Charter School Heterogeneity: CF Output Tables

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October 16, 2024

I display the following figures and tables for each of the 3 main outcomes (Graduation rates, Math scores, ELA scores) in this order:

1. **Variable Importance Factors (VIF)** – These represent the depth-weigthed share of trees that split along a given covariate in the causal forest. Earlier splits are weighted more heavily. This produces a simple measure for the relative predictive power of each covariate in mapping heterogeneous treatment effects. For example, a VIF = 0.2 for variable k would indicate that approximately 20% of trees split on variable k. This is approximate because it may be that fewer than 20% of the trees used variable k if the trees that did use k tended to split earlier on it, or more than 20% if they tended to split later.

2. **CATE Distribution** – This is the distribution of district $\times$ year treatment effects. They're interpreted as average partial effects on a given district in a given year. For example, a coefficient of 0.5 indicates that increasing the charter share in district d in year t would have increased the outcome by 0.5pp.

3. **Group Covariate Means** – I display a table which examines the averages of each predictive covariate within districts that have significantly positive CATEs vs. districts that have significantly negative CATES. I also include the difference-in-means, though I have not yet added stars to highlight if the difference in statistically significant.

4. **ATE's of pre-specified subgroups (GATEs)** – For now I just look at a few subgroups, but I plan to add more as we see fit. These tables display the average treatment effect within districts that meet a specified criteria. For example, I examine the group average treatment effect (GATE) for districts that are "urban" vs. "suburban" vs. "rural." I also include (arbitrarily) the GATE of districts where $> 20\%$ of students are on free lunch.

5. **Best Linear Projection (BLP)** – Here I run a regression of each covariate on the predicted treatment effect: $\hat{\tau}(x) = \alpha + \boldsymbol{\beta X}_i + \varepsilon$. The coefficients highlight the (linear) correlation between covariate values and the treatment effects. So for example, if the coefficient of log(enrollment) is positive, then this indicates that greater values of log(enrollment) are associated with larger CATE estimates. Note that I only use the top 5 covariates according to VIF score.

Overview of results:

- Treatment effect distributions: The good news is that the ATE estimates are more-or-less similar to the ATE estimates from the original paper. The first thing to note, however, is that these are early results based on shallow forests (only 1,000 trees – I would probably use around 10,000 in the final model) and that I perform global recentering which we know is not the correct approach (i.e. we need the local-recentering approach from the "causal forest with fixed effects" algorithm). So, I suspect that this is causing some bias in the estimates of the ATE and the heterogeneous treatment effects. It also might be affecting precision, since we don't observe many statistically significant district $\times$ year CATE estimates.

- Important covariates: We notice many of the same variables popping up with high VIF scores in each case.

    1. "Teacher salary" is in the top 3 VIF scores in each model, though it is only associated positively with higher test scores and not with graduation rates.

2. "log(enrollment)" is also a top variable. Greater enrollment tends to be associated positively with greater graduation rate and ELA scores, but negatively with math scores.
3. "Percent black" is a top 3 variable regarding test scores, but not with graduation rates. For both Math and ELA it is associated with lower test scores.
4. "Student-teacher ratio" is in the top 4 in both Math and ELA, but not graduation rates. In both ELA and Math a higher S/T ratio seems to be slightly associated with positive test scores

- <u>GATEs I looked at:</u> So far all I have checked as far as within-group ATEs are the Urban vs. Suburban vs. Rural, and if the district has a $> 20\%$ free lunch rate. Urban and Suburban districts tent to have (sometimes imprecisely) higher ATEs for graduation rates and Math scores, but Rural districts haev (fairly precisely) greater ATEs in ELA. "$> 20\%$ Percent free lunch" is assocated positively with larger ATEs for both graduation rates and ELA, but not with Math.

Next steps:

- Some more tables to make: (1) GATEs within states, (2) GATEs within more subgroups, (3) GATEs within different levels of the treatment dosage, (4) CATEs within districts (here I examine district $\times$ year treatment effects, we likely want to average over district).
- Need to make deeper forests and use CFFE. These are relatively shallow forests (only 1000 trees, which is fewer than probably needed for valid CI's), and I use global recentering which we know will yield biased estimates. So these results are merely a flavor of what the real results will be.

1 Graduation Rate Results

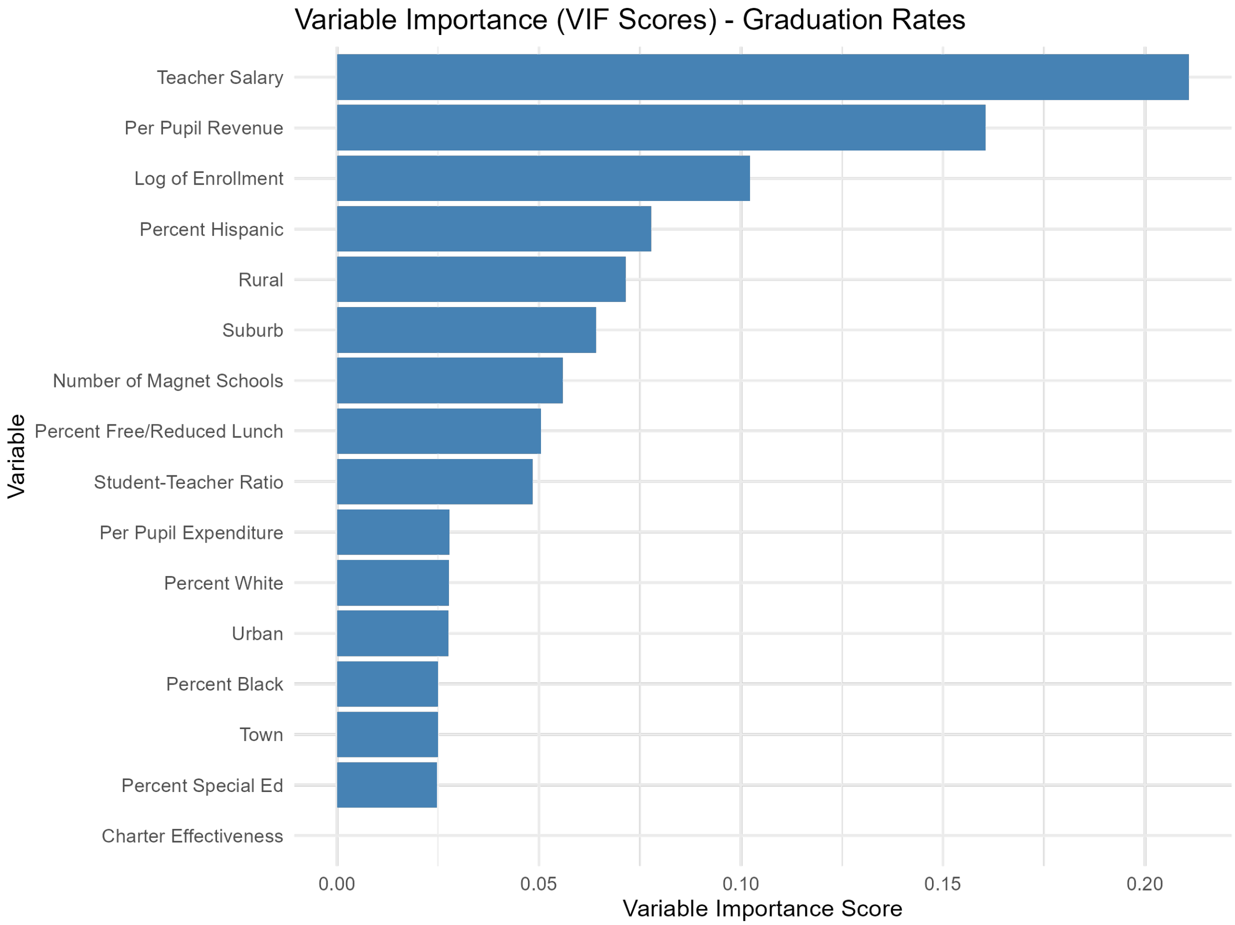


Figure 1: VIF Scores: Graduation Rates

Notes: Figure 1 plots VIF scores – the share of total trees which use a given baseline covariate to perform splitting, weighted by the depth at which the split occurred so that earlier splits within a tree count for slightly more.

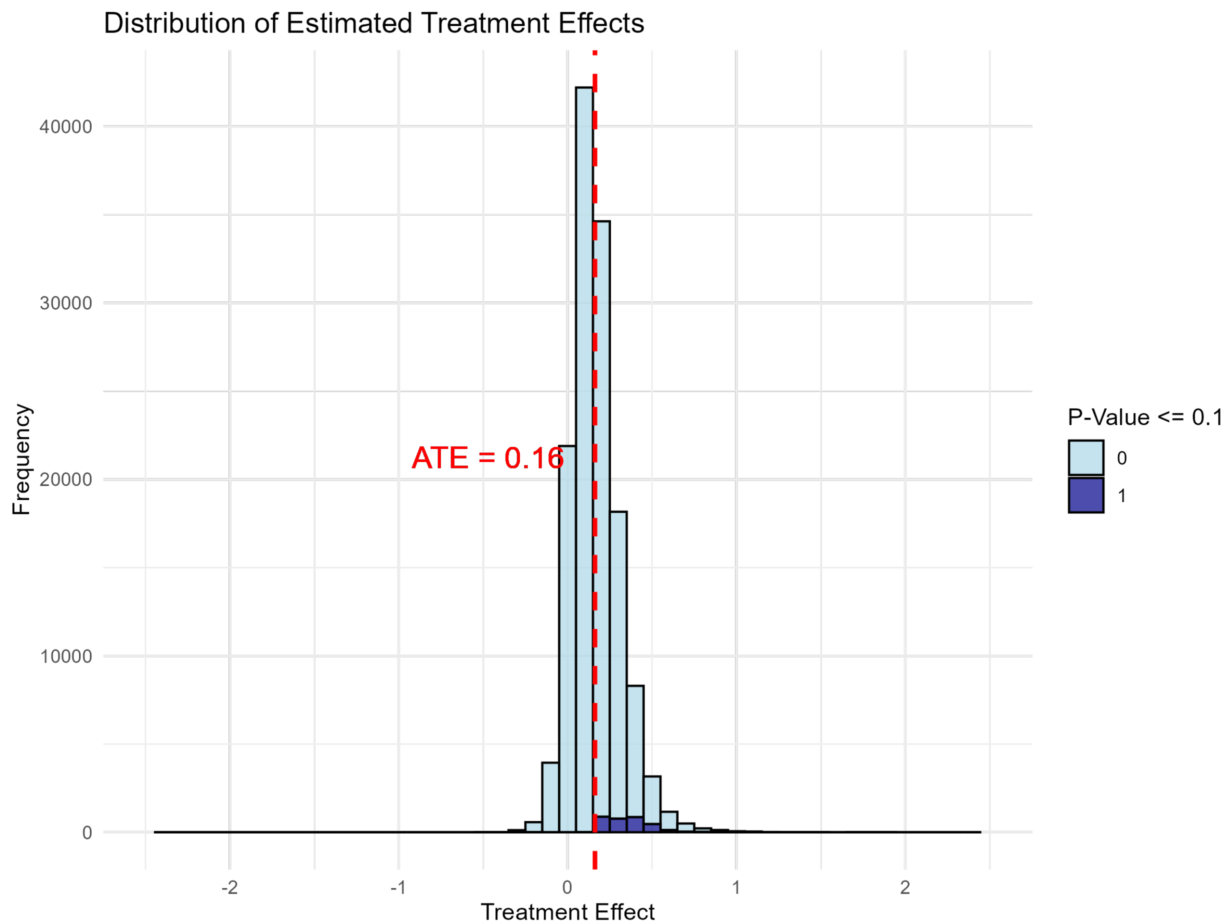


Figure 2: Treatment Effect Distribution: Graduation Rates

Notes: Figure 2 plots the distribution of district $\times$ year treatment effects for graduation rates. These are interrpeted as average partial effects of a given district in a given year. That is, each point represents $\frac{Cov[Y,W|X=x]}{Var[W|X=x]} = E\left[\frac{\partial\tau(x)}{\partial x}\right]$, the predicted treatment effect from increasing the charter share in year t by 1 percentage point.

Table 1: Group covariate means between significantly positive districts vs. significantly negative districts

	Covariate	Significantly Positive	Significantly Negative	Difference (Positive - Negative)
1	Log of Enrollment	8.03	7.86	0.17
2	Percent White	0.64	0.69	-0.05
3	Percent Black	0.16	0.25	-0.09
4	Percent Hispanic	0.15	0.03	0.12
5	Percent Free/Reduced Lunch	0.35	0.30	0.05
6	Percent Special Ed	0.13	0.12	0.01
7	Urban	0.14	0.00	0.14
8	Suburb	0.30	0.78	-0.48
9	Town	0.17	0.11	0.06
10	Rural	0.39	0.11	0.28
11	Per Pupil Revenue	9094.52	9297.58	-203.06
12	Per Pupil Expenditure	9148.21	9972.02	-823.81
13	Student-Teacher Ratio	15.87	18.13	-2.26
14	Teacher Salary	74712.97	85269.40	-10556.42
15	Number of Magnet Schools	0.15	0.11	0.04
16	Charter Effectiveness	0.82	0.89	-0.06
17	Number of Observations	3177.00	9.00	3186.00

Table 1: Avg treatment effects within US states

Table 3: Avg treatment effects of pre-specified subgroups

	Group	GATE	SE	p.value	Share.of.N
1	Urban	0.07	0.05	0.18	0.06
2	Suburban	0.12	0.02	0.00	0.23
3	Rural	-0.01	0.04	0.85	0.52
4	Percent Free Lunch > 20%	0.06	0.03	0.08	0.60

Table 4: Best linear projection $\tau(X) = \alpha + \beta X + e$

Variable	Estimate	Std..Error	t.value	Pr...t..
(Intercept)	0.16	0.05	3.10	0.00
Teacher salary	0.00	0.00	0.78	0.43
Per-pupil revenue	-0.00	0.00	-0.68	0.50
log(enrollment)	0.01	0.12	0.06	0.95
Percent Hispanic	-1.41	1.69	-0.83	0.40
Rural	-0.03	0.01	-1.83	0.07

The next figure aims to map heterogeneity across dosage responses. There are 2 relevant aspects to the dose-response function with continuous treatment:

- The average causal response at different starting doses: $E[Y(d') - Y(d)|X]$
- The level treatment effect function: $E[Y(d) - Y(0)|X]$

We can approximately map the average causal response function by grouping units treated in a given period t according to their 1-period lagged dose (i.e. group by $Y(d)_{t-1}$). We group districts by deciles of this value, then compute GATEs within deciles, effectively estimating $E[Y(d')_t - Y(d)_{t-1}]$. We can approximately map the level treatment effect by grouping districts on their observed dose in period t, conditional that their period t dose is non-0 and their lagged dose is 0. This allows us to estimate $E[Y(d)_t - Y(0)_{t-1}]$.

Figure 4 plots the distribution of treatment effects aggregated to the district level for graduation rates.

Table 1: GATEs within States (Graduation Rates)

State	GATE	SE	p.value	Share.of.N
Alabama	0.206***	0.039	0.000	0.012
Alaska	-0.618*	0.342	0.070	0.004
Arizona	-0.198	0.155	0.199	0.012
Arkansas	-1.085**	0.517	0.036	0.025
California	-0.054	0.057	0.339	0.046
Colorado	0.034	0.077	0.662	0.019
Connecticut	0.185***	0.048	0.000	0.012
Delaware	0.69***	0.214	0.001	0.002
Florida	0.192***	0.071	0.007	0.007
Georgia	-0.093	0.165	0.572	0.018
Idaho	-0.148	0.198	0.454	0.012
Illinois	0.189***	0.025	0.000	0.052
Indiana	0.093***	0.029	0.002	0.032
Kansas	-1.537**	0.629	0.014	0.031
Kentucky	0.197***	0.029	0.000	0.017
Louisiana	0.033	0.107	0.756	0.007
Maine	0.121***	0.020	0.000	0.012
Massachusetts	0.073	0.058	0.203	0.025
Michigan	0.101***	0.033	0.003	0.057
Minnesota	0.24***	0.066	0.000	0.034
Mississippi	0.246***	0.030	0.000	0.013
Montana	0.14***	0.021	0.000	0.017
Nebraska	0.132***	0.012	0.000	0.025
Nevada	-0.174	0.193	0.369	0.002
New Hampshire	0.461**	0.200	0.021	0.007
New Jersey	0.126***	0.023	0.000	0.027
New Mexico	-0.434	0.317	0.172	0.010
New York	0.156***	0.019	0.000	0.070
North Carolina	0.137	0.087	0.115	0.012
North Dakota	0.143***	0.024	0.000	0.015
Ohio	0.177***	0.029	0.000	0.067
Oregon	-0.161	0.316	0.611	0.019
Pennsylvania	0.147***	0.050	0.004	0.055
South Carolina	0.01	0.121	0.933	0.009
South Dakota	0.156***	0.035	0.000	0.016
Texas	0.206***	0.031	0.000	0.103
Utah	0.075	0.114	0.507	0.004
Vermont	0.152***	0.030	0.000	0.005
Virginia	0.137***	0.033	0.000	0.014
Washington	0.205***	0.039	0.000	0.027
West Virginia	0.143**	0.064	0.025	0.006
Wisconsin	0.254***	0.046	0.000	0.042

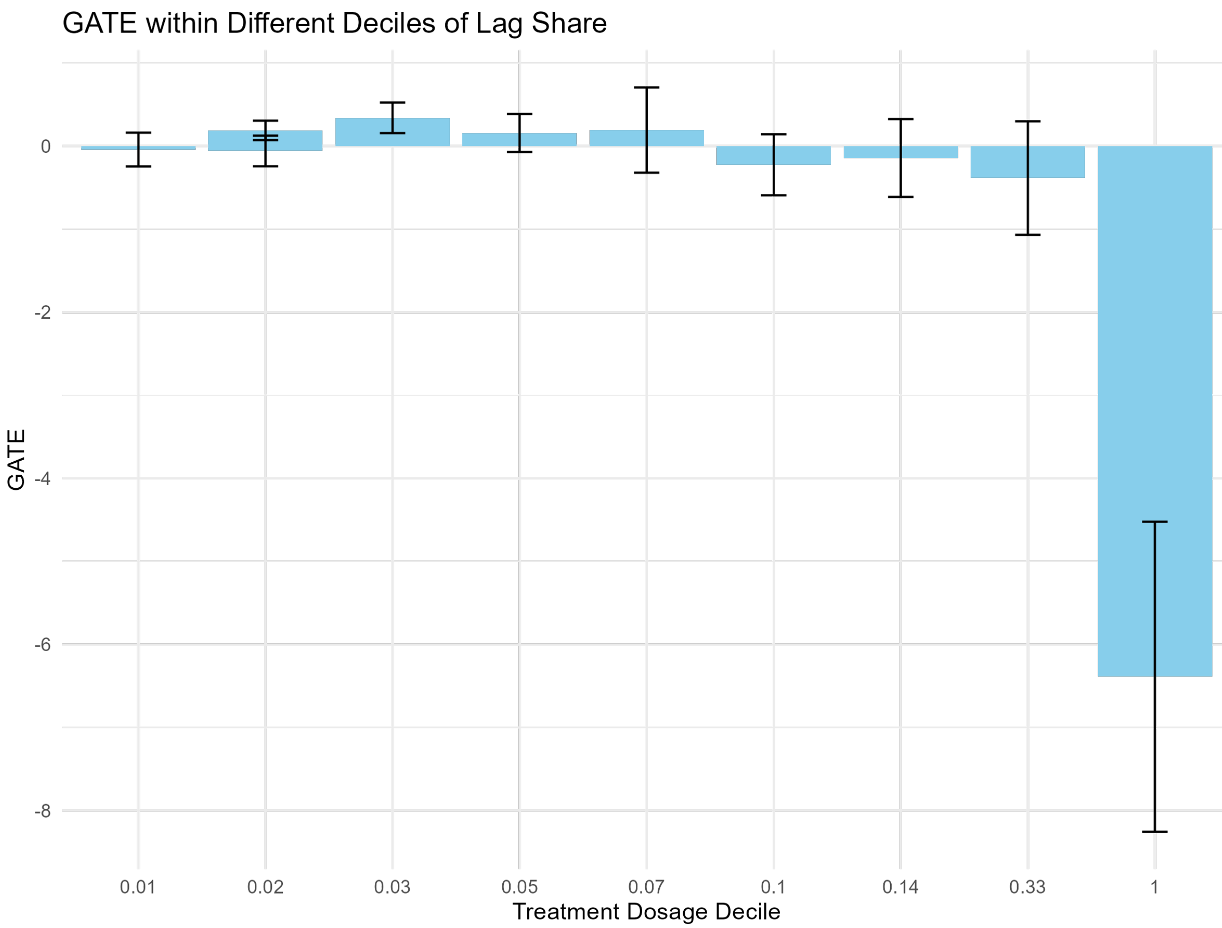
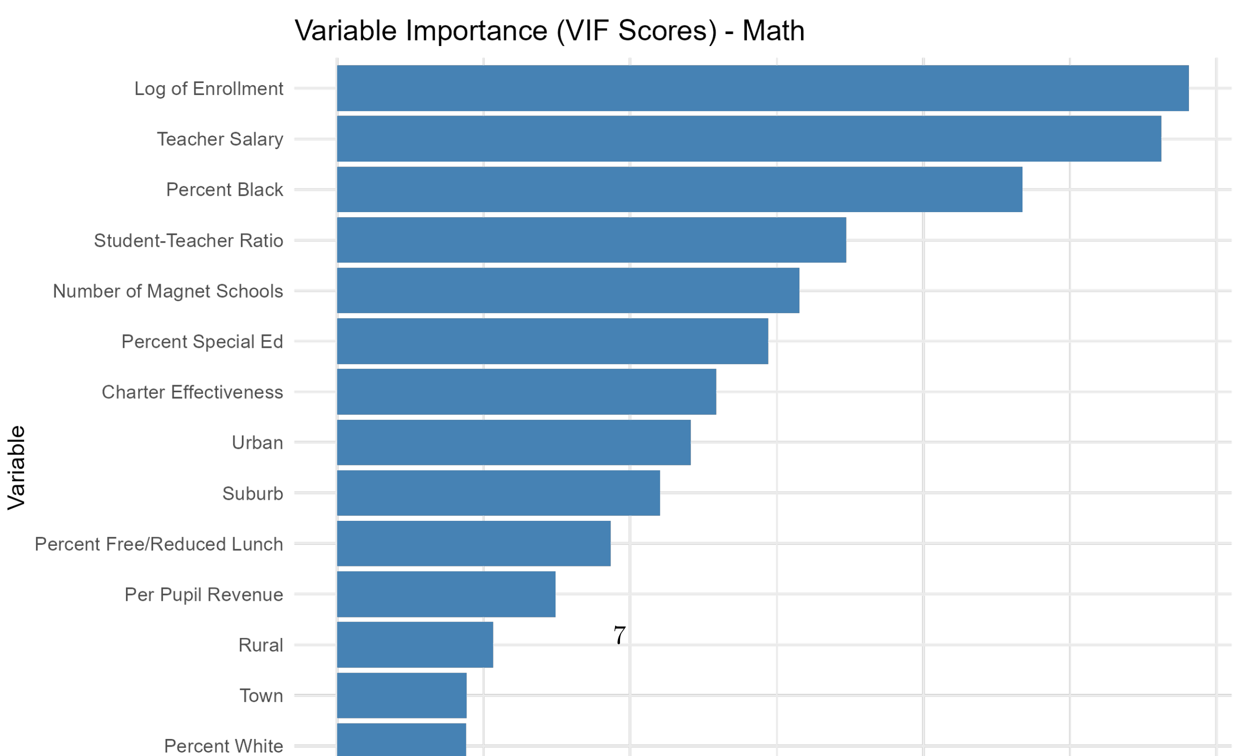


Figure 3: Treatment Effects over Dosage Deciles

Notes: Figure 3 plots the GATE for different deciles of the treatment distribution among treated districts.

2 Math Test Scores



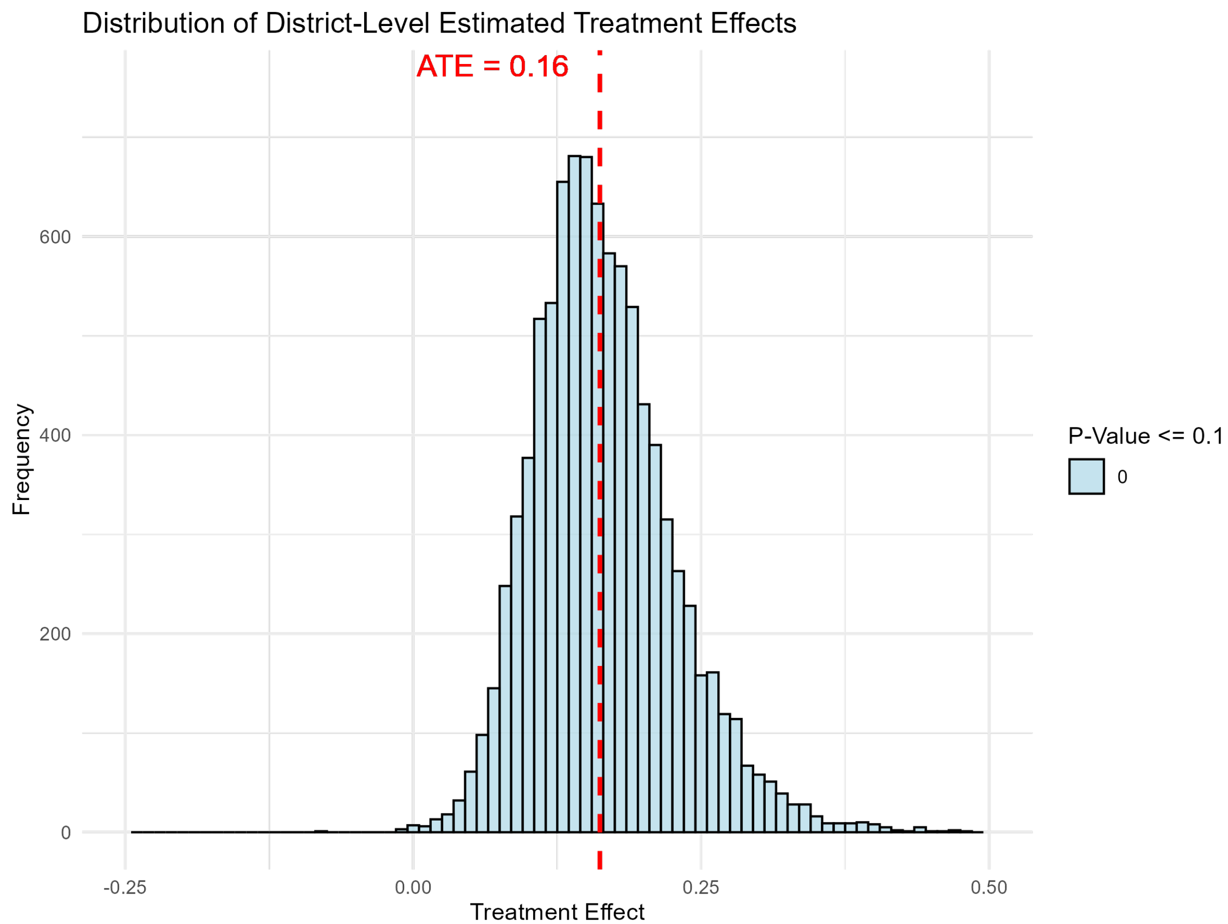


Figure 4: Distribution of District-Level Treatment Effects: Graduation Rates

Notes: Figure 3 plots VIF scores for Math – the share of total trees which use a given baseline covariate to perform splitting, weighted by the depth at which the split occurred so that earlier splits within a tree count for slightly more.

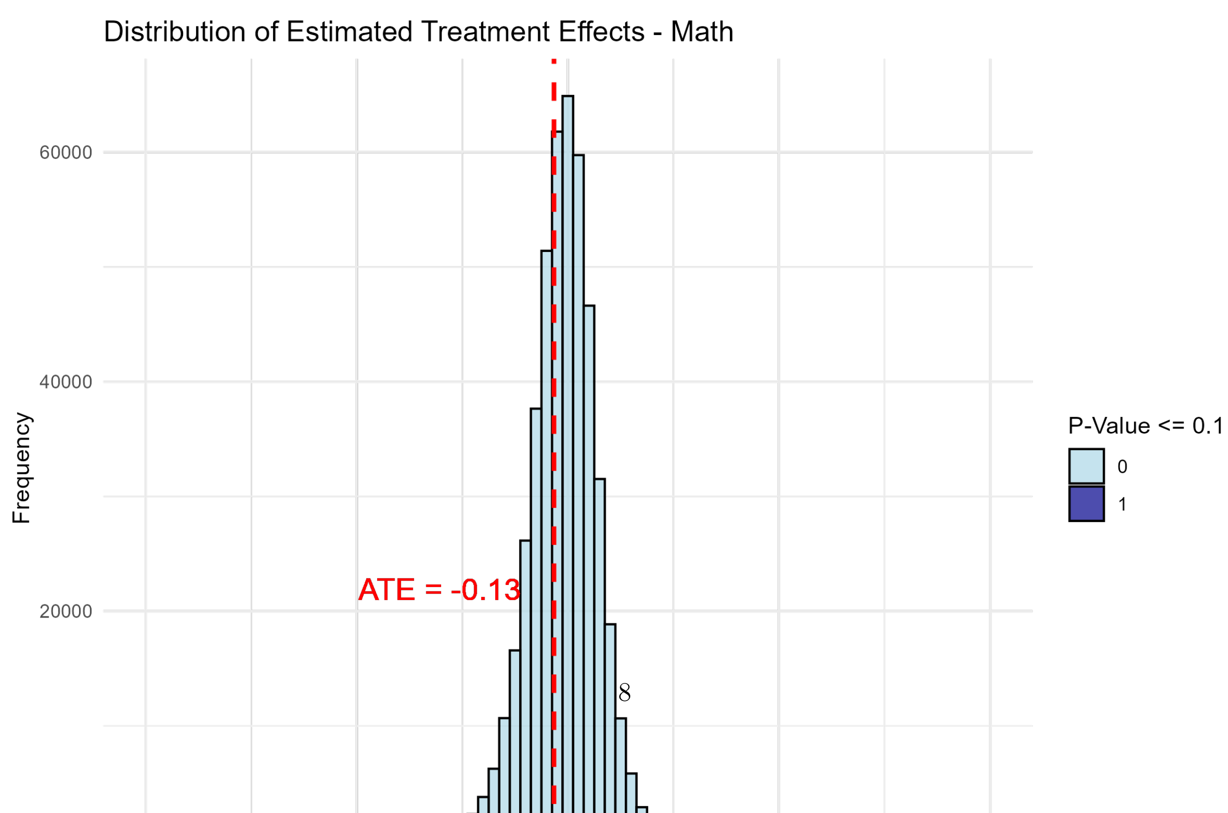


Table 4: Group covariate means between significantly positive districts vs. significantly negative districts

	Covariate	Significantly Positive	Significantly Negative	Difference (Positive - Negative)
1	Log of Enrollment	8.01	8.04	-0.03
2	Percent White	0.52	0.63	-0.11
3	Percent Black	0.06	0.13	-0.07
4	Percent Hispanic	0.30	0.19	0.11
5	Percent Free/Reduced Lunch	0.54	0.55	-0.01
6	Percent Special Ed	0.13	0.13	-0.00
7	Urban	0.16	0.09	0.08
8	Suburb	0.28	0.32	-0.04
9	Town	0.24	0.18	0.06
10	Rural	0.32	0.42	-0.10
11	Per Pupil Revenue	12343.16	11849.07	494.09
12	Per Pupil Expenditure	12293.01	12201.87	91.14
13	Student-Teacher Ratio	18.07	17.22	0.85
14	Teacher Salary	101527.23	97044.62	4482.61
15	Number of Magnet Schools	0.04	0.70	-0.67
16	Charter Effectiveness	0.97	0.96	0.01
17	Number of Observations	692.00	370.00	1062.00

Table 5: Avg treatment effects of pre-specified subgroups

	Group	GATE	SE	p.value	Share.of.N
1	Urban	0.02	0.11	0.89	0.06
2	Suburban	0.02	0.05	0.66	0.27
3	Rural	-0.07	0.05	0.14	0.48
4	Percent Free Lunch > 20%	-0.03	0.03	0.39	0.87

Table 6: Best linear projection $\tau(X) = \alpha + \beta X + e$

Variable	Estimate	Std..Error	t.value	Pr...t..
(Intercept)	-0.13	0.09	-1.54	0.12
log(enrollment)	-0.23	0.27	-0.86	0.39
Teacher salary	-0.00	0.00	-0.73	0.47
Percent black	-5.66	3.75	-1.51	0.13
Student-teacher ratio	0.03	0.07	0.40	0.69
Num magnet schools	0.02	0.01	2.84	0.00

3 ELA Test Scores

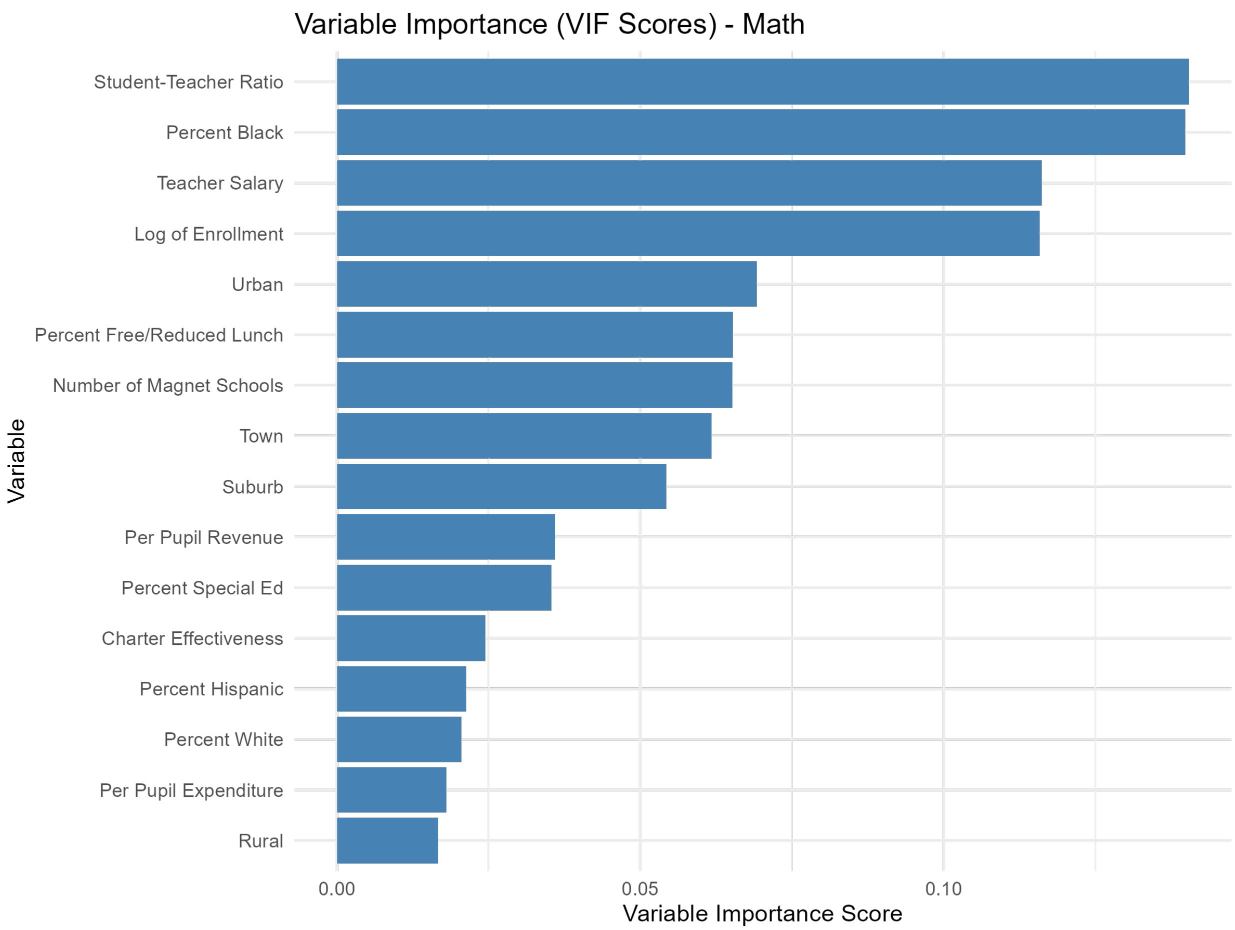


Figure 7: VIF Scores: ELA Scores

Notes: Figure 5 plots VIF scores for ELA – the share of total trees which use a given baseline covariate to perform splitting, weighted by the depth at which the split occurred so that earlier splits within a tree count for slightly more.

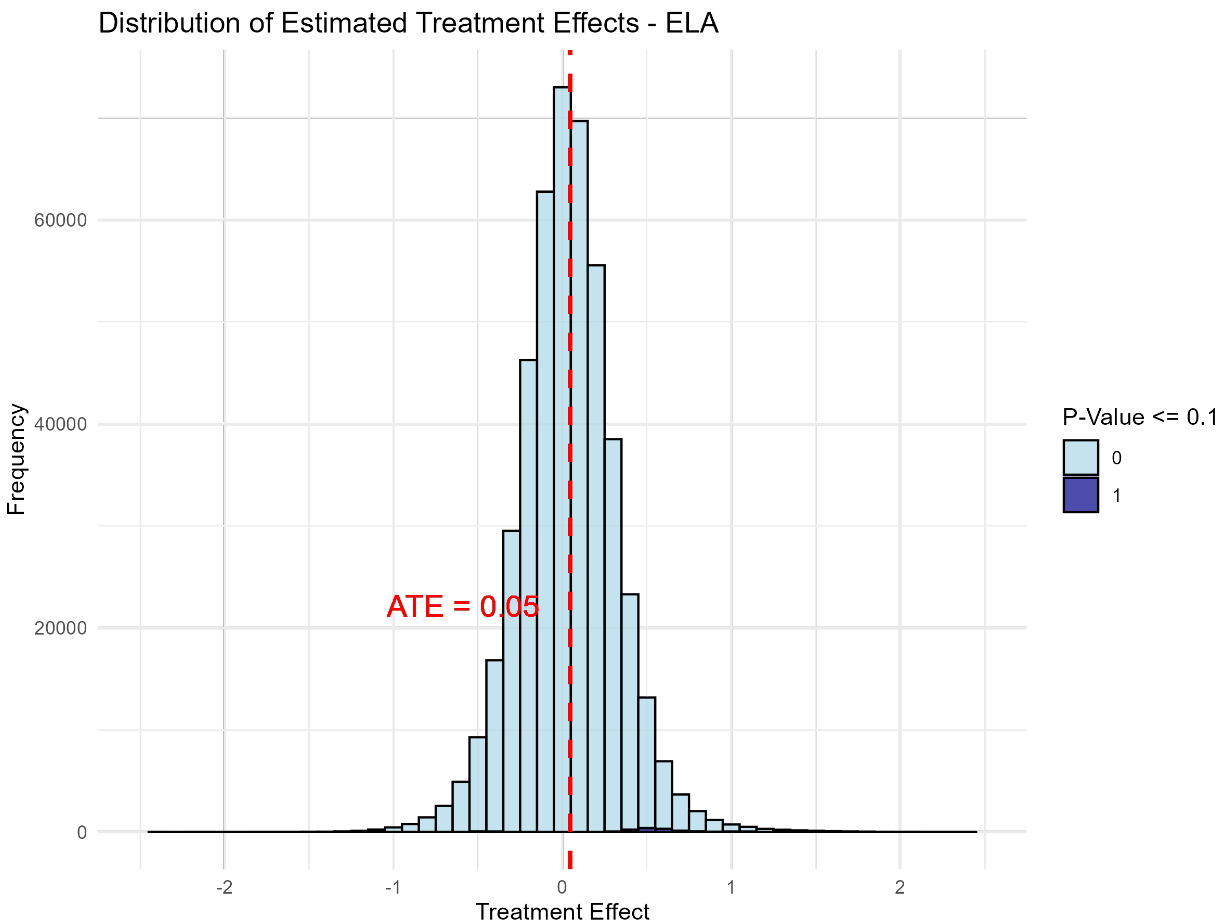


Figure 8: Treatment Effect Distribution: ELA Scores

Notes: Figure 6 plots the distribution of district × year treatment effects for ELA scores. These are interrpeted as average partial effects of a given district in a given year. That is, each point represents $\frac{Cov[Y,W|X=x]}{Var[W|X=x]} = E\left[\frac{\partial\tau(x)}{\partial x}\right]$, the predicted treatment effect from increasing the charter share in year t by 1 percentage point.

Table 7: Group covariate means between significantly positive districts vs. significantly negative districts

	Covariate	Significantly Positive	Significantly Negative	Difference (Positive - Negative)
1	Log of Enrollment	8.21	7.73	0.48
2	Percent White	0.42	0.68	-0.25
3	Percent Black	0.07	0.12	-0.04
4	Percent Hispanic	0.39	0.17	0.22
5	Percent Free/Reduced Lunch	0.57	0.51	0.07
6	Percent Special Ed	0.12	0.14	-0.02
7	Urban	0.20	0.10	0.10
8	Suburb	0.24	0.31	-0.06
9	Town	0.25	0.25	-0.00
10	Rural	0.31	0.34	-0.03
11	Per Pupil Revenue	11988.22	13031.93	-1043.71
12	Per Pupil Expenditure	12000.04	12981.64	-981.61
13	Student-Teacher Ratio	18.11	16.05	2.06
14	Teacher Salary	100441.84	95983.14	4458.70
15	Number of Magnet Schools	0.53	0.48	0.05
16	Charter Effectiveness	0.96	1.00	-0.03
17	Number of Observations	1394.00	213.00	1607.00

Table 8: Avg treatment effects of pre-specified subgroups

	Group	GATE	SE	p.value	Share.of.N
1	Urban	-0.03	0.12	0.78	0.06
2	Suburban	-0.02	0.05	0.74	0.27
3	Rural	0.09	0.04	0.02	0.48
4	Percent Free Lunch $>$ 20%	0.06	0.03	0.04	0.87

Table 9: Best linear projection $\tau(X) = \alpha + \beta X + e$

Variable	Estimate	Std..Error	t.value	Pr...t..
(Intercept)	0.05	0.08	0.58	0.56
Student-teacher ratio	-0.01	0.05	-0.32	0.75
Percent black	-5.46	3.11	-1.75	0.08
Teacher salary	0.00	0.00	1.73	0.08
log(enrollment)	0.18	0.22	0.80	0.42
Urban	0.12	0.07	1.32	0.19