Beyond Exclusion:
The Role of High-Stake Testing on Attendance the Day of the Test

Magdalena Bennett
The University of Texas at Austin

Christopher Neilson
Yale University

Nicolás Rojas
Columbia University

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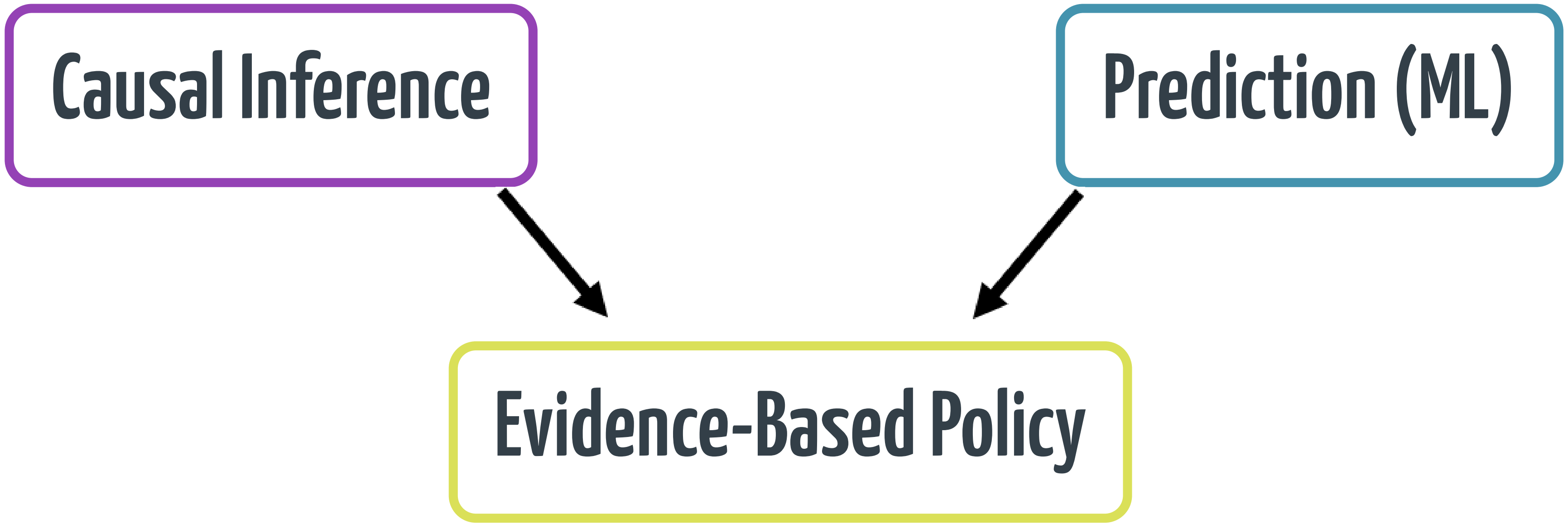
The big picture



Motivation

- Results from high-stakes tests widely used in education policy
    - E.g. funding, promotions, school closures, school choice, etc.

- Assumption: Standardize tests used as a proxy of school quality

Is it so?

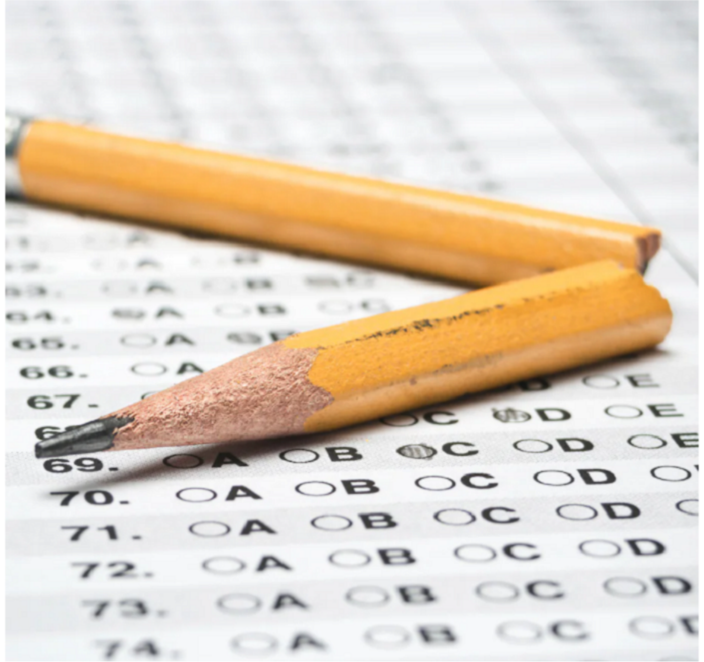
Motivation

Answer Sheet • Perspective

Remember the Atlanta schools' cheating scandal? It isn't over.

By Valerie Strauss
Staff writer

February 1, 2022 at 11:18 a.m. EST



DIVERSITY & EQUITY   TACKLING RACISM   FOLLOWING PHILANTHROPY

Looking for a home? You've seen GreatSchools ratings. Here's how they nudge families toward schools with fewer black and Hispanic students.

By Matt Barnum and Gabrielle LaMarr LeMee | Dec 5, 2019, 8:00am EST

REPUBLISH

Motivation

- Beyond explicit cheating and socioeconomic sorting: Students' exclusion
  - E.g.: Reclassification of low-performers as students with disabilities (Figlio & Loeb, 2011)
  - Use of disciplinary measures to exclude low-performers (Figlio, 2006)
- Less attention on non-representative attendance patterns
  - Differences between scores before and after imputation (Cuesta et al., 2020)
- Schools have incentives to game the system
  - Especially in high-accountability settings

This paper

Attendance Patterns

- Event study approach:
  - *How do these exclusions patterns look like? Are these the same for every (type of) school and every grade?*
  - Focus beyond bottom performers
  - Robustness checks for alternative mechanisms

Imputation Policies

- Machine learning prediction:
  - Identification of schools that are most likely gaming the system
  - Consequences of blanket policies in imputation of scores

Outline

1. Motivation
2. Chilean educational context
3. Attendance patterns:
   - Event study for different years, grades, and performance
   - Potential mechanisms
4. Prediction approach:
   - Difference between predicted and observed distributions
   - Potential consecuences of imputation
5. Conclusions and next steps

The Chilean Educational Context

The Chilean context: Standardized testing

- Chile has a universal voucher system (school choice)

- Universal standardized testing since 1980's (SIMCE)
  - For all 4th graders; then extended to other grades.

- SIMCE as high-stake testing:
  - Results widely available in a universal voucher system
  - Tied to teachers' bonuses
  - Tied to budget restrictions and school closures

SIMCE and absenteeism

- Use of pre-filled communication for parents to be sent out by schools
    - Evidence that parents from lower-income students are less likely to receive information

- No real consequences for low attendance:
    - Between 2005-2007, non-representative results where marked with symbols
    - No imputation strategy so far

- Improvement of regulation for justifying students exclusion
    - E.g. specific disabilities (blindness) or non-Spanish speakers.

Attendance Patterns for the Day of the Test

How to evaluate the effect of "day of the test" on abstenteeism?

- Some studies assessing the effect of attendance manipulation:
    - Focus on distortions (difference between imputed and observed scores) (Cuesta et al., 2020)
    - Manipulation for specific vulnerable schools (SEP) to raise scores (Feigenberg et al., 2019; Quezada & Hippel, 2017)

- This paper: Event study between 2011 and 2018 for all tested grades.
    - Focus on attendance by within-school performance
    - Use of alternative non-high-stake test to analyze potential mechanisms
    - Use of unpublished survey for communication and incentives around SIMCE

Data Available

- Standardized tests 2011-2018 (SIMCE)
  - Scores at student and school level for different subjects (Math, Language, History, and Science)
  - Student's socioeconomic characterization (parental questionnaire)

- Daily attendance data 2011-2018 (SIGE)
  - Use for voucher payments (each day has ~ 2.5 million records)

- GPA Performance 2011-2018 (Rendimiento)
  - Use GPA performance deciles within school-grade

Observations from our data

Data description

Grade	Years tested	Num Schools	Num Students
2	2013, 2014, 2015	5,266	628,073
4	2011, 2013-2018	5,673	1,461,289
6	2013-2016, 2018	5,516	1,056,243
8	2011, 2013-2015, 2017	5,545	1,078,140
10	2013-2018	2,623	1,213,067

Empirical approach for difference in attendance

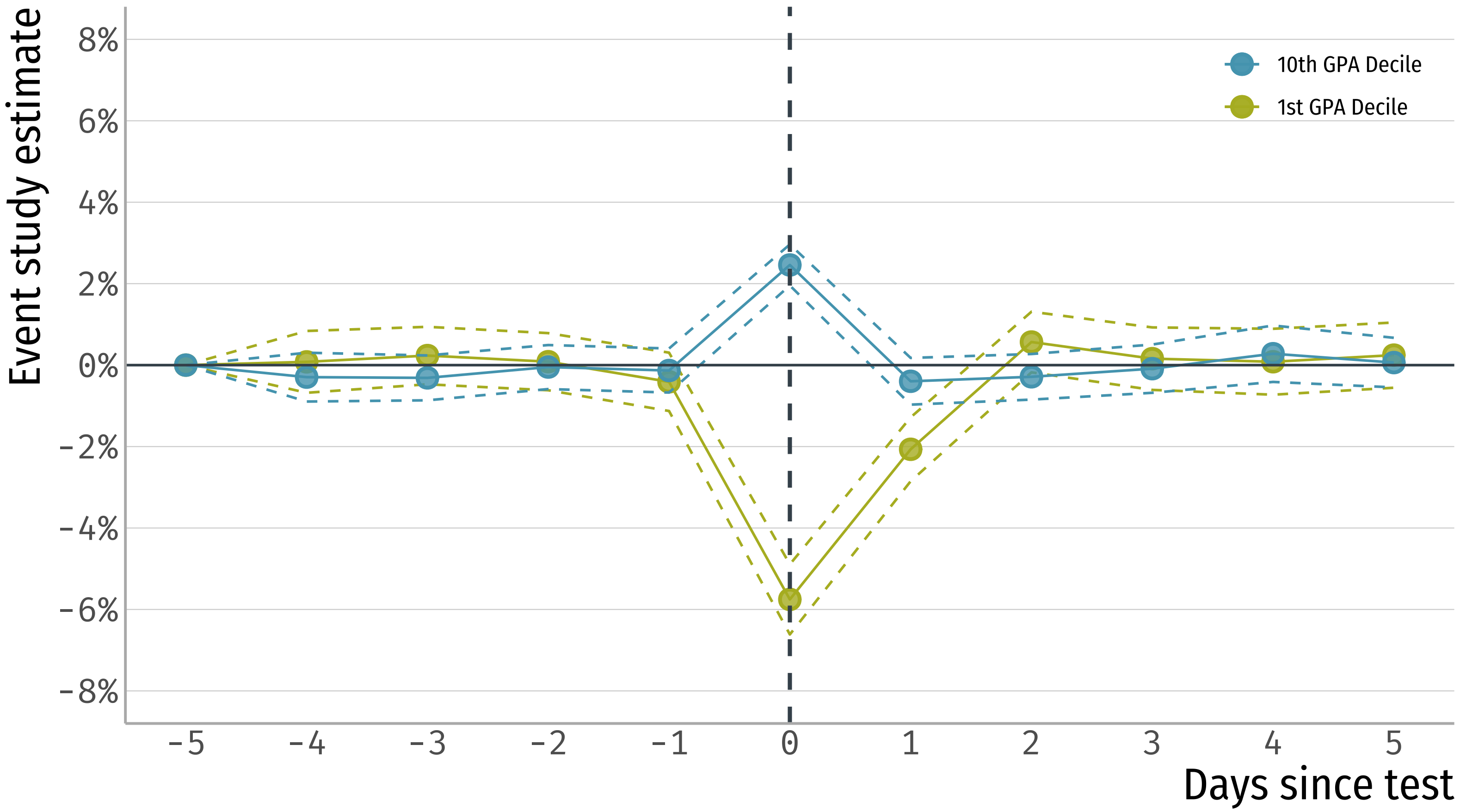
- Event study centered around the day of the test ($T=0$):

$$Y_{ipsgt} = \sum_{P=1}^{5} \sum_{T=-4}^{5} \tau^{PT} D_{ipsgt}^{PT} + \gamma_{pt} + \alpha_i + \epsilon_{ipsgt}$$

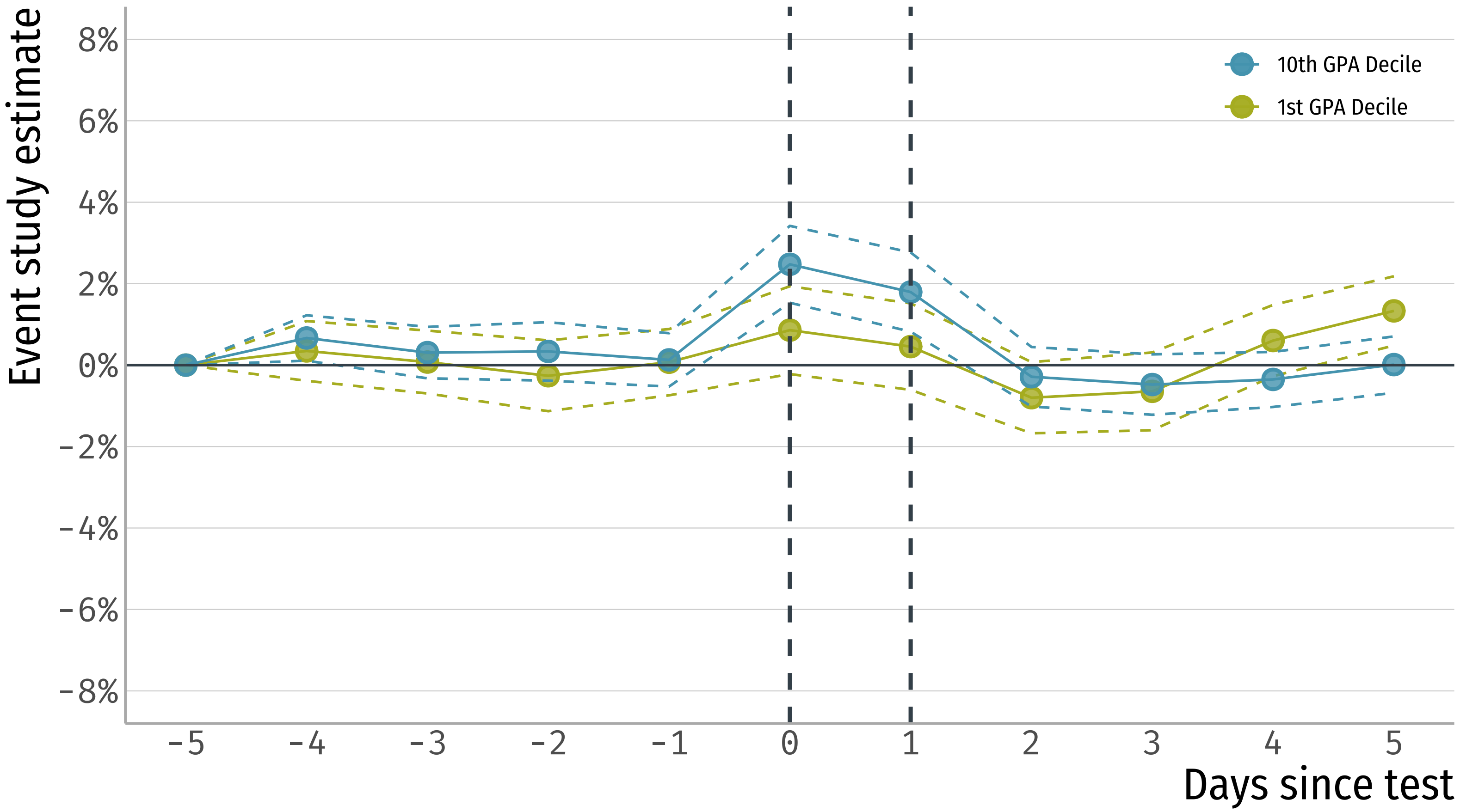
Where

- Y_{ipsgt}: Binary attendance for student i, from GPA group p, in school s and grade g, for day t.
- D_{ipsgt}^{PT}: Indicator variables (lags and leads) for students that belong to a tested grade.

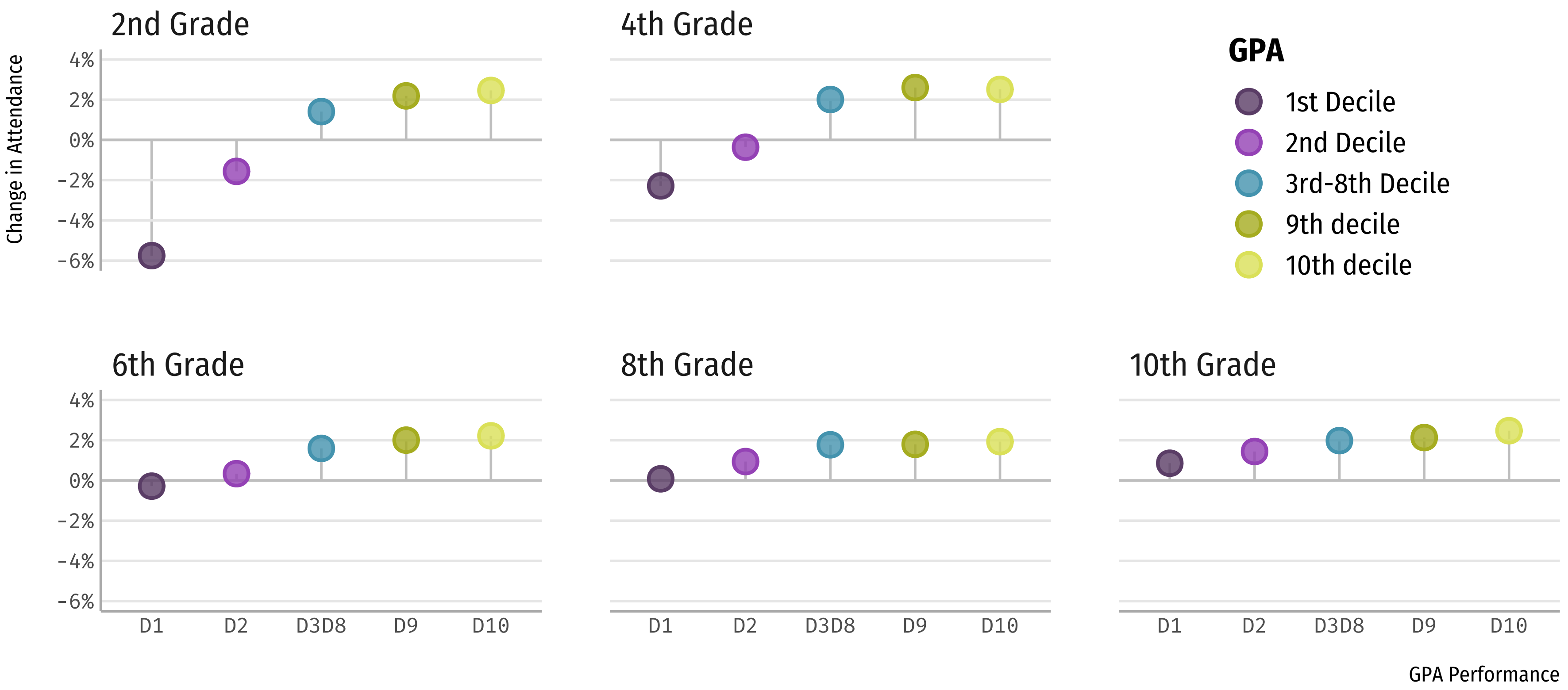
Clear difference in attendance by performance for 2nd grade



No effect on lower performers for 10th grade



Attendance patterns differ by grade



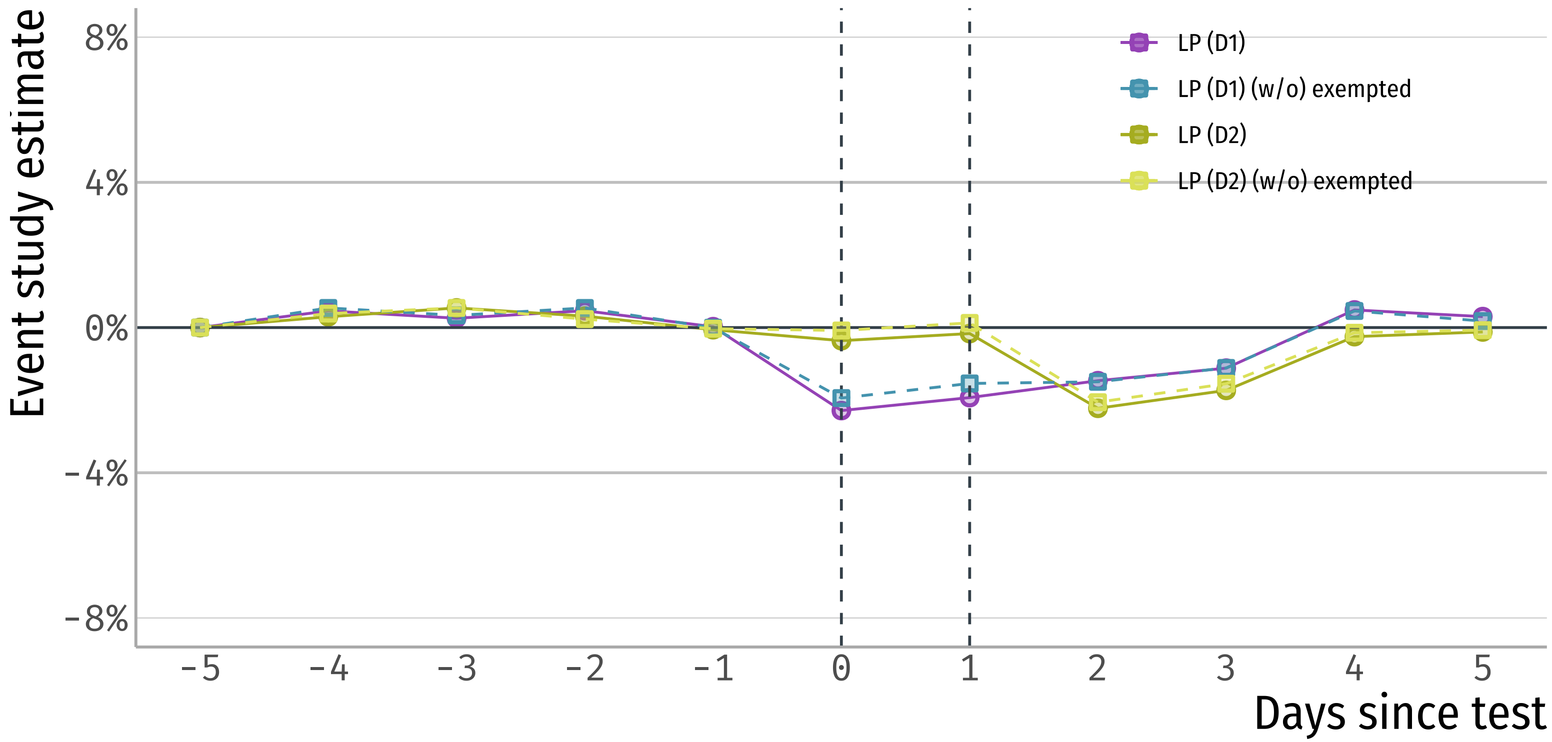
Note: $p < 0.05$ for all estimates except those touching the 0 bar.
Markers symbols are the coefficients of the effect of testing on attendance.

Potential mechanisms that explain these patterns

- Students are excluded due to other reasons (justified)
- Students experience a disutility from testing
- Schools directly (des)incentivize attendance of (lower)higher performers

Use of exemptions to exclude students don't tell the whole story

- Students are excluded due to other reasons (justified):
  - Change in exemption policy in 2012 $\rightarrow$ reduction in exempted students (flattened)
  - Results remain similar after 2012



No evidence of self-selection from students because of testing

- Students experience a disutility from testing
  - Use of no-stake test applied to schools → No effect on attendance

Results for No-Stakes Test

Grade - Year	D1	D2	D3D8	D9	D10
2nd 2011	-0.01	0.01	0.01*	0.02	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
5th 2012	0.00	-0.01	0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
6th 2011	0.02*	0.01	0.01**	0.01	0.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
6th 2017	0.00	0.03	0.01	0.01	0.00
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
11th 2012	0.00	0.00	0.00	-0.02**	0.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)

Differences in communication and incentives between high and low performers

- Schools directly (des)incentivize attendance of (lower)higher performers
  - 2017 survey for students in test-taking grades.

Results for 4th Grade

GPA Decile	Told	Notification	Preparation	Grades
D1	-0.06***	-0.11***	-0.08***	0.14***
	(0.00)	(0.00)	(0.00)	(0.00)
D10	0.06***	0.05***	0.05***	-0.2***
	(0.00)	(0.00)	(0.00)	(0.00)
Baseline	0.89***	0.87***	0.89***	0.39***
	(0.00)	(0.00)	(0.00)	(0.00)

Differences in communication and incentives between high and low performers

- Schools directly (des)incentivize attendance of (lower)higher performers
  - 2017 survey for students in test-taking grades.

Results for 10th Grade

GPA Decile	Told	Notification	Preparation	Grades
D1	-0.02***	-0.01***	-0.02***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)
D10	0.01***	0.00	0.00	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Baseline	0.95***	0.78***	0.82***	0.33***
	(0.00)	(0.00)	(0.00)	(0.00)

Predicting the Counterfactual

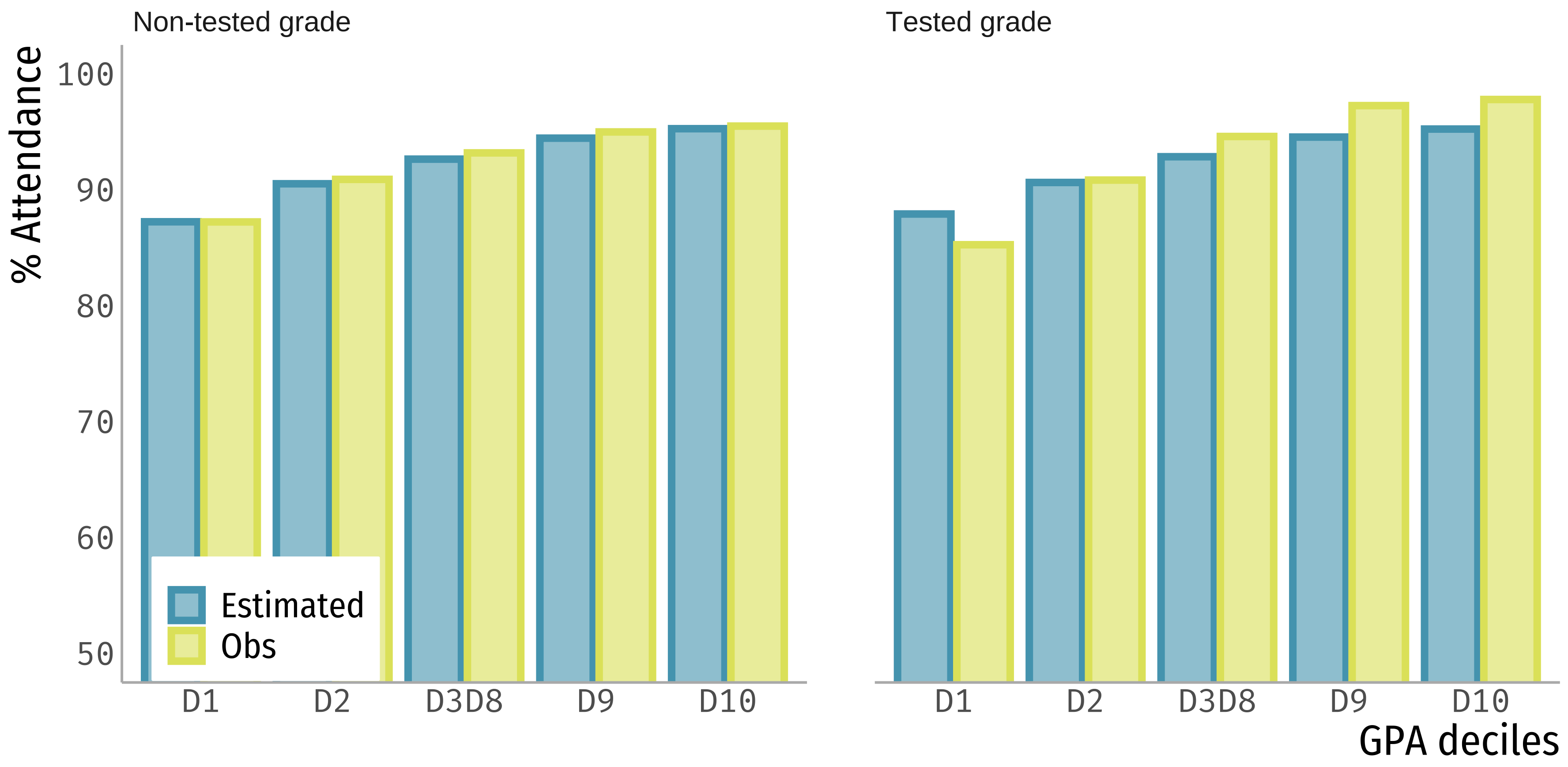
How do these results compare to predicted counterfactual?

- Can we use this existing rich panel data to predict attendance on the day of the test *as if it was a regular day*?

- Use GPBoost (Sigrist, 2020) with panel data for attendance prediction
  - Combines Gaussian Processes and Gradient Boosting.
  - Model includes random effects for both student and date.
  - Predictor variables include day of the week, grade, GPA group, and sibling's attendance.

- Use data for 4th grade (2017):
  - Data before the test to predict attendance on the day of the test.

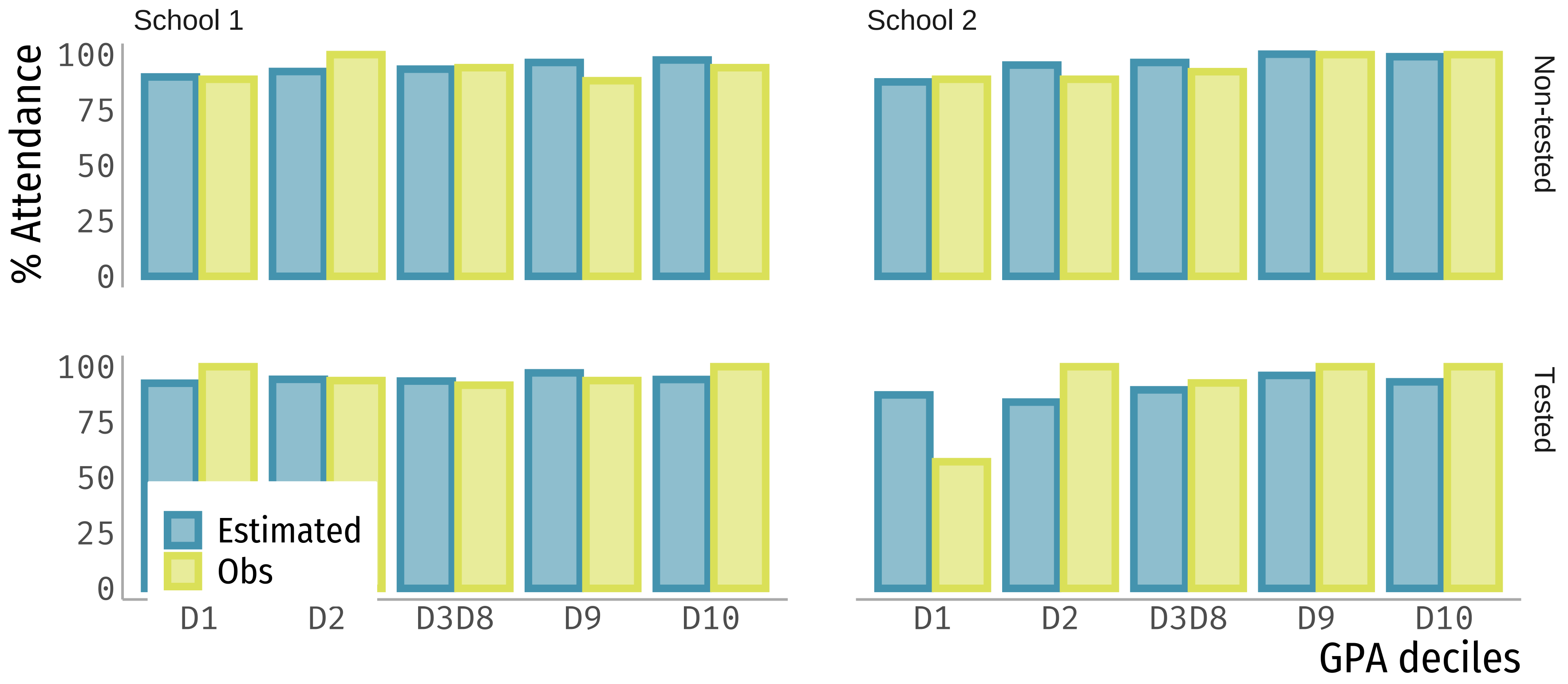
Overall predictions over performance distribution



Example: Comparisons between schools?

School1
Math: 258
Language: 260

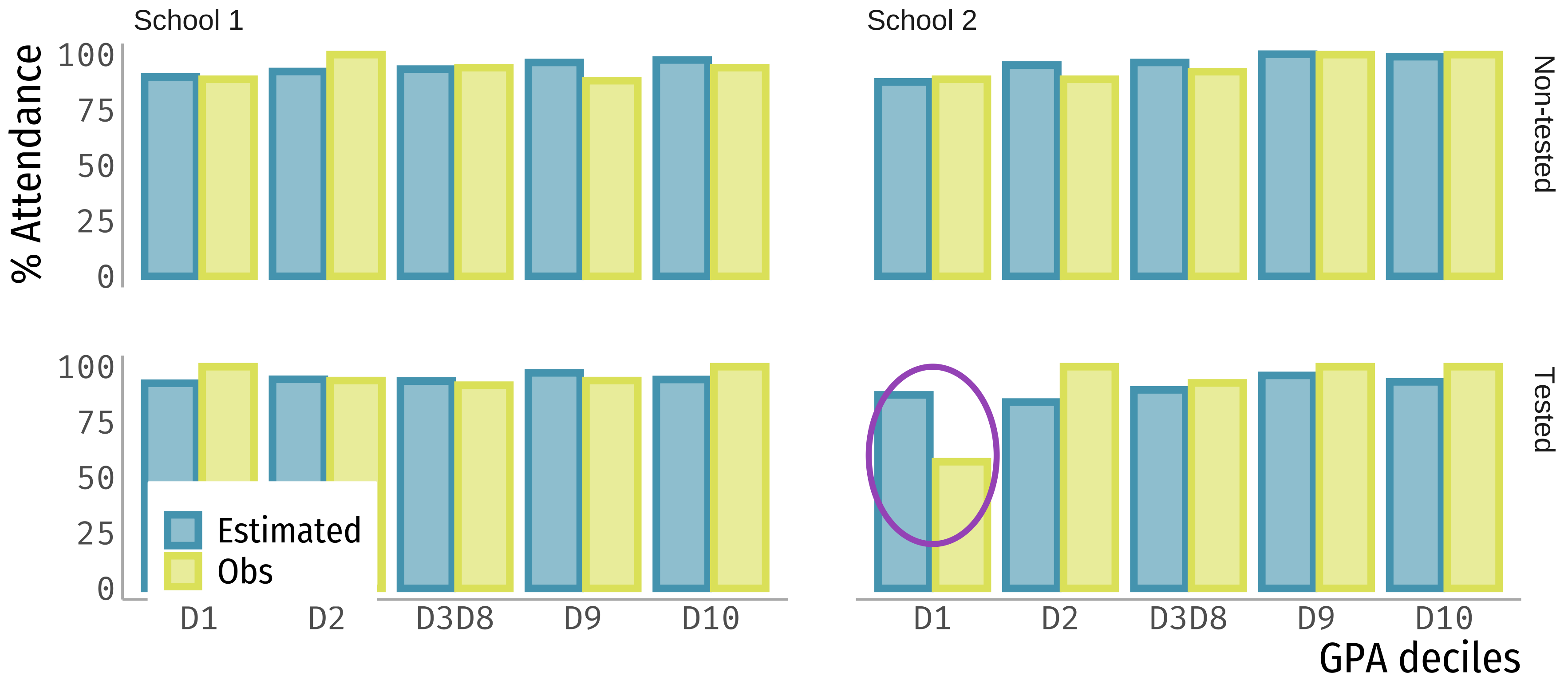
School2
Math: 259
Language: 256



Example: Comparisons between schools?

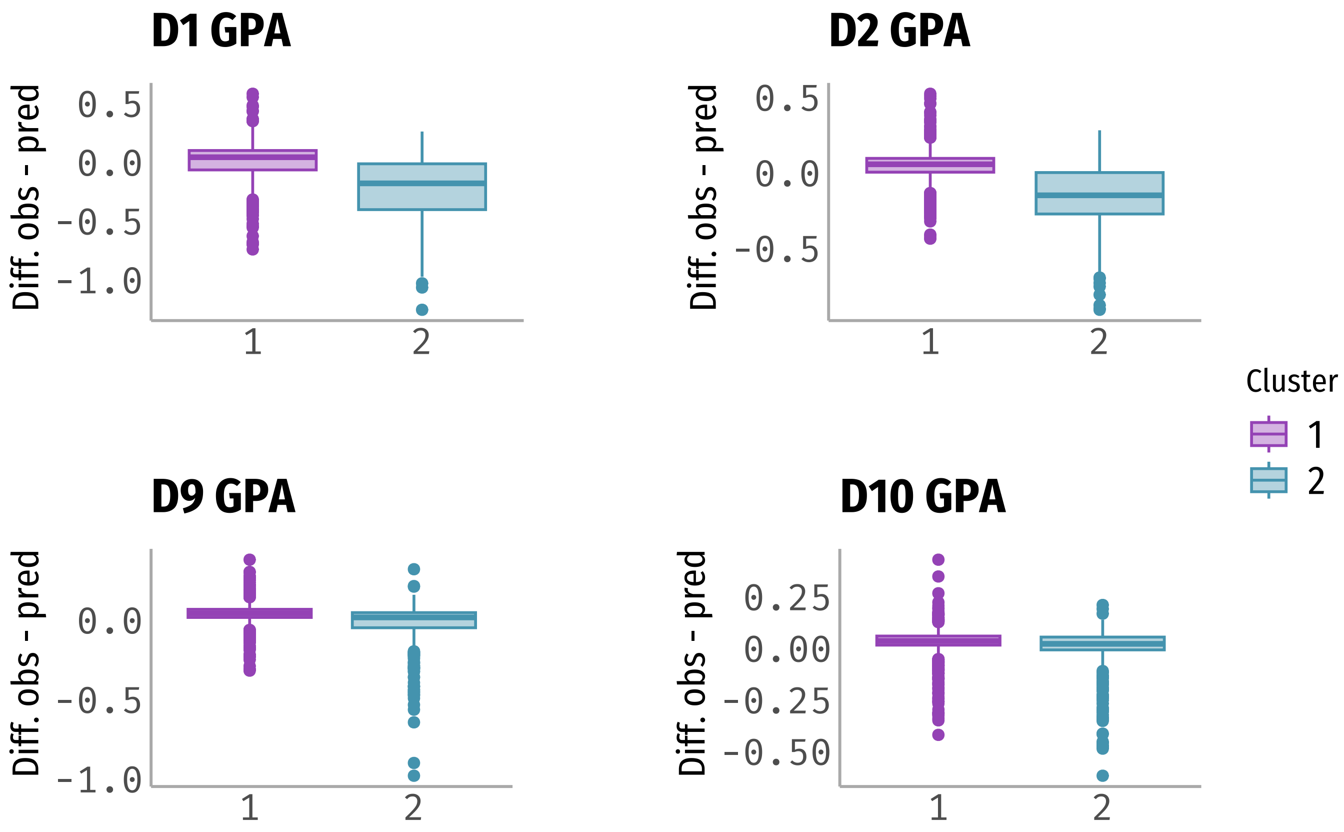
School1
Math: 258
Language: 260

School2
Math: 259
Language: 256



Can we characterize these schools?

- K-means clustering Use differences between predicted and observed attendance.
    - 2 optimal clusters



Schools that appear to exclude lower-perfoming students are also more vulnerable

	Cluster 1 Increase att (N=1094)		Cluster 2 Lower att (bottom) (N=346)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Avg. SIMCE Lang	258.84	22.38	252.62	23.84	-6.22	0.00
Avg. SIMCE Math	254.42	25.70	247.80	25.15	-6.62	0.00
Public	0.35	0.48	0.42	0.49	0.07	0.03
SEP status	0.84	0.37	0.88	0.33	0.03	0.11
% Priority Students	0.48	0.19	0.52	0.19	0.04	0.00
Diff D1 GPA	0.02	0.15	-0.22	0.27	-0.24	0.00
Diff D2 GPA	0.05	0.11	-0.17	0.21	-0.22	0.00
Diff D9 GPA	0.04	0.06	-0.03	0.15	-0.07	0.00
Diff D10 GPA	0.03	0.07	-0.01	0.12	-0.04	0.00

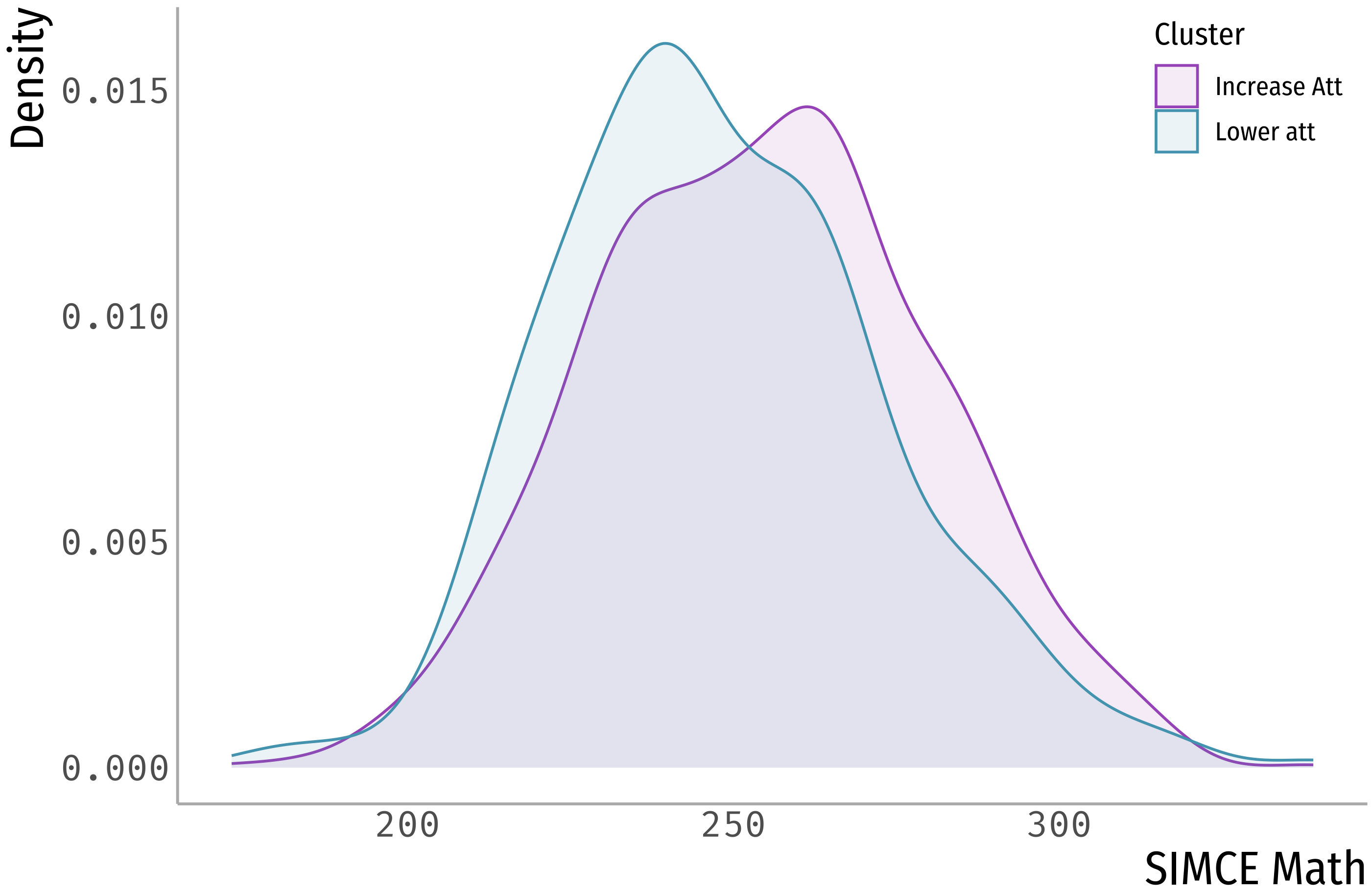
Note: Diff DX GPA represents the difference between obs. attendance and predicted attendance for decile X

Implications for imputation policies

- How to handle this absenteeism problem?
  - E.g.: Observed attendance (no imputation), attendance as if the test hadn't happened (impute "typical day"), everybody is present.

- Proposals to impute lowest scores for absent students to disincentivize arbitrary exclusion
  - Most vulnerable schools have higher absenteeism rates $\rightarrow$ Increase inequality and non-representativeness

There are differences in score distributions between clusters



Differences in scores and attendance

- The previous differences between types of schools **does not capture the true difference** given non-representative attedance patterns.

- Two incentives working simultaneously:
  - Incentive for **lower-performing students not to attend** the day of the test
  - Incentive for **higher-performing students to attend** the day of the test

- We will focus on solving the **first one**.

Some imputation exercises

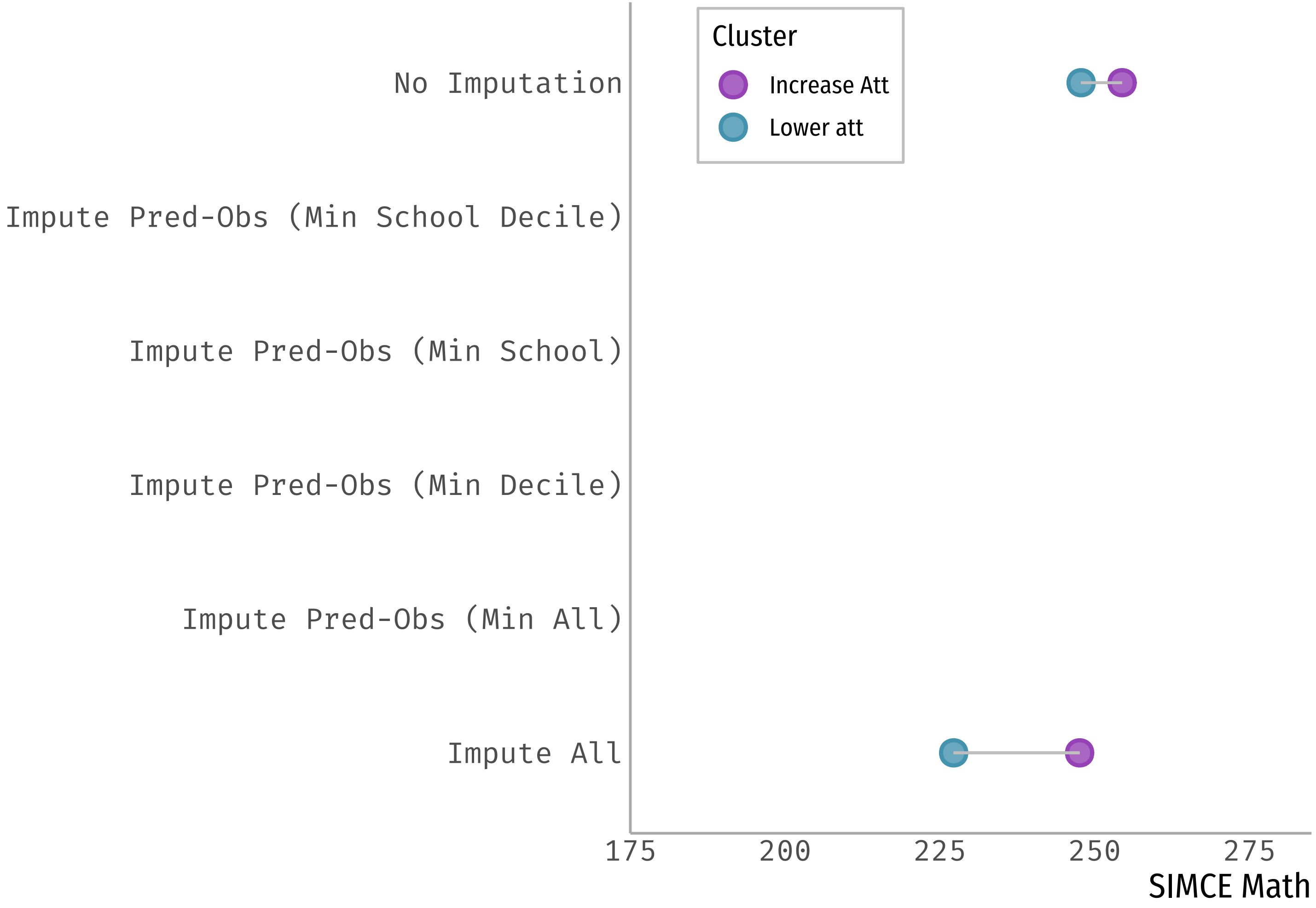
How can we impute missing scores?

- Scenario 1: Not impute at all. Show observed distributions.
- Scenario 2: Impute by decile only for the difference between predicted and observed attendance.
  - Imputed score: (a) overall min, (b) decile min, (c) min school, or (d) min decile by school.
- Scenario 3: Impute every missing student.
  - Imputed score: overall min

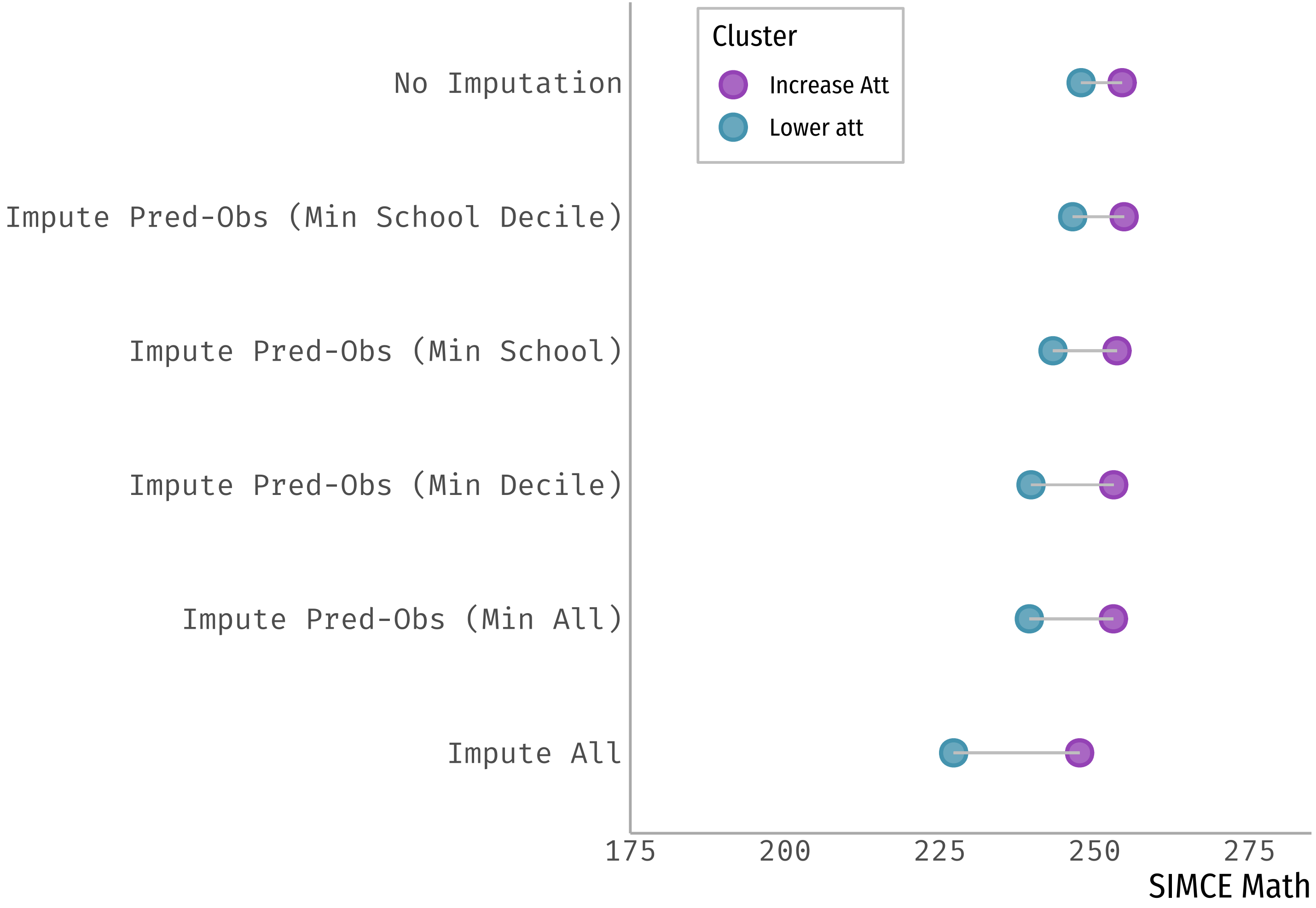
Some caveats:

- Difference between predicted and obs. captures total incentives/disincentives in attendance.
- Imputed score might be too optimistic (e.g. real score would be lower than observed distribution)

Scenario 1 vs Scenario 3: No imputation and Impute all



Imputing Predicted - Observed is less extreme



Let's Wrap Up...

Conclusions and next steps

- Non-representative patterns of absenteeism beyond exclusion of low-performers
  - High heterogeneity between schools

- Communication strategies play important role for lower-performing students

- Impact of imputation policies?
  - Work in progress: How does non-representativeness and different imputation strategies impact policies and information provision? What score do we impute and for whom?

- Importance of data availability

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