

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

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July 1, 2022

Abstract

The frequency and severity of natural disasters has increased recently, but we do not fully understand the impacts. We use an event-study design to estimate dynamic treatment effects of natural disasters on students' performance in standardized tests. There is a significant effect on the performance in mathematics in the period of the disaster. For achievement in Reading Language Arts we find no significant effect. Furthermore, we find a significantly negative effect of extreme heat exposure on standardized test scores for some groups.

1 Introduction

Natural disasters are responsible for massive economic damage and due to climate change the frequency of such disasters will increase in most regions ([Intergovernmental Panel on Climate Change, 2021](#)). Therefore, it is essential to have a good understanding of the consequences. Few studies have focused on the impact on the education system, yet this is a crucial part of understanding the economic consequences. Negative effects in education are likely to have long-term impact on earnings potential. Inequality in disaster risk exposure could therefore exacerbate economic inequality.

A causal effect of natural disasters may be driven by school closures ([Grewenig et al., 2021](#)) or lowered attendance ([Spencer et al., 2016](#)), destroyed infrastructure, and emotional stress ([Vogel and Schwabe, 2016](#)). In the very short term, emotional stress caused by extended housing instability, food insecurity, parental job loss, or social disconnection may be the most important factor, especially so in socially vulnerable communities ([United States Government Accountability Office, 2022](#)). Furthermore, some forms of disasters, e.g. extreme heat, may directly impair cognitive performance ([Ramsey, 1995](#)). Lastly, many students have to relocate and switch schools following a disaster. Such migration responses may also have a significant effect on the scholastic achievement of affected students ([Pane et al., 2008](#); [Sacerdote, 2012](#)).

To identify dynamic causal effects of experiencing natural disasters, this paper uses an event-study design. In particular, we estimate dynamic treatment effects for up to eight years after initial treatment. As a result, not only short-term but also medium to long-term effects can be found. Since treatment effects are likely very heterogeneous, we use the estimator by [Sun and Abraham \(2021\)](#).

This article uses standardized test data on a US county level for grades 3 through 8 in mathematics and reading language arts (RLA) to measure academic performance, covering the school years 2008/2009 to 2017/2018. This measure is very attractive as the test scores are standardized relative to a national reference cohort. Therefore, the outcomes are nationally comparable. For

the same period, we obtain data on natural disasters from declarations by the Federal Emergency Management Agency and data on storms from the National Weather Service.

We find strong evidence of a negative effect of disasters on mathematics performance in the same school year. Evidence of a significant effect on RLA, as well as for medium and long term effects is rather weak.

Furthermore, we investigate the effect of heat exposure as a very special case of natural disasters. We find negative effects on some groups, but there seems to be substantial heterogeneity.

Previous Work: This article contributes to the literature on the impact of natural disasters on the education system in the United States. Previous work has produced mixed results. Some authors find significant effects of natural disasters on the education system, while others find no or only small effects.

[Holmes \(2002\)](#) was among the first to study the effect of extreme weather events on academic achievement. Using a difference-in-differences approach, he finds a significantly negative effect of storms on the performance of North Carolina students. [Baggerly and Ferretti \(2008\)](#) find a statistically significant, but negligibly small effect of the 2004 hurricanes on the performance of students' test scores in Florida. [Lamb et al. \(2013\)](#) study the effects of hurricane Katrina and find a significant impact on mathematics achievement in Mississippi with the greatest effects in nonpoor and nonrural schools.

[Park et al. \(2020\)](#) find that cumulative heat exposure negatively impacts PSAT scores. At the same time, they find air conditioning to be very successful at mitigating the negative effect of heat exposure. Similarly, [Park \(2022\)](#) uses student level data from New York City to assess the impact of heat in high stakes exams. He finds a substantial negative effect on performance.

Many authors have focused on the role of student mobility as a consequence of natural disasters. [Pane et al. \(2008\)](#) focus on students who switch schools following hurricanes Katrina and Rita and find small negative effects of displacement on test scores. Similarly, [Sacerdote \(2012\)](#) finds sharp declines in test scores one year after the hurricanes, but a substantial improvement three to four years after. This is largely driven by the students' tendency to switch to higher quality schools.

Most authors have focused on a single type or even a single instance of disasters. In particular, storms and heat have been investigated predominantly. The main contribution of this article is the very comprehensive dataset which covers multiple years and many different types of disasters. To the best of our knowledge, this is the first analysis using such a broad set of natural disasters to analyze the effect on academic performance.

The rest of this paper is organized as follows: Section 2 gives some institutional background, introduces the data used and presents some descriptive statistics. Section 3 explains the empirical strategy. Section 4 discusses the results and Section 5 concludes.

2 Background & Data

2.1 Natural Disasters in the United States

Natural disasters cause numerous fatalities and billions of dollars of infrastructure damage in the United States each year ([Boustan et al., 2020](#)). With more greenhouse gas in the atmosphere the number and severity of such disasters will increase ([Intergovernmental Panel on Climate Change, 2021](#)). Figure 1 shows the number of county-level disasters per year. However, note that a single disaster that affects multiple counties counts as multiple county-level disasters. The majority of natural disasters in the US is made up by storms, such as hurricanes or tornadoes, floodings, and

fires. Some well-known examples include the 2020 wildfire season in the western United States, Hurricane Harvey in 2017, or Hurricane Katrina in 2005.

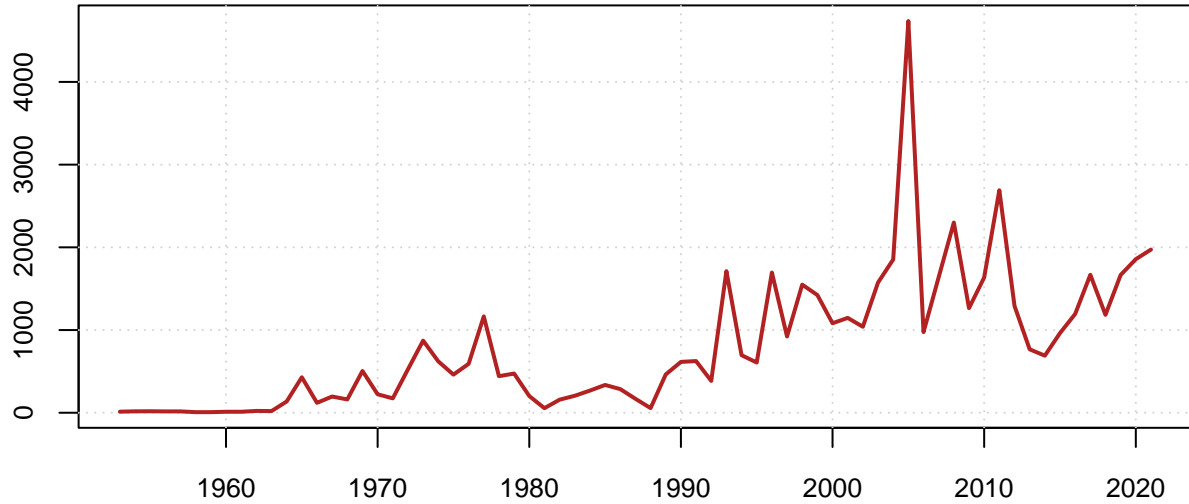


Figure 1: Number of county-level natural disasters by year

The handling of natural disasters is governed by the [Robert T. Stafford Disaster Relief and Emergency Assistance Act \(1988\)](#). It defines major disasters as follows:

Major disaster means any natural catastrophe (including any hurricane, tornado, storm, high water, winddriven water, tidal wave, tsunami, earthquake, volcanic eruption, landslide, mudslide, snowstorm, or drought), or, regardless of cause, any fire, flood, or explosion, in any part of the United States, which in the determination of the President causes damage of sufficient severity and magnitude to warrant major disaster assistance under this Act to supplement the efforts and available resources of States, local governments, and disaster relief organizations in alleviating the damage, loss, hardship, or suffering caused thereby.

Based on the Stafford Act major disaster declarations are made solely by the president upon request by the affected state’s governor. State officials must prove that the situation is beyond the capabilities of the state government or involved local governments. The Federal Emergency Management Agency (FEMA) evaluates requests for major disasters and makes recommendations to the president.

A major disaster declaration provides a wide range of federal assistance programs for individuals and public infrastructure, including funds for both emergency and permanent work. In particular, affected state and local governments can receive federal disaster assistance as part of the Public Assistance program, while individuals and households can receive aid from the Individual Assistance program. Moreover, State, Tribal, and local governments and certain private nonprofit organizations can receive assistance for preventive actions taken based on the Hazard Mitigation Assistance program.

FEMA provides data on all federally declared natural disasters, beginning in 1953. The data is easily accessible via their API ([Turner, 2022](#)). This is the main source for natural disaster data used here. Figure 2 shows the number of declared disasters between 2009 and 2018 across the US. Table 1 shows the types of disasters and their proportion in the FEMA data. Storms make up the largest share of disaster events. Fires and floods also form a substantial part.

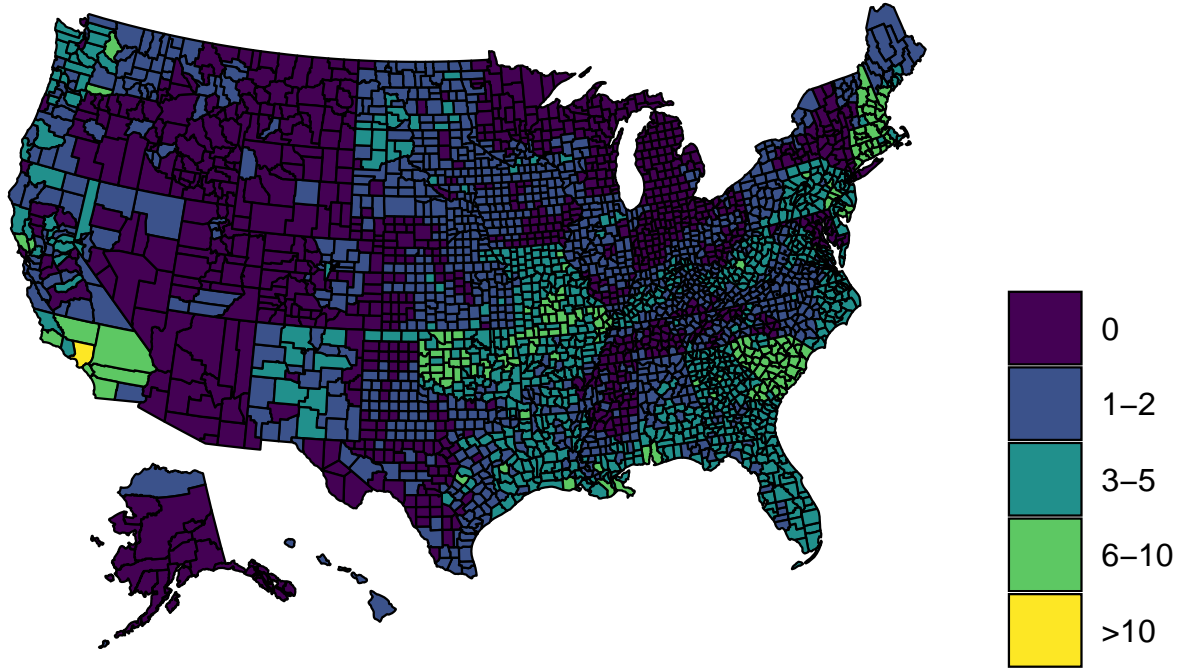


Figure 2: Number of declared natural disasters in school years 2008-09 through 2017-18

We repeat the analysis on two different datasets: Data on storms and data on heat exposure. First, this acts as a robustness check. These two datasets are based on objective measurements, while the FEMA data is based on subjective declarations. Second, this allows us to better understand heterogeneity by type of disaster.

The National Weather Service (NWS) provides data on storm events. In particular, this covers hurricanes, tornadoes, and other severe storms. These make up a very large part of all natural disasters experienced in the United States (see table 1). Combined they account for more than 80% of all disaster damage in the FEMA Public Assistance Applicants Program Deliveries database.

We only consider severe storms which are likely to cause substantial damage. Tornadoes can be classified based on estimated peak wind speeds on the Enhanced Fujita (EF) scale (for more details see [Mcdonald et al., 2004](#)). Tornadoes with an EF scale of 0 or 1 (wind speeds of up to 110 mph) are characterized as weak. Therefore, we exclude those and only keep tornadoes with an EF scale of at least 2 (wind speeds of at least 111 mph). Unfortunately, the hurricane data does not include a similar measure, but it does include an estimated amount of property damage. We exclude all hurricanes with an estimated property damage of zero. Storm exposure by county is shown in figure 3.

To measure heat exposure, we exploit daily temperature data from the Global Historical Climatology Network ([Menne et al., 2012](#)). Each county is assigned the measurement station with the lowest distance to the county’s center. Following [Park et al. \(2020\)](#), we use two measures of yearly cumulative heat exposure: The average daily maximum temperature and the number of days with a maximum temperature above 30°C in a school year. The threshold of 30°C is somewhat arbitrary, however, changing it slightly does not change the results in a meaningful way. Figures 4 and 5 show the distribution across counties. As expected, the variation in heat exposure is largely driven by

Table 1: Disasters from 2009 to 2018 by type

Variable	N	Percent
Disaster Type	6894	
... Chemical	9	0.1%
... Coastal Storm	9	0.1%
... Dam/Levee Break	3	0%
... Earthquake	18	0.3%
... Fire	304	4.4%
... Flood	637	9.2%
... Freezing	1	0%
... Hurricane	2308	33.5%
... Mud/Landslide	3	0%
... Other	1	0%
... Severe Ice Storm	732	10.6%
... Severe Storm(s)	2519	36.5%
... Snow	297	4.3%
... Tornado	48	0.7%
... Toxic Substances	1	0%
... Tsunami	3	0%
... Volcano	1	0%

location.

2.2 Assistance Applications

FEMA also provides a dataset on their Public Assistance Applicants Program Deliveries. It contains information on applicants and their recovery priorities, including the amount of damage caused and amount of federal disaster assistance granted. This is the main program for federal public disaster assistance, averaging USD 4.7 billion in assistance each year. However, note that counties that do not receive public assistance may still benefit from individual assistance or from the Hazard Mitigation Assistance program.

Unfortunately, this data is only available starting in October 2016. Based on the temporal overlap between this dataset and our main dataset, that is schoolyears 2016/2017 and 2017/2018, it is possible to analyze whether counties that are affected by disasters receive federal assistance. This can be done by checking whether a county that experienced a disaster in 2016/2017 or 2017/2018 appears in the Public Assistance Applicants Program Deliveries database. In fact, only about 17.78% of counties that experienced a disaster in that period did apply for federal assistance. Table 2 shows the number of disasters and the share of counties that applied for assistance following such a disaster by disaster type. It seems that the number varies dramatically by disaster type. While about 80% of counties affected by a tornado applied for federal assistance, only about 10% of counties affected by fires or floods did so.

It may be interesting to see how these counties differ from the ones that did apply. Figure 6 shows boxplots by county application status. Counties that did apply for federal disaster assistance tend to have lower median income, higher poverty rates, and higher shares of single motherhood. Thus, it seems that counties that had to apply for federal disaster assistance were more socially

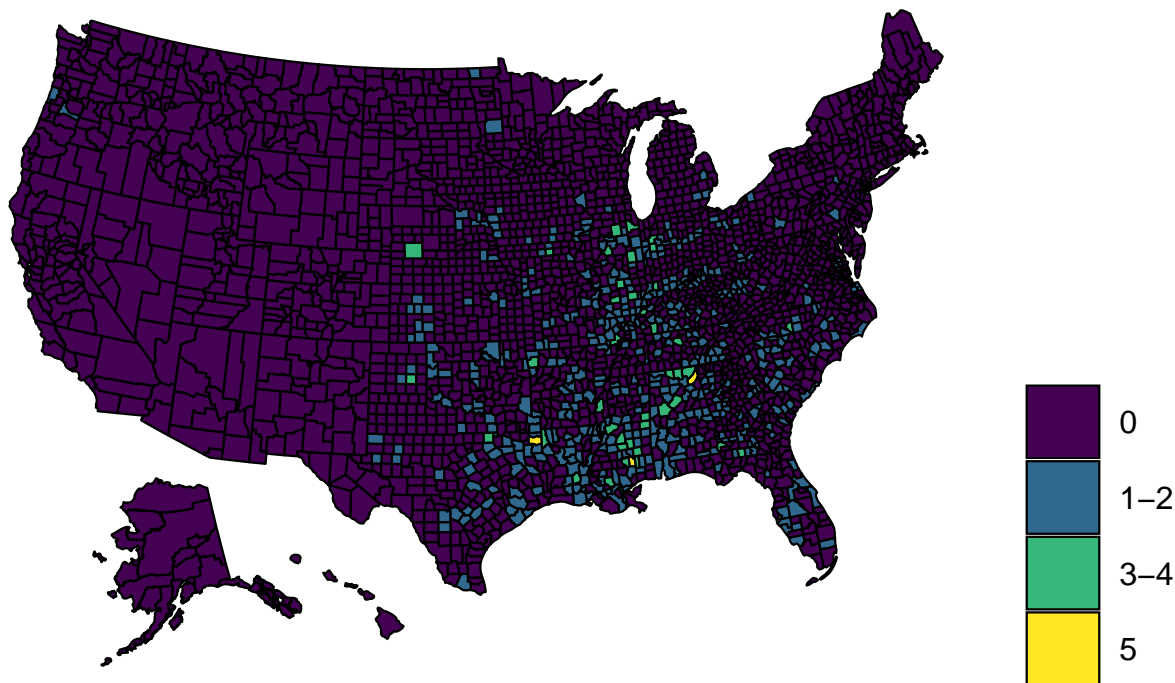


Figure 3: Number of storms in school years 2008-09 through 2017-18

vulnerable in the first place. This is consistent with the findings in [United States Government Accountability Office \(2022\)](#).

However, the direction of causality is not clear. Possibly these counties are more frequently affected by natural disasters and are also poorer or more socially vulnerable because of it. Alternatively, counties that are poorer could be more likely to apply for public disaster aid as they have fewer private resources. While there is some correlation between disaster risk and economic conditions (for example [Park et al., 2020](#)), the latter explanation seems more likely overall.

It is also interesting whether variation in the federal assistance procedure may be driven by political factors. Visually, democratic votes in the 2016 election (almost coincides with the start of the Public Assistance Applicants Program Deliveries dataset) tend to be lower in counties that applied. That is, counties that applied for federal assistance tend to vote more Republican. Logistic regression results confirm the visual impression (see Appendix [A](#)). While this is not necessarily a causal effect, it could be an indication that a Republican president may be more hesitant awarding disaster assistance to Democratic counties.

2.3 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)¹ over the 2008-09 through 2017-18 school years.

¹RLA assesses students' ability to understand what they read and to write clearly.

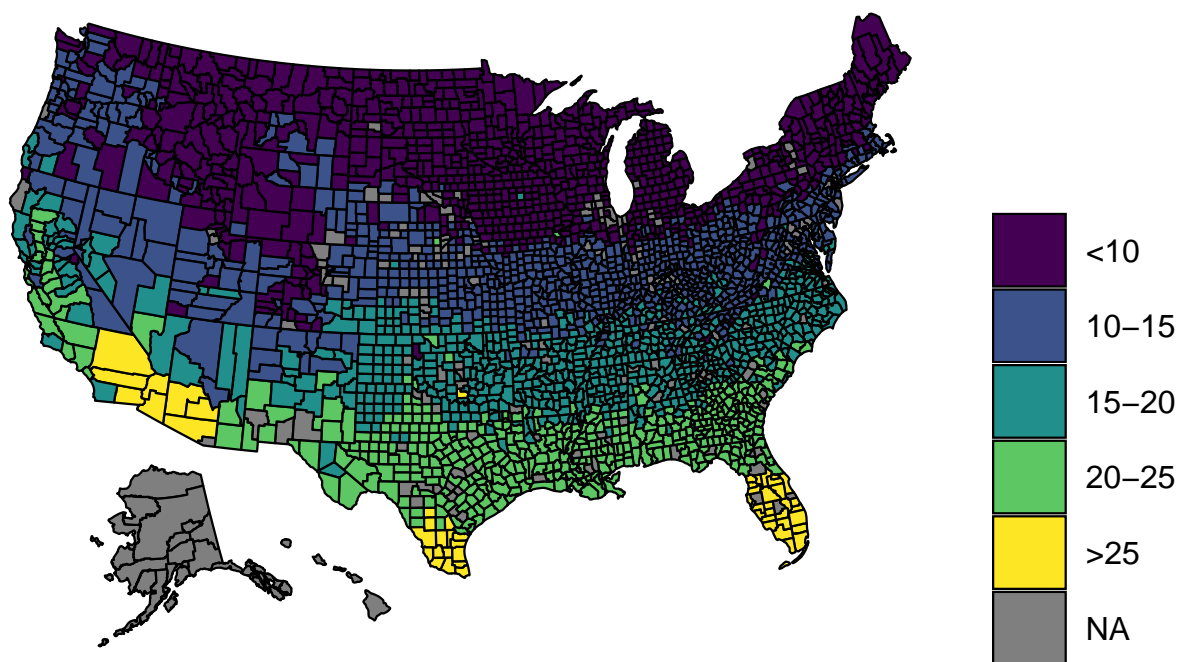


Figure 4: Average daily maximum temperature in school years 2008-09 through 2017-18

Test scores are cohort-standardized, meaning they can be interpreted relatively to an average national reference cohort in the same grade. This makes the dataset very attractive, as test scores are nationally comparable. 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 overall mean test scores, the data includes mean test scores for various subgroups, e.g. by ethnicity. In particular, we consider mean test scores for black, hispanic, female, and economically disadvantaged students to investigate whether the effects differ by ethnicity, gender, or socioeconomic position. These are only reported if the subgroups' sample sizes are large enough to guarantee anonymization. Thus, the number of observations for some of the groups is substantially smaller.

The outcomes of interest are overall mean test scores by county, and mean test scores for black, hispanic, female, and economically disadvantaged students. Figure 7 shows boxplots for the five outcomes of interest. All five mean test scores are measured on the cohort standardized scale, that is a given observation measures the distance in standard deviations from the national reference cohort.

Due to the way the scale is constructed, overall test scores are distributed symmetrically around zero, except for a few outliers. The mean scores for black, hispanic, and economically disadvantaged students are shifted downwards by -0.48, -0.281, and -0.283 standard deviations respectively. Female mean scores are slightly above overall mean scores, meaning that female students perform slightly better than male students on average.

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

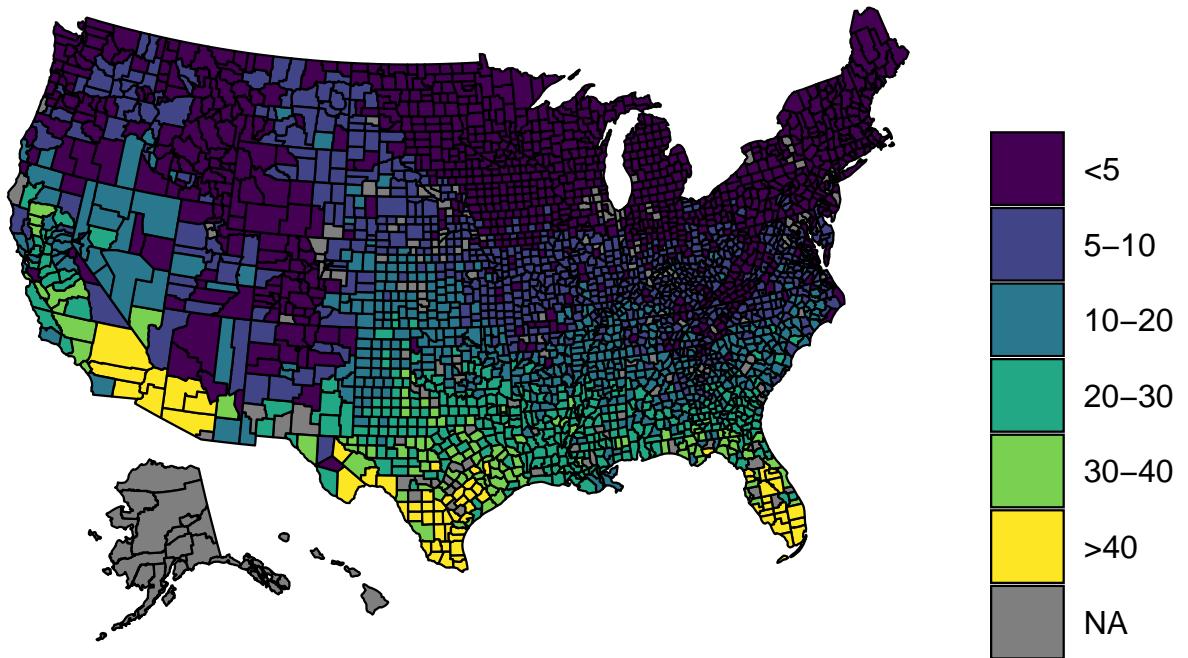


Figure 5: Average number of days above 30°C in school years 2008-09 through 2017-18

poverty rate.

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. Disasters occurring in the summer or in the spring after the exams should have much less influence on performance. Thus, we do not consider disasters that occur between March 1st and September 1st.

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.

3 Empirical Strategy

3.1 Setting

We employ an event study design to measure the effect of natural disasters on standardized test outcomes. An event study design is a staggered adoption design where units are first-treated at different points in time, and there may or may not be never-treated units (Sun and Abraham, 2021).

Note that treatment must be absorbing, meaning the sequence of treatment indicators $(D_{i,t})_{t=1}^T$ must be a non-decreasing sequence of 0s and 1s. In other words, after being treated for the first time a county stays treated. In the present application this means treatment refers to having experienced

Table 2: 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

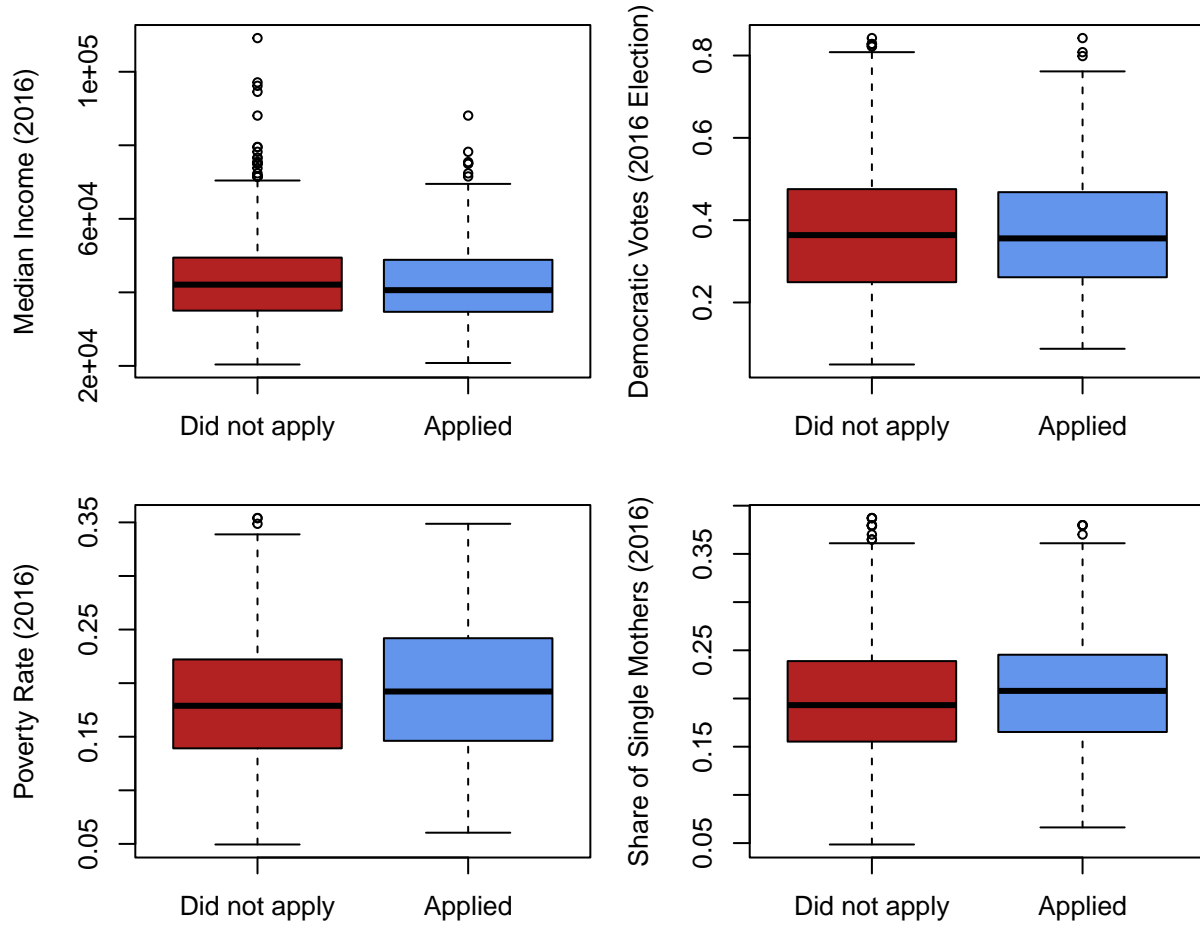


Figure 6: Boxplots by application status

a disaster rather than experiencing a disaster in that year. While a disaster itself may be transient, the effects caused by the disaster may not be. This is common practice and does not cause bias due

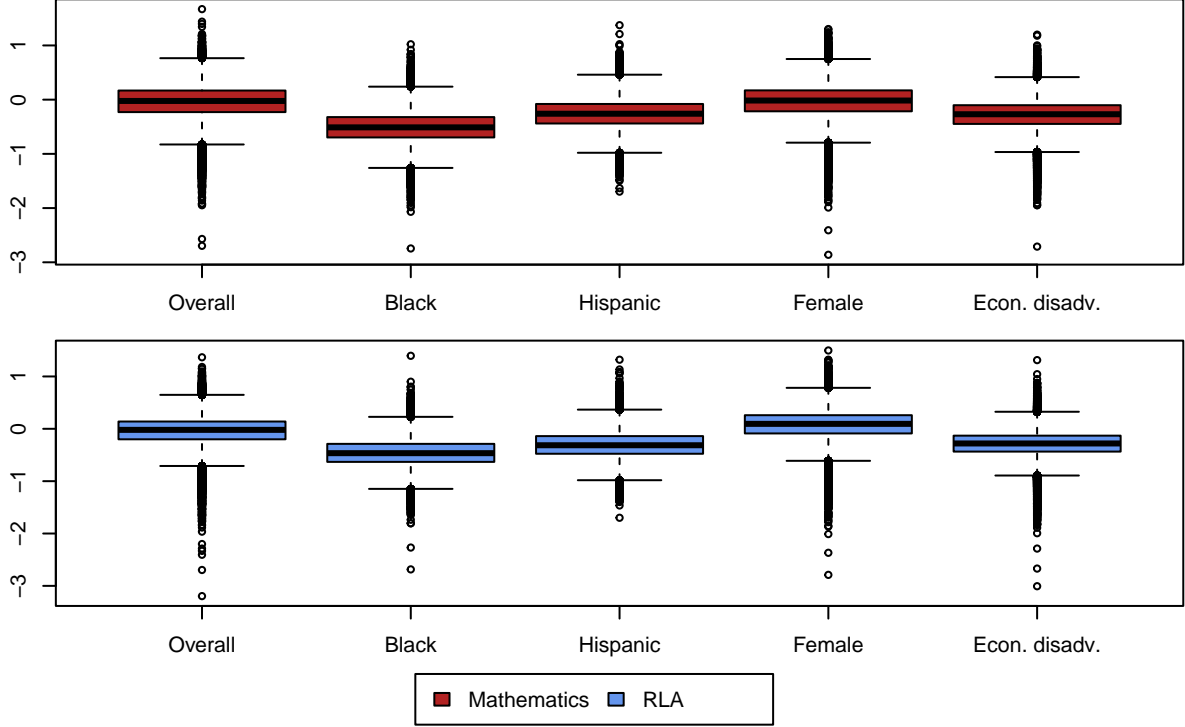


Figure 7: Boxplots of the outcomes of interest

to the conditionally random nature of natural disasters (Deryugina, 2017). Thus, the emphasis lies on cumulative long-term effects rather than instantaneous short-term effects.

In order to identify a causal effect, unobservable determinants of a county's test scores must be unrelated to natural disasters conditional on observable characteristics of that county. The occurrence of natural disasters is plausibly random conditional on location. Furthermore conditioning on the year should account for an increasing trend in natural disasters due to climate change. Thus, independence of mean test scores and natural disasters is plausible conditional on county and year fixed effects.

Consequently, the baseline specification is

$$y_{i,t,g} = \sum_{l=-9}^8 \beta_l \mathbb{1}\{t - E_i = l\} + \alpha_i + \lambda_t + \zeta_g + \varepsilon_{i,t,g}, \quad (1)$$

where $y_{i,t,g}$ is the outcome of interest for county i , year t , and grade g . County, year, and grade fixed-effects are given by α_i , λ_t , and ζ_g respectively. E_i denotes the first year of treatment and $\mathbb{1}\{t - E_i = l\}$ is a treatment indicator for county i l years after initial treatment. That is, it is 1 if the county had already experienced the first disaster l years ago. The set of counties which experience their first disaster in the same period, i.e. have the same E_i , are referred to as a cohort.

Since we consider the time period 2009-2018, $-9 \leq l \leq 9$, but note that $l = 9$ would correspond to a unit that experienced a disaster in the first period and is therefore always treated. As recommended by Sun and Abraham (2021) and Callaway and Sant'Anna (2021), these units are dropped from estimation. Neither can treatment effects be identified for that group nor are they useful as a comparison group under standard parallel trends assumptions.

Also, we need to drop at least two leads or lags to avoid a multicollinearity problem. A complete set of treatment leads and lags is perfectly collinear with unit and time fixed-effects (for an extensive discussion of this issue see [Borusyak et al., 2021](#), section 3.2). It is common to drop the first relative indicator prior to treatment (i.e. $\beta_{-1} = 0$). This acts as a normalization of treatment relative to the period before treatment. Furthermore, we bin the distant leads, that is we combine the treatment indicators for $l \leq -5$. Thus, equation (1) turns into

$$y_{i,t,g} = \beta_{-5} \mathbb{1}\{t - E_i \leq -5\} + \sum_{l=-4, l \neq -1}^8 \beta_l \mathbb{1}\{t - E_i = l\} + \alpha_i + \lambda_t + \zeta_g + \varepsilon_{i,t,g} . \quad (2)$$

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. Also, some counties may experience additional natural disasters after the first one, while others only experience one. Naturally, we would expect larger treatment effects for the former group.

With heterogenous treatment effects, standard two-way fixed-effects estimators are inadequate ([de Chaisemartin and D'Haultfoeulle, 2020](#); [de Chaisemartin and D'Haultfoeulle, 2021](#); [Sun and Abraham, 2021](#)). Therefore, we use an alternative estimation procedure by [Sun and Abraham \(2021\)](#), which will be explained below. A similar estimator was introduced by [Callaway and Sant'Anna \(2021\)](#). However, the latter is unable to handle multiple observations for the same unit-period combination. Since we have multiple grades for each county-year combination this would be a severe restriction in our setting. That is why, [Sun and Abraham \(2021\)](#) is better suited.

Treatment adoption varies in time: Counties that are first treated in a given year form a cluster, that is treatment assignment happens in clusters. The results in [Abadie et al. \(2017\)](#) show that in such settings it is necessary to cluster standard errors at level of treatment assignment. Therefore, standard errors are clustered at the cohort level.

3.2 Interaction-weighted estimator

We utilize the interaction-weighted (IW) estimator proposed by [Sun and Abraham \(2021\)](#) that is robust to treatment effects heterogeneity. The main interest lies on the cohort average treatment effect on the treated (CATT),

$$CATT_{e,l} := \mathbb{E} [Y_{i,t+l} - Y_{i,t+l}^{\infty} | E_i = e] ,$$

where $Y_{i,t+l}^{\infty}$ is the counterfactual of being never treated and E_i denotes the first treatment period. Thus, $CATT_{e,l}$ is the average treatment effect on the treated l years after being treated for the first time for the cohort that was first treated in year e .

The estimation procedure consists of three main steps:

1. Estimate $CATT_{e,l}$ using a linear fixed effects specification with interactions between relative period indicators and cohort indicators:

$$y_{i,t,g} = \sum_{e \notin C} \sum_{l \neq -1} \delta_{e,l} (\mathbb{1}\{E_i = e\} \mathbb{1}\{t - E_i = l\}) + \alpha_i + \lambda_t + \zeta_g + \varepsilon_{i,t,g} , \quad (3)$$

where C is the set of comparison cohorts. In our case C is the never treated cohort, i.e. $C = \infty$. If there is a cohort that is always treated, i.e. that already receives treatment in the first period, then we need to exclude this cohort. The coefficient estimator $\hat{\delta}_{e,l}$ that we obtain from (3) estimates $CATT_{e,l}$.

2. Weight the estimators by the share of the respective cohort in the sample in that period. Let \hat{W}^l be a weight matrix with element (t, e)

$$[\hat{W}^l]_{t,e} := \frac{\mathbf{1}\{t - e = l\} \sum_{i=1}^N \mathbf{1}\{E_i = e\}}{\sum_{e \in h^l} \sum_{i=1}^N \mathbf{1}\{E_i = e\}},$$

where $h^l := \{e : 1 - l \leq e \leq \max(E_i) - 1 - l\}$ is the set of cohorts that experience at least l periods of treatment.

3. Take the average over all $CATT_{e,l}$ estimates weighted by the cohort shares in the weight matrices. Let $vec(A)$ be the vectorize operator that vectorizes matrix A by stacking its columns and let $\hat{\delta}$ be the vector that collects $\hat{\delta}_{e,l}$ for all e and l . Then, the IW estimator \hat{v}_g for bin g can be written as

$$\hat{v}_g := \frac{1}{|g|} \sum_{l \in g} [vec(\hat{W}^l)]^\top \hat{\delta}. \quad (4)$$

For a singleton bin $g = \{l\}$, this simplifies to

$$\hat{v}_g := [vec(\hat{W}^l)]^\top \hat{\delta}.$$

Under some standard assumptions, \hat{v}_g is asymptotically normal (for a proof and a detailed description of said assumptions see [Sun and Abraham, 2021](#), Appendix C). Under the additional assumptions of parallel trends and no anticipatory behavior, \hat{v}_g is consistent, that is it converges in probability to

$$\hat{v}_g \xrightarrow{P} [vec(W^l)]^\top \delta = \sum_{e \in h^l} \mathbb{P}(E_i = e | E_i \in h^l) CATT_{e,l},$$

where W^l is the probability limit of the weight matrix \hat{W}^l .

We use \hat{v}_g as an estimator for β_g in equation (2) and we exploit the existing implementation in the **fixest** R package ([Bergé, 2018](#)).

3.3 Identifying assumptions

Below we discuss the identifying assumptions.

Parallel Trends: Parallel trends in the sense of [Sun and Abraham \(2021\)](#) refers to the following: $\mathbb{E}[Y_{i,t}^\infty - Y_{i,s}^\infty | E_i = e]$ does not depend on e for any $s \neq t$. That is, the expected temporal difference, i.e. the trend, in the potential outcomes of being never-treated is the same for all treatment timings. A conditional version of the assumption, as in [Callaway and Sant'Anna \(2021\)](#), should definitely hold, as test scores and natural disasters are plausibly independent given location. However, we cannot be sure about the unconditional version required by [Sun and Abraham \(2021\)](#).

Testing for parallel trends is problematic for two reasons: These tests tend to have very low power and they introduce selective inference type issues if inference is conditional on passing a parallel trends test ([Rambachan and Roth, 2019](#)). A purely visual inspection of pre-treatment trends does not indicate a violation of the parallel trends assumption (see appendix B). In fact, the trends look almost identical for treated and control (never-treated) units for most cohorts.

No Anticipatory Behavior: There is no treatment effect prior to treatment, that is $\mathbb{E}[Y_{i,e+l} - Y_{i,e+l}^\infty] = 0$ for all e and all $l < 0$. This assumption is plausible as the treatment path is not known. Natural disasters are quasi-random and cannot be reliably forecast more than a few days in advance. Thus, anticipatory behavior is implausible.

Both identifying assumptions should be fulfilled and the IW-Estimator consistently estimates a weighted average of the cohort average treatment effects on the treated.

3.4 Heat

For the effect of heat exposure we utilize a different design. A binary treatment indicator is not well suited to capture the effect of cumulative heat exposure. Instead, we rely on the two aforementioned measures: average maximum daily temperature and days above 30°C. These give rise to an interesting marginal interpretation: What is the effect of a 1°C hotter school year or of one additional day above 30°C on average test scores?

Again, conditional on location and year heat exposure should be independent of other factors determining academic performance. Also, there is no threat of endogenous selection into test-taking (as in [Park et al., 2020](#)), since all students are required to take these standardized tests. Thus, we estimate a simple linear model with county, year, and grade fixed effects,

$$y_{i,t,g} = \beta H_{i,t} + \alpha_i + \lambda_t + \zeta_g + \varepsilon_{i,t,g} , \quad (5)$$

where $H_{i,t}$ is the measure of heat exposure at the county-schoolyear level. Since there are likely no confounding factors, a least squares estimate of β can be interpreted causally.

4 Results

4.1 Main Results

Figure 8 shows estimated dynamic treatment effects and 95% confidence intervals for all students and the four subgroups of interest.

For the period of treatment there is a significant² effect of natural disasters on the performance in mathematics. The effect size is between just above zero and -0.01 standard deviations. Also, one year after the disaster there is an even larger significant decrease in test scores. For all subsequent periods the effect is not significant. There are some point estimates well below zero, but the uncertainty around those is relatively large. For performance in RLA, there are no significant effects.

Note that the number of observed units decreases with the distance in time from treatment. The reason for this is that in order to experience eight treated years, the county has to experience its first disaster very early. Similarly, it has to receive treatment very late to experience more than five years before treatment. As a result, the uncertainty increases with the distance in time from treatment.

For the subgroups we find some surprising results. Black students seem to perform better in RLA in the medium term after a disaster. That is, there are significantly positive results one to seven years after treatment. The effect sizes are substantial: Seven years after treatment the increase in RLA performance goes up to 0.1 standard deviations. In other words, the average black student sees an increase in performance of up to 0.1 standard deviations of the national reference cohort. Also, hispanic students score significantly lower in mathematics in the year following a disaster.

Positive effects of disasters on performance are not unheard of in the literature. In fact, this is somewhat consistent with the findings by [Sacerdote \(2012\)](#). Many students have to switch schools and some may even benefit from attending a higher quality school after the disaster. Black students may disproportionally attend lower quality schools and are therefore more likely to benefit from having to switch schools.

Among the subgroups, we see a few significant pre-treatment estimates. Therefore, the treatment led to a significant difference in average test scores between treatment and control group

²Significant is used here in the sense that a confidence interval with nominal coverage of 95% does not include zero, that is a corresponding t-test would reject the null hypothesis of a zero effect at the 5% level.

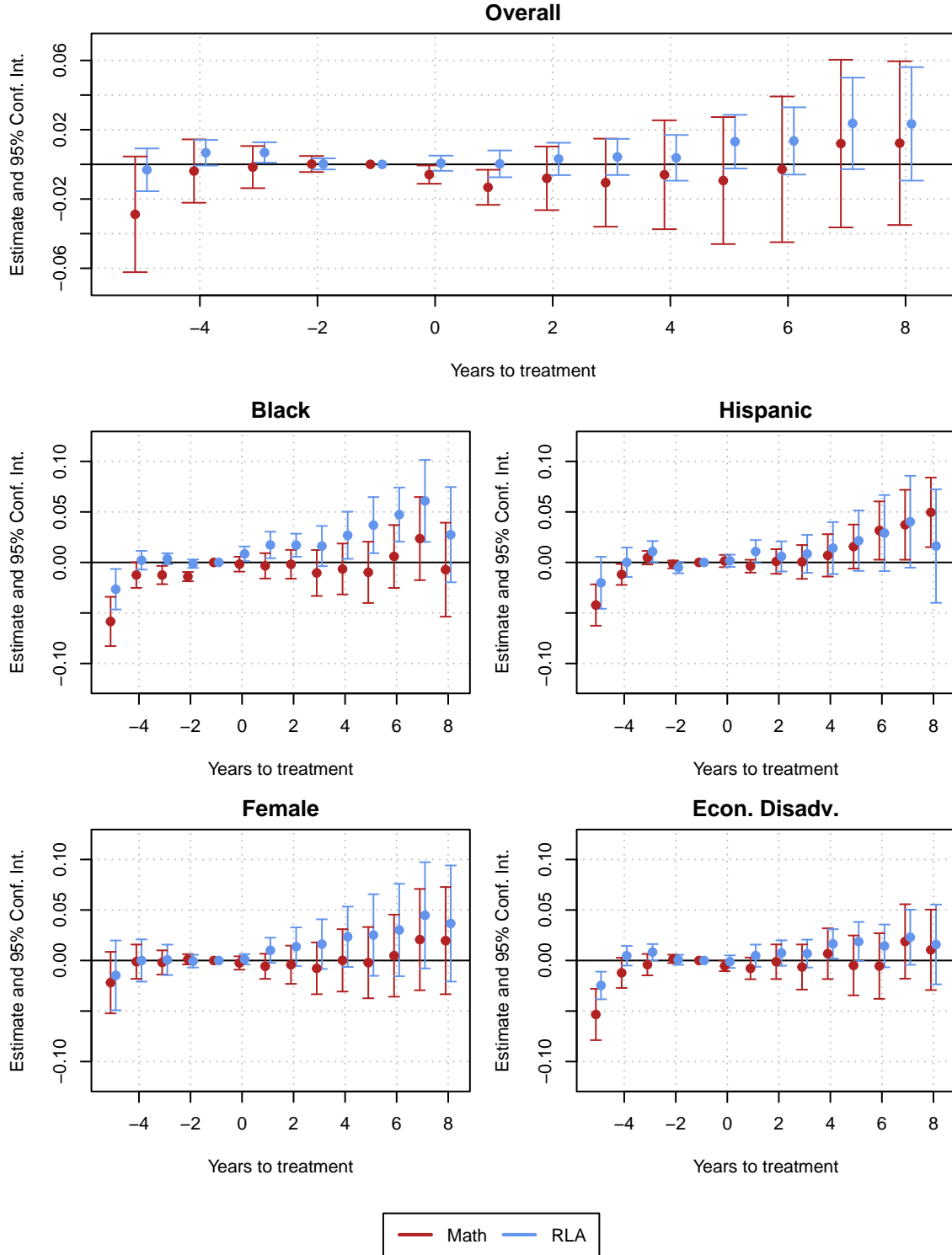


Figure 8: Dynamic Treatment effects in relative time: FEMA disaster data

before the treatment even began. This is likely caused by a violation of one of the two identifying assumptions: Either the trends in outcomes of treatment and control group are not parallel or

Table 3: 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

treated units anticipated treatment and therefore already saw an effect earlier. Since the latter is rather implausible, we conclude that there might be a violation of the parallel trends assumption. Thus, the affected results have to be interpreted with caution.

Figures 9 shows the same graphs based on the storm treatment. The results look very similar. In the period of the storm there is a significant decrease in mathematics scores of up to -0.015 standard deviations. For the years following treatment there are no significant effects.

For female students there is a significant decrease in both subjects in the period of the storm. For RLA we even find a significantly negative effect one year after the storm. Similarly, economically disadvantaged students perform worse in the period of treatment and in RLA one year after treatment. The effect sizes range from barely above zero up to -0.015 or even -0.02 standard deviations. For black and hispanic students we do not find any significant effects of the storm treatment.

4.2 Heat Results

Table 3 provides the estimation results for the heat models. Rows 1 and 2 show the estimated coefficients and standard errors for the maximum temperature variable for mathematics and RLA respectively.

At a 0.05 significance level the estimate is not significant for the entire student population in both mathematics and RLA. However, we find significant results for the subgroups with point estimates between -0.001 and -0.002 . This implies, the effect of an on average 5°C hotter school year is comparable to the average effect of a natural disaster in the same year.

Rows 3 and 4 of Table 3 show the same results for the number of days above 30°C . Here, we only find a significant effect on hispanic and female students in RLA. For hispanic students the point estimate is -0.0005 , meaning about 20 additional days above 30°C would be somewhat comparable to the average effect of a natural disaster in the same year.

In total, we only find weak evidence for a negative effect of heat on the achievement in standardized tests. However, it is more pronounced among some subgroups. For hispanic students the estimates indicate significantly negative effects in three out of four specifications with rather large effect sizes. The larger impact on the academic performance of minority students is consistent with other authors' findings (for example [Park et al., 2020](#))

One explaining factor could be the presence of air-conditioning. The results in [Park et al. \(2020\)](#) suggest that air conditioning offsets about three quarters of the negative effect of heat exposure. Possibly, counties with higher shares of minority students tend to have a lower presence of air-

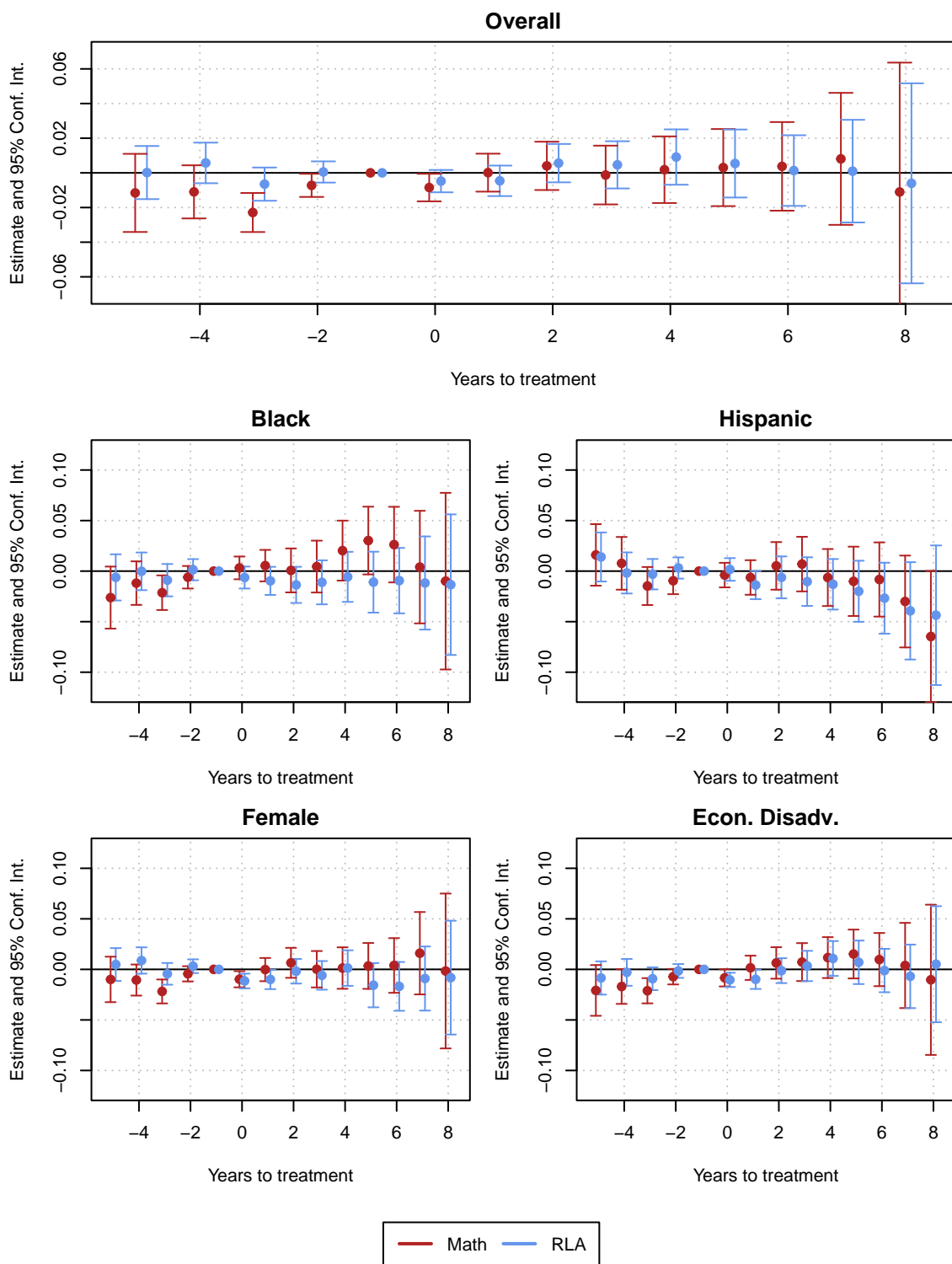


Figure 9: Dynamic Treatment effects in relative time: NWS storm data

conditioning in schools. Also, black and hispanic households tend to be poorer on average and may therefore be less likely to have air-conditioning at home. This could explain some of the

heterogeneity in the effect of heat.

4.3 Discussion

It could be the case that medium- and long-term effects are largely driven by migration. This is a prominent theme in previous studies on disasters and learning (Pane et al., 2008; Sacerdote, 2012). That's why it may be interesting to have a look at the ethnic composition of the counties relative to initial treatment. Figure 10 shows ethnic shares for the treated counties in relative time.

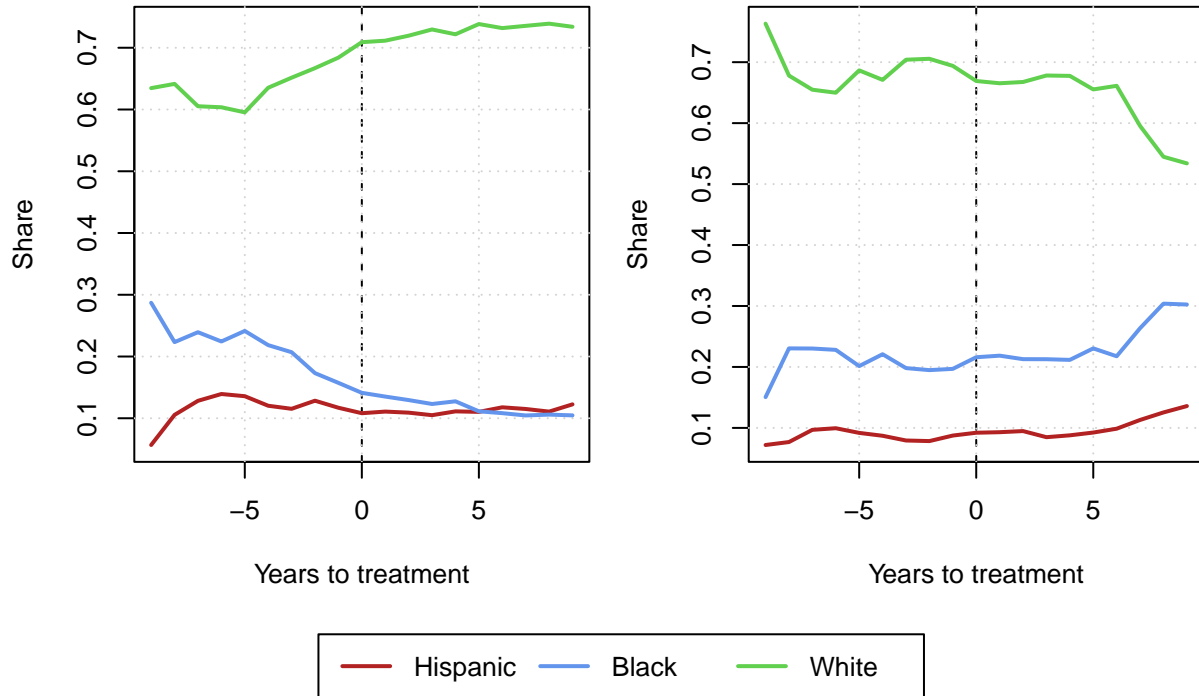


Figure 10: Aggregated ethnic shares by treatment timing based on FEMA disasters (left) and on NWS storms (right)

In the left panel we see that the share of black students decreases in counties that experienced a disaster. This supports the hypothesis that black students disproportionately switch schools after disasters and may explain the positive long term effect as described above. However, the share of black students already decreases before treatment, so this may not be a causal effect of the disaster.

The same plot based on the NWS storm data shows a different picture. Here, all three shares remain somewhat constant until five years after treatment. Then the share of black students increases, while the share of white students decreases. This suggests that the migration response to storms may be qualitatively different than the response to other forms of disasters. At least for the storms data this does not seem to be a major driver of the results.

A more in-depth analysis of migration responses to natural disasters and their role in academic achievement is unfortunately not possible with this data. There is some prior research based on individual level data indicating that it does play an important role (for example Sacerdote, 2012). Analyzing migration responses and their link to academic achievement for different types of natural disasters may be a promising area for future research.

For the main results, we conducted a power analysis. Based on the overall test scores, Appendix C provides graphs of the t-test’s statistical power as a function of the true parameter value. For the short-term effects the power is relatively large for plausible true parameter values. Thus, we can be relatively certain that non-significant results for the periods close to treatment are actually true negatives.

For the heat results, we find substantial heterogeneity: Minorities seem to be more prone to adverse effects of heat exposure. The results in [Park et al. \(2020\)](#) indicate that air-conditioning mitigates a large part of the negative effect. Based on that, we speculate that inequality in air-conditioning is the main driver of said heterogeneity, since minority students tend to have less access to air-conditioning. Improving the air-conditioning coverage in more affected schools could be an easy way for policymakers to address the adverse effects of heat on academic achievement. However, to the best of our knowledge [Park et al. \(2020\)](#) is the only paper to study this relationship. More research on the interconnection between heat, learning, and air-conditioning may be useful to make policy decisions.

Obviously, our results come with limitations. First, the parallel trends assumption may be violated in some subgroups. While a visual inspection of pre-treatment trends does not indicate so, we find significant pre-treatment effects. This is typically a sign for such a violation. In particular, this applies to the results for black, hispanic and economically disadvantaged students based on the FEMA data. Therefore, we have to be more careful when interpreting these results.

Second, the measures of heat exposure used here are based on daily maximum temperature only. However, this likely does not fully capture the physiological impact of heat. Other variables, like humidity or minimum temperatures overnight, can also contribute to the negative effect of heat on learning (for an extensive discussion of heat exposure measurement see [Rennie et al., 2021](#)).

5 Conclusion

This study estimates dynamic effects of natural disasters on academic performance measured by standardized test results in mathematics and Reading Language Arts (RLA). For both datasets we find a negative effect on the performance in mathematics in the year the disaster occurred. The effect reaches up to 0.01 or even 0.015 standard deviations of the national reference cohort. For RLA we find no significant effects on the overall mean score.

Based on FEMA natural disaster data we find that the performance in RLA among black students increases substantially in the years following a natural disaster. The reason could be that black students may disproportionately benefit from having to switch schools after a disaster ([Sacerdote, 2012](#)). However, the same model estimated on the NWS storm data does not confirm these findings.

In total, there is strong evidence for a negative effect of disasters on performance in mathematics in the same school year. For RLA, on the other hand, there is no significant effect. Evidence for medium and long term effects is weak. There are some significant effects among minority students, but they do not seem to be very robust, that is they only appear in one of the datasets used.

Based on temperature data, we also analyze the effect of heat exposure on academic performance. For the overall student population, we do not find a significant effect. However, for hispanic and to a weaker degree also black and economically disadvantaged students we find significantly negative effects. These discrepancies are likely driven by differing access to air-conditioning.

Mitigating such negative effects should be a concern for policymakers. Even if effect sizes are small, such negative effects can quickly compound in regions that are frequently affected by disasters.

A Additional Results

A.1 Logistic regression for assistance applications

Below we report logistic regression results for the applicant status, that is whether a county applied for federal disaster assistance based on the Public Assistance Applicants Program Deliveries data. More specifically, the applicant variable is 1 if the county experienced a disaster and applied for federal assistance, that is it appears in the Public Assistance Applicants Program Deliveries database, and 0 otherwise. This is regressed on a few covariates, including the share of democratic votes in the 2016 election. All independent variables are as of 2016.

Table 4: Determinants of Assistance Application

Dependent Variable: Model:	Applied (1)
<i>Variables</i>	
(Intercept)	-26.13*** (2.053)
Share of democratic voters (2016)	-1.712*** (0.1700)
Median Income (logs)	2.197*** (0.1824)
Poverty Rate	10.93*** (0.8545)
Share of single mothers	5.153*** (0.6200)
<i>Fit statistics</i>	
Observations	9,894
Squared Correlation	0.05322
Pseudo R ²	0.03890
BIC	13,004.3
<i>IID standard-errors in parentheses</i>	
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>	

B Pre-Treatment Trends

Here we show plots of aggregated pre-treatment trends to justify the parallel trends assumption. Mean test scores are aggregated by cohort (year of first treatment) and relative time to treatment, and never treated units act as the control group. We only display these plots for overall test scores for both datasets, but not for subgroups. However, the plots for the subgroups look very similar.

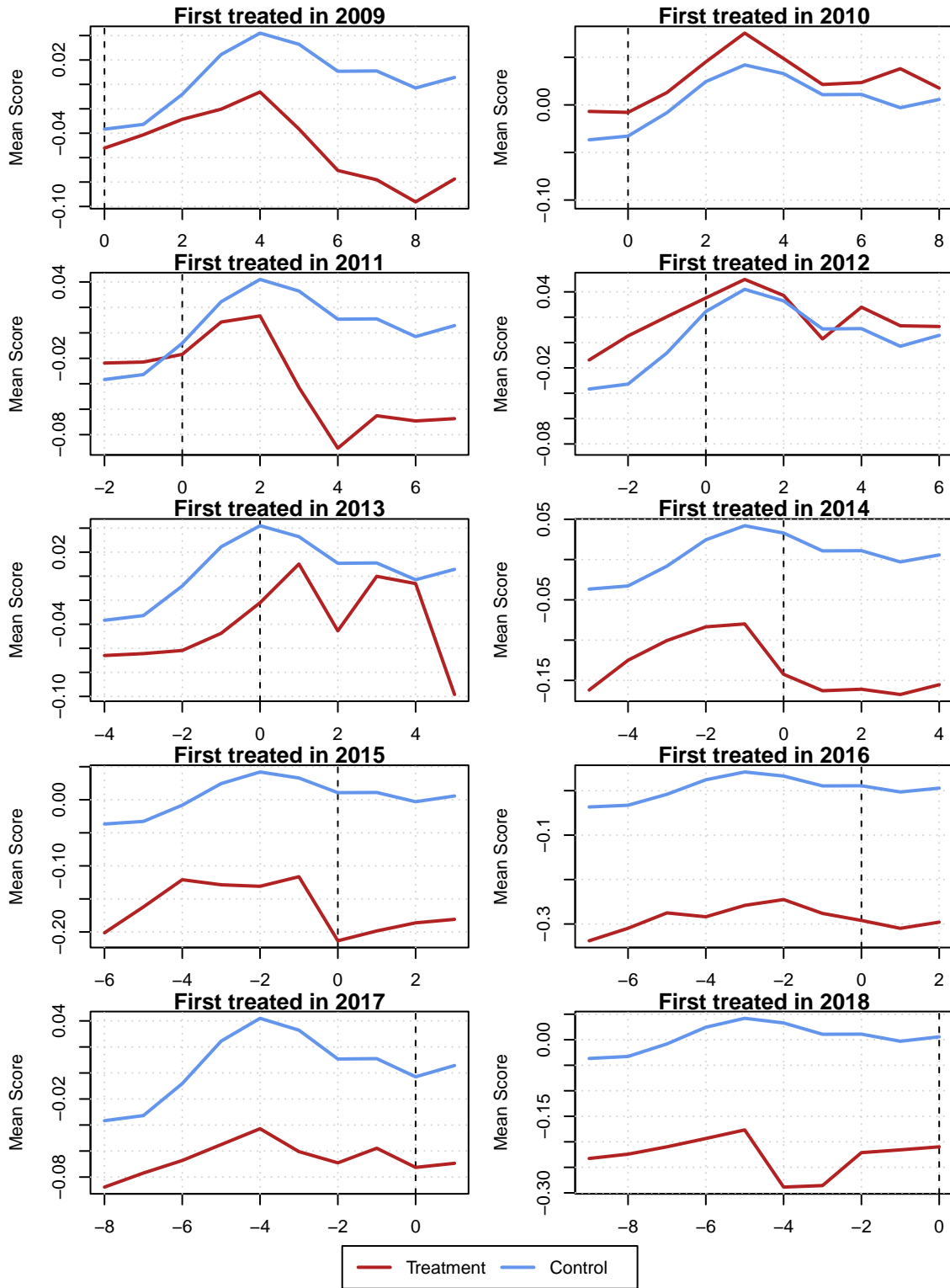


Figure 11: Aggregated mean scores in mathematics based on FEMA data in relative time to treatment

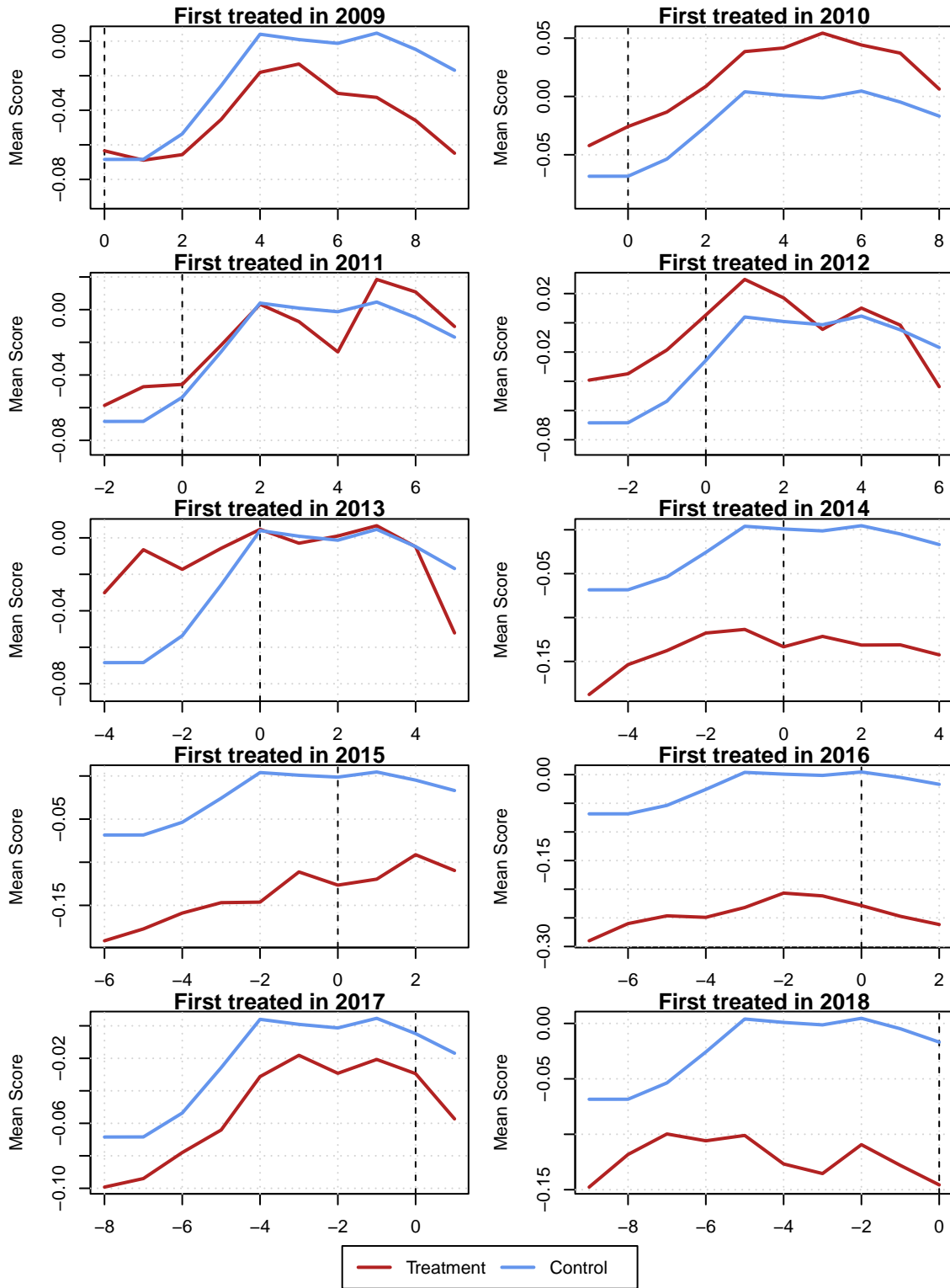


Figure 12: Aggregated mean scores in RLA based on FEMA data in relative time to treatment

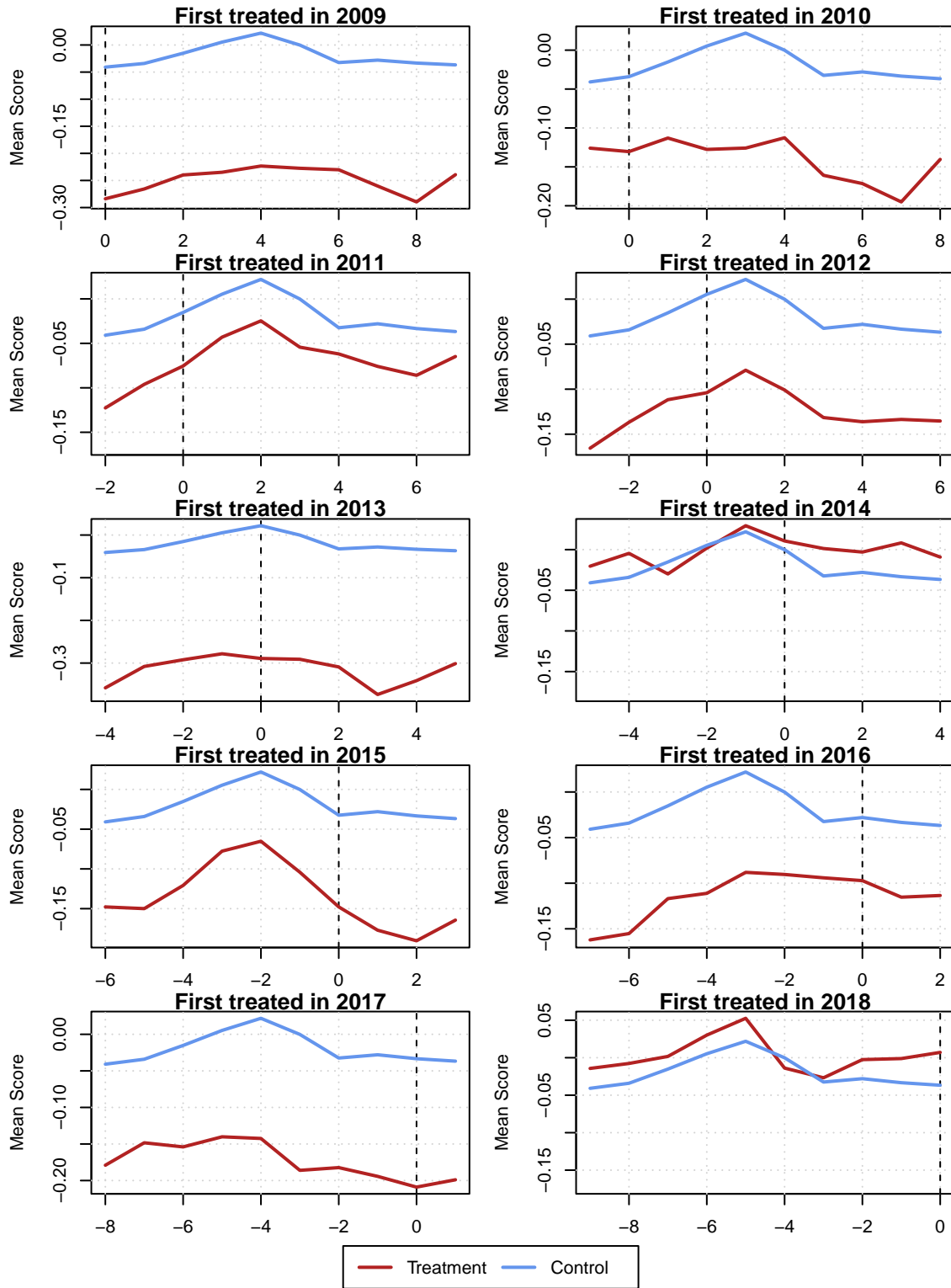


Figure 13: Aggregated mean scores in mathematics based on NWS storm data in relative time to treatment

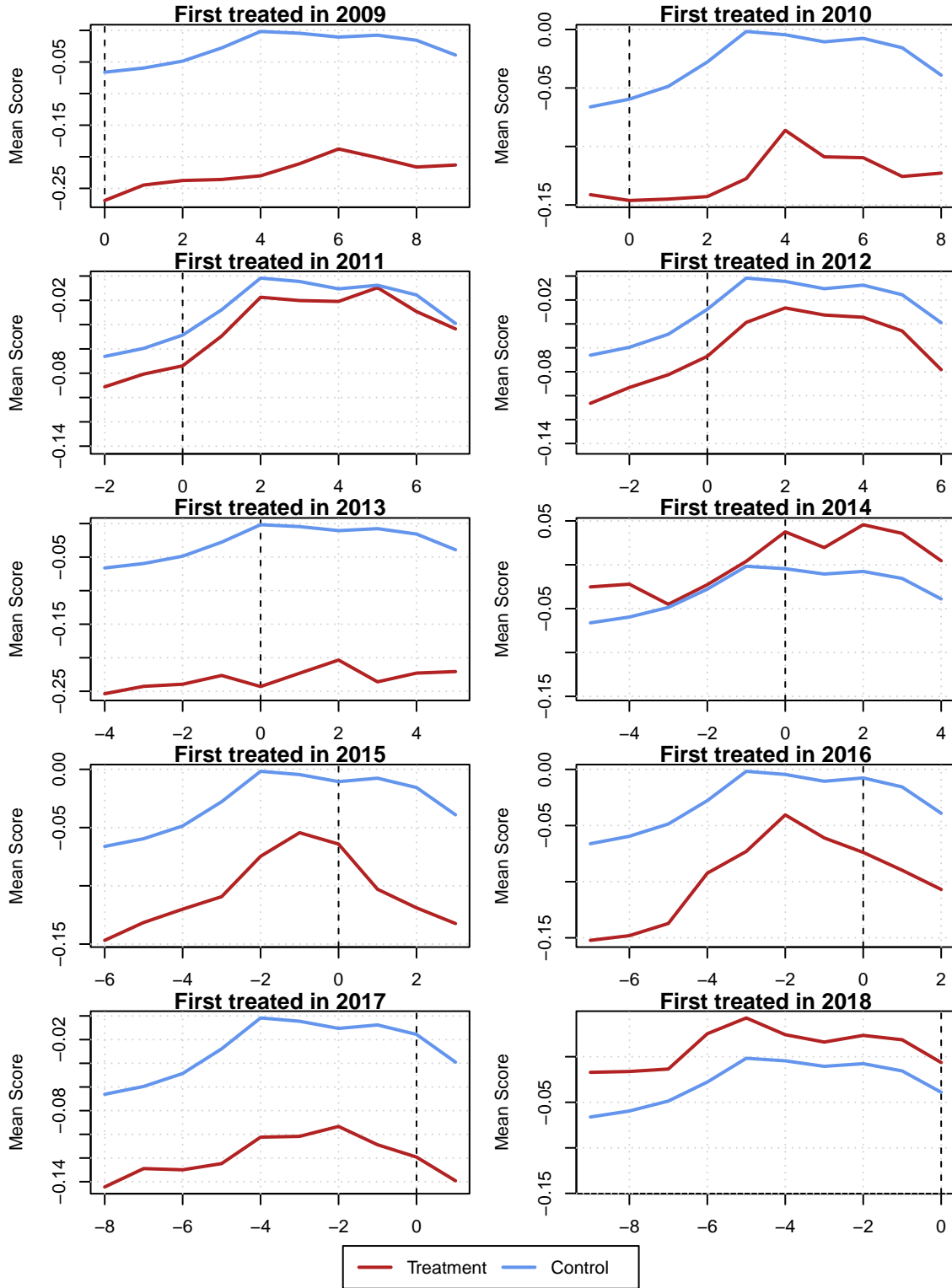


Figure 14: Aggregated mean scores in RLA based on NWS storm data in relative time to treatment

C Power Analysis

A power analysis can be used to check how much we can trust the non-significant results. High Power implies a low type 2 error probability, that is it is unlikely to not reject the null hypothesis

when it actually should be rejected. Based on the asymptotic distribution of our estimators,

$$\sqrt{N}(\hat{\beta}_g - \beta_g) \xrightarrow{d} N(0, \sigma^2)$$

we can compute the power of the t-test. Since, the variance has to be estimated,

$$\sqrt{N} \frac{\hat{\beta}_g - \beta_g}{\hat{\sigma}} \stackrel{a}{\sim} t(n - k),$$

where k is the number of parameters in the model. The t-test rejects $H_0 : \beta_g = 0$, with probability

$$\begin{aligned} \mathbb{P} \left(\left| \sqrt{N} \frac{\hat{\beta}_g - 0}{\hat{\sigma}} \right| \geq t_{1-\alpha/2} \right) &= \mathbb{P} \left(\sqrt{N} \frac{\hat{\beta}_g}{\hat{\sigma}} \leq -t_{1-\alpha/2} \right) + \mathbb{P} \left(\sqrt{N} \frac{\hat{\beta}_g}{\hat{\sigma}} \geq t_{1-\alpha/2} \right) \\ &= \mathbb{P} \left(\sqrt{N} \frac{\hat{\beta}_g - \beta_g}{\hat{\sigma}} \leq -t_{1-\alpha/2} - \frac{\sqrt{N}}{\hat{\sigma}} \beta_g \right) + \mathbb{P} \left(\sqrt{N} \frac{\hat{\beta}_g - \beta_g}{\hat{\sigma}} \geq t_{1-\alpha/2} - \frac{\sqrt{N}}{\hat{\sigma}} \beta_g \right) \\ &= T \left(-t_{1-\alpha/2} - \frac{\sqrt{N}}{\hat{\sigma}} \beta_g \right) + 1 - T \left(t_{1-\alpha/2} - \frac{\sqrt{N}}{\hat{\sigma}} \beta_g \right) \end{aligned}$$

where T is the cumulative distribution function of a t-distribution with $n - k$ degrees of freedom. Thus, for all $\beta_g \neq 0$ this expression is the power of the t-test. Using this expression, we can have a look at the power based on our data.

Figure 15 shows the power on the relative treatment indicators after treatment as a function of the true parameter value for overall mean scores based on the FEMA declarations. Power is decreasing in the temporal distance to treatment, which is not surprising since the variance increases in the temporal distance as already mentioned above. Also, power for mathematics scores tends to be lower overall than power for RLA scores.

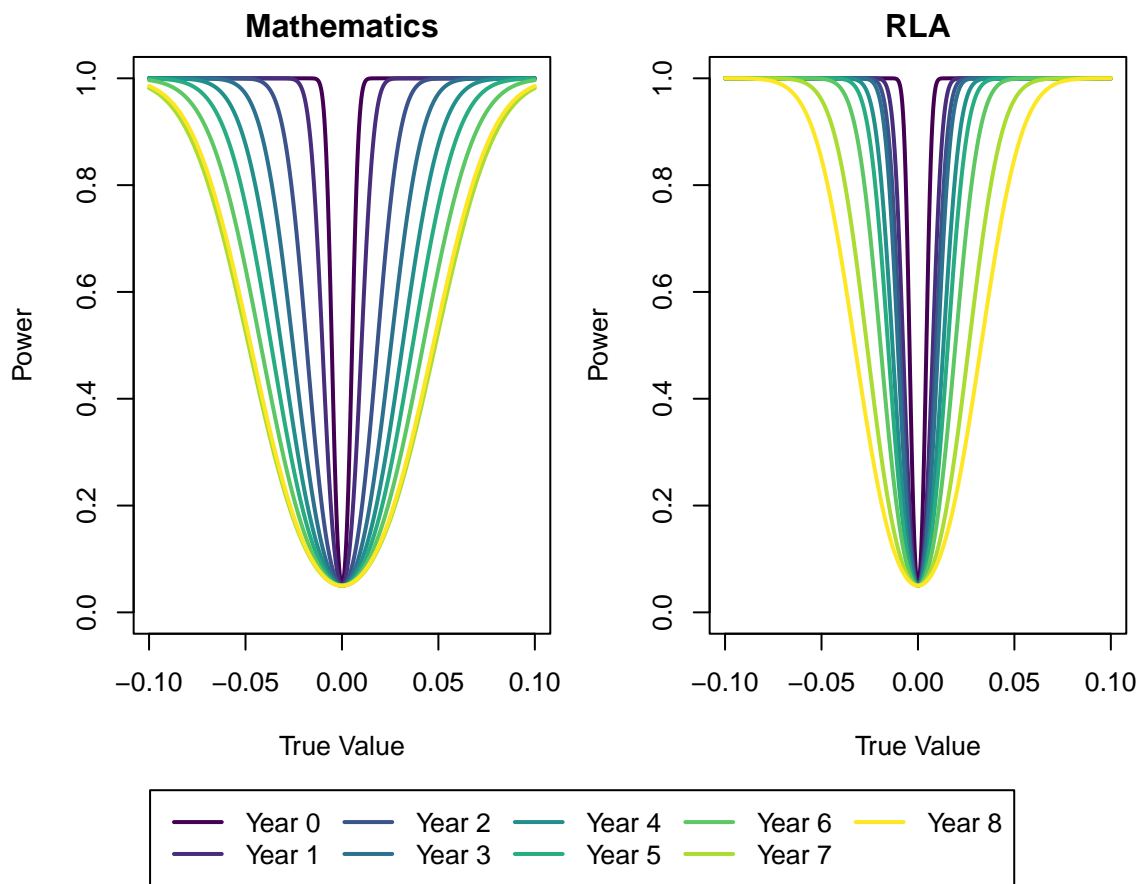


Figure 15: Power of the t-test as a function of the true parameter value

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