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Promoting Equitable Access to Effective Teachers

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Citation	Sass, T. R., & Lawson, M. C. (2024). Promoting equitable access to effective teachers. Georgia Policy Labs. https://doi.org/10.57709/9v5p-kc41
DOI	https://doi.org/10.57709/9v5p-kc41
Download date	2026-03-06 21:11:18
Link to Item	https://hdl.handle.net/20.500.14694/7310



**GEORGIA
POLICY LABS**



Appendix to:

Promoting Equitable Access to Effective Teachers

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March 2024

Empirical Model

Our formal value-added model is specified as follows:

$$Y_{igjst} = \beta_0 + Y_{igjs(t-1)}\beta_1 + X_{ist}\beta_3 + Z_{igjst}\beta_4 + \gamma_g + \eta_t + \mu_s + \epsilon_{igjst}$$

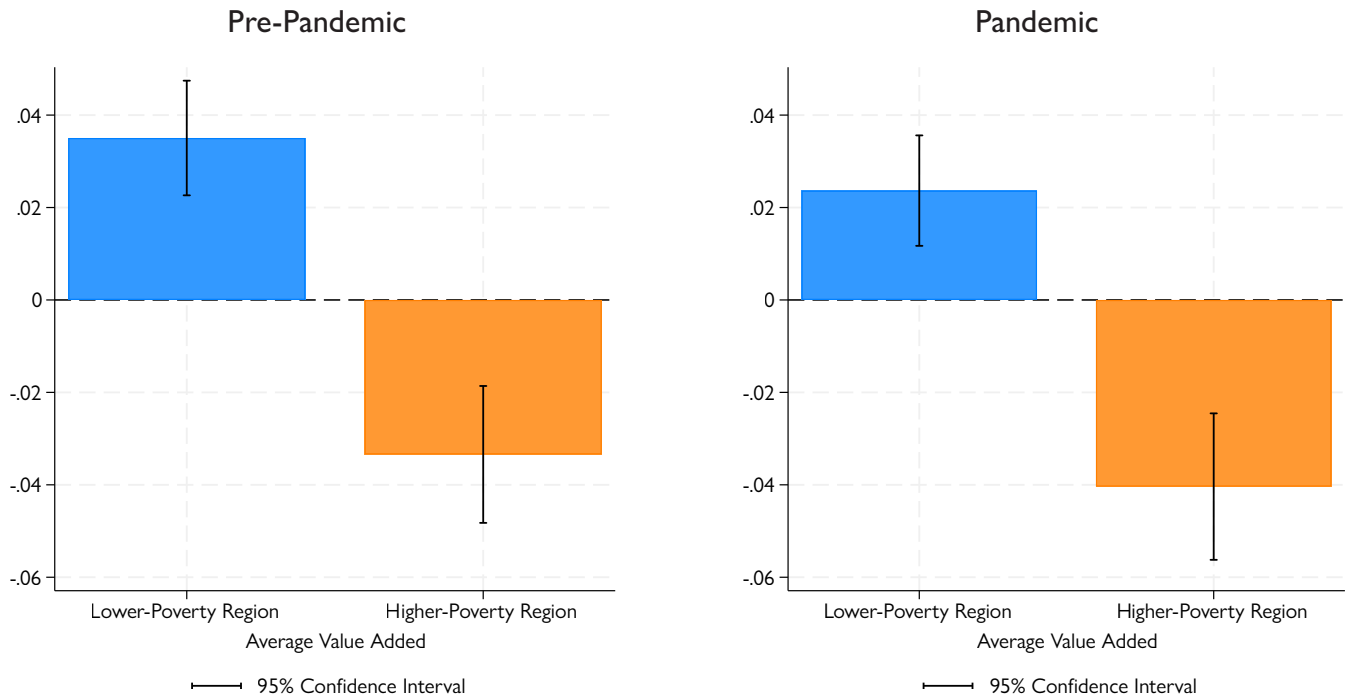
In the equation above, Y_{igjst} denotes the test score of student i , in subject j and grade g , with teacher s , in year t . X_{ist} is a vector of student characteristics including gender, free or reduced-price meals status, English Learner status, race, and identified disability status. Z_{igjst} is a vector of non-student factors, including the student's class size, the number of instructional days between the first and second testing period, and the square of the student's prior test score. γ_g and η_t are grade and year fixed effects, respectively, and ϵ_{igjst} is the idiosyncratic error term. The parameter of interest is μ_s , the teacher fixed effect and our measure of teacher effectiveness. We omit school fixed effects to avoid making comparisons within-school.

We estimate our models using the *felsdvmregdm* routine in Stata, which imposes a sum-to-zero constraint on fixed effects with respect to a reference group.¹ We define our reference group as all teachers in Grades K–8 across the district in each of math and reading/ELA. Since usual fixed effects models would report fixed effects coefficients with respect to an arbitrary teacher, the sum-to-zero constraint is necessary to calculate standard errors that can be used in the Empirical Bayes shrinkage estimation described in the main report. Our teacher fixed effects (value-added) estimates can therefore be interpreted as distance (in formative assessment standard deviations) from the average K–8 teacher in the district.

Given that test scores are noisy measures of student performance, we employ an Empirical Bayes (EB) shrinkage method to stabilize our estimates of teacher effectiveness. The EB method involves “shrinking” especially noisy value-added estimates toward the mean for all teachers (which is, by construction, 0). For example, imagine a teacher is observed teaching just 10 students in our sample and is assigned a very low value-added estimate. By applying Empirical Bayes shrinkage, we account for the likelihood that this teacher's low value-added is driven by a few students having unusually poor exam performances and places less weight on the estimate by adjusting it toward the population mean. If we were able to observe the teacher with more students, these random fluctuations would tend to cancel out and their estimate would likely be closer to the true value.

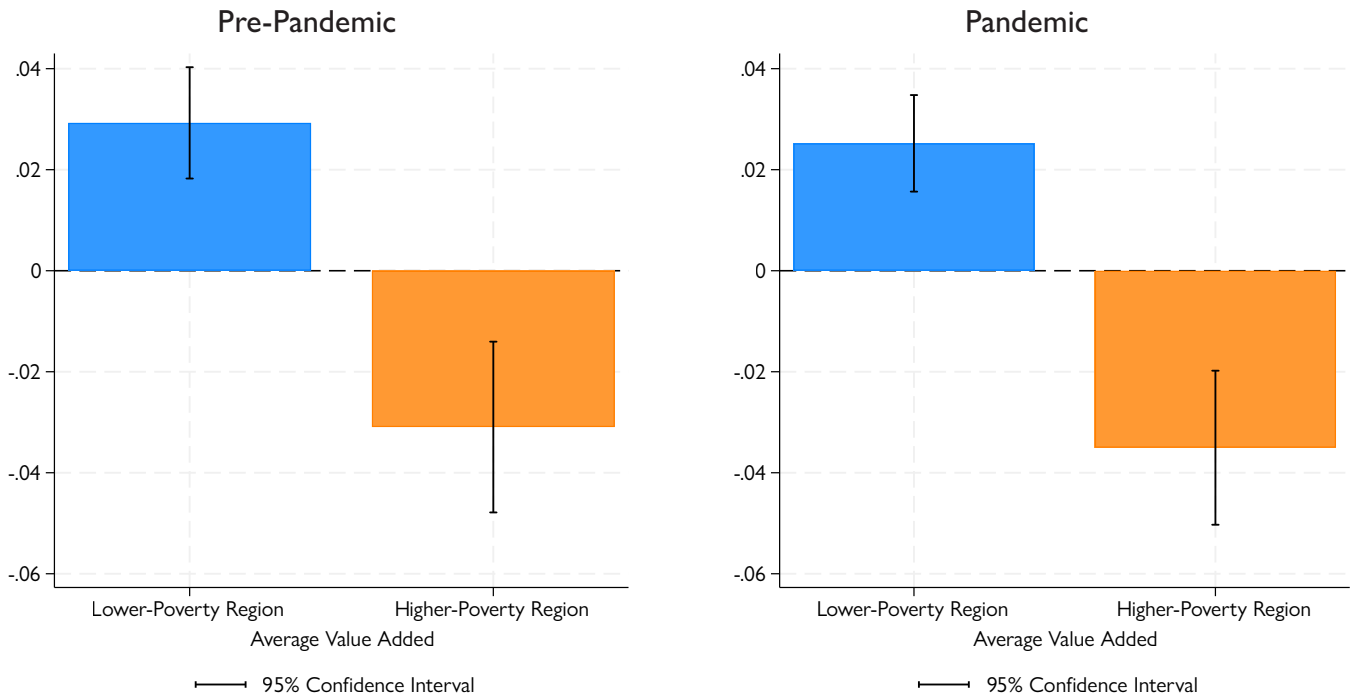
Supplemental Figures

Figure A1. Differences in Average Math Teacher Effectiveness Before and During the Pandemic, Higher- vs. Lower-Poverty Region



Notes. The left panel shows pre-pandemic average value-added by region. The right panel shows average value-added during the pandemic. Value-added, measured in standard deviations, is estimated using data from SY 2017–18 to SY 2019–20 for the pre-pandemic period and SY 2020–21 to 2021–22 for the pandemic period. Models include students in grades K–8 in the appropriate subject. Reported estimates are adjusted using Empirical Bayes shrinkage prior to averaging.

Figure A2. Differences in Average Reading/ELA Teacher Effectiveness Before and During the Pandemic, Higher- vs. Lower-Poverty Region



Notes. The left panel shows pre-pandemic average value-added by region. The right panel shows average value-added during the pandemic. Value-added, measured in standard deviations, is estimated using data from SY 2017–18 to SY 2019–20 for the pre-pandemic period and SY 2020–21 to 2021–22 for the pandemic period. Models include students in grades K–8 in the appropriate subject. Reported estimates are adjusted using Empirical Bayes shrinkage prior to averaging.

In the main report, we discuss the distribution of teacher value-added before and after the pandemic and between the Higher- and Lower-Poverty Regions separately. In Figures A1 and A2 above, we demonstrate the robustness of these findings by comparing average teacher effectiveness between the Higher- and Lower-Poverty Region before and during the pandemic jointly across math and reading/ELA. Statistically significant differences in teacher effectiveness are present between the Higher-Poverty- and Lower-Poverty Region in both math and reading/ELA both before and during the pandemic—with no evidence that the magnitude of the gap changed much after the onset of the pandemic.

Supplemental Tables

Table A1. Comparing Average Teacher Effectiveness in the Higher vs. Lower-Poverty Region Under Alternative Value-added Model Specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	
Average math effectiveness	Lower-Poverty Region (N = 1,318)	0.031	0.032	0.028	0.027	0.078	0.083
	Higher-Poverty Region (N = 846)	-0.038	-0.039	-0.034	-0.033	-0.108	-0.116
	Mean difference	0.069***	0.070***	0.061***	0.061***	0.186***	0.199***
Average reading/ELA effectiveness	Lower-Poverty Region (N = 1,393)	0.030	0.029	0.029	0.031	0.067	0.074
	Higher-Poverty Region (N = 868)	-0.037	-0.034	-0.036	-0.039	-0.090	-0.103
	Mean difference	0.067***	0.063***	0.064***	0.070***	0.156***	0.177***
Controls	Days between exam dates	X	X	X	X	X	
	Student demographics	X	X	X	X		
	Square of prior score	X	X	X		X	
	Class size	X	X	X		X	
	Year fixed effect	X				X	
	Grade fixed effect	X	X			X	

Notes. Mean differences significant at ***1%, **5%, *10% levels. Reported area-level averages and mean differences are rounded to the nearest 0.001. Mean differences calculated before rounding of individual means. Results presented are after Empirical Bayes shrinkage and are calculated using the full analysis sample: SY 2017–18 to SY 2021–22.

Table A1 explores the robustness of differences in average teacher effectiveness between the Lower- and Higher-Poverty Region by a variety of value-added specifications. Column 1 corresponds to our preferred model, referenced throughout the report. The first four specifications produce very similar results. Models that omit controls for student characteristics (columns 5 and 6) yield much larger estimates of mean differences in value-added between teachers in the two regions. This finding is consistent with non-random assignment of students to teachers, whereby students with greater learning challenges are more likely to reside in the Higher-Poverty Region. By omitting controls for

Table A2: Comparing Average Teacher Effectiveness among Teachers who Switch between the Higher-Poverty and Lower-Poverty Regions.

	Lower-Poverty Region	Higher-Poverty Region	Mean Difference (N-S)
Average Math Effectiveness	0.053	-0.045	0.098
Average Reading Effectiveness	0.054	-0.057	0.111
N (math)	11	11	22
N (reading)	13	13	26

Notes. Mean differences significant at ***1%, **5%, *10% levels. Results above are Empirical Bayes-shrunken and calculated over our full sample: SY 2017–18 to SY 2021–22. The underlying value-added model is estimated using the same controls as our primary specification. Reported area-level averages and mean differences are rounded to the nearest 0.001. Mean differences calculated before rounding of individual means.

student characteristics, the estimates of teacher value-added are likely biased, as they capture both true teacher effectiveness and the abilities and household resources of the students they teach.

To rule out the possibility that estimated differences in average teacher effectiveness between the Lower- and Higher-Poverty Regions are driven by unobserved factors such as student engagement or family resources, we compare teachers who taught in both regions between SY 2017–18 and SY 2021–22. By calculating value-added for these teachers separately for years spent in the Higher-Poverty Region and the Lower-Poverty Region, we can hold teacher effectiveness constant and attribute any differences in effectiveness to differences in the student population. However, we observed so few teachers teaching in both the Higher- and Lower-Poverty Region during our sample that this analysis was not conclusive. Results are presented in Table A2. We observe differences in teacher effectiveness when teachers switch between the two regions that are not statistically different from zero but are too noisy for meaningful inference due to the small sample sizes.

Endnotes

1. Mihaly, K., McCaffrey, D. F., Lockwood, J. R., & Sass, T. R. (2010). Centering and reference groups for estimates of fixed effects: Modifications to `felsdsvreg`. *The Stata Journal*, 10(1), 82-103.