasons, infrastructure, and other reasons between 2009 and 2018.

FIGURE 2
Location of Schools and Wildfires



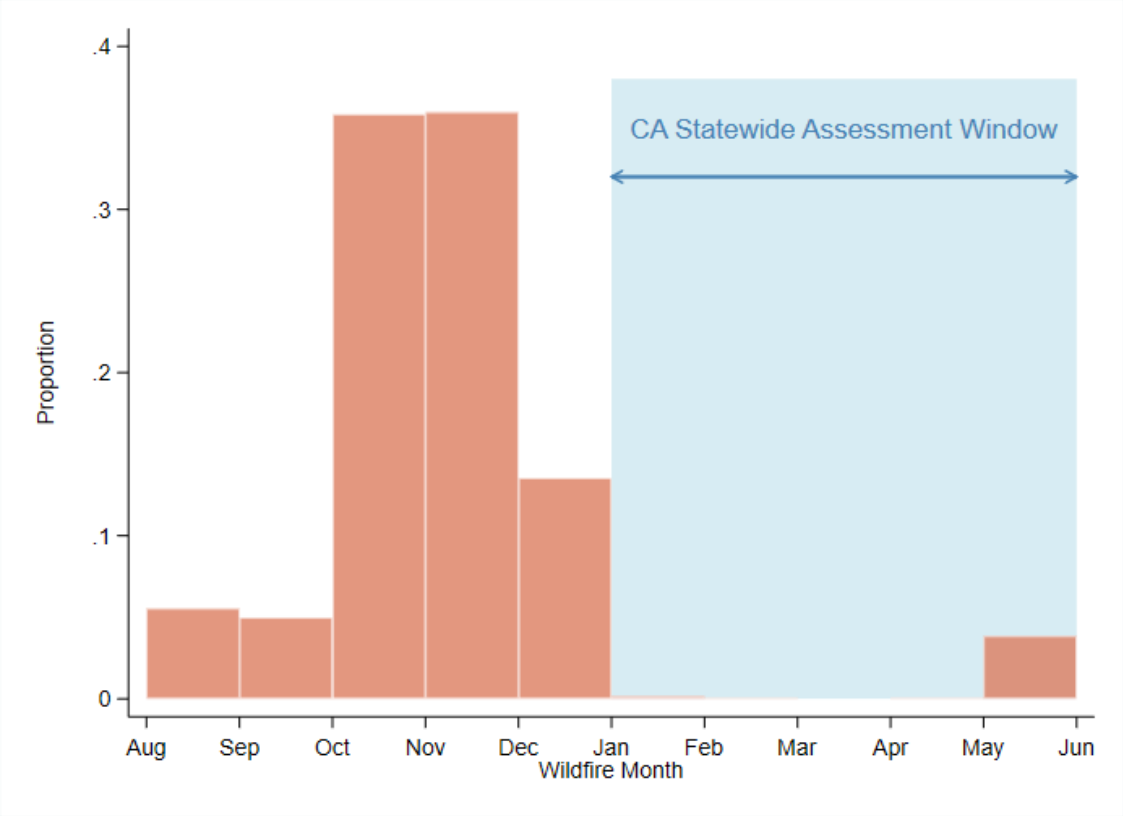
Notes: This figure shows the location of wildfires that burnt at least 1,000 acres between 2009 and 2017 in California.

FIGURE 3
Average smoke exposure across California, 2011-2019



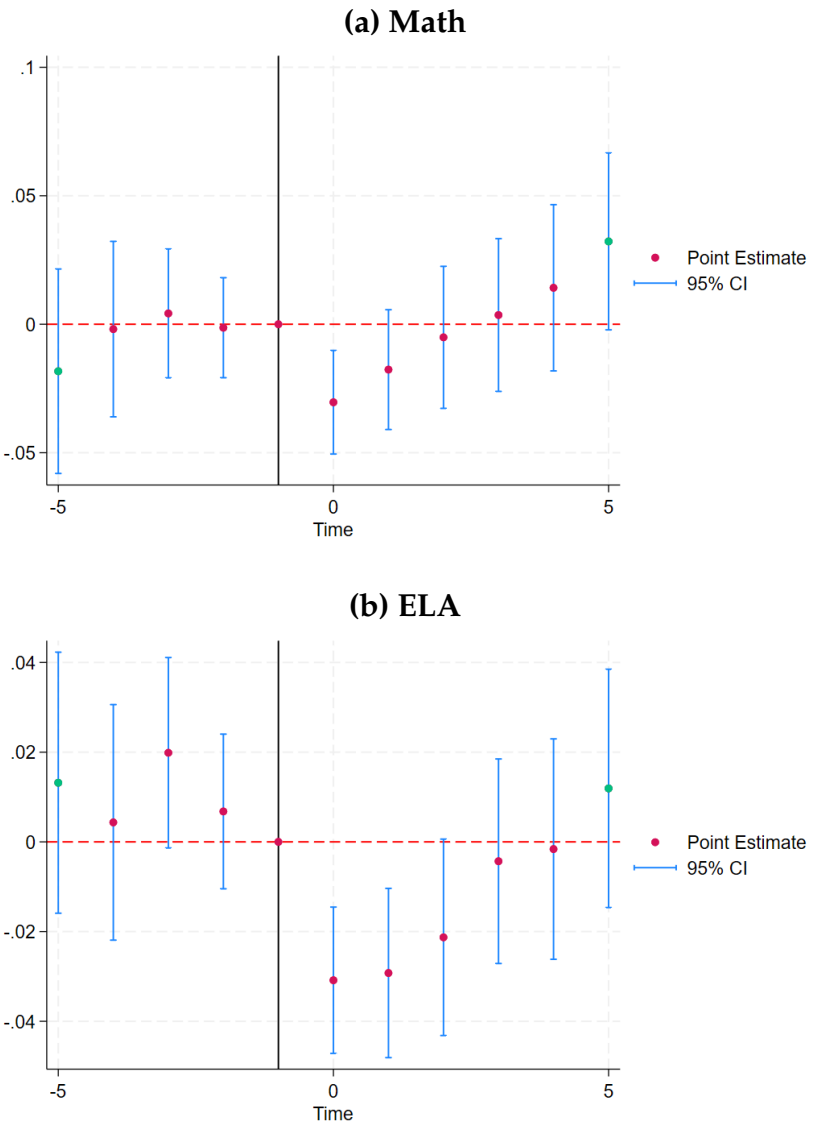
Notes: This figure shows the district level smoke exposure concentrations averaged across the period 2011 to 2013, 2013 to 2015, 2015 to 2017, and 2017 to 2019.

FIGURE 4
Timing of Wildfire School Closures and CA Academic Assessment



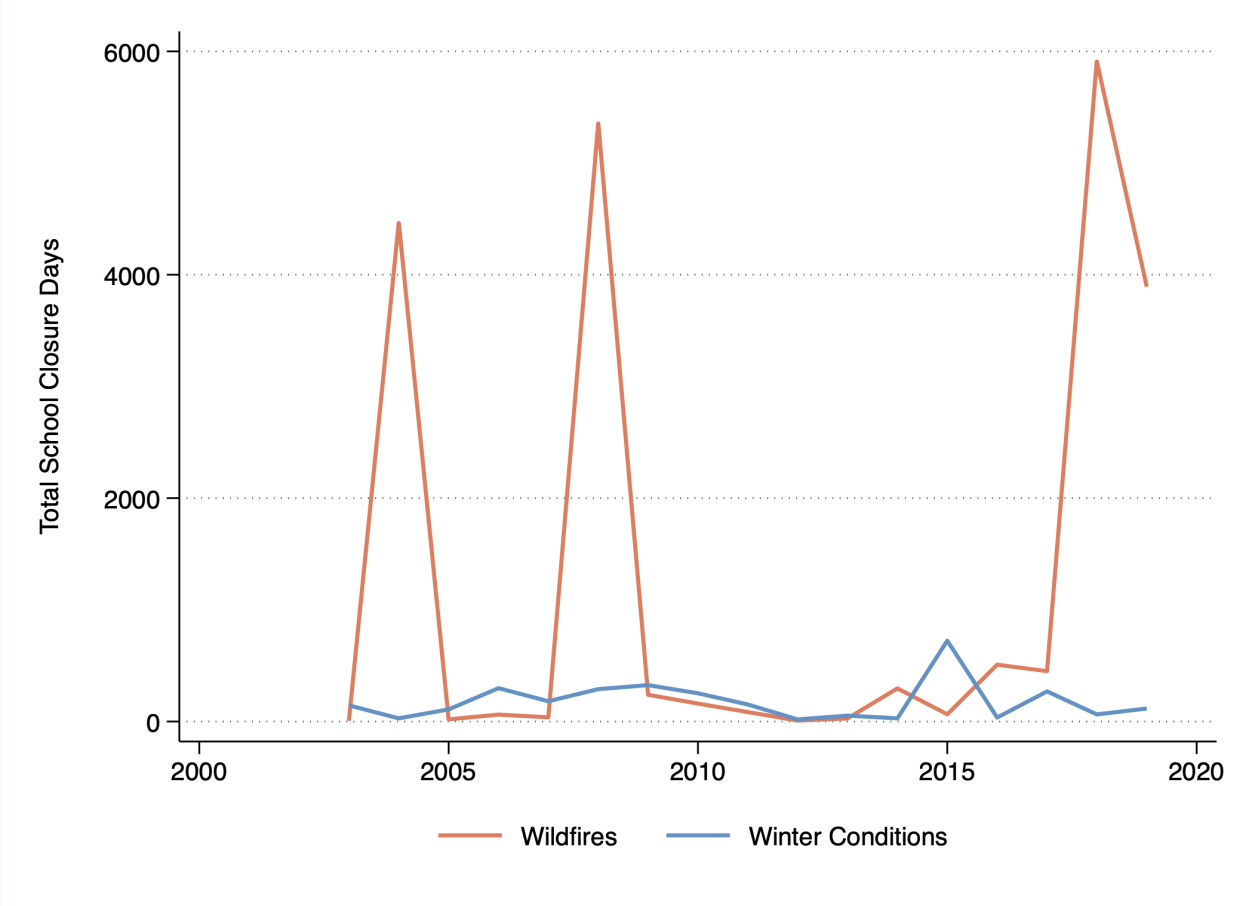
Notes: This figure shows the timing of wildfire school closures and state academic assessments in California.

FIGURE 5
Effects of Wildfire Exposure on Math and ELA Scores



Notes: This figure shows estimates of Equation 2. It presents coefficients from the event-study specification estimating the dynamic effects of wildfire exposure on test scores, relative to the timing of initial exposure. Estimates are shown relative to the omitted baseline period (the year prior to exposure). Vertical bars denote the point estimates and 95% confidence intervals.

FIGURE 6
Total School Closure Days Caused by Wildfires and Winter Conditions in California



Notes: This figure shows the number of school closure days caused by wildfires and winter conditions between 2009 and 2018 in California.

A. Supplementary Tables

TABLE A.I
Decomposition of Wildfire Instrument Variation

Instrument	Overall SD	Between SD	Within SD	Between (%)	Within (%)
Any wildfire exposure	0.0438	0.0139	0.0415	10.16	89.84
Largest fire size / distance	0.5250	0.1752	0.4949	11.13	88.87
Distance to closest wildfire	7.837	2.499	7.428	10.17	89.83
Largest fire size in downwind area	1180.80	408.57	1107.86	11.97	88.03

Notes: This table decomposes variation in the instruments into between- and within-school–grade components. Overall SD reports the weighted standard deviation of each instrument. Between SD captures variation in school–grade-specific mean instrument values across school–grade units, while Within SD captures variation over time within the same school–grade unit. Between (%) and Within (%) report the corresponding shares of total variance and therefore sum to 100 percent. The sample is restricted to school–grade–year observations for math from 2009 to 2019, consistent with the IV estimation sample, and observations are weighted by grade-level enrollment.

TABLE A.II
Wildfire Exposure and Enrollment

	(1) ELA	(2) Math
Exposure	-0.424	-0.457
	(1.129)	(1.130)
Mean Dept. Var.	110.239	104.946
Observations	269,983	271,063

Notes: This table reports the impact of wildfire exposure on school-grade-year level enrollment. Both regressions include cohort fixed effects, year fixed effects, school-x-grade fixed effects, and post-2014 dummies for each county. Robust standard errors clustered at the school level are reported in parentheses.

TABLE A.III
Fire Exposure and Racial Composition (in percentage points)

	Asian		Black		Hispanic		White		Other	
	(1) ELA	(2) Math	(3) ELA	(4) Math	(5) ELA	(6) Math	(7) ELA	(8) Math	(9) ELA	(10) Math
Exposure	-0.037	-0.037	0.026	0.021	0.082**	0.083**	-0.023	-0.022	-0.000	-0.000
	(0.050)	(0.049)	(0.098)	(0.098)	(0.034)	(0.034)	(0.096)	(0.096)	(0.001)	(0.001)
Mean Dept. Var.	0.077	0.077	0.059	0.059	0.507	0.510	0.282	0.279	0.075	0.075
Observations	269,983	271,063	269,983	271,063	269,983	271,063	269,983	271,063	269,983	271,063

Notes: This table reports the impact of wildfire exposure on school-grade-year level student racial composition. The outcome variables are the school-year-subject level percentages of students by race. All regressions control for cohort fixed effects, year fixed effects, school-x-grade fixed effects, and dummies for post-2014 for each county. Robust standard errors clustered at school level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE A.IV
Exposure to Wildfires in June/July and Test Scores: Robustness Check

	Math Scores					
	(1)	(2)	(3)	(4)	(5)	(6)
	$< 1km$	$< 2km$	$< 3km$	$< 4km$	$< 5km$	$< 10km$
Exposure	0.034	-0.001	0.007	-0.012	0.010	0.007
	(0.040)	(0.030)	(0.019)	(0.016)	(0.013)	(0.007)
Observations	99,376	99,376	99,376	99,376	99,376	99,376
	ELA Scores					
	(1)	(2)	(3)	(4)	(5)	
	$< 1km$	$< 2km$	$< 3km$	$< 4km$	$< 5km$	$< 10km$
Exposure	0.073**	0.028	0.018	0.007	0.005	-0.005
	(0.036)	(0.025)	(0.017)	(0.014)	(0.012)	(0.007)
Observations	103,333	103,333	103,333	103,333	103,333	103,333

Notes: This table reports the effect of wildfire exposures in June and July on student achievement by different criteria for severe wildfires. All regressions include cohort fixed effects, year fixed effects, school-x-grade fixed effects, controls for lagged school level student race and gender composition, the percentage of students eligible for free/reduced price lunch, closure days due to reasons other than wildfires, and post-2014 dummies for each county. Estimates are weighted by school-year-grade enrollments. Robust standard errors clustered at the school level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE A.V
Exposure to Wildfires and Test Scores: Treated Only

	Math Scores					
	(1) $< 1km$	(2) $< 2km$	(3) $< 3km$	(4) $< 4km$	(5) $< 5km$	(6) $< 10km$
Exposure	-.039*	-.031*	-.028***	-.026***	-.022***	-.014***
	(.020)	(.016)	(.011)	(.009)	(.007)	(.004)
Observations	7,584	16,647	26,517	38,813	50,521	104,129
R-squared	.885	.884	.881	.873	.871	.879
	ELA Scores					
	(1) $< 1km$	(2) $< 2km$	(3) $< 3km$	(4) $< 4km$	(5) $< 5km$	$< 10km$
Exposure	.004	-.011	-.018*	-.016**	-.013**	-.011***
	(.018)	(.014)	(.010)	(.008)	(.006)	(.004)
Observations	7,896	17,415	27,784	40,584	52,797	108,837
R-squared	.906	.912	.909	.903	.900	.906

Notes: This table reports the effect of exposure to wildfires on test scores using a restricted sample. Never-treated samples are excluded, and there is no always-treated sample. All regressions include cohort fixed effects, year fixed effects, school-x-grade fixed effects, school level student race and gender composition, the percentage of students eligible for free/reduced price lunch, and post-2014 dummies for each county. Estimates are weighted by school-year-grade enrollments. Robust standard errors clustered at school level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE A.VI
Impact of Wildfire School Closures on Other Closures

	(1) Schools with ELA Scores	(2) Schools with Math Score
Wildfire Closure days	0.004	0.003
	(0.003)	(0.003)
Mean Dept. Var.	0.06	0.06
Observations	68,950	65,780

Notes: This table reports the impact of wildfire school closures on other types of school closures. Both regressions include year fixed effects and school-district effects. Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE A.VII
Robustness Check: Impact of Wildfire School Closures on Test Scores

	(1) Math	(2) ELA	(3) Math	(4) ELA	(5) Math	(6) ELA
Panel A: First Stage (Dept. Var.: *closuredays*)						
$Exposure(<10km)$	0.080***	0.071***	0.081***	0.072***	0.086***	0.075***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Largest FireSize	0.109***	0.093***	0.082***	0.062***	0.080***	0.052***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
InvDistFire	30.417***	30.786***	33.858***	34.238***	37.710***	38.202***
	(1.496)	(1.445)	(1.595)	(1.538)	(1.725)	(1.661)
p-value on joint F test	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: OLS						
Closure days	-0.0143***	-0.0091***	-0.0157***	-0.0096***	-0.0187***	-0.0132***
	(0.0021)	(0.0019)	(0.0022)	(0.0020)	(0.0024)	(0.0021)
Panel C: IV Estimates						
Closure days	-0.0075**	-0.0084***	-0.0044	-0.0048	-0.0100**	-0.0096***
	(0.0035)	(0.0031)	(0.0039)	(0.0034)	(0.0041)	(0.0036)
Cragg-Donald Wald F-statistic	328.009	346.426	302.379	319.979	309.270	326.864
Excluding obs. exposed to wildfires within	6km		7km		8km	
Observations	206,888	216,331	204,112	213,448	201,246	210,476

Notes: This table reports first-stage, OLS, and IV estimates of the effect of school closures caused by wildfires on student achievement. *InvDistFire* is defined as $\frac{1}{DistFire+1}$, where *DistFire* is the distance to the nearest wildfire. All regressions include cohort fixed effects, year fixed effects, school-x-grade fixed effects, controls for lagged school level student race and gender composition, and dummies for post-2014 for each county. Estimates are weighted by school-year-grade enrollments. Robust standard errors clustered at the school level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE A.VIII
Robustness Check: Impact of Air Pollution Caused by Wildfires on Test Scores

	(1) Math	(2) ELA	(3) Math	(4) ELA
Panel A: First Stage				
Downwind	1.72154	1.88191	0.97583	1.17983
	(1.32289)	(1.24580)	(1.26878)	(1.19433)
Largest Firesize	0.00306***	0.00285***	0.00292***	0.00273***
$*$*Downwind*	(0.00023)	(0.00020)	(0.00022)	(0.00020)
p-value on joint F test	0.000	0.000	0.000	0.000
Observations	201,429	210,898	201,429	210,898
Panel B: IV Estimates				
Cumulated smoke	-0.00053**	-0.00010	-0.00055**	-0.00005
	(0.00022)	(0.00019)	(0.00023)	(0.00019)
Downwind spanning	35 degrees		40 degrees	
Cragg-Donald Wald F-statistic	98.12014	109.53699	94.50670	105.87300
Observations	201,429	210,898	201,429	210,898

Notes: This table reports first-stage, OLS, and IV estimates of the effect of smoke exposure on student achievement, using alternative definitions of downwind areas. Specifically, instead of defining the downwind sector as spanning $\pm$30 degrees around the prevailing wind direction, we construct alternative measures using wider sectors of $\pm$35 (Columns (1) and (2)) and $\pm$40 degrees (Columns (3) and (4)). All regressions control for cohort fixed effects, year fixed effects, school-x-grade fixed effects, lagged school level race and gender composition, percentage of students eligible for free/reduced price lunch, and dummies for post-2014 for each county. Estimates are weighted by school-year-grade enrollments. Robust standard errors clustered at the school level are reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$