

Working Title:
Natural Disasters and Education

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Abstract

1 Introduction

2 Data

2.1 Natural Disaster Data

Natural disasters are declared as such by the president, usually upon request by the affected state’s governor. Once a disaster is federally declared, states or local governments can receive federal assistance. The Federal Emergency Management Agency (FEMA) provides data on all federally declared natural disasters, beginning in 1953. The data is easily accessible via their API ([Turner, 2022](#)).

Figure 1 shows the number of declared disasters since 1953 across the US. It seems that the variation in the number of declared disasters may be driven by the governor’s proactiveness in requesting a declaration. Thus, it could be interesting to compare counties on different sides of state borders, whose actual disaster exposure is likely very similar in order to analyze the effect of a declaration.

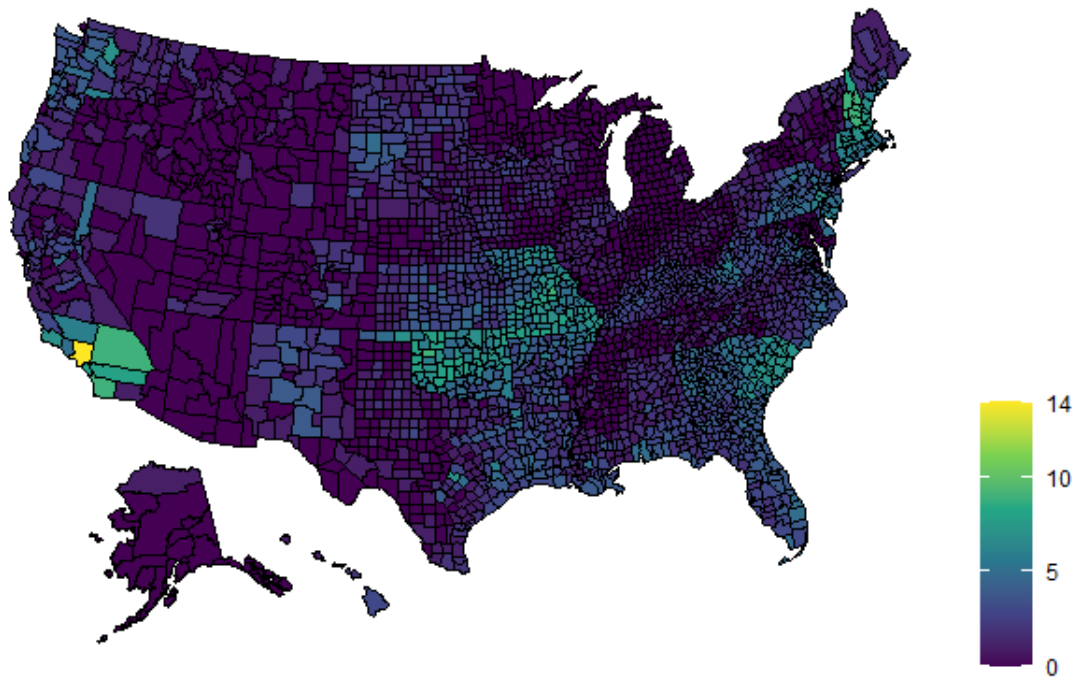


Figure 1: Number of declared natural disasters from 2008 to 2018

FEMA also provides federal disaster assistance data. This includes the amount of damage caused and amount of federal disaster assistance granted. Unfortunately, this data is only available since October 2016. Figure 2 shows the total federal assistance awarded to counties.

2.2 Standardized Testing Data

Data on academic achievement is available from the Stanford Education Data Archive ([Reardon et al., 2021](#)). They provide mean test results from standardized tests by county, year, grade and subject among all students and various subgroups (including race, gender, and economically disadvantaged). The most recent version 4.1 covers grades 3 through 8 in mathematics and Reading Language Arts (RLA) over the 2008-09 through 2017-18 school years.

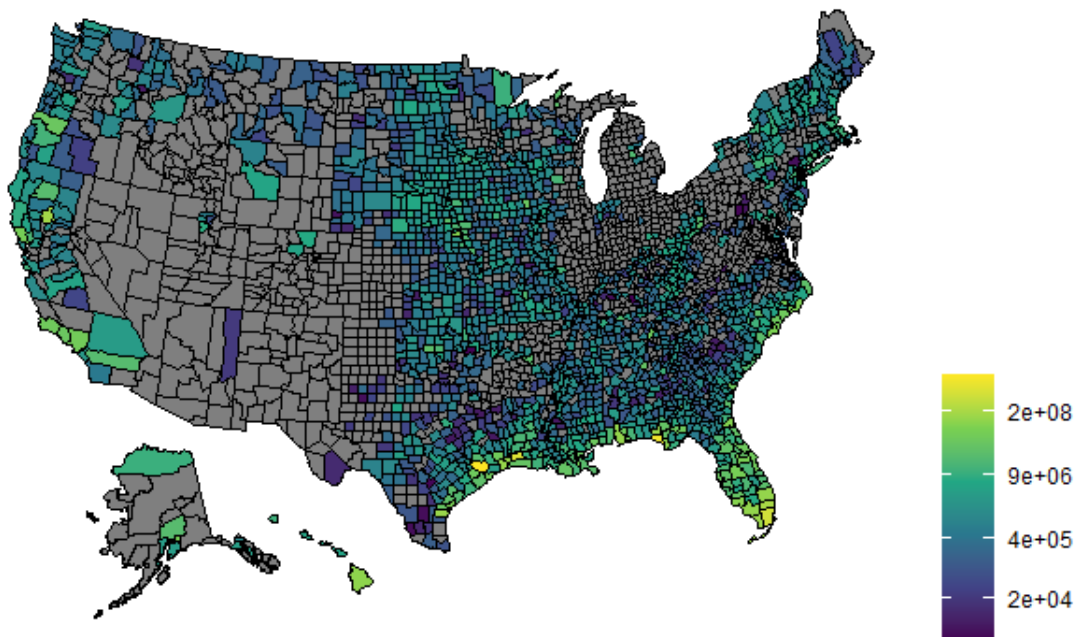


Figure 2: Amount of federal disaster assistance (in USD) awarded to counties since October 2016

Test scores are cohort-standardized, meaning they can be interpreted relatively to an average national reference cohort in the same grade. For instance, a county mean of 0.5 indicates that the average student in the county scored approximately one half of a standard deviation higher than the average national student in the same grade.

In addition to mean test scores, the data includes estimates of gap estimates for various subgroups, e.g. mean difference in test scores among white and black students. These are only reported if the subgroups' sample sizes are large enough. Thus, the number of observations for some of the gap statistics is substantially smaller.

Furthermore, the Stanford Education Data Archive maintains a large set of covariates for each county and year. They include variables like the county's median income, unemployment and ethnic proportions.

2.3 Combining disaster and testing data

Natural disasters should only have an effect on test scores if they occur before the test. Standardized tests are generally administered during spring. We will use March 1st as a cut-off point. Thus, any disaster happening within the same school year before the 1st of March will be considered. School years tend to start in late August or early September with some variation across states. We will use September 1st, meaning any disaster happening between September 1st and March 1st will be counted for a given school year.

Each disaster is assigned to a school year as described above. Then, disaster and test score data can be merged by school year and county. This yields a panel data set with six grades and two subjects for each county-year combination. Table 1 shows summary statistics for all relevant variables

Table 1: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Disasters	331778	0.222	0.569	0	0	0	6
Disaster Dummy	331778						
... 0	278656	84%					
... 1	53122	16%					
Cumulative Disasters	331778	1.259	1.645	0	0	2	14
Grade	339264						
... 3	58762	17.3%					
... 4	58660	17.3%					
... 5	57417	16.9%					
... 6	57146	16.8%					
... 7	54538	16.1%					
... 8	52741	15.5%					
Subject	339264						
... Mathematics	165780	48.9%					
... RLA	173484	51.1%					
Mean test score	328273	-0.041	0.294	-3.196	-0.214	0.152	1.669
White-Black gap	131047	0.618	0.256	-0.754	0.454	0.771	2.358
Male-Female gap	306961	-0.131	0.199	-1.612	-0.258	0.001	1.248
Disadvantaged gap	283272	0.543	0.211	-0.995	0.413	0.669	2.052
Log Income	339003	10.693	0.253	9.305	10.547	10.835	11.727
Unemployment	339003	0.078	0.032	0.001	0.057	0.096	0.3

3 Empirical Strategy

In order to identify a causal effect, unobservable determinants of a county’s mean test score must be unrelated to natural disasters conditional on observable characteristics of that county. Potential confounders are likely to fall into one of the following categories: Effects varying by county but constant across time, time varying effects constant across counties, and characteristics of the county that vary across time and counties. Thus, a two way fixed-effects design with some sociodemographic control variables can credibly deliver causal estimates.

Consequently, the baseline specification is

$$y_{i,t,g,s} = \alpha_i + \lambda_t + \zeta_g + \xi_s + \beta D_{i,t} + X_{i,t}\gamma + \varepsilon_{i,t,g,s} , \quad (1)$$

where $y_{i,t,g,s}$ is the outcome of interest for county i , year t , grade g , and subject s . Note that D and X do not vary by grades and subject. That is, treatment and covariates are constant for all grades and subject within a given county-year combination.

Let $\widehat{\beta}$ be the OLS estimator for β in (1). [de Chaisemartin and D’Haultfoeulle \(2020\)](#) show that under the common trends assumption,

$$\mathbb{E} \left[\widehat{\beta} \right] = \mathbb{E} \left[\sum_{(i,t): D_{i,t}=1} w_{i,t} \Delta_{i,t} \right] ,$$

where $\Delta_{i,t}$ is the average treatment effect (ATE) in county i and year t . That is, the estimated coefficient is a weighted combination of average treatment effects across all treated county-year combinations. Importantly, these weights can be negative. This does not lead to problems if the treatment effects are constant, but it may cause substantial bias if they are not.

It is implausible that the treatment effects are constant in our setting. The extent of disasters varies substantially, and also the level of preparation for such disasters likely displays high variance across counties. If treatment effects are heterogenous, this can lead to a situation where the treatment effect is positive in each group and period, but the weighted average is negative, or vice versa ([de Chaisemartin and D’Haultfoeulle, 2021](#)).

[Zhang and de Chaisemartin \(2021\)](#) provide an R implementation for the weights computation which makes it easy to check the signs. If all the signs are positive, a conventional estimator can be used. If they are not, [de Chaisemartin and D’Haultfoeulle \(2020\)](#) propose an alternative estimator.

4 Results

Table 2 and 3 show the results of the estimated models for mathematics and RLA respectively.

Table 2: Results (Mathematics)

Dependent Variables: Model:	Mean test score (1)	White-Black (2)	White-Hispanic (3)	Male-Female (4)	Adv.-Disadv. (5)
<i>Variables</i>					
Year=-9	-0.0277*** (0.0083)	0.0767*** (0.0105)	0.0211* (0.0111)	0.0015 (0.0073)	0.0608*** (0.0083)
Year=-8	-0.0380*** (0.0066)	0.0644*** (0.0088)	0.0136 (0.0090)	-0.0024 (0.0060)	0.0487*** (0.0067)
Year=-7	-0.0434*** (0.0056)	0.0589*** (0.0077)	0.0211*** (0.0077)	-0.0162*** (0.0050)	0.0499*** (0.0057)
Year=-6	-0.0387*** (0.0053)	0.0343*** (0.0074)	0.0067 (0.0072)	-0.0164*** (0.0049)	0.0421*** (0.0055)
Year=-5	-0.0198*** (0.0041)	0.0176*** (0.0056)	-0.0069 (0.0057)	-0.0067* (0.0037)	0.0223*** (0.0042)
Year=-4	-0.0126*** (0.0041)	0.0088 (0.0056)	-0.0059 (0.0058)	-0.0049 (0.0037)	0.0164*** (0.0042)
Year=-3	-0.0063* (0.0037)	0.0109** (0.0050)	-0.0073 (0.0051)	-0.0017 (0.0032)	0.0075** (0.0037)
Year=-2	-0.0040 (0.0032)	0.0044 (0.0046)	-0.0041 (0.0045)	-0.0045 (0.0029)	0.0027 (0.0032)
Year=0	-0.0061** (0.0028)	-8.67×10^{-5} (0.0041)	0.0055 (0.0039)	-0.0042 (0.0025)	0.0004 (0.0028)
Year=1	-0.0086*** (0.0030)	0.0019 (0.0044)	0.0069 (0.0043)	-0.0084*** (0.0027)	0.0025 (0.0030)
Year=2	-0.0067** (0.0033)	-0.0044 (0.0048)	0.0011 (0.0046)	-0.0023 (0.0029)	-0.0036 (0.0032)
Year=3	-0.0093*** (0.0034)	-0.0061 (0.0050)	0.0083* (0.0048)	-0.0046 (0.0030)	-0.0032 (0.0033)
Year=4	-0.0145*** (0.0037)	-0.0087 (0.0055)	0.0036 (0.0052)	-0.0084*** (0.0033)	-0.0073** (0.0036)
Year=5	-0.0133*** (0.0042)	-0.0244*** (0.0065)	0.0038 (0.0059)	-0.0073** (0.0037)	-0.0066 (0.0041)
Year=6	-0.0049 (0.0042)	-0.0235*** (0.0068)	0.0088 (0.0061)	-0.0099*** (0.0038)	-0.0083** (0.0041)
Year=7	0.0098** (0.0048)	-0.0282*** (0.0075)	0.0189*** (0.0070)	-0.0074* (0.0043)	-0.0051 (0.0047)
Year=8	0.0134** (0.0063)	-0.0086 (0.0104)	0.0209** (0.0092)	-0.0044 (0.0056)	-0.0046 (0.0062)
<i>Fixed-effects</i>					
Year	Yes	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes	Yes
Grade	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	158,110	62,653	68,294	147,998	136,249
R ²	0.72285	0.61365	0.63448	0.21976	0.49781
Within R ²	0.00372	0.00510	0.00208	0.00151	0.00368

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Results (RLA)

Dependent Variables: Model:	Mean test score (1)	White-Black (2)	White-Hispanic (3)	Male-Female (4)	Adv.-Disadv. (5)
<i>Variables</i>					
Year=-9	-0.0359*** (0.0070)	0.0716*** (0.0102)	-0.0037 (0.0114)	0.0061 (0.0079)	0.0530*** (0.0085)
Year=-8	-0.0116** (0.0055)	0.0534*** (0.0086)	0.0094 (0.0092)	0.0183*** (0.0066)	0.0438*** (0.0069)
Year=-7	-0.0060 (0.0046)	0.0690*** (0.0076)	0.0104 (0.0079)	0.0090* (0.0055)	0.0498*** (0.0058)
Year=-6	-0.0013 (0.0044)	0.0598*** (0.0072)	0.0161** (0.0073)	0.0103* (0.0053)	0.0510*** (0.0056)
Year=-5	-0.0007 (0.0034)	0.0101* (0.0053)	0.0022 (0.0058)	0.0006 (0.0039)	0.0195*** (0.0042)
Year=-4	0.0073** (0.0033)	0.0086 (0.0053)	-0.0052 (0.0057)	0.0099*** (0.0038)	0.0058 (0.0041)
Year=-3	0.0036 (0.0029)	-0.0079* (0.0047)	-0.0040 (0.0051)	-0.0005 (0.0034)	-0.0068* (0.0036)
Year=-2	-0.0041 (0.0026)	-0.0014 (0.0043)	0.0001 (0.0045)	-0.0005 (0.0030)	0.0030 (0.0032)
Year=0	-0.0012 (0.0023)	0.0029 (0.0038)	0.0089** (0.0039)	-0.0033 (0.0026)	0.0003 (0.0028)
Year=1	0.0028 (0.0024)	-0.0112*** (0.0041)	0.0014 (0.0043)	-0.0143*** (0.0028)	-0.0018 (0.0030)
Year=2	0.0002 (0.0026)	-0.0045 (0.0044)	0.0134*** (0.0046)	-0.0128*** (0.0030)	-0.0011 (0.0032)
Year=3	0.0013 (0.0027)	-0.0191*** (0.0046)	0.0173*** (0.0048)	-0.0171*** (0.0031)	-0.0030 (0.0033)
Year=4	-0.0024 (0.0029)	-0.0312*** (0.0049)	0.0184*** (0.0052)	-0.0215*** (0.0033)	-0.0150*** (0.0035)
Year=5	0.0006 (0.0033)	-0.0486*** (0.0059)	0.0131** (0.0060)	-0.0207*** (0.0038)	-0.0257*** (0.0040)
Year=6	0.0028 (0.0034)	-0.0500*** (0.0060)	0.0178*** (0.0061)	-0.0242*** (0.0039)	-0.0253*** (0.0040)
Year=7	0.0195*** (0.0039)	-0.0470*** (0.0070)	0.0272*** (0.0070)	-0.0267*** (0.0045)	-0.0150*** (0.0047)
Year=8	0.0284*** (0.0050)	-0.0255*** (0.0092)	0.0513*** (0.0089)	-0.0143** (0.0057)	-0.0089 (0.0059)
<i>Fixed-effects</i>					
Year	Yes	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes	Yes
Grade	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	169,246	67,940	72,032	158,055	146,172
R ²	0.74481	0.58872	0.61099	0.23741	0.46345
Within R ²	0.00242	0.00951	0.00262	0.00301	0.00506

5 Conclusion

References

- de Chaisemartin, C. and D’Haultfoeuille, X. (2021). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey.
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