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Conference Paper

Going to School During Climate Change: The Effect of Natural Disasters and Student Achievement

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2023: Growth and the "sociale Frage"

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Gust, Sarah (2023) : Going to School During Climate Change: The Effect of Natural Disasters and Student Achievement, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2023: Growth and the "sociale Frage", ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg

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Going to School During Climate Change: The Effect of Natural Disasters and Student Achievement*

Sarah Gust[†]

Preliminary draft; please do not cite or circulate without author's permission.

February, 2023

Abstract

The risk and the cost of extreme weather events are rising. Natural disasters can force schools to close temporarily or completely, but the effects on students are often overlooked when assessing the costs of natural disasters. I combine data on student achievement and achievement gaps with the Geocoded Disaster dataset. I exploit the differential timing in natural disasters across US counties. Student achievement decreases especially one to two years after the natural disaster hit a county. The learning losses are larger for students from economically disadvantaged homes.

Keywords: students, natural disasters

JEL classification: H75, I21, Q54

*For helpful comments and discussion, I would like to thank Ludger Woessmann, Todd Jones, and the participants of the econometric evaluation of economic policy seminar.

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1 Introduction

The risk and the costs of extreme weather events are rising. This is due to a combination of population growth and development but also due to climate change (Smith 2022). 2021 was the seventh year in a row when more than ten 1 Bn dollar disasters hit the US (Smith 2022). There is impressive research that describes the relationships between climate change, natural disasters, and their impacts on the economy and society (Nordhaus 2019). However, the impact of natural disasters on students and learning is not well-studied. When a natural disaster strikes, it can damage schools or critical infrastructure. The disruption of the educational process can have lasting effects on students' achievement and future earnings. Learning losses are often overlooked when assessing the overall costs of natural disasters. However, understanding the costs is crucial to provide guidance for pre-disaster investment. In this paper, I study how natural disasters affect the development of student achievement and achievement gaps.

Research on the school closures during the Covid-19 pandemic has shown that the cognitive and socio-emotional development was seriously impeded (Werner and Woessmann 2021; Engzell, Frey, and Verhagen 2021). Students from disadvantaged homes experienced more serious learning losses. The school closures during a natural disaster differ from the school closures during the covid-19 pandemic where students were often taught at home. Natural disasters can destroy homes and critical infrastructure such that home schooling is not possible. They can also force schools to close permanently which leads to a relocation of students to other schools. Sacerdote (2012) shows that for students that were forced to switch school after hurricane Katrina and Rita, there was a sharp decline in test scores in the first year after the hurricanes. The long run effects are mixed but Sacerdote (2012) finds an improvement in test scores for low-performing students.

Most studies focus only on one type of natural disaster, i.e., they analyze the effect of hurricanes (Spencer, Polachek, and Strobl 2016) or an earthquake (Di Pietro 2018). In this paper, I can distinguish between different types of natural disasters. Nguyen and Minh Pham (2018) show that the type of a natural disaster matters. Floods have a more harmful effect on students than droughts, frosts, and hailstorm in Ethiopia, Vietnam, and Peru but not in India. It is not clear if Nguyen and Minh Pham (2018)'s results for those four countries are generalizable to the US.

I contribute to the literature on teacher absence (e.g. Miller, Murnane, and Willett 2008) and student attendance (e.g. Lamdin 1996). Both student and teacher attendance suffer from endogeneity issues while school closures due to natural disasters offer an exogenous source

of variation for absenteeism.

To study the effect of natural disasters on students in the US, I combine the Stanford Education Data Achieve (SEDA) that contains student achievement and achievement gaps for 2009 to 2018 with the Geocoded Disaster (GDIS) dataset. I exploit the differential timing in natural disasters across US counties with a two stage difference-in-difference model proposed by Gardner (2021) that addresses recent concerns about difference-in-difference settings with staggered treatment. A remaining concern is that the effects of the natural disaster could spill over to neighboring counties. To address this, I estimate two alternative models: I run a donut regression for the standard TWFE model and I correct the two stage difference-in-difference model for spatial spillovers.

I find that natural disasters have a negative effect on student achievement. The effect is most severe one to two years after a natural disaster. Three years after the disaster the results move closer to zero or become insignificant, depending on the specification. Four years after the natural disaster the effect is positive. The negative effect is driven by storms, while the positive effect is driven by floods. Natural disasters increase the achievement gaps between students from economically disadvantaged homes and not-disadvantaged homes.

The next step of this paper will be to analyze if students had to change to other schools due to natural disasters. To this end, I will combine my data with school counts of students from the Common Core of Data.

The remainder of the paper is organized as follows: Section 2 describes the SEDA and GDIS data in more detail, Section 3 outlines the empirical strategy, the results are presented in Section 5, and Section 6 concludes.

2 Data

2.1 Natural disasters

The Geocoded Disasters (GDIS) is a recently published database that geocodes the natural disasters from the Emergency Events Database (EM-DAT) (Rosvold and Buhaug 2021). It combines information on the location of specific types of natural disasters (e.g., storms, floods, drought, extreme temperature, and others) with information on the disasters impact from the EM-DAT (injuries, fatalities, affected, homeless, insured damages, reconstruction costs, total damage). The GDIS consists of 39,953 locations for 9,924 disasters that occurred worldwide

between 1960 and 2018. GDIS tracks only larger natural disasters.¹ I restrict the data to the US and to very large disasters that affected more than 1000 people and caused more than 1 Bn dollar total damage. As the outcome variables start in 2009, I restrict the sample to the years between 2005 and 2018, i.e., when the first cohort of third graders was enrolled. In the final data set, there are only storms and floods among the natural disasters.

Figure B1 shows the number of natural disasters in the final sample. Around 50% of the counties are never treated units. Some of the disasters are defined on a county level. However, some of the very large natural disasters are defined on a state level. If a natural disaster is defined on both a county and on a state level, I keep only the county identifier. However, one disaster can still affect more than one county. Removing all natural disasters that are only defined on a state level would harm the analysis as those are the very large disasters with the most destructive effects.²

2.2 Student Achievement

The Stanford Education Data Archive (SEDA) offers a unique source for school district and county level student achievement measured by standardized test scores for the 2008/09 to 2017/18 school years (Reardon and Chavez 2021). SEDA also contains achievement gaps by gender, race, ethnicity, and socio-economic status, and district level demographic and socio-economic data. The disadvantage of the data is that it is aggregated to school districts if counties but as the treatment is also on a county level it does not impair the main analysis. Table A1 lists the descriptive statistics of each outcome variable. Achievement is centered around zero and relative to the expected grade level in the United States. One-unit below zero means that students in the county are one grade level behind the average, one-unit above zero means that students in the county are one grade level above the average.

3 Empirical Strategies

To estimate the effect of natural disasters on student achievement, I exploit a difference-in-difference with differential timing. The first difference compares schools in counties that were hit by a natural disaster over the past years to districts where no natural disaster occurred. The second difference exploits the timing of the natural disaster. While some students within

¹Those are disasters that led to more than 10 fatalities, that affected more than 100 people, that led to a declaration of state of emergency, or if a country called for international assistance.

²An alternative data source for future analysis is the Spatial Hazard Events and Losses Database for the United States (SHELDUS) that tracks extreme weather events specifically for the US and not globally. To my knowledge, the disasters in SHELDUS are not geocoded but they still identify disasters on a county level.

a county were affected by a natural disaster during their school time, other cohorts were not. The latter serve as a control group. Recent advances in the difference-in-difference literature raises and addresses concerns the two-way fixed effects difference-in-difference when treatment timing varies.³ Gardner (2021) proposes to estimate the difference-in-difference in a two stage procedure that is robust to treatment-effect heterogeneity. In my second specification, I address the issue of spatial spillovers that we can expect in the case of natural disasters.

3.1 Two-stage difference-in-difference

The intuition behind the two-stage difference-in-difference procedure by Gardner (2021) is to first remove the group and time fixed effects based on the parallel trend assumption. The group-time ATT is then identified by comparing treated and untreated outcomes after removing these group and time fixed effects.

The first stage regresses the outcome on the group and time fixed-effects for all not yet treated or never treated units, i.e., where $D_{gt} = 0$. This can be formalized as follows:

$$Y_{gt} = \lambda_g + \gamma_t + \epsilon_{gt} \quad (1)$$

Equation (1) gives consistent estimates of the group and time fixed effects under parallel trends. We can use this outcome to residualize the outcome variable: $\hat{Y}_{gt} = Y_{gt} - \hat{\lambda}_g - \hat{\gamma}_t$.

The second stage regresses the adjusted outcome \hat{Y}_{gt} on the treatment indicator:

$$\hat{Y}_{gt} = \beta D_{gt} + u_{gt} \quad (2)$$

where the new error term u_{gt} is no longer correlated with group and time fixed effects under common trends. Under common trends, Equation (2) estimates the overall ATT. The second stage can be easily extended to an event-study setting:

$$\hat{Y}_{gt} = \lambda_g + \gamma_t + \sum_{r=-R}^T \beta_r D_{rgt} + \epsilon_{gt} \quad (3)$$

³The treatment is staggered as I compare county results over time that switch between control and treatment group.

3.2 Spatial spillover

The effects of the natural disaster could spill over to neighboring counties which would violate the Stable Unit Treatment Value Assumption (SUTVA). In such a case, the control group no longer identifies the counterfactual trend, and the treated units reflect the effect by their own treatment and the effect from neighboring counties.

To overcome this problem, I estimate two alternative specifications. First, I apply a donut approach to the standard TWFE model where I exclude counties that neighbor treated counties from the control group. While this way I can remove contaminated control groups, this does not yet solve the issue of spillovers onto the treatment group. Unfortunately, there is little work on spillover effects in a staggered difference-in-difference design. Butts (2021) provides some initial work and proposes to include an indicator for being affected by a spillover in the model. Butts (2021) also shows that those spillover indicators can be included in the framework proposed by Gardner (2021) if timing of the treatment is staggered. To this end, I run Equation (1) for all counties that are not yet treated or affected by spillovers in year t . The second stage form Equation (2) corrected for spatial spillovers can then be written as:

$$\hat{Y}_{gt} = \beta D_{gt} + \beta_{spill,treat} S_{gt} \times D_{gt} + \beta_{spill,control} S_{gt} \times (1 - D_{gt}) + u_{gt} \quad (4)$$

where $S_{gt} = 1$ if a neighboring county is part of the treated group and zero otherwise. $\beta_{spill,treat}$ captures the effect of treated counties on their neighbors⁴. $\beta_{spill,control}$ captures the effect on treated counties with respect to whether or not their neighbors are treated. The identifying assumptions are that spillovers are local, that is, SUTVA holds outside the neighboring counties.

4 Carryover Effect

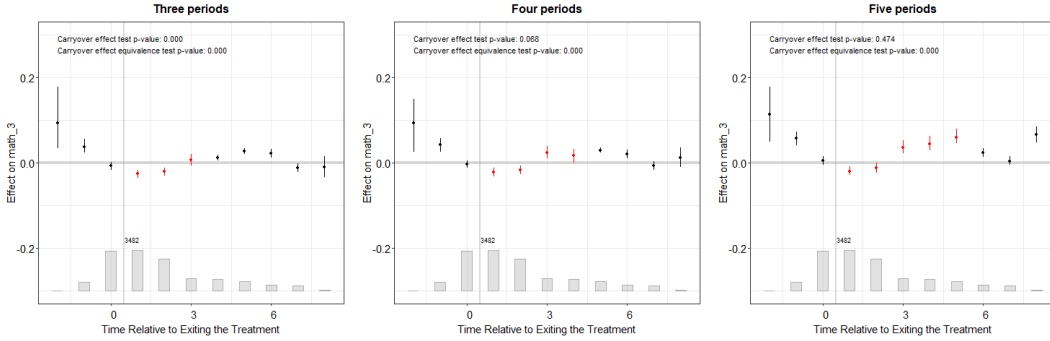
A natural disaster hits a county in one specific year but how many years after the natural disaster should be defined as treated? This question can be thought of as serial carryover effect. One possibility is to define all county-year combination as treated as soon as a natural disaster hits a county. However, natural disasters existed before our observed time frame. Liu, Wang, and Xu (2022) propose a simple placebo test to define the carryover effect. The institution is to hide a few periods after a disaster hits and predict $Y_{gt}(0)$ in those periods. If

⁴Rook's contiguity neighbors

carryover effects do not exist, then the average prediction error in the hidden periods should be close to zero (Liu, Wang, and Xu 2022).

Figure 1 shows that there is a significant carryover effect three periods after a natural disaster occurs. Four periods after the natural disaster the effect is still significant on a 10 % level. The carryover effect disappears five periods after the natural disaster. Liu, Wang, and Xu (2022) suggest to include periods with a carryover effect in the treatment group. For the natural disaster treatment variable this means that county-year combinations that have been treated in the past four years remain in the treatment group. county-year combinations that have never been treated or that have been treated more than four years ago are the control group.

Figure 1: Carryover effect



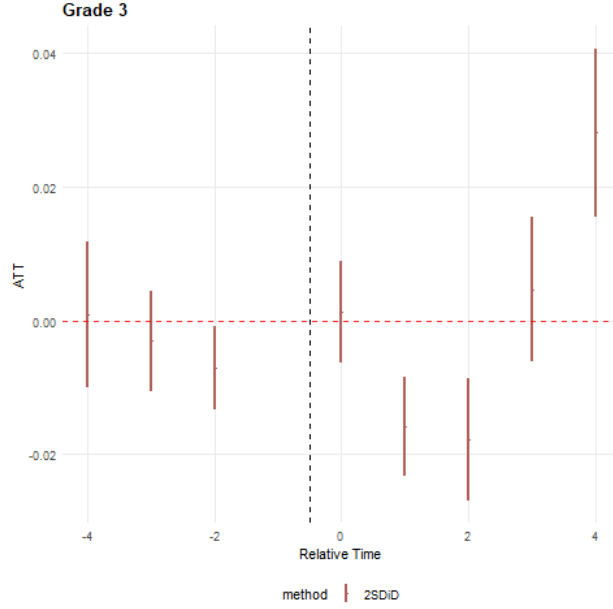
Note: The figure shows the results for the test for carryover effects based on the FEct estimator proposed by Liu, Wang, and Xu (2022). The bar plots represent the number of treated units. There is a significant carryover effect up to four periods after the treatment.

5 Results

There is a negative effect of natural disasters on student achievement in the first and the second year after the natural disaster. Figure 2 visualizes the effect for students in grade three for the two-stage difference-in-difference model. Note that this approach compares different cohorts in grade three.⁵ In the third year after a disaster, the effect becomes insignificant and four years after the disaster the effect is positive. Four years after the disaster, the students that are in grade three by then were still in kindergarten when the natural disaster occurred. They might have benefitted from post-disaster investments without being negatively affected in their learning routine.

⁵A value-added approach, i.e., comparing the same cohort in different grades does not produce conclusive results. Taking the first difference removes most of the variation in the outcome variable.

Figure 2: 2SDiD Event Study: Student Achievement in Grade 3



Note: The figure shows the event study results for grade 3 for the two stage difference-in-difference model.

Table 1 presents the static effect on student achievement in grade 3 in math for the TWFE model (Column 1 & 2) and the two-stage difference-in-difference estimation (Column 3 & 4). In line with Figure 2, the negative effect is stronger if we consider only three (Column 1 & 3) instead of four (Column 2 & 4) post treatment periods. In a next step, I consider the effect on achievement separately for floods (Column 5) and storms (Column 6). As all natural disasters in the relevant period were either storms or floods, this indicates that the negative effect of natural disasters is driven by storms while the coefficient on floods is positive significant. A possible explanation for the positive effect could be that severe floods destroyed some schools and that affected primarily low performing schools. This is in line with Sacerdote (2012).⁶

Figure B2 compares the results of the two-stage difference-in-difference estimate for grade three to the standard, dynamic TWFE method, the corrected version proposed by Sun and Abraham (2021), and the fixed effects counterfactual estimator (FECT) proposed by Liu, Wang, and Xu (2022). All estimators show a similar pattern. The TWFE estimator shows a negative effect already in the same year of the disaster and remains negative until it turns positive three years after the disaster. The estimates following Sun and Abraham (2021) generally produces slightly more negative results with larger standard errors. The FECT estimator shows a negative result until three years after the natural disaster.

⁶Generally, there are no significant effects on enrollment on a county level (see Table A3). However, I will include a more granular analysis using the Common Core of Data.

Table 1: Static Effect of Natural Disasters on Student Achievement

Dependent Variable:	achievement					
Model:	TWFE (3)	TWFE (4)	2SDiD (3)	2SDiD (4)	floods	storms
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
treated	-0.0121*** (0.0031)	-0.0048 (0.0030)	-0.0099*** (0.0031)	-0.0063** (0.0030)	0.0199*** (0.0050)	-0.0133*** (0.0035)
<i>Fixed-effects</i>						
stateXcounty	Yes	Yes			Yes	Yes
year	Yes	Yes			Yes	Yes
<i>Fit statistics</i>						
Observations	27,465	27,465	27,456	27,447	27,465	27,465

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Standard errors clustered at unit level. Estimated using Two-Stage Difference-in-Differences proposed by Gardner (2021).

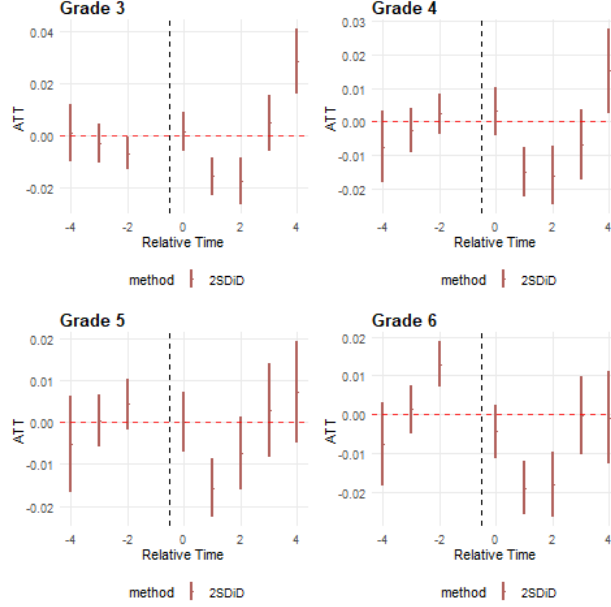
Liu, Wang, and Xu (2022)’s approach is useful to further investigate the common trend assumption. The intuition is to jointly test the null hypotheses that the average treatment effect is zero for all pre-treatment periods. Figure B3 show the results of the pre-trend test for grade three to six. All grades pass the test for no pre-trends. However, the model fit for grade three is much better (F test p-value = 0.928) than for the other grades.

Overall, students in grade four to six experience similar learning losses to the students in grade three (Figure 2). In grade five, the second post-treatment period is not significant and in grade six, there is a positive pre-trend one year before the natural disaster.⁷ Overall, the pattern is very consistent and of similar size. In terms of effect sizes, it does not matter in which grades the students are affected by the natural disaster.

Natural disasters could have heterogeneous effects on different groups of students depending on their gender, socio-economic status, or race. Figure B5 shows how natural disasters affected Asian, Black, Hispanic and, White students. Surprisingly, there is no clear pattern for Asian and Hispanic students. The negative effect on student achievement seems to be driven by Black and White students. However, the sample size is smaller for the here and the pre-trends are less stable which calls for a cautious interpretation of these results. Figure B4 shows a increase in the gap between students from economically disadvantaged homes and from not disadvantaged homes ($p - value = 0.08$). The stronger learning losses for

⁷Note that the sample is a bit smaller for higher grades (compare Table A1)

Figure 3: 2SDiD Event Study: Student Achievement in Grade 3 to 6



Note: The figure shows the event study results for grade 3 to 6 for the two stage difference-in-difference model.

students from disadvantaged homes are in line with the literature on the school closures during the covid-19 pandemic. Engzell, Frey, and Verhagen (2021) showed that students from disadvantaged background experienced stronger learning losses. Another explanation could be that their neighborhoods are more strongly affected by the natural disasters which could lead to a higher number of missed school days or stronger psychosocial effects (compare Trejo, Yeomans-Maldonado, and Jacob 2021). The male-female gap is not significant.

One concern is that the effects of the natural disaster could spill over to neighboring counties which would violate the SUTVA. I control for this in two different ways. First, I exclude counties that are next to treated counties from the control group. The results are shown in Column 1 of Table A2. There is still a negative significant effect of natural disasters on students' achievement. However, the donut specification controls for spillovers onto the control group but not on the treatment group. To control for such spillovers, I directly model the spillover effect in the TWFE model and the two-stage difference-in-difference model (Column 2 and 3 respectively). The spillover effect is not significant in both specifications. The treatment effect remains negative significant and is thus robust to controlling for spillovers.

6 Discussion and Conclusion

This paper analyses the effect of natural disasters on student achievement. I combine US data from the Stanford Education Data Achieve with the geocoded natural disaster database. The results from the two-stage difference in difference model show that there a strong negative effects one to two years after a natural disaster occurs. The negative effects are driven by storms. There is also an increase in the achievement gap between students from economic disadvantaged homes and from not disadvantaged backgrounds. A drawback of the study is that I cannot disentangle school closure effects from other effects of natural disasters such as socioemotional effects.

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A Appendix A: Additional Tables

Table A1: Descriptive Statistics of Student Achievement

Variable	N	Mean	Std.Dev.	Min	Max
math grade 3	27465	-0.015	0.311	-1.920	1.438
math grade 4	27417	-0.038	0.311	-2.696	1.170
math grade 5	26576	-0.058	0.311	-1.605	1.099
math grade 6	26451	-0.044	0.311	-2.570	1.048
male-female gap	23773	-0.006	0.094	-0.554	0.589
non-ECD ECD gap	21308	0.535	0.168	-0.168	1.391
White-Black gap	9264	0.640	0.221	-0.402	1.651
proportion in urban school	27759	0.066	0.178	0.000	1.000
proportion in suburban school	27759	0.091	0.209	0.000	1.000
proportion in town schools	27759	0.287	0.304	0.000	1.000
proportion in rural school	27759	0.556	0.333	0.000	1.000
number of students in grade	27759	6977.350	23157.630	9.000	735415.000
percent Native American students	27759	0.024	0.086	0.000	0.997
percent Asian students	27759	0.013	0.032	0.000	0.744
percent Hispanic students	27759	0.127	0.179	0.000	0.998
percent Black students	27759	0.110	0.189	0.000	1.000
percent White students	27759	0.726	0.252	0.000	1.000
percent students free lunch	27759	0.459	0.173	0.005	0.990
unemployment rate	27731	0.077	0.030	0.001	0.218
poverty rate	27731	0.160	0.057	0.005	0.473
single mother HH rate	27731	0.164	0.055	0.005	0.495

Note: Descriptive statistics for the Stanford Education Data Archive. Achievement is centered around zero and relative to the expected grade level in the United States.

Table A2: Spatial Effect of Natural Disasters on Student Achievement

Dependent Variable:	achievement		
Model:	TWFE donut (1)	TWFE with spillover (2)	2S DiD with spillover (3)
<i>Variables</i>			
treated	-0.0123*** (0.0033)	-0.0114*** (0.0033)	-0.0117*** (0.0034)
spillover		0.0128 (0.0171)	-0.0019 (0.0072)
<i>Fixed-effects</i>			
stateXcounty	Yes	Yes	
year	Yes	Yes	
<i>Fit statistics</i>			
Observations	25,893	27,465	27,407

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Standard errors clustered at unit level. Estimated using Two-Stage Difference-in-Differences. proposed by Gardner (2021).

Table A3: Static Effect of Natural Disasters on Enrollment

Dependent Variable:	log enrollment			
Model:	grade 3 (1)	grade 4 (2)	grade 5 (3)	grade 6 (4)
<i>Variables</i>				
treated	-0.0012 (0.0018)	-0.0011 (0.0018)	0.0028 (0.0018)	0.0021 (0.0019)
<i>Fit statistics</i>				
Observations	27,742	27,742	27,728	27,709

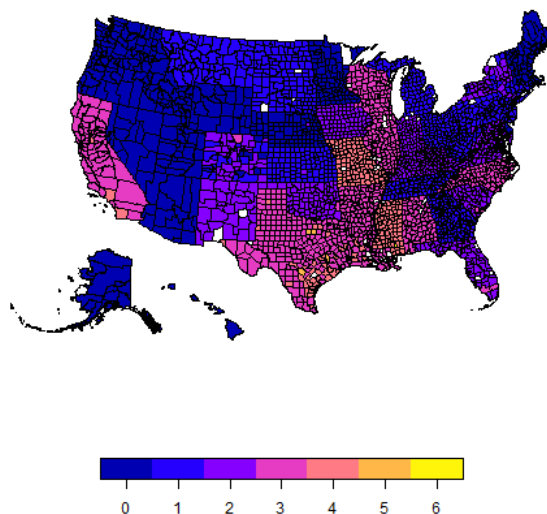
Custom standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Standard errors clustered at unit level. Estimated using Two-Stage Difference-in-Differences. proposed by Gardner (2021).

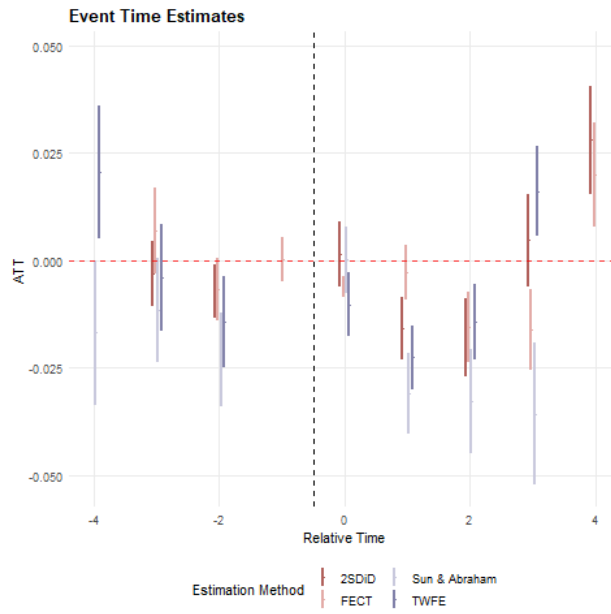
B Appendix B: Additional Figures

Figure B1: Number of large natural disaster between 2009 and 2018



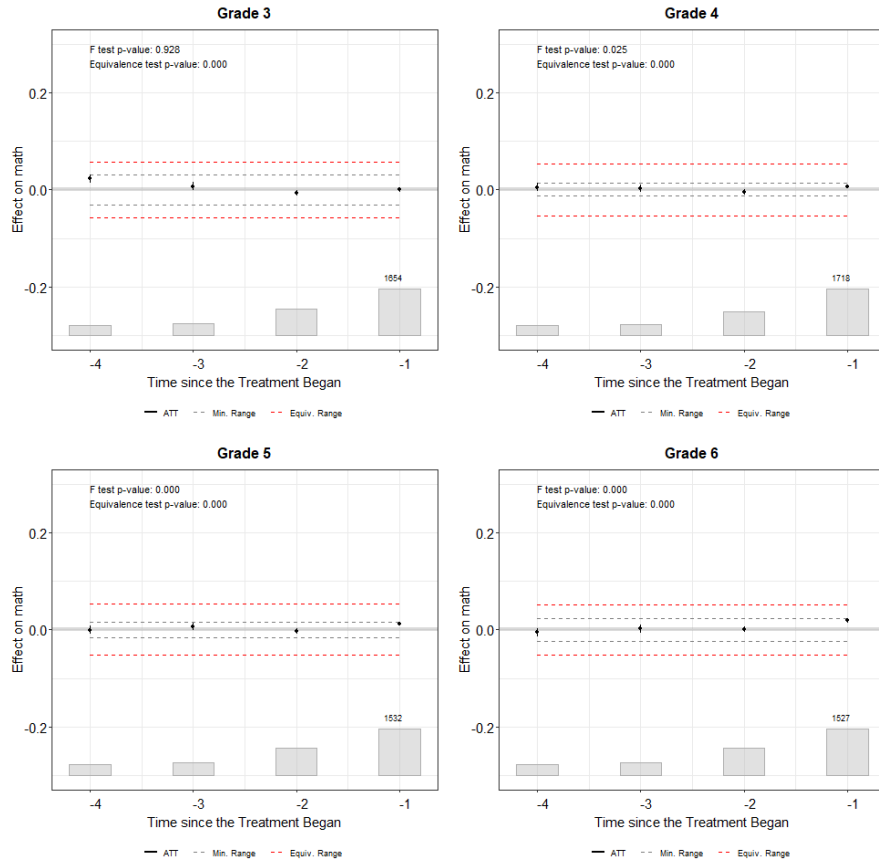
Note: The figure shows the number of large natural disasters on a county level between 2005 and 2018 in the GDIS database. The sample is restricted to large natural disasters that affected at least 1000 people and that caused more than 1 Bn US dollar total damage.

Figure B2: 2SDiD Event Study: Methodological Comparison



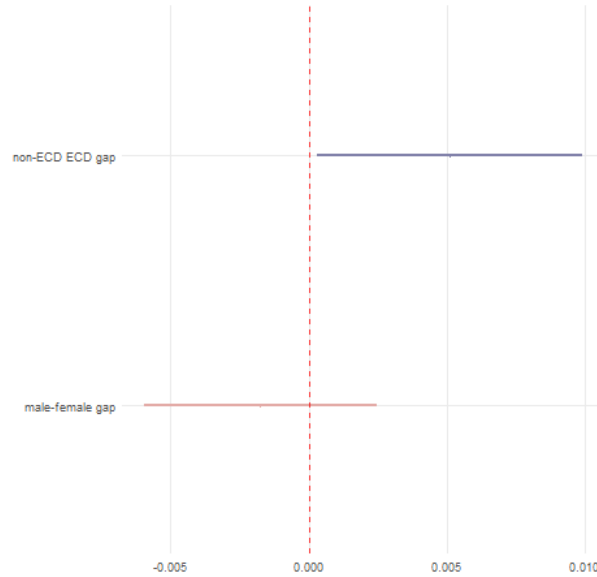
Note: The figure shows the effects of natural disasters on grade 3 math achievement using the two stage difference-in-difference method (2SDiD) following Gardner (2021) with 95% confidence intervals, the event study correction (Sun & Abraham) proposed by Sun and Abraham (2021), the counterfactual estimate by Liu, Wang, and Xu (2022), and the standard TWFE model.

Figure B3: Testing Pre-Trend



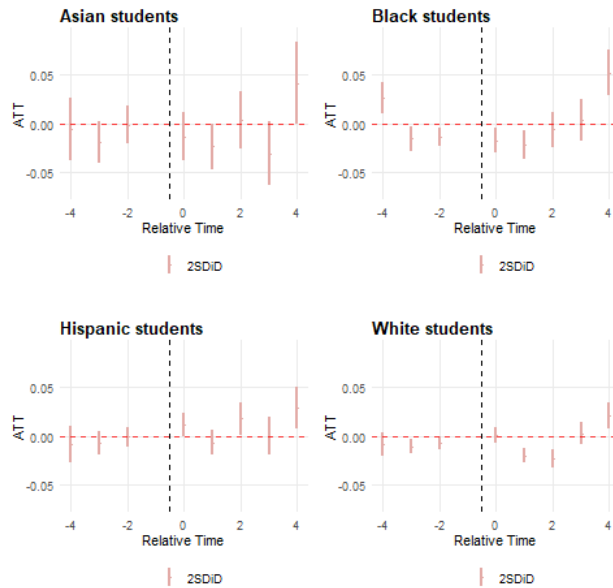
Note: The figure shows the results for the equivalence test based on the FEct estimator following Liu, Wang, and Xu (2022). The red line marks the equivalence range, the gray line marks the minimum range. The bar plot illustrates the number of treated units.

Figure B4: Coefficients for Achievement Gaps



Note: The figure shows the coefficients and the 90% confidence interval for the effect of natural disasters on grade 3 achievement gaps between not economically disadvantaged students and economically disadvantaged students, and between male and female students using the two stage difference-in-difference model.

Figure B5: 2SDiD Event Study: Student Achievement by Race



Note: The figure shows the effect of natural disasters on math achievement with 95% confidence intervals in grade 3 separately for Asian students, Black students, White students, and Hispanic students using the two stage difference-in-difference model.