Working Title: Natural Disasters and Education

Gregor Steiner

April 27, 2022

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.

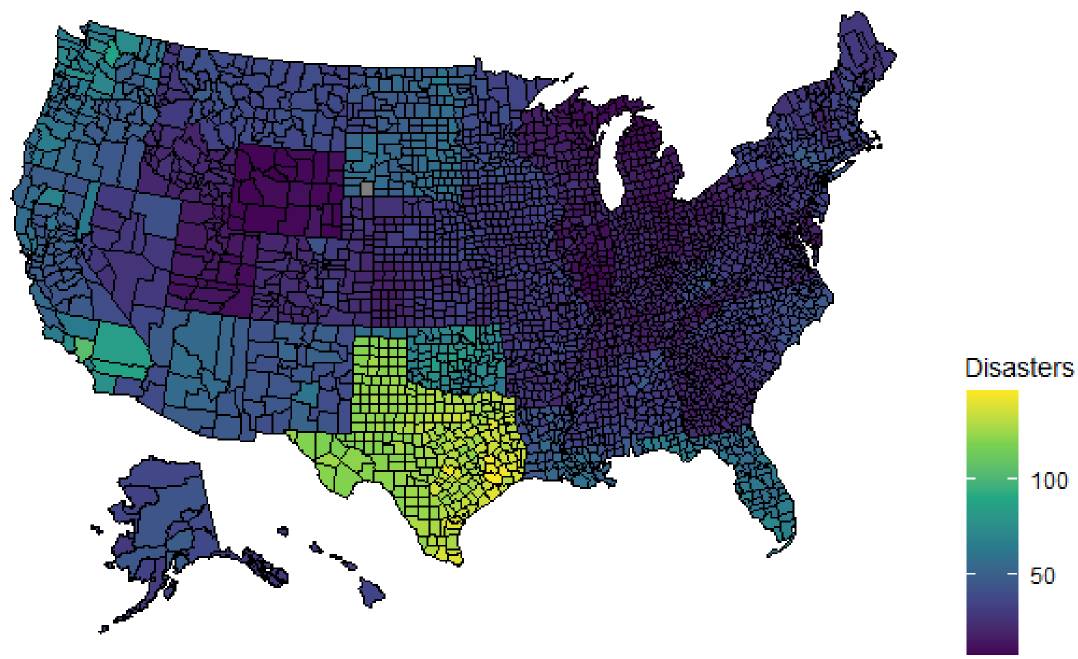

Figure 1: Number of declared natural disasters by county

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.

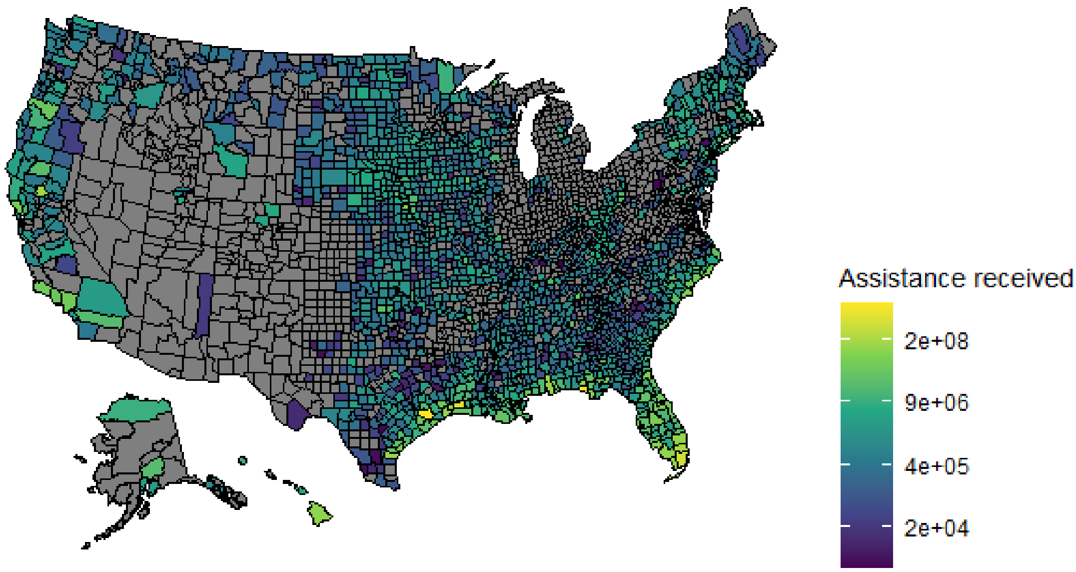

Figure 2: Amount of federal disaster assistance (in USD) awarded to counties since October 2016

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	330087						
... 3	57046	17.3%					
... 4	56946	17.3%					
... 5	55962	17%					
... 6	55694	16.9%					
... 7	53113	16.1%					
... 8	51326	15.5%					
Subject	330087						
... Mathematics	159977	48.5%					
... RLA	170110	51.5%					
Mean test score	323218	-0.04	0.291	-2.696	-0.213	0.153	1.669
White-Black gap	129071	0.617	0.256	-0.754	0.454	0.77	2.358
Male-Female gap	302398	-0.131	0.199	-1.612	-0.257	0.001	1.248
Disadvantaged gap	279288	0.542	0.21	-0.908	0.413	0.668	2.052
Log Income	329826	10.701	0.232	9.826	10.552	10.834	11.727
Unemployment	329826	0.077	0.03	0.001	0.056	0.095	0.218

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

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

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'Haultfœuille (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'Haultfoeuille, 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'Haultfœuille (2020) propose an alternative estimator.

4 Results

Table 2 shows the results of the estimated models.

Table 2: Results

Dependent Variables:	Mean test score	White-Black gap	Male-Female gap	Disadvantaged gap
Model:	(1)	(2)	(3)	(4)
Variables				
Disaster	-0.0002	0.0002	-0.0033***	-0.0057***
	[-0.0019; 0.0015]	[-0.0023; 0.0028]	[-0.0050; -0.0017]	[-0.0075; -0.0040]
Log Income	-0.0207***	0.0807***	-4.41×10^{-5}	0.0196**
	[-0.0337; -0.0077]	[0.0538; 0.1075]	[-0.0134; 0.0134]	[0.0044; 0.0347]
Fixed-effects				
Year	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes
Grade	Yes	Yes	Yes	Yes
Subject	Yes	Yes	Yes	Yes
Fit statistics				
Observations	323,218	129,071	302,398	279,288
R^2	0.69411	0.57790	0.41405	0.46097
Within R^2	3.03×10^{-5}	0.00027	5.29×10^{-5}	0.00018

IID co-variance matrix, 95% confidence intervals in brackets
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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.

de Chaisemartin, C. and D'Haultfœuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

Reardon, S., Kalogrides, D., Ho, A., Shear, B., Fahle, E., Jang, H., and Chavez, B. (2021). Stanford education data archive (version 4.1).

Turner, D. (2022). rfema: Access the openfema api. *rOpenSci*.

Zhang, S. and de Chaisemartin, C. (2021). *TwoWayFEWeights: Estimation of the Weights Attached to the Two-Way Fixed Effects Regressions*. R package version 0.1.0.