Spending Matters, but It's Not Enough: the Effects of Socioeconomic Conditions on Education Outcomes in the Tri-County Area

Jonathan Rauh, PhD
Vice President, Evaluation & Public Policy
Trident United Way
6296 Rivers Avenue
North Charleston, SC 29406
(843) 740-7730
jrauh@tuw.org

Abstract

Objective: The objective of this study was to determine the effects of poverty on early literacy outcomes for students in the Tri-County area of South Carolina.

Design and Setting: This study uses descriptive techniques, multilevel models, and regression techniques for early literacy performance using the DRA-2 assessment. De-identified student data were provided by three school districts to Trident United Way and include indicators for school, grade, race/ethnicity, poverty status, parental education level, and Fall and Spring DRA-2 performance scores. Per student allotments were used as additional economic indicators.

Participants: 2,394 students in grades K-2 in five schools across three school districts.

Outcomes & Measures: Dependent variable is the DRA-2 reading composite score for Spring 2018. Independent variables are race/ethnicity, parental education level, school, grade, IEP/504 status and poverty status. Comparative models supplementing per student spending were used to determine the adequacy of cost as a predictor of student outcomes. Multilevel models were used to assess the effects of poverty and spending on education outcomes. The results show that poverty alone accounts for 10% of variation in student outcomes and this variation suggests that students in poverty are up to 25% less likely to be reading at grade level than the average student. Additionally, spending does not perform well in predicting education outcomes.

Conclusions: This study provides researchers and policymakers with a reference detailing the impact of poverty on education outcomes in the Tri-County. Using spending to supplement low income students in lieu of addressing poverty fails to provide demonstrable results.

Background

Socioeconomic conditions have a significant effect on education expenditures and quality of education for students in South Carolina. Students' poverty status, the education level of their parents and the assessed property value in their school districts lead to higher cost burdens for higher poverty districts, lower social capital for educational attainment and diminished relative quality of education resources. It would be useful to have a single value that would reflect the overall utility of a student with specific socioeconomic priors. Government agencies, including the US Department of Education and South Carolina Department of Education have begun to advocate for cost-utility analyses for decision-making (Chetty & Rockoff 2014; Kennedy et al 2008; Hanushek 2008; Hanushek & Rivkin 2010; SC EVAAS 2016). Despite the methodological concerns of cost-utility in value-added models for teacher evaluation[1], it is still desirable to have cost-utility functions based on socioeconomic conditions in order to establish the relative cost and effort necessary to educate children from different socioeconomic backgrounds. A key reason for this is the maldistribution of resources under current funding schemes. As Hanushek and Woessmann (2007; 2012) demonstrated, schools in districts with higher property values and fewer low-income students tend to receive more resources; however there are diminishing returns for each additional dollar spent beyond the median since the socioeconomic characteristics of students in median to upper income areas already predict a significantly higher probability of success than students from areas with property values below the median. Specifically, socioeconomic factors that are exogenous to the school explain between 40% and 46% of variation in education outcomes (Chiu & Chow 2015; Chiu 2009; Sirin 2005).

[1] It is currently not the case that we can create a model that is sensitive enough to all extraneous factors that one could make accurate and reliable point estimates of the amount an individual teacher contributes to student growth (Hanushek & Rivkin 2010; Rockoff, Koedel & Mihlay 2015).

Parameter estimates of both in-school and socioeconomic effects reflect coefficients that serve as quality weights for calculating adjustments to educational outcomes attained by examining median performance, i.e. we can expect performance to increase or decrease by the coefficient value as an individual's characteristics move relative to the mean. Multiple studies have examined the relationship between socioeconomic conditions and education outcomes, both in specific state and district examples as well as between countries. We recommend evaluating student outcomes based on socioeconomic and parent characteristics using Monte Carlo methods in order to specify a range of utilities of student characteristics. Current approaches seek point estimates which are almost certainly inaccurate for any given student. By specifying a range based on student characteristics we can identify the likely range of relative costs and difficulty for educating a given child. We can then specify a cost function at which returns to spending diminish for a given student and thereby show the need for school improvement, supplemental services, etc. in lieu of funding qua funding as a solution.

South Carolina provides specific funding levels to schools based on weighted pupil units. Each student-type receives a specific weight that is then multiplied by the base student cost. For example, a traditional first grade student has a weight of 1 whereas a student with a diagnosed visual impairment as defined by the Individuals with Disabilities Education Act (IDEA) receives a weight of 2.57[2]. The share allotted to each district is then weighted by the district's index of taxpaying ability (ITA). The ITA is an imputed index specifying the share of the state's total fiscal capacity located in that district. Ostensibly this is the sum of all property, less owner-occupied property (see Act 388 of 2006), divided by the sum of all taxable property in the state. Finally, districts are responsible for 30% of their total budget as provided by the Education Finance Act – the EFA is

[2] See S.C. Code Ann. § 59-20-10 et seq. (2004); Education Finance Act of 1977 (Act 163)

the primary funding source for operations to districts. Therefore, the formula for district allocations is as follows:

$$Allocation_{District} = (WPU_{District} \times BSC) - \left(\sum WPU_{State} \times BSC \times ITA_{District} \times 0.3\right)$$

where BSC is the base student cost, WPU is the weighted pupil units, and ITA is the index of taxpaying ability.

Because we can know the allocation per student in a district, we can therefore estimate the efficiency of those dollars by determining how much factors outside of the school affect education outcomes. For example, if we accept the effect sizes determined by Chiu & Chow (2015), Chen (2018), Sirin (2005) showing that between 40% - 46% of the variation in student outcomes stem from socioeconomic conditions, we could assume there is 40% - 46% that cannot be affected by funding. If we take this in unison with the findings from Hanushek and Woessmann (2007; 2012) though, it is not the case that spending does not matter; rather it is the strategy for allocating resources that is at question. Note that this also does not imply that we can bring students to parity simply by providing 40% - 46% more funding, but that we should identify a different means of distributing resources for students who are currently below the median, ideally from those areas where we see diminishing returns. In doing so we can increase the returns to education for each dollar spent.

Methods

The focus of this analysis is the Tri-County area of South Carolina, specifically Berkeley, Charleston and Dorchester counties. Three school districts (Berkeley, Dorchester Two and Dorchester Four) provided data to Trident United Way as part of the Reading by Third Demonstration Project – a three-year, early reading intervention in partnership with the school districts, Trident United Way and the University of Florida Lastinger Center. These are de-identified student data with information on students in grades K-2 across five schools. The data include student race/ethnicity, grade level, IEP/504 status[3], parental education level, poverty status (WIC, TANF, SNAP, Medicaid), and unique class id. Additionally, the data include Fall and Spring Development Reading Assessment – Second Edition (DRA-2) scores. The DRA-2 is a formative reading assessment that allows teachers to observe and measure a student's reading engagement, oral reading fluency, and comprehension. By comparing comprehension data from the Fall to the Spring, we can identify the levels of student growth and whether the student is reading at their expected grade level. We can also model the effects socioeconomic characteristics have on student reading levels. In doing so, we can determine how much socioeconomic versus school and teacher characteristics contribute to student outcomes. Table 1 displays the distribution of student performance and attributes by grade level.

Table 1. Distribution of Students

	Kindergarten, n(p)		First Grade, n(p)		Second Grade, n(p)	
IEP/504	65	(0.117)	93	(0.147)	83	(0.189)
Poverty	385	(0.695)	464	(0.735)	314	(0.717)
Parental Education, median(s)	2	(0.806)	2	(0.797)	2	(0.687)
White Non-Hispanic	377	(0.681)	399	(0.632)	259	(0.591)
African American	198	(0.357)	226	(0.358)	152	(0.347)
Hispanic/Latinx	106	(0.191)	93	(0.147)	89	(0.203)
Other Race/Ethnicity	77	(0.139)	96	(0.152)	54	(0.123)
Fall DRA2, m(s)	1.012	(1.980)	6.023	(6.013)	11.710	(8.547)
Spring DRA2, m(s)	4.981	(4.245)	14.227	(8.729)	21.823	(10.818)
At Grade-Level	488	(0.881)	382	(0.605)	98	(0.224)

Median parental education 2 = Associates/Some College. Note that per data sharing agreements the schools from which these data are drawn cannot be publicly disclosed.

To assess the effects on student outcomes, several different models were used. First, we use a series of robust least squares regressions and ANOVA models to identify any systematic variation or nesting of variables, i.e. is there systematic variation of poverty between schools, systematic

[3] IEP is an individualized education plan and 504 indicates a federally mandated accommodation for the student. Typically, these are assigned to students with differing cognitive abilities or learning methods.

variation of parental education between schools, and so on. If so, then we cannot use a linear model since effects on student outcomes would vary systematically by something that is not unique to the student.

After identifying systematic variation, we proceed with a series of hierarchical linear models and hierarchical logistic regressions. These models account for the variation that is present due to student groupings (students grouped within grades and within schools) and also provide the fitted effects for student outcomes – the things that have an average effect on students individually. For robustness check we use the likelihood ratio test to determine if the HLM and HLR explain more variation than linear models. The likelihood ratio tests show that this is indeed the case.

We begin by identifying any systematic variation in the Fall scores since Fall scores are the strongest predictor of Spring scores. We then test if there is variation based on socioeconomic conditions measured by parental education level and whether the student is in poverty. Grade level is considered in this model since performance is expected to vary by grade level. Next, we ensure that Fall scores are indeed strong predictors of Spring scores, again including grade level as a variable. Following on, we test for variation based on student and school-level characteristics, i.e. variation between racial/ethnic groups and between schools, for both Fall and Spring DRA-2 scores. We also test for systematic variation of socioeconomic conditions and academic conditions between schools that will then allow us to specify random effects such as the socioeconomic and academic conditions nested within schools and within grade levels, as well as the fixed effects for those components of student performance that are linear. In this way, we have controlled the fact that students are nested within grades and within schools, and that socioeconomic conditions vary between schools while initial performance varies between grades.

After determining the effects of socioeconomic conditions on student performance, we then identify the effects of expenditures on student performance. Because expenditures correlate with socioeconomic conditions (recall that the ITA is a weight for the funding formula) and with student level characteristics such IEP/504 status, we replace the student-level characteristics with the expenditure data. We estimate each student's expenditure using the district allotment formula provided above. We then estimate each student's share of that by using the state poverty weighting (1.39) and the average disability weighting for IEP/504 students (2.32) to estimate the individual per pupil allotment for each student. Next, we replace the student level data, i.e. IEP/504 and poverty status, with the expenditure and examine whether there is a similar amount of variation explained. We then provide a second expenditure variable that does not include the IEP/504 weighting and only includes the poverty weighting. We then model this, including IEP/504 as a variable. Therefore, we have models that account for total weights for poverty and IEP/504 and those which account for only poverty while still allowing IEP/504 to be unique to the student.

If the amount of variation explained is similar, and the linear effects on students are relatively consistent, then we can conclude that although socioeconomic conditions do affect student outcomes, per pupil allotments are enough to offset this. If the results are not consistent, then we can examine the differences in coefficients to determine the differences that are not accounted for by funding. Additionally, we would be able to conclude whether the funding levels provided are enough to offset the effects of poverty and whether they are sufficient to provide for students with disabilities.

Results

Initial effects for socioeconomic conditions on Fall DRA performance is presented in table 2. As grade level increases, we see an average 5-point increase in student performance, i.e. the baseline score for a second grader is on average 5 points higher than a first grader which is in turn five points higher than a kindergartener. Parental education level has no significant effect in Fall DRA performance, however students in poverty start, on average 1.5 points below their peers who are not in poverty. To put this into perspective, 1.5 points is 50% to grade level for a kindergartener and 25% to grade level for a first-grade student. We can confirm these relationships with the ANOVA, i.e. F value. The ratio of variances between grades is significantly greater than the ratio of variances within the groups. In other words, there is more variation between grades and between poverty status than there is among individuals within the same grade and within the same poverty status.

Given that the intent of this model is to show a relationship, we cannot take these coefficients as the final word on the effects of socioeconomic conditions. However, the initial effects are informative since we can show that there is systematic variation in the Fall DRA scores. This suggests that modelling these variables using standard OLS to predict Spring scores could lead to autocorrelation. This provides initial support for weighted or hierarchical modeling.

Table 2. Variation in Fall DRA based on Socioeconomic Conditions, (robust s)

	b	s		F	
Intercept	1.501	(0.519)	***		
Grade Level	5.385	(0.185)	***	842.046	***
Parental Education	0.055	(0.188)		0.673	
Poverty Status	-1.493	(0.289)	***	26.589	***
DF	1814				
RSME	8.095				
RESET	2.769				
DW Test	0.547	***			

*p<0.05; **p<0.01; ***p<0.001

We see that Fall DRA scores vary based on poverty status but not parental education level. Given the nearly nonexistent correlation between poverty and education (r = -0.086) we can deduce that they are independent of each other. For poverty we see that students in poverty begin 1.493 points behind their peers who are not in poverty.

The results in table 3 show us both grade level and Fall DRA scores predict Spring DRA scores, confirming that Fall DRA (per grade level) has the greatest explanatory power. We see that as grade level increases, the size of the coefficient for Fall DRA on Spring DRA decreases by .256 points. In other words, kindergarten students score 1.454 points in the Spring for every 1 point they score on their Fall exams, however first graders score 1.198 points for every one point they score on their Fall exam and so on. Again, this is simply confirming initial relationships. Therefore, given the findings in table 2 and table 3 we can confirm that Fall DRA scores have the strongest predictive power for Spring DRA scores, but those same Fall DRA scores are influenced by socioeconomic conditions.

Table 3. Variation in Spring DRA based on Fall DRA, b(s)

Intercept	3.571		(0.216)	***
Grade Level	2.958		(0.222)	***
Fall DRA	1.454		(0.059)	***
Grade Level * Fall DRA	-0.256		(0.032)	***
DF	1617			
RSME	5.913			
RESET	45.953	***		
DW Test	1.387	***		

*p<0.05; **p<0.01; ***p<0.001

We see that Fall DRA scores are strong predictors of Spring DRA scores, i.e. for every 1-point increase Fall DRA we see a 2.96 point increase in Spring scores – an overestimation but still significant.

After determining the effects of socioeconomic conditions on Fall DRA and the effects of Fall DRA on Spring DRA, we now turn our attention to whether there are differences between schools and between race/ethnic groups in terms of both Fall and Spring performance. We see that there are differences between race/ethnic groups and that this difference is centered primarily between White Non-Hispanic students and all others. Specifically, White students perform on average 1 point better than their non-white peers on both the Fall and Spring DRA tests. To put this in perspective, this is 33% of grade level for kindergarten. Turning to the schools, we see significant differences between schools on both the Fall and Spring DRA scores. Additionally, we see that the variation between the schools is greater than the variation within the schools, i.e. the variation between Schools A, B, C or D is greater than the sum of variation within each school. We can determine therefore that certain schools are performing, at baseline, significantly higher than other schools. Additionally, we can conclude that on average the baseline performance of White students is significantly higher than that of Non-White students.

Table 4. Variation in Fall and Spring DRA based on Race and School Characteristics

	Fall DRA					Spring DRA					Spring DRA		
	b	s		F		b	s		F		b	s	
Intercept	-1.011	(0.381)	**			2.204	(0.501)	***			3.259	(0.402)	***
Fall DRA											0.871	(0.031)	***
Grade				1027.713	***				1544.021				
Grade Level	5.801	(0.180)	***			9.147	(0.239)	***			3.83	(0.249)	***
Grade Level * Fall DRA											-0.235	(0.034)	***
Race/Ethnicity				5.767	***				23.412	***			
Hispanic/Latinx	0.361	(0.462)				-0.909	(0.603)				-0.882	(0.491)	
Other Race/Ethnicity	0.311	(0.494)				-1.209	(0.652)				-1.151	(0.527)	*
White Non-Hispanic	1.003	(0.344)	**			1.715	(0.431)	***			0.738	(0.361)	*
School				23.092	***				35.517	***			
School A	1.099	(0.419)	**			3.547	(0.579)	***			2.554	(0.447)	***
School B	2.853	(0.368)	***			2.865	(0.501)	***			0.666	(0.401)	
School C	3.454	(0.481)	***			5.815	(0.521)	***			0.590	(0.521)	
School D	1.251	(0.482)	**			3.373	(0.643)	***			2.728	(0.520)	***
IEP/504 Status	-2.712	(0.444)	***	38.268	***	-4.74	(0.554)	***	73.164	***	-2.107	(0.473)	***
DF	1560					1746					1538		
RSME	5.42					7.431					5.734		
RESET	64.515	***				22.582	***				23.047	***	
DW Test	1.179	***				1.385	***				1.487	***	

*p<0.05; **p<0.01; ***p<0.001

Hispanic/Latinx students perform no differently than African American students (the baseline) but White Non-Hispanic students perform .738 better than baseline and students of some other race/ethnicity perform 1.151 points worse than African American Students and 1.889 points worse than their White peers. We see significant variation in performance between school with two schools (A and D) performing approximately 2.5 points better than baseline. Students with an IEP/504 perform, on average 2.1 points worse than their peers without an IEP or 504 plans.

Table 5. Systematic Variation of Education and Socioeconomic Factors by School, b(s)

	IEP/504 Plan			Probs	Poverty			Probs	Parental Education	
Intercept	-1.954	(0.117)	***	12.41%	0.627	(0.081)	***	65.18%	4.45	(3.101)
School A	0.091	(0.183)		52.27%	-0.719	(0.126)	***	32.76%	4.578	(3.101)
School B	0.075	(0.191)		51.87%	-0.402	(0.131)	**	40.08%	5.455	(3.102)
School C	-0.492	(0.199)	*	37.94%	-1.043	(0.114)	***	26.06%	5.474	(3.101)
School D	0.066	(0.221)		51.65%	-0.762	(0.150)	***	31.82%	5.461	(3.103)
HS | Some College									2.909	(3.099)
Some College | AA									5.336	(3.100)
AA | BA									8.321	(3.102)
BA| Masters									10.078	(3.109)
N. Obs	2,264				2,394				2367	
AIC	1641.96				3231.38				5199.27	
Log Likelihood	-815.98				1610.69				-2589.64	

*p<0.05; **p<0.01; ***p<0.001

We see that the probability of a student being identified with an IEP/504 increase by 37.94%. Given likelihood of a student being in School C of 37.8% this yields a posterior probability of a student being in School C and having an IEP/504 of 14.34%, approximately 2% above the baseline. We see that poverty varies significantly by school and have seen that poverty and IEP/504 are significant in explaining DRA scores. Therefore, a more complete model should account for the school groupings on these factors.

Table 6. Full Model Explaining Change in Scores and Change in Probability of being at Grade Level

	Prob At Level HLR			Spring Score			Spring Score (Expenditure)			Spring Score (Expenditure - IEP)		
Random Effects $\sigma^2(\sigma)$												
School (Intercept), N=5	0.182	(0.426)		0.786	(0.886)		0.035	(0.188)		29.601	(5.441)	
Poverty Status	0.318	(0.564)		2.398	(1.548)							
Expenditure							0.000	(0.000)		0.000	(0.003)	
Grade (Intercept),N=3	1.659	(1.288)		27.295	(5.224)		61.200	(7.823)		15.892	(3.986)	
Fall DRA Score	0.235	(0.485)		0.082	(0.287)		2.571	(1.604)		0.095	(309.000)	
Residual				31.343	(5.598)		31.670	(5.628)		31.233	(5.588)	
N. Obs	1307			1550			1620			1620		
Fixed Effects b(s)												
Intercept	-0.467	(0.807)		8.232	(3.072)	**	5.160	(4.550)		1.620	(4.507)	
Fall DRA Score	0.553	(0.290)		0.996	(0.168)	***	1.076	(3.383)		1.031	(0.184)	***
Hispanic/Latinx	-0.243	(0.251		-0.608	(0.482)		4.097	(3.482)		6.220	(2.736)	*
Other Race/Ethnicity	-0.514	(0.275		-0.691	(0.536)		-0.675	(0.481)		-0.763	(0.482)	
White Non-Hispanic	0.419	(0.200)	*	0.852	(0.371)	*	-0.796	(0.506)		-0.909	(0.537)	
IEP/504	-1.166	(0.245)	***	-2.153	(0.459)	***	0.595	(0.352)		-2.095	(0.370)	***
Poverty	0.079	(0.326)		0.343	(0.773)							
Expenditure							0.000	(0.000)	*	0.000	(0.001)	
AIC	1136.117			9793.961			10312.010			9817.533		
log Likelihood	-555.059			4883.011			-5142.066			-4893.767		
LR chi-sq v Logit/Linear	79.332	***		35.129	***		45.937	***		37.812	***	

*p<0.05; **p<0.01; ***p<0.001

Hierarchical logistic regression predicting odds of reading at grade level based on DRA. Hierarchical linear model predicting Spring DRA scores. Models are based on nested relationships observed in tables 1 – 5, i.e. poverty varies by school and Fall DRA varies by grade.

Having examined the effects of school and socioeconomic status on student performance, it is necessary to determine if there is significant variation between schools based on socioeconomic status. Given that we see that each can affect student outcomes, we need to determine if these effects operate independently, i.e. socioeconomic conditions and race independently effect student outcomes, or if there is greater representation of higher or lower socioeconomic conditions within schools. To do this, we use a logistic regression to determine the odds that one would find an individual with a given status (poverty or IEP/504) in a given school and to also determine the odds of finding parents of a given educational background in a school.

Table 5 shows us that there is clustering of IEP statuses between C and all other schools, i.e. the probability of finding a student with an IEP/504 plan in School C is 25% greater than in the baseline school. Additionally, we see significant variation in the probability of finding students in poverty between all schools, but we see no difference in the probability of finding varying parental education levels. We can therefore conclude that poverty levels vary significantly by school whereas parental education level does not. Given these findings, as well as the findings in table 3 regarding Fall DRA and grade level, it is necessary to account for the systematic variation in poverty between schools and the systematic variation in Fall scores between grades.

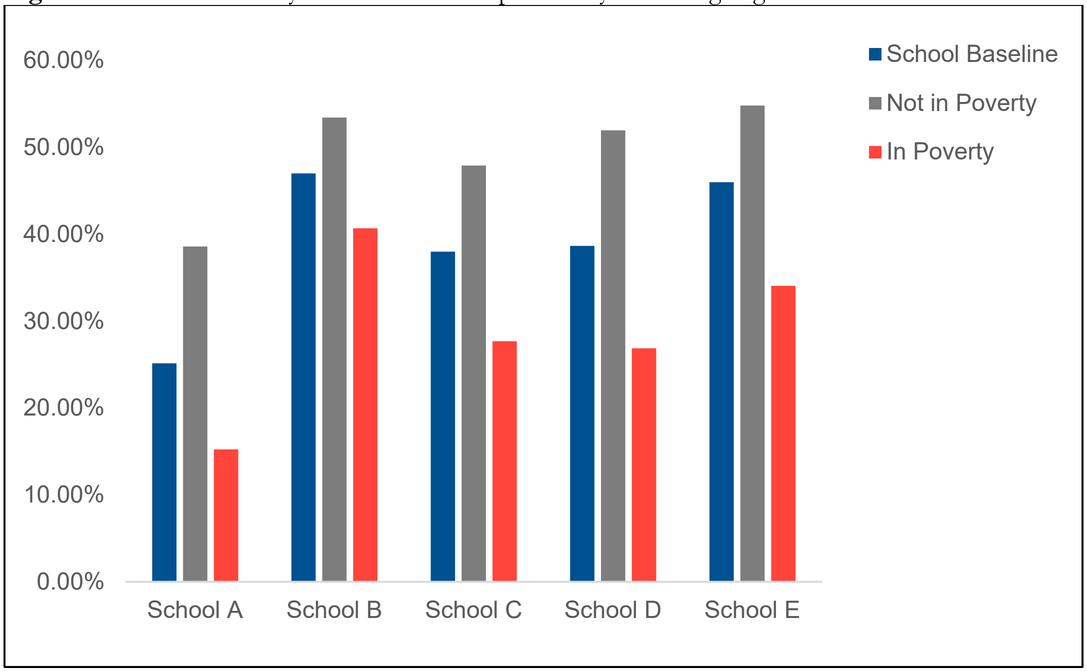
Table 6 shows that poverty status within and between schools accounts for 10.16% of the total variation in Spring outcomes and does not have a direct linear effect on student outcomes. In other words, being in poverty or not does not specify an average performance level that students are likely to be below. However, the Spring DRA score for the average student in poverty can vary by as much as 2.4 points relative to their peers who are not in poverty and by as much as 3.1 points between schools for these same students. While this is a significant effect, it is more telling to examine the effect of poverty on the probability that a student will be at grade level. Examining model 1 in table 6 shows that the probability of a student in poverty being at grade level can vary by as much as 58% and by as much as 62% between schools for students in poverty.

Table 7. Effects of Poverty on Probability of Reading at Grade Level

	School A	School B	School C	School D	School E
School Baseline	25.15%	47.00%	37.98%	38.65%	45.99%
Not in Poverty	38.58%	53.43%	47.89%	51.94%	54.80%
In Poverty	15.24%	40.68%	27.68%	26.87%	34.06%
Δ Poverty - Not in Poverty	-23.35%	-12.75%	-20.21%	-25.07%	-20.74%
Δ Poverty – Baseline	-9.92%	-6.32%	-10.30%	-11.79%	-11.93%

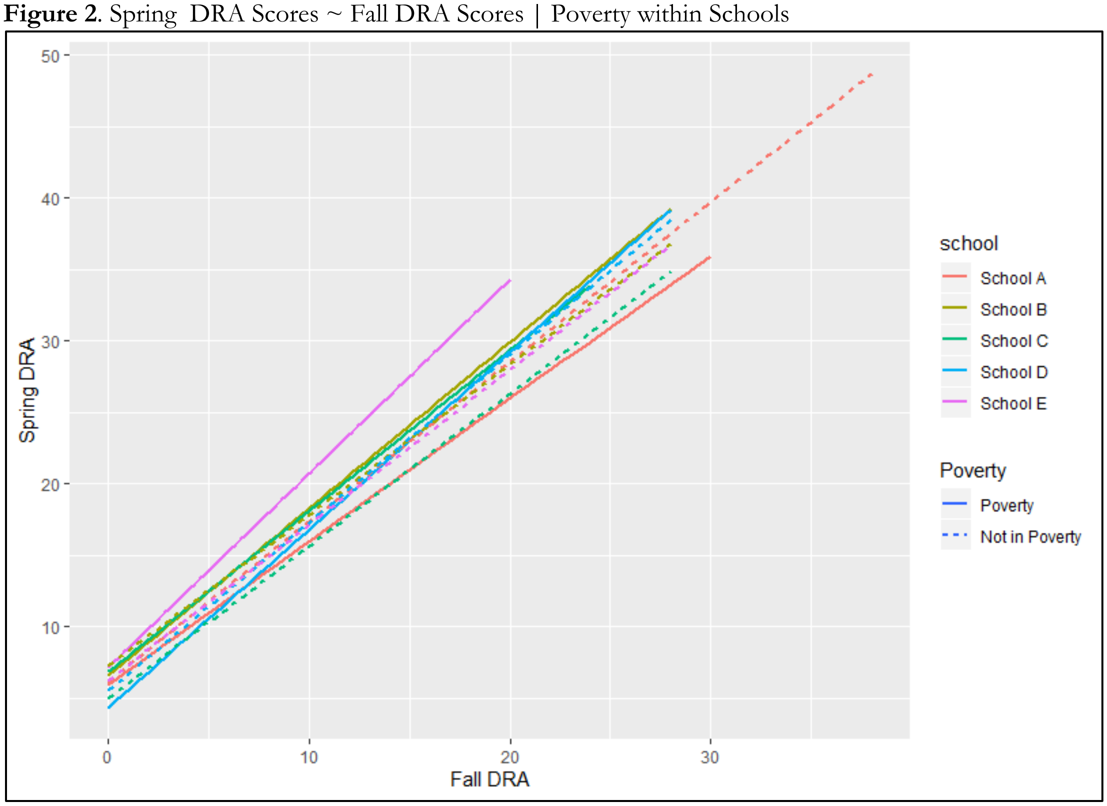
Table 7 and figures 1 and 2 show the effects of poverty on the probability of students reading at grade level. In School A, the max average difference in performance between students in poverty and students not in poverty, after accounting for all other factors, is -23.35%. In other words, students in poverty in School A have a 23.5% lower probability of reading at grade level than the average student who is not in poverty. If we examine the probability of students in poverty versus baseline performance, then we see that students in poverty in School E have a 11.93% lower probability of reading at grade level than students who are not in poverty. If we discuss this in terms of likelihoods, then the average student in School E who is not in poverty has a likelihood of reading at grade level of 1.24 to 1, whereas a student in poverty in the same school has a likelihood of 0.516 to 1. Therefore, we can conclude that in School E it is twice as likely that a student not in poverty will read at grade level as it is for a student in poverty.

Figure 1. Effects of Poverty within Schools on probability of reading at grade level.



Poverty affects the performance by as much as 25%

Figure 2. Spring DRA Scores ~ Fall DRA Scores | Poverty within Schools



Turning to the substitution of expenditure effects for student poverty and IEP/504 status, we see that in both cases (table 6) expenditures appear to do a poor job of explaining student performance, e.g. a coefficient of 0.000. In fact, this is 0.000079, e.g. for every $1 increase there is a 0.000079-point improvement in DRA scores inclusive of students in poverty. With an average, local expenditure per pupil across the state of $6,550 and an average for the schools in question of $3,324.26, this represents a difference of 0.25 points even if all students were funded at the state average, local allotment (which would amount to $14,383 per student in total funding inclusive of state and federal dollars). We can therefore conclude that spending as a measure of student performance is a poor proxy for addressing issues of poverty. If we wish to address the effects of poverty on performance, then one must address issues of poverty.

This is not a new finding since cost functions generally perform poorly in predicting student performance (Rivkin, Haushek, & Kain 2005; Costrell, Hanushek & Loeb 2008; Scafidi 2018). However, proposed policy solutions have focused on funding issues as a means of addressing issues of poverty, rather than addressing the root cause – overty.

Discussion

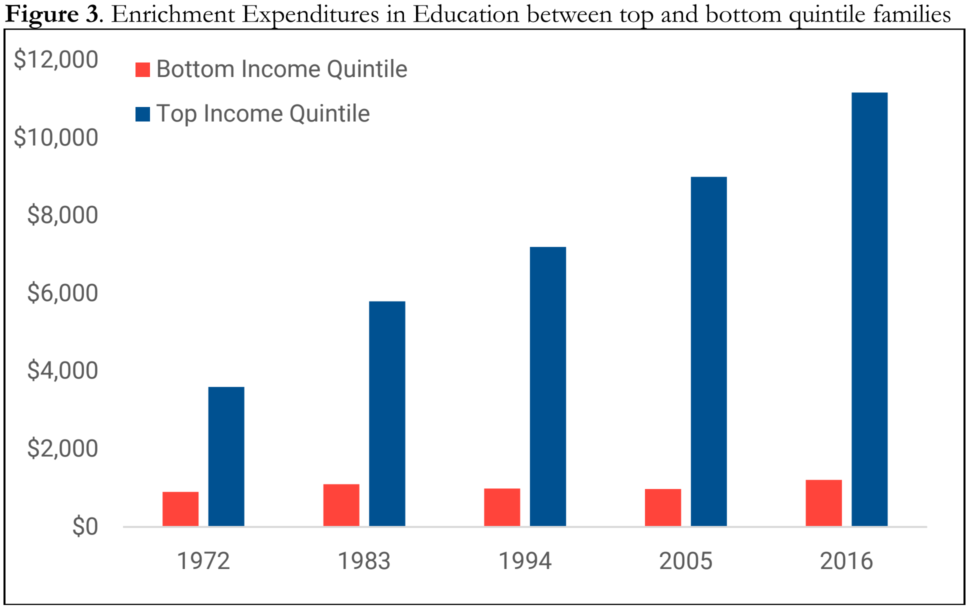
This analysis examined the effects of poverty on early literacy outcomes and further examined the effects of supplementing spending as a means of addressing poverty. In general, the results showed that students in poverty perform 2 -3 points worse at baseline than their peers. There is significant variation in early learning outcomes and in poverty status between schools. Additionally, White students tend to perform 1 point better at baseline than their minority peers, even after accounting for poverty. Parental education level did not show the same negative effects as is traditionally seen in later educational outcomes, i.e. SAT and ACT preparation and Exit Exam performance.

To date, both educators and policymakers in South Carolina have acknowledged that students in poverty performed worse than their peers, but their evidence for this has simply been to examine aggregate performance as opposed to how much effect poverty has on education. Policy responses to this have been to provide additional weights for students in poverty in an effort to provide additional funding to schools with higher ratios of students in poverty. For example, beginning in 2015 the SC General Assembly added a poverty weighting of 1.39, e.g. if the base student cost were $3,000 then a student in poverty would account for $4,170, whereas a traditional student would account for the standard $3,000. The analysis herein shows that increasing funding alone without broader strategies for addressing the fact that a student is in poverty does not provide significant leverage over student outcomes.

In terms of student outcomes, the evidence herein that students in poverty begin behind so early in their academic career should cause policymakers to reexamine strategies for addressing both students in poverty but also reading outcomes. Currently, the strategy under the Read to Succeed Act is to provide remediation to students who fail to meet the Met category in third grade. This approach is highly suboptimal though since we can identify that students in poverty begin behind as early as kindergarten. Given this fact, a more optimal solution addressing reading outcomes would be early intervention.

In terms of poverty, the effects of poverty do not have a mysterious power of causing students to perform below their peers. Poverty is simply an indicator of a myriad of social, economic, physiological, and psychological hardships faced by students who come from low-income backgrounds. Students from low-income and high-poverty backgrounds lack the same levels of social capital for educational attainment as other students. This simply means that the communities in which they exist do not have elements that bind them (as individuals) together, or bond them (as a group) to the broader community in a way that values education. By way of analogy, consider that a student whose point of reference is a parent who does not make a living wage, who lives in a community with high unemployment and few legitimate businesses, who does not see individuals in the community with a higher standard of living, and who receives messages that education is not necessary for those in that community. All of these are deprivations of connections to the broader society that provides a value for education.

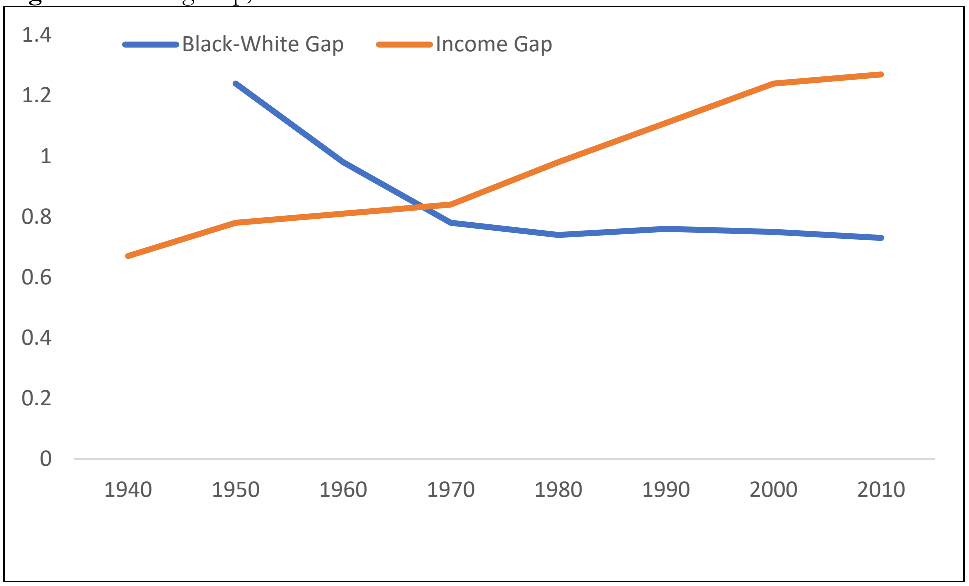
Figure 3. Enrichment Expenditures in Education between top and bottom quintile families



Source: Duncan, Greg & Richard Murnane. "The American Dream: Then and Now [Introduction]," in *Whither Opportunity? Rising Inequality, Schools, and Children's Life Chances*. Edited by Duncan, Greg & Richard Murnane (New York: Russel Sage, 2011), 3-26. 2016 extrapolated using 2005 – 2016 inflation.

In addition, parents from median to higher-income backgrounds have the capacity to provide their children with advantages that low-income parents simply cannot. Consider figure 3; this is a wealth gap representing enrichment expenditures between the top and bottom income quintiles over a 44-year period. We see clearly that the disposable income used by the top quintile of income earners to advantage their children is greater than the bottom quintile by a factor 10. The gaps created by this level of advantage are not something that can be addressed by increased spending qua spending, since parents are strategic about how they advantage their children – they do not simply give their children $11,000 and tell them to advantage themselves.

Figure 4. Reading Gap, Grade 3 for Income and Black-White



The education gap between wealthy and poor students is greater than between gap between Black and White students at the height of Jim Crowe.
Source: Duncan & Murnane, 2011

Figure 4 provides a good summary of what has happened due to treating poverty as tangential to lower education outcomes rather than a cause of lower education outcomes. Today, the gap between students from the top quintile of income earners and the bottom quintile is larger than the gap between African Americans and Whites during the height of Jim Crowe. This suggests an inability or lack of desire to address the issue of poverty as a cause of lower education outcomes.

References

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff. 2014. "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood." *American Economic Review* 104 (9): 2633–79.

Chiu, Ming M. & Bonnie W. Chow. 2015. "Classmate Characteristics and Student Achievement in 33 countries: Classmates' Past Achievement, Family Socioeconomic Status, Educational Resources, and Attitudes Toward Reading." *Journal of Educational Psychology* 107(1): 152-169.

Chiu, Ming M. 2009. "Inequalities' Harmful Effects on Both Disadvantaged and Privileged Students: Sources, Mechanisms, and Strategies." *Journal of Education Research* 3(1): 109-128

Cochran-Smith, S. Feiman-Nemser, and J. McIntyre (Editors*).* *Handbook of Research on Teacher Education: Enduring Issues in Changing Contexts. 3rd edition*., (Mahwah, NJ: Lawrence Erlbaum Associates, Inc., 2008).

Costrell, Robert M., Eric A. Hanushek & Susanna Loeb. 2008. "What Do Cost Functions Tell Us About the Cost of an Adequate Education?" Peabody Journal of Education 83(2): 198-223.

Hanushek, Eric A. & Ludger Woessmann. "Education and Economic Growth." In: Penelope Peterson, Eva Baker, Barry McGaw, (Editors), *International Encyclopedia of Education*, (Oxford: Elsevier, 2007).

Hanushek, Eric A. & Steve G. Rivkin. 2008. "Pay, Working Conditions, and Teacher Quality." Future of Children 17(1): 69-96.

Hanushek, Eric A. & Steve G. Rivkin. *Using Value-Added Measures of Teacher Quality*. Washington, D.C.: The Urban Institute, 2010).

Hanushek, Eric A., Paul Peterson, & Ludger Woessman. "Achievement Growth: International and U.S. State Trends in Student Performance." *Harvard Kennedy School of Government PEPG Report No.: 12-03,* July 2012.

Kennedy, Mary M., Soyeon Ahn & Jinyoung Choi. "The value added by teacher education." In M.

Rivkin, Steven G., Eric A. Hanushek, & John F. Kain. 2005. "Teachers, Schools, and Academic Achievement." *Econometrica* 73(2): 417-458.

SC EVAAS 2016. Measuring Student Growth. Available at: https://ed.sc.gov/educators/educator-effectiveness/measuring-student-growth/

Scafidi, Benjamin. 2012. "The Fiscal Effects of School Choice Programs on Public School Districts." EdChoice. Available at: https://www.edchoice.org/wp-content/uploads/2015/07/The-Fiscal-Effects-of-School-Choice-Programs.pdf

Sirin, Seluck R. 2005. "Socioeconomic Status and Academic Achievement: A Meta-Analytic Review of Research." *Review of Educational Research* 75(3): 417-453.

Appendix

Table A1. Linear Model predicting DRA Performance, b(s)

	m(s)	MODEL 1	MODEL 2	MODEL 3
Fall DRA (Std Score)	6.973	0.691***	0.643***	0.677***
		(0.019)	(0.020)	(0.019)
Poverty Status	0.527		0.016	
			(0.030)	
Parental Education	2.000		-0.016	-0.020
			(0.017)	(0.017)
IEP/504	0.118		-0.186***	
			(0.043)	
Per Pupil Expenditure	$3,324.27			-0.00005***
				(0.000)
African American	0.263	-0.064*	-0.072*	-0.058
		(0.032)	(0.034)	(0.033)
Hispanic/Latinx	0.163	-0.136***	-0.155***	-0.134**
		(0.041)	(0.042)	(0.041)
Other Race/Ethnicity	0.115	-0.139**	-0.184***	-0.149***
		(0.043)	(0.044)	(0.043)
Grade Level	1.000	0.350***	0.380***	0.351***
		(0.028)	(0.028)	(0.028)
School A	0.181	0.192**	0.187**	0.192**
		(0.059)	(0.059)	(0.059)
School B	0.161	0.227***	0.215***	0.222***
		(0.057)	(0.057)	(0.057)
School C	0.274	0.129	0.041	0.119
		(0.066)	(0.068)	(0.066)
School D	0.105	0.338***	0.341***	0.325***
		(0.064)	(0.065)	(0.065)
Grade : School A	0.181	0.120	0.139*	0.115
		(0.071)	(0.070)	(0.070)
Grade : School B	0.161	-0.182***	-0.149***	-0.172***
		(0.045)	(0.045)	(0.045)
Grade : School C	0.274	-0.108*	0.035	-0.118*
		(0.052)	(0.061)	(0.051)
Grade : School D	0.105	-0.135*	-0.158*	-0.161*
		(0.064)	(0.070)	(0.070)
Intercept	14.527	-0.422***	-0.404***	-0.221**
		(0.040)	(0.057)	(0.070)

Observations	1,619	1,527	1,597
R2	0.680	0.689	0.684
Adjusted R2	0.677	0.686	0.681
Log Likelihood			
Akaike Inf. Crit.			
Bayesian Inf. Crit.			
Residual Std. Error	0.525	0.517	0.521
F Statistic	261.013***	209.267***	227.915***
Durbin-Watson	1.493***	1.514***	1.496***
Breuch-Pagan	170.340***	180.910***	173.071***
LR v Linear			208.683***
LR v MODEL 1		190.643***	57.498***
Note:*p<0.05; **p<0.01; ***p<0.001			