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

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Motivation: Natural disasters over time

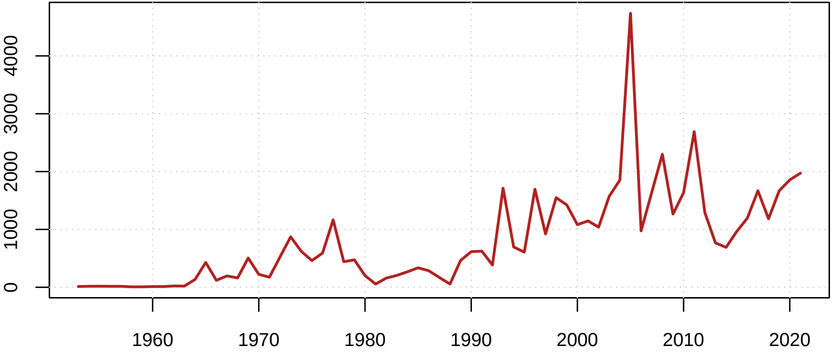

Figure: Number of county-level natural disasters by year

Motivation: Distribution of natural disasters

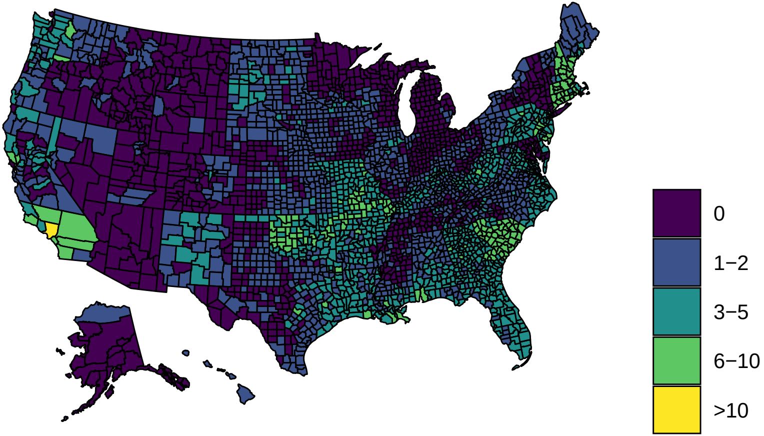

Figure: Number of declared natural disasters in school years 2008-09 through 2017-18

Research question

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 $\Longrightarrow$ 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

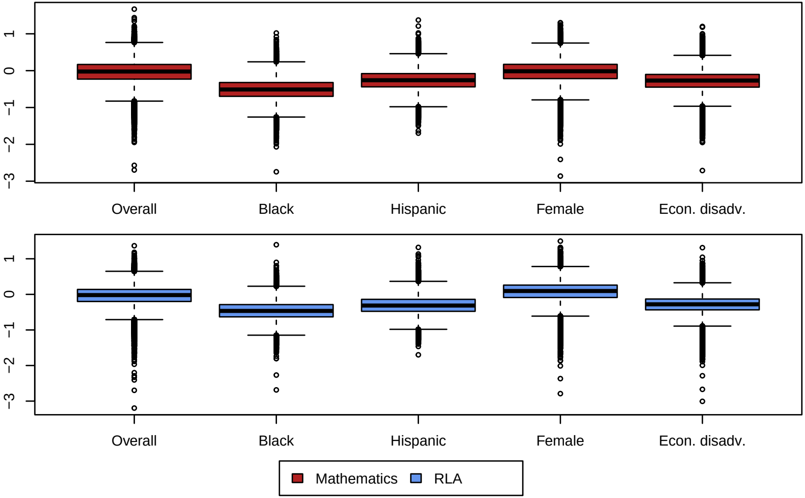

Figure: Boxplots of mean test scores by subgroup

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?

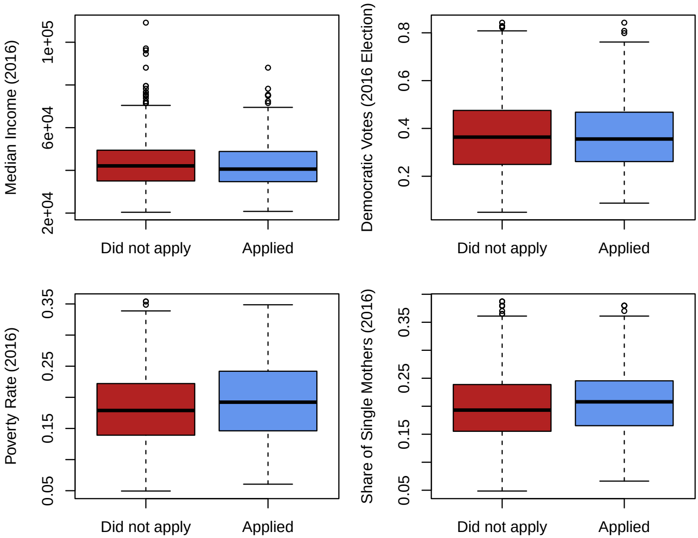

Figure: Boxplots by application status

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

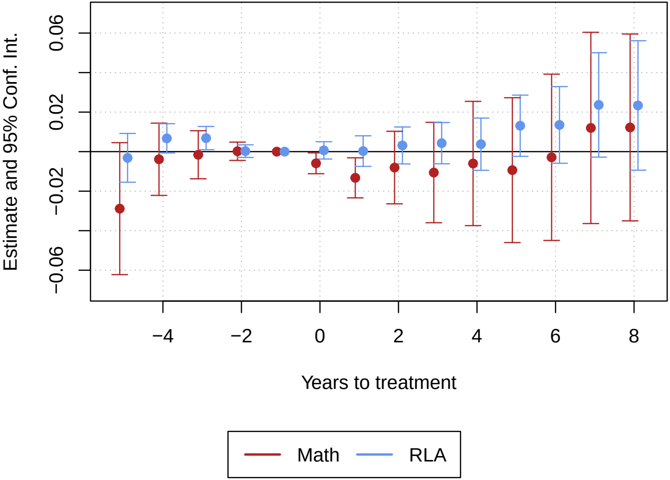

Figure: Dynamic Treatment effects in relative time: FEMA disaster data

Main Results: Subgroups, FEMA

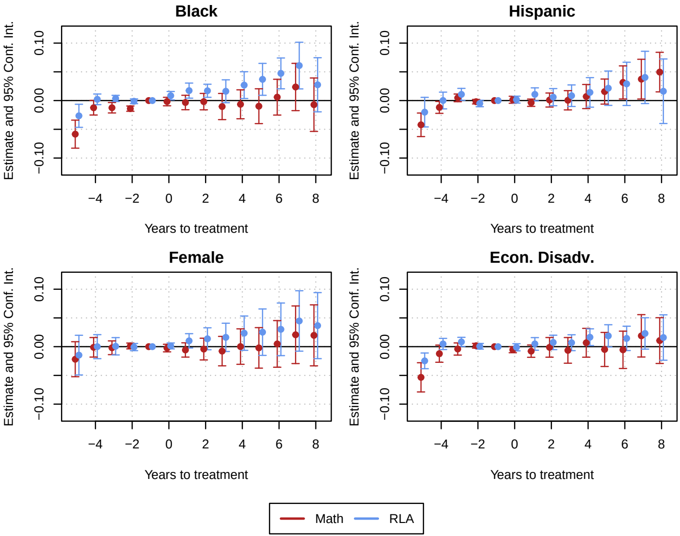

Figure: Dynamic Treatment effects in relative time: FEMA disaster data

Main Results: Storms

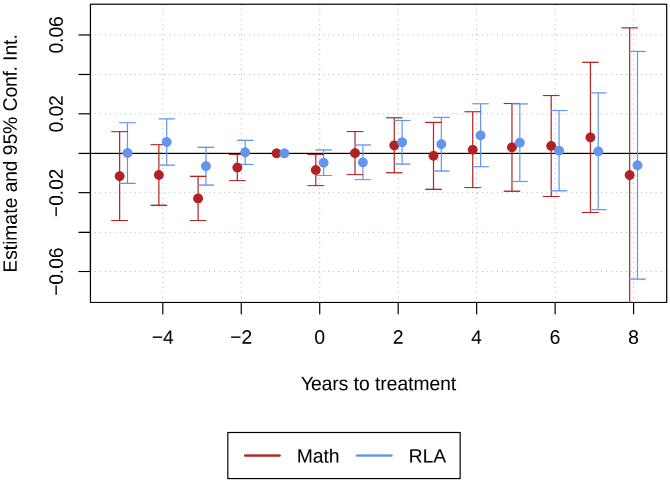

Figure: Dynamic Treatment effects in relative time: NWS storm data

Main Results: Subgroups, Storms

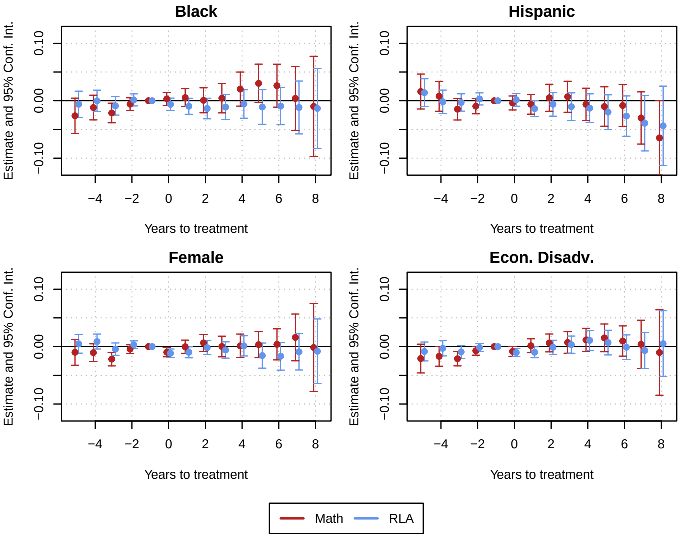

Figure: Dynamic Treatment effects in relative time: NWS storm data

Are these results driven by changes in county composition?

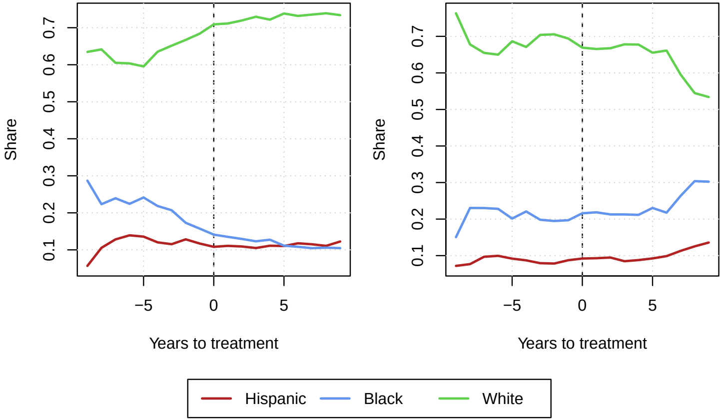

Figure: Aggregated ethnic shares by treatment timing based on FEMA disasters (left) and on NWS storms (right)

Empirical Strategy: Heat

- A binary treatment indicator is not well-suited to measure cumulative heat exposure. Following Park et al. (2020), I use two measures:
  - Average daily maximum temperature
  - Number of days above 30°C
- Linear model with county, year, and grade fixed effects:

$$y_{i,t,g} = \beta H_{i,t} + \alpha_i + \lambda_t + \zeta_g + \varepsilon_{i,t,g}$$

- Conditional on location and year, heat exposure is exogenous
- Interesting marginal interpretation of β: What is the effect of a 1°C hotter school year or of one additional day above 30°C on average test scores?

Heat: Average daily maximum temperature

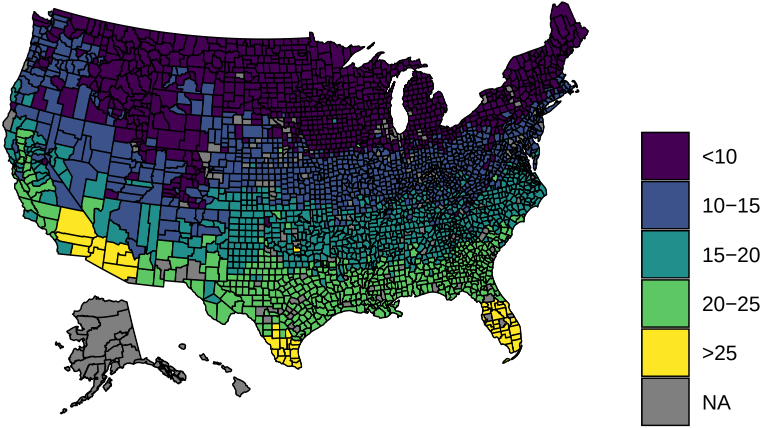

Figure: Average daily maximum temperature (in °C) in school years 2008-09 through 2017-18

Heat: Average number of days above 30°C

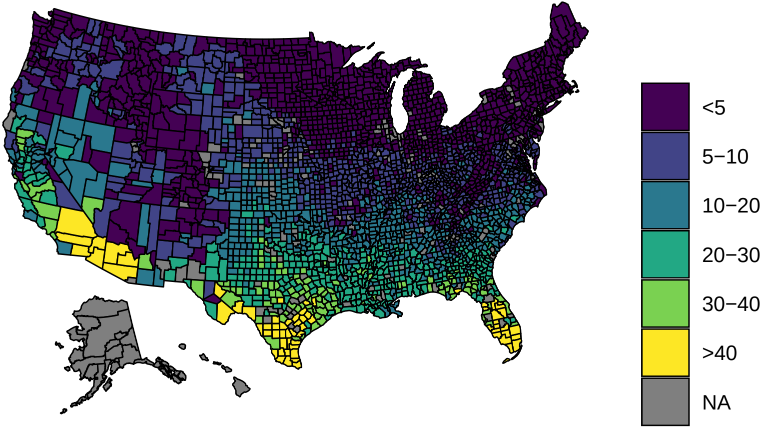

Figure: Average number of days above 30°C in school years 2008-09 through 2017-18

Heat Results

- No significant overall effect, but minorities seem to be more affected
- Possibly driven by unequal access to air-conditiong (Park et al., 2020)

Table: Estimated coefficients for heat models

	Overall	Black	Hispanic	Female	Econ. Disadv.
Max. Temp. (Math)	−0.0007 (0.0003)	−0.0006 (0.0008)	−0.0021*** (0.0006)	−0.001*** (0.0004)	−0.0011*** (0.0004)
Max. Temp. (RLA)	−0.0001 (0.0003)	−0.0015*** (0.0007)	−0.0011*** (0.0006)	−0.0002 (0.0003)	−0.0004 (0.0003)
Days ab. 30 (Math)	−0.000169 (0.000089)	0.000033 (0.000143)	−0.000196 (0.000136)	0.000003 (0.000095)	0.000003 (0.000096)
Days ab. 30 (RLA)	−0.000095 (0.000071)	−0.00014 (0.000122)	−0.000483*** (0.000117)	−0.000202*** (0.000079)	−0.000027 (0.000079)

Note: Standard errors in parentheses. Stars (***) indicate significance at a 5% level

Limitations/Weaknesses

- Potential violations of the parallel trends assumption in the main results based on the FEMA data
- "Better" heat data would be desirable
- Greater overlap between the disaster and public assistance data would allow for a more detailed analysis of the role of aid

Conclusion

- Negative short-term effect of disasters on achievement in mathematics
- Some positive long-term effects among subgroups (but not very robust)
- No overall effect of heat on average test scores, but negative effects for some subgroups
- Socially vulnerable counties are more likely to need federal assistance following a disaster

References

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