ABSTRACT

DAVID J. MALISON
Separate But Equal? An Analysis of Racial Inequality and Student Achievement in Georgia Public Schools
Under the Direction of DR. DAVID B. MUSTARD

I estimated a linear fixed effects model using panel data collected from the Georgia Department of Education to analyze the impact changes in student body demographics have on African American student performance. The dataset contained detailed information on every public middle school in the state of Georgia over the five school years from fall 2003 to spring 2008. I found that a ten percent increase in the percentage of the student body that is African American corresponds to an approximately three percent rise in the percentage of African American students failing the math section of the Criterion-Referenced Competency Test (CRCT). Increasing the percentage of African Americans at a school had a negligible impact on white student outcomes. These effects persisted after adding a variety of student and school control variables and after allowing past student performance to explain current outcomes by including a lagged dependent variable in the regression. My results, consistent with other findings in the area, suggest that recent trends toward resegregation could cause the black-white achievement gap to expand.

INDEX WORDS: School Performance, Education, Education Policy, Segregation, Integration, Achievement Gap, CRCT, Inequality, Public Schooling, Georgia Public Schools

SEPARATE BUT EQUAL?

AN ANALYSIS OF RACIAL INEQUALITY AND STUDENT ACHIEVEMENT

IN GEORGIA PUBLIC SCHOOLS

by

DAVID J. MALISON

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DEDICATION

To my wonderful parents, to whom I owe so much. What a journey it has been!

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It would have been impossible to complete this project without the support of my best friend, Jeremy McKibben-Sanders. Thank you for everything, and best of luck in San Francisco!

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CHAPTER 1
INTRODUCTION

"We come then to the question presented: Does segregation of children in public schools solely on the basis of race, even though the physical facilities and other 'tangible' factors may be equal, deprive the children of the minority group of equal educational opportunities?"

Chief Justice Earl Warren
Oliver L. Brown et.al. v. the Board of Education of Topeka (KS) et.al.
(1954, p. 493)

It has been more than fifty years since the Supreme Court delivered the landmark *Brown v. Board of Education* opinion, banning compulsory segregation in public schools across America. Although overt racial discrimination remains prohibited by law, Gary Orfield et al. showed that changes in residential patterns, increases in school choice, and a decline in the numbers of court-ordered desegregation plans have begun to reverse racial integration that occurred in the decades following the *Brown v. Board of Education* ruling (2001, p.121). Schools today are increasingly divided across racial lines: Orfield and Chung-mei Lee found the average white student attends a school that is four-fifths white while the average African American student attends a school composed of more than two-thirds minorities (2005, p.1). How have such trends influenced the black-white achievement gap the authors of the *Brown v. Board of Education* opinion sought to narrow?

To address this question I fit a fixed effects model to a panel dataset containing detailed information on every public middle school in the state of Georgia over five school years. Such a model is attractive because it focuses entirely on within-school variation, controlling for unobserved endogenous heterogeneity across students and schools. I found evidence that increasing the percentage of black students enrolled at a school adversely affects black student performance, while having a negligible influence on the outcomes of white students. The effect remained significant after allowing past performance to be a determinant of current outcomes. These findings, consistent with the Supreme Court's conclusion in the *Brown vs. Board of Education* opinion and with results from a recent study by Eric Hanushek, John Kain, and Steven Rivkin (2009, p. 349), indicate that increased segregation may widen the black-white achievement gap on standardized tests.

The remainder of this paper is organized as follows. In Chapter 2 I derive the fixed effects and dynamic models I use during analysis. Chapter 3 discusses details about the dataset I used to estimate the models I introduce in Chapter 2. Chapter 4 discusses model selection methodology and estimation techniques. Chapter 5 displays and discusses my results. Chapter 6 concludes.

CHAPTER 2
THEORETICAL FRAMEWORK AND ECONOMETRIC MODEL

In this chapter I develop a theoretical framework for testing how student demographics affect student performance. It is useful to begin by defining the general form of an education production function (EPF), the mechanism by which schools transform a set of educational inputs (e.g. student characteristics, expenditures) into outputs (e.g. test scores, graduation rates):

$$Q_{sctr} = f_{sctr}(ST_{sct}, SC_{sct}, S_{str}, \delta_{sctr}) \qquad (1)$$

Q_{sctr} signifies the educational output of racial group r in school s in cohort c at time t, ST_{sct} represents a $K_1 \times 1$ vector of observable student characteristics, SC_{sct} denotes a $K_2 \times 1$ vector of observable school inputs, S_{str} represents an unobservable measure of a school-specific effect, and δ_{sctr} represents the impact of unobservable student characteristics. Because I used data aggregated over schools, observable student and school characteristics are identical across racial groups (*ST* and *SC* do not contain an *r* subscript).

After defining the output measure as the percentage of students failing a standardized test and assuming a linear relationship between variables, the EPF can be written in the following explicit form:

$$\%fail_{sctr} = \beta_{1r} \cdot ST_{sct} + \beta_{2r} \cdot SC_{sct} + S_{str} + \delta_{sctr} + \varepsilon_{sctr} \qquad (2)$$

$$t = 1, 2, \ldots, \mathrm{T}\ ; s = 1, 2, \ldots, \mathrm{N}\ ; c = 1, 2, 3\ ; r = w, b$$

$\%fail_{sctr}$ represents the percentage of students in racial group r (w and r correspond to white and black student variables, respectively) in school s in cohort c at time t failing an exam and ε_{sctr} is a stochastic error term. Primary interest lies in estimating β_{1r}, which corresponds to the partial effects student demographics have on the failure rates of a particular racial group. Estimation of β_{2r} may also be of interest due to the obvious policy implications (the partial effect of teacher salary on performance could be relevant in school funding discussions, for example), but data aggregated over entire schools are not well-suited for this purpose.

The normal OLS estimates of β_{1r} and β_{2r} in (1) are consistent if S_{str}, δ_{sctr}, and ε_{sctr} are uncorrelated with ST_{sct} and SC_{sct}. This seems quite unlikely, however, given that the observed percentage of students that are African American or on free or reduced lunch is probably related to an unobserved measure of household stability or student motivation that affects performance. Observed school inputs like teacher salary or experience are also likely correlated to unobserved school effects. Consistent estimation can be recovered by using a fixed effects model that exploits changes in observables over time.

The Fixed Effects Model

The original model contains $2 \times (K_1 + K_2) + 2 \times N \times T + 2 \times N \times T \times 3$ parameters to estimate, but only $2 \times N \times T \times 3$ observations are available for analysis (recall that a set of coefficients is estimated for both racial groups). Clearly additional structure must be placed on the problem in order to proceed. The two leading approaches are to assume the individual effects are randomly distributed or are constant across time. The latter approach seems most appropriate in EPF estimation, a specification assumption I verified using the Hausman test (see chapter 4). The fixed effects formulation of the EPF in (2) can be written as

$$\%fail_{sctr} = \beta_{1r} \cdot ST_{sct} + \beta_{2r} \cdot SC_{sct} + T_{tcr} + S_{sr} + \delta_{scr} + \varepsilon_{sgtr} \qquad (3)$$

which is identical to (2) except that the unobserved school and student effects are no longer indexed by t and a set of time dummies T_{tcr} is now included to allow the intercept to vary across cohorts and years. As long as $E(\varepsilon_{sctr} \mid ST_{sct}, SC_{sct}) = 0$ (i.e. ST_{sct} and SC_{sct} are correlated only to the time-invariant factors S_{scr} and δ_{scr}), β_{1r} and β_{2r} can be consistently estimated by incorporating a dummy variable for each cohort from every school into the regression (i.e. each cohort within a school is treated as a unit containing T observations). Only $2 \times (K_1 + K_2) + 3 \times 2 + 2 \times N \times 3$ parameters remain to be estimated, a feasible task if $K_1 + K_2 < 3 \times N \times (T - 1) - 2$.

One problem with this strategy is that the estimator, sometimes called the least-squares dummy variable (LSDV) estimator, is based entirely on within-unit variation. As a result the partial effects of factors that do not vary significantly across time will be imprecisely estimated. Another problem with the LSDV is that the fixed effects, S_{sr} and δ_{scr}, are not identified. Moreover, William Green demonstrated that the estimators of the fixed effects are inconsistent in short panels (datasets in which $N \rightarrow \infty$ but T is small and fixed) (2008, p.196). Although Amy Schwartz and Jeffrey Zabel suggested using the fixed effects estimators to measure relative school performance (2005, p. 37), this approach does not seem appropriate since school effects are confounded with student effects and the LSDV estimator is inconsistent. Other modeling strategies (such as comparing matched student outcomes as Randall W. Eberts and Kevin M. Hollenbeck did in their analysis of Michigan charter schools (2006, p.103)) provide more promising methods for school evaluation. The LSDV estimator does permit identification of the partial effect of student demographics on performance, the goal of this analysis.

The Dynamic Model

The fixed effects model described above, often called a “level” model in education policy analyses, does not allow previous student performance to be a determinant of current student outcomes. It may be more insightful to instead estimate a dynamic, “value-added” model that allows the present fail rate of a cohort of students to depend on the fail rate of that cohort in the previous year:

$$\%fail_{sctr} = \gamma \cdot \%fail_{sc(t-1)r} + \beta_{1r} \cdot ST_{sct} + \beta_{2r} \cdot SC_{sct} + T_{tcr} + S_{scr} + \delta_{scr} + \varepsilon_{sctr} \quad (4)$$

As before, the OLS estimators of (4) are inconsistent because $\%fail_{sc(t-1)r}$, ST_{sct} and SC_{sct} are correlated to the unobserved factors S_{sr} and δ_{scr}. In this case, however, the LSDV estimator does not recover consistency. As shown by Green, the LSDV estimator of (4) is equivalent to the OLS estimator of the following "within" model (the *r* subscript is dropped to simplify notation) (2008, p. 195):

$$\begin{aligned} &\%fail_{sct} - \overline{\%fail}_{sc} = \gamma \cdot (\%fail_{sc(t-1)} - \overline{\%fail}_{sc,-1}) + \\ &\beta_1 \cdot (ST_{sct} - \overline{ST}_{sc}) + \beta_2 \cdot (SC_{sct} - \overline{SC}_{sc}) + T_{tc} + \varepsilon_{sct} - \bar{\varepsilon}_{sc} \end{aligned} \quad (5)$$

Variables displayed with bars represent averages over T time periods (with the exception of $\overline{\%fail}_{sc,-1}$ which denotes $\frac{1}{T-1}\sum_{t=2}^{T}\%fail_{sct}$). Although the time invariant unobservables are differenced out in this transformation, $\%fail_{sc(t-1)}$ is correlated to $\varepsilon_{sc(t-1)}$ and hence $\bar{\varepsilon}_{sc}$.

In this case, consistent estimation can be recovered by instead first-differencing (4) to yield:

$$\Delta_t \%fail_{sct} = \gamma \cdot \Delta_t \%fail_{sc(t-1)} + \beta_1 \cdot \Delta_t ST_{sct} + \beta_2 \cdot \Delta_t SC_{sct} + \Delta_t T_{tc} + \Delta_t \varepsilon_{sct} \quad (6)$$

where Δ_t denotes differencing across a single time period. Although the OLS estimates of this model are still inconsistent ($\Delta_t \%fail_{sc(t-1)}$ is correlated to $\varepsilon_{sc(t-1)}$ and hence $\Delta_t \varepsilon_{sct}$), if the error terms are serially uncorrelated and $\%fail_{sc(t-2)}$ is predetermined, $\%fail_{sc(t-2)}$ is weakly exogenous and a valid instrument for $\Delta_t \%fail_{sc(t-1)}$. Furthermore $\%fail_{sc(t-2)}$ is likely to be a good instrument because it is highly correlated to $\Delta_t \% fail_{sc(t-1)}$. Indeed all realizations of the dependent variable prior to *t - 1* could be used as instruments, as is done in the generalized method of moments estimator proposed by Arellano and Bond (1991, p. 277). Each cohort of students spends only three years in middle school, however, so such additional instruments are unavailable for this analysis.

In the next chapter I discuss the dataset I used to estimate these two models.

CHAPTER 3
DATA

This chapter describes details concerning the panel dataset I assembled to perform the analysis. To promote school accountability, Georgia governor Sonny Perdue established an agency in 2001 charged with the task of improving the public's access to information regarding school performance. Every year since its inception, this agency, entitled the Governor's Office of Student Achievement (GOSA), has published statistics from the Georgia Department of Education in school reports readily accessible from the agency's website.[1] These school reports contain standardized tests results broken down by grade and racial category, as well as detailed information concerning school demographics and personnel. Using the information available from the GOSA reports, I compiled a database containing details on all schools enrolling more than 10 students in the sixth, seventh and eighth grades over the five school years from fall 2003 until spring 2008. This original dataset contained information from approximately 750,000 students enrolled in 520 schools. I then organized the data into three cohorts corresponding to students entering the sixth grade in 2004, 2005, and 2006. Because data from three consecutive time periods was necessary to estimate the dynamic model, I deleted records from schools that did not have three years of consecutive observations available. I also deleted observations that lacked records on student or school characteristics relevant to this analysis (see chapter 5 for a discussion of these variables). The final dataset contained information on approximately ~240,000 students (~80,000 enrolled in each cohort) from 405 schools.

[1] http://www.gaosa.org/

To determine if the final sample remained representative after deleting these observations, I compared the fail rates of students in schools in the original database to fail rates of students in the sample of schools I used in the analysis. I also compared student and school characteristics between the two groups. These results are displayed in Tables 1 and 2. Table 1 shows that the percentage of African Americans not meeting state standards on the math CRCT was ~15-20% higher than the percentage of white students not meeting standards, an achievement gap that narrowed slightly from the sixth grade (~18%) to the eighth grade (~14%). When compared against schools in the overall population, schools in the subset used for analysis had similar fail rates for the sixth and seventh grades but had notably lower fail rates in the eighth grade. This observation led me to compare the overall distribution of eighth grade fail rates between schools in the sample and schools in the original database, the results of which are displayed in figure 1. The distribution of fail rates from the sample was notably less skewed, containing fewer schools with high percentages (>60%) of students not meeting standards. Upon further analysis I determined that many schools with high failure rates opened and closed during this time period, perhaps a consequence of sanctions mediated by the No Child Left Behind Act of 2001. Such schools often lacked data from three consecutive years, and therefore were often excluded from the sample. Given this observation the results of the analysis may only be relevant to schools with moderate to low failure rates.

Table 1: Percentage of Students Not Meeting Standards on the Math Section of the CRCT.

*Each observation represents a record from one school at a single time period. The number of observations fluctuates slightly because schools enrolling few black or white students do not report test results for that demographic group.
**Summary statistics were computed using weighted averages, with the weights reflecting the number of students enrolled.

		N*	Mean**	S.D.**	Min	Max
		Overall Population				
6th grade	**Blacks**	2036	41.2	15.2	0	100
	Whites	1951	22.8	14.5	0	100
7th grade	**Blacks**	2041	29.0	12.5	0	100
	Whites	1966	15.0	10.9	0	100
8th grade	**Blacks**	2040	31.2	14.4	0	100
	Whites	1972	17.5	12.4	0	100
		Cohorts used in analysis				
6th grade	**Blacks**	999	39.2	14.0	5	84
	Whites	1016	20.9	12.6	0	73
7th grade	**Blacks**	1006	29.4	11.9	0	71
	Whites	1010	14.4	9.5	0	79
8th grade	**Blacks**	1045	26.6	12.7	0	100
	Whites	1039	14.8	11.6	0	100

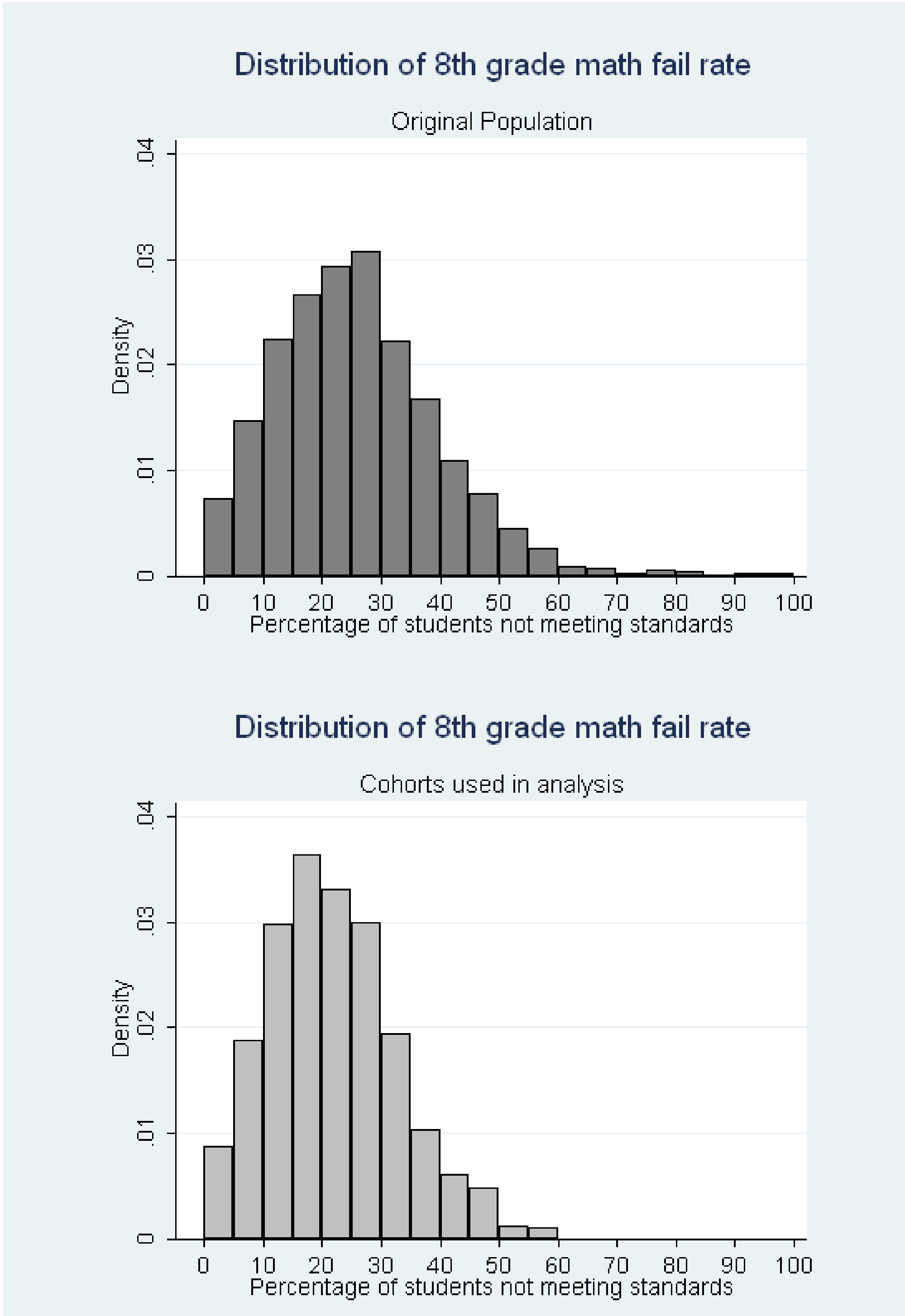

Figure 1: Distribution of 8^{th} grade CRCT math fail rates in the original population (above) versus the sample used in analysis (below).

Table 2 indicates that the average student body in the sample was ~40% African American. The distribution of the percentage of students that were African American was somewhat bimodal (figure 2), suggesting a moderate level of racial segregation in the Georgia public school system. Table 2 also shows that on average 50% of the student body in schools in the sample were enrolled in the free or reduced lunch program. I plotted the percentage of students on free and reduced lunch against the percentage of students who are black in figure 3. There was a clear relationship between these two variables (the correlation coefficient is .676), a result consistent with the expectation that schools enrolling higher percentages of African Americans are more likely to have impoverished students. I also plotted the percentage of students enrolled on gifted programs against the percentage of students who are African American in figure 4. These two variables were inversely related (the correlation coefficient is –.4317), suggesting that schools enrolling higher percentages of African Americans may have students of somewhat lower ability. The summary statistics for the school and student characteristics listed in table 2 are similar between the overall population and the subset I used for analysis.

In the next section I discuss how the models I describe in chapter were fit to the dataset I discuss here.

Table 2: Summary statistics of variables used in analysis.

*****Each observation represents a record from one school at a single time period. The number of observations fluctuates slightly because some schools do not report all variables for all years.
**Summary statistics were computed using weighted averages, with the weights reflecting the number of students enrolled.

	N*	Mean**	S.D.**	Min	Max
Overall Population					
% black	6581	40.3	29.9	0.3	100.0
% FRL	6685	50.2	24.9	0.4	100.0
% blacks absent less than five days	6678	61.7	12.1	0.0	100.0
% gifted	6213	13.2	8.4	0.1	46.8
Avg Teacher Salary	6729	47,647	3,542	33,306	77,037
Avg Admin Salary	6729	75,559	7,141	38,282	124,244
Avg Teacher Exp	6729	11.7	2.5	0.4	22.4
Avg Admin Exp	6729	18.5	4.7	2.7	38.0
Student:teacher ratio	6729	14.9	1.7	4.6	40.5
Cohorts used in analysis					
% black	3319	39.1	29.0	0.3	100.0
% FRL	3373	49.5	24.5	0.6	100.0
% blacks absent less than five days	3375	62.0	11.9	0.0	100.0
% gifted	3390	13.4	8.3	0.2	46.8
Avg Teacher Salary	3390	47,604	3,275	35,148	59,352
Avg Admin Salary	3390	75,333	6,787	38,282	103,209
Avg Teacher Exp	3390	11.7	2.5	3.0	19.7
Avg Admin Exp	3390	18.3	4.6	6.0	37.0
Student:teacher ratio	3390	15.0	1.6	7.2	23.3

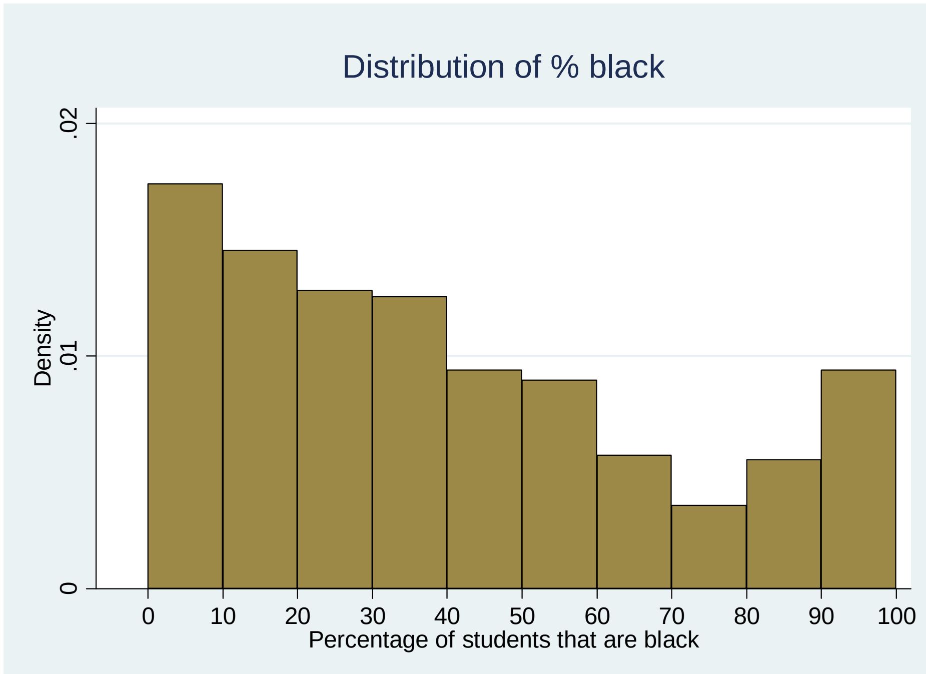

Figure 2: Distribution of the percentage of students that are African American across schools.

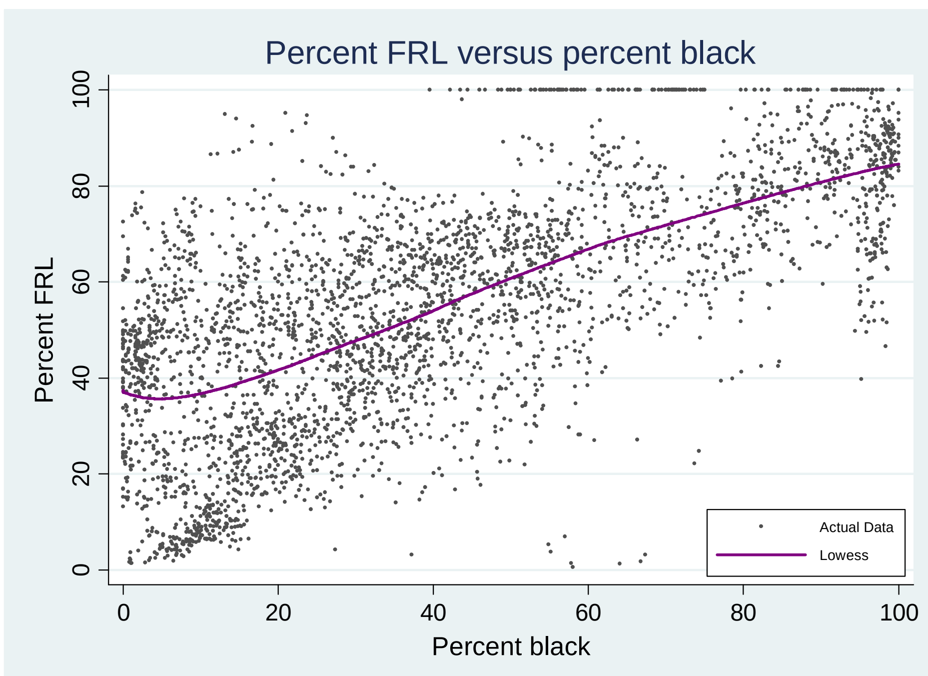

Figure 3: Percent of students on free and reduced lunch (FRL) versus percent of students that are black. Locally weighted regression with bandwidth of 0.8 displayed. Correlation coefficient equals .676.

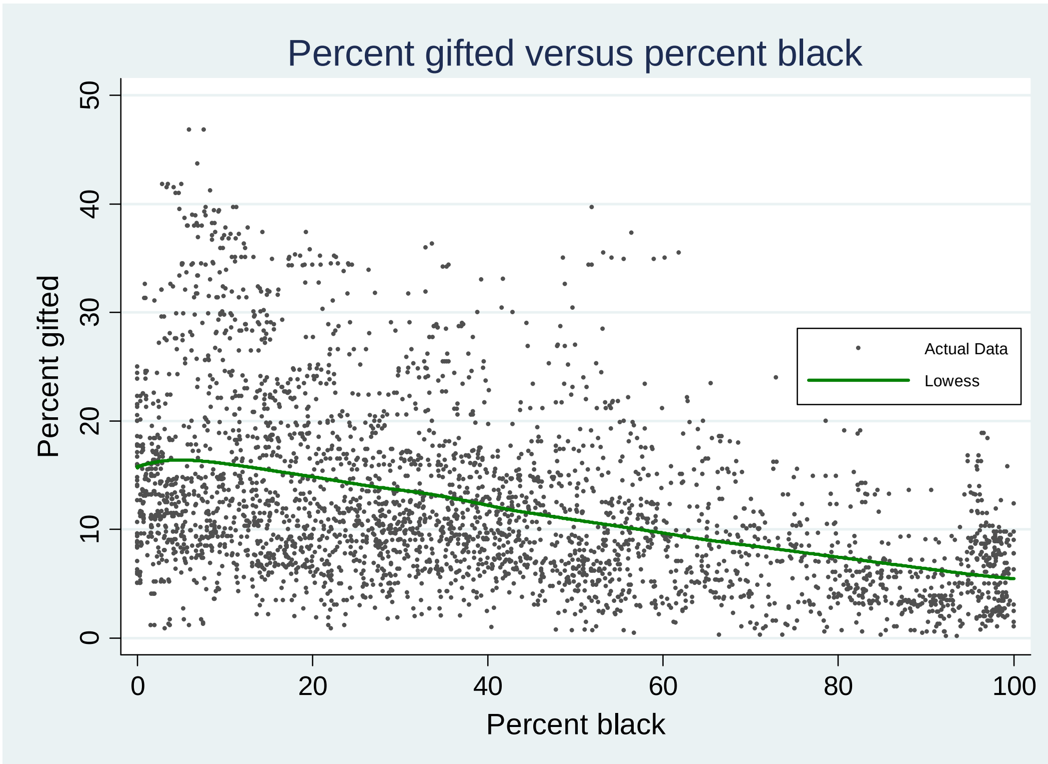

Figure 4: Percent of students enrolled in gifted programs versus percent of students that are black. Locally weighted regression with bandwidth of 0.8 displayed. Correlation coefficient equals –.4317.

CHAPTER 4
EMPIRICAL MODEL AND ESTIMATION

This section discusses the reasoning and methodology I used to fit the models developed in chapter 2 to the data obtained from the GOSA. Earlier I defined the percentage of students not meeting state requirements on the math section of the Georgia Criterion-Referenced Competency Tests (CRCT) as the relevant educational output in this analysis. Primary interest lies in calculating the effect increasing the percentage of African Americans enrolled at a school has on this measure of student performance for both whites and blacks. As figure 3 demonstrates, the percentage of African Americans enrolled at a school is highly correlated to the percentage of students participating in the free and reduced lunch program, a measure often used to gauge the socioeconomic status of the student body. Lower socioeconomic status would likely adversely affect student performance, so I included this variable to separate the effect of poverty from the effect of increasing black enrollment.

It is also necessary to control for potential confounding from systematic differences in student ability and motivation. As figure 4 shows, schools with higher percentages of African Americans tended to have lower percentages of students enrolled in gifted programs. Since the percentage of students enrolled in gifted programs is likely to be relevant to student performance, I included this variable in the regression. I further controlled for student ability by including the percentage of African American students absent less than five days from school. Although these variables are imperfect measures of unobserved student characteristics, including them reduces the bias caused from omitting ill-defined and hard-to-measure factors like cohort ability or motivation.

Besides student characteristics, it is also important to consider the possible effect school resources may have on outcomes. Schools enrolling higher percentages of African Americans may have lower paid teachers, less experienced administrators, or larger class sizes. I removed the confounding effect of these school input variables by including them in the regression. In the specification analysis conducted in chapter 6, I show that including the additional student and school covariates discussed here does not change the conclusions about the coefficient of interest, mainly that increasing the percentage of African Americans enrolled at a school adversely affects black student performance and has a negligible effect on white student outcomes.

Because the data are aggregated over grades, I estimated all models using weighted least squares with weights proportional to the total number of students aggregated in each observation. To determine if the fixed effects model was appropriate, I performed a Hausman specification test. The p-values obtained from this test were less than .001, providing strong evidence that the fixed effects model was appropriate. I report heteroskedasticity-robust standard errors, further corrected for errors clustering around cohorts from individual schools. All analysis was performed using Stata/IC 11.0.

CHAPTER 5
RESULTS

This section discusses the results I obtained from estimating the models described in chapter 3 with the dataset detailed in chapter 4. I first estimated a simple baseline model of the following form:

$$\%fail_{sctr} = \beta_{1r} \cdot \%black_{sct} + \beta_{2r} \cdot \ln(avg\ teacher\ salary_{st}) + \beta_{3r} \cdot STratio_{st} + T_{tcr} + \delta_{scr} + \varepsilon_{sgtr} \quad (7)$$

$$t = 2004, 2005, \ldots, 2008\ ;\ s = 1, 2, \ldots, 402\ ;\ c = 1, 2, 3\ ;\ r = w, b$$

where $\% fail_{sctr}$ is the percentage of students in racial group r in school s in cohort c at time t failing the math section of the CRCT, $\%\ black_{sct}$ is the percentage of students in school s in cohort c at time t that are black, ln($avg\ teacher\ salary_{st}$) is the natural logarithm of the average teacher salary at school s at time t, $STratio_{st}$ is the total number of students divided by the total number of teachers at school s at time t, T_{tcr} corresponds to a set of dummy variables entered for each cohort-year (i.e. coded as 1 if the observation is from cohort c in year t, 0 otherwise), δ_{scr} corresponds to a set of dummy variables for each cohort from every school (i.e. coded as 1 if the observation is from cohort c at school s, 0 otherwise) and ε_{sctr} is a stochastic error term. The results obtained from estimating this regression are displayed in column 1 of tables 3 and 4.

Table 3: Fixed effects regression results with percentage of African American students not meeting state standards as the dependent variable. Heteroskedasticity-robust standard errors are reported in parenthesis, further corrected for clustering around school cohorts. Asterisks correspond to marginal statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	% of Black Students Not Meeting Standards on the Math CRCT		
% black	0.360***	0.318***	0.313***
	(0.0698)	(0.0693)	(0.0691)
% FRL		0.0534**	0.0533**
		(0.0241)	(0.0241)
% blacks absent less than five days		-0.0650***	-0.0649***
		(0.0243)	(0.0243)
% gifted		-0.0495	-0.0459
		(0.0829)	(0.0831)
ln(avg teacher salary)	-11.98*	-12.01*	-0.195
	(7.175)	(7.166)	(11.04)
Student:teacher ratio	0.773***	0.765***	0.763***
	(0.170)	(0.169)	(0.169)
Avg teacher exp			-0.940
			(0.888)
(Avg teacher exp)^2			0.0232
			(0.0352)
ln(avg admin salary)			2.413
			(3.035)
Avg admin exp			-0.165
			(0.289)
(Avg admin exp)^2			0.00291
			(0.00721)
Constant	141.2*	145.3*	1.253
	(77.40)	(77.54)	(117.9)
Observations	3037	3037	3037
Number of idcohort	1045	1045	1045
R^2 (mean-detrended data)	0.591	0.594	0.595
R^2 (overall)	0.874	0.875	0.875

Table 4: Fixed effects regression results with percentage of white students not meeting state standards as the dependent variable. Heteroskedasticity-robust standard errors are reported in parenthesis, further corrected for clustering around school cohorts. Asterisks correspond to marginal statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	% of White Students Not Meeting Standards on the Math CRCT		
% black	0.0366	0.00593	0.00618
	(0.0515)	(0.0544)	(0.0545)
% FRL		0.0508**	0.0468*
		(0.0246)	(0.0241)
% blacks absent less than five days		-0.00814	-0.00942
		(0.0129)	(0.0131)
% gifted		0.00504	0.0106
		(0.0677)	(0.0680)
ln(avg teacher salary)	-15.55**	-15.50**	-7.477
	(6.427)	(6.399)	(9.182)
Student:teacher ratio	0.571***	0.565***	0.549***
	(0.183)	(0.183)	(0.180)
Avg teacher exp			-0.477
			(0.745)
(Avg teacher exp)^2			0.0100
			(0.0285)
ln(avg admin salary)			-3.276
			(2.711)
Avg admin exp			-0.249
			(0.315)
(Avg admin exp)^2			0.00492
			(0.00759)
Constant	177.9**	176.6**	134.6
	(69.19)	(68.85)	(95.81)
Observations	2993	2993	2993
Number of idcohort	1026	1026	1026
R^2 (mean-detrended data)	0.432	0.433	0.436
R^2 (overall)	0.886	0.886	0.887

Column 1 in table 3 shows that after controlling for teacher salaries and student teacher ratio, a ten percent increase in the percentage of students who are black increased the percentage of black students not meeting state standards by 3.6 percent. This small but significant effect is consistent with results obtained in recent analyses by Hanushek, Kain and Rivken (2009, p. 349), and David Card and Jesse Rothstein (2007, p. 2158). Column 1 in table 4 shows that the marginal effect of increasing the percentage of black students on white student performance is fairly negligible. Together, these results indicate that increasing levels of school segregation could widen the black-white achievement gap mainly by adversely affecting black student outcomes. Column 1 in tables 3 and 4 also shows that higher teacher salaries and lower student-teacher ratios correspond to better student outcomes. It should be emphasized, however, that because this dataset aggregates inputs over entire schools the coefficients on input variables are difficult to interpret and should be viewed with a certain degree of skepticism. Classroom or student level data is more appropriate for analyzing the marginal effect of class size or teacher salary, as Rivkin, Hanushek, and Kain showed in their report discussing how teachers impact student performance (2005, p. 417).

As I discuss in chapter 4, it is possible that the coefficient on *% black* displayed in column 1 is biased because variables relevant to student performance, such as poverty, ability and motivation, were omitted from the regression. To correct for this, I estimated the following model that includes more controls for student characteristics:

$$\begin{aligned}&\%\,fail_{sctr} = \beta_{1r}\cdot\%\,black_{sct} + +\beta_{2r}\cdot\%\ FRL_{sct} + \beta_{3r}\cdot\%\ gifted_{st} + \beta_{4r}\cdot\%\ absent_{st} + \\ &\beta_{5r}\cdot\ln(avg\ teacher\ salary_{st}) + \beta_{6r}\cdot STratio_{st} + T_{tcr} + \delta_{scr} + \varepsilon_{sgtr}\end{aligned} \tag{8}$$

where $\%\ FRL_{sct}$ is the percentage of students in school *s* in cohort *c* at time *t* who are enrolled in the free or reduced lunch program, $\%\ gifted_{st}$ is the percentage of students in school *s* at time *t* who are enrolled in gifted programs, and % $absent_{st}$ is the percentage of African Americans in school *s* at time *t* who are absent fewer than six days from school. The results obtained from estimating this regression are displayed in column 2 of tables 3 and 4.

Column 2 in table 3 shows that although controlling for these additional student characteristics reduced the estimated coefficient on the *% black* variable by slightly more than 10 percent, the effect remained both economically and statistically significant. Column 2 in tables 3 and 4 also shows that increasing the percentage of students on free and reduced lunch increased the percentage of students not meeting standards, a result consistent with expectations. This coefficient was small relative to the estimated coefficient for the *% black* variable, suggesting that segregation across race has an independent and more marked effect on black student outcomes than segregation based on socioeconomic status. Column 2 in table 3 shows that as the percentage of students enrolled in gifted programs or the percentage of black students absent less than five days increased, the percentage of students failing the exam decreased. The estimated coefficients on these variables are much smaller and less precisely estimated than the coefficient on the *% black* variable.

I also ran a regression containing more controls for school inputs. The form of this regression was as follows:

$$\begin{aligned}
\%fail_{sctr} &= \beta_{1r} \cdot \%black_{sct} + \beta_{2r} \cdot \%\,FRL_{sct} + \beta_{3r} \cdot \%\,gifted_{st} + \beta_{4r} \cdot \%\,absent_{st} + \\
&\beta_{5r} \cdot \ln(avg\,teacher\,salary_{st}) + \beta_{6r} \cdot avg\,teacher\,exp_{st} + \beta_{7r} \cdot (avg\,teacher\,exp_{st})^2 + \\
&\beta_{8r} \cdot \ln(avg\,admin\,salary_{st}) + \beta_{9r} \cdot avg\,admin\,exp_{st} + \beta_{10r} \cdot (avg\,admin\,exp_{st})^2 + \\
&\beta_{11r} \cdot STratio_{st} + T_{tcr} + \delta_{scr} + \varepsilon_{sgtr}
\end{aligned} \tag{9}$$

where *avg teacher* exp_{st} is the average years of experience of teachers in school *s* at time *t* (the quadratic term allows for diminishing returns to experience), and the *admin* terms are administrator variables defined analogously to the corresponding teacher quantities. The results from this regression are displayed in column 3 of tables 3 and 4.

Column 3 of tables 3 and 4 shows that including these additional school inputs did not substantially alter the estimated coefficients for the student characteristics. Inclusion of the additional regressors did reduce the estimated coefficient on *ln(avg teacher salary)*, an expected result since teacher experience is likely positively correlated to teacher salary and student performance. Besides the student:teacher ratio, column 3 in tables 3 and 4 indicates that none of the school input coefficients were estimated very precisely. An F-test of the null hypothesis that the coefficients on the teacher and administrator variables were all equal to zero yielded a p-value of .222 for the regression using black fail rates and .0599 for the regression using white fail rates, suggesting that jointly these variables do not contribute substantially to black student performance and may only be marginally significant for white student outcomes.

The R^2 values obtained from these regressions all exceeded .87, indicating that the fixed effects model fit the data quite well. Comparison of the mean-detrended and overall R^2 values indicates that a substantial portion of the model's goodness of fit can be attributed to inclusion of the fixed effects dummies. This result implies much of the variation in student performance originates from unobserved heterogeneity. That the estimate of the marginal effect of increasing black enrollment remained significant after allowing for such unobserved heterogeneity suggests segregation is a significant factor in perpetuating the black-white achievement gap.

I also estimated dynamic formulations of models (7), (8), and (9). These models allow previous student performance to be a determinant of current student outcomes by including a lagged dependent variable as a regressor. Consistent estimation required first-differencing the variables, treating the lagged dependent variable as endogenous, and using the percentage of students failing the exam in sixth grade as an instrument (see chapter 2 for a more detailed discussion). The dynamic formulation of model (7) is displayed below for illustration:

$$\begin{aligned}\Delta_t \% fail_{sctr} &= \gamma_r \cdot \Delta_t \% fail_{sc(t-1)r} + \beta_{1r} \cdot \Delta_t \% black_{sct} + \\ &\beta_{2r} \cdot \Delta_t \ln(avg\ teacher\ salary_{st}) + \beta_{3r} \cdot \Delta_t STratio_{st} + \delta_{cr} + \Delta_t \varepsilon_{sct}\end{aligned} \tag{10}$$

where Δ_t denotes differencing across a single time period and δ_{cr} is a set of cohort dummy variables (i.e. coded 1 if the observation is from cohort *c*, 0 otherwise). The first-differencing procedure obviated the need to include the fixed effects dummies. The results from these regressions are displayed in tables 5 and 6.

Table 5: Dynamic fixed effects regression results with percentage of African American students not meeting state standards as the dependent variable. Heteroskedasticity-robust standard errors are reported in parenthesis, further corrected for clustering around school cohorts. Asterisks correspond to marginal statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	% of Black Students Not Meeting Standards on the Math CRCT		
% of blacks not meeting standards in previous period	0.177**	0.174**	0.183***
	(0.0706)	(0.0702)	(0.0696)
% black	0.298***	0.289***	0.286***
	(0.105)	(0.110)	(0.109)
% FRL		0.0180	0.0145
		(0.0402)	(0.0406)
% blacks absent less than five days		-0.00344	-0.00501
		(0.0363)	(0.0362)
% gifted		0.00431	0.0176
		(0.139)	(0.140)
ln(avg teacher salary)	-2.067	-2.056	18.38
	(11.22)	(11.22)	(15.90)
Student:teacher ratio	0.501**	0.502**	0.483*
	(0.253)	(0.252)	(0.251)
Avg teacher exp			-2.548*
			(1.491)
(Avg teacher exp)^2			0.0809
			(0.0606)
ln(avg admin salary)			3.892
			(4.286)
Avg admin exp			-0.319
			(0.427)
(Avg admin exp)^2			0.00714
			(0.0106)
Constant	-4.899***	-4.930***	-5.526***
	(1.146)	(1.136)	(1.163)
Observations	986	986	986

Table 6: Dynamic fixed effects regression results with percentage of white students not meeting state standards as the dependent variable. Heteroskedasticity-robust standard errors are reported in parenthesis, further corrected for clustering around school cohorts. Asterisks correspond to marginal statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	% of White Students Not Meeting Standards on the Math CRCT		
% of whites not meeting standards in previous period	0.118	0.118	0.128
	(0.0934)	(0.0930)	(0.0924)
% black	-0.126	-0.122	-0.117
	(0.0764)	(0.0793)	(0.0798)
% FRL		-0.0103	-0.0161
		(0.0291)	(0.0290)
% blacks absent less than five days		-0.0154	-0.0186
		(0.0164)	(0.0168)
% gifted		-0.0165	-0.0110
		(0.0874)	(0.0878)
ln(avg teacher salary)	1.712	1.755	16.24
	(8.150)	(8.147)	(12.92)
Student:teacher ratio	-0.401*	-0.408*	-0.435*
	(0.237)	(0.237)	(0.234)
Avg teacher exp			-0.838
			(1.101)
(Avg teacher exp)^2			0.0151
			(0.0421)
ln(avg admin salary)			0.476
			(3.547)
Avg admin exp			-0.373
			(0.397)
(Avg admin exp)^2			0.00571
			(0.00927)
Constant	0.145	0.178	-0.138
	(0.886)	(0.889)	(0.846)
Observations	977	977	977

The first row of tables 5 and 6 indicate that higher percentages of students failing the exam in the previous period increased the percentages of students failing the exam in the current period, as would be expected. Even after I controlled for this effect, however, row 2 in table 5 shows that increases in the percentages of black students enrolled in a school still caused the percentage of black students failing the exam to rise. The estimated effect is approximately 10-15% smaller than the estimated effect from the level model, but remained both economically and statistically significant and persisted as I added additional student and school controls. Row 2 in Table 6 shows that after controlling for performance in the previous period, increases in the percentages of black students enrolled may in fact decrease the number of white students failing the exam. Overall, these results are largely consistent with what was obtained from estimation of the level model.

CHAPTER 6
CONCLUSION

My results demonstrate that increases in segregation lower black performance without having a substantial positive impact on white student outcomes. This observation suggests that the recent trends toward resegregation could widen the black-white achievement gap, primarily by hurting black student performance. These findings confirm the Supreme Court's assessment in the *Brown vs. Board of Education* opinion and are consistent with other research in the area.

I emphasize that my results do not imply mandated integration plans will improve outcomes or narrow the achievement gap. The relationship between performance and demographics in an artificial setting created by forced integration would likely be different than the voluntary relationships analyzed here. These findings only suggest that demographic trends may widen the achievement gap that has persisted decades after integration. What can be done to mitigate the effects of such trends is outside the scope of this project but could be the subject of future research in this area.

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