State Contexts in the Associations between Family Poverty, School Poverty, and Academic Achievement

Heewon Jang
Sean F. Reardon
Stanford University

Background and Purpose

Students from affluent families tend to perform better on standardized tests than their poor peers (e.g., Reardon, 2011; Sirin, 2005). There are many factors that may lead to this advantage. For example, students from affluent family backgrounds have access to more educational resources within their homes and neighborhoods (e.g., preschool programs and parental spending on educational activities) that are predictive of academic success (Kornrich & Furstenberg, 2013; Magnuson & Waldfogel, 2016). In this paper, we are interested in the extent to which school and state context moderate the association between student poverty and academic performance. Put simply, we are interested in understanding if, and why, low-income students have higher educational opportunities and outcomes in some settings than in others.

A few previous studies can provide insight into this question. First, studies on frog-pond effects have examined whether poor-performing students do better when they go to schools with more high-achievers, showing that the presence of higher-performing students could improve individual learning (Burke & Sass, 2013; Kang, 2007). Moreover, recent evidence on school segregation demonstrate that minority students achieve higher test scores when they go to schools with lower poverty rates (Reardon et al., 2019). The degree to which they do better, however, might vary depending on which state they are in, as states function as key organizational levels in the decentralized educational system of the United States. Jang & Reardon (2019) recently showed that state characteristics such as between-district income segregation explain test score gaps between high- and low-SES achievement districts. This implies that the source of between-state variation in the poverty-achievement association may lie in state-level factors such as socioeconomic inequality or educational policy.

The current paper explores several questions: (a) how are both family poverty and school poverty rates associated with students' academic performance and learning?; (b) is the association between school poverty and academic performance different for poor and nonpoor students?; (c) to what extent do these associations vary across states?; and, (d) is the variation across states explained by state-level characteristics? Answers to these questions help lay a foundation for understanding how state and school contexts might be altered to improve educational opportunities for low-income students.

Data and Analysis

This study uses the Stanford Education Data Archive (SEDA; Reardon et al, 2019), which provides school average test scores from grade 3 to 8 in 2009-2016. We use school-by-subgroup (poor students and nonpoor students) data[1] to fit a set of hierarchical linear models, represented in stylized form below:

$$\hat{y}_{ist} = \alpha_{0st} + \alpha_{1st}(P_{ist} - poverty\ rate_{st}) + \hat{e}_{ist}$$
$$\alpha_{0st} = \beta_{00t} + \beta_{01t}(poverty\ rate_{st}) + u_{0st}$$
$$\alpha_{1st} = \beta_{10t} + \beta_{11t}(poverty\ rate_{st}) + u_{1st}$$

[1] This data is not yet publicly available; however, has been obtained via permission from Sean Reardon.

$$\beta_{00t} = \mathbf{\Gamma_{00}} \boldsymbol{X_t} + v_{00t}$$
$$\beta_{01t} = \mathbf{\Gamma_{01}} \boldsymbol{X_t} + v_{01t}$$
$$\beta_{10t} = \mathbf{\Gamma_{10}} \boldsymbol{X_t} + v_{10t}$$
$$\beta_{11t} = \mathbf{\Gamma_{11}} \boldsymbol{X_t} + v_{11t}$$

Where $\hat{y}_{ist}$ is average achievement (or average grade 3-8 learning rates) for subgroup i (poor or nonpoor students, indicate by the binary variable P) in school s in state t. Here there are four parameters of interest: the state-level association between school poverty rates and school average achievement and learning rates (β_{01t}), the difference in this association between poor and non-poor students in state t (β_{11t}), and the associations that each of these parameters has with state-level characteristics ($\mathbf{\Gamma_{01}}$ and $\mathbf{\Gamma_{11}}$). We specifically focus on state-level socioeconomic inequality (e.g., income inequality and difference in exposure to school poverty) and state educational policies (e.g., affluent-poor preschool enrollment difference, state-level gradients in per pupil revenue, experienced teacher, and teacher absenteeism).

To date, we have fit these models using test scores for all students ($\hat{y}_{st}$ instead of $\hat{y}_{ist}$, without α_{1st} terms). The models provide school poverty gradients—the association between average test score and the percentage of nonpoor students (i.e., not eligible for free/reduced-priced lunch) in each school. In these models, we add state characteristics to analyze their associations with state-level gradients and the growth of the gradients.

Results

There is a considerable variation in state-level gradients (Figure 1) as well as their rate of growth per grade (Figure 2). The percentage of nonpoor students is positively associated with school test scores across all states, having an average coefficient of 1.27. This indicates that schools with less poor peers are more likely to show higher average school achievement, without exception. Ohio has the highest gradient (1.64), twice as large as that of Wyoming (0.81), implying substantial variability in the distribution of between-school socioeconomic achievement gaps. Similarly, the association between the growth rate of school average achievement and the percentage of nonpoor varies widely from South Dakota (-0.05) to New Hampshire (1.21).

We find that difference in preschool enrollment between affluent and poor families is significantly associated with state-level gradients (Table 1). A state is expected to have 0.09 higher gradients when its preschool enrollment difference is 1SD higher than the average state, which corresponds to 7% of the average gradient. Moreover, state-level income school segregation has a significant positive relation to the growth rate of gradients. A 1SD increase in income school segregation is predicted to increase the growth of the school poverty achievement gradients by 0.01. This corresponds to 33% of the average growth of the gradient.

Conclusion

The preliminary findings of this study suggest that high poverty schools are generally disadvantaged in all places, but the degree to which states provide more or less equal opportunities to them varies. The difference in preschool enrollment between affluent and poor families within each state is positively related with the school poverty gradients in grade 3 achievement, while between-school income segregation has a positive relation to the growth of the school poverty achievement gradients. This implies that state-level preschool enrollment equity and school segregation may affect the relative performance of higher-poverty schools, highlighting the importance of policies around preschool access and income segregation between schools. The final version of the paper will expand on these findings to explore if/how the patterns differ for poor and nonpoor students.

Tables and Figures

Figure 1.

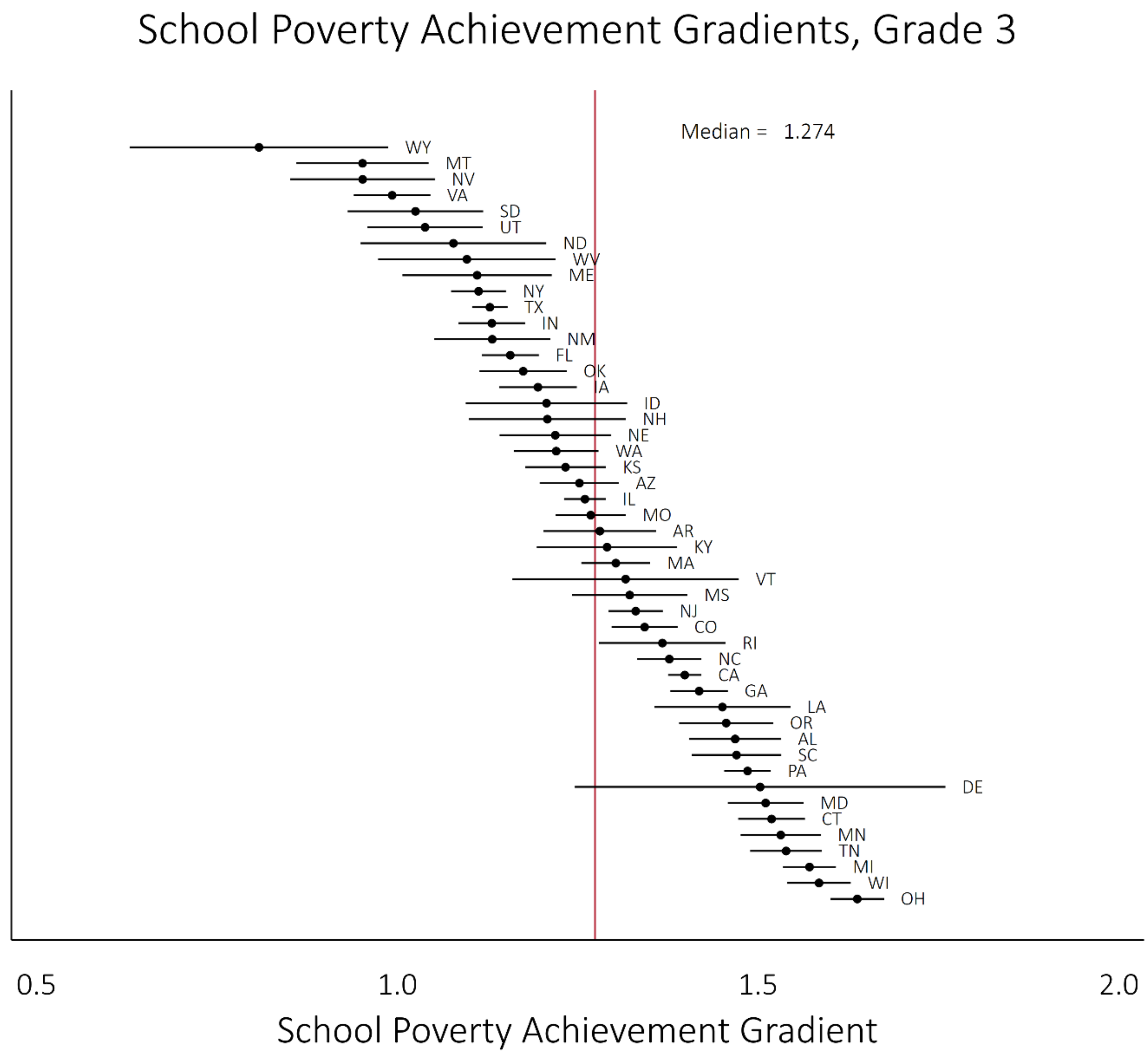

Figure 2.

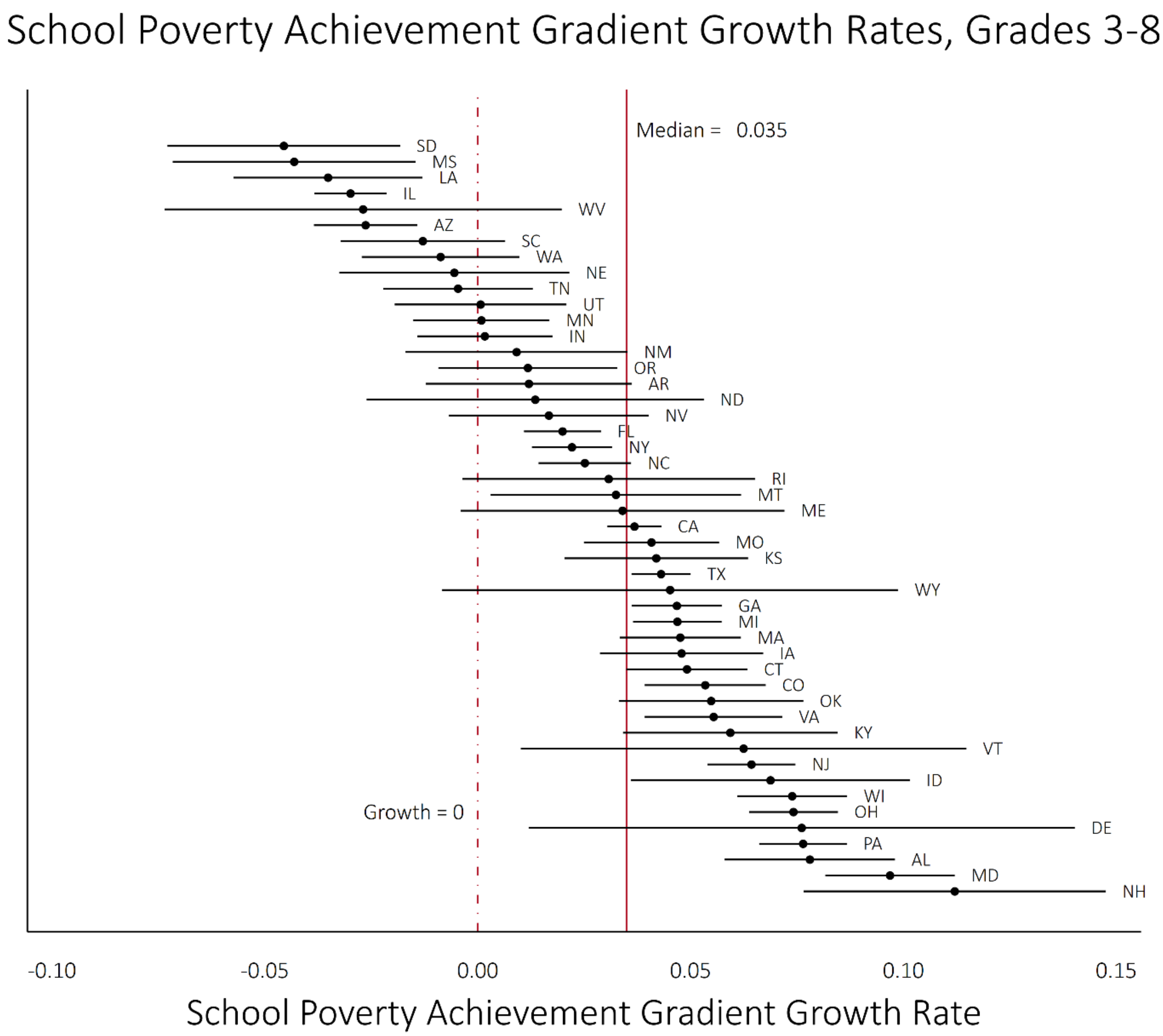
School Poverty Achievement Gradient Growth Rates, Grades 3-8
Median = 0.035
Growth = 0
SD
MS
LA
IL
WV
AZ
SC
WA
NE
TN
UT
MN
IN
NM
OR
AR
ND
NV
FL
NY
NC
RI
MT
ME
CA
MO
KS
TX
WY
GA
MI
MA
IA
CT
CO
OK
VA
KY
VT
NJ
ID
WI
OH
DE
PA
AL
MD
NH
-0.10
-0.05
0.00
0.05
0.10
0.15
School Poverty Achievement Gradient Growth Rate

Table 1. Multivariate Model

	b	(se)	
Intercept			
Intercept	0.020	(0.011)	+
Q5-Q1 Preschool Difference	0.118	(0.182)	
Funding Gradient	-0.087	(0.111)	
Experienced Teacher Gradient	0.173	(0.195)	
Teacher Presence Gradient	0.000	(0.145)	
Income Segregation	-0.261	(0.192)	
Income Inequality	2.393	(0.760)	**
Race-%NFRL Association	-0.056	(0.051)	
%NRFL Slope	1.293	(0.021)	***
Q5-Q1 Preschool Difference	1.263	(0.361)	**
Funding Gradient	-0.296	(0.217)	
Experienced Teacher Gradient	-0.061	(0.389)	
Teacher Presence Gradient	-0.450	(0.291)	
Income Segregation	-0.145	(0.378)	
Income Inequality	2.160	(1.505)	
Race-%NFRL Association	0.210	(0.104)	*
Grade			
Intercept	0.008	(0.002)	**
Q5-Q1 Preschool Difference	-0.058	(0.041)	
Funding Gradient	0.000	(0.025)	
Experienced Teacher Gradient	-0.025	(0.044)	
Teacher Presence Gradient	-0.005	(0.032)	
Income Segregation	0.091	(0.043)	*
Income Inequality	-0.287	(0.170)	+
Race-%NFRL Association	-0.010	(0.011)	
%NRFL Slope	0.028	(0.004)	***
Q5-Q1 Preschool Difference	0.039	(0.065)	
Funding Gradient	-0.012	(0.038)	
Experienced Teacher Gradient	-0.047	(0.070)	
Teacher Presence Gradient	-0.073	(0.053)	
Income Segregation	0.147	(0.067)	*
Income Inequality	-0.096	(0.270)	
Race-%NFRL Association	-0.054	(0.019)	**
Math			
Intercept	-0.009	(0.001)	***
%NRFL Slope	-0.040	(0.002)	***
Cohort			
Intercept	0.000	(0.000)	**
%NRFL Slope	0.016	(0.001)	***
Number of Observations	3,205,927		
Number of Schools	74,221		
Number of States	48		
Within-School SD	0.136		
Within-State Intercept SD	0.253		
Within-State Grade Slope SD	0.062		
Within-State Math Slope SD	0.140		
Within-State Cohort Slope SD	0.037		
Between-State Intercept SD	0.068		
Between-State %NFRL Gradient SD	0.129		
Between-State Grade Slope SD	0.015		
Between-State Grade*%NFRL SD	0.022		

References

Burke, M. A., & Sass, T. R. (2013). Classroom peer effects and student achievement. *Journal of Labor Economics, 31*(1), 51-82.

Jang, H., & Reardon, S. F. (2019). States as Sites of Educational (In) Equality: State Contexts and the Socioeconomic Achievement Gradient. *AERA Open, 5*(3), 2332858419872459.

Kang, C. (2007). Classroom peer effects and academic achievement: Quasi-randomization evidence from South Korea. *Journal of Urban Economics, 61*(3), 458-495.

Kornrich, S., & Furstenberg, F. (2013). Investing in children: Changes in parental spending on children, 1972–2007. *Demography, 50*(1), 1-23.

Magnuson, K., & Waldfogel, J. (2016). Trends in income-related gaps in enrollment in early childhood education: 1968 to 2013. *AERA open, 2*(2), 2332858416648933.

Reardon, S. F., Ho, A. D., Shear, B. R., Fahle, E. M., Kalogrides, D., Jang, H., … DiSalvo, R. (2019). Stanford Education Data Archive (Version 3.0). Retrieved from http://purl.stanford.edu/db586ns4974

Reardon, S.F., Weathers, E.S., Fahle, E.M., Jang, H., & Kalogrides, D. (2019). Is Separate Still Unequal? New Evidence on School Segregation and Racial Academic Achievement Gaps (CEPA Working Paper No.19-06). Retrieved from Stanford Center for Education Policy Analysis: http://cepa.stanford.edu/wp19-06