

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

Gregor Steiner

June 10, 2022

# 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)
  - ▶ Work in progress: Data on extreme heat
- ▶ **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 2008/2009 to 2017/2018
- ▶ **Public Assistance applications and payments** from FEMA

# Distribution of mean test scores by subgroup

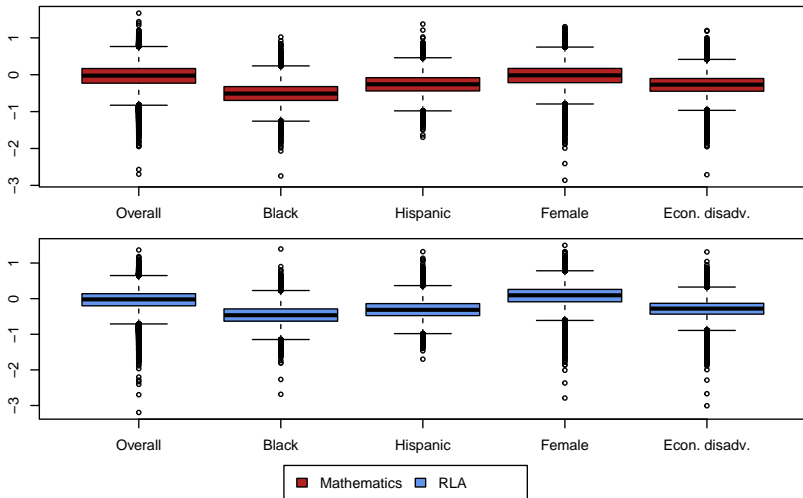


Figure: Boxplots of mean test scores by subgroup

# When do counties apply for assistance?

**Table:** Share of counties that applied for federal assistance following a disaster by disaster type (schoolyears 2016/2017 and 2017/2018)

	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?

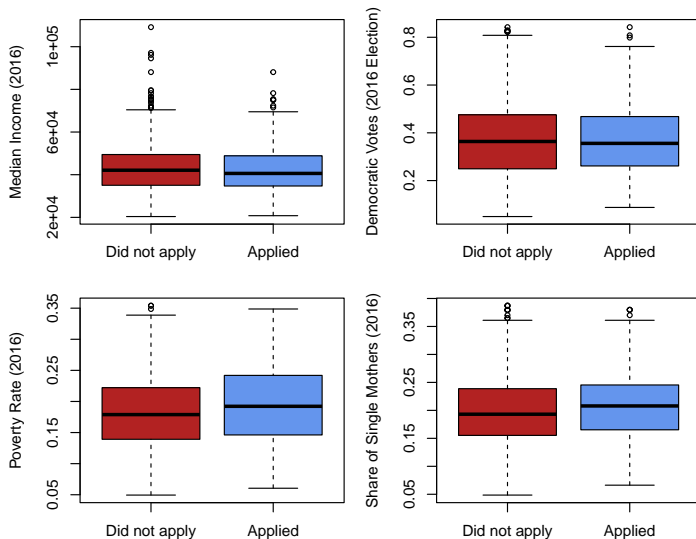


Figure: Boxplots by application status

# 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 and test scores are plausibly **independent conditional on location** (county fixed-effects)
- ▶ Heterogenous treatment effects  $\implies$  simple TWFE is inadequate (de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2021)
- ▶ Solution: Interaction-Weighted Estimator 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

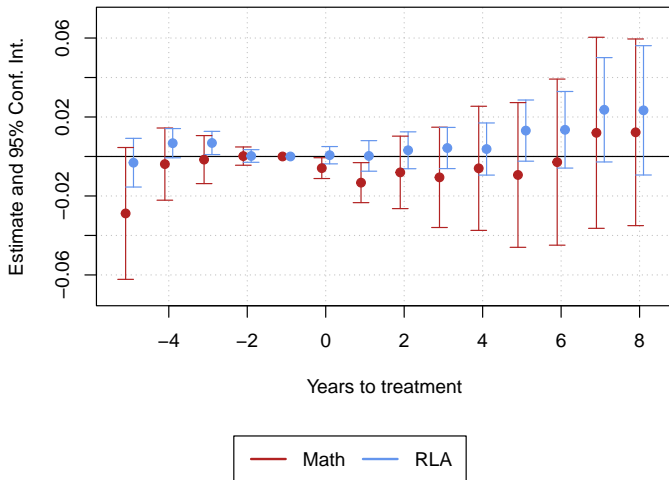


Figure: Dynamic Treatment effects in relative time: FEMA disaster data

# Main Results: Subgroups, FEMA

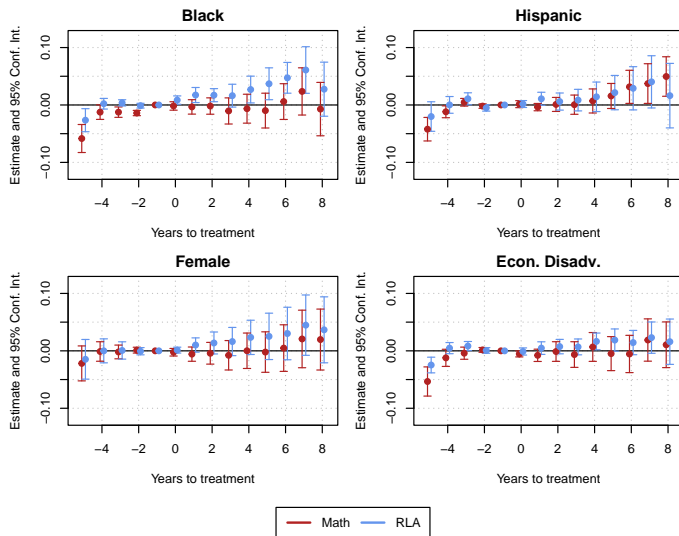


Figure: Dynamic Treatment effects in relative time: FEMA disaster data

# Main Results: Storms

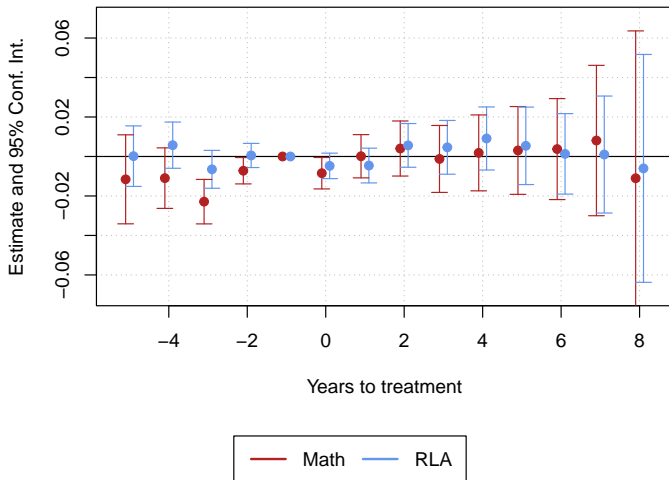


Figure: Dynamic Treatment effects in relative time: NWS storm data

# Main Results: Subgroups, Storms

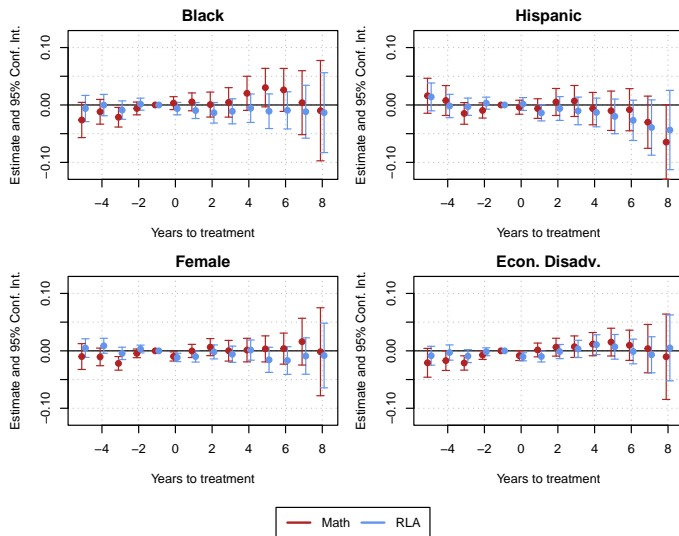
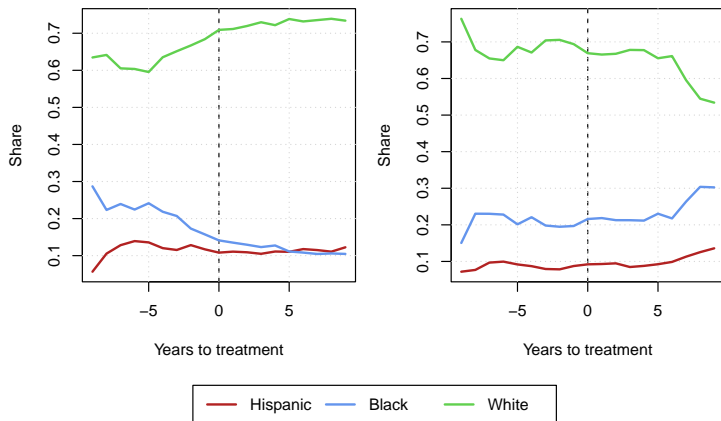


Figure: Dynamic Treatment effects in relative time: NWS storm data

# 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.
- 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).
- Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.