Schooling amidst displacement from California fires: bright spots and blind spots

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ABSTRACT

Fire-related displacement is no longer a problem unique to rural California. With urban wildfires displacing a growing number of staff and students, their effects on schooling warrants investigation. To this end, we use school-level assessment information from 2015 to 2025 to quantify the destructive effects of fires on learning outcomes: number of students tested, participation rate, proficiency rate, and mean scores. Using a localized differences-in-differences estimator, we find that the most obvious effect of displacement is a drop in the number of students tested, as well as a drop in participation rate. Effects on proficiency and scores were moderate, but this is likely because of selection effects, where the students that are testing are the least affected. A further fire-level analysis demonstrates differences in how schools manage disasters. Few schools affected by Camp Fire reported grades the following April, but most Eaton and Palisades fire area schools reported grades despite fires occurring in January. We hypothesize that urban school districts have more flexibility relocating students due to having more vacant premises. Remote learning also seems to have been a useful stopgap.

For California schools, disruptions related to wildfires range from complete displacement to a few lost days of instruction. Those within the wildfire perimeter see the worst of these impacts. Usually even if the school is not damaged in a fire, cleanup of ash, soot and other debris can take several weeks. Outside of damage to the school itself, wildfires displace the students and staff in the school's catchment area. In the case of fires like the Camp Fire, the displacement of the catchment area is long term, but for most other fires the displacement is temporary and schools return to normal operation once evacuation orders are lifted.

Previous studies have considered the effect of wildfire related school closures in California on student proficiency rates and mean scores[1]. Proficiency outcomes and mean scores, however, are contingent upon students appearing for spring testing. Since displacement affects the domestic circumstances of students, it creates a unique challenge for understanding student outcomes. To get a fuller picture of the effects we also consider the number of students enrolled at the time of testing as well as the participation rate.[1] Privacy-related masking of smaller school-grade cohorts further complicates the study of displacement. When a large number of the students in a school are displaced and fall below a threshold (usually 10), their results are masked. This means that the outcomes of the worst affected schools are never seen, but can be salvaged somewhat by imputing the highest masking threshold. Expanding the outcome set to include participation is necessary for the interpretation of the proficiency outcomes. In this analysis, we consider four outcomes: number enrolled at testing, the participation rate (0-100), proficiency rate (0-100), and mean score of grade-cohort. These outcomes are analyzed separately for each grade.

The extent of the school's catchment area displaced in the fire is not directly observable. We proxy this information using CalFire's parcel-level reporting on fire damage. Even when houses are not destroyed, they become uninhabitable in the aftermath of fire emergencies either because of disruptions to utilities, or buildup of soot and ash. To allow for many of these effects, we include all types of damage in the CalFire dataset, even when the damage is recorded as only minor. We identify affected schools as those that have more than 10 houses with any damage within a 2 mile radius. The schools identified in this way are termed the in-perimeter schools. There can be much heterogeneity of damage even among in-perimeter schools of the same fire. Therefore, when analyzing the data, we further segment affected schools based on the level of damage they experience. Evacuation data is more difficult to obtain. We assume that evacuation orders are generally limited to the 2 mile radius around the fire-perimeter.

Our method of analysis is a localized differences-in-differences, where the displacement effect is estimated by taking a difference from the pre-fire outcomes of each school and comparing these differences to a schools in the vicinity but unlikely to have the same displacement effects. Specifically, the in-perimeter schools are compared to a set of schools outside the 2-mile radius, but within 20 miles of the furthest affected schools. This restriction is to keep comparisons to schools within areas that have similar built environments (urban vs remote) and to allow for similar trends in population shifts. Schools in towns such as

[1]Participation rate is calculated as the percentage of students who were tested from those that were enrolled in April. This number can change from Census Day.

Paradise which is a fairly remote town are best compared to schools within the area, because they likely to also be rural. Nearby schools also have similar population shifts. Rural towns such as Paradise in California were seeing population declines even before fires. School districts can also differ in their administrative quality, which in turn affect the schools' performance. But it is difficult to limit comparisons within school districts if all schools in the district are in-perimeter schools. Therefore, we assume that schools in adjacent school districts are similar. Taking differences from pre-fire outcomes also helps account for school quality.

Compared to their out-perimeter counterparts, in-perimeter schools of all grades showed significant declines in enrollment, with the largest declines for schools that had more than a thousand houses affected in their in-perimeter. Participation rates of all but the third grade showed significant declines among the schools where more than a thousand homes were affected.

On the other hand, for most grades, proficiency outcomes show little difference between the in-perimeter and out-perimeter schools. Among schools that had the worst damage, fourth, sixth, and eleventh graders saw score drops. It is important to reiterate that these estimates are obtained from a selected sample of schools and students. That is, the schools that we analyze are those who report grades. Fire-impacted schools that do not offer the test in that year, or schools whose enrollment losses at testing reduce class sizes below the masking threshold will not appear in the data. For example, eight schools burned down in the Camp Fire, and none of these schools reported data in that year. The catchment areas of high schools Piner High, Maria Carillo High, and Santa Rosa High were severely affected by the Tubbs Fire and did not report grades in that year. Even when schools report data, the students that sit the test will be the least affected in the school.

Displacement and its effects on learning outcomes are most commonly studied in hurricane-prone areas such as North Carolina and Louisiana[2,3]. In general, the immediate effects are reduced proficiency. However, long term effects seem to vary. Displacement by Katrina led to an overhaul in the school system that benefited students in the long term[4]. In the aftermath of Hurricane Florence and Hurricane Matthew (North Carolina), in contrast, proficiency worsened in the years following the disaster[5]. A nationwide county-level analysis finds disaster-related property damage to be a negative shock to academic achievement, and college enrollment[6]. We add to this literature by specifically considering wildfire displacement.

The next section describes the sources of data and elaborates on the localized differences-in-differences. State-wide results are presented consequently, followed by disaster-level results.

1 Data and methodology

School-grade level data was obtained from the California Department of Education. The earliest test year the data is available for is 2015, and the latest is 2025. The test results for years 2020 were not available, and the test year 2021 was removed because of low participation rates statewide in the test. This data contained the number enrolled at the time of testing, the number of students tested, the number of students that attained proficiency, and the mean score for that grade in the school. The participation rate is the number that tested as a percentage of the number that was enrolled at time of testing. The proficiency rate is the number that achieved proficiency as a percentage of those who tested.

If the number of students enrolled at testing were below a threshold, all information was masked. The masking threshold changed year to year. The highest masking value was for 10 students.

In addition to enrollment at the time of testing, we also obtained Census Day enrollment numbers from the Common Core of Data maintained by the Department of Education. The 2025 enrollment numbers were from the California Department of Education since this information was not yet available in the Common Core. Unlike test score information, enrollment data was not masked. This additional information helps identify schools that are still in operation in the testing year.

Since masking also removes information on the number enrolled at testing, we create an additional imputed variable where any grade that has its enrollment at testing masked is imputed as 10. If the school did not have a positive Census Day enrollment, no imputation was done. In addition, in years where the masking threshold was lower than 10, enrollment values smaller than 10 were changed to 10. The imputation zeroes out any year-on-year difference between small schools, but allows us to study the enrollment drops in larger schools which would otherwise be incalculable due to masking. The imputation did not affect the calculation of participation rates. If the number enrolled at testing was above the masking threshold but 10 or fewer, the participation rate was calculated using the original number.

The geographical location of the school in that particular year were obtained from the Common Core of Data. The school location was then used to identify the number of houses within 2-miles of its radius that were affected or destroyed. Parcel level information of wildfire related destruction is maintained by CalFire. Any house with reported damage was spatially merged to the school's 2-mile buffer. Schools were marked as in-perimeter schools if more than 10 homes were affected in the 2-mile radius. Out-perimeter schools were schools that had recorded damage of less than 10 homes within a 20-mile radius of the school. Figure 1 shows the yearly counts of the in-perimeter schools split by damage class. The three damage classes are marked by the following symbols: the worst damage class of more than a 1000 homes by the square, the medium damage class of more than a 100 but less than a thousand homes by the triangle, and the minor damage class of less than a 100 but more than 10 by the circle.

Schools with catchments affected

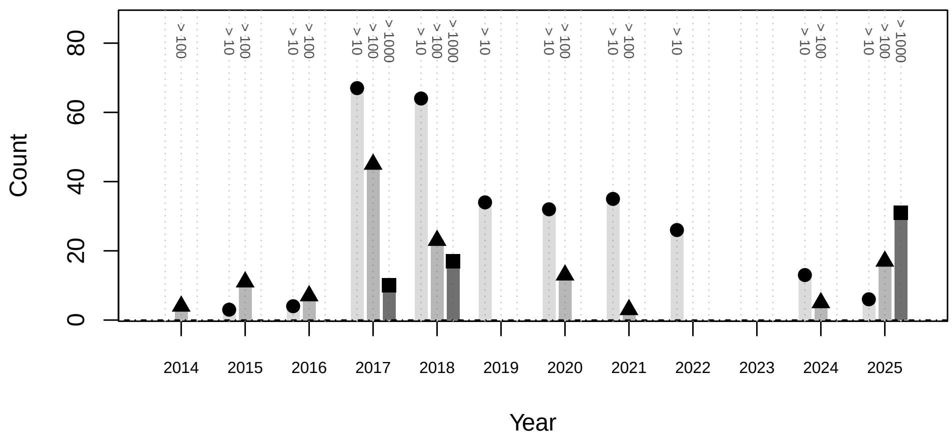

Figure 1. Counts of in-perimeter schools in the year

Fourteen of California's top 20 most destructive fires occurred after 2015. The figure above shows 2017, 2018, and 2025 to be the most destructive years for school catchment areas. The fires responsible for the largest amount of destruction close to schools are Tubbs in 2017, Camp in 2018, and Eaton and Palisades in 2025. Even though some fires such as Dixie in 2021 burnt close to a million acres it did not create the same extent of catchment losses for schools.

As mentioned above, out-perimeter schools were restricted to geographically close subsets to avoid comparisons between urban and rural schools. Although school district level characteristics affect the quality of the school, we cannot restrict comparisons to the same school district because there are usually not enough schools in the same district that are not affected by the fire. Therefore, we extend the comparison set to be neighboring schools in a 20 mile radius, which may include schools from other districts.

The figure 2 demonstrates the in-perimeter and out-perimeter schools for four fires. The fires shown are the Tubbs (2017), Camp (2018), Eaton (2025), and Palisades (2025). The fire's burn scar is depicted in the darker orange shade and a 2-mile buffer of the perimeter is depicted in the lighter orange shade. The red dots show the in-perimeter schools, while the black triangles show the out-perimeter schools. The in-perimeter schools generally lie within the 2-mile buffer, but a few out-perimeter schools also lie within the buffer. There is much heterogeneity in the damage extent for schools even within the in-perimeter. We specify three damage classes: more than 10 homes but less than a 100, more than a 100 homes but less than a 1000, and more than a 1000 homes.

Isolating the in-perimeter and out-perimeter schools at the fire level is the first step in the localized differences-in-differences estimation. The second step is ensuring that the estimation routine can keep these contained within these sets. Commonly used regression implementations of differences-in-differences such as two-way fixed effects regressions (where a fixed effect is implemented at the school-grade level and year level) cannot be easily adapted to a setting where local sequestration of control and treatment sets are important. Regressions also do not allow us to enforce the baseline year. Since we want to restrict the baseline year to be the year immediately prior to the fire, we use a more flexible algorithm. We estimate differences-in-differences estimates for each grade of each in-perimeter school first. These sub-estimates can them be aggregated flexibly. For instance, when schools within the fire perimeter differ in their extent of damage, having access to school-grade level effects allow aggregation within damage classes.

To formally describe this algorithm, let $Y_{s,g,t}$ be some outcome (enrollment numbers, participation rate) observed for school s, grade g at testing year t. All out-perimeter schools have the class of damage normalized to 0. Also define the set of in-perimeter schools for each fire as In_f and Out_f, and let the set cardinalities be $|In_f|$ and $|Out_f|$respectively. For any school in In_f and a grade offered by that school g, let the school-grade level estimate be,

$$DID_{s,g,t} = |In_f|^{-1} \sum_{s \in In_f} (Y_{s,g,t} - Y_{s,g,t-1}) - |Out_f|^{-1} \sum_{s \in Out_f} (Y_{s,g,t} - Y_{s,g,t-1}).$$

The baseline year that the post-fire outcomes are differenced against is the testing year prior to the fire.

Further averaging of these estimates allows us to obtain fire level damage.

Figure 2. In-perimeter (red) and out-perimeter (black) schools for Tubbs (2017), Camp (2018), Eaton (2025) and Palisades (2025) fires

$$DID_f = |In_f|^{-1} \sum_{s \in In_f} DID_{s,g,t}.$$

These sub-estimates are further aggregated to produce total grade-level aggregates. Assuming that for a grade g, there are S_g schools in the in-perimeters of all fires, we denote the aggregate as,

$$DID_g = |S_g|^{-1} \sum_{s \in S_g} DID_{s,g,t}.$$

Damage-level averages can also be obtained. Assuming that for a grade g, there are $S_{g,d}$ schools that are within a fire perimeter and also sustains d level of damage.

$$DID_{d,g} = |S_{g,d}|^{-1} \sum_{s \in S_{g,d}} DID_{s,g,t}.$$

Due to the small size of the in-perimeter sets, we opt to use a conformal predictive interval instead of a confidence interval. The conformal intervals will be wider than a confidence interval produced by standard techniques such as regressions. The conformal interval for these initial estimates $DID_{s,g,t}$ are obtained by assuming that the variance of the in-perimeter school is equivalent to the variance calculated of the out-perimeter schools. Intervals for aggregates are obtained from averaging these intervals.

2 Results

The results in this section are presented in two parts. The first part describes the aggregate disruption effects (equivalent to DID_g and $DID_{d,g}$). The second part describes fire-level aggregates for select fires. All results are presented in four panel graphs where the top-left panel is the number of students enrolled at testing, the top-right panel is the percentage of the students that presented for the tests, the bottom-left are the percentage of the students that attained math proficiency, and the bottom-right has the mean math score. All intervals estimates are 95%.

2.1 Aggregate results

Figure 3 shows destructive effects of all fires in the sample for the four outcomes. There were a total of 63 fires that had at least one in-perimeter school in the sample from 2015-2025. The total number of in-perimeter schools in the sample is marked on in red above the grade axis in the plot. Figure 4 presents these same results for schools with the worst damage. To see a figure with all damage extents plotted, see the Appendix (7).

Enrollment declines are observable for all grades, and most striking for high school students (grade 11). Figure 4 shows that the schools contributing to this decline are those that have the worst catchment damage. Grades 4, 5, 8, and 11 in the medium damage class also see significant decline in enrollment. If the damage is minor, none of the grades see significant declines in enrollment (7 in Appendix). Because we only observe enrollment at the school level, the enrollment declines should not be interpreted as indicating the number of students that did not test. Students could move to other schools that offer the test. Post-fire enrollment can increase even in-perimeter schools if they accept new students from neighboring schools that are destroyed in the fire (see grade 11 in Figure 6). Although they are not a perfect measure of displacement, losses in enrollment still indicate disruption.

Average effects on participation rate are not as consistent across grades as in the case of enrollment. Participation rates significantly decline for 5th and 7th graders, but not for the other grades. When disaggregated by damage extent, the participation rates for the worst damage category show significant declines for all grades except the 3rd. The estimates on participation are underestimating the true impact on participation because participation is calculated as a percentage of students that were enrolled at time of testing. So participation rates are calculable for only those students that did not drop out before testing enrollment.[2] Also notice the changes in sample size between the two top panels. For instance, there are 161 in-perimeter 3rd grade cohorts that were active on Census Day, but only 133 of them have participation information. The remaining schools either did not report grades data or were excluded due to masking. We cannot be certain of the effect on participation declines if

[2]An alternative calculation of participation rate is the number tested as a percentage of the number enrolled at Census Day. However, a Census Day enrollee is not always eligible to take the test. Using the Census Day enrollment can be misleading if particular schools enroll more students that are ineligible than others.

this information was available. However, we can show specific evidence of this occurring where schools drop from the sample because of fire damage.

As with participation rates, the mean scores and proficiency rates did not decline consistently for all grades. The average estimates among all in-perimeter schools were significantly negative for only the 4th graders. When disaggregated by damage average effects declined for grades 4 and 6 in the worst damage class and in grade 5 for the medium damage class. Although proficiency didn't change significantly for grade 11, mean scores did in the worst damage class.

Proficiency estimates are derived from a selected sample of schools that reported grades. Even among the schools that report grades, displaced students would be the least likely to participate in the tests. Fire related disruptions can worsen the selection effects even among students that are not directly displaced because affected schools are usually given reprieves such

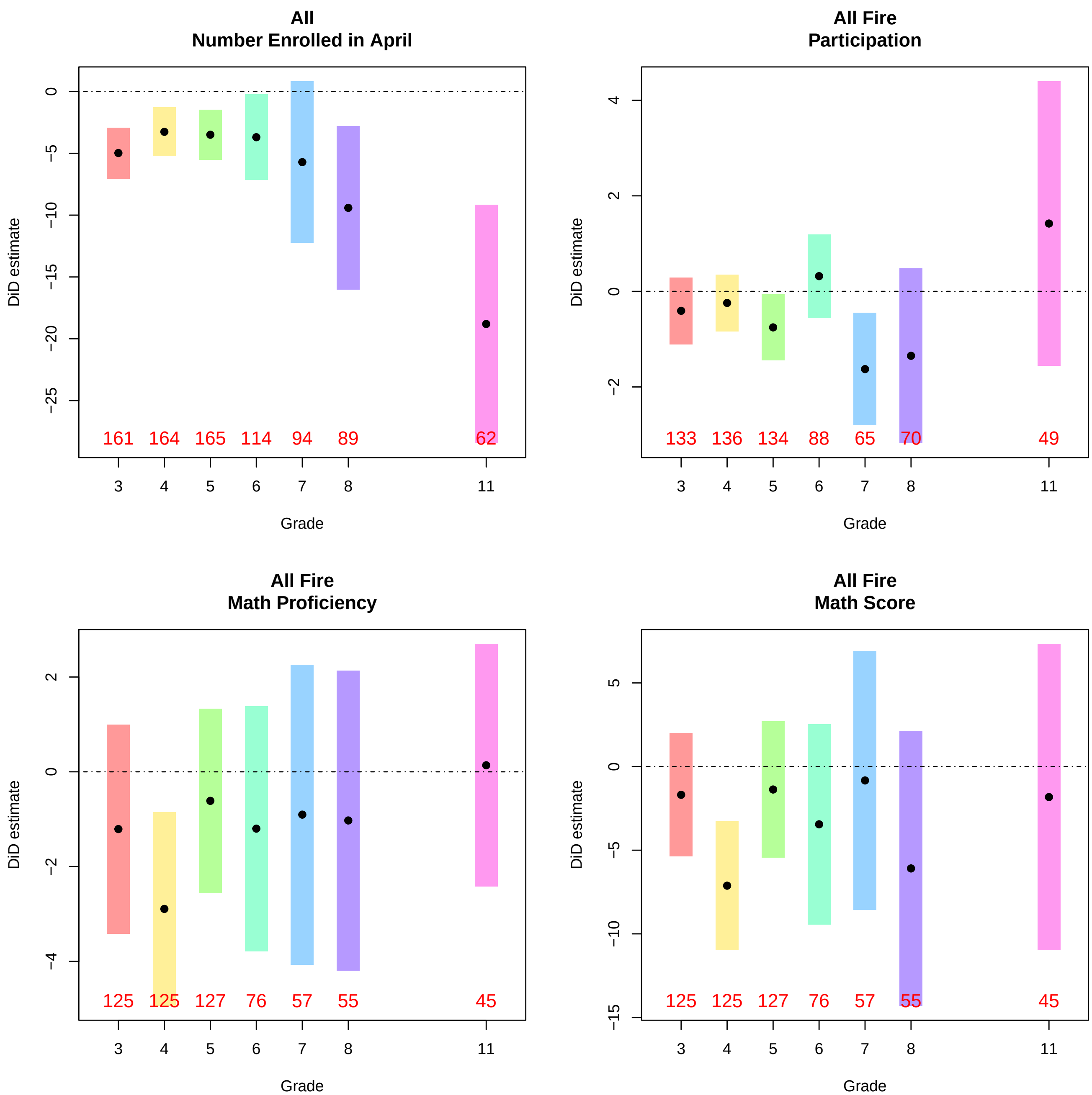

Figure 3. The displacement effect of fires from 2015-2025 on several outcomes

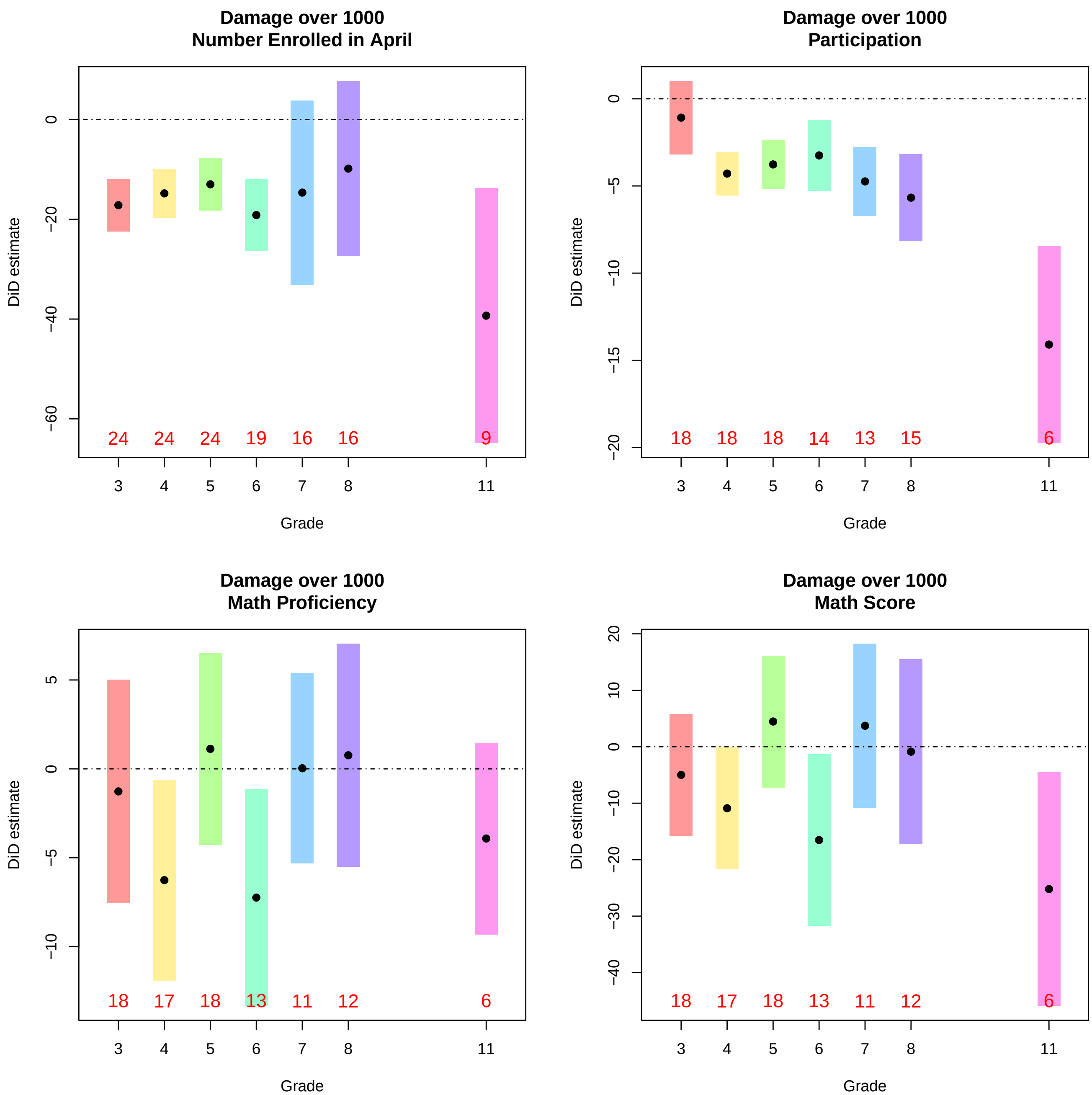

Figure 4. The displacement effect of fires from 2015-2025 on several outcomes among worst affected schools

as in the form of guaranteed funding despite low participation. This may cause students that expect to under-perform to opt out of testing. A common pattern we observe in the data is that an affected school sees drops in number of students tested but sees improvements in test performance. For example, Palisades High was entirely destroyed in the Palisades Fire. Out of the 724 students enrolled in Census Day of October 2024, only 305 appeared for testing. But those who appeared for testing did markedly better, with proficiency rate rising to 61%, when the school had never seen a proficiency rate above 52% before that year, even accounting for pre-Covid years.

Taken together, results show that fire-related displacement adversely affects test participation when the damage is extensive. Proficiency rates and scores, although are not showing declines, are likely underestimating the effect of the disruption to catchment area, because of selection effects. On the other hand, when the damage is minor (less than a 100 homes), we do not see declines in any of the four outcomes considered. This shows that there is some resilience among the

2.2 Fire level results

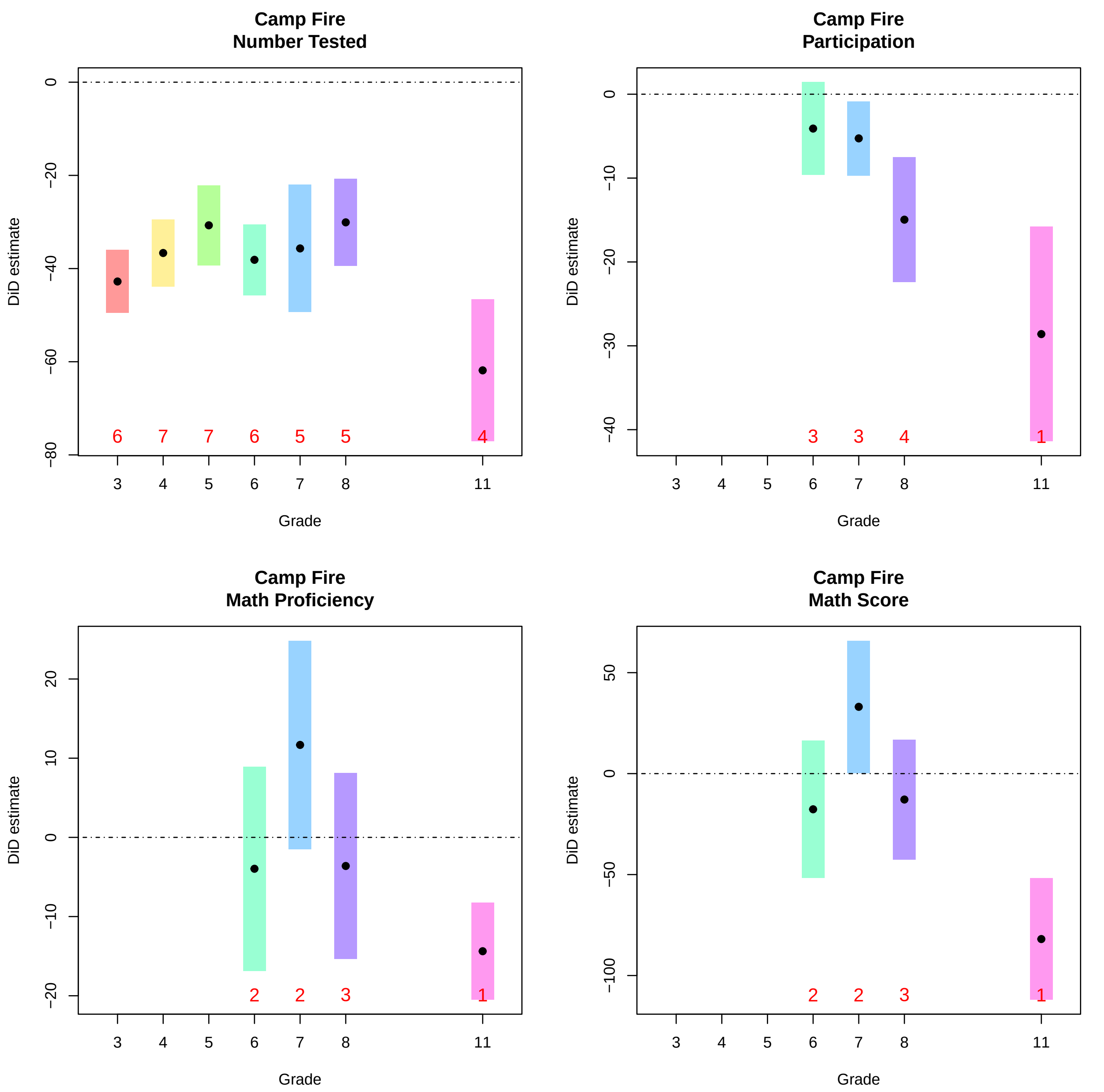

Figure 5. The displacement effect of Camp Fire (2018)

Disruption effects can differ among even the most destructive fires. Figures 5 and 6 show the estimates for our interested outcomes when considering the Camp (2018) and Eaton (2025) fires separately. The Appendix includes similar figures for Tubbs (2017) and Palisades (2025) fires.

The Camp Fire directly damaged eight schools. Paradise Elementary, Achieve Charter, and Ridgeview High completely collapsed, while others sustained various levels of damage[7]. Many affected schools consolidated to offer instruction in August 2019, but none of the affected schools offered the test in Spring 2019. This is observable from the top-left panel in Figure 5 where enrollment at testing dropped significantly for all schools. Participation rates declined significantly for grades 7, 8, 11. More importantly, there were considerable sample losses. None of the in-perimeter schools reported grades and therefore we do not observe any information for grades 3, 4, and 5. Even for grades we observe participation rates, sample losses are a

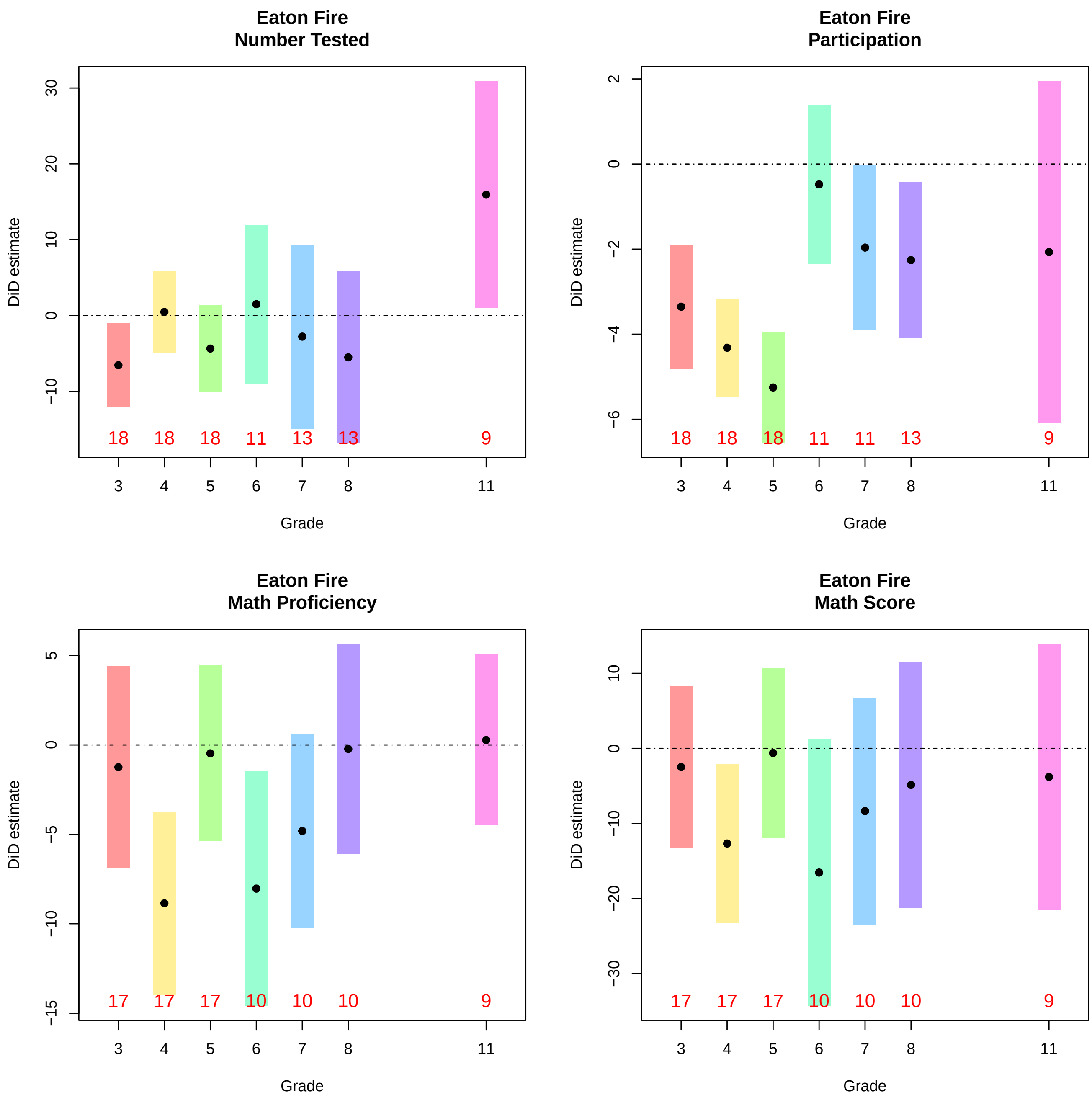

Figure 6. The displacement effect of Eaton Fire (2025)

concern. For example, out of the 4 in-perimeter high schools, only 1 reported grades. Among the schools that reported grades, significant declines in proficiency and scores were only observed for grade 11. But this is because the students that appeared for the tests were selected.

The effects of Eaton Fire seems much less devastating. Significant enrollment losses were only noticeable for grade 3, and except for two middle schools, all in-perimeter schools reported grades. Participation rates significantly dropped for all grades except 6 and 11. But these drops were much less pronounced than Camp Fire, where participation rate drops were in double digits for grades 8 and 11. Significant proficiency declines were observed for some grades 4 and 6, with the grade 7 at the cusp of significance.

The Tubbs Fire (results in Appendix Figure 10) showed similar patterns to the Camp Fire, with large declines in enrollment at testing as well as a number of in-perimeter schools that did not report any grades at testing. None of the in-perimeter high schools offered the test. Enrollment losses were significant for lower grades and half the elementary schools did not offer the test. For the schools that did offer the test, however, there were no significant drops in participation rate, math proficiency, or math score. Palisades Fire (results in Appendix Figure 11) showed a similar pattern; enrollment declined significantly, but other outcomes did not. There were also no sample losses, implying that all schools offered the test.

There are many possible conditions that could explains the difference between the Camp Fire and Eaton Fire. For one, the Camp Fire was more destructive. It destroyed a large percentage of the building stock in the town. Eaton Fire, although the second most destructive fire after Camp, did not destroy as many schools, and a much smaller percentage of the building stock. This would have allowed the school district to relocate affected students to other campuses in the vicinity in time for April tests. For example, the Aveson Global Leadership Academy moved to a nearby campus at the end of January and the Aveson Student Leaders did so in mid-February. Schools consolidated and relocated after Camp Fire, but this was not in time for April tests. For example, Paradise Ridge Elementary opened in 2019 consolidating the destroyed Paradise Elementary and Ponderosa Elementary.

We also hypothesize that practice with remote learning and teaching during 2020-21 helped students and teachers transition faster. Learning losses could be mitigated by moving to online instruction while administrators find new campuses. Moving to online instruction seems to be a useful stopgap for high schools whose cohorts tend to be large. Palisades High that was destroyed in the fire moved to online instruction for some time before finding a new campus in an abandoned department store in Santa Monica. This is in contrast to the high school affected by Tubbs Fire, none of which reported grades in the April testing. State guidelines, issued after destructive fires in 2017 and 2018, seems to have encouraged quicker transition by tying funding to plans for independent study[8].

3 Conclusion

When working with school-level data, disaster-related displacement effects on learning is challenging to get a full picture of. There are several data blind spots. The first type of blind spot is that the worst affected schools tend to not report grades, or their grades are reported out of a cohort size smaller than the masking threshold. Therefore any proficiency result is underestimating the total effect. A second blind spot is that the proficiency outcomes are reported out of the group of students that chose to undergo testing. They tend to be the least affected and most willing to be tested. This selection effects also occurs because schools in fire affected areas are given reprieves for low participation.

Participation based outcomes see large declines in affected schools. But partly because of the selection effects, we do not see significant declines in proficiency or mean scores. Because displacement is generally not a positive experience for students, it is more likely that the proficiency outcomes we observe do not give a full view of displacement. Additionally, selection also occurs because mandatory testing requirement are relaxed for affected schools. These type of selection effect was observed in previous studies in California that tracked school closure prior to 2020, and find no significant declines due to extended closures as opposed to short-term closures[1]. We hypothesize that the reason for this non-linearity in outcomes in response to different closure lengths occur because of the selection effects that are associated with extended closures.

A third type of blind spot occurs when students reenroll from in-perimeter schools in other schools. If a large contingent of students reenroll in out-perimeter schools, they may also affect the assessment outcomes in those schools and therefore the differences-in-differences estimate. Student level data can provide some insight into these blind spots. But, even with student level administrative data selection can occur if loss of homes causes relocation to other states, or opting for home schooling.

There are also several bright spots. Schools that see only minor damage to their catchment area saw little change in enrollment, participation, or proficiency from the out-perimeter schools. This shows that schools are resilient in responding to short-term disruptions such as evacuations. Schools affected by the January 2025 wildfires Eaton and Palisades returned to operation much faster than comparably destructive fires such as Camp and Tubbs. This may partly be due to the ease of finding nearby campuses in urban areas, and partly due to better practice using remote learning technology.

We also make a methodological contribution here. Our use of a localized differences-in-differences strategy allows us to control for differences local level factors that may be driving outcome trends. One such local level factor is changes in the demography. Schools in California's north have faced problems of declining enrollment since even before the pandemic. Keeping comparisons to local areas can control for these differences within the state. School level differences are accounted for by differencing from the pre-fire outcome.

One limitation of this methodology is that the out-perimeter schools we use as our control group is also affected by the fire. School districts of Pasadena and Los Angeles closed for a week after the fire due to air pollution concerns. Some evacuation orders may have extended beyond the in-perimeter. Out-perimeter schools also would have absorbed many of the displaced students. The results we report are therefore likely underestimates of the true impacts. Other impacts such as wildfire smoke affects an even larger numbers of students that can extend even beyond the out-perimeter and sometimes the entire state[9].

Our focus here is displacement. Most studies on long-term displacement and learning have been in the context of hurricanes. But with greater prevalence of wildfires and their increased destructiveness, wildfires are quickly becoming non-negligible cause of long-term displacement. Our findings here show that the immediate effect of fires seems to be absenteeism from testing. As more data comes in, we would be able to assess the persistence of these effects, particularly from the January 2025 fires.

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Appendix

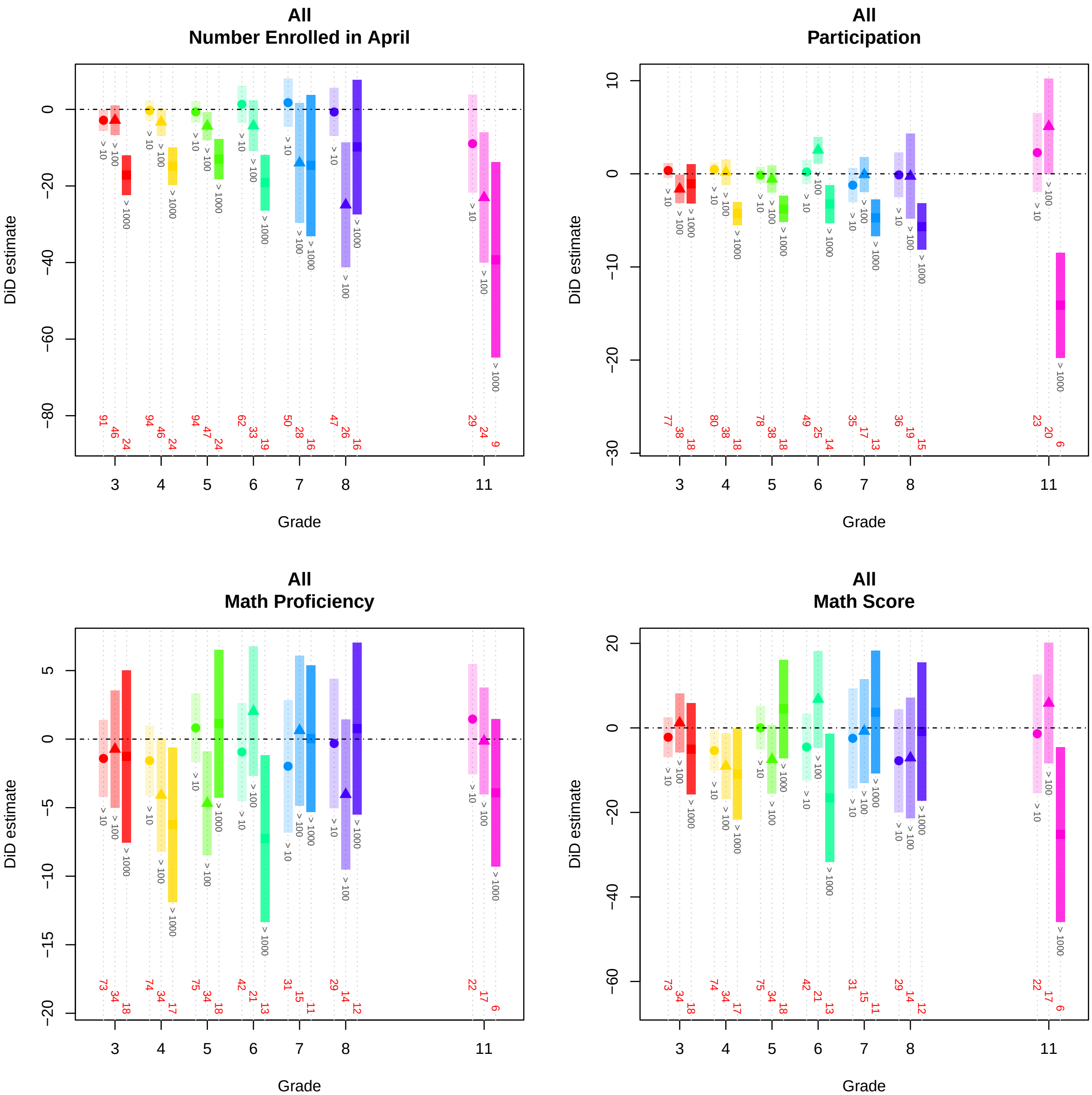

Figure 7. The displacement effect of fires from 2015-2025 on Mathematics test outcomes by damage to catchment area

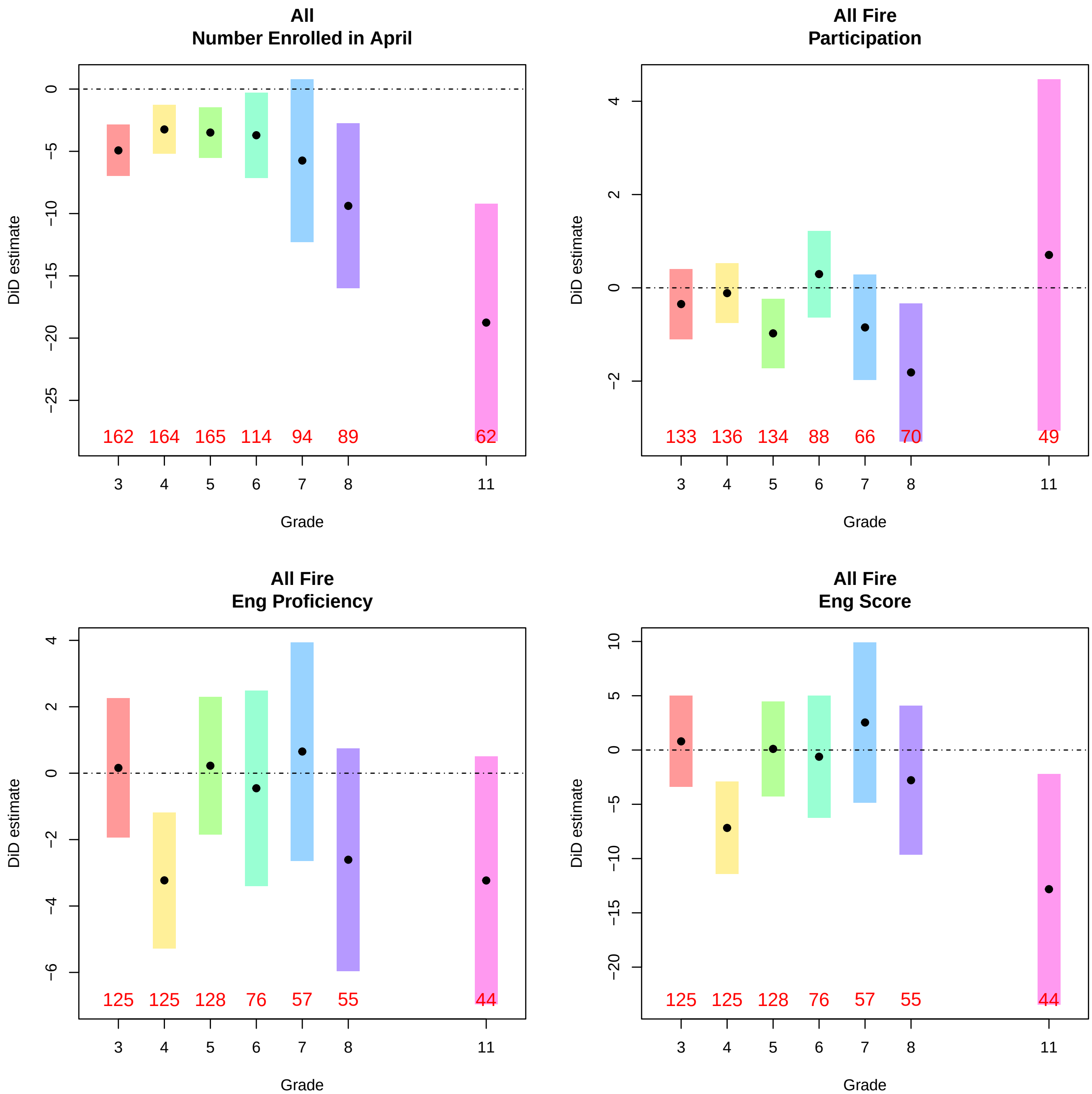

Figure 8. The displacement effect of fires from 2015-2025 on English Language Arts test outcomes

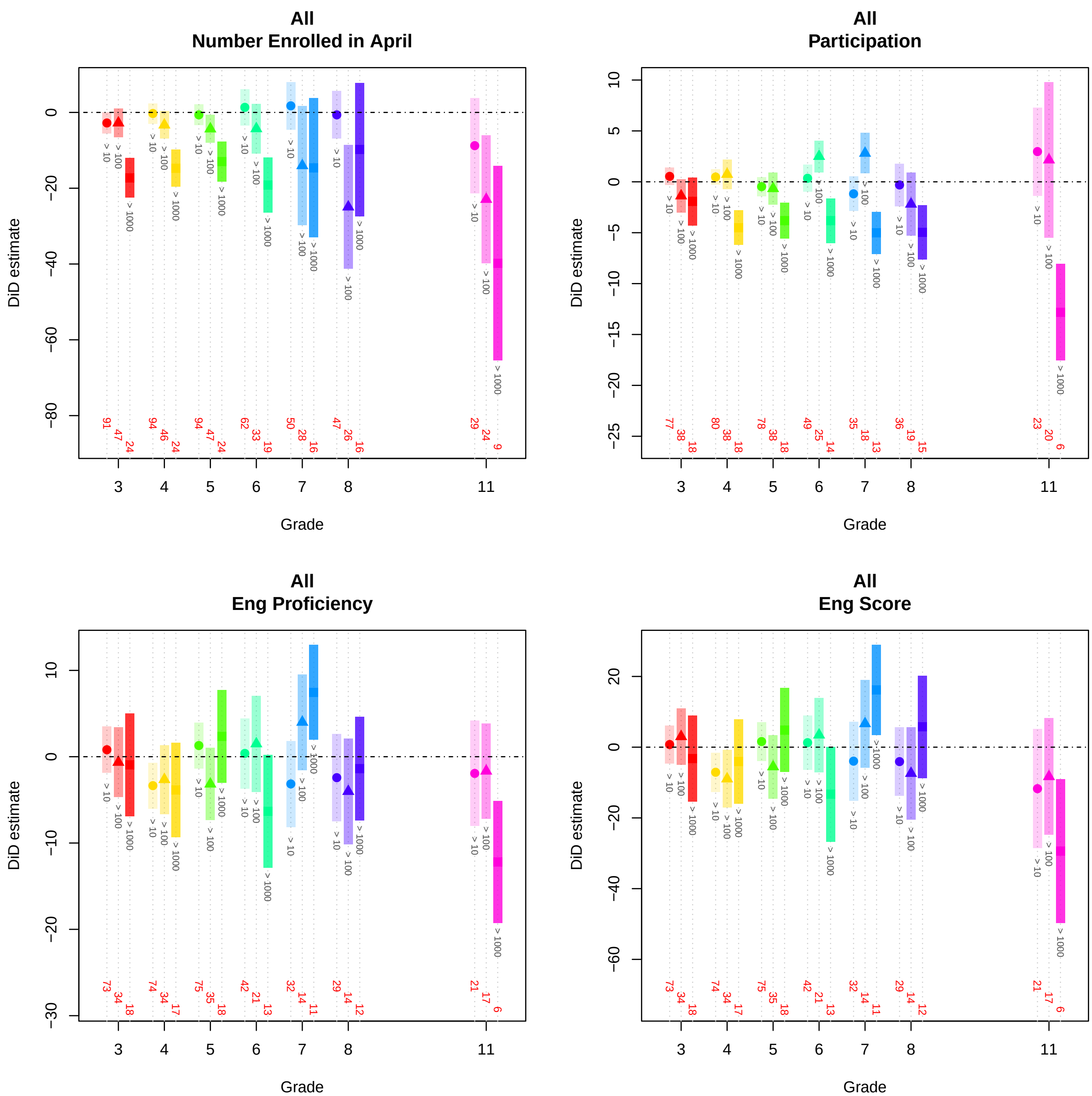

Figure 9. The displacement effect of fires from 2015-2025 on English Language Arts test outcomes by damage to catchment area

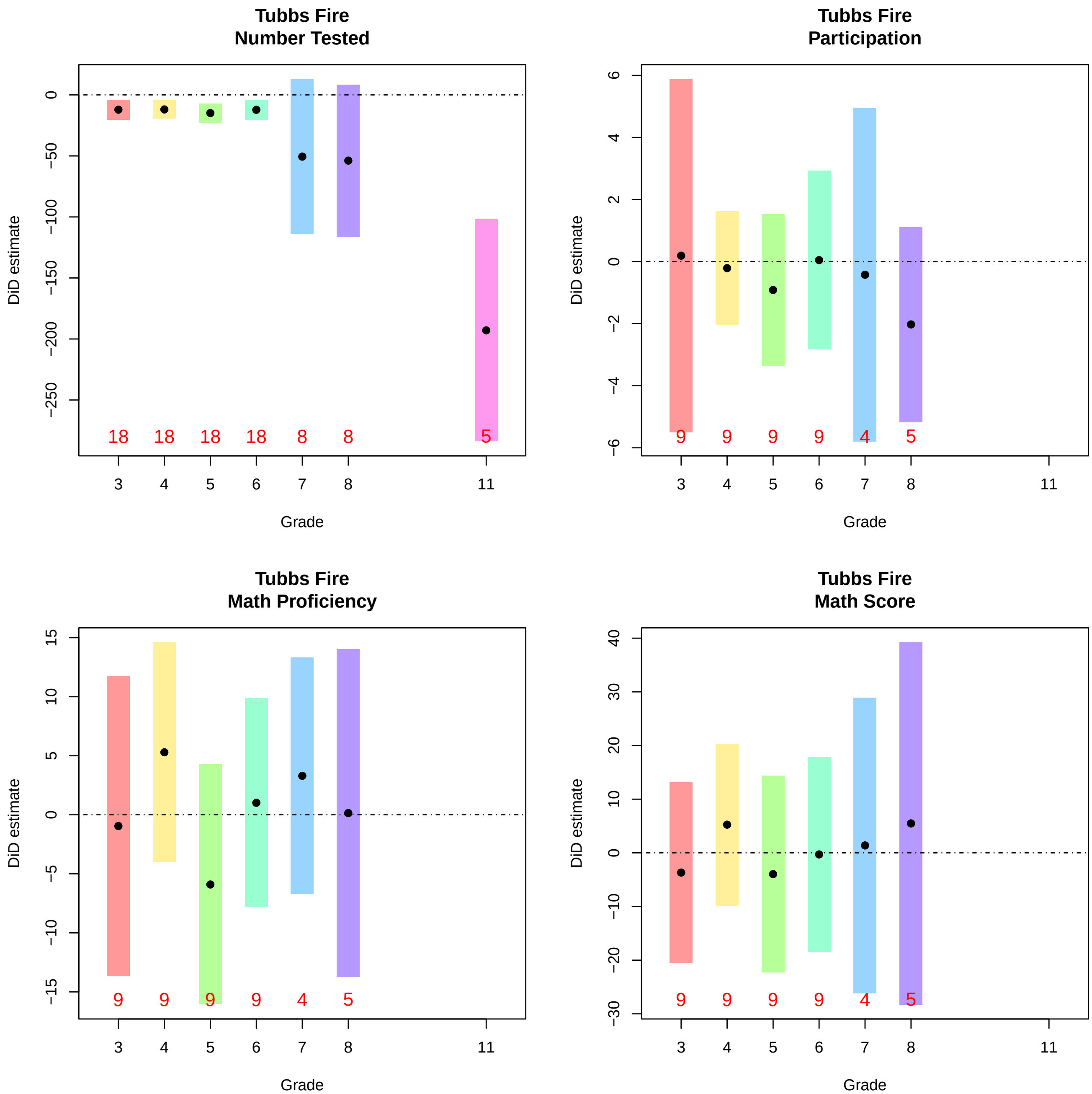

Figure 10. The displacement effect of Tubbs Fire (2017)

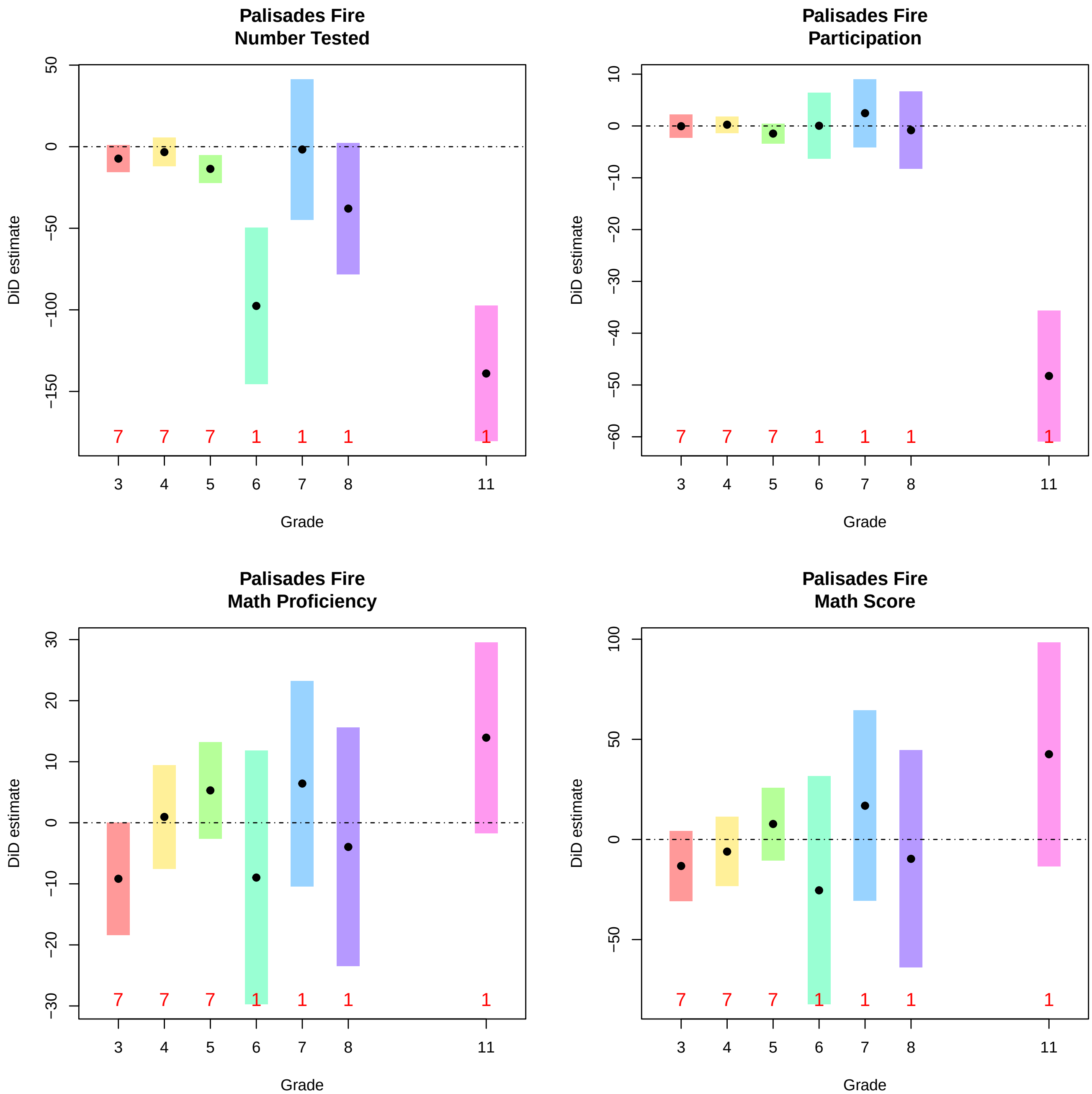

Figure 11. The displacement effect of Palisades Fire (2025)