Closing the achievement gap between high-poverty schools and low-poverty schools

J. Rody Borg
Jacksonville University

Mary O. Borg
University of North Florida

Harriet A. Stranahan
University of North Florida

ABSTRACT

We examine the achievement gap between low-income minority students in inner city (high-poverty) schools and their white high-income counterparts who attend suburban (low-poverty) schools. Our data include the 4th and 5th grade math and reading scores for over 15,000 students in a large urban school district. We use a multilevel model to show that school resources do matter. We find that high quality teachers have a significant and positive effect on student test scores and that smaller class size, especially in low performing schools, contributes to higher student achievement.

Although school resource variables do matter in our model, they are far less important predictors of student test scores than are the student background variables. Unfortunately, our results lead to the conclusion that schools, alone, cannot close the achievement gap although we do find that better schools raise reading and math scores for the average student in a low performing school by about 12%.

Keywords: Economics of education, School reform, Class size, school characteristics, student characteristics, student achievement

INTRODUCTION

It is frustrating that over fifty years after the historic Brown v. Board of Education decision that an educational achievement gap still exists between low-income minority students in inner city schools and their white higher income counterparts who live in the suburbs. Over these 50 years, educators and social scientists have strived to discover the reasons for this persistent gap. Obviously, we struggle to understand the gap so that we can ultimately close it. Yet, we are hardly closer to understanding the gap or closing it than we were 50 years ago.

In this paper, we make one more attempt to better understand the achievement gap. We believe we have a very good dataset with which to examine this issue. Our data include all of the 4th and 5th grade math and reading scores for the entire school system of Duval County (Jacksonville), Florida, which encompasses over 15,000 students in those two grades alone. Jacksonville incorporated all of Duval County into its city limits in 1967, making Jacksonville the largest city in the United States in geographic area with 841 square miles within the city limits. Because of its size, the Duval County school system contains a mix of inner city and suburban schools in one unified school district. This vast area within the purview of one school district also prevented much of the white flight of students from the inner city schools into other nearby school districts, a trend that accompanied desegregation in many similar sized cities across the United States. Thus, the inner city schools in Jacksonville have not seen the erosion in their property tax base that many urban school districts have seen over the last 30 years. This means that “inner city” schools in Duval County receive the same state and local funding per student as “suburban” schools receive.[1]

Of course, the terms “inner city” and “suburban” are not completely accurate in reference to Duval County public schools, since all schools are technically within the city limits; however, the terms refer to schools that are within the original city limits of Jacksonville, and schools that are in the newer parts of Jacksonville, primarily to the east and south of the core city. With few exceptions, most of the schools within the original city limits have a percentage of students who receive free or reduced lunch that is greater than the median for all Duval County public elementary schools, and most of the schools in the newer parts of the city have percentages of students receiving free and reduced lunches below the median. Therefore, in the remainder of the paper, we refer to the “inner city” schools as high-poverty schools and the “suburban” schools as low-poverty schools. The cut-off for a high-poverty versus a low-poverty school is 56% of the schools’ children qualifying for a free or reduced lunch. This is the median in Duval County public elementary schools.

Duval County represents an excellent case study for examining differences in student achievement between high-poverty and low-poverty schools because many aspects of the school environments between the two types of schools are the same. They all operate under the same school board, with the same superintendent and the same textbooks chosen by the Duval County public school administration. Policies on attendance, school conduct, and other school governance issues are the same as well. The consistency of these elements allows for a comparison of apples with apples when it comes to explaining the variation in student achievement levels between the high-poverty and the low-poverty schools. We believe this is a

[1] Actually the funding per student in the “inner city” schools is almost $800 higher on average than the funding per student in the “suburban” schools due to federal funding received by schools with high percentages of students receiving free or reduced price lunches. See Table 2.

major advantage of our research over similar attempts to explain the variation in educational achievement between students in inner city school districts and suburban school districts.

LITERATURE REVIEW

Literally thousands of pages have been written in journals and scholarly books about the factors that explain student achievement levels. In addition, student achievement is measured in many different ways, including years of schooling completed, standardized test scores, and likelihood of going to college. In summarizing this plethora of information, we divide the topic into the research that examines the effect of school resources on student achievement and the research that examines how student background characteristics affect student achievement.

SCHOOL RESOURCES AND STUDENT ACHIEVEMENT

Much of the interest in what determines student achievement began in 1966 with the publication of the controversial Coleman report that implied that school inputs have almost no effect on schooling outcomes. According to the Coleman Report, family background is clearly the most important and dominant predictor of educational attainment. Eric Hanushek (1986,1989, 1994) has been a leading proponent of the view that increased spending on school resources has little, if any, substantive pay-offs in terms of student achievement. Hanushek and his co-authors' more recent work finds that specific school resources do actually have significant effects on student outcomes, but the effective resources either have very small effects or are hard to measure. For example, using a large longitudinal study of Texas public school students in grades 3 through 7 during the mid 1990s, Rivkin, Hanushek, and Kain (2005) find that smaller class size does have a small but significant positive impact on student achievement in the lower grades, although the effect dissipates in the higher grades and becomes insignificant. They also find that teacher quality makes a positive difference in student achievement; however, none of the measurable characteristics that are normally used as indicators of teacher quality (for example, whether the teacher has a masters degree) has a significant impact. They do find that teachers in their first years of teaching have lower student achievement gains, but the effect disappears after a very few years. Looking at the totality of their results, they conclude that the small benefit achieved from lowering class size is not worth the high infrastructure cost of building more classrooms. They also worry that lowering class size may do more harm than good since it would require hiring many more inexperienced teachers. Their policy recommendations call for more administrative discretion on the part of principals to hire and fire teachers and better mentoring of new teachers.

Many other researchers share Hanushek's skepticism of the ability of more school resources to improve student outcomes. Julian Betts (1995) who examines the effect of several school quality indicators, such as teacher-pupil ratios, relative teacher salaries and percent of teachers with Master's degrees, on the earnings of white males who had attended a public high school. He finds no significant relationships between the indicators of high school quality and male earnings. Similarly, Caroline Hoxby (2000) examines the effect of natural variation in class size due to population changes in 649 elementary schools and finds no significant relationship between class size and student achievement.

However, some of the more recent research on the effectiveness of school resources on student achievement has begun to tease out more subtle effects. This new research suggests that school resources targeted at specific methods of improving student achievement may work. For example, Akerlof and Kranton (2002) conclude that teacher quality measured in the traditional way of advanced degrees and years of experience often shows no significant positive effect on student outcomes because students' backgrounds are not in line with the academic values that most schools promote. Teachers who see 120 students per day do not have the time to make a difference in a student's self–image or alter a student's character. However, investing in smaller class size may make a difference in the ability of good teachers to be effective because students and teachers form the kind of personal bonds that will effect a change in the student's self-image. They believe this is the reason that students who participated in the Tennessee Star experiments with smaller class sizes took the SAT and ACT tests at much higher rates than their counterparts, even eight years after they participated in the program.

Other education researchers disagree. Grissmer, Flanagan, Kawata and Williamson (2000) cite evidence that indicates measurement errors are the primary reason that Hanushek and others obtain their results (Rothstein and Miles, 1995; Ladd, 1996.) Card and Krueger (1996) reexamine the evidence presented in Hanushek's own 1996 study on the effect of school resources on student test scores and reach a much different conclusion. Hanushek examines 146 studies and concludes that the estimated coefficients on the expenditures per pupil variables are so mixed between positive and negative signs that the evidence clearly supports no effect. However, Card and Krueger (1996) point out that there were over twice as many positive coefficients as negative among the 146 coefficient estimates. Given that each estimate has a 50-50 chance of being positive or negative, the odds are less than one in a million that more than twice as many would be positive by chance. In addition, several authors have conducted meta-analyses of the coefficient estimates of the multitude of studies that examine the effect of resources on student test scores (Glass and Smith, 1978; McGiverin, Gilman and Tillitski, 1989; Hedges and Stock, 1983; Hedges, Laine, and Greenwald, 1994). They all conclude that the evidence strongly suggests that increased resources do lead to increases in student test scores.

Jonathan Guryan (2001) used the 1993 Massachusetts Educational Reform Act as a natural experiment to examine whether the increased educational funding to historically low-funded school districts made a difference to their student test scores. He found that increased spending made a positive and significant effect on the test scores of fourth graders but had no significant effect on the test scores of eighth graders. He hypothesized that this result obtained from the fact that fourth graders had the benefit of the increased funding for a longer period of time (since kindergarten) than the eighth graders had. He also found that the improvement in the fourth-graders test scores came predominantly from the lower end of the student distribution, meaning it was the lower scoring students who improved the most.

Furthermore, even though there is disagreement over the effect that increases in overall educational spending have on overall educational achievement, researchers agree that there are some specific categories of spending that show dramatic effects on the test scores of certain groups of students. For example, research from the Tennessee Student/Teacher Achievement Ratio (STAR) experiment shows that when increased funds are used to reduce class size for minority and economically disadvantaged students at the kindergarten through 2nd grade level, test scores for this group of students increase. What's more, the effect seems to be long-term because the students who experienced smaller class sizes in those years were more likely to take the ACT and SAT college entrance exams than students in the control group (Finn and Achilles, 1999; Krueger, 1999, Hanushek, 1999).

STUDENT CHARACTERISTICS AND STUDENT ACHIEVEMENT

Whereas there is some uncertainty regarding the effect of school resources on student achievement, there is consistency in the empirical results that examine the effect of individual student characteristics on student achievement. These student characteristics include family background variables such as household income level and parents' educational attainment, as well as demographic variables such as race and gender.

In a 1989 article that examined the relationship between parent's income and children's completed years of education, Paul Taubman reported the results of his own work with Jere Behrman and Robert Pollack as well as the results from a number of other empirical studies (Alvin and Thornton, 1984; Hauser and Daymont, 1977; Corcoran and Datcher, 1981; Hill and Duncan, 1987; Shaw, 1982). He concluded that the estimated coefficients on parental income were generally positive and resulted in income elasticities in the range of 3% to 80%. Putting this into context, if two children are identical in every way, including high school grade point averages and SAT scores, except for the fact that one child resides in a household with income of $25,000 and the other resides in a household with income of $50,000, the child in the $50,000 household will complete 3 – 80% more schooling than the child in the $25,000 household. A review article by Robert Haveman and Barbara Wolfe (1995) also looked at several studies that examined the educational attainment of children measured by years of schooling completed (Datcher, 1982; Hill and Duncan, 1987; Krein and Beller, 1988; Case and Katz, 1991; Duncan, 1994; Graham, Beller and Hernandez, 1994). They found that household income had a positive effect on the educational attainment of children in all but one (Datcher, 1982) of the studies they reviewed, and the income variable was statistically significant in over half of the studies in which it was positive.

The Haveman and Wolfe article (1995) also reported on the effect that parental education has on children's educational attainment measured by years of schooling. They found unequivocal evidence that both parents' education levels have significant positive effects on children's educational attainment (Corrazzini, Dugan, and Grabowski, 1972; Mare, 1980; Datcher, 1982; Hill and Duncan, 1987; Krein and Beller, 1988; Case and Katz, 1991; Duncan, 1994; Graham, Beller and Hernandez, 1994; Kane, 1994). In addition, most of the studies found evidence that the mother's education has a stronger positive effect than father's education on the educational level obtained by the child.

Not surprisingly, the effects of income and parental education on student test scores are very similar to their effects on years of schooling and likelihood of attending college. Grissmer, et al. (2000) analyzed math and reading standardized test scores from the National Education Longitudinal Study (NELS), a nationally representative sample of approximately 25,000 8th graders begun in 1988. They found that the income variable had a statistically significant positive effect on both math and reading test scores. They also found that both mother and father's educational attainment had a positive and significant effect on math and reading test scores, with the greatest effect realized from having college educated parents. In the same study, the authors analyzed state NAEP test scores over the period 1990-1996. They created state level socio-economic status (SES) variables, and found that states with higher average SES levels had higher NAEP test scores, on average. In fact their SES variables, which they used as family control variables, explained about 75% of the variation in state NAEP scores.

Many studies of the effect of parental income on the test scores of children are marred by the effects of endogeneity and measurement error. However, a recent study by Dahl and Lochner (2009) mitigates the errors associated with unobserved heterogeneity, endogenous transitory income shocks, and measurement error in income. They use a panel of 4700 children matched to their mothers from National Longitudinal Survey of Youth datasets and the large non-linear changes in the EITC over the last two decades as an exogenous source of variation in family income levels. Over the time period of their study the EITC expansions raised average family income by 10% for EITC eligible families with two or more children. Since the families eligible for the EITC were already "poor" this study isolates the effects of income changes on student test scores without muddling the effects of income with all of the other characteristics that are associated with being poor. They find that the extra family income positively affects a child's math and reading test scores. Their baseline estimates imply that a $1,000 increase in income raises contemporaneous math and reading test scores by 6% of a standard deviation. They also find that the effect is slightly larger for young children.

Unfortunately, the persistence of gaps in the test scores of white students and their black and Hispanic counterparts is universally acknowledged (Jencks and Phillips, 1998; Bali and Alvarez, 2003). What is not universally acknowledged is why these gaps persist and what to do about them. One obvious explanation of the gap is that black and Hispanic students, on average, come from families with lower incomes and less parental education than white students (Brooks-Gunn, et al., 1996; Hanushek, 1986; McLanahan and Sanderfer, 1994; and Phillips, Brooks-Gunn, et al., 1998.) According to Phillips and Crouse, et al. (1998), about two thirds of the black-white test score gap is accounted for by these differences in family background variables. However, school factors undoubtedly contribute to the unexplained one-third, since Phillips, Brooks-Gunn, et al. (1998) indicate that the difference in black-white test scores gets wider after blacks enter school.

Race also plays a role in the years of education completed and the probability of attending college. In spite of almost thirty years of affirmative action policies in college admissions, African Americans and Hispanics are still under-represented in college enrollments. Although it may seem that race, itself, is causing these discrepancies in college attendance, the situation is actually more complex. African Americans and Hispanics are under-represented in colleges and universities primarily because they come disproportionately from households with low-income and low levels of parental education. In studies that control for household income, parent's education, and other family background variables, being African American often has a positive and significant effect on college attendance (Boggess, 1998; Case and Katz, 1991; Cook and Ludwig, 1997; Hill and Duncan, 1987; Kane and Spizman 1994; Krein and Beller, 1988; Ludwig, 1999; Sander, 1992).

With such unequivocal evidence about the role that student socioeconomic background factors play in student achievement and such uncertainty about the role that school resources and other school factors play in that achievement, we provide new evidence exploring the impact of school resources on the achievement gap, across both the high-poverty and low-poverty schools. We link student information to their census block group characteristics which allows us to get a clear picture of the effects of individual and neighborhood characteristics compared to school characteristics on student achievement.

METHODOLOGY

We estimate a multilevel model of student achievement for 15,552 students in the Duval County school system. We first analyze the impact of school level versus student level characteristics on achievement for the whole sample and next, we separate half the schools into the so called high-poverty schools (those whose student body has more than 56% of the population eligible for free/reduced price lunches) and low-poverty schools (those with less than 56% eligible for free/reduced price lunches). We will use these regressions to predict whether a typical student in the high-poverty school environment (a student with lower socioeconomic (SES) characteristics) could achieve significantly higher test scores in a more resource abundant school (a low-poverty school environment). In particular, we hope to add to the evidence about whether additional school resources can close the achievement gap.

Our multilevel model predicts student achievement measured as norm referenced math and reading standardized test scores. Our model includes both school level and individual student predictors. We use a multi-level or random components model because the data are organized at two different levels of aggregation. There are 102 different schools and within the schools, there are 15,552 individual students. A random components model predicts that student scores vary due to student characteristics and by school clustering of similar students within a particular school. In the multilevel model, there is a variance component representing the variation between schools (τ_{00}) and a second representing variation within schools (σ^2).

A multilevel model is a better specification than OLS for these types of data. An OLS specification treats student characteristics as fixed effects across all schools (each student characteristic has the same effect in each school). One problem that arises if there is indeed statistically significant "clustering" across schools is that the standard errors of the OLS coefficients are biased downward. It may be possible to fit an OLS that accounts for school specific effects by including a dummy variable for each of the schools (and a school*student characteristic interaction where appropriate). But with a large number of schools (such as 102 in our sample), estimating so many fixed effects is inefficient. The multilevel model deals with this problem more efficiently by estimating the variance between school intercepts.

A multilevel model where the average value of student test scores varies across schools can be expressed as follows. In equation 1, Yij is the test score for the ith student in the jth school, the Xij's represent student level characteristics and r_{ij} is the random variation in student scores within schools. In equation 2, the Wqj's represent school level variables. This equation allows the intercept term (or average test scores) to differ based upon school characteristics. In equation 2, μ_{0j} is the random variation in intercepts between schools. It is possible to substitute equation 2 into equation 1 and arrive at equation 3 (which looks more like the one for which we report results). The terms in brackets are the fixed effect parameter estimates, and the last two terms represent the random effects. Again, the random effects are composed of a school level variation μ_{0j} and variation among students within schools r_{ij}.

This model can be made more complicated by adding random components for other student level parameters, βij. In the multilevel modeling literature, several studies point out the importance of not over-specifying the relationship and keeping the model as simple as possible (Kreft and De Leeuw, 1998). For our data, we tried various specifications but the model described below, where only the intercept was random, provided the best fit for the data (as measured by standard measures for goodness of fit).

(1) $Y_{ij} = \beta_{oj} + \beta_{ij} X_{ij} + r_{ij}$
(2) $\beta oj = \Upsilon_{00} + \Upsilon_{q1} W_{qj} + \mu_{0j}$
Where $r_{ij} \sim N(0, \sigma^2)$ and $\mu_{0j} \sim N(0, \tau_{00})$
(3) $Y_{ij} = [\Upsilon_{00} + \Upsilon_{q1} W_{qj} + \beta_{ij} X_{ij}] + \mu_{0j} + r_{ij}$

DATA

Our data come from the Duval County (Jacksonville, FL) public school administration, which has provided us with Florida Comprehensive Assessment Test (FCAT) scores for 4th and 5th grade students who took the test during the 1999-2000 school year. Student data also include demographic information on race, gender, number of times the student has withdrawn from school (an indicator of student mobility), whether the student is gifted, and whether the student is in a magnet program. We also include the student's 1998 Lexile scaled score from the Scholastic Reading Inventory. This score is a measure of the student's reading ability at the beginning of the school year.

We add to this individual student data by using the student's address to link each student with census block level demographic data. This allows us to create a demographic profile for each student using the census block level values for variables such as parents' education levels. In addition, we add school level variables to the data set. The school system collects a variety of school level data such as number of teachers with advanced degrees, teachers' years of experience, proportion of teachers newly hired, magnet school indicators, and proportion of students in the school who receive free or reduced lunch. These data allow us to specify a number of school factors that may affect student performance on the FCAT. Therefore, we have available a wide variety of family background and school specific factors included in one model.

Table 1 Variable Descriptions

Name	Variable Definition
Reading	Norm Reference Reading FCAT Score
Math	Norm Reference Math FCAT Score
Less Than 9th Centered	% Above or Below Mean Proportion of Adults in the Block Group with Less than 9th Grade Education
Less Than 12th Centered	% Above or Below Mean Proportion of Adults in the Block Group with 9th Grade - Less than 12th Grade
High School Centered	% Above or Below Mean Proportion of Adults in the Block Group High School Graduate
Less Than 9th	% of Adults in the Block Group with Less than 9th Grade Education
Less Than 12th Centered	% of Adults in the Block Group with 9th Grade - Less than 12th Grade
High School Centered	% of Adults in the Block Group High School Graduate
Some College	% of Adults in the Block Group with Some College
College Graduate	% of Adults in the Block Group with 4 Year College Degree or Higher
White	Dummy Variable Indicating Student is White
Black	Dummy Variable Indicating Student is Black
Hispanic	Dummy Variable Indicating Student is Hispanic
Other Race	Dummy Variable Indicating Student is "Other Race"
Female At Home	Dummy Variable Indicating the Majority of Mothers with Children in the Block Group Do Not Work in the Labor Market
Median Income	Median Family Income in the Block Group
Free/Reduced Lunch	Student is Eligible for Free or Reduced Priced Lunch
Withdrawals	Number of Withdrawals from School
Male	Dummy Variable Indicating Male Gender
Gifted	Dummy Variable Indicating Student is in Gifted Program
Magnet Student	Dummy Variable Indicating Student is in Magnet Program
Magnet School	Dummy Variable Indicating Student Attends a Magnet School
Percent Magnet Enrollment	Proportion of Student Body Enrolled in Magnet Program
Lowest Readiness	Dummy Variable Indicating Student in Lowest Quartile Lexile Reading Score
Class Size	Average Class Size in the School
Enrollment	Average Enrollment at the School
Class Size and School Readiness	School Average Class Size / School Average Lexile Reading Score
Cost Per Student	School Average Cost Per Student
Yrs. Of Experience	School Average Teacher's Years of Experience
Advanced Degree	School Average Percent of Teachers Hold Advanced Degrees
Experience* Advanced	Years of Experience * % with Advanced Degrees
New Hire	Percent Newly Hired Teacher or Percent of Teacher Turnover
High Rate of New Hires	Dummy Variable Indicating Student Attends a School in the Quartile with Highest Rate of Teacher Turnover

Table 2 Descriptive Statistics

Variable	Full Sample		Low-poverty Schools Less than 75% of Students Free/Reduced Price Lunch		High-poverty Schools 75% or More of Student Free/Reduced Price Lunch	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Reading	53.98	26.69	61.22	24.93	46.32	26.34
Math	58.51	26.80	65.99	24.37	50.60	26.97
Less Than 9th	6.9	7.0	4.2	4.3	9.8	8.0
Less Than 12th	15.8	9.5	11.6	7.3	20.1	9.5
High School	31.6	8.3	30.2	8.1	33.2	8.2
Some College	28.1	8.1	30.8	6.3	25.3	8.7
College Graduate	17.6	12.9	23.2	13.3	11.7	9.4
Less than 9th Centered	.033	6.7	-2.7	4.3	2.89	7.99
Less than 12th Centered	-.047	9.4	-4.17	7.31	4.27	9.52
Less than High School Centered	.043	8.29	-1.42	8.14	1.58	8.16
White	0.523	0.499	0.659	0.474	0.381	0.486
Black	0.406	0.491	0.258	0.438	0.561	0.496
Hispanic	0.030	0.170	0.033	0.179	0.027	0.161
Other Race	0.012	0.109	0.014	0.116	0.010	0.100
Female At Home	0.058	0.234	0.029	0.167	0.089	0.285
Median Income	34631	11999	40159	10997	28851	10135
Free/Reduced Lunch	0.452	0.498	0.265	0.441	0.647	0.478
Withdrawals	0.028	0.162	0.020	0.137	0.036	0.129
Male	0.488	0.500	0.494	0.500	0.482	0.500
Gifted	0.058	0.233	0.079	0.270	0.035	0.185
Magnet Student	0.124	0.330	0.118	0.323	0.130	0.337
Magnet School	0.598	0.49	0.676	0.468	0.516	0.50
Lowest Readiness	0.351	0.477	0.254	0.435	0.453	0.498
Class Size	24.1	4.4	26.3	4.9	21.7	1.9
Enrollment	744.3	302.3	903.2	315.1	578.0	170.5
Cost Per Student	3902	583	3498	354	4325	462
Yrs. Of Experience	14.245	3.178	15.398	2.965	13.039	2.938
Advanced Degree	30.099	11.804	32.863	12.703	27.209	9.999
Experience* Advanced	448.3	234.1	521.0	238.3	372.2	203.7
New Hires	11.489	8.171	9.736	7.087	13.322	8.803
High Rate of New Hires	0.257	0.437	0.133	0.339	0.386	0.487
	N = 15823		N = 8088		N=7735	

The variable definitions are listed in Table 1and the means and standard deviations for each variable are shown in Table 2. We include statistics for the sample as a whole and separately for the high-poverty and low-poverty schools. Not surprisingly, the data show that high-poverty schools have students with lower socioeconomic characteristics. Students in high-poverty schools grow up in neighborhoods with half as many college graduates and twice as many high school dropouts. Almost 30% of the adults have less than a high school education, and only 11% of adults in these households have a college education. In contrast, in lower-need schools, 15% of the adults have less than a high school education and 23% are college graduates.

Family median income is almost 30 percent lower for students in the high-poverty schools, and poverty is more the norm. In high-poverty schools, 65% of the students with recorded test scores are eligible for free and reduced priced lunches compared with only 26% of the students in low-poverty schools, on average. The census data indicate that students in high-poverty schools are more likely to live in households where the mothers do not work in the labor market. Almost 9% of students in high-poverty schools live in a block group where the *majority* of mothers with children stay at home. This is in contrast to just 2% of the children attending low-poverty schools.

More than twice as many of the students are black in high-poverty school as in low-poverty schools. Blacks represent 56% of the student population in high-poverty schools, but only 25% of the population in lower need schools. It is not just higher rates of poverty that characterize high-poverty schools: there are fewer gifted students, slightly higher rates of student withdrawals, and lower reading levels. Almost 45% of the students in high–need schools score in the lowest quartile of reading achievement as measured by their Lexile scaled score.

Magnet students are fairly evenly divided among high-poverty and low-poverty schools. Magnet programs are very diverse and range from a Montessori program for elementary and middle school students, K-12 gifted and talent programs, K-12 art and music programs, and career-focused magnets at the high school level. Participation in the magnet curricula ranges from 3% to 97% of the student bodies at the various magnet schools, although on average about 20% of the student body participates in the magnet curriculum at each school. Just about 12% of the students in both high-poverty and low-poverty schools are magnet students.

The fact that all of these schools are in the same district means that state and local expenditures per student are not very different across schools, although funding is about 800 dollars (or 18%) higher per student in the high-poverty schools due to extra federal funding for free lunch and other grant programs targeted to high-poverty schools. High-poverty schools get more funding per student, but other resources are *not* as plentiful. A lower proportion of teachers, about 10% fewer, hold advanced degrees, and these teachers have fewer years of experience. This is partially due to the fact that teacher turnover is much higher in high-poverty schools. Thirty-nine percent of the students in high-poverty schools attend schools that rank in the highest quartile of teacher turnover compared to just 13% in low-poverty schools. Teacher turnover is clearly a greater problem for high-poverty schools. These school characteristics, combined with the students' demographic characteristics, suggest that students in high-poverty schools have fewer resources to draw on in the home, community, and school environments.

It is not just teachers that want to leave high-poverty schools, the low enrollments in these schools show that many families vote with their feet and move to more crowded suburban schools. Low enrollments in high-poverty schools are usually accompanied by smaller average class sizes. This spurious correlation has led some researchers to conclude that smaller class sizes do not improve learning outcomes, because those schools with the highest test scores also have the largest classes. In order to get around this confounding effect of class size and enrollment, we create a variable which is class size interacted with student achievement potential (as measured by the Lexile Reading Score, which measures students achievement at the beginning of the school year). This information will show whether small class size benefits high versus low need schools equally.

Table 3. Variance Components

Variance Estimate	Full Sample		High-poverty Schools		Low-poverty Schools	
	Reading Score	Math Score	Reading Score	Math Score	Reading Score	Math Score
τ_{00} Variance Across Schools	99.222	110.31	47.84	64.7	33.86	30.89
σ^2 Within School Variance	618.01	614.11	646.87	663.04	590.78	567.93
% Variation in Scores Due to School Clustering						
% Explained by School Clustering	13.83%	15.23%	6.89%	8.89%	5.42%	5.16%
Ratio of Student to School Variance	6.23	5.57	13.52	10.25	17.45	18.39
% Variation in Scores Due to School Clustering After Inclusion of all Explanatory Variables						
% Explained by School Clustering with all variables included	1.48%	2.19%	0.75%	1.90%	1.58%	1.44%

ESTIMATED RESULTS

The variance components model results are reported in Table 3. Results are reported for all schools in column 1 and for the high-poverty and low-poverty schools, in columns 2 and 3, respectively. There are several different model specifications possible for variance components, but the best fitting, as measured by log likelihood measures, is the one shown in Table 4. In this model, just the intercept term contains a school specific random component.

One interesting question that the random components model can answer is what proportion of the variation in test scores can be explained by across school clustering compared to variation in scores within schools? Table 3 shows the variance components estimates for variance across schools (variance due to clustering of scores by school), $\tau_{00,}$ and within schools, σ^2 (Bryk and Raudenbush , 1992). All of the estimates are significantly different than zero (p-values < .0001) indicating that test scores tend to "cluster together" within schools and a significant proportion of the variation of test scores is explained by school characteristics. Variation across schools is about 13-15% of total variation leaving 85-87% of the variation due to within school student characteristics.

When we separate the schools into the high-poverty versus low-poverty groups, the proportion of variation in test scores explained by schools drops to 5-6%. Apparently, student poverty is a key characteristic that helps explain why scores cluster across schools. For high-poverty schools, school characteristics explain at most 6-9% of the variation in test scores and at most 5% in the low-poverty schools.

In summary, although schools explain a statistically significant amount of variation in scores, the proportion of the total variation explained by school characteristics is small. The variance due to student characteristics is 10 times greater than school characteristics for high-poverty schools and 17 times greater for low-poverty schools. However, in spite of their small absolute explanatory power, school effects are statistically significant and slightly more important for high-poverty than low-poverty schools.

Finally, in Table 3, the last row shows the amount of across school variation that is left after all the explanatory variables were included in the model. There is very little (about 1%) school level variation left in the model. Thus, the school characteristics that were included in the model explained the vast majority of the clustering in scores across schools.

The fixed effects estimates for the models are listed in Table 4. Once again, we compare results from the whole sample with results for the high-poverty and low- poverty schools. Next, in Tables 5 and 6, we use the model to predict test scores for different types of students in the high-poverty and low-poverty schools. For example, we examine whether a typical student from the high-poverty school (one with lower socioeconomic background variables) would have higher predicted test scores if she attended a low-poverty, more affluent school. We also look at the effects of the magnet programs in Duval County on achievement in order to shed light on whether magnet programs are more effective in high-poverty or low-poverty schools.

The full sample uses 15,554 students at 102 different elementary schools in Duval County to estimate standardized reading and math scores. There are 7,566 students at 65 high-poverty schools and 7,988 students at 39 low-poverty schools. Most of the coefficients on the individual student characteristics are significant in all the models. In some cases, school level fixed effects coefficients are not significant.

As expected, the results show that a student's home environment is an important predictor of test scores. Students growing up in neighborhoods where the majority of mothers don't work outside the home was positively associated with student test scores. However, in the separate samples, this variable did not seem to affect student achievement for low-poverty schools, but it was very important for students in the high-poverty schools. Scores rose by 1-2% in reading and math if these students lived in neighborhoods where the majority of mothers don't work outside the home. This may indicate that students living in poverty benefit educationally from the attention and support of non-working mothers. Another important household characteristic is adult's education level. Education was significant in the sample as a whole, but students at high-poverty schools were adversely affected by growing up in a neighborhood with low levels of adult education. This was not the case for students at low-poverty schools; they were not significantly affected by the neighborhood education levels except when there was a high percentage of adults with less than a 9th grade education. These variables are proxies for available resources in the home that help provide a sound basis for student readiness to learn. Students in high-poverty schools seem to suffer most from a lack of resources at home.

Table 4 Fixed Effect Coefficient Estimates

Variable	Full Sample		High-poverty School		Low-poverty School	
	Reading	Math	Reading	Math	Reading	Math
Intercept	78.58***	86.28***	84.00***	89.71***	83.12***	91.28***
Female at Home	1.56*	1.55**	2.20*	2.31**	0.31	-0.210
Less than 9th Centered	-0.119***	-0.136***	-0.100***	-0.097**	-0.10	-0.209***
Less than 12th Centered	-0.092***	-0.077***	-0.082***	-0.071**	-0.08	-0.029
High School Grad Centered	-0.047*	-0.068***	-0.068**	-0.073*	-0.006	-0.044
Black	-10.49***	-11.42***	-10.34***	-10.67***	-9.98***	-11.37***
Hispanic	-4.52***	-4.15***	-7.17***	-4.24***	-2.25*	-3.71***
Free/Reduced Lunch	-4.46***	-4.52***	-3.69***	-3.24***	-4.73***	-5.47***
Withdrawals	-5.66***	-1.941	-5.04***	-2.39	-6.81***	-0.824
Male	-3.69***	1.03***	-3.69***	0.99**	-3.71***	1.03**
Gifted	21.56***	18.32***	25.27***	20.61***	19.87***	17.24***
Magnet	4.19***	4.11***	5.89***	6.32***	2.35**	2.45***
Lowest Readiness	-20.13***	-21.44***	-20.00***	-22.19***	-19.97***	-20.31***
Percent Magnet Enrollment	0.952	-1.45	-5.94***	-8.23***	5.60*	2.83
Class Size and School Readiness	-79.81	-87.48	-282.96**	-248.09*	-63.621	-108.5
Yrs. of Experience	-0.581*	-0.77**	-0.564	-0.757	-0.822	-0.969**
Advanced Degree	-0.414**	-0.530***	-0.346*	-0.458*	-0.463*	-0.584**
Experience*Advanced	0.028**	0.034***	0.020*	0.028*	0.031*	0.037**
New Hires	-0.051	-0.112**	-0.048	-0.129**	-0.028	-0.023

The race variables show a persistent minority achievement gap in the Duval County school district, just as other studies of minority performance on standardized tests have shown (Jencks and Phillips, 1998). These test score deficits remain even after accounting for student readiness (whether they are in the lowest quartile for reading ability) and household poverty. Across the board in both high-poverty and low-poverty schools, the results show that blacks score about 10 points below whites in both math and reading. Hispanics also have an achievement gap, but a smaller one. In low-poverty schools, Hispanics score about 4 points lower in math and about 2 points lower in reading than whites. However, the gap in reading scores increases up to 7 points lower than whites in high-poverty schools. This may reflect poor command of the language in higher poverty areas.

The key poverty indicator in our models is free/reduced price lunch eligibility. When examining the model that includes all schools, students who are eligible for free/reduced price lunch score 3 to 5 points lower on reading and math tests than an equivalent student who is not eligible for free/reduced price lunch. Students who are eligible for free/reduced price lunch score about 3 points lower in a high-poverty school, but the gap increases to 4 to 5 points lower in a low-poverty school. This suggests that high-poverty schools seem to do as well or perhaps better than low-poverty schools at teaching students who live in poverty.

High mobility, as proxied by the number of withdrawals during the school year, can also be an indicator of poverty. Poor students often withdraw and reapply to the same school several times during the school year as they move from one rental property to another. Although high mobility is not a significant predictor of reading scores, students who have higher mobility (withdraw from school more than once) do significantly worse on standardized math exams. Consistent attendance is associated with math achievement.

Consistent with previous research (Hedges and Nowell, 1995), males perform better on math exams than females but worse on standardized reading exams. Children in the gifted program score about 20 points higher on standardized exams than other children. Interestingly, this effect seems to be somewhat stronger in the high-poverty schools[2]

The student's Lexile reading score at the beginning of the year (school readiness) is perhaps the strongest explanatory variable for both math and reading test scores. In addition, we are better able to isolate the effect of school characteristics after accounting for school readiness. The effect of poor readiness is uniform throughout the regressions and suggests that students who score in the lowest quartile for reading at the beginning of the school year, have reading and math scores about 20 points lower than other students.

Individual students who are enrolled in a magnet program have significantly higher test scores than non-magnet students. The Duval County school system instituted magnet programs in 1990 to promote economic and racial integration in older, urban schools. Highly motivated students are the most likely magnet participants so it is not surprising that students in magnet programs score 2 to 6 points higher on standardized tests than non-magnet students. This effect is about the same for high-poverty and low-poverty schools. If we look at the experience of black students in magnet programs in Duval County, we find that they do not benefit from magnet

[2] In Duval County, non-minority students must score at least 130 points on a standard IQ test and minority students must score at least 120 points to be placed in the gifted program. This effect is confirmed if we include an interaction term for high-poverty and gifted in the full sample regressions. We find a positive and significant effect in the regression for reading scores suggesting that gifted students have scores that are 20 points higher than non-gifted students in the overall sample, and their scores are another two to three points higher when they attend a high-poverty school. Furthermore, this effect is unrelated to magnet schools.

participation as much as other racial and ethnic groups. In fact, a variable interacting black and magnet (regressions results not shown) is significant and negative. This suggests that blacks who are enrolled in the magnet programs do *worse* than other non-black magnet students but not worse than other black students as a whole.

The most successful magnet programs have greater enrollment and a high proportion of the school's student body participating in the magnet program. When we look at the distribution of magnet enrollments across schools, the proportions are very similar in high-poverty and low-poverty schools. The results show a negative and significant coefficient on the magnet proportion variable in high-poverty schools, but a positive and insignificant coefficient in low-poverty schools. This means that having a more populated magnet program in a high-poverty school will not necessarily increase student achievement, especially in math. This is also the case for low-poverty schools where we find that more magnet enrollment has little or no effect on standardized test scores. Ironically, the most popular magnet programs were chosen for the most distressed areas of the city; however, our results show that the magnet programs, although successful at racial and economic integration, do not appear to be successful at raising test scores in high-poverty schools, except for their effect in changing the overall socioeconomic and demographic profile of the students in the high-poverty schools. Magnet schools have been a primary method of achieving racial integration in many large school systems and our results provide additional evidence to explain how these programs affect student achievement; an area of the academic literature which has had few studies examining this issue.

As mentioned previously, class size is one of several important school characteristics associated with school effectiveness. We include a variable of class size interacted with average test score for the school[3]. We find that the marginal effect of class size on student test scores depends upon whether the school is classified as low poverty or high poverty. For example, there is a negative and significant coefficient on class size and school readiness in high poverty schools which implies that as class size increases by one student in a high-poverty school, standardized reading scores decline by .41 points, on average. In general, class size matters most in high-poverty schools and significantly affects test scores in schools with the least prepared students. In contrast, in low-poverty schools, the coefficient on the class size variable is insignificant, indicating that class size is not important to student achievement in high performing schools. Our results are consistent with the results of the Tennessee STAR experiment, which show that class size has a significant positive effect on academic achievement for disadvantaged students (Finn and Achilles, 1999; Krueger, 1999, Hanushek, 1999).

Two other indicators of school quality are years of teacher experience and percent of teachers with advanced degrees. The results suggest that average teacher years of experience and the percent of teachers with advanced degrees act as complementary inputs. There seems to be a threshold level that these two inputs must reach after which they become productive in increasing student achievement. More years of teacher experience have a positive effect on reading achievement only when 20% - 28% of the teachers at a given school have advanced

[3] The variable is school average class size divided by school average beginning Lexile Test score. The sample average beginning Lexile Score is 870 across all students, tested at the beginning of school year. The marginal effect of class size on student test scores for high poverty schools evaluated at the means of the data is - .41.

degrees[4]. For math achievement, teachers' years of experience become effective at raising student math scores when at least 25% of the teachers have advanced degrees.

A similar analysis shows that advanced degrees are effective at increasing student test scores as long as teachers have an average of 14 to 17 years of teaching experience. Since low-poverty schools have adequate teaching resources to reach both of these critical thresholds, years of experience and the advanced degrees of their teachers are likely to positively affect student achievement. *Unfortunately*, high-poverty schools don't have as many highly educated and long term teachers available. The high-poverty schools have an average of 6% fewer teachers with advanced degrees and an average of 2.5 fewer years of teaching experience. Our results suggest that this gap in teachers' years of experience and advanced degrees has a negative effect on student test scores in high-poverty schools. High-poverty schools could benefit by having more experienced and highly qualified teachers.

Another teacher quality variable that has a significant effect on student test scores is the percent of new hires at a school. The coefficient is negative and significant for math achievement in high-poverty schools. The teacher turnover rate is about 4% higher in high poverty schools than in low-poverty schools, and this has a negative impact on student test scores in high-poverty schools. The inability to retain teachers in these schools is adversely affecting student achievement.

PREDICTED TEST SCORES FOR LOW AND HIGH SES STUDENTS

We use the regression results to predict test scores for students with low versus high socioeconomic characteristics[5] in both a high-poverty and a low-poverty school. This will illustrate the degree to which school characteristics versus individual student characteristics are responsible for student test scores. It will also illustrate if the test scores of low socioeconomic students would improve if they attended a low-poverty school versus their own high-poverty school. We then repeat the exercise for students with high socioeconomic characteristics to determine if their test scores would decline if they attended a high-poverty school. The results are reported below in Table 5.

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[4] These numbers change slightly for the full sample versus the separated samples. For the full sample the minimum required percent of advanced degrees is 20% and in the separated samples the results suggest that schools need 27-28% of teachers with advanced degrees for years of experience to be effective at increasing reading scores.

[5] The student with low socioeconomic characteristics lives with adults who have lower levels of education, has a mother who works outside the home, is black, is eligible for free/reduced price lunch, has withdrawn from school 2 times during the year, is not gifted or a magnet student, and is classified as having low intake readiness. The high socioeconomic student lives with adults who have higher levels of education, has a mother who works outside the home, is white, is not eligible for free/reduced price lunch, has not withdrawn from school, is gifted and is not a magnet student and is not classified as having low intake readiness. The typical low-poverty and high-poverty schools have values of school inputs equal to their sample mean values.

Table 5. Predicted Test Scores for Low and High SES Students in High Poverty versus Low-Poverty Schools

	Predicted Test Scores (95% Confidence Interval) Reading	Math
Low SES Student in High-Poverty School	24.1 (19.2, 29.1)	31.9 (24.9, 38.9)
Low SES Student in a Low-Poverty School	27.4 (20.3, 34.4)	38.3 (31.7, 44.8)
High SES Student in a Low-Poverty School	90.4 (84.3, 96.1)	93.3 (87.9, 98.3)
High SES Student in a High-Poverty School	90.2 (85.8, 94.7)	92.7 (86.0, 99.3)
Magnet School with a Low SES Student	25.4 (19.7 , 31.5)	34.2 (27.4 , 40.9
Non-Magnet School with a Low SES Student	21.4 (15.6 , 27.1)	31.6 (24.9, 38.3)

They show that low SES students would do better in low-poverty schools. Their predicted math scores increase by 20% (about 6 points), and their predicted reading scores increase by 10% when they attend the low-poverty as opposed to the high-poverty school. This suggests that students living in poverty would benefit from increased school resource quality. However, the predicted math and reading scores for the low SES students in the different categories of schools are not *statistically* different from each other. Therefore, although these results suggest that low SES students would do better in a low-poverty school, it is not possible to generalize these results to the population as a whole.

However, the picture is clearer for the high SES students. Their math and reading scores are unaffected by whether the students attend a high-poverty or low-poverty school. Math scores for the high SES students would decrease by only 0.6 percentage points if they attended a high-poverty school instead of a low-poverty school, and reading scores would decline by only 0.2 percentage points. These students, who are well-endowed with family and community support, are predicted to do well no matter what school they attend.

We also estimate reading and math scores for a low SES student in the magnet versus the non-magnet schools. The school characteristics for class size, teachers' years of experience, and percent of teachers with advanced degrees are very similar for magnet and non-magnet schools, but they do differ a bit. We find that magnet programs increase low SES students' test scores by 10% to 20% for reading and math. Although these estimates are not statistically significant, they do suggest that magnet schools have the potential to positively affect academic achievement for low SES students. More empirical research is needed to verify this effect in other school districts.

CLOSING THE ACHIEVEMENT GAP?

Can high quality schools close the achievement gap between the average student at a high-poverty school and the average student at a low-poverty school? In order to answer this question, we create two "average students" – one in the high-poverty school and one in the low-poverty school[6]. The average high-poverty student has demographic and background variables that match the average values for the separate sample of high-poverty schools shown in Table 2. He attends a school with school characteristics that match the average values for the high-poverty school sample shown in Table 2. Similarly, the average low-poverty student has the demographic and background variables that match the low-poverty sample values shown in Table 2 and attends a school with school characteristics that match the average values for the low-poverty school sample shown in Table 2.

Table 6. Can School Resources Close the Achievement Gap?

	Predicted Test Scores	
	Reading	**Math**
Low-Poverty School with a "Typical" or "Average" Low-Poverty Student	68.2 (62.8, 73.6)	75.9 (69.7, 82.1)
High-Poverty School with a "Typical" or "Average" High-Poverty Student (95% Confidence Interval)	31.4 (26.3, 36.9)	36.8 (30.5, 43.0)
High-poverty School with Improved Resources Teaching a "Typical" or "Average" **High-poverty Student**	37.1 (30.5, 43.7)	43.1 (35.5, 50.6)

Table 6 shows the predicted test scores of these average low and high-poverty students attending their average low and high-poverty schools. When the average high-poverty student attends the average high-poverty school, his predicted test scores are 31.4 for reading and 36.8 for math. When the average low-poverty student attends the average low-poverty school, his predicted test scores are much higher – 68.2 for reading and 75.9 for math. The question we now wish to answer is: Can giving the average high-poverty school more resources close the achievement gap that exists between high-poverty (inner-city) and low-poverty (suburban) students?

[6] The "average student" attending the high-poverty school lives in a household with adults who have the mean level of education shown in Table 2 for high-poverty schools, is a black male, has a mother who works outside the home, is eligible for a free/reduced price lunch, has low intake readiness, is not a gifted or magnet student, and has school characteristics as shown in Table 2 for the average high-poverty school.
Similarly, the "average" low-poverty student lives in a household with adults who have the mean levels of education shown in Table 2, is a white male, has a mother who works outside the home, is not eligible for a free/reduced price lunch, is *not* in the low intake readiness group, is not gifted or a magnet student, and has school characteristics as shown in Table 2 for an average low-poverty school.

The third row of Table 6 shows the predicted test scores of the average high-poverty student when we give the typical high-poverty school more school resources. This new school has twice as many teachers with advanced degrees and a 50% increase in teachers' years of experience. The new school also has very low teacher turnover (only 4% per year) and a 50% reduction in average class size (only 11 students per classroom). Yet in spite of this dramatic increases in school quality, the average high-poverty student's test scores do not improve by enough to close the gap.

SUMMARY AND CONCLUSIONS

What do our results add to the literature on student achievement and school effectiveness? This study provides new information about the effects of class size, magnet school program performance and teacher quality on student achievement. We use the most sophisticated statistical techniques to analyze data on 15,000 students in Duval County, Florida. This large urban/suburban district allocates similar resources and has equal administrative policies for both high-poverty and low-poverty schools and thus provides a natural case study in which to examine these issues. With these data, we use an innovative geo-coding technique to link student information to their neighborhood characteristics in order to examine the effects of individual and neighborhood characteristics versus school characteristics on student achievement. Therefore, we have great confidence in our empirical results, which show *unequivocally that school resources do matter.*

Specifically, we find that high quality teachers, measured by the interaction of the average years of teacher experience and the percentage of teachers with advanced degrees at each school, have a significant and positive effect on student test scores. Unfortunately, both values for these teaching variables are lower in the high-poverty schools; thus, the undersupply of well-educated, experienced teachers in the high-poverty schools contributes to the achievement gap in those schools. We also find that smaller class size adjusted for the school readiness of the students does indeed contribute to increased student test scores in all schools, but the effect is larger in the high-poverty schools. The new specification of the class size variable adjusted for school readiness is an important contribution to the literature because the effect of class size on student achievement is confounded by the fact that student populations are declining in the high-poverty schools and increasing in the low-poverty schools. This often leads to the misleading conclusion that schools with the largest class sizes have the highest test scores when the adjustment for students' level of school readiness is not made.

Although school resource variables do matter in our model, not surprisingly they are less important predictors of student test scores than are individual student background variables. The multilevel model shows that variation in test scores due to school clustering in the total sample is about 13-15% of total variation leaving 85-87% of the variation in test scores due to within school student characteristics. When we separate the schools into the high-poverty and low-poverty categories, the proportion of variation in test scores explained by school characteristics drops. Apparently, student poverty is a key characteristic that causes scores to cluster across schools. Interestingly, for high-poverty schools, school characteristics are more important for explaining variation in student achievement than in low-poverty schools.

The predicted test scores for low SES students in the high-poverty schools versus the low-poverty schools show that the test scores of disadvantaged students would improve if they transferred to a low-poverty school. Similarly, the low SES students' test scores would improve somewhat by transferring to a magnet school. However, the improvement in test scores caused by both of these changes are small.

These findings suggest that school resources do matter: smaller class sizes, more highly educated teachers with more years of experience and a school climate with low teacher turnover improve student achievement (and these resources may have a bigger impact in high-poverty schools). The results also lead to the unsettling conclusion that schools, alone, cannot close the achievement gap that persists between the economically disadvantaged and disproportionately minority students who inhabit the high-poverty schools and their higher income, disproportionately white counterparts who inhabit the low-poverty schools. When we create an extremely high quality school by increasing the resources in the high-poverty schools by an unrealistically high amount, the resulting increases in reading and math scores for the average student in the high-poverty schools increase only modestly.

The policy conclusions of our results are difficult to enact. There are no easy fixes for the achievement gap that exists between the average students in the high-poverty schools and the average students in the low-poverty schools. Additional resources in the high-poverty schools would be a useful first step to closing the achievement gap, but they cannot close the gap entirely. Two avenues remain as potential solutions to closing the gap, and both are harder to accomplish than increasing school resources. The first avenue is to work to alleviate the poverty and low parental education levels that plague the average student in the high-poverty school. The second avenue requires a more intensive examination of the *why* and *how* school resources affect student achievement, rather than the usual examination of *if* school resources affect student achievement. It is time to stop quibbling over "if money matters" and get on to the more important issue of how to use school resources in ways that benefit students living in poverty.

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AUTHOR INFORMATION

J. Rody Borg is a Professor of Economics at Jacksonville University. His research interests include economic history, early twentieth century mergers, and economic education. He has published articles in the *Journal of Academic and Business Ethics*, *College Teaching*, and the *International Journal of Industrial Organization.*

Mary O. Borg is a Professor of Political Economy and the Director of the Honors Program at the University of North Florida in Jacksonville, FL. Her research interests include public sector economics and economic education. She has published articles in the *National Tax Journal*, *Demography*, and the *Journal of Economic Education.*

Harriet A. Stranahan is a Professor of Economics at the University of North Florida. Her research interests include public sector economics, applied microeconomics and economic education. Her research has been published in the *National Tax Journal, Public Finance Review* and the *Journal of Economic Education*.