



Lessons Learned Estimating Impacts of Extreme Weather on District-Level Achievement

Paul Burkander, Nicholas Ortiz, and Anne Partika
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Introduction

Extreme weather events—unusually severe weather or climate conditions that can cause widespread damage—are becoming more frequent and intense, and education systems are increasingly affected by these events.^{1,2} School building damage or closure, displacement, and disruptions to instruction affect students and educators, often alongside housing instability, food insecurity, and other stressors that impact learning and well-being.

If state and district education leaders better understood the degree to which extreme weather events are likely to affect student outcomes, and how long those effects are likely to last, they might better mitigate the harm from such events through improved planning. For example, if leaders knew that the effects of an extreme storm were likely to last for three years before subsiding, they could better budget for sustained support for affected communities over that period.

To explore the degree to which the effects of extreme weather can be measured, we linked national disaster data on Federal Emergency Management Agency (FEMA) declarations with district-level demographics and achievement data to estimate the effects of extreme weather events on students' math and English language arts (ELA) outcomes. We then used an event study model to estimate the short- and long-term effects of such events on student achievement in math and ELA. Event study models can flexibly estimate both the impacts of an event in the immediate aftermath of that event, and how those impacts evolve over time in the periods following the event. These models have been used to estimate effects from a wide range of phenomena, including effects from switching from five- to four-day school weeks,³ school closures,⁴ and school finance reform.⁵

This brief summarizes the methods used in these exploratory analyses and highlights key lessons learned about the opportunities and limitations of using integrated disaster and education data. Below, we summarize the methods used in this analysis and the methodological limitations stemming from data limitations and suggest next steps for using geographically linked disaster and school records for informing efforts to mitigate the effects of extreme weather on student outcomes.

Methods

To estimate the dynamic effects of weather events on student math and ELA achievement, we linked county-event-level FEMA disaster declaration data, district-year-level Common Core of Data (CCD) school district data, district-grade-year-level Stanford Education Data Archive (SEDA) achievement records, and district-level Education Demographic and Geographic Estimates (EDGE) geospatial school district data. We first defined our sample using CCD data to include all public school districts that were open as of the 2009–10 school year and did not change boundaries between the 2009–10 and 2019–20 school years. Next, we spatially analyzed

the intersection of EDGE school district and county boundaries in ArcGIS to create unique district-county segments. We then linked these segments to county-year-level FEMA data to quantify the number of extreme weather events across the United States and by school district.

We considered an event to have occurred during a given school year if the event began between August 1 of the year in which the fall semester occurs and July 31 of the year in which the spring semester occurs. Districts may have experienced multiple events in a given year. We aggregated these events by creating county-level indicators for having experienced a particular event at least once in a year or not. To account for the fact that district catchment areas may encompass multiple counties and that sometimes only a subset of those counties experiences a weather event, we defined exposure to an event for a district as the proportion of the population in that district's catchment area who were in a county experiencing an event, derived from U.S. Census block-level population centroids. For example, if a district catchment encompasses two counties, one of which experiences an event, and half the total population in that catchment area is in each county as determined by the centroids, our measure of treatment for that district would be 0.50.

We then estimated an event study model⁶ where the outcome was district-grade-year measures of cohort standardized math and ELA achievement as reported in SEDA—for example, grade 4 ELA achievement scores for the district in 2011. Specifically, we estimated models of the following form:

$$y_{gdst} = \sum_{j=\underline{j}}^{\bar{j}} \beta_j b_{dst}^j + \mu_d + \theta_t + t * \omega_s + \epsilon_{gdst}$$

In this model, y_{gdst} is the outcome for grade g , district d , in state s , and at time t ; b_{dst}^j is an indicator equal to one if the district is j years away from the event, where negative values of j indicate a future event and positive values indicate an event in the past; μ_d is a district fixed effect accounting for time-invariant differences across districts; θ_t is a period fixed effect accounting for shocks common to all districts; and ω_s is the slope on a state-specific linear trend accounting for changes over time within states. All standard errors were clustered at the district level to account for correlated errors across grades within districts and within districts across years. Under the assumption that trends in districts not affected by weather events can serve as the counterfactual for trends that would be observed in affected districts in the absence of an event, these models estimate the causal effects of such events.

Lessons Learned

Publicly available data on extreme weather events do not provide sufficient geographic information to reliably estimate impacts on student learning

Estimating the impact of extreme weather events on scholastic outcomes requires accurate measures of which districts were affected by the weather event. As described above, FEMA data were at the county-event level, which we linked to district data. We linked event data to district data using the share of a district's total population in counties exposed to that disaster.

However, this method of linking data may not accurately measure district exposure to an event. In a larger county, for example, areas of the county affected by the weather event may be far from some school districts overlapping that county. As a result, treatment effect estimates may be biased down because the “treated” group of districts may include some districts that did not experience any consequences of remote weather events occurring within the county. This result may be especially true of highly localized weather events such as tornadoes, which tend to strike a narrower path.

Without more specific information on which geographic areas are affected by a weather event, it is not possible to identify the districts directly impacted by the event. The consequences of some weather events—such as extreme heat or exposure to wildfire smoke—can more accurately be linked to districts, and thus there exists more evidence of their effects on student achievement. However, we are not aware of similarly granular data on which districts are impacted by storms, floods, or hurricanes. Although the National Oceanic and Atmospheric Administration provides publicly available data on the latitude and longitude where storms began and end, these data do not capture the full set of areas impacted by storms.

It is not clear how best to model the intensity of weather events for the purpose of understanding the impacts on schools

Districts vary in the number, type, and severity of weather events they are exposed to. Ideally, analyses would account for this variation to, for example, allow for differential effects for districts experiencing short-lived versus prolonged disasters. However, accounting for differences in the number and severity of weather events requires a measure of event intensity. Intensity can be operationalized in various ways, such as duration, costs of total damage, or use of event-specific criteria such as the Enhanced Fujita scale for tornados.

In our main analyses, we did not account for differences in the number and severity of weather events. We did, however, conduct exploratory analyses in which our treatment variable was the number of school days in which there was an active event leading to a FEMA declaration, summing across all events in a year. For example, if a district experienced two FEMA-declared storms—one lasting five days of the school year and the other 10 days—our measure of exposure

for storms would be 15 days. If a district experienced a FEMA declaration for a fire lasting 40 days during the school year and for a storm lasting five days, our measure of exposure to any event would be 45 days. Results of these analyses were similar to those that did not account for the intensity of the event.

Yet the number of days a weather event was active during the school year may not be the best measure of intensity. For example, some long-smoldering fires that necessitated a FEMA declaration during the study period are still active today, six years after the study period. In the case of prolonged events, families and districts may eventually adapt to them, mitigating any negative impacts on achievement. Similarly, a single-day or short-lived event may nonetheless have profound impacts on achievement if that event causes significant damage to infrastructure or housing. Without a more direct measure of the intensity of weather events in terms of their impact on teachers, students, and infrastructure, it is not possible to reliably estimate how the severity of an event affects student achievement.

Analyses of the relationship between extreme weather events and student achievement must account for preexisting differences across districts

If weather events were randomly distributed with equal probability across districts, then a simple difference in outcomes between districts experiencing and districts not experiencing an event would capture the causal effect of weather events on that outcome. Although the specific timing and location of weather events is quasi-random, the probabilities of experiencing a particular type of event vary across location and across time for sufficiently long panels. If these differences in probabilities are correlated with potential outcomes and these differences are not accounted for, the estimated effects will be biased.

Our exploratory analyses attempted to control for differences across districts in the probability of experiencing a weather event by using district fixed effects, and differences across time using both year fixed effects and state-specific linear trends. However, several models in these exploratory analyses showed small but statistically significant differences in pre-event trends, indicating that these fixed effects and linear state trends did not sufficiently account for changes in probability over time. This result suggests that any observed differences in outcomes cannot be attributed to the event because of preexisting differences between districts that do and do not experience an event.

A common approach to addressing this issue is to include a sufficiently rich set of time-varying covariates in the model such that - conditional on those covariates - exposure to an event is independent of potential outcomes. Yet a challenge of using covariates capturing local population characteristics for widespread weather events is that these precise characteristics may be channels through which weather events affect district- or school-level student achievement. For example, if a weather event disproportionately displaces socioeconomically disadvantaged families, resulting in an increase in local socioeconomic status (SES) following

the event and, in turn, an increase in test scores, holding constant measures of local SES would understate the full effect of the weather event on districts' average student achievement.

District-level impacts may be sensitive to year-to-year changes in composition of schools and students within schools

A key challenge in using district-level data to estimate the impacts of extreme weather events on students is that forced displacement is an important channel through which weather events may affect students. For example, Hurricane Katrina and, a few weeks later, Hurricane Rita led to the displacement of over one million people from the central Gulf Coast.⁷

This displacement presents two challenges. First, students moving to districts not experiencing a weather event violates the assumption that trends in those districts can serve as the counterfactual for trends that would be observed in districts experiencing an event in the absence of an event. Outcomes in those comparison districts cannot serve as a counterfactual measure of what would happen in the absence of an event because the districts are also affected by the event via the influx of new, displaced students who were themselves affected by the event. Second, because displaced students may be those who are most disadvantaged and therefore typically score lower on tests of achievement, their displacement may lead to an increase in district-level achievement in the affected districts. The displacement of more disadvantaged students from “treated” districts to comparison districts may therefore systematically understate the effects of weather events on individual student achievement.

Similarly, if weather events are so severe that they lead to districts closing or being reconfigured with different boundaries, those districts would not contribute to analyses of the impacts of extreme weather events on student achievement using event study models because we cannot observe achievement in districts that are closed, nor can we reliably link districts to counties for districts that change boundaries over time. As a result, these analyses may systematically exclude some of the most severe impacts on student achievement from the disruption of school districts closing.

Analyses should prespecify substantively important differences

With a sample of more than 50,000 school districts over 11 years, our preliminary analysis was able to detect trivially small deviations from zero. This posed a challenge for assessing equivalence of pre-trends because we frequently rejected the joint null hypothesis of no difference across pre-event periods, even when pre-trend differences were as small as 0.005 standard deviations. Similarly, statistically significant differences in outcomes after the event often were not substantively important. For example, we found a statistically significant impact on ELA achievement of 0.015 standard deviations. With the power to detect such small impacts, there is a risk that even a small degree of statistical bias may be driving the impact.⁸

Future analyses using these methods with such large sample sizes should focus on testing whether impacts are larger than a prespecified threshold rather than focusing only on whether they are statistically different from zero. These thresholds could, for example, be based on known impacts of other disruptive events, such as exposure to neighborhood violence.⁹

Conclusion

Our exploration demonstrated both the promise and the challenges of using an event study model with integrated education and disaster data to understand how extreme weather affects student outcomes. While district-level analyses of achievement provide a broad picture of potential educational impacts, they may mask more immediate or localized disruptions experienced by schools, educators, and students. For example, the effects of extreme weather on students who are displaced by those events are not captured in district-level data. Additionally, more fine-grained measures of areas affected by weather events, such as individual schools, and methods for accounting for differences in event intensity may provide a more accurate measure of impacts.

Future researchers attempting to measure the impact of extreme weather on student achievement using event study models should seek more detailed information on schools affected by weather events. This information may include, for example, data on which schools were closed because of a weather event, property damage due to extreme weather within a school catchment area, or more detailed geographic data on where events occurred. These data may also provide more natural measures of intensity, such as the cost of property damage within a catchment area as a proportion of the total value of housing stock in that region. Future researchers should also consider the use of more detailed baseline measures to adjust for preexisting differences across districts and schools, and the use of more proximal outcomes, such as days attending school, which may be more sensitive to weather events.

Close partnership with state and local education agencies may support better access to relevant outcome and location data, as well the ability to refine hypothesis testing to identify whether impacts are substantively meaningful. With more proximal measures of student outcomes and event data better linked to districts, the methods described in this brief show promise for supporting districts to better predict and manage the consequences of extreme weather events.

Contact us to learn more and collaborate

SRI researchers and technical assistance providers are available for further discussion about the impacts of extreme weather on school systems. Please contact education@sri.com for more information and to discuss potential partnerships, technical assistance opportunities, and other ways to expand this model for supporting K–12 systems.

Suggested citation: Burkander, P., Ortiz, N., & Partika, A (2026). *Lessons learned estimating impacts of extreme weather on school-level achievement*. SRI.

Endnotes

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Silicon Valley
(SRI headquarters)
333 Ravenswood Avenue
Menlo Park, CA 94025
1.650.859.2000

Washington, DC
1100 Wilson Boulevard
Suite 2700
Arlington, VA 22209
1.703.524.2053

education@sri.com

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