The Impact of Natural Disasters on Education: Evidence from Standardized Testing

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Introduction

I exploit quasi-random variation in natural disaster exposure in the United States to answer two questions:

- **What is the causal effect of natural disasters on academic achievement as measured by standardized test scores?**
- What is the role of federal disaster assistance? Which counties apply for assistance?

Why is this important?

Negative effects in education affect earnings potential $\implies$ Inequality in disaster risk exposure could exacerbate economic inequality

Data

- **Natural disasters**:
  - Federal Emergency Management Agency (FEMA) declarations
  - Storms from the National Weather Service (NWS)
  - Daily temperature data from the Global Historical Climatology Network
- **Standardized testing outcomes** from the Stanford Education Data Archive (Reardon et al., 2021):
  - Cohort standardized average scores by county in Mathematics & Reading Language Arts (RLA)
  - Grades 3 through 8 for schoolyears 2008-09 to 2017-18
- **Public Assistance applications and payments** from FEMA

Distribution of mean test scores by subgroup

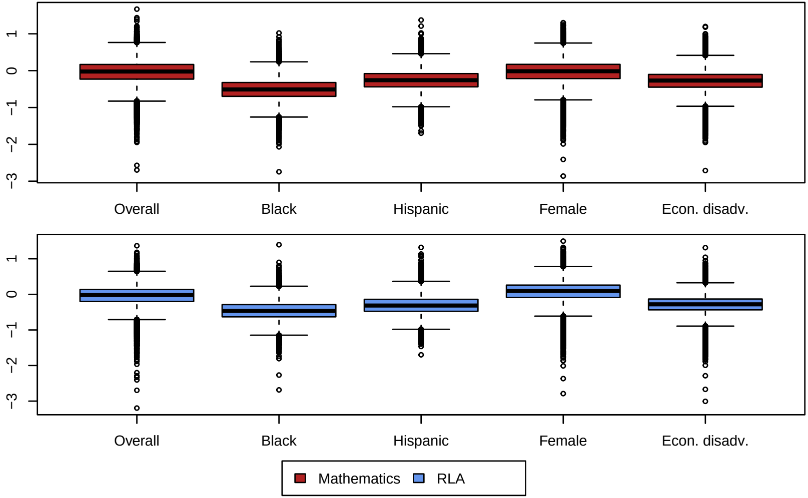

Figure: Boxplots of mean test scores by subgroup

Natural Disasters in the US

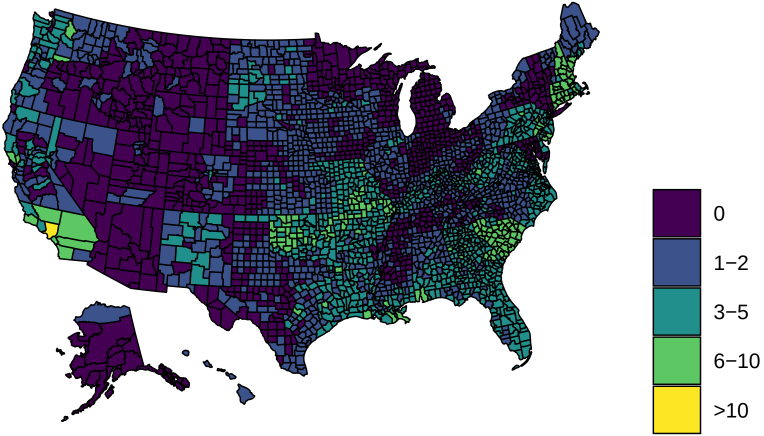

Figure: Number of declared natural disasters in school years 2008-09 through 2017-18

When do counties apply for assistance?

Table: Share of counties that applied for federal assistance following a disaster by disaster type (schoolyears 2016-17 and 2017-18)

	Number of Cases	Applied for Assistance (in %)
Dam/Levee Break	3	0.00
Fire	106	10.38
Flood	85	9.41
Hurricane	1263	23.91
Mud/Landslide	1	0.00
Severe Ice Storm	20	0.00
Severe Storm(s)	154	30.52
Tornado	29	79.31
Total	1661	23.54

Which counties apply for assistance?

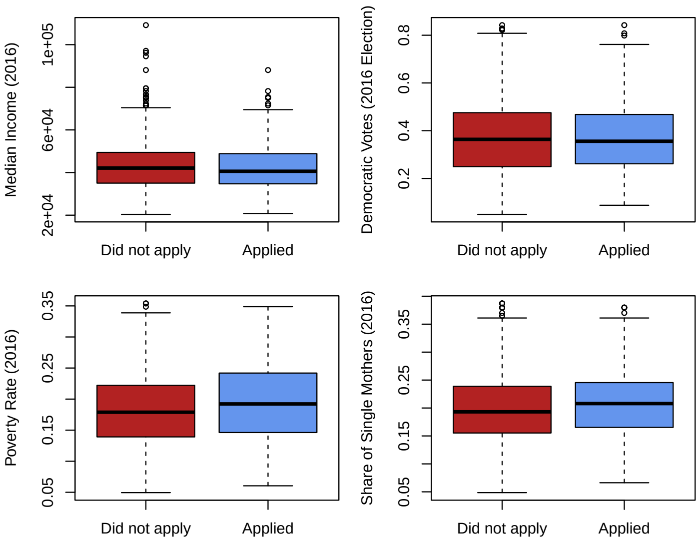

Figure: Boxplots by application status

Empirical Strategy

- Event-study design:

$$y_{i,t,g} = \beta_{-5}\mathbb{1}\{t - E_i \leq 5\} + \sum_{l=-4,\, l\neq -1}^{8} \beta_l \mathbb{1}\{t - E_i = l\}$$
$$+ \alpha_i + \lambda_t + \zeta_g + \varepsilon_{i,t,g}$$

- Treatment begins in the period of first disaster (E_i) and is absorbing (staggered adoption)
- But: Always-treated (i.e. disaster in the first year) counties are dropped
- Never-treated counties act as the baseline
- Standard-errors clustered at the cohort level (Abadie et al., 2017)

Empirical Strategy: Identification

- Natural disasters are plausibly independent of unobserved determinants of test scores conditional on location and year
- Heterogenous treatment effects $\implies$ simple TWFE is inadequate (de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2021)
- Solution: Interaction-Weighted Estimator (IW) by Sun and Abraham (2021)
- Identifying Assumptions: Parallel Trends & No Anticipatory Behavior
- IW consistently estimates a weighted average of cohort average treatment effects on the treated (CATT)

Main Results: FEMA

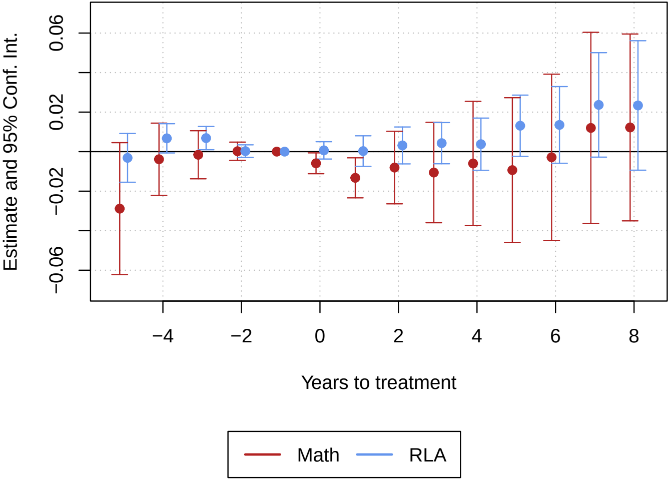

Figure: Dynamic Treatment effects in relative time: FEMA disaster data

Main Results: Subgroups, FEMA

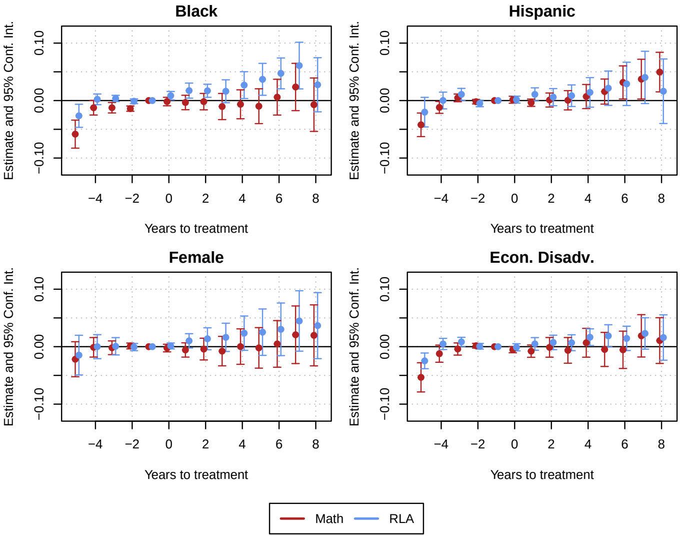

Figure: Dynamic Treatment effects in relative time: FEMA disaster data

Main Results: Storms

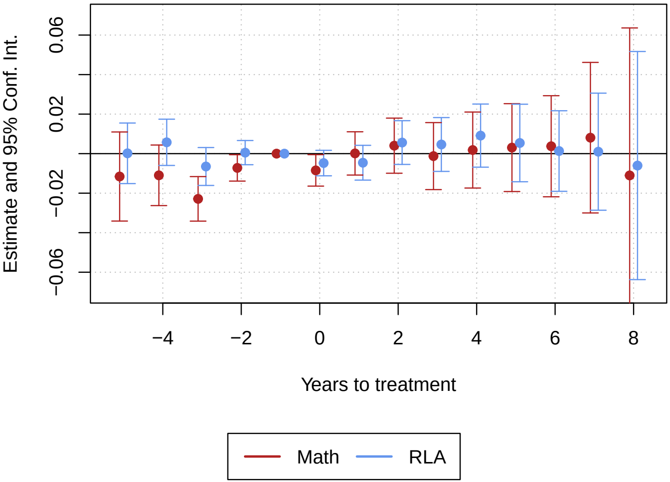

Figure: Dynamic Treatment effects in relative time: NWS storm data

Main Results: Subgroups, Storms

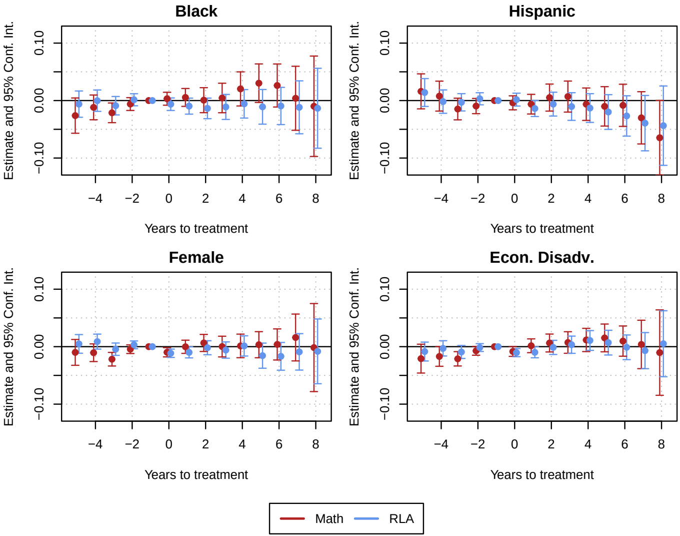

Figure: Dynamic Treatment effects in relative time: NWS storm data

Are these results driven by changes in county composition?

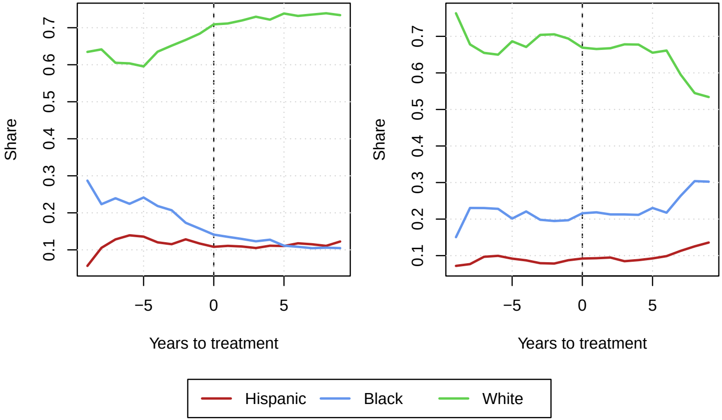

Figure: Aggregated ethnic shares by treatment timing based on FEMA disasters (left) and on NWS storms (right)

Conclusion

- Negative short-term effect of disasters on achievement in mathematics
- Some positive long-term effects among subgroups (but not very robust)
- Socially vulnerable counties are more likely to need federal assistance following a disaster

References

Abadie, A., Athey, S., Imbens, G. W., and Wooldridge, J. (2017). When should you adjust standard errors for clustering? Technical report, National Bureau of Economic Research.

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

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