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DISSERTATION

Exploring Family, Neighborhood and School Factors in Racial Achievement Gap

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This document was submitted as a dissertation in February 2010 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of Roland Sturm (Chair), Brian Stecher, and Paco Martorell.

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Dissertation Abstract

The racial achievement gap has been at the center of the educational debate for decades in the United States. Although disparities in educational outcomes have declined in part of the 20th century, the process has stalled in this decade. For instance, in mathematics the gap in raw scores for students aged 13 has decline from 41 points in 1978 to stable 27-30 points since 1990. In August 2009 results from the SAT scores confirm a widening in the racial achievement gap, thus questioning the success of some policy initiatives. The goal of my dissertation is to examine the contribution of family, school and neighborhood factors to the achievement gap and to highlight promising areas for policy intervention.

This dissertation is structured in three papers. The first paper studies the association between neighborhood socioeconomic composition and student achievement. The findings show that the fraction of college-educated adults and median household income in the neighborhood are positively associated with students' achievement. High levels of poverty have a negative and significant effect only when a threshold of 30% of poor households in the area has been reached. Overall, neighborhood factors can account, on average, for about 5% of student achievement with larger impacts for some subgroups, particularly for Hispanics and Blacks.

The second paper analyzes the effect of enrolling students in Algebra 1 in 8th grade instead of 9th grade. Using a propensity score matching method, this study estimates the average treatment effect on the math section of the tenth-grade North Carolina's High School Comprehensive Test. Results show that low-achieving, low SES, Black students are more likely to take Algebra 1 in ninth-grade than their White peers. Despite the positive average treatment, the effect is small and not statistically significant for low achieving students. Our findings do not suggest that the "Algebra 1 for everyone" policy encouraged since the early 1990s is not equally effective for all students. Students who had low test scores prior to 8th grade did not improve at the same rate or not improve at all, though we can not affirm they are harmed by such policy. The question that remains is how to turn this effect into achievement gains for this group.

The third paper explores factors underlying the achievement gap between White and Hispanic students using the North Carolina Public School Database. We use the Page-Murnane-Willett, Oaxaca–Blinder and Juhn–Murphy–Pierce methods to decompose the gap into school and parental factors. The analysis provides three key results. First, within school factors exceed between school factors. Second, parental education is the most important individual variables: White students have on average better educated parents and that translates to higher test scores. Third, the achievement gap narrows between grades 3 and 10 with the improvement mainly associated with a reduction in within school disparities.

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Chapter 1: Introduction or Why Racial Gap Matters

Since the Coleman report in 1966, researchers and policy-makers have given considerable attention to racial and socioeconomic segregation in the United States and their contribution to the inequality of educational opportunities (Neal, 2005; Rumberger and Palady, 2005). The racial gap is at the center of many debates regarding how to allocate school resources, the advantages or not of grouping students by ability, among other policy alternatives (Clotfelter et al, 2006; Dillon, 2009). These debates have translated into many initiatives, with the 2001 (President George Bush's) No Child Left Behind as an example of a major national change in the last decde.

A recent study from the U.S. Department of Education confirmed that, although disparities in educational outcomes have declined in part of the 20th century, the process has stalled in the last decades. For instance, in mathematics the gap in raw scores for students aged 13 has decline from 41 points in 1978 to a stable 27-30 points since 1990 (U.S. Department of Education, 2009:6). Furthermore, in August 2009 results from the SAT scores confirm a widening in racial achievement gap, thus questioning the success of reforms (Hechinger, 2009).

Disparities in test scores are shaped by many factors and strongly influenced by the communities to which children are exposed. The two most common communities children are exposed to are the school they attend and the home neighborhoods in which they live. Empirical evidence suggests that school and residential segregation might have contributed to the current stagnation of the racial achievement (Hanushek et al, 2002; Hoxby, 2000; Rumberger and Pallardy, 2005; Neal, 2005; Vigdor and Ludwig, 2007; Watson, 2009).

As policies can be designed to intervene in either of these settings, it is relevant to understand where disparities stem from and how they interact, reinforce or offset each other. For example, disadvantaged children from disadvantaged neighborhoods may perform better if they attend less disadvantaged schools, but they tend to attend disadvantaged schools. Rumberger and Pallardy (2005) report a "double disadvantage" for Black and Hispanic students: in 2000 more than 70% of all Black and Hispanic students attend schools that have predominantly minorities, and the same schools have twice the poverty rate compared to their predominantly White counterparts. (Rumberger and Pallardy, 2005: 2002).

Education policies may reinforce or mitigate disparities in test scores. Tracking or ability grouping practices, the general practice of sorting student into apparently homogenous groups, boost racial and socio-economic disparities as minority children are over-represented in “lower-ability” courses and are more likely to be selected into special education and compensatory programs. Within-school policies utilized to “resegregate” schools on a racial basis might include the sanctions and students discipline management, as well (Eyler et al, 1982; Rumberger and Pallardy, 2005).

Many government-led community-based projects have specifically acknowledged the influence of the geographical area of residence on an individual’s well-being. Such initiatives include the 1960’s War on Poverty and mid 1990’s Empowerment Zone and Enterprise Communities Program under President Clinton. Likewise, states and school districts have been fostering racial integration in their school systems through both, court mandated and voluntary “detracking”, school choice programs, and involuntary ‘‘busing’’ plans (Rumberberg and Palardy, 2005).

In contrast to the high level of litigation that characterized the 1970s and 1980s, the strategies to address the achievement gap in the last decade have centered more on improving school resources than on desegregation efforts. Parents have also introduced their own adjustment mechanisms: moving away to other neighborhood and/or school by either using the school choice possibilities or by enrolling kids in private schools. As a result of either of these factors, residential segregation, education policy or both, school segregation has been increasing and racial disparities are not disappearing (Clotfelter et al, 2006; Neal, 2005; Neal, 2007).

The goal of this dissertation is to examine whether disadvantaged and segregated neighborhoods affect children’s development, and how the practice of ability grouping –usually referred to as tracking- impact on students’ achievement.

Altogether, this study contributes to the policy debates on educational achievement gaps by measuring the influences of family, neighborhood segregation and school policies on students’ outcomes. The findings elucidate the role of a combination of multiple adverse contexts may have on young children's development and academic achievement.

1.2. Significance of Proposed Study

The proposed research adds to the literature on school and neighborhood effects through:

- the identification of the impact of the individual, the school and the neighborhood on student's outcomes in elementary education.
- the approximation of the factors at each level which affect student's outcomes. This will provide a basis for understanding the channels through which environmental effects occur.
- the appraisal of the differential effect of neighborhood and, more specifically, the role of poverty and deprivation on children's outcomes. The empirical findings contribute to the understanding on how poverty affects student's educational disparities and provides evidence of whether or not concentrated poverty exacerbates the constraints on progress for individuals who already have difficulties.
- the estimate of the impact of ability grouping policies on students' outcomes. The exploration of the heterogeneity in students' response to placement represents a huge progress towards understanding the impact of placement policies on the achievement gap.

1.3. Structure

After this introduction the dissertation is structured in four sections. The second chapter studies the association between neighborhood socioeconomic composition and student achievement. The third chapter analyzes the effect of enrolling students in Algebra 1 in 8th grade instead of 9th grade. Using a propensity score matching method we estimate the average treatment effect on the math section of the tenth-grade North Carolina's High School Comprehensive Test. The fourth chapter explores the factors underlying the achievement gap between White and Hispanic students using the North Carolina Public School Database using alternative decomposition methods. The last chapter concludes this dissertation.

Chapter 2: Neighborhood Effects on Students' Achievement

I. Introduction

During the last decades, there has been growing interest in the role of the social environment on shaping children's development. The social environment includes the people and institutions with which children interact. Research on communities and families has grown significantly consistently, so have concerns about the effects of poverty concentration on individual and community well being (city, region, and country). The empirical literature on educational outcomes has taken two general approaches. First, the school effectiveness approach tries to isolate the impact of school and classroom resources on children's outcomes. Second, the neighborhood impact literature explores the influence of neighborhood attributes on these outcomes.

Thus far, empirical findings related to school and neighborhood effects are controversial and, sometimes, contradictory. For example, Hanushek (1997), in a review of school effects, found neither a strong nor a consistent correlation between school resources and student's achievement whereas recent papers on school effectiveness has found evidence supporting school influence on children's educational outcomes (Thrupp et al, 2002). Similarly, although the literature on neighborhood effects indicates the relevance of the environment on children's behavior, there is no agreement on either the size of the impact or the mechanisms through which it occurs. In addition, there are few papers which simultaneously analyze the influence of both schools and neighborhoods.

Identification of neighborhood effects faces conceptual and empirical obstacles. From the theoretical point of view, there are several potential ways neighborhoods may affect individuals' outcomes but not every hypothesized association between neighborhood and child's outcomes could be isolated in size and significance. From the empirical standpoint the specification of geographical neighborhood boundaries constitutes the first issue to resolve. Although census units are generally used as synonymous of neighborhood, they do not necessarily coincide with the idea of "community of influence". Most of the empirical literature refers to neighborhood influence effects found as the upper bound of neighborhood's influence. Additional obstacles include simultaneity, selectivity and omitted variables bias. The last, but not the least, obstacle is translating empirical findings into policy recommendations.

From the policy-maker's point of view, it is necessary to understand and identify the size and significance of all sources of influence. Although both residential location and family decisions may be influenced by government policies, school factors are potentially more amenable to public policy than neighborhood attributes and family processes. In particular, characteristics of families such as income, living arrangements, parenting and decision-making styles may be under the control of the policy-maker solely through indirect channels.

This paper explores and assesses the importance of neighborhood and school effects on students' mathematics and reading test scores in elementary education in the U.S. The study is largely based on the Early Childhood Longitudinal Survey (ECLS-K), which follows a nationally representative sample of students from kindergarten (1998-1999 school year) through 8th grade. My contribution to existing literature consists of the incorporation of a richer set of family background and neighborhood-level variables as well as the separate identification of the influence of the school and the neighborhood on children's achievement.

This study's results, based on an HLM model, point out the association between neighborhood's socioeconomic composition and student's out comes and confirm that school and neighborhood are overlapping but independent sources of influence. The findings of this study support both socialization and epidemic theories. The presence of well-educated adults in and the median income of the neighborhood have positive impacts on a student's achievement. Nevertheless, high levels of poverty have a large and significant negative influence on student's tests scores. The impact occurs when a threshold of 30% of poor households has been reached. Even when our findings are stable over different specifications for the whole sample, the implicit assumption that school and neighborhood have a uniform effect on all children regardless their ethnicity, gender and socio economic status is challenged. Neighborhoods appear to have higher impact on minorities (Black and Hispanics, for instance) than on the whole sample.

After this introduction, this paper is divided into six parts. Section 2 briefly outlines hypotheses about contextual effects on the psychosocial situation and behavior of children and adolescents, discussing methodological problems and reviewing international research findings. Section 3 synthesizes the analytic framework and the hypothesis of the paper. Sections 4 and 5 describe the data sources and the methods employed, respectively. Section 6 and 7 present and discuss the results, respectively.

II. Background and Motivation

Theoretical and empirical research recognizes the importance of neighborhood and school environments as structural conditions which may exert influence (both positive and negative) on youths' attitudes, norms and values (Jencks and Mayer, 1990; Brooks-Gunn et al, 1997; Ginther, Haveman and Wolfe, 2000; Sampson et al, 2008; Kirk, 2009). The focus on individual-level factors, generally associated with little or no interest in area characteristics, has shifted in the last decades toward the exploration of neighborhood effects and the clarification of the mechanisms through which they exert influence on children's behaviors. Although there are still methodological challenges and alternative explanations for the effects, a vast literature suggests that neighborhood characteristics matter (Brooks-Gunn et al, 1997; Kawachi and Berkman, 2000).

Theoretical and empirical work has proposed several hypothetical links between neighborhood characteristics and individual outcomes (Vigdor, 2006). For instance, Duncan and Raudenbusch (2001) based on Jencks and Mayer (1990) distinguish five main models: a) "epidemic/contagion" theories, based on peer's influences and peer's pressure; b) "collective socialization theories" in which neighborhood role models have a decisive influence in child' future as control and/or support for children (Sampson et al, 1999; Oberwittler, 2004); c) "institutional" models in which neighborhood's institutions or structured interactions make the difference; d) "competition" models in which inhabitants compete for area resources suggesting that relatively affluent neighbors are a disadvantage and; e) "relative deprivation" approaches in which individuals compare their success or failure with the neighbors[1].

Neighborhood effects have been studied from other perspectives. The ecological perspective considers individual attainment as the product of the interactions with a set of contexts which can influence individual's development directly or indirectly (Bronfenbrenner, 1979; Bronfenbrenner and Ceci, 1994; Sampson et al, 1999; Arum, 2000)[2]. In contrast, economic theory incorporates neighborhood effects as part of the production function that children's

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1 The policy implications of each theory are different. While the first three imply that "low quality" neighborhoods increase social problem, the remaining two predicts that "high quality" neighborhoods produce such results (Crane, 1991).

2 Ecologic studies try to determine whether differences across areas are due to characteristics of the areas themselves or to differences between the types of individuals living in different areas (Diez-Roux, 2001).

outcomes. Among other mechanisms, economics models highlight the role of labor markets conditions on children[3].

II.1. The definition of neighborhood

Research on neighborhood effects faces conceptual, methodological and empirical problems. The first problem is the definition of neighborhood or, the "geographic areas whose characteristics may be relevant" (Diez-Roux, 2001: 1784). The "relevant characteristics" are difficult to define as long as they depend on the theoretical background and the outcome under study. Conceptually, the idea of neighborhoods as "ecological units nested within successively larger communities" has seen difficulties in implementation and measurement.

Empirical literature has taken a variety of approaches to define neighborhood. The majority relies on the geographic boundaries defined either by some administrative unit (school districts, policy beats) or by the Bureau of Census geographical units. Table 1 summarizes some of the administrative definitions used in the empirical studies reviewed by Gephart (1997), Sampson et al (2002) and Durlauf (2003) and points out the widespread use of census tract. As census's units (tracts, blocks and counties), are not perfect, accurate indicators of either residential neighborhoods or functional communities, the use of census tract may introduce measurement error and retrieve biased coefficient of the impact of neighborhood factor on individual outcomes (Duncan et al, 1997). Nevertheless, Census data have countervailing benefits: data are free and uniform for the whole country (Vigdor, 2006).

Few alternative methodological approaches have been considered (Duncan and Raudenbush, 2001). Economic-based approaches consider communities boundaries defined by the competition between business and between population groups. Table 2 reports some studies which explore economic-type of sorting mechanisms. A second type of approach incorporates knowledge on some other dimensions beyond the economics such as history, culture and social networks (Diez-Roux, 2001; Sampson et at, 2002: 470)[4]. This group comprises, among others, survey-based methods and Survey-based Social Observation (SSO). Survey-based methods have been implemented in some empirical settings; for instance it was instrumented through the

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[3] For instance, high levels of local unemployment generate stress on parents and affect, thus, family dynamics including decisions to invest in human capital (Pebley and Sastry, 2003).

[4] Survey-based approaches are subject to measurement error problems (Duncan and Raudenbush, 2001:6).

Neighborhood Assessment of Community Characteristics (NACC) questionnaire of the Center for Health Achievement and Neighborhood Growth and Ethnic Studies of the University of Pennsylvania (Connell et al, 1997)[5]. SSO has also been implemented as part of the Project on Human Development on Chicago Neighborhood (PHDCN) (Sampson and Raudenbush, 1999)[6].

Table 1
Definition of Neighborhood in Empirical Studies

Neighborhood Definition	Number of Studies		
	Gephart (1997)	Sampston et al (2002)	Durlauf (2003)
Census Tract	15	24	10
Policy beats		2	
Neighborhood Clusters		4	
Political Constituencies		4	
Enumeration districts		2	
Face Blocks		1	
Enumeration Areas		2	
Block Group	2	5	
Neighborhood	2	2	
Postal Sector		1	
Zip Code	3	4	5
Community Cluster		1	
City/County			2
Educational Authority	1		
SMSA	1		
Locality	1		

Source: *Elaboration based on Gephart (1997), Table 1.1., Sampson et al (2002) Tables 1, 2 and 3 and Durlauf (2003), Table 2.*

Table 2
Neighborhood Formation Mechanisms

Mechanism	Number of Studies
Rental Prices differences	3
Rental Prices/Education	1
Neighborhood Income Barriers	1
Housing Prices	2
Property Taxes/ Public Good Provision	2
Taxes/Education Expenditures	1
Income/Public Education Provision	1

Source: *Elaboration based on Durlauf (2003), Table 1.*

Regardless all the progress in the methodologies to define neighborhood boundaries on alternative basis, there is still a lot of room for improvement (Sampson et al, 2002:449) with

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5 Briefly, the methodology consists on windshield surveys of the two major cross streets in each census tract of the participants' neighborhoods.

6 The SSO was used to observe the physical, social, and economic characteristics of neighborhoods in 1995 by the PHDCN. The methodology combined person-based and videotaped approaches as methods of collection.

some scholars calling for a specific area of measurement, "ecometrics" (Raudenbush and Sampson, 1999; Sampson et al, 2002; Duncan, 2003)[7].

II.2. Methodological challenges in the identification of "neighborhoods effects"

The empirical identification of neighborhood effects faces several interrelated challenges (Sampson et al., 2002). The first obstacle relates to the process of assigning or sorting families into neighborhoods. The second challenge is the empirically identification of effects. A third, though related, problem is the difficulties of establishing causal mechanisms in presence of multiple factors. A final problem is the impossibility of including all factors in the estimates.

II.2.1. Selectivity

Differential selection of individuals into communities is, probably the biggest obstacle to causal inference in neighborhood studies. Without a research design that controls for neighborhood choice it is difficult to ascertain whether differences in outcomes are the result of neighborhood factors or family self-selection into certain areas (Durlauf, 2001). Statistically, this may lead to either an under- or an over-estimation of contextual effects in cross-sectional studies if self-selection bias is poorly controlled for (Duncan and Raudenbush, 1999; Ginther et al, 2000:618). The majority of the literature has opted for assuming that the covariates that in typical regression represent causal pathways for characteristics of individuals and families simultaneously influence both selections into neighborhood and outcomes (Ginther et al, 2000; Kauppinen, 2008).

In the last decade, a growing body of research tackled the issue of endogeneity bias by employing alternative research designs. For instance some studies have opted for experimental assignment -such as the Gautreaux Assissted Housing Program (Gephart, 1997) and the MTO program (Katz et al, 2001; Sanbonmatsu et al, 2006) - while others have relied on longitudinal surveys (Raudenbush, 1993; Sampson et al, 2008; Hong and Raudenbush, 2005; Timberlake, 2009)[8]. Alternative approaches to tackle endogeneity bias include the use of instrumental variables to predict contextual characteristics (see for example Evans. Pates and Schwabb, 1992)

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[7] The need to measure a multitude of constructs may lead to omitted variable bias in case only one or two variables are used to approximate neighborhood processes and mechanism.

[8] Durlauf (2001) and Winship and Morgan (1999) discuss non-experimental and sociological approaches to the endogeneity of neighborhood processes and social interactions.

and, the employment of sibling fixed-effects models to eliminate unmeasured family characteristics which may introduced bias through differentiation (see Aaronson, 1997).

II.2.2. Simultaneity

A second problem comes from the reflection problem referred to by Manski (2000). Because mean behavior is determined by individual behavior, it is not possible to determine whether individual outcome is affected by group behavior or group behavior is the aggregation of individual behaviors[9]. Manski distinguishes between endogenous interactions, contextual interactions, and correlated effects. Individual behavior may vary with mean behavior in the group (endogenous interactions), with the mean values of exogenous attributes of group members (contextual interactions), and with personal characteristics which may be similar among group members (correlated effects) (Manski, 2000: 25)[10]. The isolation of total effects between endogenous, contextual and correlated has important policy implications: there are some feedbacks in case of endogenous effects which are not present in contextual and correlated effects. For instance, if group behavior has impact on the child's behavior a policy focus in the group of reference may have a larger impact than actions focus only on the individual[11].

II.2.3. Causal Mechanisms

Although a vast amount of research has examined the association between socio-demographic characteristics of contexts and children's behavior, socio-demographic measures do not provide information for exactly how and why given social environments change a given behavior (Cook et al., 2002; Sampson at al, 2002). Partly due to the need of capturing constructs corresponding to the competing theoretical ways in which neighborhood effect may occur, there are many decisions to consider regarding the number of the levels (individual versus group) at which they should be defined and measured (Diez-Roux, 2003). In that sense, Sampson et al (2002) report inconsistencies across studies in the operationalization of neighborhood processes and mechanisms (Sampson et al, 2002:457). Duncan and Raudenbush (2003), in their review of

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9 The reflection problem has implications in terms of the definition o neighborhood boundaries or, in other words, the "relevant" geography of reference.

10 In case of educational outcomes, there are endogenous effects if the child's score varies with the average score in the group of reference; contextual effects if scores vary with the characteristics of the group; and correlated effects if the children share the same classroom school or family.

11 Manski (2000) points out that there are disciplinary interests in the study of neighborhood effects. While sociologists care more about contextual effects, economists focus their studies in the elucidation of endogenous effects.

empirical literature, report four classes of neighborhood mechanisms: social ties/interaction; norms and collective efficacy; institutional resources; and routines activities (transportation mixed of residential with commercial use of the land, etc).

II.2.4. Omitted Variable Bias

Omitted variables bias (OVB) may be an issue if individual or contextual characteristics which are relevant to the analysis are neglected. If this case, the correlation between the residual and the omitted variables may lead to biased estimates of the neighborhoods effects (Sampson et al, 1999; Duncan, 2004). A branch of the literature stresses that OVB is particularly high in the case of using an administrative-approach to define neighborhood. Nonetheless, as some authors point out, the bias come in most empirical studies from the use of only one or two variables (tract poverty or welfare rates, for instance) to represent all of a neighborhood's relevant characteristics and processes (Duncan and Raudenbush, 2003: 5). Table 3 provides an example of the contextual and individual variables used in the catalog of studies reviewed by Ginther at al (2000).

Another type of omitted variable problem which may lead to bias in the estimates of neighborhood effects is the lack of empirical information on the multiple contexts. In the case of educational outcomes, most studies consider one context or the other (school or neighborhood) when evaluating contextual effects. The exclusion of school effects may result in an overestimation of neighborhood effects (Duncan and Raudenbush, 2001).

Table 3
Neighborhood and Individual Variables in a sample of studies

Neighborhood Variables	Individual Controls
Average Family Income	Parent's Education
Workers with Managerial Jobs	Family Income
Percent of Disadvantaged Students	Number of Siblings
Percent Families with Income larger than certain threshold (U$10,000/U$ 40,000)	Parental expectation
	Parental efficacy
Percent College Graduates	Urban/Rural Status
Male Unemployment Rate	Presence of mother and father
Percent Families in Welfare/Public Assistance	Marital Status
Percent of Adult dropouts	Age/Gender/Race
Percent of female-headed families	Religious Activism
Percent of poor individuals/Households	Income Quartile
Ethnic Diversity	Immigrant Status
Percent of Affluent Families	Birth-Weight
	Neonatal health region

Source: *Elaboration based on Ginther et al (2000), Table 1.*

In some cases, bias has a conceptual source as they restrict the contextual influence to only one community. In that sense, studies based on school contexts (mainly grounded on school-effectiveness type of approaches) assume that schools act as mediators of any neighborhood impact (Kauppinen 2008: 422). Although it might be true that parents may base school choice on neighborhood characteristics, schools are influenced by the neighborhood and district characteristics as well (Arum, 2000; Kirk 2009: 1023).

However, recently a growing group of studies have simultaneously examined the influence of schools, neighborhoods and children and youth's outcomes (Garner and Raudenbush, 1991; Cook et al., 2002; Elliott et al., 2006; Sameroff, Peck, and Eccles, 2004; Kirk, 2006; Kauppinen, 2008; Brannstrom, 2008; Kirk, 2009).

II.2.5. Misspecification bias: non linearity and heterogeneity

There are two sources of misspecification. The first one is brought by the existence of non-linearity. Some empirical research has found that tipping and/or threshold points for the influence of contextual factor exist. Tipping points may occur either along racial lines or socio-economic lines (Vigdor, 2006). For instance, Sampson et al (2008) utilize a threshold of 30% of poor population in the neighborhood. Card and Rohstein (2007) search for the existence of tipping points at the neighborhood level establishing their existence and differentiation across metropolitan areas.

A second source of misspecification is heterogeneity in contextual effects due to the differential influence of some variables depending on the group of the population the individual belongs to. In that sense, since the Coleman Report in 1996 literature has documented the non-homogenous influence of context in Black and males.

II.3. Modeling strategies

In terms of research design and modeling strategies many approaches have been taken with an increasing use of multilevel analysis in the last decade (Raudenbush and Sampson, 1999). . Empirical literature has widely used OLS to estimate the impact of context on children's outcomes (see Table 4). Nevertheless, the usage of OLS varies by discipline: educational psychologists rely more on Hierarchical Linear Models, sociologist on multilevel models and econometricians on random-coefficient models (Duncan et al, 1997:222).

The use of hierarchical linear modeling (HLM) has recently become common in studies of contextual effects due to the need to separate contextual from compositional effects (Duncan & Raudenbush 1999; Sampson et al 2002; Kauppinen, 2007; Pebley and Sastry, 2008; Kirk, 2009). HLM is suitable when the usual assumption of uncorrelated error terms in regression analysis, does not hold. In neighborhood effects studies this is the case, multiple observations in the data set share the same contexts. Thus, the statistical significance of the parameter estimates of the explanatory variables may be overestimated (Goldstein, 1995: 25). Multilevel analysis allows tackling this limitation and examining neighborhood or area effects after individual-level confounders have been controlled (Subramanian, 2004).

Table 4
Modeling Strategies used in Empirical Work

Specification	**N**
OLS	8
Logit/Probit/LPM	6
Reduced Form	4
Neighborhood Fixed Effects	1
Multivariate ANOVA	1
Number of Studies	**20**

Note: *Linear Probability Model*
Source: *Elaboration based on Ginther et al (2000), Table 1.*

II.4. Empirical finding on the impact of neighborhoods on Educational Outcomes

There are many reviews and thorough analyses in the empirical literature on neighborhoods effects, including Duncan and Raudenbush (2001), Leventhal and Brooks-Gunn (2000); Sampson et al. (2002), Pebley and Sastry (2003. The study of the effect of neighborhood characteristics on education includes a variety of educational outcomes such as education attainment (Garner and Raudenbush, 1991; Sastry and Pebley, 2008; Caughy and O'Campo,2006; Sampson et al, 2008), high school choice (Brannstrom, 2008; Kaupinnen, 2007 and 2008), high-school drop-out/graduation (Crane 1991; Ginther et al, 2000) and school suspension (Kirk, 2009).

To date, research has provided mixed evidence for the existence of 'pure' effects of neighbor/schoolmate characteristics on individual educational outcomes. Empirical findings are quite diverse depending on the outcome studied, the methodology employed and the context. While in many studies neighborhood characteristics appear as important determinants of outcomes, in several others they are statistically insignificant. Overall, positive neighborhood

characteristics (in particular, the presence of affluent families) are positively associated with youth attainments, while a number of adverse neighborhood characteristics are negatively related to success.

Most of the research conducted in the US context, concludes that neighborhood characteristics do have impact on child's outcomes (Duncan, 2003; Kawachi and Berkman, 2000; Craddock et al 2009; Pebley and Sastry, 2008; Sampson et al, 2008). For instance, a number of studies reported in Brooks-Gunn, Duncan, and Aber (1997) found that (a) the most consistent evidence of neighborhood occurs among school-age children; (b) neighborhood influences are higher for cognitive than for mental-health measures; (c) concentration of affluence (measured by high-SES) was the most important neighborhood factors; and (d) Whites are more sensitive than Blacks to neighborhood factors. Yet, the majority of these studies focused on the Black-White gap (Caughy and Ocampo, 2002; Card and Rothstein, 2007; Sastry and Pebley, 2008, Sampson et al, 2008).

European-based research, on the other hand, has identified some effect of neighborhood characteristics on student's scores as well, despite the lower neighborhood differentiation which characterizes the European settings -compared to the US's (Brannstorm, 2007; Kaupinnen, 2008; Garner and Raudebusch, 1993). Moreover, those findings have questioned the role of the school claiming that compositional effects at the school level may be either irrelevant or non existent. Nevertheless, the so-called "school effectiveness" literature has shown that school organizational features may have an impact; conclusions should be taken with caution as these types of studies only consider school-level variables (Kauppinen 2008:381).

Regarding the neighborhood attributes that matter the salient characteristic is the socioeconomic composition of the population. Ginther et al (2000) highlight that the most consistent relationships have been found in studies which utilize neighborhood characteristics linked to the child's outcome under study; for example, drop-out rate in the neighborhood and children's drop-out rate as outcome(Ginther et al, 2000: 607). Table 5 summarizes some studies on the links between neighborhood effects and educational outcomes.

Vigdor (2006) points out four general conclusions of research on neighborhood effects: a) neighborhood effects are modest; b) neighborhood effects are heterogeneous: they are stronger

among females, whites, and children of early school age[12]; c) difficulties to model the possible mechanisms linking neighbors and individual outcomes; d) absence of specific policy recommendations associated with research.

Table 5
Some Examples of Neighborhood Effects on School Outcomes

Neighborhood Variable	Individual Outcome	Study	Impact
Deprivation Score	Test Scores	Garner and Raudenbush (1993)	(-)
Affluence	IQ at age five/ Cognitive functioning HS School Drop-Out	Gephart (1997), Table 1.1. Gephart (1997), Table 1.1.	(+) (-)
Poverty	HS School Drop-Out College Attendance	Gephart (1997), Table 1.1. Gephart (1997), Table 1.1.	(+) (-)
Professional/Managerial Workers	HS School Drop-Out	Gephart (1997), Table 1.1.	(-)
Race./ Black Neighbors	HS School Drop-Out	Gephart (1997), Table 1.1.	(+)
Family-Income	Years of Schooling	Gephart (1997), Table 1.1.	(+)
High Income Low Income Unemployment Rate	HS Graduation Years of Schooling	Ginther et al (2000)*	(-)/(-) ** (+)/(+)** (-)/(-)**
Index of High Status Adults	Test Scores	Ainsworth (2002)	(+)
Index of Poverty and Joblessness	HS Drop-out	Crowder and South (2003)	(+)
Median Income	Index of Educational Achievement	Lopez Turley (2003)	(+) (stronger for Whites)
Median Family Income Immigrant Concentration Residential Stability	Test Scores	Sastry and Pebley(2006)	(+) (+) (-)
Social Assistance University Degrees Immigrants	Test Scores	Branstrom (2008)	(-) (+) (-)
Concentrated Disadvantage	Verbal Ability (African-American Sample)	Sampson et al (2008)	(-)
Poverty Migrants Residential Stability	School Suspension	Kirk (2009)	(+) (-) (+)

Note: ** Results are very sensitive to individual variables specification.*
*** Double Entries are for the two outcomes in the study in the order they are listed in the second column.*
Source: *Elaboration based on empirical research.*

III. Analytic Framework and Research Hypotheses

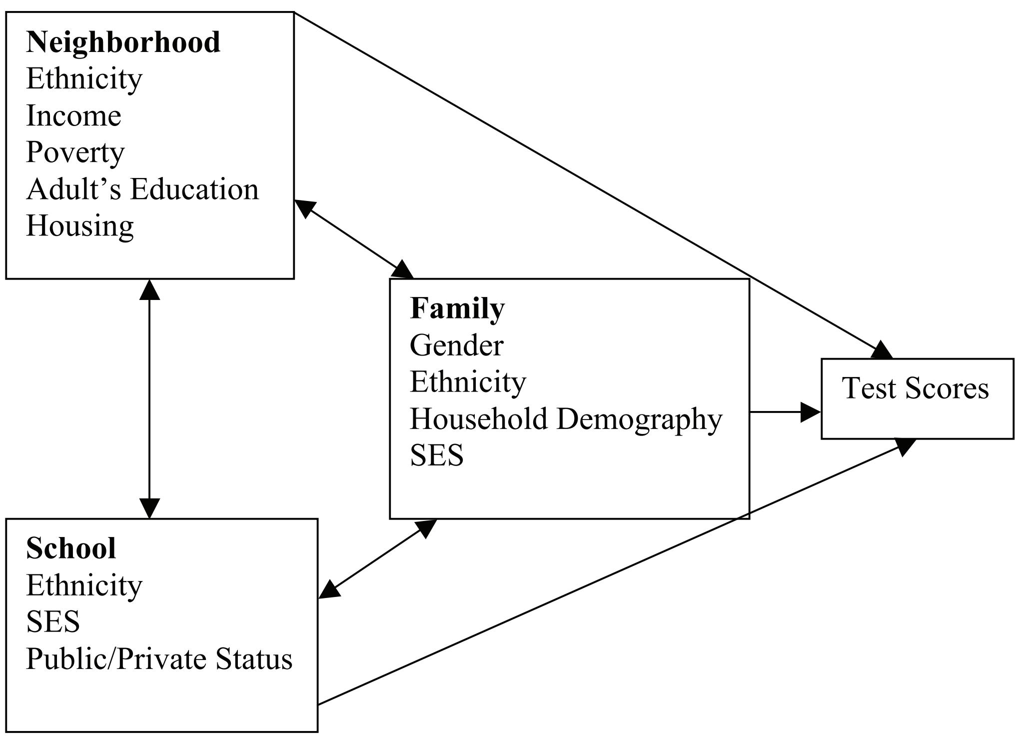
As a conceptual framework we use the social ecological model (Bronfenbrenner, 1979; Arum, 2000), which encompasses the interrelationships that exist between the individual and his environment. This conceptualization recognizes that, although learning outcomes are determined

[12] This problem might be related to the existence of non-linearity.

by teachers and school processes, learning may be shaped by the multiple contexts the child interacts with.

The framework, depicted in Figure 1, considers as exogenous the macro structures. Distinct social processes characterize schools, neighborhoods, and families, each of which may affect children's outcomes. At the neighborhood level structural socioeconomic characteristics such as ethnicity, poverty, adult's education and unemployment are included as attributes of the neighborhoods which vary across communities and may exert influence individual's outcomes. Family structures including household demographics are assumed to mediate the effects of neighborhood processes on children's outcomes. Nonetheless, socio-demographic measures do not provide information for exactly how and why given social environments change a given behavior (Cook et al., 2002; Sampson at al, 2002).

Figure 1
Conceptual Model



In this research, we consider that multiple theoretical perspectives may serve, in a complementary way, as guidance about the attributes of neighborhoods that may affect children's development and the mechanisms through which they occur. For instance, collective socialization and epidemic theories provides a framework for considering educated and relatively

affluent adults in the community serving as role models to internalize social norms and behaviors. The inclusion of poverty and deprivation measures along with ethnicity of the neighborhood may be grounded in social disorganization theory as well. Economic theories which support the impact of resources and incentives on families justify the inclusion of unemployment rate, percentage of adult's high-school completion and female-headed households in the neighborhood. On the other hand, household ownership may be framed within either the social capital or the collective efficacy theories. In the absence of more precise measures, ownership status may be associated with affluence and residential stability. Ownership status may also be linked to voice and involvement in local issues (Sampson et al, 1997)

We include educational level of the adult population to control for"reflection" and assume that that the family and individual characteristics included account for neighborhood selection. This paper assesses the following research questions and hypotheses:

Research Question #1. Are neighborhood characteristics correlated to a student's test scores in elementary school?

Hypothesis: Once individual background and school factors are controlled for, neighborhood socioeconomic composition is still associated with students' performance, accounting for at least ten percent of the total variance in student's achievement.

Research Question #2. Which neighborhood-level factors are the most strongly associated with a student's achievement?

Hypothesis: Higher levels of neighborhood poverty are negatively correlated with scores in math and reading. Concentration of white population in tract has a positive impact on student's achievement.

IV. Data Sources

The data for the analysis comes primarily from the Early Childhood Longitudinal Study administered by the US Department of Education. The ECLS-K began in the fall of 1998 with a nationally representative sample of approximately 21,000 kindergartners from about 1,000 kindergarten programs, both public and private. These children were followed longitudinally through the eighth grade, with data collections in the fall and spring of kindergarten and first grade, in the spring of third and fifth grade, and follow-ups in eighth grade.

The survey includes questionnaires from the child, the child's parents/guardians, teachers, school administrator and facilities inspectors. Measures of child cognitive and non-cognitive skills are included in every wave of the survey as part of the Self-Description Questionnaire in

the child direct assessment and the Social Rating Scale in the teacher assessment. Non-cognitive skills include child's competence and interest in academics as well as social skills. School administrators and teachers are asked about school/classroom facilities and characteristics.

As schools and kids in the ECLS-K have census tract identification codes it is possible to merge with environmental data corresponding to the 2000 Census extracted from RAND's CPHHD Data Core, which houses a large number of measures on Population and Housing Characteristics. Based on this link, we are able to include information related to a variety of socio-economic and demographic characteristics of Census's tracts.

IV.1. The Definition of Neighborhood

Empirical work has been based on two main criteria (Pebley and Sastry, 2003). The first one uses the spatial definition of neighborhood, spaces where residents' are exposed to "specific social and physical environments" and uses Census geographies) as approximation to meaningful areas. The second one demarcates neighborhood boundaries based on resident's sense of resident's attachment. In this paper, we use the administrative approach and define neighborhood as "the one corresponding to the census tract[13] where the house the child lives is located".

IV.2. Sample size and Exclusions

There is no exclusion to the sample except the attrition which occurs with the survey (about 36% between the base year and 5th grade). Wave 3 (fall 1st grade) will not be used as the collection was reduced to 30% of the original sample. However, due to the substantial number of school, neighborhood and individual variables involved some times, the intersection of non-missing values of all these variables reduces the sample size in the final model.

The summary in Table 6 is hiding, however, the fact that both distributions are heavily skewed to the left with many neighborhoods and schools having only one child or few as shown in Appendix 1, Tables A-1 and A-2. Figure A-1 depicts a distribution skewed to the left with a high concentration of cases with few schools per neighborhood, and few neighborhoods per school is a feature of all ECLS-K waves.

While the latter feature would not threaten the isolation of neighborhood and school effects from each other, the cases where only there is one child per either school or neighborhood

---

[13] Census tracts are small, statistical subdivisions of a. Census tracts have in average of about 4,000 inhabitants. There are 65,443 census tracts in the United States in 2001 (U.S. Bureau of Census).

raise an additional problem: it would be impossible to split individual from contextual effects. Another potential threat to identification may occur if the proportion of students for whom neighborhood and school are the same is high as it would impede to disentangle school from area effects., as reflected in the last row of Table 6, the proportion of kids who have same school and neighborhood remains no larger than a third of the remaining sample in all waves.

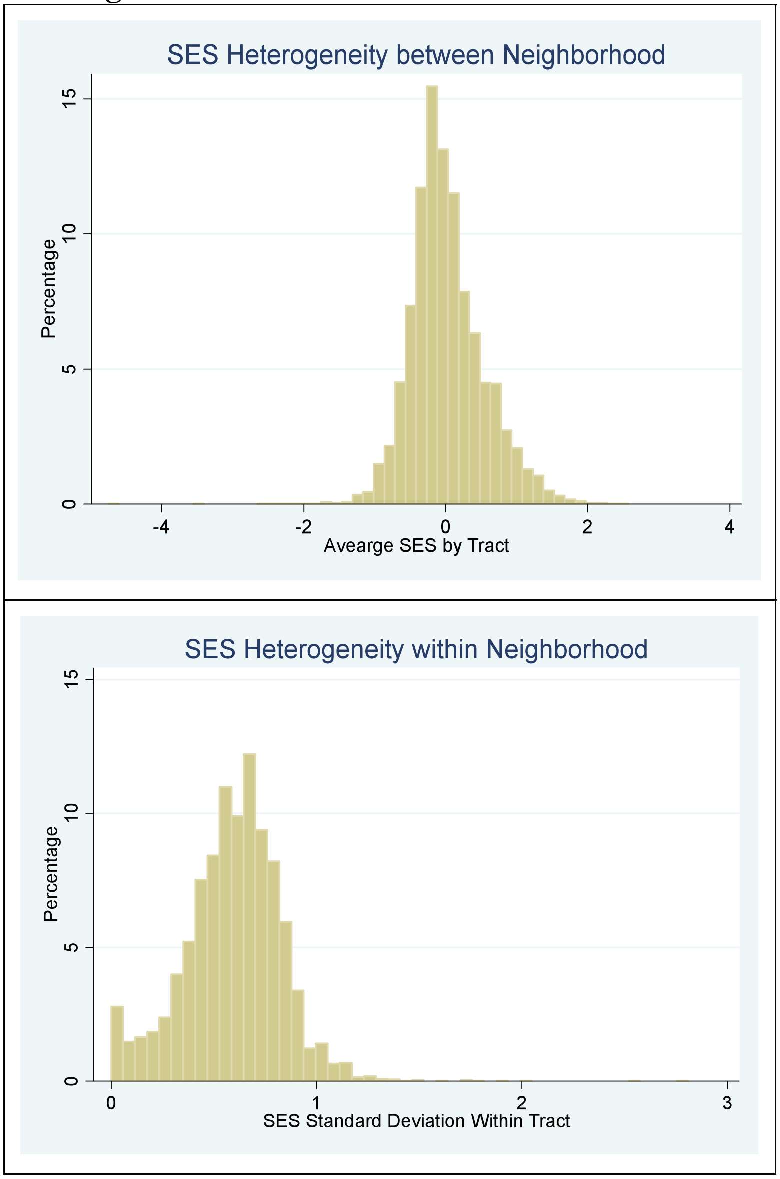
Table 6
Summary Statistics of Students, Schools and Neighborhoods

		Students per School					
Wave		**1**	**2**	**4**	**5**	**6**	**7**
Total Schools		**1018**	**1469**	**2006**	**2659**	**1271**	**989**
	Mean	**21**	**13**	**8**	**5**	**5**	**9**
	SD	5	10	8	6	5	10
	Min	1	1	1	1	1	1
	Max	27	27	39	34	26	183
	Total	**21260**	**20642**	**16976**	**14574**	**6321**	**9725**
		Students per Neighborhood					
Wave		**1**	**2**	**4**	**5**	**6**	**7**
Total Tracts		**3304**	**3393**	**3450**	**3355**	**1929**	**2848**
	Mean	**5**	**5**	**5**	**4**	**3**	**3**
	SD	10	10	8	7	5	6
	Min	1	1	1	1	1	1
	Max	142	135	114	94	57	88
	Total	**21260**	**20642**	**16976**	**14574**	**6321**	**9725**
Same School and Neighborhood							
Total		6825	6927	6117	4844	2519	426
Percentage over Total		0.32	0.34	0.36	0.33	0.40	0.21

Note: **Summary statistics per Neighborhood are for observations with non-missing track information.*
Source: *Elaboration based on ECLS-K.*

Homogeneity of families living within neighborhoods may represent as well an issue in terms of identification. Similarity among families, especially in the extreme cases, would make it difficult to tease out neighborhood from individual effects (Sastry et al, 2006). From the analysis of the standard deviation of Socioeconomic Status within neighborhood in Figure 2 we could inferred that, except for a few cases for which the SD is zero, variance in SES composition is large enough to allow identification.

Figure 2
Neighborhood SES between and Within Variance



Source: *Elaboration based on ECLS-K.*

IV.3. Outcome Measures

Standardized Item Response Theory scores in reading and mathematics in kindergarten, first, third and fifth grade are the outcome of interest. Separate estimation are carried out for reading and math scores based on empirical evidence which suggest that, although home environments have been linked to academic performance, family factors exert more influence on language and literacy learning than on mathematics achievement (Campbell, 1996; Argys et al,1996; Figlio and Page, 2000; Sampson et al, 2008).

IV.4. Explanatory Variables

A fairly large literature on the determinants of educational attainment suggest that parents' educational attainment, family income, race, family size, rural origin have effect on educational attainment. School and neighborhood variables have been found to have an effect on students' outcomes.

The control variables were chosen largely on the basis of both theoretical considerations and previous empirical work. We sort the variables into three groups: a) individual and Family Factors; b) school characteristics; and c) neighborhood characteristics.

Individual- and family-background variables as well as school variables included in this study are many of the usual variables found as significant on educational research and which are partially summarized in Ginther et al (2000). In the case of the neighborhood variables, we have selected seven variables to describe the conditions which could affect student's attainment. Economic variables have been found to be significant in many neighborhood studies (e.g.: Brooks-Gunn et al, 1993; Duncan, 1994; Ginther et al, 2000)[14]. The variables are split into two groups; the first contains the factors related to concentration of disadvantage while the second one encompasses the variables which may be associated with concentration of affluence. In the first group, deprivation, we included the percentage of population defined as poor and the percentage of unemployed males in the neighborhood as measures that reflect the local labor market opportunities. Among the affluence measure, we included the percentage of urban population, the percentage of owners, and the tract median income. Finally, following Manski (1993) and Ginther et al (2000), we include an educational variable of the adult population to tackle the potential biases "reflection" may create, the percentage of adult women with at least High School.

The selected background and explanatory variables described in Table 7 were re-coded when necessary. Categorical variables were converted to a set of dummy variables. Variables related to housing characteristics at the tract level (such as percentage of houses with plumbing) were not taking into account as long as there is not enough variance either within or between tracts. Demographic and the descriptive statistics for all variables listed in Table 7 are

[14] We explore a couple of variables to account for the extent of racial diversity, percentage of Hispanic and White population in tract but the Likelihood Ratio Test rejected their inclusion.

summarized in Table A-4 the Appendix. The correlations between explanatory variables and outcomes are reported in Table A-5; in all cases correlations are significant for a p-value < 0.01. Correlations between contextual variables are described in Table A-6 in the Appendix. Only six of the 36 correlation coefficient between the contextual variables are around 0.70, which rules out co-linearity concerns.

Table 7
Explanatory Variables

Individual and Family Factors	Definition
Gender	1 if Male; 0 otherwise
Race	Dummy for Each Race
SES Quintile	Categorical; 5 dummies
Number of Siblings	Continuous, centered at the Grand Mean
School Factors	
Public/Private School Status	1 if Public; 0 otherwise
Title 1	1 if Public; 0 otherwise
Percentage of Hispanic Students	Categorical; 5 dummies
Neighborhood Factors	
Deprivation	
Poverty Percentage	Categorical; 5 dummies
Percentage of Adult Unemployed	Standardized
Affluence	
Percentage of Urban Population	Categorical; 5 dummies
Percentage of Females with High School	Standardized
Percentage of Owners	Categorical; 5 dummies
Tract Median Income	Standardized

Note: *See Table A-2 in the Appendix for details on the categorization of the dummy variables.*
Source: *Elaboration based on ECLS-K.*

We do not include other factors which may affect students' outcomes such as family involvement (parent's expectations, parent's interests, school events' attendance and homework supervision). Previous work has proven that students may benefit in multiple domains from family involvement, including improvements in academic self-confidence, attendance, homework completion, school behavior, academic performance and high school completion rates (Henderson and Mapp, 2002; Fan & Chen, 2001). Although we acknowledge the relevance of these factors, which could be equally or more important than the ones included in our estimates, we assumed that they are all captured in the child's random effect.

V. Methods

From the empirical point of view, the setup is straightforward: factors explaining students' outcomes can be approximated through the estimation of a simple education production function (Hanushek, 1979). The only relative novelty is the extension of the "classical" education production function to consider achievement of individual students being dependent

not only on schools resources but also by factors associated to the geographical areas where students live and the schools they are enrolled. In Equation (1), the outcome formulation considers test scores in the grade n^th^ (Y_i) as a function of a set inputs that include individual, family, school and neighborhood characteristics. The model is formulated as follows:

$$Y_i = f\,(Individual/\,Family\,Factors, School\,Factors, Neighborhood\,Factors) \quad (1)$$

Our interest is to decompose the total variance in student's outcomes into: a between-student, within school and within neighborhood components; and a between-school and between-neighborhood components. We want to answer questions such as: how much variation in student outcomes is due to individual characteristics and family background; how much occurs within and among school/neighborhoods?; to what extent is the relationship among group factors and student's outcome moderated by a between group factor?

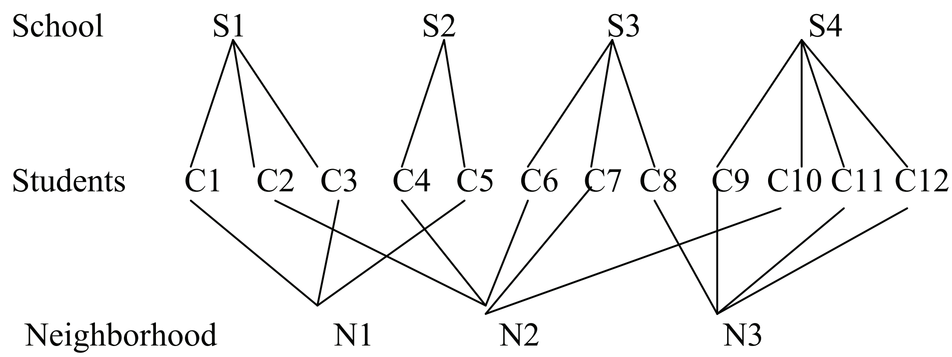
This is a typical crossed-classification structure where influences for the child (first level) at the second level come from both, school and neighborhood. To address the Level 2 influences we will use a Hierarchical Linear Model (HLM). Figure 2 depicts the nesting structure that is operating. Children (Level 1) are nested within the neighborhood areas they live in and the schools they attend.

A HLM has some advantages over linear regression model. Linear regression models treat the student as the unit of analysis ignoring the nesting within schools/geographical areas. Students attending the same school share many common factors, mostly related to the educational process and, consequently, there is correlation in the residuals. Ignoring such correlations would invalidate conclusions as long there is a violation of one of the basic assumption linear regression models: the independence between student outcomes.

At the lower level (Level 1) there is a regression equation for each school/neighborhood relating student's outcomes to student characteristics. The relationship between test scores and students' characteristics can differ from one school/neighborhood to another. At the higher level (level 2), each school'/neighborhood's set of regression coefficients is predicted by a set of school/neighborhood factors. Level 1 outcome tells how much of the variation in test scores between students within schools and within neighborhoods (i.e., the first component) can be accounted for by differences in student characteristics. Level 2 results tells how much of the

variation in school means (i.e., the second component), can be accounted for by differences in school and/or neighborhood characteristics.

Figure 3
Cross Classified Structure



To make the specification more concrete, we start by considering the following model for student *i* in school *s* and neighborhood *n*:

V.1. Level 1 – Model

$$Y_{i(s,n)} = \beta_{(s,n)} + \beta_{1(s,n)} X_{i(s,n)} + \varepsilon_{0i(s,n)} \qquad (2)$$

V.2. Level 2 – Empty Model

$$\beta_{0(s,n)} = \beta_0 + \mu_{0s} + \mu_{0n} \qquad (3.1)$$

Equation (3.1) stresses that a school's and neighborhood's intercepts varies around an overall average. μ_{0s} *and* μ_{0n} are the divergences coming from school s and neighborhood n from their average, β_0. The individual, school and neighborhood random effects ($\varepsilon_{it(s,n)}$, μ_{0s} *and* μ_{0n}) are assumed to be normally distributed independent of one another and independent of any of the covariates included in the model with mean of zero and standard deviation . The models presented in (2) and (3.1), empty from contextual variables, will allows us to examine how variation in outcomes is attributable to differences between schools, between neighborhoods areas and between students after controlling for neighborhood and school random effects.

V.3. Level 2 – Random Intercept Model

We seek as well to estimate the contribution of explanatory variables at the neighborhood and school level in individual test score's variance. Thus, we will extend the previous model by including Z_{school} and Z_{nbhood} which encompass the contextual factors associated to school and neighborhood, respectively, in the Level-2 equation:

$$Y_{i(s,n)} = \beta_{0s,n)} + \beta_{1(s,n)} X_{i(s,n)} + \varepsilon_{0i(s,n)} \quad (2)$$

$$\beta_{0(s,n)} = \beta_0 + \mu_{0s} + \mu_{0n} + \beta_{01} Z_{school} + \beta_{02} Z_{nbhood} \quad (3.2)$$

In Equation (3.2) two sets of contextual explanatory variables were added , where M and N are the numbers of units at level 2; M schools and N neighborhoods. In the model above only the intercept is allowed to be random; all other regression coefficients are fixed. After introducing contextual variables we will approximate the residual components of variance. These will give us an idea of the extent to which variation in outcomes might be attributable to unobserved influences operating at the level of each of the three types of unit in the model[6]. This model is the base used later to investigate the random structure of the slopes, and identify which neighborhood; school and student attributes might explain some part of the components of variance.

V.4. Level 2 – Random Coefficient Model

We want to explore whether associations between student characteristics vary over schools and over neighborhoods. We also will consider whether some factors might have a differential effect, as well. The effect of students going to a public school, for example, might be greater for students from some neighborhoods than from others. It might be also the case that social background of the students is not the same in all schools or geographical areas.

Equation (3.4) allows for the both intercepts and slopes to vary between groups:

$$Y_{i(s,n)} = \beta_{0s,n)} + \beta_{1(s,n)} X_{i(s,n)} + \varepsilon_{0i(s,n)} \quad (2)$$

$$\beta_{0(s,n)} = \beta_0 + \mu_{0s} + \mu_{0n} + \beta_{01} Z_{school} + \beta_{02} Z_{nbhood} \quad (3.3)$$

$$\beta_{1(s,n)} = \gamma_{10} + \mu_{1s} + \mu_{1n} \quad (3.4)$$

The random coefficient specification presented above adds, in terms of number of parameters, not only two random effects but also two covariance terms between the intercept and the slope of the random components.

V.5. Adding the time dimension: Longitudinal Specification

If we include the time dimension, by considering the repeated measures on student's outcome –from kindergarten for 8th grade- the model intercept model presented above turns to be a three level model, t for time, if for individual and (s,n) for school and neighborhood:

$$Y_{ti(s,n)} = \beta_{0i(s,n)} + \beta_{1i\,(s,n)} X_{ti(s,n)} + \varepsilon_{ti(s,n)} \qquad (2.1)$$

$$\beta_{0i(s,n)} = \beta_{00(s,n)} + \beta_{0\,i(s,n)} X_{i(s,n)} + \mu_{child} \qquad (3.2.1)$$

$$\beta_{00(s,n)} = \gamma + \beta_{01} Z_{school} + \beta_{02} Z_{nbhood} + \mu_{0s} + \mu_{0n} \qquad (4)$$

Where $X_{ti(s,n)}$ and $X_{i(s,n)}$ are individual-level time related and time invariant covariates; Z_{school} and Z_{nbhood} are school- and neighborhood-level covariates. Level 1 (Equation 2.1) estimates the relationship between student achievement and child's time-varying covariates. $\beta_{1i\,(s,n)}$ are assumed to be fixed across all students but the intercept is allowed to vary across students with a random component μ_{child} in Level 2. Equation 3.2.1 models the intercept of Level 1 - $\beta_{0i(s,n)}$ - as a function of child-level time invariant child covariates. $\beta_{0\,i(s,n)}$ are assumed to be fixed across schools but the intercept $\beta_{00(s,n)}$ varies across schools and neighborhoods with two random terms, μ_{0s} *and* μ_{0n} . Equation (4) estimates the intercept as a function of school and neighborhood characteristics.

V.6. Intra-Class Correlation Coefficients

The degree of clustering in children's test scores provides an extremely useful measure of the importance of unmeasured factors operating at each particular data level. The intra-class correlation coefficient (ICC) reflects the level of clustering. The ICC is a measure of the percentage of the total variance in the outcome accounted by all unmeasured factors operating at a each of the two cross-classified levels (neighborhood, school, and individual).

The total variance in the model is the sum of the variance at each level as follows:

Var(Y_i) = Var(μ_{school}) +Var($\mu_{neighborhood}$)+Var($\varepsilon_{i(s,n)}$),

Where Var(μ_{school})=$\sigma^2_{\mu S}$, Var($\mu_{neighborhood}$)=,$\sigma^2_{\mu N}$ and Var($\varepsilon_{i(s,n)}$)= σ^2_{ε}

The most basic multilevel model, the "empty model", is one that includes no covariates, other than a constant which returns the overall sample mean. The empty model provides information about the overall degree of clustering in the outcome at each level being as well an indication of the magnitude of unmeasured factors at each level. The ICC, thus, reflects *all observable and unobservable factors*.

We can define three ICCs:

- one for the correlations of students for the same school across neighborhoods:

$$\rho = \frac{\sigma^2_{\mu S}}{\sigma^2_{\mu S} + \sigma^2_{\mu N} + \sigma^2_{\varepsilon}}$$

- one for the correlations of students in the same neighborhood across schools:

$$\rho = \frac{\sigma^2_{\mu N}}{\sigma^2_{\mu S} + \sigma^2_{\mu N} + \sigma^2_{\varepsilon}}$$

- and one corresponding to the kids who go to the same school and live in the same neighborhood:

$$\rho = \frac{\sigma^2_{\mu S} + \sigma^2_{\mu N}}{\sigma^2_{\mu S} + \sigma^2_{\mu N} + \sigma^2_{\varepsilon}}$$

The results yielded by the former specification could not be interpreted to entail causal associations. Ideally, to ascertain the difference between the two types of schools, an experiment would be conducted in which students are assigned (by an appropriate random mechanism) to schools and neighborhoods. With a sufficiently large sample, such a procedure would guarantee that, on average, there are no initial differences between students living in different areas and attending different schools, and would facilitate a fair comparison. Nevertheless, results presented might suggest ways in which interventions might be designed and, eventually, helped to assess alternatives.

V.7. Specification Tests

One assumption of the model presented above is that the random errors in the level 1 and level 2 equations are independently and normally distributed across individuals/schools/neighborhoods with a mean zero and a constant variance of $\sigma^2_{\mu S}$, $\sigma^2_{\mu N}$ and σ^2_{ε}, respectively. Homoskedasticity, or the assumption that the distribution of the random terms is unconditional of particular values of the Xs and the Zs, needs to be checked, as well. Unrecognized level-one heteroskedasticity may lead to high variance at level 2 (Sneijders and Berkhof, 2008).

Alternative models, empty and explanatory in the different version will be tested using the likelihood ratio test and information criteria, or the Akaike (AIC) and Bayesian (BIC) information criteria to compare models.

V.8. Location of the Xs

All individual background variables which are continuous are centered on the grand mean[15]. In this case interpretation changes and the results are to be interpreted as the achievement score in math/reading for a student who has the sample mean for all continuous variables included in the model.

V.9. Treatment of Missing Data

Missing observations could be a big problem in research design as they may raise two problems: loss of power and, potentially, bias. Given the size of the sample, bias and power is not a source of concern. There are two types of missing data in our sample. The first category is composed of individuals who have missing information for the outcome but contain information on the explanatory variables. The second, the majority of the missing cases, are observations which have missing information for specific explanatory variables. To check on potential sources of bias due to missing data we carried out a t-test of the two subsamples. The problem is serious when the missing data is on the dependent variable as it is more difficult to impute values.

[15] The grand mean is the mean of the means across subsamples.

The proportion of missing values for outcome and selected explanatory variables in Table 8 shows that Wave 1 of the ECLS-K might raise problems in terms of loss of information[16]. The percentage of missing data is not a problem in itself especially when the sample size is large enough to guarantee power. The trouble of bias arises when data is not missing at random (MAR)[17].

Table 8
Resulting Samples with Missing Values

	1	2	4	5	6	7
Total	21260	21259	17565	12706	10168	9745
Math	12114	12792	8456	7290	5606	4129
Reading	11736	12401	8319	7263	5602	4108

Source: *Elaboration based on ECLS-K.*

To check on potential sources of bias due to missing data we carried out two tests. In the first case, we split the sample in two groups: the one formed by the individuals who have missing the outcome variable and the one formed by the individuals who have the scores. An independent-samples t-test was conducted to compare the mean of the two groups to check differences in the explanatory variable listed in Section IV.4. In all cases – Table 9 - it was found a significant difference in the composition of the two populations for a p-value of 0.05. These results suggest that bias may occur as the observations with missing scores have an overrepresentation of lower SES and minorities (Black, Hispanics, etc) subgroups. However, and despite the former results, we did not impute values for the missing information on the outcomes variable.

In a second test reflected in Table 10, we assessed differences but with different categorization. We compare the bias that might be brought by list-wise deletion of those observations which have missing information for each explanatory variable. Thus, I apply this procedure for each explanatory variable separately we split population into two groups: the first the individuals who have not missing for the observable and the group of individuals who have missing data for the observable. Again, an independent-samples t-test was conducted to compare the means of the two groups. In all cases, the mean of the two groups in terms of both outcome measures were different for a p-value of 0.001. Specifically, results suggest that with the list wise

[16] Table A-7 in Appendix 1 reports the number of missing and the remaining sample for each of the explanatory and dependent variables.

[17] In other words the problem arises when the probability that an observation x_i is missing is related to the value of x or to the value of any other variable

deletion option, we will lose observations which have lower mean in math and reading scores than the remaining observations in the sample. This is a potential source of bias to be aware off.

Table 9
T-test of Missing Values for Outcome Variables

	P value of the Difference <0.05	
	Significant	
	Math	Reading
Individual		
Male	X	X
White	X	X
Hispanic		X
Asian	X	X
SES	X	X
Number of Siblings	X	X
School		
Public School	X	X
Title 1	X	X
Percentage of Hispanic	X	X
Neighborhood		
Poverty	X	X
Unemployed Males	X	X
Urban	X	X
Percentage of Owners	X	X
Median Income	X	X
Female With HS	X	X

Source: *Elaboration based on ECLS-K.*

There is another type of missing which forces the deletion of some individuals even in case they have no missing data for either the outcomes or the explanatory variables. This is the case of missing information for the home neighborhood. When tract ID is missing for either school or neighborhoods the whole observation at the individual level should be deleted as there is no way to assign the ID.

This study's estimates utilize the list-wise deletion, which means we drop the observations with missing information for either the outcome variable or the explanatory variables. The simplest alternative to our approach is the use of a missing dummy indicator; method may lead to biased estimates of coefficients and under-estimation of the standard errors (Cohen and Cohen, 1985; Jones, 1996), but is less deemed to bias results if the missing observations are fewer than 5% of the sample. Since the number of missing observations is above that threshold, the "missing dummy" methodology is used as part of a robustness analysis

of the final model[18]. Missing values at Level 2 represent an additional problem. If a level-two units has missing data then the whole unit is not included in the analysis, whether it is the school or the neighborhood[19]. Even with the deleted level-two units, there were enough remaining units to fulfill the "optimal size of between 30 and 62 units" suggested by Sneijders and Boskher (2003).

Table 10
T Test of Missing Value for Explanatory Variables

Explanatory Variable	P value of the Difference <0.05	
	Significant	**Not Significant**
Male		
Math		X
Reading		X
Race		
Math		X
Reading		X
SES		
Math	X	
Reading	X	
Number of Siblings		
Math	X	
Reading	X	
Public School		
Math	X	
Reading	X	
Title 1		
Math	X	
Reading	X	
Perc. Hispanic		
Math	X	
Reading	X	
Poverty Perc		
Math	X	
Reading	X	
Median Income		
Math	X	
Reading	X	
Female HS		
Math	X	
Reading	X	

Source: *Elaboration based on ECLS-K.*

18 We follow the standard procedure As a first step of the imputation, a so-called "missing dummy" variable was created for all variables with missing values regardless of whether a variable was continuous, categorical or dichotomous. A missing dummy variable was set to 1 if the data were missing on that variable and it was set to 0 if the data were not missing. As a second step, we impute a value of 0 for the observation in the original sample that have missing.

19 This implies that all the individuals who belong to these groups will not be included in the estimation.

V.10. Weights

In this research we choose not to use sample weights as we follow a structural approach. For a discussion of whether and how to incorporate weights when fitting an HLM to survey data see Rabe-Hesketh and Skondrall (1996) and Pfefferman et al, 2006.

V.11. Software and Maximization Algorithm

Estimation of the Cross Classified Hierarchical Linear Models were conducted in STATA 10 using the xtmixed package (StataCorp. 2007. Stata Statistical Software: Release 10. College Station, TX: StataCorp LP). Given the limitations of the default, restricted maximum likelihood which requires same fixed effects to compare alternatives model we fitted models using maximum likelihood via the Newton–Raphson algorithm.

VI. Results

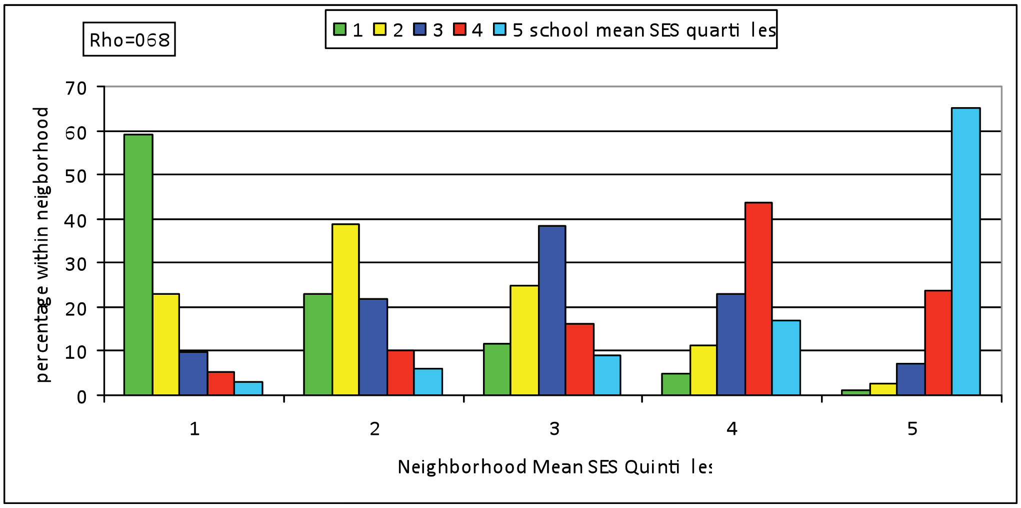
There is a considerable variation between neighborhood-level and school-level social composition. Figure 4 depict how students from different levels of neighborhood SES are allocated to schools of different levels of SES, both measured as student' average parental SES[20]. Even though the correlation between mean family SES at the neighborhood and school level is high and statistically significant (0.68) is not one. More than half of the students living in a very low mean family SES at the neighborhood level (first quintile) also attend a school with a very low mean family SES; less than a fifth of the group attend schools with an above average mean family SES (quintiles 3 and up). Meanwhile, students from the middle quintiles of neighborhood SES are more equally distributed across various degrees of the school level SES. At the highest level of the social scale, almost 90% of the students of the two highest quintiles of the neighborhood-level SES attend high school-level SES.

Social segregation of students seems to be higher on the school level than on the neighborhood level. Figure 5 shows that children from a lowest quintile of SES background are overrepresented into schools with a low mean parental SES than the children who reside in neighborhoods with lower mean parental SES. Very few low SES children manage to get into high SES schools or live in high SES neighborhoods. The strong association between school SES and individual SES (Rho=0.63 and 0.58, respectively) suggests that both school and

[20] In this case we averaged out the family SES of students according to ECLS-K metrics to keep comparability at the individual, school and tract level. The alternative, use ECLS-K for individual and school level and Census for tract level might have introduced some bias to the analysis.

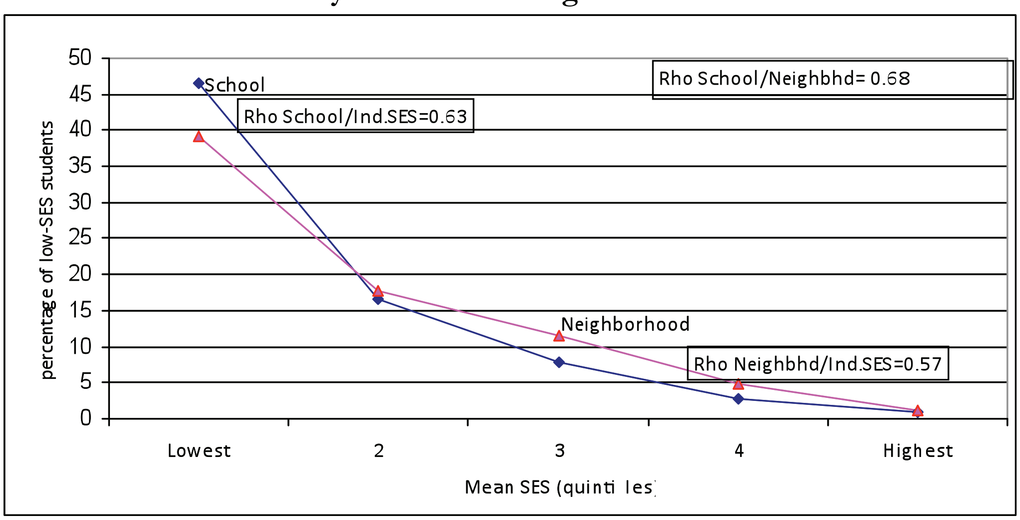
neighborhood may reinforce home disparities in SES. Although is difficult to confirm sustain that this were the case, as long as low SES kids do better in low SES schools than they would in high SES schools, results point to the need for further investigation.

Figure 4
Neighborhood and School Segregation
Children's distribution by School and Neighborhood SES



Note: *The correlation coefficient is significant for a p-value < 0.01.*
Source: *Elaboration based on ECLS-K.*

Figure 5
Concentration of children of the lowest quintiles of SES by School and Neighborhood



Note: *Correlations coefficients are significant for a p-value < 0.01.*
Source: *Elaboration based on ECLS-K.*

Empirical evidence suggests that the concentration of social disadvantage within particular schools contributes to lower school performance which translates into barriers to school improvement. In this scenario, the classic policy recommendation of improving school's

physical and monetary resources does not work[21]. Once the reputation of failing school has been established, it is quite difficult –if not impossible- to change parent's perception of school quality no matter the quality of their educational offerings.

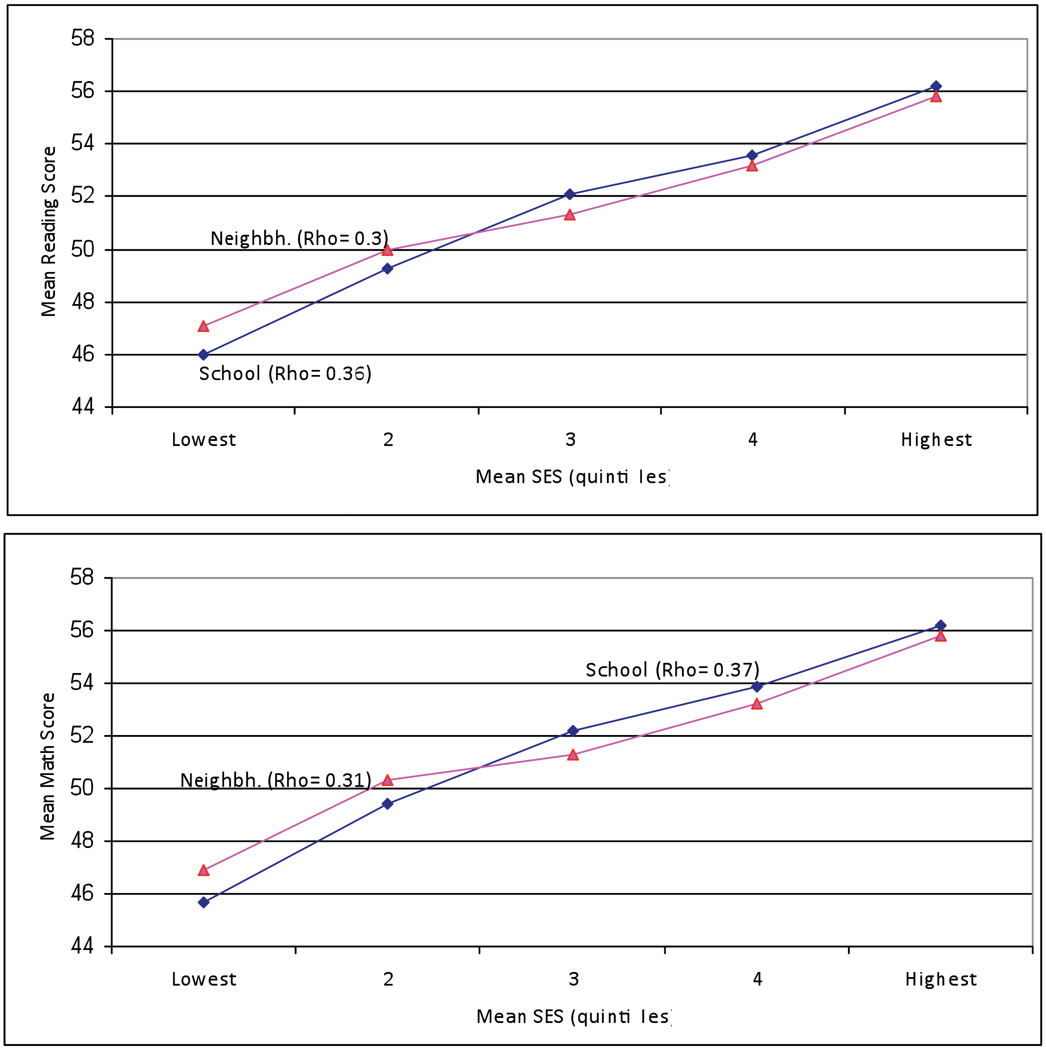
As "low achieving schools" tend to be located in neighborhood with a high proportion of minorities (Black, Hispanic and/or immigrants) and White population tends to avoid these neighborhoods and schools. This pattern has been documented in various countries; in Germany people from German heritage avoids schools dominated by non-German background (especially Turkish) children; the U.S. middle-class parents maximize educational advantage for their children by avoiding non-middle-class and non- White children (Andre-Bechely, 2007; Holme, 2002). Some branch of literature argues that parents move to the 'catchment areas' of good schools or "close neighbors" (Crane, 1991, Croft, 2004; Goux and Maurin, 2006)[22]. Cascio et al (2009) and Boustan (2009) explore the willingness to pay to avoid some areas in the presence of school desegregation policies. Their results suggest that parents's response to the enactment of school integration policies was moving out while districts "required" U$ 320 per pupil per year "voluntary" engage in desegregation (Boustan, 2009:3).

Our interest is to ascertain whether this higher segregation between affluence and poverty, between low and high social status in schools and neighborhoods translates into contexts which may be harmful for children. Figure 6 approximates a first answer. Despite the high correlation between mean parental SES at the school and neighborhood levels (Rho= 0.68), Mathematics and Reading achievement are strongly associated to student SES with a higher correlation on the school level (0.37 and 0.36) than on the neighborhood level (0.30 and 0.31). However, SES is not the only factor which is associated to student's outcomes. We attempt alternative answers to the question in the following section by including more controls and using a cross-classified multilevel model.

[21] Houses overprice may be a byproduct of the reputation (Crane, 1991:1246).

[22] Moreover, Boustan (2009) suggests that "the median southern voter was three times as resistant that the Northern marginal voter" (Boustan, 2009:3).

Figure 6
School and Neighborhoods Association between Family SES and Student's Achievement



Note: *Correlations coefficients are significant for a p-value < 0.01.*
Source: *Elaboration based on ECLS-K.*

VI.1. Do neighborhoods have effects?

In order to answer our research questions we estimate various specifications for a 2-level cross-classified HLM and carry out separate estimation for selected population subgroups. Table 11 reflects the strategy: we start with the empty model for school, neighborhood and cross classification in order to assess the relevance of each level in total student's outcomes **when no covariates are included**. After testing the goodness-of-fit of the three empty models using the likelihood ratio test, we decided to pursue the Level-two cross classified specification. Thus, as a second step we investigate the impact of introducing additional individual and contextual variables one at a time. We also explored the possibility of differential effects of neighborhood in

some subgroups of the population and, thus, allow the slope to vary across neighborhoods (random coefficient models). The alternative specifications are summarized in Table 11; basic statistics and LR tests results are reported in Table A-8 in the Appendix.

Table 11
Alternative Specifications

	Explanatory Variables Included			
	Family	**School**	**Neighborhood**	**Slope**
Empty				
School				
Neighborhood				
Cross Classification				
Random Intercept				
Family (F)	X			
School (S)	X	X		
Neighborhood (N)	X	X	X	
Random Coefficient				
SES	X	X	X	X
Hispanic	X	X	X	X
Black	X	X	X	X

Source: *Elaboration based on ECLS-K.*

As Table 12 (and Table A-11 and A-12 in Appendix 1) shows, the neighborhood-level variance before controlling for the individual-level variables (empty model) was statistically significant in all models, accounting for around 5%-20% of the variance in the outcome, depending on the model and on the outcome (math or reading).

Table 12
Neighborhood-level variance and ICC before and after adding explanatory variables

	Empty Model			Random Intercept		
	School (1)	**Neighbh. (2)**	**Crossed (3)**	**F* (4)**	**S** (5)**	**N*** (6)**
A) Mathematics						
ICC						
Child	0.574	0.612	0.586	0.641	0.647	0.653
School	0.247	-	0.157	0.078	0.071	0.068
Neighborhood	-	0.210	0.081	0.047	0.046	0.041
School + Neighborhood	0.247	0.210	0.238	0.125	0.117	0.109
B) Reading						
ICC						
Child	0.537	0.585	0.523	0.578	0.586	0.593
School	0.249	-	0.181	0.100	0.089	0.083
Neighborhood	-	0.204	0.075	0.045	0.044	0.040
School + Neighborhood	0.249	0.204	0.257	0.145	0.133	0.123

Note;*: *Includes Only Family Factors; **: Includes family and school factors; ***: Includes all covariates; All Random Effects are significant for a p-value < 0.01.*
Source: *Elaboration based on ECLS-K.*

Therefore, it is justifiable to consider family background variables and examine their impact on the between neighborhood variance. Individual factors explain as much as 50% of the neighborhood-level variance. The percentage of variance explained remains almost unchanged after introducing level-two variables related to school and neighborhood. Overall, context once everything is controlled for explains around 10 - 12% of student's outcomes. The differences in variance explained for reading and math scores are small enough to keep the analysis for only one of the subareas of testing for the rest of the paper.

Table 13 illustrates the effects of the family-background variables on mathematics and reading scores[23]. All the variables included are significant and have a large impact in explaining academic achievement. The effects of SES and race are strong, especially the latter. Student's test scores rise steeply as the family moves up in the SES quintile scale. Given that the dependent variable is standardized, the interpretation is straightforward: a child whose family is in the fifth quintile of the SES has almost eight standard deviations more that the child whose family belongs to the first quintile of SES, the omitted category. The race categories are statistically significant and with the expected signs; Black and Hispanic children have 3.5 and 2.4 SD lower than White children (the base category) with a lower effect for reading than for math. Asian children, like in most empirical research, exhibit higher achievement than their White peers (1 SD). Family size, represented by the number of sibling has a negative and significant impact on test scores.

In summary, we find that family background variables have a strong influence in educational achievement but, per Table 12 we know that they only explain half of the between-neighborhoods variance. The analysis including contextual variables follows below.

[23] Tables A-9 and A-10 in Appendix 1 report full results of each model for both math and reading.

Table 13
The effect of family-background on test scores
Random Intercept Model - All Covariates

Variable	Mathematics	Reading
Individual Factors		
Male	0.82***	-1.56***
	(8.94)	(-17.0)
Ethnicity (Base Category = White)		
Black	-3.73***	-2.20***
	(-19.8)	(-11.7)
Hispanic	-2.44***	-1.60***
	(-14.6)	(-9.54)
Asian	0.83***	1.30***
	(3.62)	(5.66)
Other	-1.50***	-0.58**
	(-6.07)	(-2.35)
SES (Base Category= Quintile 1)		
Quintile 2	2.29***	2.43***
	(14.4)	(15.0)
Quintile 3	4.10***	4.04***
	(24.7)	(24.0)
Quintile 4	5.51***	5.63***
	(32.3)	(32.6)
Quintile 5	7.68***	7.86***
	(42.1)	(42.7)
Number of Siblings	-0.21***	-0.64***
	(-5.34)	(-15.7)

***Note**: z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1*
***Source:** Elaboration based on ECLS-K.*

VI. 2. Which school and neighborhood-level factors have effects?

The incorporation of neighborhood factors does not reduce the between neighborhood variance as Table 12, columns (5) and (6) described. Table 14, shows that the socio-economic structure of the neighborhood affects both, math and reading scores. Nevertheless, the impact occurs when poverty concentration is above 30%, in which case the scores lowers in 1.5 SD with respect to the children living in neighborhoods with less than 20% of poor population, the base category. Unemployment has the expected sign but is not significant except for reading scores: one SD in male unemployment percentage decreases reading tests scores in around 0.8 SD.

Among the variables considered for representing affluence, urban concentration has a diverse impact on student's test scores: while in mathematics the impact is positive it reverts for reading scores. The percentage of owners is not statistically significant. On the other hand, the proportions of highly educated women and median income have positive impact of around half SD on test scores. The relevance of adult education is consistent with previous findings which

have highlighted that a good neighborhood environment has benefits for the children who grow in it (Ginther et al, 2000).

Table 14
The effect of neighborhood factors on test scores
Random Intercept Model - All Covariates

	Mathematics	Reading
Neighborhood Factors		
Deprivation		
Percentage of Poor Population (Base Category less than 10%)		
Between 10 and 20 %	-0.30	-1.39***
	(-1.56)	(-7.56)
Between 20 and 30 %	-0.36	-0.80***
	(-1.19)	(-5.48)
Between 30 and 50 %	-1.76***	-0.017
	(-4.31)	(-0.20)
More than 50%	0.35	-1.39***
	(0.41)	(-7.56)
Percentage of Male Unemployed	0.026	-0.80***
	(0.72)	(-5.48)
Affluence		
Urban Percentage (Base Category = Less than 20%)		
Between 20 and 40 %	0.35	-0.37*
	(0.78)	(-1.91)
Between 40 and 60 %	0.48	-0.34
	(1.43)	(-1.10)
Between 20 and 80 %	0.73**	-1.67***
	(2.25)	(-4.00)
More than 80%	0.69***	-0.57
	(3.05)	(-0.64)
Percentage of Owners (Base Category = More than 80%)		
Between 20 and 40 %	-0.28	-0.14
	(-0.65)	(-0.31)
Between 40 and 60 %	-0.35	-0.14
	(-1.14)	(-0.45)
Between 20 and 80 %	-0.23	-0.45**
	(-1.03)	(-2.05)
More than 80%	-0.35**	-0.36**
	(-2.22)	(-2.27)
Percentage of females with high school	0.33***	0.54***
	(2.90)	(4.54)
Median Income	0.43***	0.25**
	(4.21)	(2.43)

Note*: z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1*
Source: *Elaboration based on ECLS-K.*

It is often argued that children are not only influenced by the behavior and status of those with whom the children socialize (particularly those whom the children are likely to accept as role models) but by neighborhood's social capital quality (educational). The results presented suggest that the presence of deprivation is more important than the concentration of affluence,

though the effect is non linear and increases after a certain level of concentration of poor population

Lastly, although the size of the coefficient for the individual and family background decreases when contextual variables (school and neighborhood) are introduced, the reduction is small and they still remain statistically significant.

VI. 3. Interactions between individual-background variables and neighborhood

In addition to the assessment of the main effect of neighborhood-level variables, we consider the possibility that the impact of individual variables vary across neighborhoods. Studies on disadvantage and social segregation have, in general, focused on the key role of education and residential location in shaping social mobility and integration and have suggested that contexts have a differential impact on some groups of population[24].

In this study, we explored this possibility for thee groups of populations by the use of random coefficient model which have different intercepts and different slopes for each neighborhood. Neighborhoods with high intercept are predicted to have children with higher scores than a neighborhood wit a low value for the intercept. Similarly, a difference in the slope for race between neighborhoods indicates that the relationship between children's ethnicity and their predicted test scores is not the same in all neighborhoods. Some neighborhoods may have a lower value of the slope for race: in theses neighborhoods the difference between black and not black children is smaller. Other neighborhoods have a larger slope which means that the difference in scores between black and not black students is large.

The results from the random coefficients model presented in Table 15 trigger two conclusions. First, the impact of the context is higher when we allow the impact to vary across neighborhoods (the whole effect jumps to around 10%) which arises mainly from the reduction in the size of the coefficient in the explanatory variables as reflected in Tables A-13 and A-15 in Appendix 1[25]. Second, the influence of the context is not homogenous and varies across neighborhoods.

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[24] Many empirical work in education points out the differences in provision, facilities and teaching along different dimensions (Hanushek, 1997).

[25] Details of the size of each random effect for math and reading are reported in Tables A-14 and A-16 in Appendix 1.

Table 15
Interaction between individual factors and the neighborhood
Alternative Random Coefficient Model

Dependent Variable	Mathematics			Reading		
ICC	Hispanic	Black	SES	Hispanic	Black	SES
Child	0.595	0.621	0.594	0.560	0.553	0.540
School	0.062	0.065	0.063	0.079	0.078	0.080
Neighborhood	0.123	0.086	0.124	0.088	0.101	0.102
School + Neighborhood	0.184	0.151	0.187	0.167	0.179	0.182

***Note**: All Random Effects are significant for a p-value < 0.01.*
***Source**: Elaboration based on ECLS-K.*

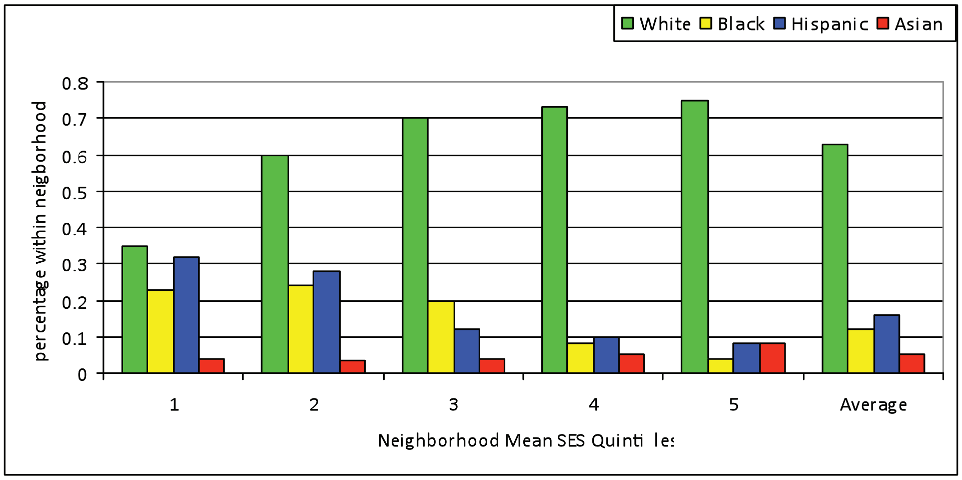
VI. 4. Heterogeneity in Neighborhood Influences

In order to shed some more light in the latter findings, we estimate the full random intercept model for subsamples of the population. It might be the case that for some social or race/ethnic groups, the context (either the school or the neighborhood) does not have the same influence than for average of the population. In that sense, some previous research have suggested that certain groups (males and Black students, for instance) are more affected by contextual factors than others (Crane, 1991; Croft, 1994).

In our sample, students' classified by their ethnicity are non-homogeneously distributed over neighborhoods according to quintiles of average family SES (Figure 7): White children are underrepresented in the population with the lower half of SES, whereas Hispanic and Black children are overrepresented. Likewise, and not surprisingly, students classified by race are distributed unequally by quintiles of student's achievement with Hispanics and Black overrepresented again in the lowest quintiles of performance (Figure 8). These results are consistent with the students' performance varying along racial lines depicted in Table 13 for mathematics[26].

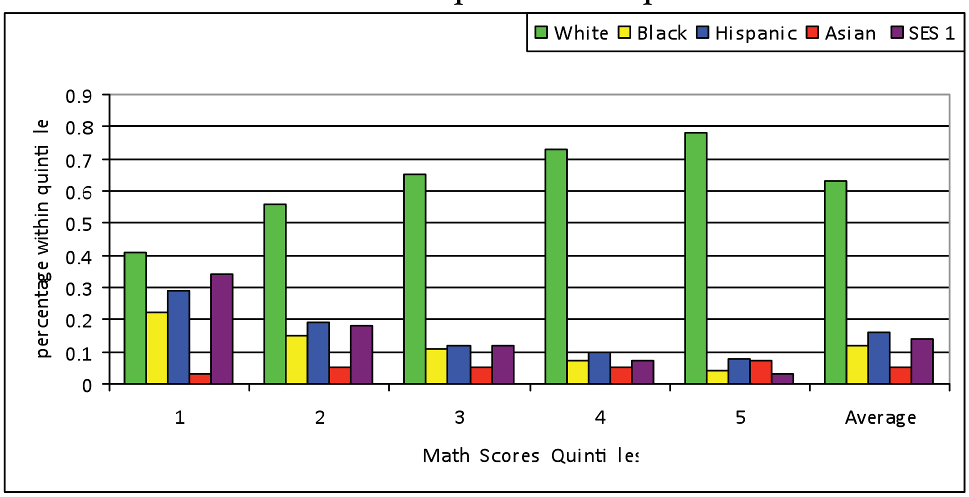
[26] See Table A-10 for reading.

Figure 7
Distribution of Selected Population Groups by Neighborhood Quintiles of Family SES



Source: Elaboration based on ECLS-K.

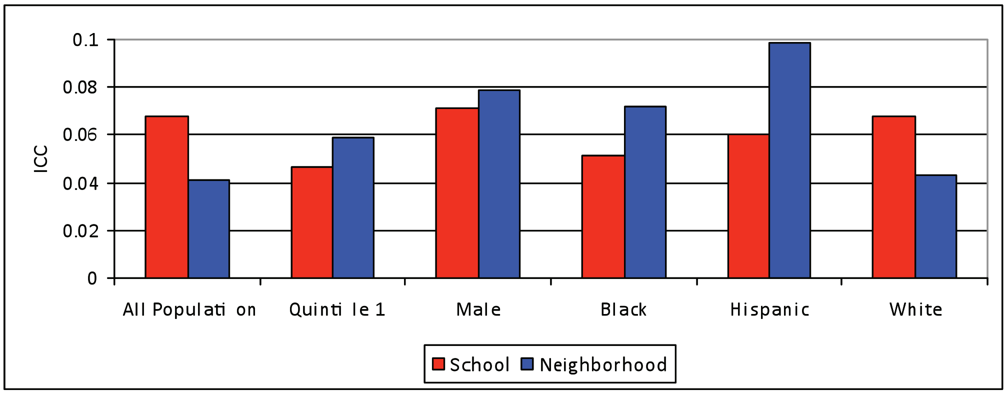
Figure 8
Distribution of Students by Quintiles of Achievement by Selected Population Groups



Source: *Elaboration based on ECLS-K.*

The estimate of the HLM for subgroups -summarized in Figure 9- highlights that the ICC for the average students differs by population sub-groups. There is a huge jump in the influence of context for students who are male, Black, Hispanic and/or belong to the first quintile of the SES distribution. This evidence suggests that the estimate for the whole sample may bias downwards the impact of the context potentially by a large percentage. For instance, the impact of context on Hispanic students more than doubles the one corresponding to the average student.

Figure 9
ICC in Selected Population Groups



Source: *Elaboration based on ECLS-K.*

A detailed analysis of the influence of the covariates utilized in the final model for each sub sample -reported in Table A-17 in Appendix 1- points out that the effect of the covariates change across groups in size and statistical significance. The effect of SES quintile declines for Black children while concentration of poverty has slightly higher impact for Hispanic and Black population, once the threshold of 30% has been reached. The impact of high levels of human capital in the neighborhood are much larger (and significant) for White and more economically disadvantaged students (first quintile) than for the average child. Finally, the impact of median income is double than for the average for Black children and not present for Hispanics. Overall, these findings provide strong support for the epidemic theory.

VI. 4. School Effects

Although this paper is mainly focused on teasing out the influence of neighborhood, school variables were included and a school effect was estimated as well. Similar to the neighborhood, the size of the variance explained by school gets reduced to half of the corresponding to the empty model and accounts for around 6% of students' scores variance. The percentage does not diminish when covariates at the school level were introduced. Educational research has well documented the impact of students-body racial and socioeconomic composition on school average achievement. These effect works on individual achievement

through *peers* and was captured by three covariates: school public status, Title I status and racial/ethnic composition of the school measured by percentage of Hispanic peers.[27]

In our study, all estimates show that all three covariates have a negative and significant impact on student's individual scores. Nevertheless, as Tables A-7 and A-8 show, Public and Title 1 status are more significant in size (negative) than racial composition. The latter, even being statistically significant does have an effect of around a fifth of a SD on student's scores.

The most interesting results come from the subgroup analysis. Table A-13 hints that Public School has an impact of 4.3SD for children who belong to the first quintile of parental SES and 1.6 SD for Black children, effects which are 6 and twice the one for the overall population.

V.5. Model Robustness

We report alternative model specifications in order to check the robustness of our estimates as Table 16 depicts. These alternatives samples varied three aspects: the inclusion of a dummy for missing values, the restriction of the sample to only the children who did not change schools and the waves included.

Table 16
Sensitivity Analysis

Model	Dummy For Missing	Kids who Change School	Waves
Final	No	Yes	1-7
Model 1 -OLS	No	Yes	1-7
Model 2 –Dummy for Missing	Yes	Yes	1-7
Model 3 – Balanced Panel	No	Yes	1-6

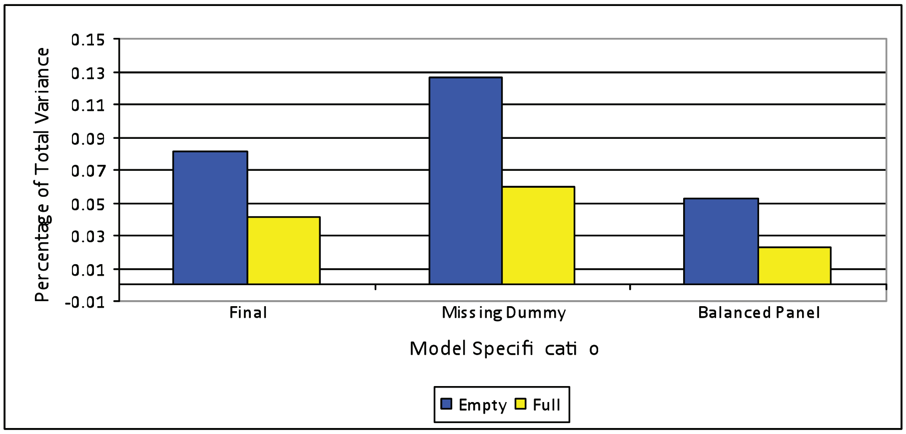
Note: *In all cases wave 3 of ECLS-K is excluded.*
Source*: Elaboration based on ECLS.*

Figure 10 reports the results of the simulation exercise. The size and significance of the explanatory variables does not changed dramatically across specifications [28]. The ICCs at the neighborhood level decrease always by a half when individual and contextual variables are included.

[27] We explore a couple of variables to account for the extent of racial diversity, percentage of Hispanic and White population in tract but the Likelihood Ratio Test rejected their inclusion.

[28] The full model report for each simulation is reported in Tables A-19, A-20 and A-22.

Figure 10
Neighborhood Variance as Percentage of Total Model



Source: *Elaboration based on ECLS.*

V.6 Prediction and Residual Analysis

Misspecification may lead to problems in terms of bias and efficiency. A first problem may come from using a random effects specification versus the alternative, a fixed effect model. Statistically, the choice of random versus fixed coefficients depends on the assumptions made on the random coefficients: zero expectations, homoskedasticity and normal distribution[29]. If the fixed effects are uncorrelated to the regressors, the coefficients from the random effects will be the same than the ones as those in the fixed effects model. In other words, the fixed effect (the cluster means) should be orthogonal to the contextual variables and the parameter for the fixed effect will absorb the non–orthogonality. This is similar to testing the equality between the within-group and the between group regression. Schneider and Berkhof (2003) points out unbiased estimates of the fixed effect could be obtained through the random effect model provided that the group means are included.

The generally accepted way of choosing between fixed and random effects is running a Hausman test. We test the null hypothesis that the coefficients estimated by the efficient random effects estimator are the same than the ones estimated by the consistent fixed effects estimator. If the tests were not significant then it is safe to use random effects. A significant p-value would reject the null hypotheses and would imply that the coefficients of the random effects estimates are biased. In this case the estimate for the level-two variance will be affected but the estimate for the level 1 variance will still be consistent. The solution would be to add the cluster means to

[29] Homoskedasticity is closest to the assumption that the level 2 units are a random sample of the population (Sneijders and Berkhof, 2003).

the regression. The results summarized in Table 17,[30] confirm the goodness of fit of the random effects specification.

Table 17
Specification Tests

Test	
Heteroskedasticity	No
Kurtosis	2.24
Skewness	-.36
Fixed Effects	
Non signicant	2/22

Source: *Elaboration based on ECLS-K.*

A second problem may come from heteroskedasticity: if the variance of residuals is not constant, the standard errors and the t test would not be reliable. However, the point estimates will not be change unless heteroskedasticity is associated with omitted variables. In the multilevel case dealing with level-one heteroskedasticity is even more relevant than in non hierarchical case; an unrecognized level-one heteroskedasticity may be caused by the dependence of level-one residuals on the Z (the contextual factors) and may lead to a significant random slope variance which disappears if the heteroskedasticity is taken into account. We explored potential heteroskedasticity by analyzing kurtosis, skewness and the plot of the residuals. Although ideally for a normal distribution skewness should be zero the slightly negative skewness (-0.36) implies that the mass of the distribution of the residuals is concentrated to the right with few values to the left which may be due to the presence of outliers as Figure A-3 exhibits. A last check of the model assumptions consists on testing the normality and constant variance of the three random effects. The examination of the distribution of the random effects detailed in Figures A-4 through A-6 in Appendix 1 does not suggest non normality[31].

VII. Discussion

The presumption that children's outcomes are influenced by the characteristics and outcomes of their neighbors and school peers has been a concern of researchers and policy-makers for decades. This paper presents empirical evidence for the existence of neighborhood and school effects on students' academic achievement.

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30 See Table A-24 for details.

31 Random effects were checked upwards following Sneijders and Boskhorf (2003).

Using a cross-classified hierarchical linear model, the study finds that school and neighborhood are overlapping but independent contexts, both associated with educational attainment in the U.S. elementary education. Our analyses reveal that individual and family-background variables account only for fifty percent of the total variance being SES and race/ethnicity the most relevant factors at the individual level. A child who belongs to the fifth quintile of the SES has a tests score almost 8 SD higher than the child who belong to the first quintile, the base category. Being Black or Hispanic is associated as with lower scores in both mathematics and reading.

The concentration of affluent and educated people in the neighborhood -measured, respectively, by median income and females over 25 years olds who have completed at least high school- has positive influence on students' achievement. The impact of female educated women in child's outcomes is consistent with collective socialization views of the type proposed by Duncan (1994), Brooks-Gunn et al (1993) and Kaupinnen (2008) who emphasize the positive role of affluent and educated adults in child's outcomes. Nonetheless, the results presented add evidence in favor of concentration of disadvantage as the prevalent contextual factor. The influence of poverty concentration is non-linear presenting a big jump at the 30% threshold; thus, social problems increase with certain characteristics but not at a constant rate.

After controlling for some of the most relevant school and neighborhood factors we found that there is still variance at the both the neighborhood the school level. This random effect may be interpreted as a social effect or, the effect occurring when "the whole was greater than the sum of its parts" (Crane, 1991).

Even when our findings for the whole sample are stable over different specifications, the implicit assumption that school and neighborhood have a uniform effect on all children regardless their race/ethnicity, gender and socio economic status is challenged. Consistently with previous findings in other fields,[32] context has higher than average rates on certain groups. Both the random coefficient specifications that allow the effects to vary across neighborhood, and the estimates of separate regressions for selected subgroups indicate that neighborhood effects vary

[32] For instance, see evidence on crime and violence in Oberwittler (2007) and Sampson et al (2008).

by gender, ethnicity and SES. Neighborhoods appear to have higher impact on Black and Hispanics than on the whole sample[33].

The results of this study indicate the presence of two types of effects: contextual and endogenous effects[34]. As long as we have confirmed that some neighborhoods' characteristics are associated (either positively or negatively) with outcome, we expect lower achievement in poor, minority populated neighborhoods. The reminder of the unexplained variance implies the existence of positive and negative peer's influence (or endogenous effects in Manski's terminology) that, we hypothesize, takes place once certain thresholds for the contextual variables have been reached.

As for applications for policy action, the generic recommendation of improving neighborhood quality is insufficient. It is necessary to distinguish and hypothesize the type of effect. In order to create inclusive neighborhood, policies should address local job markets conditions as well as the human capital in the area. These include affordable housing, anti-poverty measures and access to community services aimed to improve the whole community quality of life. Solutions of the type of moving people across metropolitan areas has had very limited and, short-term effects on children, and would be unfeasible to be scaled-up.

As education is geographically based, educational policy is one of the available instruments to create cohesive neighborhoods. Given that family's spatial locations depend in part on educational policies there is an interrelation between neighborhood and school choice decisions that calls for policies which address simultaneously neighborhood and school conditions[35].

Experiences of such policies are not new. Comprehensive neighborhood policies have been implemented in the last 15 years, though not fully evaluated yet, along these lines. In the

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[33] This evidence might be interpreted as a validation of a peer contagion effect as the modeling strategy controls for the individual characteristics that are more likely associated to low achievement The epidemic theory of neighborhood effects points out two basic conditions for a community "to be "at risk": a) the residents' risks of developing social problems, and b) their susceptibility to peer influence" (Crane, 1991).

[34] We could assimilate the effects we found to Raudenbusck and Wilms's Type A and Type B effect. Type A effect comprises school practice and the contextual influence, while Type B refers only to the influence of the practices and interactions among peers. Raudenbusck and Wilms's (1995) sustain that Type A effects are the ones parents look at when deciding the school to enroll the child while Type B is the type which is under the domain of the policy-maker.

[35] For instance, in the UK the neighborhood renewal agenda has taken up the issue of educational achievement in deprived areas and has specific policies to deal with low educational quality (Croft, 2004).

U.S., most initiatives taken during the Clinton's administration such as Empowerment Zones and Enterprise Communities Program (EZ/EC) were implemented along with anti-poverty and transportation measures[36].

In the context of limited resources, the optimal strategy may encompass universal and targeted actions and the choice should be based on a good diagnosis of the underlying neighborhood processes For instance, programs aimed at generating positive peer pressure could be effective, in terms of improving outcomes, both as targeted or universal programs. The presence of peer contagion effects generates feedback in the student's group of peers adding an indirect impact to the direct impact on the student[37].

The main threat to our modeling strategy adopted may be the control for endogeneity. As in most other observational research we included variables related to both the outcome of interest and the choice of the neighborhood. Family and individual background variables may be insufficient to fully account for neighborhood's choice due to unobservable differences which drive choice. However, we consider that the assumption that families choose based on observable characteristics is solid, as unobservable characteristics are, by definition, difficult if not impossible to observe not only for the researcher but also for "potential neighbors"(Schelling, 1979) [38].

Some bias may be due to the definition of neighborhood utilized in this paper. Census tract boundaries may or may not coincide with the true neighborhood boundaries. Though the same argument may apply to school effects, it is easy to isolate the "boundaries" of the school. This issue does not affect indeed the basic interpretation of the results presented and the relevance of both "social contexts".

Finally, we can anticipate some lines for further research. First, neighborhood selection mechanisms need further exploration utilizing alternatives methodologies using observational data; matching mechanisms, longitudinal follow-up of kids who change neighborhood and exposure time to the neighborhood among other topics. Second, some other covariates

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[36] See Freiler (2004) and Katz (2004) for a discussion on this point.

[37] Manski (2000:23) points out that while economists call this effect endogenous interactions sociologist define them as contextual interactions.

[38] In that sense, Crane (1991) sustains that "for tipping to occur, people must be able to observe characteristics reliably, so that people generally agree on which individuals belong to which groups" (Crane, 2991:1250).

accounting for parental styles and school practices (ability grouping, retention, etc) need to be explored as they would provide more accurate measures of neighborhood and school effects[39]. Third, our findings and preliminary tests conducted points toward further examination of non-linearity of some individual variables; not only random slopes but also the existence of tipping-points for some characteristics. Fourth, although our research contributes to the vast amount of research which examined the association between socio-demographic characteristics of contexts on children's behavior, there is still need to explore alternative theories and the mechanisms effects channelize in order to acquire information for exactly how and why given social environments influence student's achievement. Lastly, although some research has been done exploring the determinants of family location decisions there is still a lot to explore about the relationship between school choice and housing decisions.

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[39] Policies and school practices which could reinforce or attenuate initial differences are analyzed for instance by Reiker and Walker (2006) and include NCLB, the Gun free School Act (1994), Children with disability Act (IDEA 1997), retention, tracking, and alternative programs for students with problems.

Chapter 3: Isolating the impact of Algebra 1 in 8th grade on the test scores in North Carolina

I. Introduction

Tracking is a school practice characterized by grouping students into classes based on ability (or prior achievement) and organizing the curriculum by its level of difficulty. Grouping students by ability level is an enduring characteristic of Western educational systems. Debates about placement policies –alternatively called tracking, streaming or ability grouping- focus on the trade-off between equity and efficiency (Fryer and Levitt, 2005; Hanushek and Rivkin, 2006; Brunello and Checchi, 2006). Advocates of equality argue that exposure to more rigorous courses and more able peers help students become academically more capable. Efficiency arguments rely on the gains derived from teaching to homogenous groups in terms of customizing classes according to student's ability, interest and engagement which are increased through tracking.

Ability grouping is closely related to the discussion about upgrading the curricula and the contents of the courses in high school especially in mathematics (Allensworth et all, 2008; Burris, 2008; Gamoran and Hannigan, 2000; Loveless, 2008). The prevalence of the efficiency argument through time has led high school curricula to include a broad range of academic and vocational courses with different level of complexity (Gamoran et al, 1997; Lee et al, 1998; Oakes, 1985). As a result, high-school students show a variation in their academic experiences with curriculum operating as a "social stratification" instrument (Allensworth et al, 2008:2). However, the awareness that advanced math courses are needed to succeed not only in college but in the job market has motivated an increasing rigor characterized by upgrades in the curricula and toughening of the graduation requirements (EdSource, 2009; Gamorn and Hannigan, 2000; Loveles, 2008; National Governor's Association, 2005).

The elimination of ability grouping may lead to achieve equal educational opportunity and, potentially, to reduce the achievement gap (Woessman and Peterson, 2007). The U.S. has faced movements towards the elimination of tracking in the last two decades (Guryan, 2004). The so-called "detracking movement"[40] has been highly controversial and has led to court mandated detracking reforms in a number of school districts and states (Ariga et al, 2006; Card

[40] Detracking could also be referred as desegregation (Eyler, 1982).

and Rothstein, 2007). The *detracking* initiatives are parallel to the changes many states have introduced to toughen graduation and upgrade the curricula (Chicago, 1997; New York, 2001; Texas, 2003; California, 2005; Minnesota, 2006)[41].

The urge to enroll students into Algebra 1 in eight-grade was a common denominator in the reforms and constitutes a gatekeeper to more advance math courses in most states. As a consequence, the distribution of course-taking has changed dramatically over time; enrollment differences in participation in college-preparation courses by race and prior ability have shrunk in the last two decades (Allensworth et al, 2008; EdSource, 2009; Loveless, 2008). Nonetheless, preliminary evaluation of the impact of these changes on students' outcomes raises concerns: not all students are either prepared for this transformation and/or received adequate support to be successful (Burris, 2008; Gamoran and Hannigan, 2000; Jacobson, 2008). Moreover, some reports consider that massive enrolment in Algebra 1 in 8th grade is "inappropriate" (Loveless; 2008).

The objective of this chapter is to assess the effect of enrolling in Algebra 1 on student's achievement. The outcome variable of interest is the score in the math section of the tenth-grade High School Comprehensive Test (HSCT). Using a propensity score matching method we estimate the average treatment effect and explore potential heterogeneity in average treatment effect.

The paper contributes to previous literature on the field in two aspects. First, to date most analysis has been based on nationally representative surveys[42] with a few analysis based on specific case studies being one the first studies that includes all academic history to estimate the impact of placing students in Algebra 1 in 8th grade. Second and more important, we provide a more complete picture of the effectiveness of the by assessing the heterogeneity in student's response across various dimensions (individual background and prior ability).

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41 Though the policies were different, they all end by requiring more advanced courses at the time of graduation. For instance, in 1997 Chicago eliminated the remedial courses while New York and Texas mandated all students to complete a college-prep course sequence.

42 The Longitudinal Survey of American Youth (LSAY) and the National Longitudinal Educational Survey of 1988 (NELS- 88).

II. Background and Motivation

There are different positions as to what tracking means. Slavin (1987, 1990) classifies ability grouping in American schools into three types or categories. The first type, "class assignment," takes place when students are put in one self-contained class according to ability level. The second type, "streaming", happens when students are grouped according to achievement level for specific subjects. The third form, grouping "within class" by ability level, implies working with different materials according to the level of ability of each student.

There are different ways through which tracking may work in practice, starting with the institutional features of the educational system or the "school design". In the American system ability grouping occurs within a comprehensive school system. In the same way, in the European context, tracking is associated with well-defined separate segments of schools, general and vocational institutions. Tracking varies by cycle. The practice is more prevalent in high school than in primary education, although the phenomenon has started to extend to tertiary education (Arum, R et al, 2007). Lately, some concern has been raised about the growing adoption of tracking policies in elementary education and the impact that early tracking may have on later educational and labor market outcomes, as well (Ariga et al, 2005; Brunello and Cecchi, 2006).

Ability grouping varies by academic discipline, as well; ability grouping is more widespread in mathematics than in other areas. The regular procedure is to require "low-ability students" to take fewer and/or different math classes; high ability students are offered advanced classes which are rarely offered to less able peers (Oakes, 1986, 990). It is also common to offer a course with the same name but with different objectives and complexity, which is generally associated with the ability of the students. Placing a student in an Honor course may be one of the various forms of differentiating students by ability. For instance, a qualitative study done on six districts provides evidence in that direction (Gamoran, Porter et al, 1997). Some research has suggested that the quality interaction between the teacher and the student varies significantly with student's ability (Davenport, 1993).

The arguments for and against placement polices center on the trade-off between equity and efficiency (Hanushek and Woessmann, 2005; Slavin, 1990; Card and Rothstein, 2007). Efficiency arguments rely on the gains derived from teaching to homogenous groups in terms of customizing classes according to student's ability. Advocates of equality argue that exposure to

more rigorous courses and more able peers help students become academically more capable (Zimmer, 2003).

II.1. Empirical Evidence

The empirical work done in the American context does not provide clear-cut conclusions about the impact of placement on student's outcomes and they face, in most cases bias associated to lack of control of selection bias. While some evidence suggests that grouping within class has positive impact on student's achievement, other empirical work suggests that class assignment based on ability does not have any effect (Hollifield, 1987). In particular, a brand of research, mostly based on case studies, insinuates that tracking fails to improve students' performance creating some times larger gaps in achievement between various population sub-groups (Gamoran et al, 1987; Slavin, 1987 and 1990; Brunello and Cechhi, 2006). Likewise, another set of studies based on either the principal's or a teacher's report of the "tracked" status of a student has examined the impact of school placement in students' outcomes with mixed results (Hoffer, 1992; Betts and Shkolnik, 2000; Figlio and Page, 2002; Argys et al, 2000). Table 18 summarizes previous findings and shows, overall, those achievement gains, if different from zero, are smaller in size that what the theory say it would be the case.

Part of the empirical literature argues that that students with strong academic skills choose college oriented sequences whereas students with weak academic skills often take low level or less-demanding coursework courses (Attewell & Domina, 2008; Horn & Kojaku, 2001; Gamoran and Hannigan, 2000)[43]. For example, Hoffer (1997) reports a high correlation between college preparatory tracks and students outcomes, and suggests that which courses students' take matter more than the number of courses. However, given the size of the average treatment effect it is difficult to sustain that the gain of ability would translate in better outcomes in the labor market later on. The modest achievement gains do not justify a human capital type of approach but suggest that some sort of credentialsm might take place: if a student enrolls in Algebra 1 in 8th grade, she signals to colleges and employers about her ability.

Some research has explored the integration at the school level and how influences the achievement gap. For instance, a recent study, based on a sample of SAT takers, found that

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[43] These findings are consistent with studies reporting that the *type of course* is more important than the *number of courses* (Allensworth et al, 2008:1).

within school segregation prevails over neighborhood segregation in terms of explaining student's achievement gaps (Card and Rothstein, 2007). Furthermore, in cities characterized by highly segregated neighborhoods, school integration initiatives are offset by within-school segregation mechanisms, mainly tracking (Clotfelter, Ladd and Vigdor, 2006)[44].

Table 18
Some Empirical Findings on the Effects of Tracking

Article	Outcome	Effect Sizes
Slavin (1990)	Summary of 29 studies on the impact of tracking	20 studies no difference Negative in the reminder
Hoffer (1992)	Math and Science Achievement	General effect is negative, positive in the High ability group, negative in the rest, very negative for the low achieving group
Argys, Rees and Bower(1996)	Change in math score	8.4 % moving from a below to an above average class Same in the opposite direction if above average
Figlio and Page (2002)	Change in math score from 8th to 10th grade	2.2. High Ability - Raw Scale -6.0 Low Ability- Raw Scale
Betts and Shkolnik (2000)	Math score. Two Cohorts - LSAY	7.4 raw scale
Zimmer (2003)	Score in SIMS	2.14 Raw Scale
Manning and Pischke (2006)	Score in 11th grade	3.4 (SD=22)
Duflo et al 2007)	Score in 11th grade	0.14 SD 0.19 top half 0.16 bottom half
Clark (2007)	Score in 11th Grade	0.30 SDs
Gamoran and Hannigan (2000)	Score in 10th Grade	3.64 points, Raw Scale
Allensworth et al (2008)	Score 9th Grade/ End of HS	-0.13/0.63 NCE*
Attewell and Domina (2008)	Score in 12th grade	0.10/0.19 SD

Note: *SIMS: Second International Math and Science Test; *NCE: Normal Curve Equivalent.*
Source: *Author's Elaboration.*

II.2. Policy Context: the timing of Algebra 1

Ability grouping is usually made in grade 9 or 10 and is based upon achievement, preference, and counselor'/ teacher' recommendation depending on offer. Since Keyes v. Denver (Boustan, 2009) school districts were called to integrate heterogeneous groups of students. Nevertheless, court-ordered desegregation has lead to other mechanisms of adjustment, some of

[44] As part of the empirical evidence of racial segregation in high school, Card and Rothstein (2007) report that white students are more likely to enroll in honors classes than their black peers in cities with more integrated schools (Card and Rothstein, 2007:3).

them external to the school such as moving out, private school and some internal such as placing students in different tracks in High School, compensatory policies, etc[45]. Ability grouping in High School works by assigning high achieving students to college preparatory curriculum over general or vocational tracks to which are assigned low achieving students. As long as minority students are over-represented in low achieving groups, the practice which represented a way of tracking is a way of "resegregating"[46] in a school desegregation context (Eyler, 1982: 7). The college track is associated with a more intensive curriculum and, in other words, with taking of Algebra 1 at early stages of High School and, sometimes, in Middle School a course that operates as a gatekeeper to advanced math sequence (trigonometry, calculus, etc)[47].

In the early nineties enrollment in Algebra 1 in 8th grade was only 1 out of 6 students. In that moment, the Clinton Administration -as a response to the "bad results" of the U.S. in the Third International Mathematics and Science Study Repeated (TIMSS-R) decided to foster enrolment in Algebra 1 in 8th grade as a key objective in the education agenda. This policy was coupled with stricter graduation requirements (Loveless, 2008:2). In the 1990s many states have encouraged schools to enroll students earlier in Algebra 1. Furthermore, not only has Algebra 1 enrolment in 8th grade has doubled by the beginning of the 21 century (2 out of 6 students) butthe course has become, since 2005, the default math course in 8th grade[48] (Honawar, 2006; Jacobson, 2008; EdSource, 2009).

Students who take Algebra 1 in 8th grade take more advanced math courses and have a higher probability of entering into college. Not all students are prepared to succeed in Algebra 1 in middle schools partly due their departure points in terms of achievement and partly due to the lack of support either at home and/or at school to deal with the increasing difficulties in math contents (Gamoran and Hannigan, 2000; Burris, 2008)49. Information reported by some states confirmed that enrollment in Algebra 1 has expanded along with the difficulties for many

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45 Eyler (1982) suggests that the more intensive use of these practices have been the school immediate response to desegregation mandates.

46 Resegregation is the process by which students are separated into racially or ethnically isolated groups within desegregated schools.

47 The decision about when to take Algebra 1 and, if a preparatory course is necessary, depends on principal, teachers and parents' decisions conditional on course offer.

48 And the corresponding exam is the test of record for federal accountability purposes in most states.

49 Moreover, some reports consider that the early algebra placement "inappropriate" (Loveless; 2008).

students. In California 40% of the students who took Algebra 1 in 9th grade in 2008 were repeating the course. The “troubled” students share some characteristics with the “misplaced” students in other states: they are predominantly Black, Hispanic and belong to families with low levels of education (Jacobson, 2008; Loveless, 2008; EdSource, 2009:8).

In general, ability grouping practices have been discussed within the efficiency-equity trade-off. Nonetheless, since evidence has shown that the math skills needed to succeed in the workplace are the same as the ones needed to succeed in college (Attewell and Domina, 2008), concerns are raised about the economy’s competitiveness if only one quarter of the students who graduate from High School have those skills.

III. Research Questions and Hypotheses

The specific aims of this research are to assess the following questions and hypothesis:

Research Question #1: Do the characteristics of the students differ according to the grade they participate in Algebra 1?

Hypothesis: The characteristics of the students are different depending on which grade they take Algebra 1. They differ in their socioeconomic background and prior levels of ability.

Research Question #2: What is the impact of enrolling in Algebra 1 in 8^{th} grade on the math section of the HSCT?

Hypothesis: The participation in Algebra 1 in 8^{th} grade has a positive or non zero average impact on achievement.

Research Question #3: Do all students benefit the same from enrolling in Algebra 1 in 8^{th} grade?

Hypothesis: The benefits derived from enrolling in Algebra 1 in 8th grade differ along different dimensions (student background, school and district).

IV. Data

We employ administrative data of students in North Carolina Public Schools housed at the North Carolina Education Research Data Center (NCERDC) at Duke University. North Carolina has a statewide testing program, known as the ABCs of Public Education, which defines the performance standards for each elementary, middle, and high school in the state. As part of the system End-of-grade (EOG) and end-of-course (EOC) tests on various disciplines are used, along with other selected components, to measure the schools' growth and performance as described in detail in Appendix 2.

The databases contain demographic of the student, characteristics of the teachers, the schools and the districts and the courses the student has taken, if the course has either an EOG or and EOC test. For this study, we are utilizing the cohorts that take the HSCT in 2003 and 2004 for which we have information on priori achievement from 3rd to 10th Grade based on the EOC tests.

IV.1. Outcome Measure

The outcome is the standardized score in the math section of the high school comprehensive test (HSCT)[50]. The HSCT is a component of the ABCs accountability model for high schools and is aimed at measure growth in student achievement in Reading and Mathematics from grade 8 to grade. Although the test is curriculum-based, the content measured is not course specific. All students officially classified as tenth graders by the school principal participate in the test administration unless specifically exempted.

IV.2. Definition of the treatment

The Treatment Variable is built based on the classes the student had taken by the times she passes the HSCT. As long as the datasets provides information only for the classes which have End of Course Tests, analysis is restricted to the math score. This restriction will not invalidate the conclusions of the current study as long as math achievement is a strong, it not the strongest, predictor of individual's outcomes (Rose, 2006)[51].

Algebra 1 is a graduation requirement[52] and, according, to the NCSCS is supposed to be taken at the end of 8th grade. Nevertheless students may take the class as early of 7th Grade, depending on the school offering. According to the information reflected in Table 19 most of the students take Algebra1 (or its equivalent Algebra 1B) in 9th grade.

The fact that the student takes Algebra 1 in 8th Grade does not mean that it is the first Math class she takes. Schools districts can decide locally to offer courses that they develop. School districts may decide to offer preparatory courses such as Pre-Algebra, split Algebra 1 in

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50 Details on the HSCT are provided in Appendix 2.

51 For instance, Argys et al (1996), based on previous studies on the determinants of student's achievement, claim that math ability –unlike verbal ability whose primary determinant is family background- is highly influenced by school policies. Figlio and Page (2002), on the other hand, argue that most empirical work has revealed a strong correlation between math achievement and labor market outcomes.

52 See Appendix 2 for details.

two separate classes or offer it as the first math course. Algebra 1/1b could be taken as either a first math course or as a second o third course after some preparatory course. In general school districts have opted for either offer a preparatory class (Pre-Algebra or Introductory Algebra) and/or split the Algebra 1 contents in a two sequence courses (Algebra 1A and 1B). For instance, Pre-Algebra, Algebra 1A, and Algebra 1B are not courses outlined in the North Carolina Standard Course of Study. If Algebra 1 is offered in parts students may only receive 1/2 credit for each part. Table 20 describes the combination of math courses students may take.

Table 19
Distribution of Algebra 1 by grade

Grade	Student take HSCT in	
	2003	2004
7	0.99	1.71
8	20.64	20.33
9	54.81	56.48
10	23.56	21.47

Source: *Elaboration based on NCPSDB.*

Table 20
Possible Curricular Sequences

Algebra 1 in Grade	Sequence Number	Grade				Distribution of Students
		6	7	8	9	
8th	1	Pre-Alg.	Alg. 1A	Alg. 1 B		4.4
	2		Alg. 1A	Alg. 1 B		31.8
	3			**Alg. 1 B**		**60.1**
	4		Pre-Alg.	Alg. 1 B		3.7
Total						**100**
9th	1		Pre-Alg.	Alg. 1A	Alg. 1B	4.5
	2			Alg. 1A	Alg. 1 B	11.5
	3				**Alg. 1 B**	**76.7**
	4			Pre-Alg.	Alg. 1 B	7.3
Total						**100**

Note: *Algebra 1B is equivalent to Algebra 1 in terms of the EOC test and the graduation requirements. See Appendix A for details. Algebra 1A does not have an EOC test. To fulfill Algebra 1 requirements student take the Algebra 1 EOC test at the end of Algebra 1 or Algebra 1B.*
Source: *Elaboration based on NCPSDB.*

Students who enroll in Algebra 1 in 8th grade Algebra 1 are more likely to take more advance math courses as reflected in Table 21. Half of the students who enroll in Algebra 1 in 8th grade take more than one advanced math course (51%) while only 13% of the students who enroll in 9th Grade take more than 1 course.

Table 21
Number of Advanced Math Courses
(in %)

Grade	Number of Total Advanced Courses			
	0	1	More than 1	Total
8	7	42	51	100
9	8	79	13	100

Source: *Elaboration based on NCPSDB.*

Enrollment in Algebra 1 in 8th grade may be reasonably considered as an indicator of participation in higher math and constitutes the treatment we want to evaluate. We examine the effect of taking Algebra 1 in eighth-grade for the students who did not take any preparatory course that is sequence 3 is the only one which does not include any preparatory course[53]. This treatment is expected to have positive effect on student's outcomes.

IV.3. Control Variables

We include a set of control variable that were chosen largely on the basis of both theoretical considerations and previous empirical work. Unfortunately, the number of covariates is limited at the individual background characteristics. We only count with maximum formal educational level at home that we use as a proxy for income and socio-economic status[54].

The control variables described in Table 22 were classified into five main categories[55]:

1. Individual and Family Background which are likely to affect achievement such as race, gender and parents' education levels.

2. Prior Achievement. Prior educational achievement is indicated by EOG test results in reading and math.

3. School Characteristics. Assuming that students who share the same school share the same characteristics, we averaged individual-level background characteristics by school. The group includes ethnicity and parents' education.

4. School District attributes. A number of variables were introduced to represent school district characteristics that are supposed to have effect on student's outcomes.

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[53] Academic history is self-reported by the student when taking the HSCT. This allows us to build the treatment variable for the entire sub-sample that take the HSCT.

[54] Parents' education might be subject to measurement error. The maximum level of education is filled by teachers' perception/knowledge of family's education. Some research has shown that teachers tend to underestimate education of minorities (Black, Hispanics, for instance) and over-estimate the level of education of White students.

[55] See Table A-28 for descriptive statistics.

5. Year fixed effect. A dummy for the year 2004 was included in order to control for temporal differences.

Variables were re-coded when necessary; for estimation; categorical variables were converted to a set of dummy variables. Correlations between the outcome and between explanatory variables are presented in the Tables A-29 through A-32. Background variables are all expressed in terms of dummies; thus, reported coefficients may be read as the difference in intensity in SD units between the active and the reference category (e.g., between African American and White students). Prior ability predictors are standardized, as well. The coefficients are measured as changes in the probability) associated with a 1-SD increase in that predictor.

Table 22
Explanatory Variables

	Variable Definition
Individual and Family Factors	
Male	1 if Male; 0 otherwise
Race	Dummy for Each Race
Parents' Education	4 dummies
Prior Ability	
Scores EOG test from grade 3 through 8 Math and Reading	Standardized z scores
School Characteristics	
Percentage of White Students	Continuous
Average Parent's Education	Continuous
Mean of School Test Scores	Continuous
District Characteristics	
Percent of Students at or above Level 3	Continuous
Percent of District Population Aged 5 to 17 Living Below the Poverty Line	Continuous
Percent of Public School Students Living in a Single Parent Family	Continuous
Percent of Public School Students Who Have At Least One Parent With Less Than a High School Education	Continuous
Percent of AYP targets met by LEA	Continuous
Percent of Classes Taught by Highly Qualified Teachers*	Continuous
Percent of Students Identified as Black	Continuous
Amount spent per student from local sources	Continuous
Amount spent per student from state sources	Continuous
Dropout Rate, Grades 7-12	Continuous
Dropout Rate, Grades 9-12	Continuous
Year Fixed Effect	2004=1; 0= 2003

Note: **Highly qualified" teachers are defined as teachers who are fully licensed by the state. They hold at least a bachelor's degree from a four-year institution, and they demonstrate competence in the subject area(s) they teach.*
Source: *Elaboration based on NCPSDB, NCERDC Codebooks.*

V. Methods

Our interest is to measure the impact of a treatment T, Algebra 1 in 8th grade in the math section of the HSCT (Y_i). Mathematically, we want to measure

$$Y_i / T_i = T_i * Y_i(1) + (1 - T_i) * Y_i(0) \quad (1)$$

Where Y_i the outcome and T_i is the treatment. The estimation of (1), though, faces some problems. The key assumption is that individuals selected into treatment and non-treatment groups have potential outcomes in both states: the one in which they are observed and the one in which they are not observed. Unfortunately, this is not the case. For the treated group, we have observed mean outcome under the condition of treatment E($Y_1 / T = 1$) and unobserved mean outcome under the condition of non-treatment E($Y_0 / T = 1$). Similarly, for the non-treated group we have both observed mean E($Y_0 / T = 0$) and unobserved mean E($Y_1 / T = 0$). Under this framework, an evaluation of E($Y_1 / T = 1$)- E($Y_0 / T = 0$) uses E($Y_0 / T = 0$) to estimate the counterfactual E($Y_0 / T = 1$). Because individuals can not be observed in both states, treated and not treated, it is not possible to compute the expectations on the right-hand side of (1). The simplest way to approximate this effect is to compare is the use of the OLS framework:

$$Y_i = \beta X_i + \delta Z + \gamma T_i + \varepsilon_i \quad (2)$$

The outcome (Y_i) is a function of a set of individual background and school and district contextual variables (X_i and Z, respectively) and the treatment (T_i).The coefficient on T_i , γ , in Equation (2) will provide the size of the effect. Nonetheless, in the presence of correlation between individual characteristics and treatment status, estimates of γ will be biased estimates[56] and will reveal the true treatment effect.

[56] The bias (mean selection bias) is zero only when participants and non-participants are identical in the base state. Heckman (1997) explains that mean bias "tells us how the outcome in the base state differs between program participants and non-participants. Absent any general equilibrium effects of the program on non participants, such differences cannot be attributed to the program."

V.1. Propensity Score Matching

To deal with selection bias we propose the propensity score (PS) method[57]. The basic idea underlying this methodology is to compare students who were subject to the treatment with students who were not under treatment but who are similar to treated students in all relevant characteristics except the treatment status. The difference in the outcomes can, then, be attributed to treatment (Rosenbaum and Rubin, 1983).

The propensity score methodology consists on replacing the set of confounding covariates with one scalar function of these covariates: the propensity score. The propensity score is the probability of receiving the treatment given a set of covariates:

$$p(X,Z) = p\,(T = 1 / X, Z) \qquad (3)$$

One strong assumption, and limitation, of the propensity score methodology is that all potential confounders are included, in other words, that there is no selection on observables. When this assumption is met the average treatment effect is not biased (Rosenbaum and Rubin, 1983; Imbens, 2004)[58]. A second necessary assumption is that there is overlap in the joint distribution of covariates of treatment and covariates.

The first step is to estimate each student' propensity score by running a logistic regression. The magnitude of a propensity score ranges between 0 and 1; the larger the score, the higher the likelihood the student takes the treatment.

The second step is the estimate of the average effect of treatment given the propensity score. In this step we divide students into groups of similar (estimated) propensity scores, compute the effect of treatment for each value of the propensity score and obtain the average of these conditional effects. This is infeasible in practice because it is rare to find two units with exactly the same propensity score. There are alternative procedures to perform this step and how the propensity score is used or not to create a balanced sample of treated and control observations. These methods differ from each other with respect to the way they select the control units that are matched to the treated and the way they select the controls to estimate the

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[57] The first alternative to this approach is Instrumental Variables (IV). The basic logic of this approach is to use one or more variables (IV) as instruments. Such variables should have two properties: they cause variation in the treatment or control group and they have no effect on the outcome (in this case, score in HSCT).

[58] Imbens (2004: 7-11).

counterfactual outcome of the treated (Abadie et al, 2004). In this paper, we used three alternatives matching methods:

a) Local linear weight match. Given that the simple difference in average outcomes for treated and a control is not unbiased because the distribution of covariates differs, weights are used to create a balanced sample of treated and control observations. We use kernel weights to estimate the estimate the average treatment effect: The matching outcome is the kernel-weighted average of the outcome of all control units with weights given by the closeness between treated and control unit.

$$ATT_{\ker nel} = \frac{\sum_{i=T_i=t} Y_i * K\left(\frac{X_i - x}{h}\right)}{\sum_{i=T_i=t} K\left(\frac{X_i - x}{h}\right)} \qquad (4)$$

Where K(.) is a kernel function and h is the bandwidth parameter (see Methodological Appendix for a discussion on the choice of the bandwidth).

b) Nearest neighbor matching (1-to-1 match). The control with the value of P_j that is closest to P_i is selected as the match to compare the outcome.

$$C(P_i) = \min_j \left\| P_i - P_j \right\| \qquad (5)$$

$$ATT_{neighbor} = \frac{1}{N^T} * \sum_{i \in T} Y_i^T - \frac{1}{N^T} \sum_{j \in T} Y_j^C * w_j \qquad (6)$$

Where N_T is the number of units in the treated group and weighs w_i are defined by $w_j = \Sigma_i w_{ij}$.

c) Blocking on the Propensity Score: Rosenbaum and Rubin (1983) suggest blocking-on-the-propensity-score estimator where overall treatment effect is the weighted (by the number of treated) average of the block-specific treatment effects[59]. The procedure consists on using the (estimated) propensity score, divide the sample into M blocks of units of approximately equal probability of treatment[60], J_{im} be an

[59] Blocking may be considered as a non parametric method.

[60] Under normality it has been shown that five blocks are enough to remove at least 95% of the bias associated to one covariate, reasoning could be extended to the propensity score (Imbens, 2004).

indicator for unit i being in block m. The average treatment effects (ATT) in each block and the estimated overall treatment effect are defined as:

$$ATT_m = \frac{1}{N_{1m}} \sum_{i=1}^{N} J_{im} * T_i * Yi - \frac{1}{N_{0m}} \sum_{i=1}^{N} J_{im} * (1 - T_i) * Y_i \qquad (7)$$

$$ATT_{block} = \sum_{m=1}^{M} ATT_m * \frac{N_{1m} + N_{0m}}{N} \qquad (8)$$

Finally, in all cases asymptotic variance is estimated by using bootstrapping. Bootstrap leads to valid standard errors -and confidence intervals- specially when there is limited overlap in the covariate distribution of the two treatment groups: the smallest the overlap, the higher the variance.

V.2. Non parametric model: Kernel Regression

We attempt a non-parametric estimate of the average treatment effect that has the advantage of avoiding constraints related o the distributional formsof the data. The simplest non-parametric methods are the kernel density and the kernel regression. One shortcoming of kernel regression is that weights are not necessarily symmetric which may lead to bias in the estimation of the ATT. For instance, if the data are decreasing toward the right boundary all y-values used in the weighted sum to obtain the average treatment effect are, most likely, greater than the value of the outcome at the fit location resulting in a too high (biased) prediction of ATT.

For this reason, we use a local polynomial fit to that consists on weighted least squares to fit a dth degrees polynomial to data[61].

$$\underset{\beta_j}{Min} = \left\{ \sum_{i=T_i=t} Y_i * \sum_{j=0}^{p} \beta_j * (X_i - x_0) \right\}^2 * K_h * (X_i - x_0) \qquad (9)$$

Which is a weighted least squares regression with weights equal to $K_h * (X_i - x_0)$.

V.3. Sample size and exclusions

We make no exclusions to the sample except the students who were not obliged to take the HSCT. However, there are two underlying processes which force the reduction in the sample

[61] Kernel regression is a special form of local polynomial regression in which d=0. Bandwidth choice is reported in Table A-41.

size as reflected in Table 23. A first process is associated with the individuals who are enrolled in 7th Grade but do not take the HSCT in 10th Grade. There are two "types" of students in this group: one integrated by the ones who drop- or move-out before the treatment could be observed and, a second one which has information for treatment but do not take the HSCT. The first group is not considered for the estimation. The second group (N=548) is also eliminated even though the t-test on observables characteristics confirm that students are statistically different from the ones remaining in the sample (specially, in terms of parents' education) the size does not represent a threat in power- and bias-wise.

A second process is associated with students who take the HSCT but do not have information on prior achievement. This group is again integrated by two categories: one has information on treatment so they join the NC Public school system after 7th grade and the other that do not have information for either treatment of prior achievement. The first subgroup, students who have both HSCT score and treatment information, is again statistically different from the group who has full information (lower parents' education). Given the relevance of prior achievement in explaining HSCT scores, we discarded this group as well.

Table 23
Observed Non-Random Selection Processes

7th Grade Score	Treatment Algebra 1	10th Grade = Take Exam		Outcome= HSCT scores	Distribution	
Prior Achievement						
Yes	No	No	Drop/Move	Unobserved	22444	0.58
Yes	Yes	No	Drop/Move	Unobserved	548	0.01
No Prior Achievement						
No	Yes	Yes	Take Exam	Observed	5368	0.14
No	No	Yes	Take Exam	Observed	10557	0.27
Total					38917	1

Note: *Students either have 7th Grade or HSCT Math score observed.*
Source: *Elaboration based on NCPSDB.*

Summarizing, the sample -depicted in Table 24- utilized to estimate the impact of treatment fulfills two conditions: a) there is enough information to build the treatment status and b) the student has some information of previous achievement and the HSCT scores.

Table 24
Sample Sizes

Cohort HSCT	Number of Students		
	Total	With 7th grade scores*	Final Sample**
2003	88852	64596	24001
2004	92804	68821	46476

Notes: ** Information on 7th grade scores is available;*
***Students both took Algebra1b in 8th or 9th grade and did not take Pre-Algebra or Algebra 1A.*
Source: *Elaboration based on NCPSDB.*

V.4. Treatment of Missing Data

Missing observations could be a big problem in research design as they may problems in terms of loss of power and, potentially, bias. The proportion of missing for explanatory variables is never above 5% of the sample -Table A-33- so it does not represent a problem in terms of power. The only threat would be bias, if data is not missing at random (MAR). Table A-34 reports that the differences between missing and not missing sample is significant for a p-value <0.005 only for parent's education.

We use a missing dummy indicator for dealing with observation that have missing values for some of the explanatory variables. The "missing dummy" imputation methodology may lead to biased estimates of coefficients and under-estimation of the standard errors (Jones, 1996) when the percentage of missing values is above a threshold of 5% of the sample. Given that the percentage of missing values in our sample is below that level[62] we decided to pursue with this method[63]. To reduce the problems associated to this technique and, based on the correlation between 7th grade scores and previous years (around 0.7 and 0.8 and always significant per Table A-7), we control only for 6th and 7th scores[64].

V.5. Software

Estimation was conducted in STATA 10 (StataCorp. 2007. Stata Statistical Software: Release 10. College Station, TX: StataCorp LP) and use the atts, pscore, psmatch2, nnmatch and locpoly packages

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[62] Cohen (1985) argues that these two risks are minimum when missing are under 5% of the sample which is the case in our sample.

[63] We follow the standard procedure. As a first step, a "missing dummy" variable was created for each variable with missing regardless of whether a variable was continuous, categorical or dichotomous. The "missing dummy" variable was set to 1 if information was missing on that variable and it was set to 0 if data were not missing.

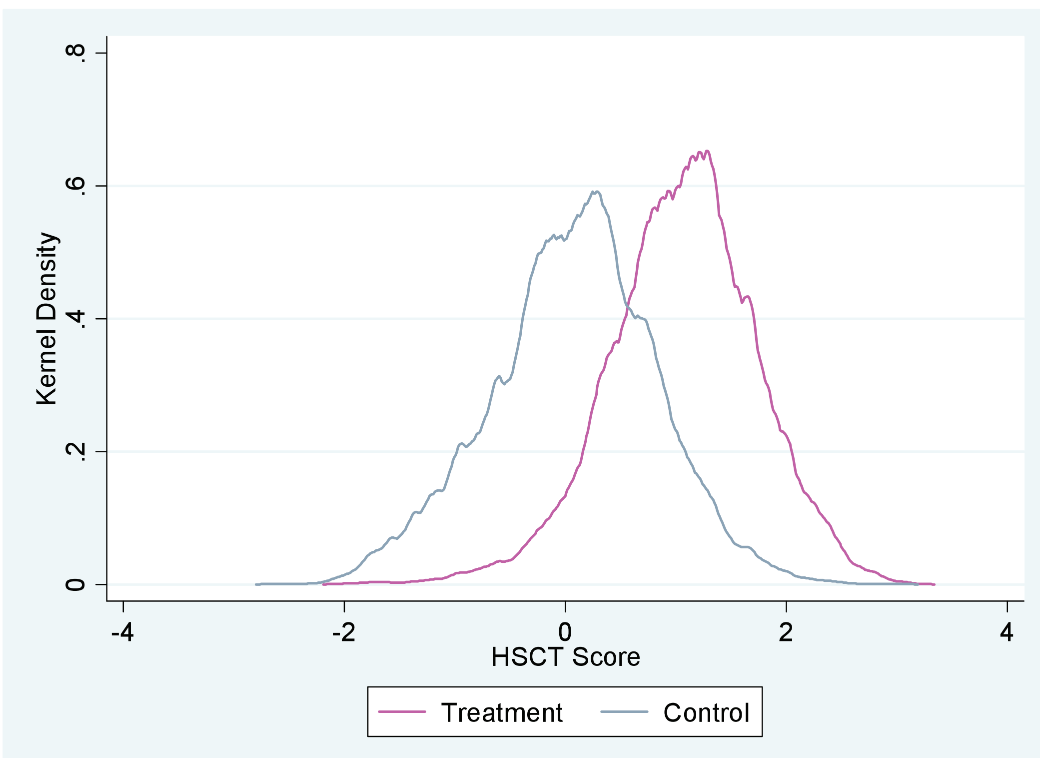
[64] See Table A-30 for correlations.

VI. Results

Figure 11 compares the distribution of the standardized scores in the math section of the HSCT of treatment and control group. The distributions of scores of both groups differ substantially. The raw differences reflected in Figure 1 are only a starting point. We do not know is students who belong to the control and treatment group differ in their background characteristics and/or in prior achievement. In other words, we do not know the existence and relevance of the selection bias.

The most basic premise of our analysis is that, all other things being equal; those exposed to the treatment should have on average higher score in the math section of the HSCT in tenth grade. So in a second step we explore the characteristics of treatment and control group and assess their comparability.

Figure 11
HSCT Scores by Treatment Status

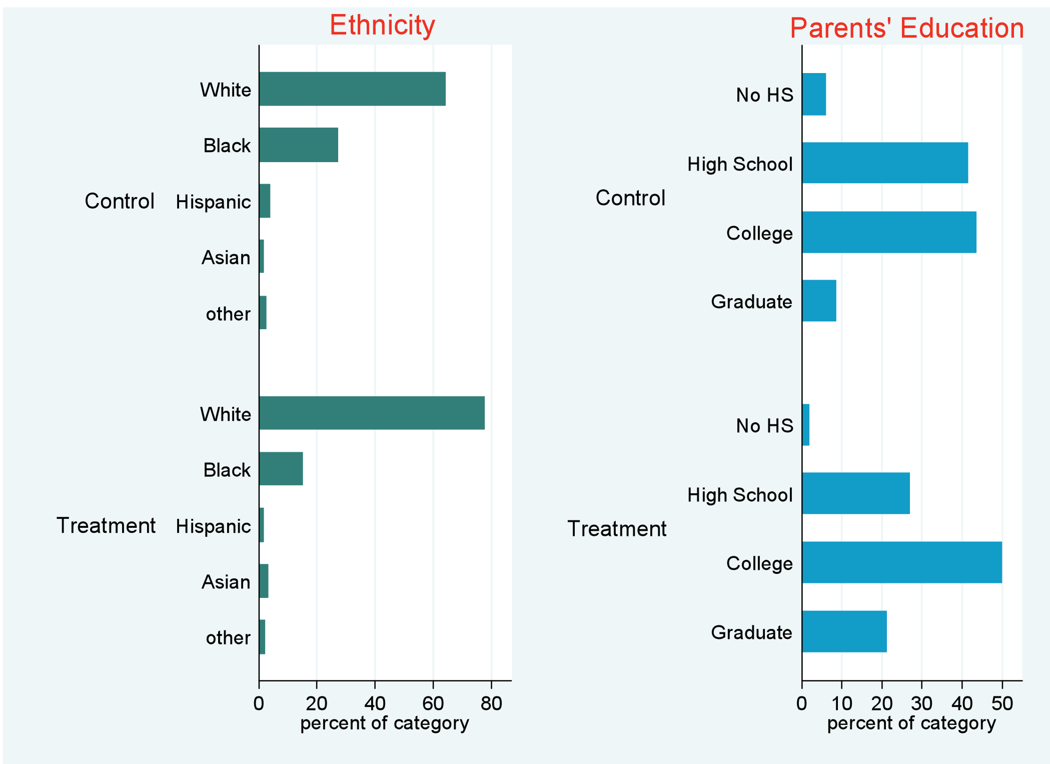


Note*: A Kolmogorov-Smirnov test for equality of the distribution functions was run. The two distributions are not drawn from the same sample for a p-value <0.001*
Source: *Elaboration based on NCPSDB.*

VI.1. Who takes Algebra 1 in 8th Grade?

Students who take Algebra 1 in 8thGrade differ in various background aspects form the 9th Grade Takers. Figure 12 shows that African Americans and Hispanic students are under-represented in this group. Moreover, students who took Algebra 1 in 9th grade have lower SES (proxied by parents' highest educational achievement) as well. The opposite results hold for those who took algebra in eighth grade: prior test scores and SES are at their highest levels with high proportions of Whites and Asian Americans.

Figure 12
Who takes algebra 1 in 8th and in 9th grades?
Ethnicity and Education

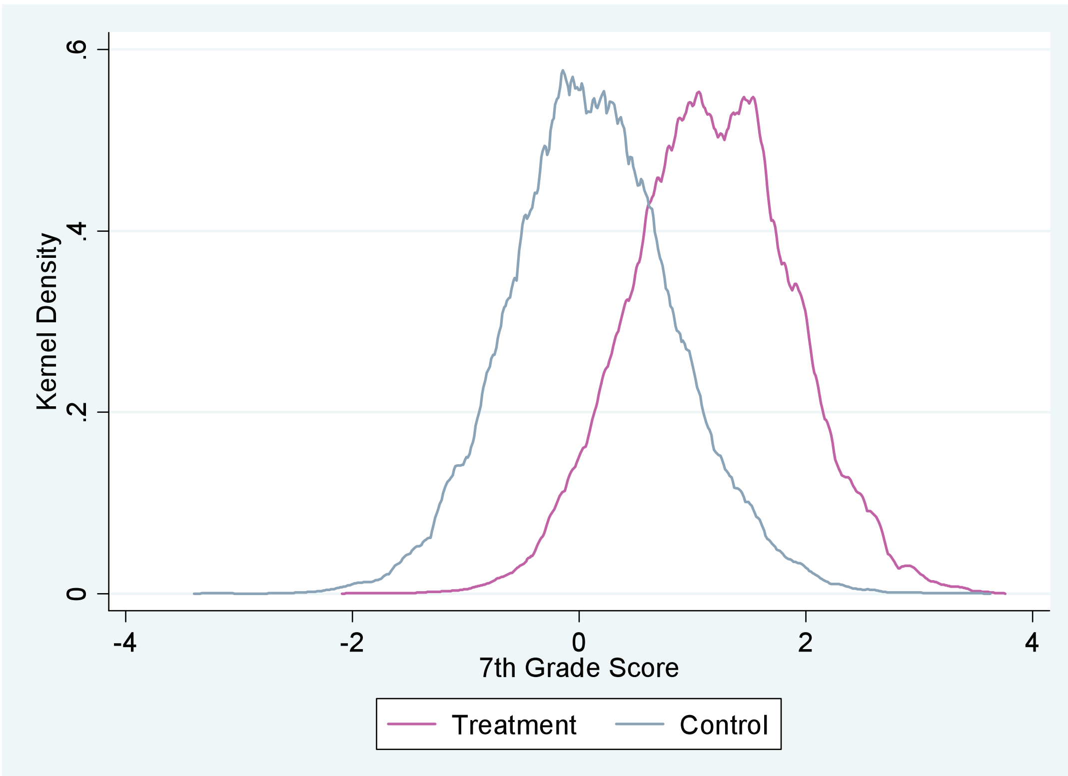


Note: *t- tests of the variables are significant for a p-value<0.001.*
Source: *Elaboration based on NCPSDB.*

With respect to prior achievement the control group is skewed to the left and, thus, located to the left of the treatment group as Figure 3 reflects: treatment group have higher scores in the 10th grade exit exam but hade better scores in 7th grade. This last finding confirms the existence of selection bias and the need to deal with it. Synthesizing, the control group is integrated by students who have lower prior achievement, lower SES and are likely Black or Hispanic while White, Asia, higher SES and higher achiever are most of the treatment group. All

in all, these results suggest the existence of selection bias at the student level and the invalidity of comparing outcomes without adjusting by the different composition of treatment and control groups. These findings are consistent with previous research (Attewell and Domina, 2008; Burris et al, 2006; Gamoran and Hannigan, 2000)[65].

Figure 13
Who takes algebra 1 in 8th and in 9th grades?
Prior Achievement



***Note**: A Kolmogorov-Smirnov test for equality of the distribution functions was run. The two distributions are not drawn from the same sample for a p-value <0.001*
***Source:** Elaboration based on NCPSDB.*

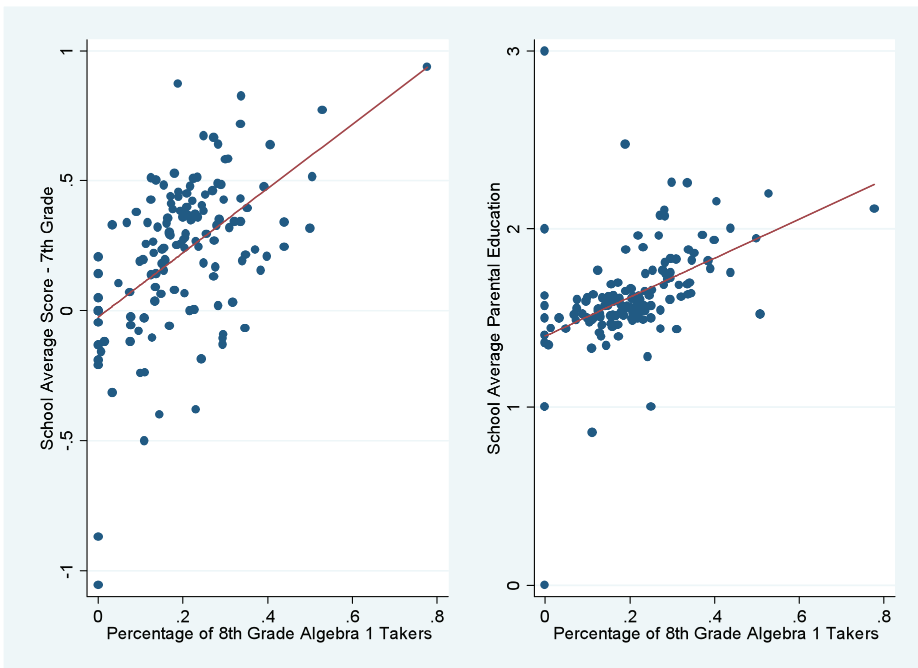
When the analysis is extended to the contextual variables there is no difference between treatment and control group (see Table A-35 for details) but the level and composition of spending; students in the treatment group go to schools in districts that have a larger share of local resources for their educational budget that might be, eventually, related to wealthier communities.

[65] The results of the selection equation and the marginal effects are in Tables A-36.

VI.2. Do schools differ in intensity of treatment?

Schools may differ in treatment intensity. It might even be the case that a school does not offer the possibility of enrolling in Algebra 1 in 8th Grade. Nevertheless, this is a highly improbable scenario given the encouragement schools have had in the last decades to enroll children in Algebra 1. Schools differ in the proportion of children they enroll according: intensity in treatment is positively associated with school average score in standardized score in 7th grade and with average parents' education (Figure 14). Schools that appear to be more aggressive in terms of placement are, thus, likely to attend groups which are better prepared to succeed.

Figure 14
School Treatment Intensity and Average 7th Grade Math Score



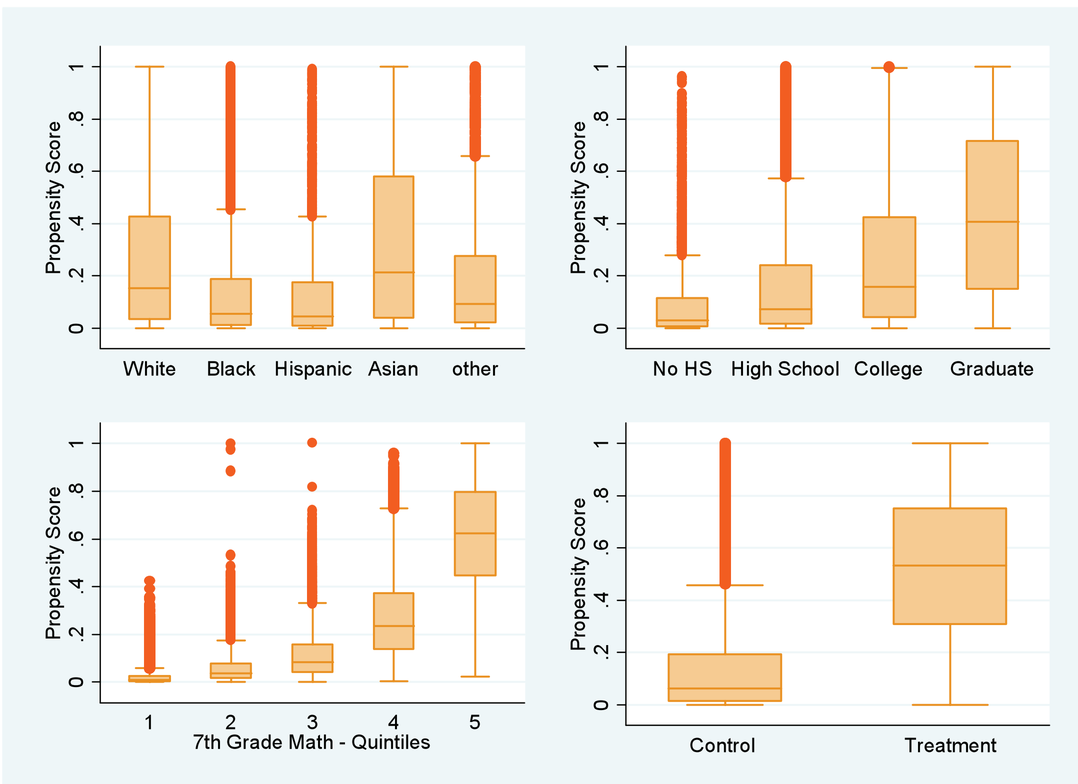
Source: *Elaboration based on NCPSDB.*

VI.3. Probability of Treatment: The propensity Score

The propensity score, or the probability of participating in the treatment, synthesizes all the characteristics that influence treatment status in a single score. Figure 15 confirms that the index differs dramatically by selected characteristics: the likelihood of enrolling in Algebra 1 in 8th Grade is higher the higher the SES and the higher the level ability (measured by prior achievement). Black and Hispanic students have a lower probability of participating in Algebra 1 in 8th Grade compared to more affluent, White and Asian students. The odds ratio of taking the treatment detailed in Table A-36 are very illustrative: a 1-SD increase in early grades math

achievement triples the probability of participating in Algebra 1 in 8th grade. Initial math ability appears more important in access to demanding courses than initial reading ability. Likewise, the probability of enrolling in Algebra 1 in 8th grade increases with parental education: a student whose parents attended graduate school has twice the probability of enrolling in Algebra 1 in 8th grade (and of taking advanced mathematics courses beyond Algebra 2) than an individual whose parents did not finish high school. Nevertheless, we found a relatively surprising result: once controlled for background and prior achievement Black students are more likely to enroll in Algebra 1 in 8th grade than White students, evidence that coincides with previous findings reported by Attewell and Domina (2008:54).

Figure 15
Propensity Score by Selected Characteristics and Treatment Status



Note: *The line in the middle of each box is the median of the propensity scores for that group. The top and bottom of each box represent the 75th and 25th percentiles, respectively. The distance between the upper and lower box sides and the upper and lower lines is 1.5 times the interquartile range of the farthest point, whichever is closest. Circles represent outliers.*
Source: *Elaboration based on NCPSDB.*

Figure 15 lower right hand side highlights that extrapolation will be difficult in both extremes of the propensity score distribution as long as there is no much overlapping between

the treatment and control group distribution. Control and treatment group not only differ in the median but 75% of the control observations do not overlap the treatment control group. In the absence of intersection, there is no real comparison as there are no "similar" students to compare.

VI.4. What is the effect of taking Algebra 1 in 8th grade?

The impact of "treatment", without accounting for selection is substantial: almost one standard deviation on the outcome. When prior achievement is included the size of the effect reduces to a fifth of a SD and does not change much when contextual variables are included as controls. The results of a series of propensity score algorithms used to assess the impact of treatment suggest that, *on average*, the effect is positive and statistically significant. Enrolling in Algebra 1 in 8th grade contributes positively to achievement in the HSCT but only in a range of 0.15 to 0.20 SD of the standardized HSCT math score.

Table 25
Average Treatment Effect
Effect Sizes

Covariates Included in the Model	**OLS**	**Propensity Score**		
		Kernel Matching	**Nearest Neighbor (1-to-1)**	**Blocking**
Empty – No Covariates	0.99 *(0.01)*	0.99 *(0.01*	0.99 *(0.01*	0.99 *(0.01*
Individual and Family	0.86 (*0.006)*	0.87 (0.03)	0.81 *(0.028)*	0.81 *(0.028))*
Individual, Family and Prior Achievement	0.19 *(0.005)*	0.16 *(0.009)*	0.158 *(0.009)*	0.164 *(0.007)*
All Covariates	**0.19** ***(0.005)***	**0.16** ***(0.011)***	**0.16** ***(0.01)***	**0.169** ***(0.008)***

Note: *Bootstrapped standard error in parenthesis.*
Source: *Elaboration based on NCPSDB.*

It is interesting to note that results from different algorithms are almost the same[66]. The smallest average absolute error is attained using stratification matching or blocking whereas algorithms that use a larger distance (kernel and nearest neighbor) produce smooth results with larger errors on average[67]. Thus, the Kernel matching estimator exhibits larger error than nearest neighbor algorithm.

[66] In the blocking algorithm, the propensity score was stratified in five blocks of individuals with balanced covariates with the aim of eliminating some of the imbalances.

[67] This occurs, partially, due to the presence of fewer individuals who have matches as the distance decreases.

VI.5. Do all students benefit from taking algebra 1 in 8^{th} Grade?

The former results not, however, indicate whether *all students* benefit similarly from enrolling in Algebra 1 in 8^{th} Grade. In general, the propensity score does not work very well if almost everyone with a high propensity score gets treatment and almost everyone with a low score does not: it is necessary to find and compare people with similar propensities in both states. From Figure 15 we know this is very likely for some sub-groups: low prior achievers, low parental education children, Black and Hispanic.

As a first way to approximate heterogeneity, we study the effect of treatment per decile of the propensity score distribution. Table 10 report the estimates the average treatment effect sized by decile of the propensity score distribution. Achievement gains vary over deciles ranging from no gain (given the significance of the SE) in the first two deciles of the propensity to gains of around 0.20 SD of the standardized score of the math section of the HSCT in the third to eighth quintile of the propensity score distribution[68].

Nevertheless, there are at least two issues that demand a caution analysis. First, 15% of the sample is lost due to the lack of match (or mismatch) between treatment and control units along the propensity score distribution. These losses are unevenly distributed as Table A-13 shows: too many control observation do not find math in the lowest part of the propensity score distribution and too many treated individuals do not encounter control observations to math them in the upper deciles. Second, even when match is possible as the propensity score are within the caliper there are still issues related to the unbalances in the characteristics of treatment and control groups as Table A-38 in Appendix 4 exhibits. Furthermore, the only case in which the characteristics of the control and treatment group are balanced is the average student. All together these findings confirm that more work needs to be done to properly control for selection bias.

The local polynomial fit of the data under two alternative distribution forms, Gaussian and Epanechnikov, are depicted in Figure 16. Results, consistent with the ones presented in Table 10, confirms the findings of other studies suggesting that prior low-achieving students do not benefit from more intensive curriculum. Moreover, gains in test scores are stable in around 0.15 - 0.20 of a SD from except for the first quintile of the PS. Table 25 and Figure 16 might

[68] Table A-37 depicts the distribution of on- and off-support observation per decile of the propensity score.

build the case for ceiling effects in high score students (Attewell and Domina, 2008: 55; Gamoran and Hannigan, 2000: 248).

Table 25
ATT by Deciles of the Propensity Score

PS Decile	Effect Size	Number of Units*	
		Control	**Treatment**
1	-0.53		
	(0.22	**705**	**14**
2	-0.03		
	(0.14)	**5924**	**45**
3	0.16		
	(0.08)	**5548**	**129**
4	0.17		
	(0.05)	**5980**	**265**
5	0.18		
	(0.03)	**6151**	**526**
6	0.17		
	(0.03)	**5756**	**1005**
7	0.17		
	(0.02)	**5137**	**1637**
8	0.19		
	(0.02)	***4139***	**2694**
9	0.20		
	(0.01)	**2816**	**3860**
10	0.11		
	(0.02)	**1388**	**4973**

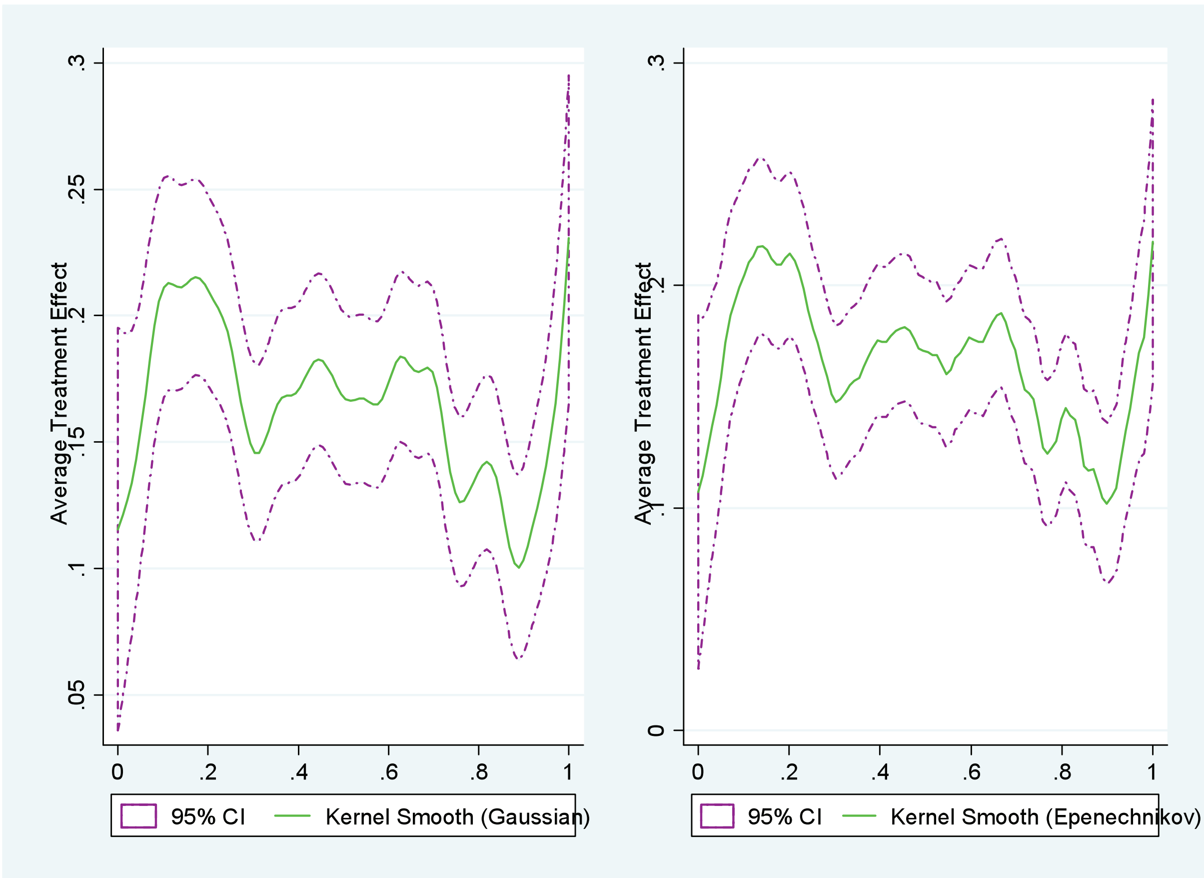
Note: *Bootstrapped standard error in parenthesis. Nearest Neighbor Algorithm*
****On Support:*** *are the observations that have matches in the non treated group whose propensity scores within a region of +/- 0.005 of the value of the propensity score of the treated observation.*
Source: *Elaboration based on NCPSDB.*

In order to asses if the previous results imply the identification of causal effect of our treatment we run a falsification test consistent on estimate of the impact of our treatment on the reading score of the HSCT. A zero impact would imply that the 0.17SD effect size we have found is meaningful. Nonetheless, the estimates yields a value of 0.056 (SE: 0.01) for the average student utilizing the nearest neighbor matching algorithm[69]. The "final" effect size would then be lower that the one reported in Table 24: 0.17SD – 0.056SD. Thus the "true" treatment effect is around 0.10SD of the HSCT math score. Two alternative explanations might be adequate. The effect on reading reflects some "spillovers" from being assigned to the

69 This is different from zero for a p-value of <0.001.

advanced track in math that is not observed[70] and/or, selection bias is different for math and reading (and, we are not controlling properly the confounding factors).

Figure 16
Kernel Regression - ATT
Nearest Neighbor Algorithm



Source: *Elaboration based on NCPSDB.*

Finally, in Figure 17[71] we examine whether the ATT is homogenous across subpopulation groups. Results show slight differences across race/ethnicity, gender and parental education. Effects are always below the 0.30SD.

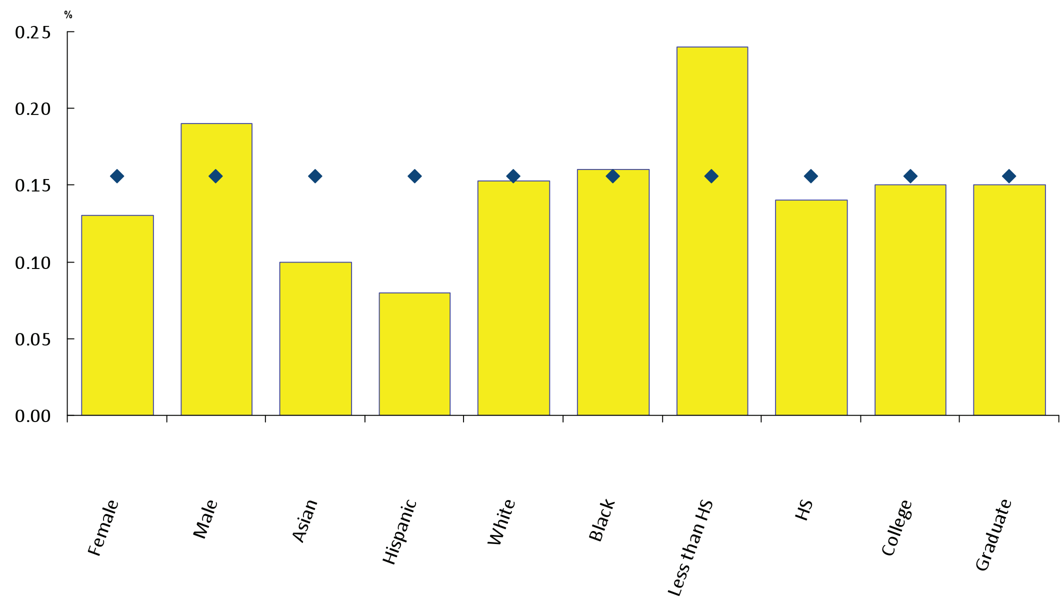
Our findings suggest that previous policy interpretations are both too optimistic and too pessimistic. They are too optimistic regarding the achievement gains derived from taking Algebra 1 in 8th grade given the modest size of the achievement gains for the average student.

[70] This might happen due to peer effects, or tracking in English, Literature (or other subjects) facts that we are not able to observe.

[71] See Table A-40 to check standard errors.

Previous findings are also too pessimist regarding the harm that early placement in Algebra 1 might have on minorities though we did not ruled out the possibility that some students are harmed. Our finding stress out two findings: most of the selection happens before 8th grade and the effect of treatment is positive but small for the students who are in the middle of the score distribution prior to 8th grade.

Figure 17
Heterogeneity in ATT
Nearest Neighbor Algorithm



Source: *Elaboration based on NCPSDB.*

VII. Discussion

Public interest in upgrading curricula and changing graduation requirements have two opposed forces behind. On one side, equality defenders support the idea of non exclusion from access to more demanding high school courses which has been occurred since the beginning of the high school more than a century ago. Moreover, arguments about the concentration of human and financial resources in some segments of the society might harm children coming from disadvantaged households. On the side, efficiency defenders highlight the gains associated to teaching homogenous groups and point out that that not all students are prepared to succeed in Algebra 1 in middle school.

In this paper, we addressed three questions concerning the effect of a treatment, taking Algebra 1 in 8^{th} grade, on the math section of the HSCT. First, do students who participate in the treatment differ from the ones who do not? Second, does the treatment increase student achievement on average? Third, does treatment have varying effects on achievement depending on the initial level of class ability or student ability?

Our findings indicate that there are statistically significant differences between the students who enroll in Algebra 1 by grade. These differences are associated with SES (proxied by parental education) and race/ethnicity: we find that White, Asian and high-SES students are overrepresented in the groups that enroll in Algebra 1 in 8^{th} grade. Due to the fact that Black and Hispanic students are overrepresented among low-educated parents, students of these races are over represented among Algebra 1 ninth-grade takers. Our most relevant finding related to differences in background between treatment and control groups is that the strongest predictor of students' enrollment in 8^{th} grade is ability (measured by prior academic achievement). Therefore, studies that do not properly control for prior achievement are very likely facing serious omitted variable bias issues.

Do these differences in enrollment have consequences on HSCT outcomes?, Using a propensity score matching methodology, we found that enrollment in Algebra 1 in 8^{th} grade is associated with higher test scores. However, this effect of the treatment is, though statistically significant, small in size: around 0.15-0.19 SD of the HSCT math score, depending on the controls and the algorithm employed. After a falsification test was run the ATT is even small and around 0.10SD.

We do not find evidences that the benefits for the average student from taking Algebra 1 in 8th grade is stable across sub population groups classified by either prior ability or students' background. The "benefits" of the treatment on HSCT scores could be not existent or, even, negative for students at the lower end of the propensity score distribution and, might be eventually very large for the ones in the upper side of the propensity score distribution.

Overall, the results suggest that policy interpretations drawn from earlier research were excessively optimistic: average effects are smaller in size and not consistent across sub-groups of the population. Moreover, the selection happens before 8^{th} grade as long as the students who did not enroll in Algebra 1 in 8^{th} grade belong to minorities and disadvantaged groups in terms of

parental education. Our findings raise some warning flags about the potential "benefits" of enrolling all students in Algebra 1 in 8^{th} Grade. Although we can not affirm that the most of the students who enroll in Algebra 1 in 9^{th} grade would fail if they enroll before, this is very likely scenario.

This paper does not analyze curricular content in detail. Courses may have the same name and still differ in complexity depending on the grade the course is taken and the school district. Another limitation is that although, in all cases the propensity score appears to have removed much of the selection bias imbalances persisted.

In general, the findings of this study do not provide definitive answers to the debate about *detracking a*nd curriculum upgrading. Results do not provide support to the claims of many educators who have been reluctant to increase demands on high-school students arguing lack of readiness of most of them but urge to explore with more depth the characteristics of schools, the school and classroom practices to avoid generalizations.

Methodologically, the main threat to the modeling strategy adopted is the lack of control for unobservable characteristics. We did not control for unobserved factors which might have influenced the outcome such as student's motivation and effort, parental styles and teacher's expectations that affect both group placement and math achievement. Some bias may occurs due to measurement error from two sources. The first one is teacher's reported parents' education as long as some studies show some bias on teacher towards overestimating the level of education of White parents and underestimated the level of education of Black and Hispanic parents. The second source of error comes from the students' academic self-reported history (use to build the treatment variable) that may be introducing some noise in the results.

Finally, we can anticipate many lines for further research. First, it would be good, in terms of inference, to control for unobservable factors that could influence students' outcomes. Second, although this research contributes to the current debate about the timing for Algebra 1, the analysis could be enriched by extending it to other outcomes such as scores in 12th grade and completion and/or drop-out rates.

Chapter 4: Decomposing the Racial Achievement Gap

I Introduction

Racial achievement gap has been at the center of the educational debate for decades. Current beliefs that test scores are associated with later labor market outcomes have supported policy initiatives, most notably the No Child Left Behind Act. Despite the reduction in the gap in the seventies and the eighties, this trend has halted, and even, reversed. Recent evidence from the labor markets confirm that the picture has not changed that much in the last two decades; the December 2009 report of the Bureau of Census statistics reveals that unemployment among Black workers almost double the unemployment figure for White workers in the same period, reproducing the ratio of unemployment rate by race that was observed in the early eighties for the whole country (The Economist, 2009: 34)[72].

A large number of studies have focused on the White-Black achievement gap in terms of educational outcomes as well as labor market outcomes. Some branch of the empirical literature has focused on different dimensions including the size of the gap, the role of school resources, its evolution through time and its variation across states. For example, Neal (2005) explores the evolution of the achievement gap over time while Clotfelter, et al. (2006) follow one cohort in North Carolina from grade 3 to grade 8 and Hoxby (2000) and isolate the impact of peers on child's outcomes.

This paper aims to provide additional insight into the study of racial achievement gaps by also considering the White-Hispanic gap in addition to White-Black one. The paper explores the causes underlying the gap utilizing some methodologies conventionally used to address labor market outcomes. With a descriptive analysis, we attempt to estimate the extent to which differences in achievement relate to differences in parental education and whether within- or between-school factors are more powerful predictors of racial disparities in educational outcomes.

We estimate an educational production function in order to isolate the effect of different characteristics on student scores, using the North Carolina Public Schools Database. Regression results are used to decompose the gap using various methods. First, total gap is split into

[72] Unemployment rate among Black was in November of 2009 16% o the Labor Force in contrast to the 10% among White workers.

between- and within-school components using the method proposed by Page et al. (2008). As an alternative we extend the Oaxaca-Blinder and Juhn-Murphy-Pierce decomposition (ordinarily utilized to explain racial or gender wage disparities) and break down the gap into the effect due to dissimilarities in characteristics and due to differences in the returns to those characteristics. As a last step, a simulation of Hispanic scores using White student returns show that although the gap does not fully disappear, it significantly decreases. We carried out simulations which consisted of applying Hispanic or Black characteristics to the "White educational production process". In both cases, the simulated distributions are positioned to the right of the original ones.

Our analyses provide three key results. This study provides three key results. First, within-school factors continue to explain a substantial portion, of the gap between White and Hispanic students' test scores. Second, parental education is the most important individual factor; White students have, on average, better educated parents and get a higher return on parental education. In other words, Hispanic and Black experience a much lower return to their background characteristic than their White peers. This disadvantage is deeper for Black students. Third, in line with prior research on the filed, the achievement gap narrows from grades 3 to grade 10.

The analysis does not support causal inference, but examines some selected characteristics of students and their peers and how they influence the achievement gap. Our results do not shed light on the causes of the differential education process and how the educational production process differ between races to which factor they could be attributed those differences in "return". More precisely, we can not explain whether the causes are related to differential parental styles, the schools the child attend and/or the neighborhood families live in.

Following the introduction, this paper is organized as follows. Section 2 briefly presents the background and motivation for the study. Our research questions and hypotheses are described in Section 3. Sections 4 and 5 describe the Data and the Methods for the study, respectively. In Section 6, all three decompositions are performed. Finally, the last section summarizes the main results.

II. Background and Motivation

The achievement gap between Black and White students narrowed for two decades between 1970 and the beginning of the nineties (Cook and Evans, 2000:730). This trend has been consistent regardless of the metrics and/or the test considered. For instance, measured by NAEP, the achievement gap declined by 34%, 54% and 60% for 9, 13, 17 year old students respectively during that period (Vigdor and Ludwing, 2007).

Most empirical work agrees that the main driver for the gap reduction has been Black student improvement with respect to White student achievement that has remained stable over this period. More specifically, improvement in relative Black achievement is explained by two trends. The first one is the convergence in family characteristics (convergence in the level of education of Black parents to the White parents). The second is the convergence in the quality of schools attended by Black and White students. This second factor has been associated with policies that relocated resources toward high-minority, segregated schools and to the desegregation efforts following court mandates during the seventies and eighties.

Unfortunately this reduction in the achievement gap stopped in the late nineties and has potentially starting to rise again (Neal, 2005; Neal 2007). Despite the efforts to desegregate schools in the previous two decades, government policies have failed to integrate schools and the trend has reversed by the beginning of the 21s century (Vigdor and Ludwig, 2007: 4). The response to mandatory desegregation has been relocation of families and school re-segregation (e.g., ability grouping, honor courses). School choice has played a role in facilitating the reversion as well. Some studies have also found that in the eighties, families moved out of neighborhoods when the schools in their geographical areas had started to become more diversified. Thus, some families (more likely affluent and White) relocated in order to avoid increasing integration in their neighborhood schools.

Since Brown vs. Board, the implicit assumption is that school racial segregation contributes to Black-White inequality in student outcomes (Vigdor and Ludwig, 2007). This was basically the philosophy underlying the Coleman Report (1966). School segregation (fostered by re-segregation practices) has stopped the decreasing trend in the achievement gap. However, in the hypothetical case that school had followed neighborhood segregation trends, the racial gap would have declined in around 0.01 SD to 0.02 SD of the scores distribution. In terms of the total

gap (0.7SD/1SD) the reduction would have been almost zero. (Vigdor and Ludwing: 2003:20) find that, despite the higher correlation between race and SES the two factors, socio-economic school composition is more important than racial composition

From the methodological point of view, the main problem in isolating the impact of racial segregation is non-random selection into schools (or neighborhoods). Three big strategies have been used in the empirical literature to tackle this problem. The first one is the use of within-school variation in minority exposure. Hoxby (2000) uses Texas administrative data and identifies variation comparing adjacent cohorts in terms of gender and racial makeup?. Hanushek et al. (2002) utilize the idiosyncratic components of each group and determine whether the components are correlated. A second type of strategy identifies the effect of racial composition using experimental and quasi-experimental variation. For instance, Sanbonmatsu (2006) finds that neither neighborhood nor school racial segregation play a role in explaining the racial gap in the Moving to Opportunity experiment (MTO). Guryan (2001) studies the impact of desegregation on high school dropout rate between 1970 and 1980 using a difference-in-difference strategy and found that while dropout rates of blacks declined by one to three percentage points, desegregation plans had no effect on the dropout rates of whites. A third type of strategy is the aggregation to the city- or county-level to later compare areas with different levels of racial segregation. Cutler and Glaeser (1997) use disaggregation and exposure indexes to isolate the impact of racial segregation on student outcomes. Card and Rothstein (2006), alternatively, aggregate the information to the metropolitan level and relate the black-white achievement gap in a metropolitan area to Black-White differences in exposure to minority neighbors and schoolmates. In this case, differencing eliminates the effect of city-wide variables that may be correlated with racial segregation adding other variables as controls (city size and income inequality for instance).

A second methodological issue is the sensibility of results to the methodology. Sometimes, authors find the opposite conclusions regarding which is the most important source of variation in student outcomes using the same database. For instance, Hanushek and Rivkin (2006) argue that between-school variance is the dominant explanation for the Black-White achievement gap while Fryer and Levitt (2005) argue in favor of within-school variance using the same data (ECLS-K), but different methodologies.

Potential heterogeneity along the scores distribution has been ex-lored and tackled with the introduction of an indicator variable for student position in the achievement distribution. Alternatively, some empirical research addresses heterogeneity by centering the analysis in some particular groups such as the low performing students, or students in highly deprived areas for instance while other studies offer a detailed analysis of the low performing group. Clotfelter et al. (2006), for instance, found that the black-white score gap in math narrowed at the low end of the distribution but widens at the high end. Math gap is in general smaller than the reading gap, as it is associated with the re-distribution in favor of low performing kids in schools. Clotfleter et al (2006), for instance, found that the Hispanic-White achievement gap has been slightly smaller than the White-Black one (Clotfelter et al, 2006: 11) and recognize that the policy issues for both racial groups differ.

III. Research Question and Hypotheses

In this study we address the following research questions and hypotheses:

Research Question #1: To what extent are gaps attributable to between- and within-school differences?

Hypothesis: Most of the variation in achievement comes from within-school variance.

Research Question #2: How much of the White-Hispanic achievement gap can be explained by racial differences in parental socioeconomic status?

Hypothesis: White and Hispanic students differe dramatically in terms of level of parental education

Research Question #3: Does the relative importance of factors that affect achievement gap change as students progress through their education?

Hypothesis: Within-school variation does not change or increase as Hispanic students progress through education.

Research Question #4: Do level and return effects due to parental education have the same affect on achievement gap?

Hypothesis: The level of parental education exceeds the return effect to parental education as explanatory cause of the achievement gap.

Research Question #5: Does the analysis change when the whole distribution of residuals is taken into account?

Hypothesis: The distribution of unobservables, such as motivation and innate ability, does not dramatically affect the achievement gap.

IV. Data

The State of North Carolina has the 11th largest public school system in the country. Although African Americans are the largest minority group more important minority, there is a well diversified student population with a significant share of Hispanic, Asian and Native American children in the student body. We employ administrative data of students in North

Carolina Public Schools housed at the North Carolina Education Research Data Center (NCERDC) at Duke University. The databases contain students' demographic information, characteristics of the teachers, the schools and the districts and the courses each student has taken, and whether the course has an End of Grade (EOG) or End of Course (EOC) test at the end of the academic year. Using unique student identifying numbers, we matched records over time.

To facilitate comparison across years, we use standardized test scores for each test over all students so each test has a mean of zero and a standard deviation of one. For this paper, we use the group of students who took the High School Comprehensive Test (HSCT) in 2004 and look at the achievement gap in 3rd and 10th grades. Nevertheless, two alternative cohorts could be built. The first one, the intact cohort (that follows Clotfelter et al. (2006) criteria) is composed by the students who have test scores for all grades[73][74]. The second cohort includes all the students who were in 3rd grade in 1997 and all students who took the HSCT in 2004 regardless of when they started. Given that the sizes of the students who move from grade 3 to grade 10 are almost the same, it could be assumed that this second cohort represents a synthetic cohort which encompasses two groups of students: the "intact" cohort and a group of students who change from year to year because they move in and out of the state, the public school system and/or they repeat grades belonging to another cohort. We assume that these students are "like" the ones who started 3rd grade in 2004 and migrate for either reason. As we will see in the paper both cohorts differ markedly in the composition of the student body and the information they provide. While the first cohort (the intact cohort) only includes full observation students is unrepresentative of the public school system population, the second one (the complete cohort), provides a closer approximation of the achievement gap.

We first present an analysis for 3rd and 10th grades, for the two alternative cohorts (intact and complete) to give a general idea of the size of the achievement gap. The remaining analyses only include the 10th grade complete cohort, except when specifically specified that the two cohorts are included. Sample sizes for both, the intact and complete, cohorts are reported in

---

[73] Given the characteristics of the data set this implies that students have information on test score from 3rd to 8th grade and took the HSCT in 10th grade.

[74] We slightly differ from Clotfelter et al (2006) in the treatment of retained students who include the repeating students as the rates of retention are much higher between minorities than among White students.

Table 26. The means and standard deviations of the test scores and descriptive statistics for the explanatory variables are presented in Tables A-42 and Tables A-43. Table A-44 reports the correlation between explanatory variables and outcomes.

Table 26
Sample sizes

Grade	Intact		Complete	
	Reading	Math	Reading	Math
3rd			92595	92664
10th	51935	51817	89510	89471

Source: *Elaboration based on NCPSDB*

IV.1. Treatment of Missing Values

Missing values for student and school background variables are the main problem in the data. Table A-45 confirms that parental education has the largest problem in terms of missing values. Commonly, the whole observation corresponding to the student is dropped from the regression if the value of any explanatory variable is missing. This leads to a reduction in the number of observations that can be used for the estimations of approximately 3% of the sample, which would lead to sample selection bias if the values are not missing at random. A t-test of the two samples shows for a p-value that the observations lost correspond to students with lower scores (Table A-46). To avoid introducing an upward bias in the estimate and, given the percentage of missing is below 5% of the sample, we utilized a dummy for missing observations[75].

IV.2. The Racial Achievement Gap and the Distribution of test scores

The total reading score gap between White and other ethnic groups are shown in Figure 18. The difference in test scores between White and other ethnic groups has two distinctive features: the difference is always higher in absolute values for Black compared to the rest of the minority groups and is larger for the complete cohort (0.8 SD for Black and 0.6 SD for Hispanic, respectively - Figure 18, Panel B) than for the intact cohort (0.6 SD for Black and 0.50 SD for Hispanic - Figure 18, Panel A). This last result is not surprising if students who belong to the complete cohort are different in personal characteristics from the ones in the intact cohort. In general, the intact cohort has students who, faced some language difficulties at the beginning of

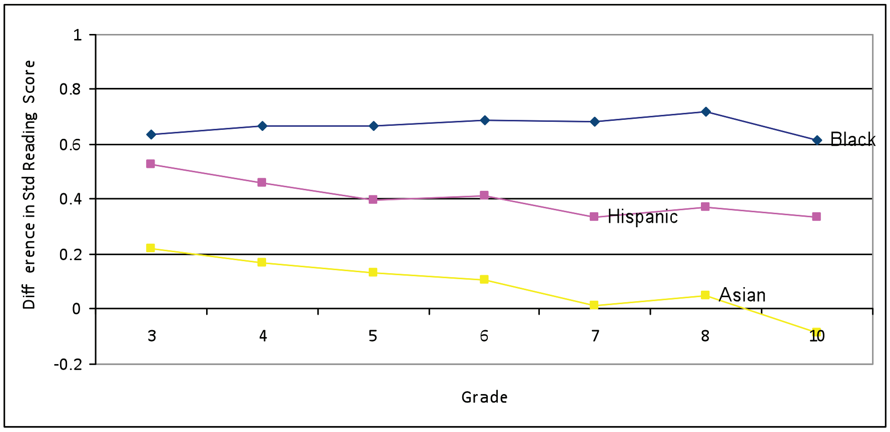
[75] We follow the standard procedure. As a first step, a "missing dummy" variable was created for each variable with missing regardless of whether a variable was continuous, categorical or dichotomous. The "missing dummy" variable was set to 1 if information was missing on that variable and it was set to 0 if data were not missing.

school (Hispanics), have already adapted by the 10th grade and acquired a level closer to White students. Further, the complete cohort is more affected for recent immigration.

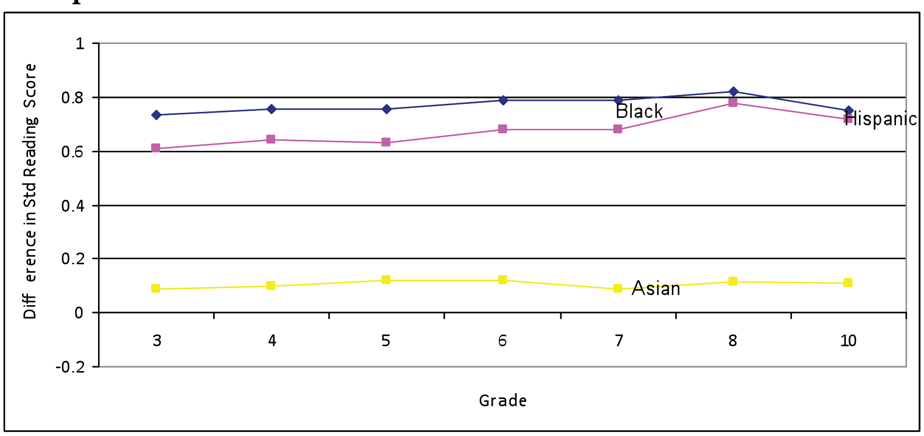
Figure 18

White-"Race" Achievement Gap - Reading

A) Intact Cohort



B) Complete

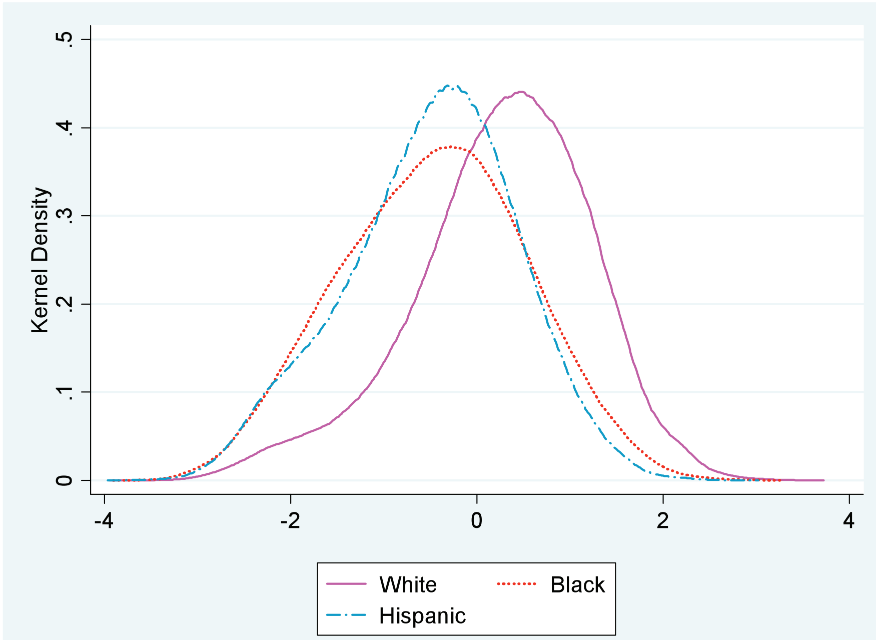


Source: *Elaboration based on NCPSDB.*

Figure 19 presents non-parametric kernel density estimates to describe the score distribution of Hispanic, Black and White students[76]. The probability density function reveals that the distribution of White students' scores is located to the right of the ones corresponding to Hispanic and Black students' scores. However, White and Hispanic densities have a higher mode. We can also see that the highest scoring Hispanic and Black students do not attain the same level as the equivalent White students. Low-performing White students also outscore low-performing Hispanic and Black peers.

[76] See Appendix 5 for details about the bandwidth choice.

Figure 19
Distribution of Test Scores by Race

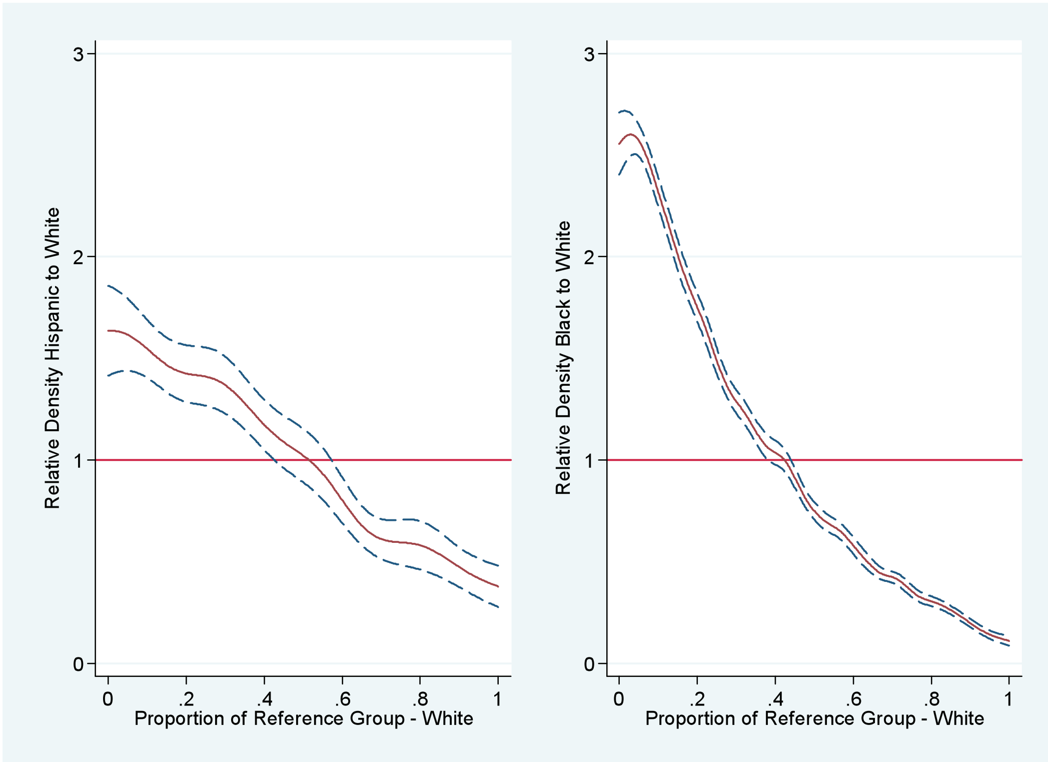


In a complementary analysis to Figure 19, Figure 20 uses a non-parametric approach to describe the relative distribution of Hispanic (on the left) and Black (on the right) distributions with respect to White[77]. We can see that ratio of Black student scores to White student scores is much higher for lower scores than for higher scores while Hispanic students are more homogenously distributed along the scores range.

These preliminary results confirm that the gap exists and is quite stable across grades. The immediate question is whether the causes of this difference in performance could be identified. In the subsequent sections, we attempt to answer these questions for the reading test scores. Additionally, some estimates of the racial achievement gap for math scores are presented in Appendix 6.

[77] See Appendix 5 for methodological specifications.

Figure 20
Relative CDF Distribution s
Intact Cohort – 10th Grade



Note: *Dotted Lines: Confidence Intervals, bootstrapped SE.*
Source: *Elaboration based on NCPSDB.*

V. Methods

This paper applies alternative decomposition methods to the racial achievement gap in Figure 18. We first explore the within- and between-school components of the racial gaps using the variant of the Cook and Evans (2000) methodology proposed by Page et al (2008). In a second stage, we decompose the gap applying the Oaxaca decomposition in an attempt to isolate the characteristic and coefficient components. In the last stage, we investigate the whole score distribution utilizing the Juhn-Murphy-Pierce decomposition.

In all stages, we first estimate a classical education production function (Hanushek, 1997) that explains the test scores in each grade as a function of a set of covariates:

$$A_{is} = X_{is}\beta_s + \varepsilon_{is} \tag{1}$$

where A_{is} , the achievement of student i in school s, is determined by a vector of family, peer and school variables (X_{is}). The error term (ε_{is}) captures unmeasured variables such as innate ability, motivation, etc.

$$A_{is} = \beta_0 + \beta_1 (R_{is}) + \beta_2 (p_s^{race}) + \beta_3 (male) + \beta_4 (p_s^{male}) + \gamma (pared_{is}) + \theta (p_s^{pared}) + \varepsilon_{is} \qquad (2)$$

where

R_{is} Is a race indicator;

male is an indicator variable which is one is male, 0 is female

pared is the level of parental education. For simplicity, we only consider two categories. 1 is more than HS; O otherwise.

p_s^{race} Represents the proportion of students in each race in school s, and

p_s^{male} Represents the proportion of students who are male in school s, and

p_s^{pared} Represents the proportion of students whose parents have more than high school education

As prior studies indicate that student background is an important factor underlying student performance, we would like to include an extensive list of family characteristics. However, the only measure available to us in the data is the highest level of education of the family. Variables like family size, family type, parental style or income were not included. As in many education production functions, these other characteristics are important predictors of student outcomes and we know that our model is underestimating the relevance of family background on student outcomes.

V.1. Between and within School decomposition

The achievement gap can be decomposed into within- and between-school decomposition using the method proposed by Page, Murnane and Willett (2008) which is similar to the ones utilized by Cook and Evans (2000). This method incorporates covariates such as student endowment at the individual and school levels. Dummies for identifying other races and proportion of racial make-up are also included in the regression. The total achievement gap between Whites and Hispanics would be:

$$
\begin{aligned}
\hat{\delta} &= \hat{\beta}_1 + \hat{\beta}_2 \left(\bar{p}_h^{\,hispanic} - \bar{p}_w^{\,hispanic} \right) \\
&+ \hat{\beta}_3 \left(\overline{male}^{\,hispanic} - \overline{male}^{\,white} \right) + \hat{\beta}_4 \left(\bar{p}_h^{\,male} - \bar{p}_w^{\,male} \right) \\
&+ \hat{\gamma} \left(\overline{pared}^{\,hispanic} - \overline{pared}^{\,white} \right) + \hat{\theta} \left(\bar{p}_h^{\,pared} - \bar{p}_w^{\,pared} \right)
\end{aligned} \tag{3}
$$

Where the first line is the portion of the gap due to racial differences, the second line is the portion due to gender differences, and the third line is the portion that accounts for differences in parental education. Following Page et al. we utilize Reardon's (2008) insights and substitute the first line to a version decomposed into within, between and ambiguous components[78].

$$
\hat{\delta} = \hat{\beta}_1 \left(1 - \hat{V} \right) + \hat{\beta}_1 \left(\hat{V} \right) + \hat{\beta}_2 \left(\hat{V} \right) \tag{4}
$$

where

$$
\hat{V} = \frac{Var(p_s^{hispanic})}{Var(R_{is})} = \left(\bar{p}_h^{\,hispanic} - \bar{p}_w^{\,hispanic} \right) \tag{5}
$$

The same procedure could be applied to analyze White and Black achievement gap, and so forth.

V.2. Endowment and Return Effects

The Oaxaca (or Blinder-Oaxaca) decomposition divides the outcome differences between two groups into a "part" that is explained by differences in the characteristics between groups (such as parental education, gender) usually denominated "endowment" effect) and a residual part which is due to the "productivity" on the assets (or the marginal products of the independent variables across races)[79]. The original method, typically used to assess the determinants of wage differences between two populations of workers (e.g. male and female), was extended to include a third component which is the interaction between return and endowments (Lauer's (2000. For

---

78 For details, see Page et al (2008), Appendix A.

79 This last part subsumes the influence of unmeasured variables or is "the measure of our ignorance" (Mac Ewan and Marshall, 2008:204).

instance, considering two subgroups, White and Hispanic, the racial gap (ΔA_{WH}) could be decomposed as follows[80]:

$$\Delta A_{WH} = \sum_{i=1}^{6} \hat{\beta}_i^H \left(\overline{X}_i^W - \overline{X}_i^H\right) + \sum_{i=1}^{6} \left(\hat{\beta}_i^W - \hat{\beta}_i^H\right) \overline{X}_i^H + \sum_{i=1}^{6} \left(\hat{\beta}_i^W - \hat{\beta}_i^H\right)\left(\overline{X}_i^W - \overline{X}_i^H\right) \qquad (6)$$

Where *Xi* includes for all categories of explanatory variables from equation (2) and $\hat{\beta}$ includes all coefficient an explanatory variables. The first term represents the achievement difference due to different endowments. The second is the difference in the marginal product of the endowments of each independent variable, say parental education and teacher training[81]. The last term is the difference which arises from the interaction between the eventually better production process between white and different endowments with respect to White students.

V.3.The whole score distribution

Figure 19 indicates that there are racial differences in the distribution of test scores. To account for these differences we use an extension of the decomposition proposed by Juhn et al (1993) to break down the wage gap between male and female workers. The methodology explicitly deals with the residuals and the fact that the mean is different from zero along quantiles of the score distribution.

The method basically is a counterfactual type of analysis that deals with the fact that each group has a different density function[82]. We build the inverse cumulative residual distribution of the scores[83]:

$$\varepsilon_i^R = F^{R^{-1}}\left(\theta_i^{R^{-1}} \mid X_i^R\right) \qquad (7)$$

Where θ_i is the percentile of individual *i* in the residual distribution, $F^{R^{-1}}$ is the distribution function of the residuals, *Xi* includes again for simplicity all categories of explanatory variables from equation (2) and *R* represents race. Thus, now the predicted value for scores for Hispanics for example has two components:

---

80 This equation could be used taken as base the Hispanic group. However, there is no obvious choice for the base while most authors recommend using as such the distribution which is supposedly would prevail.

81 The method has proven to be sensitive to the omitted category with dummy variables.

82 This method is closely related to Di Nardo, Fortin and Lemieux (1996)'s approach.

83 In this section we follow Ammermüller (2004).

$$A_H = \hat{\beta}^H X_i^H + F^{H^{-1}}\left(\theta_i^{H^{-1}} \mid X_i^H\right) \qquad (8)$$

The first components equation (8) is the predicted value of reading scores for the group estimated using the beta coefficient (returns) of the group while the second component is the inverse cumulative residual distribution of the Hispanic scores. A similar analysis for White and Black would bring their "whole" score distribution.

V.4.Simulation of alternative score distribution

Given the difference in the score distribution between races, I simulate the performance of a certain group of children using a different set of characteristics. It is of interest to hypothesize how a certain group would score in the case where they have the characteristics, the "returns", the "residuals" of a group of reference. In this case, our interest is to know how Black and Hispanic would score had they had the educational production process of the White group.

Two hypothetical distributions are simulated using the results of equation (2). The first one (Equation 9) simulates the distribution of the comparison group utilizing the "returns" (beta coefficients) and the residual distribution of the reference group. The second simulation keeps the "returns" of the comparison group and considers only the residual distribution of the reference group (Equation 10). Mathematically:

$$A_H(1) = \hat{\beta}^W X_i^H + F^{W^{-1}}\left(\theta_i^{H^{-1}} \mid X_i^H\right) \qquad (9)$$

$$A_H(2) = \hat{\beta}^H X_i^H + F^{W^{-1}}\left(\theta_i^{H^{-1}} \mid X_i^H\right) \qquad (10)$$

The total score gap could be constructed as the sum of four effects. The first, following the decomposition of (6), the *characteristics effect* is the difference between $A_W(1)$ and A_H , that is the divergence that results from applying the "returns" and the residual distribution of Hispanic students and the Hispanic distribution to white students. Thus, this first component attempts to capture only differential endowments. A second effect that could be estimated is the *return effect* that is the result of subtracting $A_H(1)$ from $A_H(2)$. These two hypothetical distributions only differ in the use of the "returns" of the reference group (White) on the characteristics of the comparison group (Hispanic). A third effect, "*residual effect*" captures the impact of residuals across group and is calculated as the difference between $A_H(1)$ and A_H (2)?.

The *interaction effect* is the difference of the two distribution that arise from extrapolating the returns of each group on the other, $(A_W - A_W(1)) - (A_H - A_H(1))$.

Summarizing, the total gap would be equal to:

$$Total\_Gap = (A_w(1) - A_H) + (A_H(2) - A_H(1)) + (A_H(2) - A_H) + (A_W - A_W(1)) - (A_H - A_H(1)) \quad (11)$$

V.4. Software

Estimation was conducted in STATA 10 (StataCorp. 2007. Stata Statistical Software: Release 10. College Station, TX: StataCorp LP) and use the oaxaca2, oaxaca8, gdecomp, jmpierce, relrank, reldist, kdens and invcdf packages. The reldist package was kindly provided by Ben Jann of the Swiss Federal Institute of Technology Zurich.

VI. Results

The difference observed between the tests scores across races may be due to several reasons. First, the characteristics might be different across races. Second, the effects of the same characteristics on the performance of students might differ if families/students have different educational production processes on a racial basis. Third, a portion of the test score gap may be due to the difference in the residuals of the estimated regressions. We now proceed to analyze all three factors and see which one is the most important.

VI.1. Endowments

VI.1.1. Parental education

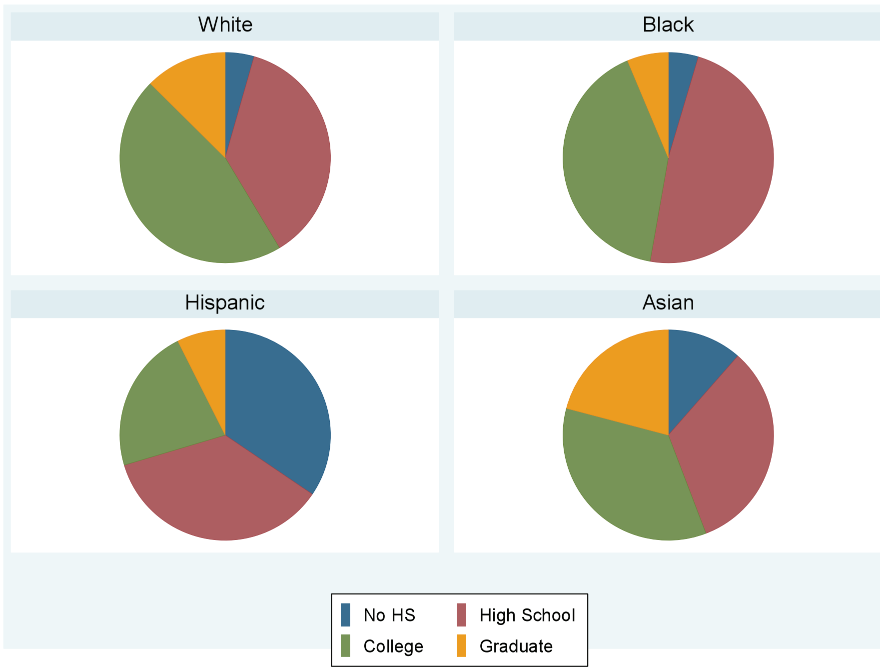
Students differ in various aspects. White students have better educated parents than both Black and Hispanic students. Figure 21 shows, for the intact cohort, that almost half of the Hispanic students in the NC Public School system have parents who did not finish High School. Furthermore, they are underrepresented in the highest educational level group of parents. The opposite results hold true for Whites who are scarce among the group of students whose parents did not finish High School and who, on average, have parents who in general have finished High School. More than half of White parents have either a college or graduate degree. Black students have better educated parents than Hispanic students but are still behind White students in terms of parental education.

Patterns for the complete cohort are not different as shown in Figure A-8. Nevertheless, as the group of students changes so do the level of parental education. As students progress

through grades, the level of parental education increases. This is likely the result of some selection process. Overall, these first results confirm that differences in the characteristics across races could cause explains the achievement gap.

Figure 21

Average Parental education - Intact Cohort



Source: *Elaboration based on NCPSDB.*

VI.1.2. Peers' Characteristics

One of the possible explanations to the achievement gap is the influence of peers on achievement. Figure 22 provides a first approximation and displays the relationship between reading scores and the proportion of Hispanic students on the left, for the average, White and Hispanic student separately. White and Hispanic students are represented by blue and red points. The blue and green lines are the fitted relationship between reading achievement and the proportion of students in their schools who are Hispanic for White and Hispanic students. The red line is the same fitted relationship but for the average student. Points A and H are the predicted performance and average racial make-up for White and Hispanic students. The same analysis was carried out for Black students on the right-hand side. The percentage of Hispanic students does not affect the average student achievement in contrast to the negative impact that the percentage of Black students at school has on the average student. The achievement gap is

the vertical distance between the two points while the variance ratio index of segregation is the net horizontal distance between A and H[84].

Table 27 summarizes the racial composition of the classes attended by Hispanic, Black and White students[85]. Tables 27 and A-47 suggest as a common feature that students of any ethnicity are more exposed to their own race/ethnicity than the average student. Nevertheless, profiles differ depending on race. White students are less exposed to other races. All minorities have more Black peers than the average student. This peer profile is clearer in grade 10 than in grade 3 for cohorts, the intact and the complete.

Table 27
Peers Racial Make-Up

A) Intact Cohort

Race Classmates	White	Black	Hispanic	Racial Make-Up
3rd Grade				
White	0.70	0.64	0.66	0.68
Black	0.25	0.31	0.28	0.27
Hispanic	0.02	0.02	0.03	0.016
10th Grade				
White	0.72	0.60	0.68	0.68
Black	0.23	0.35	0.26	0.27
Hispanic	0.02	0.02	0.02	0.016

B) Complete Cohort

Race Classmates	White	Black	Hispanic	Racial Make-Up
3rd Grade				
White	0.63	0.52	0.55	0.64
Black	0.31	0.42	0.37	0.30
Hispanic	0.02	0.02	0.04	0.021
10th Grade				
White	0.65	0.54	0.60	0.62
Black	0.26	0.37	0.30	0.29
Hispanic	0.04	0.05	0.06	0.045

Source: *Elaboration based on NCPSDB*

All in all, these results suggest the existence of selection bias at the student level and the invalidity of comparing outcomes without adjusting by peer racial composition.

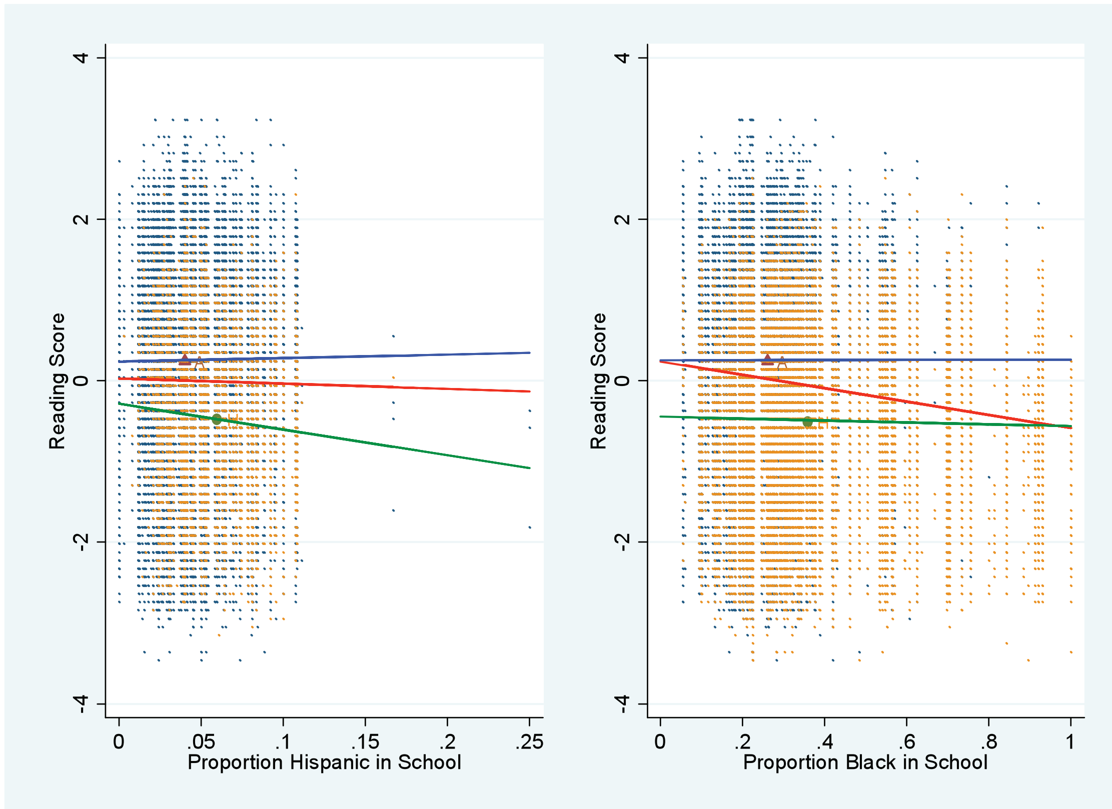
[84] More details about the decomposition are provided in Figure A-9 and in Page et al (2008), Appendix A.

[85] Table A-47 presents racial make-up for all races.

Figure 22

Fitted Relationship between Reading Scores and School Racial Make-Up

10th Grade Complete Cohort



Note: *blue: White; green: Hispanic/Black; red; Fitted*
Source: *Elaboration based on NCPSDB.*

VI.2. Between and Within School Decomposition

Table 28 presents the decomposition results associated with the model presented in equation (3) for reading scores, both cohorts, grades 3 and 10[86]. Panel A exhibits results for the intact cohort while Panel B does the same for the complete cohort. From the Table below we can infer that parental education is the most important determinant of the racial gap along with within-school factors. Consistent with the observed lower levels of parental education among Hispanic parents, education is more relevant for Hispanic than for Black students.

Table 28
Decomposition of Racial Gap – All Factors

A) Intact

	Black	Hispanic	Black	Hispanic
	3rd Grade		10th Grade	
Total Gap	**-0.73**	**-0.61**	**-0.68**	**-0.36**
School				
Within	-0.25	-0.39	-0.39	-0.03
Ambiguous	-0.35	-0.04	-0.19	-0.20
Between	0.00	0.00	0.00	0.00
Characteristics				
Gender	0.05	0.07	0.08	0.12
Education	-0.17	-0.25	-0.18	-0.25

B) Complete

	Black	Hispanic	Black	Hispanic
	3rd Grade		10th Grade	
Total Gap	**-0.89**	**-0.79**	**-0.79**	**-0.71**
School				
Within	-0.40	-0.39	-0.47	-0.51
Ambiguous	-0.18	-0.04	-0.21	-0.05
Between	0.00	0.00	0.00	0.00
Characteristics				
Gender	0.07	0.12	0.09	0.14
Education	-0.38	-0.49	-0.20	-0.29

Source: *Elaboration based on NCPSDB*

Between-school differences explain little of the difference between White students and either Hispanic or Black ones. This finding is consistent with some previous studies (Clotfelter et al, 2006:32). Intensity of exposure to other races does not influence racial gap (Tables 28 and Tables A-48 trough A-50). Trends do not differ dramatically

86 Results for Mathematics are presented in, Table A-48.

between 3rd and 10th grade although, as expected, the size of the gap is bigger for the complete cohort. The achievement gaps in Mathematics are similar to those in Reading (Table A-48).

In order to get a more accurate picture about the relevance of parental education, we decomposed the change in the gap between 3rd and 10th grade for the complete cohort. Algebraically the gap is split as follows using 3rd grade (Equation 12) and 10th grade (Equation 13):

$$\Delta Gap_{10-3} = \hat{\gamma}_3\left(\Delta\overline{X}_{10} - \Delta\overline{X}_3\right) + \left(\hat{\gamma}_{10} - \hat{\gamma}_3\right)\Delta\overline{X}_3 + \left(\hat{\gamma}_{10} - \hat{\gamma}_3\right)\left(\Delta\overline{X}_{10} - \Delta\overline{X}_3\right)$$

(12)

$$\Delta Gap_{10-3} = \hat{\gamma}_{10}\left(\Delta\overline{X}_{10} - \Delta\overline{X}_3\right) + \left(\hat{\gamma}_{10} - \hat{\gamma}_3\right)\Delta\overline{X}_{10} + \left(\hat{\gamma}_3 - \hat{\gamma}_{10}\right)\left(\Delta\overline{X}_3 - \Delta\overline{X}_{10}\right)$$

(13)

Where $\Delta\overline{X}$ is the difference in levels of parental education at the individual and school levels and $\hat{\gamma}$ is the parameter estimated in (2). The first, second and third terms in both equations are the changes due to level, return and interaction between level and return.

Table 29 demonstrate that despite the improvement in the educational production function of both Black and Hispanic students between 3rd and 10th grade, the major part of the contribution of education to the reduction in the achievement gap between the two grades comes from the level of parental education. This table also reveals that education is the main driver of the gap reduction for Black students (91%) while it explains only half of the reduction for Hispanic students (59%).

Table 29
Change in Total Gap between 10th and 3rd Grade

	Hispanic		Black	
3rd Grade as base year				
	Change	**% of Gap**	**Change**	**% of Gap**
Level	-0.01	-7	0.07	74
Return	0.03	44	0.03	28
Interaction	0.02	23	-0.01	-10
Education Effect	**0.05**	**59**	**0.09**	**91**
Gap change	**0.08**		**0.10**	
10th Grade as base year				
Level	0.01	16	0.06	63
Return	0.05	67	0.02	17
Interaction	-0.02	-23	0.01	10
Education Effect	**0.05**	**59**	**0.09**	**91**
Gap change	**0.08**		**0.10**	

Source: *Elaboration based on NCPSDB*

VI.3. The Oaxaca-Blinder Decomposition

In this section we decompose achievement gap into endowment, return and interaction effects. The decomposition of the total score gap is reflected in Table 30[87]. The share of students with parents with more than High School education, which is larger for White students, leads to a negative level of parental education effect for Hispanic and Black students with respect to White peers. This first component explains more than a third of the gap for Hispanics and about 10% for Blacks.

The second component, the coefficient effect is an estimation of the impact of the different production process between races. In this case, differences in production processes explain more than 90% of the White-Black achievement gap. This effect shows how Hispanic and Black students would perform if they had the White "educational production process" and keeping constant their own characteristics (mean level of parental education). In other words, the productivity of White parents in producing "achievement" is much higher than the productivity of Black and Hispanic parents. Due to the positive correlation between parental education and test scores, we would have expected higher achievement for Hispanic students than for Black students, with both groups outscored by White students. Nevertheless, Black students have a lower

[87] The separate effect each explanatory variables is reported in depth on Table A-51.

achievement than their Hispanic peers which is basically driven by their "relatively" bad production process. The interaction effect is not important in size or significance.

Table 30
The Oaxaca-Blinder Decomposition

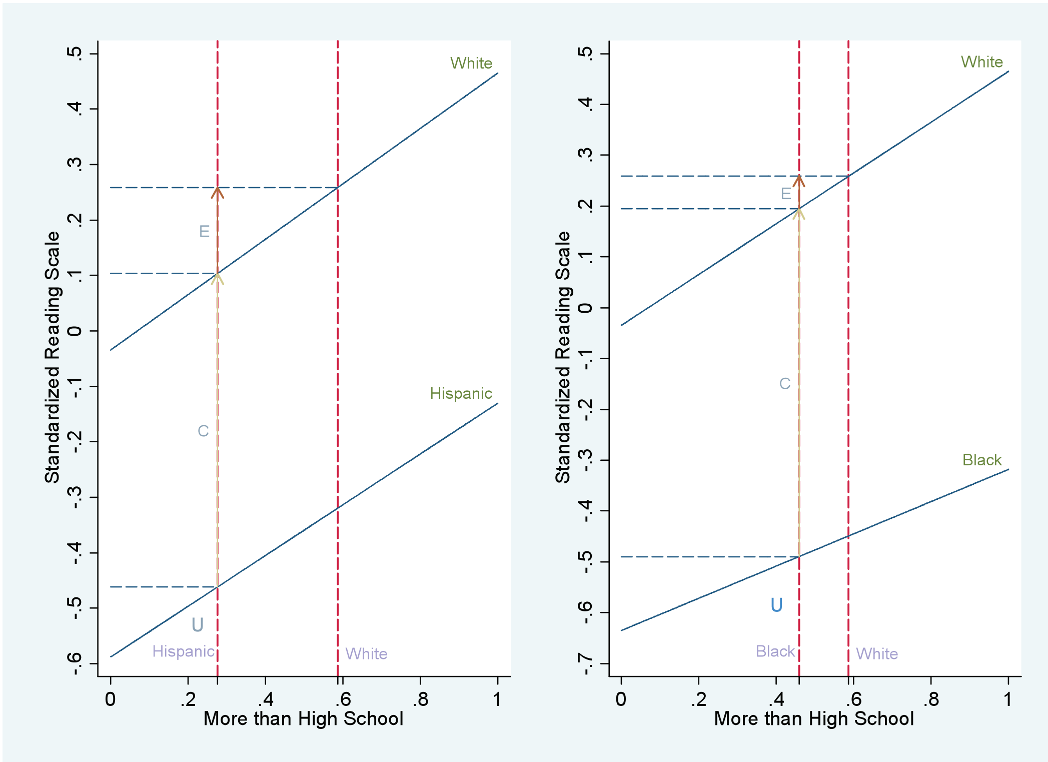
Type of Effect	Gap			
	White-Hispanic		White-Black	
	Total	%	Total	%
A) Intact Cohort				
Endowments	0.11 *(0.025)*	0.33	0.03 *(0.004)*	0.065
Return	0.21 *(0.027)*	0.67	0.58 *(0.009)*	0.935
Interaction	0.018 *(0.023)*	*0*	0.00 *(0.006)*	0
Total	0.335 (0.028)	1	0.62 (0.008)	1
B) Complete Cohort				
Endowments	0.17 *(0.006)*	0.24	0.06 *(0.007)*	0.082
Return	0.53 *(0.021)*	0.67	0.69 *(0.005)*	0.932
Interaction	0.018 *(0.014)*	0.03	-0.013 *(0.005)*	0
Total	0.72 (0.028)	1	0.74 *(0.0078)*	1

Note: *Bootstrapped standard error terms in parentheses*
Source: *Elaboration based on NCPSDB*

Figure 6 presents a graphical decomposition of the achievement gap for the most important variable, parental education. The graph decomposes the gap for Hispanic and Black students with respect to White in the left and in the right, respectively. The horizontal axis measures the percentage of parents with more than High School education by race with two vertical lines at the respective levels. It is easy to see that in both cases the White vertical lines is located at the right with the mean of Black students closer to the line for White students than the one for Hispanics. The vertical segment E represents the endowment effect; segment C and U depict the return and the unexplained effect, respectively.

Figure 23

The Oaxaca Blinder Decomposition -Effect of Parental Education



Source: *Elaboration based on NCPSDB*

VI.4. Simulation of the score distribution

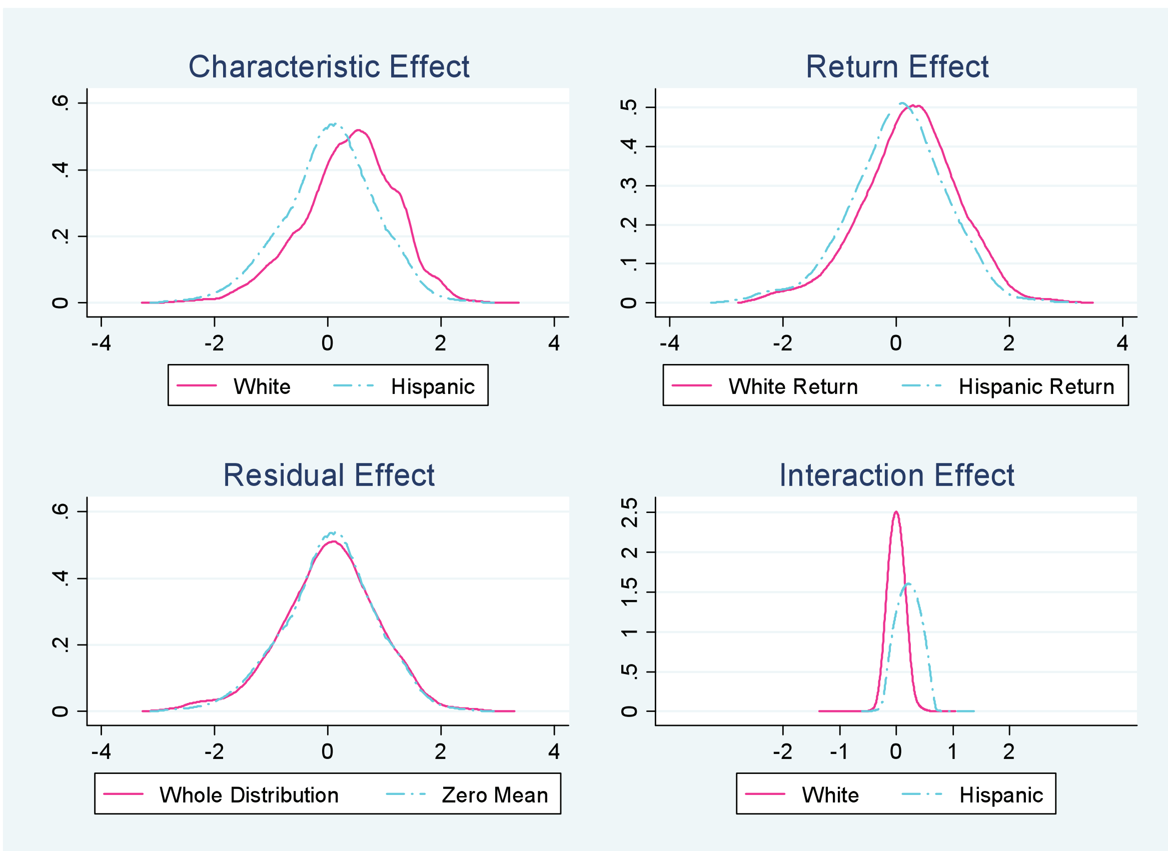
The Oaxaca-Blinder decomposition results showed that for the mean, both return and characteristics effects are relevant in size and significance for both Hispanics and Blacks, although the relative size of each effect differs by race. The consideration of the whole distribution does not dramatically change the scores gap; it only reduces the gap in 0.01 SD for both Hispanics and Blacks.

In this section, we analyze the impact of score distribution and simulate four hypothetical cases associated to each of the effects described in Section V.4. The upper left corner in Figure 24 depicts the characteristics' effect. Both kernel distributions are drawn based on the return (β) of Hispanic students and only differ in the characteristics utilized.. The White score distribution line is comes form applying the return of Hispanic students to the characteristics of White students. The Hispanic density is the distribution of scores of Hispanic characteristics and Hispanic returns. As we can see the mode of the

White distribution is located to the right of the Hispanic one implying that White students have more favorable endowments than their Hispanic peers.

The second effect, the return effect, shown in the upper right-hand of the Figure, captures the effect of different production processes. The White's return line is generated from applying the White return to Hispanic endowments while the Hispanic line is the distribution that arises from applying the Hispanic return to Hispanic endowments. The "White return" kernel density is located again on the right which implies that the White production process is more efficient than the Hispanic one.

Figure 24
Hypothetical Reading Score Distribution - Hispanic



Source*: Elaboration based on NCPSDB.*

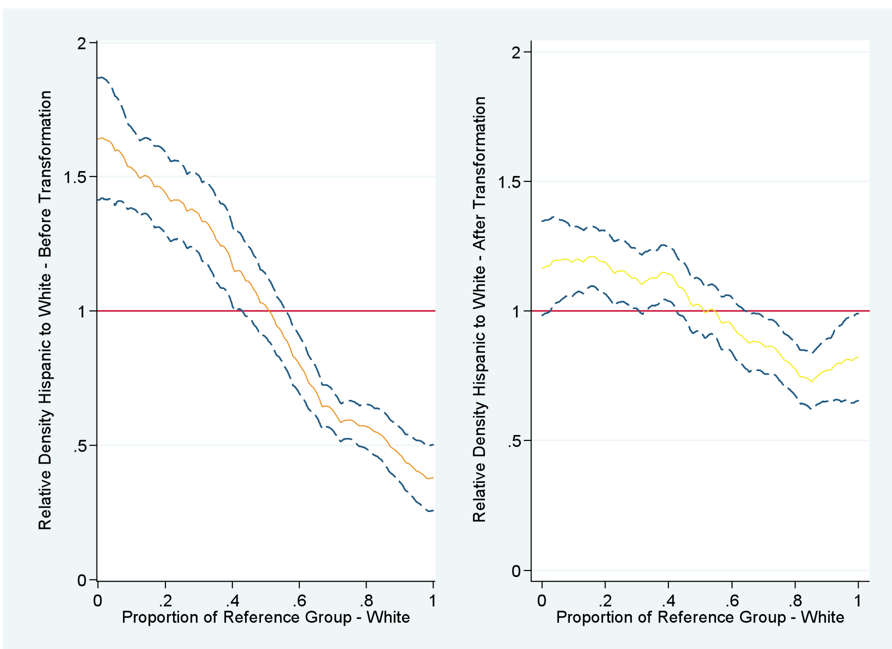
The effect of the residual is represented in the lower left-hand side of the figure. Two distributions are compared, with the Hispanic endowment as the base. The first one takes into account the White residuals distribution on Hispanic students while the second

one considers the whole distribution of residuals for Hispanics. As we can see, the two distributions overlap because White and Hispanic distribution do not differ in spread.

Finally, the interaction effect is reflected in the lower-right hand portion of Figure 24. The two densities are the results of considering the endowment of each group with the "production process' (including residual distribution) of the other group. The effect is positive for Hispanics and negative for White.

Figure 25 summarizes our results. The Figure depicts relative distribution of Hispanic to White scores that result from the Hispanic and White production processes. The first relative distribution on the left part of the Figure is the quotient of the two original distributions. The second one on the right is the quotient between the simulated Hispanic (that results from taking both return and residuals from the White group), and the original White distribution. As we can clearly see, the Hispanic distribution gets closer to the White scores distribution after this transformation.

Figure 25
Relative Distribution
Hispanic and White Production Processes



Note: *Dotted Lines: Confidence Intervals, bootstrapped SE.*
Source: *Elaboration based on NCPSDB*

Figures A-10 and A-11 exhibit the same simulation for Black scores. In this case, as expected from previous results the return effect is more relevant in size than the one for Hispanics: Black students show a lower average score than White students due primarily to a worse return to parental education. In the case where Black students achieve the White production process, their relative distribution gets closer to one as displayed in Figure A-11.

VI.5. Assessment of Research Hypotheses

The interest in racial achievement gap has been renewed in the last two decades. Concerns that minorities' lower scores impact the rest of their lives are confirmed with empirical work that found that academic performance is related to labor market outcomes and, in particular to unemployment and wages.

Measuring the racial gap has various methodological challenges and, unsurprisingly, empirical research has found contradictory evidence about the relative importance of school and individual factors in explaining the gap. Some limitations come from omitted variables bias, as it is very difficult to capture innate ability and family location choices. Family characteristics' impacts could be overestimated when only the parents' level of formal education is included in the regression. Not only could parental styles differ on a racial basis, but the same level of education does not fully capture socio-economic status, especially when there is evidence that wages vary by race after controlling for education.

Our analyses provide four key results. First, we encounter that within-school variance is substantial and exceeds between-school factors proving that there are still substantial efforts required to eliminate the barriers in school integration. The conclusion slightly changes if we assign the ambiguous component to between-school variance as Hanushek et al (2002) did in his work for Texas. In either case, within-school inequality remains the most important factor.

Second, and in line with other empirical work, we find that the achievement gap reduces as the student progresses in school. The gaps are smaller for 10th than for 3rd grade, for the intact than for the complete cohort and for Hispanic than for Black, using White students as the group of reference in each case.

Third, parental education is the main driver in explaining the gap between Hispanic and White students. Moreover, the gap decreases as the student progresses between 3rd and 10th grade along with an increase in the mean level of parental education for both races. The Oaxaca-Blinder decomposition confirms these previous results. Parental education is decisive not only regarding the level but also "return". Our findings suggest that White students have on average better educated parents who know, in parallel, how to make a better use of their human capital in producing child' achievement. Overall, the evidence presented confirms that higher levels of parental education are determinant of the racial achievement gap.

Fourth, the consideration of the whole residual distribution instead of the, usually utilized, zero mean does not dramatically change the results. Given that all unobserved factors such as ability or motivation are in the residuals we could infer that they do not depend on race.

Finally, the simulation of scores distribution using the White production parameters confirms these findings by showing that score differences significantly decrease, although they do not fully disappear.

VII. Discussion

This study uses the North Carolina Public Schools database in order to answer various questions. We assessed whether within- or between-school variance is the main determinant of achievement gap in reading scores. We decomposed the achievement gap into characteristics and return effects using the Oaxaca-Blinder decomposition and extend the study of the gap to the whole score distribution.

We found that the incidence of within school inequality is an important component of racial achievement gap. Results slightly differ between Hispanic and Black and confirm the need to duplicate the effort aimed to achieve school integration. Alternative (and complementary) policies to the allocation of more resources could be implemented to overcome the skepticism about the possibilities of the "school" as an instrument for racial gap reduction.

In a regression-based decomposition that incorporated student- and school-level covariates, we find that both the levels and return to parental education contribute

substantially to explain the achievement gap. Overall, the parental education effect is around a third of the average achievement gap. However, our results highlight that Black and Hispanic students face different issues. While differences in level of education are the key component for Hispanic students, the educational production process is the decisive one for Black students. Exposure to other races/ethnicities has no differential impact on the achievement gap either for Hispanic or for Black students.

A further step in the decomposition analysis allowed us to consider the whole distribution of scores and not only the mean of the distribution. We did not find substantial effect of unobservables, despite the higher spread and mode of the White distribution.

Although this research is merely descriptive in nature, from the policy point of view, we can infer a need to dismantle barriers within the school which currently prevent further reductions in the achievement gap. In order to improve the performance of both Hispanic and Black students we need to better understand the educational production process knowing that, in the short term, there is little possibility to compensate for background differences.

Further research is needed on the effect of school policies and parental styles on student outcomes. The production process is a black box that could encompass a variety of factors: different characteristics of the neighborhood where they live, divergences in the policies of the schools they send their children, and/or different ways of organizing family life. A better understanding would help to isolate the contribution of the various factors on the total achievement gap and would, consequently, support more effective policies (or interventions).

Chapter 5: Conclusions

The racial achievement gap has been at the center of the educational debate for decades in the United States. While the gap narrowed during the seventies and the eighties, there is evidence that it has been widening in recent years. The goal of this dissertation was to examine the contribution of family, school and neighborhood factors to the achievement gap and to highlight promising areas for policy intervention.

The dissertation was structured in three papers. The first one studied the effect of neighborhood on student's achievement. Thus far, studies of neighborhood effects on educational attainment have generally found that such effects exist for adolescents. A common deficiency of empirical research to date, the lack of information on multiple contexts, is addressed in this paper by using school data survey to gain further insight on the effect of neighborhood poverty deprivation on elementary education children in the USA.

Using a cross-classified hierarchical linear model to account for the nested structure of the samples of individuals in neighborhoods and schools, the study highlights the association between neighborhood's socioeconomic composition and student's outcomes. The study provides evidence supporting both the socialization and epidemic theories. The presence of well-educated adults in the neighborhood and the neighborhood median income has positive influences on student achievement. High levels of poverty have a significant but negative influence on student's tests scores. Nevertheless, the impact occurs when a threshold of 30% of poor households has been reached. Even when our findings for the whole sample are stable over different specifications, the implicit assumption that school and neighborhood have a uniform effect on all children regardless their ethnicity, gender and socioeconomic status is challenged. Neighborhoods have a larger impact on some subgroups (Black and Hispanics, for instance) than on the average student.

The second paper explores the role of within school policies on student achievement. Based on a different database, the North Carolina Public Schools Database explores the effect of ability grouping, a widespread practice in American schools that

has led to the existence of a broad range of courses in high school. The situation has originated not only equality problems but concern about students' readiness for life and threats to U.S. economy's competitiveness. As a result of this movement an increasing number of students are taking Algebra 1 in 8th grade. A large body of evidence shows mixed findings about the effect of ability grouping and curriculum upgrading on average achievement. Nevertheless, few papers have explored the distribution of impact across individuals. A major contribution of this paper is the assessment of the heterogeneity in students' responses to treatment across various dimensions.

The goal of this paper is to analyze the effect of enrolling students in Algebra 1 in 8th grade. Using a propensity score matching method we estimate the average treatment effect on the math section of the tenth-grade North Carolina's High School Comprehensive Test. We find that low-achieving, low SES, Black students are more likely taking Algebra 1 in ninth-grade. Despite the positive average treatment, the effect is small in size and is not different from zero for the lowest achieving students. Our findings do not suggest that the "Algebra 1 for everyone" policy encouraged since the early 1990s is not equally effective for all students. Students who had low test scores prior to 8th grade did not improve at the same rate or not improve at all, though we can not affirm they are harmed by such policy. The question that remains is how to turn this effect into achievement gains for this group.

The third paper decomposes the racial achievement gap and analyze why White students have a significantly higher performance than their peers using the North Carolina Public School Database. We estimate an educational production function for each racial group and break down the differences in reading scores into different effects, utilizing the Page-Murnane-Willett, Oaxaca–Blinder and Juhn–Murphy–Pierce methods. We contribute to the empirical literature on racial achievement gap in two aspects: we focus the analysis on White-Hispanic achievement and we consider the whole distribution of the test scores as complements to the analysis of the mean.

Our analyses provide three key results. First, we find that within school factors remain substantial in size and significance to explain the gap between Hispanic and White students test scores. Second, parental education is the most important individual

factor: Third, in line with prior studies, the achievement gap narrows between grades 3 to 10.

The dissertation confirms that both between and within school factors contribute to the racial achievement gap. Placement policies are among the factors that may be contributing to the racial achievement gap. Parental education appears as the most important individual factor in explaining the size of the achievement gap although the policy issues of Hispanic and Black are different. Despite of the increase in Black parental level of education that has been documented in the empirical literature, the gap still subsists and is related to the educational production process of Blacks.

Overall, this study finds that parental education and neighborhood factors are significant predictors of child achievement and have negative effects on the achievement of racial racial/ethnic minorities. Policies that address these factors have potential for mitigating disparities and raise overall achievement. While policies in the past have focused on reducing disparities in school resources such as textbooks and facility quality, these findings suggest a broader conceptualization of resources to include fostering parents' involvement in child education and factors related to the neighborhood environment

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2. Chapter 2

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Appendices

1. Data Appendix to Chapter 2

Table A-1
Distribution of Students per Neighborhood

Child Per Tract	Number of Neighborhoods					
	1	**2**	**4**	**5**	**6**	**7**
One	1,374	1,399	1,512	1,569	926	1561
1 to 5	1,101	1,128	1,087	1,059	674	918
6 to 10	396	420	383	310	168	221
11 to 50	403	413	343	219	91	141
51 to 100	22	27	25	14	2	7
100+	8	6	2	0	0	0

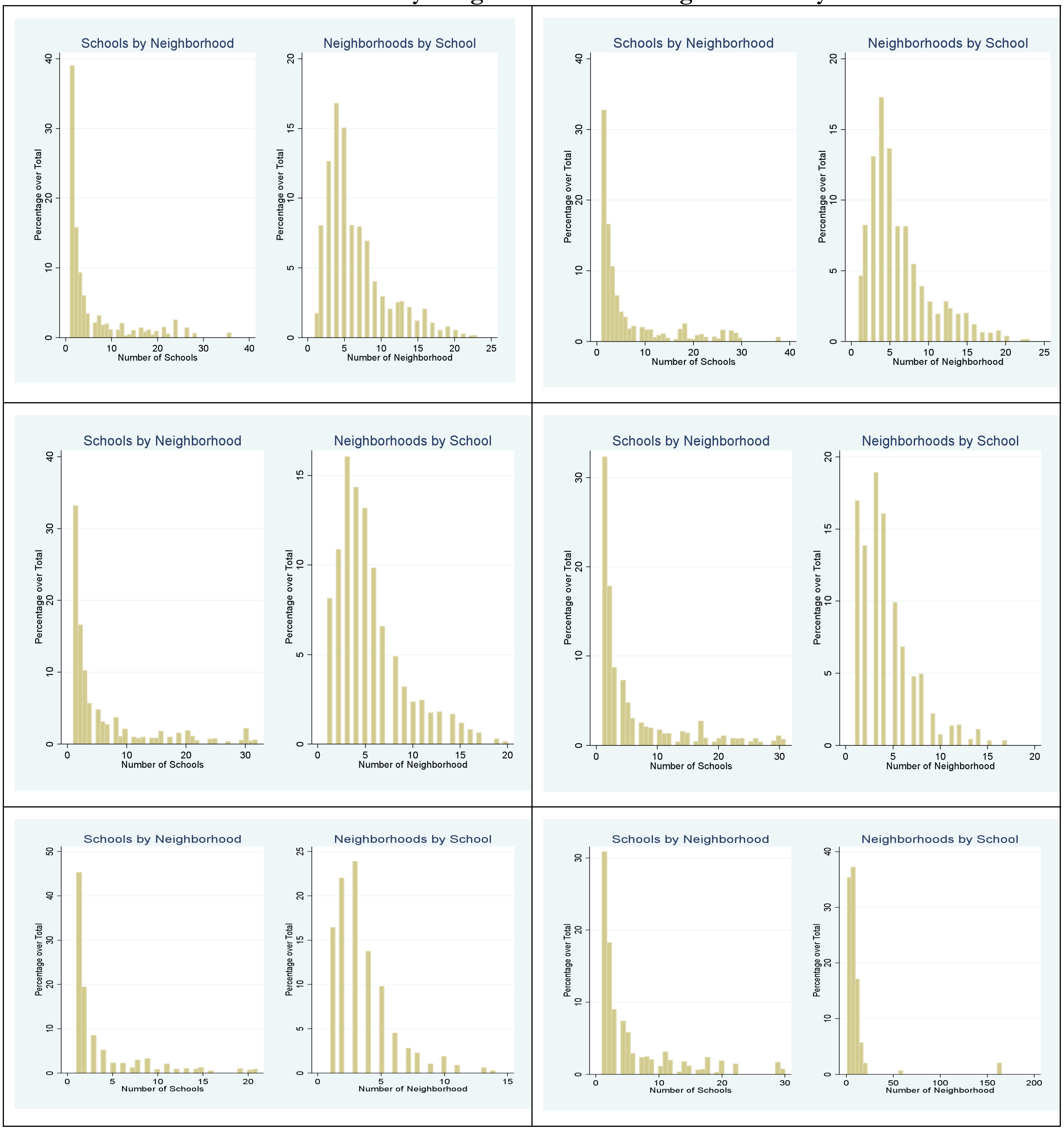
Source: *Elaboration based on ECLS-K.*

Table A-2
Distribution of Students per School

Child Per School	Number of Schools					
	1	**2**	**4**	**5**	**6**	**7**
One	8	538	881	1,372	485	44
1 to 5	24	65	248	361	300	428
6 to 10	45	45	80	200	318	199
11 to 15	47	55	260	296	145	141
16 to 20	121	291	444	217	29	89
More than Twenty	773	591	149	34	2	91

Source: *Elaboration based on ECLS-K.*

Figure A-1
Distribution of School by Neighborhood and Neighborhood by School



Source: *Elaboration based on ECLS-K.*

Table A-3
Definition of the Explanatory Variables

Individual and Family Factors	Definition	Source
SES	5 dummies, 1 for each quintile, defined by ECLS-K	ECLS-K
Neighborhood Factors		
Deprivation		
Poverty Percentage	5 dummies Group 1: 1 if perc. between 0 and 0.1 Group 2: 1 if perc. between 0.1 and 0.2 Group 3: 1 if perc. between 0.2 and 0.3 Group 4: 1 if perc. between 0.3 and 0.5 Group 4: 1 if perc. between 0.5 and 1	Census
Affluence		
Percentage of Urban Population	5 dummies Group 1: 1 if perc. between 0 and 0.2 Group 2: 1 if perc. between 0.2 and 0.4 Group 3: 1 if perc. between 0.4 and 0.6 Group 4: 1 if perc. between 0.6 and 0.8 Group 4: 1 if perc. between 0.8 and 1	Census
Percentage of Owners	5 dummies Group 1: 1 if perc. between 0 and 0.2 Group 2: 1 if perc. between 0.2 and 0.4 Group 3: 1 if perc. between 0.4 and 0.6 Group 4: 1 if perc. between 0.6 and 0.8 Group 4: 1 if perc. between 0.8 and 1	Census

Source: *Elaboration based on ECLS-K.*

Table A-4
Descriptive Statistics

Variable	N. Obs.	Mean	SD	Min	Max
Individual Background					
Male	45538	.5044259	.4999855	0	1
White	45538	.6316312	.482367	0	1
Black	45538	.115133	.3191856	0	1
Hispanic	45538	.1622273	3686629	0	1
Asian	45538	.048573	.2149758	0	1
Other	45538	.0424355	.2015827	0	1
SES	45538	3.248035	1.393167	1	5
N. Siblings	45538	0	1	-1.50869	10.49131
School Factors					
Public School	45538	.7729142	4189528	0	1
Perc. Hisp.	45538	2.755353	1.332283	1	5
Title 1	45538	.6081985	.4881581	0	1
Neighborhood Factors					
Deprivation					
Percent. Poor	45538	.0952767	.097819	0	.7065217
Unemployment	45538	0	1	-1.014416	14.70045
Affluence					
Perc. Owners	45538	.7184922	0.1992343	0	1
Urban	45538	.8186824	0	0	1
Perc. Females HS	45538	.8033072	.1419498	.1593252	1
Median Income	45538	0	1	-1.878692	6.076353

Source: *Elaboration based on ECLS-K.*

Table A-5
Correlation between Explanatory Variables and outcomes
Correlation Matrix Outcome and Individual Scores

	Standardized Score	
	Mathematics	**Reading**
Individual Factors		
Male	0.0367*	-0.0860*
Ethnicity		
White	0.2719*	0.2010*
Black	-0.2034*	-0.1690*
Hispanic	-0.1935*	-0.1487*
Asian	0.0532*	0.0551*
Other	-0.0279*	-0.0217*
SES		
Quintile 2 SES	-0.1475*	-0.1506*
Quintile 3 SES	-0.0254*	-0.0404*
Quintile 4 SES	0.0993*	0.0918*
Quintile 5 SES	0.3117*	0.3088*
Number of Siblings	-0.0722*	-0.1161*
School Factors		
Public School	-0.1709*	-0.1992*
Title 1	-0.2246*	-0.2209*
Percentage of Hispanic Population	-0.1056*	-0.0833*
Neighborhood Factors		
Poverty Percentage	-0.3172*	-0.2915*
Spanish Language Percentage	-0.1835*	-0.1558*
Adult Male Unemployment	-0.0615*	-0.0569*
Percent. Urban Population	0.0040*	0.0313*
Percentage of Owners	0.2376*	0.2005*
Median Income	0.3159*	0.3007*
Percentage of Females with HS	0.3272*	0.3028*

Note: ** p-value < 0.01*
Source: *Elaboration based on ECLS-K.*

Table A-6

Correlation Matrix - Explanatory Variables

A) School Factors

	Public School	Title 1	Perc. of Hispanic
Public School	1.0000		
Title 1	0.2119*	1.0000	
Percentage of Hispanic	0.1595*	0.0691*	1.0000

B) Neighborhood Factors

	Poverty Percentage	Male Unemployment	Urban	Percentage Owners	Median Income	Females with HS
Poverty Percentage	1.0000					
Unemployment	0.1698*	1.0000				
Percentage Urban	0.1001*	0.0216*	1.0000			
Percentage Owners	-0.6635*	-0.1353*	-0.3185*	1.0000		
Median Income	-0.6567*	-.1651*	0.0862*	0.5469*	1.0000	
Females with HS	-0.7727*	-0.1566*	-0.0583*	0.5421*	0.6606*	1.0000

C) School and Neighborhood Factors

	Poverty Percentage	Male Unemployment	Urban	Percentage Owners	Median Income	Females with HS
Public School	0.1518*	0.0287*	-0.0637*	-0.0640*	-0.1476*	-0.1461*
Title 1	0.3438*	0.0865*	-0.1605*	-0.2327*	-0.4338*	-0.3700*
Perc. of Hispanic	0.2168*	0.0507*	0.2902*	-0.3456*	-0.1458*	-0.3801*

Note: ** p-value <0.01*
Source: *Elaboration based on ECLS-K.*

Table A-7
Resulting Samples with Missing Values by Wave and Questionnaire

	1	2	4	5	6	7	Questionnaire
Total Missing	21260	21259	17565	12706	10168	9745	
Math	18636	19648	16591	11896	9657	9321	CA
Reading	17622	18936	16291	11845	9648	9269	CA
Tract ID	17539	18500	16039	12706	6141	9642	Census
Individual							
Male	21247	21246	17554	12706	10168	9745	PQ
Race	21190	21189	17527	12699	10155	9735	PQ
SES	20141	20140	13407	9534	9452	8868	PQ
Number of Siblings	18097	19269	17565	12706	10168	8868	PQ
School							
Public	21260	21259	16820	12117	9745	9429	SA
Title 1	18092	18091	13482	9873	9250	0	SA
Perc. Hispanic	16187	16186	13694	9361	9168	8503	SA
Neighborhood							
Poverty	17539	18500	16039	12705	6142	6366	Census
Unemployment							
Urban	17539	18500	16039	12705	6142	6366	Census
Perc. Owners	17539	18500	16039	12705	6142	6366	Census
Perc Females with HS	17539	18500	16039	12705	6142	6366	Census
Median Income	17539	18500	16039	12705	6142	6366	Census
All Missing							
Math	12114	12622	8181	7153	5468	4129	
Reading	11556	12222	8053	7118	5462	4108	

Note: CA: *Cognitive Assessment; PQ: Parent's Questionnaire; SA: School Administrator; Census: 2000 Census.*
Source: *Elaboration based on ECLS-K.*

Table A-8
Model Statistics
Alternative Specifications

A) Mathematics

Model	Obs	Log Likelihood	DF	AIC	BIC	LR Test
Empty Model						
School	45538	-156796.1	4	313600.2	313635.1	
Neighborhood	45538	-158060.1	4	316128.1	31616.1	
Cross- Classified	45538	-158060.1	5	314965.6	315009.2	-1355.79 1165.67
Random Intercept						
Child	45538	-155401.6	15	310833.2	310964.1	4152.34
School	45538	-155342.7	18	310721.3	310878.4	121.48
Neighborhood	45538	-155250.2	33	310566.5	310854.5	208.61
Random Coefficient						
SES	45538	-155216.3	35	310502.6	310808.1	67.83
Hispanic	45538	-155210	35	310489.9	310795.3	80.57
Black	45538	-155230.1	35	310530.1	310835.6	40.33

B) Reading

Model	Obs	Log Likelihood	DF	AIC	BIC	LR Test
Empty Model						
School	44411	-154116.8	4	308241.7	308276.5	
Neighborhood	44411	-155391.2	4	310790.5	310825.3	
Cross- Classified	44411	-154712.9	5	309435.8	309479.3	-1192.14 1356.63
Random Intercept	44411					
Child	44411	-152657.6	15	305345.1	305475.6	4110.71
School	44411	-152572.5	18	305181	305337.6	170.15
Neighborhood	44411	. -152475	33	305016.1	305303.2	194.92
Random Coefficient						
SES	44411	-165744.6	33	331555.3	331845.1	40.15
Hispanic	44411	-165766.8	33	331599.7	331889.5	44.89
Black	44411	-165778.8	33	331623.7	331913.5	40.18

Source: *Elaboration based on ECLS-K.*

Table A-9
The effect of covariates on test scores in alternative Random Intercept Models – Mathematics

	Only Family	Family and School	All
Individual Factors			
Male	0.81***	0.82***	0.82***
	(8.77)	(8.93)	(8.94)
Ethnicity (Base Category = White)			
Black	-4.39***	-4.24***	-3.73***
	(-24.3)	(-23.6)	(-19.8)
Hispanic	-2.96***	-2.69***	-2.44***
	(-19.0)	(-16.3)	(-14.6)
Asian	0.67***	0.80***	0.83***
	(2.95)	(3.48)	(3.62)
Other	-1.67***	-1.57***	-1.50***
	(-6.75)	(-6.33)	(-6.07)
SES (Base Category= Quintile 1)			
Quintile 2	2.54***	2.45***	2.29***
	(16.0)	(15.5)	(14.4)
Quintile 3	4.53***	4.36***	4.10***
	(27.7)	(26.6)	(24.7)
Quintile 4	6.16***	5.91***	5.51***
	(37.2)	(35.3)	(32.3)
Quintile 5	8.61***	8.26***	7.68***
	(49.8)	(46.8)	(42.1)
Number of Siblings	-0.23***	-0.23***	-0.21***
	(-5.78)	(-5.59)	(-5.34)
School Factors			
Public School		-0.57***	-0.57***
		(-3.19)	(-3.21)
Title 1		-1.23***	-0.77***
		(-9.01)	(-5.50)
Standardized Percentage Hispanic		-0.24***	-0.12
		(-3.23)	(-1.56)
Neighborhood Factors			
Deprivation			
Percentage of Poor Population (Base Category less than 10%)			
Between 10 and 20 %			-0.30
			(-1.56)
Between 20 and 30 %			-0.36
			(-1.19)
Between 30 and 50 %			-1.76***
			(-4.31)
More than 50%			0.35
			(0.41)
Percentage of Male Unemployed			0.026
			(0.72)
Affluence			
Urban Percentage (Base Category = Less than 20%)			
Between 20 and 40 %			0.35
			(0.78)
Between 40 and 60 %			0.48
			(1.43)
Between 20 and 80 %			0.73**
			(2.25)
More than 80%			0.69***
			(3.05)

Percentage of Owners (Base Category = More than 80%)			
Between 20 and 40 %			-0.28
			(-0.65)
Between 40 and 60 %			-0.35
			(-1.14)
Between 20 and 80 %			-0.23
			(-1.03)
More than 80%			-0.35**
			(-2.22)
Percentage of females with high school			0.33***
			(2.90)
Standardized Median Income			0.43***
			(4.21)
Constant	47.3***	48.6***	48.3***
	(285)	(207)	(160)
Observations	45538	45538	45538

***Note**: z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1*
***Source:** Elaboration based on ECLS-K.*

Table A-10
The effect of covariates on test scores in alternative Random Intercept Models – Reading

	Only Family	Family and School	All
Individual Factors			
Male	-1.58***	-1.56***	-1.56***
	(-17.2)	(-17.0)	(-17.0)
Ethnicity (Base Category = White)			
Black	-2.88***	-2.70***	-2.20***
	(-15.9)	(-15.0)	(-11.7)
Hispanic	-2.04***	-1.86***	-1.60***
	(-12.9)	(-11.2)	(-9.54)
Asian	1.15***	1.26***	1.30***
	(5.02)	(5.50)	(5.66)
Other	-0.74***	-0.64***	-0.58**
	(-3.00)	(-2.59)	(-2.35)
SES (Base Category= Quintile 1)			
Quintile 2	2.72***	2.62***	2.43***
	(16.8)	(16.2)	(15.0)
Quintile 3	4.54***	4.33***	4.04***
	(27.3)	(25.9)	(24.0)
Quintile 4	6.35***	6.04***	5.63***
	(37.7)	(35.5)	(32.6)
Quintile 5	8.88***	8.45***	7.86***
	(50.5)	(47.2)	(42.7)
Number of Siblings	-0.66***	-0.65***	-0.64***
	(-16.1)	(-15.9)	(-15.7)
School Factors			
Public School		-1.42***	-1.39***
		(-7.60)	(-7.56)
Title 1		-1.29***	-0.80***
		(-9.03)	(-5.48)
Standardized Percentage Hispanic		-0.14*	-0.017
		(-1.72)	(-0.20)
Neighborhood Factors			
Deprivation			
Percentage of Poor Population (Base Category less than 10%)			
Between 10 and 20 %			-0.37*
			(-1.91)
Between 20 and 30 %			-0.34
			(-1.10)
Between 30 and 50 %			-1.67***
			(-4.00)
More than 50%			-0.57
			(-0.64)
Percentage of Male Unemployed			-0.0089
			(-0.23)
Affluence			
Urban Percentage (Base Category = Less than 20%)			
Between 20 and 40 %			0.16
			(0.37)
Between 40 and 60 %			0.55
			(1.62)
Between 20 and 80 %			0.59*
			(1.83)
More than 80%			0.93***
			(4.09)

Percentage of Owners (Base Category = More than 80%)			
Between 20 and 40 %			-0.14
			(-0.31)
Between 40 and 60 %			-0.14
			(-0.45)
Between 20 and 80 %			-0.45**
			(-2.05)
More than 80%			-0.36**
			(-2.27)
Percentage of females with high school			0.54***
			(4.54)
Standardized Median Income			0.25**
			(2.43)
Constant	47.8***	49.8***	49.3***
	(280)	(206)	(160)
Observations	44411	44411	44411

Note*: z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Source: *Elaboration base don ECLS-K.*

Table A-11
ICC in Alternative Random Intercept Models
Mathematics

	Empty Model			Random Intercept		
	School (1)	Neighborhood (2)	Crossed (3)	F (4)	S (5)	N (6)
Random Effect						
Child	55.57	60.49	57.1	47.42	47.44	47.46
School	23.85	-	15.28	5.76	5.23	4.91
Neighborhood	-	20.75	7.87	3.46	3.37	3
Residual	17.33	17.52	17.18	17.33	17.32	17.3
ICC						
Child	0.574	0.612	0.586	0.641	0.647	0.653
School	0.247	-	0.157	0.078	0.071	0.068
Neighborhood	-	0.210	0.081	0.047	0.046	0.041
School + Neighborhood	0.247	0.210	0.238	0.125	0.117	0.109

***Note**: All Random Effects are significant for a p-value < 0.01.*

Source: *Elaboration based on ECLS-K.*

Table A-12
ICC in Alternative Random Intercept Models
Reading

	Empty Model			Random Intercept		
	School (1)	Neighborhood (2)	Crossed (3)	F (4)	S (5)	N (6)
Random Effect						
Child	51.94	57.5	48.7	43.32	43.3	43.33
School	24.14	-	16.9	7.47	6.57	6.06
Neighborhood	-	20.07	7.03	3.36	3.23	2.94
Residual	20.7	20.78	20.53	20.75	20.77	20.72
ICC						
Child	0.537	0.585	0.523	0.578	0.586	0.593
School	0.249	-	0.181	0.100	0.089	0.083
Neighborhood	-	0.204	0.075	0.045	0.044	0.040
School + Neighborhood	0.249	0.204	0.257	0.145	0.133	0.123

***Note**: All Random Effects are significant for a p-value < 0.01.*

Source: *Elaboration based on ECLS-K.*

Table A-13
The effect of covariates on test scores in alternative Random Coefficient Models - Mathematics

SLOPE	Quintile 1	Hispanic	Black
Individual Factors			
Male	0.83***	0.84***	0.83***
	(9.03)	(9.12)	(9.04)
Ethnicity (Base Category = White)			
Black	-3.73***	-3.74***	-3.80***
	(-19.8)	(-19.8)	(-18.6)
Hispanic	-2.42***	-2.39***	-2.44***
	(-14.4)	(-12.8)	(-14.5)
Asian	0.80***	0.75***	0.85***
	(3.46)	(3.25)	(3.68)
Other	-1.51***	-1.53***	-1.48***
	(-6.09)	(-6.20)	(-5.99)
SES (Base Category= Quintile 1)			
Quintile 2	2.36***	2.23***	2.28***
	(13.2)	(14.0)	(14.3)
Quintile 3	4.16***	4.04***	4.08***
	(22.6)	(24.2)	(24.6)
Quintile 4	5.57***	5.46***	5.51***
	(29.6)	(31.9)	(32.3)
Quintile 5	7.73***	7.64***	7.66***
	(39.0)	(41.8)	(42.0)
Number of Siblings	-0.21***	-0.21***	-0.21***
	(-5.14)	(-5.30)	(-5.30)
School Factors			
Public School	-0.53***	-0.56***	-0.56***
	(-3.00)	(-3.20)	(-3.17)
Title 1	-0.77***	-0.78***	-0.78***
	(-5.49)	(-5.57)	(-5.57)
Percentage Hispanic	-0.13	-0.14*	-0.12
	(-1.64)	(-1.75)	(-1.52)
Neighborhood Factors			
Deprivation			
Percentage of Poor Population (Base Category less than 10%)			
Between 10 and 20 %	-0.27	-0.30	-0.29
	(-1.39)	(-1.54)	(-1.48)
Between 20 and 30 %	-0.32	-0.31	-0.35
	(-1.04)	(-1.03)	(-1.16)
Between 30 and 50 %	-1.79***	-1.82***	-1.70***
	(-4.31)	(-4.42)	(-4.08)
More than 50%	0.46	0.47	0.46
	(0.52)	(0.55)	(0.51)
Percentage of Male Unemployed	-0.27	0.027	0.028
	(-1.39)	(0.75)	(0.76)
Affluence			
Urban Percentage (Base Category = Less than 20%)			
Between 20 and 40 %	0.34	0.33	0.35
	(0.76)	(0.75)	(0.78)
Between 40 and 60 %	0.47	0.47	0.52
	(1.41)	(1.41)	(1.53)

Between 20 and 80 %	0.73**	0.71**	0.73**
	(2.28)	(2.24)	(2.26)
More than 80%	0.67***	0.65***	0.68***
	(3.00)	(2.91)	(3.01)
Percentage of Owners (Base Category = More than 80%)			
Between 20 and 40 %	-0.24	-0.21	-0.34
	(-0.55)	(-0.47)	(-0.78)
Between 40 and 60 %	-0.30	-0.26	-0.36
	(-0.97)	(-0.84)	(-1.17)
Between 20 and 80 %	-0.21	-0.17	-0.24
	(-0.95)	(-0.76)	(-1.08)
More than 80%	-0.37**	-0.35**	-0.35**
	(-2.36)	(-2.22)	(-2.25)
Perc. of females with high school	0.36***	0.37	0.33***
	(3.07)	(3.03)	(2.90)
Median Income	0.43***	0.44	0.43***
	(4.24)	(3.96)	(4.21)
Constant	47.3***	48.6***	48.3***
	(285)	(207)	(160)
Observations	45538	45538	45538

Note: *z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1*
Source: *Elaboration base don ECLS-K.*

Table A-14
Neighborhood-level variance and ICC in alternative Random Coefficient Models - Mathematics

	Slope		
	Hispanic	**Black**	**SES=1**
Random Effect			
Child	46.54	46.91	46.71
School	4.84	4.89	4.93
Neighborhood	9.59	6.5	9.75
Intercept	2.93	3.24	2.84
Slope			
Hispanic	12.4		
Black		9.9	
SES			9.19
Covariance			
Constant/Slope	-2.87	-3.32	-1.14
Residual	17.3	17.3	17.23
ICC			
Child	0.595	0.621	0.594
School	0.062	0.065	0.063
Neighborhood	0.123	0.086	0.124
School + Neighborhood	0.184	0.151	0.187

***Note**: All Random Effects are significant for a p-value < 0.01.*
***Source:** Elaboration based on ECLS-K.*

Table A-15
The effect of covariates on test scores in alternative Random Coefficient Models – Reading

SLOPE	**Quintile 1**	**Hispanic**	**Black**
Individual Factors			
Male	-1.56***	-1.55***	-1.55***
	(-17.1)	(-16.9)	(-17.0)
Ethnicity (Base Category = White)			
Black	-2.19***	-2.20***	-2.24***
	(-11.6)	(-11.7)	(-10.9)
Hispanic	-1.61***	-1.62***	-1.60***
	(-9.54)	(-8.83)	(-9.51)
Asian	1.29***	1.26***	1.30***
	(5.61)	(5.47)	(5.70)
Other	-0.57**	-0.59**	-0.55**
	(-2.30)	(-2.39)	(-2.26)
SES (Base Category= Quintile 1)			
Quintile 2	2.51***	2.40***	2.42***
	(14.1)	(14.7)	(14.8)
Quintile 3	4.11***	4.00***	4.03***
	(22.5)	(23.7)	(23.8)
Quintile 4	5.69***	5.60***	5.62***
	(30.5)	(32.3)	(32.5)
Quintile 5	7.92***	7.83***	7.85***
	(40.2)	(42.5)	(42.6)
Number of Siblings	-0.64***	-0.64***	-0.64***
	(-15.5)	(-15.7)	(-15.6)
School Factors			
Public School	-1.37***	-1.38***	-1.39***
	(-7.45)	(-7.52)	(-7.54)
Title 1	-0.80***	-0.81***	-0.81***
	(-5.47)	(-5.51)	(-5.52)
Percentage Hispanic	-0.021	-0.019	-0.016
	(-0.25)	(-0.23)	(-0.19)
Neighborhood Factors			
Deprivation			
Percentage of Poor Population (Base Category less than 10%)			
Between 10 and 20 %	-0.36*	-0.36*	-0.37*
	(-1.87)	(-1.85)	(-1.89)
Between 20 and 30 %	-0.33	-0.32	-0.36
	(-1.07)	(-1.05)	(-1.16)
Between 30 and 50 %	-1.67***	-1.68***	-1.58***
	(-3.95)	(-4.00)	(-3.70)
More than 50%	-0.48	-0.52	-0.57
	(-0.53)	(-0.58)	(-0.61)
Percentage of Male Unemployed	-0.0081	-0.0064	-0.0073
	(-0.21)	(-0.16)	(-0.19)
Affluence			
Urban Percentage (Base Category = Less than 20%)			
Between 20 and 40 %	0.15	0.17	0.16
	(0.33)	(0.38)	(0.37)
Between 40 and 60 %	0.58*	0.55	0.58*
	(1.71)	(1.63)	(1.71)

Between 20 and 80 %	0.60*	0.59*	0.60*
	(1.84)	(1.83)	(1.86)
More than 80%	0.93***	0.92***	0.92***
	(4.11)	(4.06)	(4.04)
Percentage of Owners (Base Category = More than 80%)			
Between 20 and 40 %	-0.15	-0.13	-0.17
	(-0.33)	(-0.30)	(-0.38)
Between 40 and 60 %	-0.089	-0.12	-0.13
	(-0.28)	(-0.40)	(-0.43)
Between 20 and 80 %	-0.45**	-0.46**	-0.44**
	(-2.07)	(-2.08)	(-1.98)
More than 80%	-0.37**	-0.36**	-0.36**
	(-2.34)	(-2.29)	(-2.31)
Perc. of females with high school	0.55***	0.54***	0.54***
	(4.59)	(4.55)	(4.57)
Median Income	0.25**	0.26**	0.26**
	(2.41)	(2.52)	(2.48)
Constant	49.3***	49.4***	49.3***
	(156)	(160)	(159)
Observations	44411	44411	44411

Note*: z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Source: *Elaboration base don ECLS-K.*

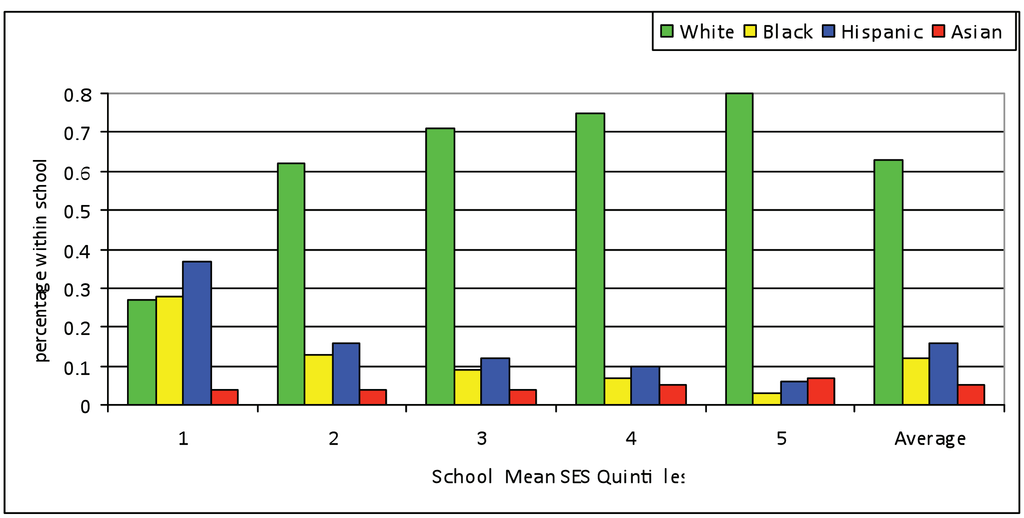
Table A-16
ICC in Alternative Random Coefficient Models - Reading

	Slope		
	Quintile 1	**Hispanic**	**Black**
Random Effect			
Child	42.6	42.78	40.78
School	6	6.06	6.04
Neighborhood	6.73	7.78	7.72
Intercept	3.21	3.07	2.93
Slope			
Hispanic	9.88		
Black		13.43	
SES			7.05
Covariance			
Constant/Slope	-3.18	-4.36	-1.13
Residual	20.72	20.73	20.91
ICC			
Child	0.560	0.553	0.540
School	0.079	0.078	0.080
Neighborhood	0.088	0.101	0.102
School + Neighborhood	0.167	0.179	0.182

***Note**: All Random Effects are significant for a p-value < 0.01.*

***Source:** Elaboration based on ECLS-K.*

Figure A-2
School Racial Composition by Mean Family SES



***Source:** Elaboration based on ECLS-K.*

Table A-17
The effect of covariates on test scores in selected subgroups
Mathematics

	Male	Quintile 1	Black	Hispanic	White
Individual Factors					
Male		0.23	0.10	0.46**	1.06***
		(0.90)	(0.37)	(1.97)	(9.25)
Ethnicity (Base Category = White)					
Black	-3.34***	-3.07***			
	(-13.4)	(-6.98)			
Hispanic	-1.91***	-3.10***			
	(-8.52)	(-6.78)			
Asian	0.76**	3.04***			
	(2.53)	(4.31)			
Other	-1.32***	-1.50**			
	(-4.00)	(-2.07)			
SES (Base Category= Quintile 1)					
Quintile 2	2.19***		2.20***	2.68***	2.64***
	(10.1)		(6.16)	(8.58)	(10.4)
Quintile 3	3.99***		3.50***	4.20***	4.51***
	(17.9)		(8.96)	(11.7)	(17.6)
Quintile 4	5.41***		4.46***	5.72***	6.13***
	(23.5)		(10.3)	(14.4)	(23.8)
Quintile 5	7.66***		5.95***	7.32***	8.20***
	(31.0)		(10.3)	(14.3)	(31.1)
Number of Siblings	-0.24***	-0.30***	-0.36***	-0.28***	-0.11**
	(-4.47)	(-3.29)	(-3.33)	(-2.82)	(-2.06)
School Factors					
Public School	-0.39*	-4.28***	-1.56***	-0.95**	-0.44**
	(-1.86)	(-5.27)	(-2.69)	(-2.08)	(-2.22)
Title 1	-0.83***	-0.92**	-1.43***	-0.95***	-0.51***
	(-4.65)	(-2.09)	(-3.34)	(-2.58)	(-3.11)
Percentage Hispanic	-0.20**	0.13	-0.36*	-0.46**	-0.054
	(-1.96)	(0.69)	(-1.87)	(-2.30)	(-0.54)
Neighborhood Factors					
Deprivation					
Percentage of Poor Population (Base Category less than 10%)					
Between 10 and 20 %	-0.20	-1.21**	0.12	-0.19	-0.53**
	(-0.76)	(-2.52)	(0.22)	(-0.42)	(-2.12)
Between 20 and 30 %	-0.47	-1.35**	0.99	-1.12*	-0.49
	(-1.19)	(-2.02)	(1.36)	(-1.71)	(-1.03)
Between 30 and 50 %	-1.45***	-2.93***	-1.54*	-1.45*	-2.72***
	(-2.72)	(-3.52)	(-1.75)	(-1.67)	(-3.09)
More than 50%	-0.65	-0.55	0.31	1.51	-1.02
	(-0.59)	(-0.40)	(0.22)	(0.85)	(-0.25)
Perc. of Male Unemployed	-0.013	-0.019	-0.0069	0.023	0.0026
	(-0.26)	(-0.21)	(-0.083)	(0.25)	(0.056)
Affluence					
Urban Ethnicity (Base Category = Less than 20%)					
Between 20 and 40 %	0.97	-0.64	1.05	-0.68	0.46
	(1.59)	(-0.50)	(0.56)	(-0.42)	(0.96)
Between 40 and 60 %	0.21	1.40*	0.20	-0.36	0.54

	(0.48)	(1.65)	(0.18)	(-0.30)	(1.48)
Between 20 and 80 %	0.40	-0.19	0.83	1.01	0.79**
	(0.96)	(-0.21)	(0.67)	(0.84)	(2.29)
More than 80%	0.25	1.81***	0.85	1.32*	0.48**
	(0.86)	(3.11)	(1.07)	(1.68)	(1.98)
Percentage of Owners (Base Category = More than 80%)					
Between 20 and 40 %	-0.20	-1.17	0.19	-3.02***	0.60
	(-0.35)	(-1.31)	(0.20)	(-3.51)	(0.77)
Between 40 and 60 %	-0.31	-0.46	0.28	-2.15***	0.32
	(-0.78)	(-0.66)	(0.35)	(-3.34)	(0.66)
Between 20 and 80 %	-0.25	-0.46	0.34	-1.94***	0.45
	(-0.87)	(-0.78)	(0.51)	(-3.69)	(1.61)
More than 80%	-0.49**	0.33	-0.52	-0.89**	-0.046
	(-2.39)	(0.68)	(-0.94)	(-2.02)	(-0.26)
Percentage of females with high school	0.45***	-0.33	0.26	-0.087	0.70***
	(3.06)	(-1.45)	(0.85)	(-0.40)	(4.02)
Median Income	0.29**	0.20	0.89**	-0.0085	0.46***
	(2.29)	(0.45)	(1.96)	(-0.028)	(3.90)
Constant	48.5***	50.9***	46.2***	46.8***	47.3***
	(127)	(52.5)	(46.4)	(52.7)	(127)
Observations	22547	6790	5434	7423	28483

Note: *z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1:[*
Source*: Elaboration based on ECLS-K.*

Table A-18
ICC in Selected Subgroups - Mathematics

	Group					
	All Population	**SES 1**	**Male**	**Black**	**Hispanic**	**White**
Random Effect						
Child	47.46	51.39	39.61	47.21	43.41	45.74
School	4.91	4.42	4.70	4.53	5.36	5.05
Neighborhood	3.00	4.03	5.20	5.29	7.80	2.97
Residual	17.30	20.14	16.40	18.12	20.78	16.32
ICC						
Child	0.65	0.64	0.18	0.63	0.56	0.65
School	0.07	0.06	0.07	0.06	0.06	0.06
Neighborhood	0.04	0.05	0.08	0.07	0.10	0.04
School + Neighborhood	0.11	0.11	0.15	0.13	0.16	0.11

Note: *All Random Effects are significant for a p-value < 0.01.*
Source: *Elaboration based on ECLS-K.*

Table A-19
Sensitivity Analysis Random Intercept -
OLS - All Covariates

	Reading	Mathematics
Individual Factors		
Male	-1.61***	0.78***
	(-19.2	(9.46)
Ethnicity (Base Category = White)		
Black	-2.00***	-3.76***
	(-13.3)	(-25.4)
Hispanic	-1.56***	-2.39***
	(-10.5)	(-16.5)
Asian	1.20***	0.61***
	(6.06)	(3.08)
Other	-1.14***	-2.10***
	(-5.42)	(-10.0)
SES (Base Category= Quintile 1)		
Quintile 2	2.61***	2.54***
	(17.0)	(17.2)
Quintile 3	4.35***	4.43***
	(27.9)	(29.3)
Quintile 4	5.98***	5.96***
	(37.7)	(38.6)
Quintile 5	8.54***	8.42***
	(50.9)	(51.4)
Number of Siblings	-0.71***	-0.29***
	(-19.0)	(-7.87)
School Factors		
Public School	-1.34***	-0.70***
	(-12.6)	(-6.66)
Title 1	-0.88***	-0.91***
	(-9.01)	(-9.41)
Percentage Hispanic	0.0093	-0.053
	(0.17)	(-0.99)
Neighborhood Factors		
Deprivation		
Percentage of Poor Population (Base Category less than 10%)		
Between 10 and 20 %	-0.50***	-0.48***
	(-3.55)	(-3.46)
Between 20 and 30 %	-0.43*	-0.23
	(-1.96)	(-1.07)
Between 30 and 50 %	-2.02***	-1.84***
	(-6.93)	(-6.57)
More than 50%	0.11	0.95
	(0.18)	(1.58)
Percentage of Male Unemployed	0.0024	0.029
	(0.061)	(0.75)
Affluence		
Urban Percentage (Base Category = Less than 20%)		
Between 20 and 40 %	0.33	0.44
	(0.99)	(1.33)
Between 40 and 60 %	0.14	0.20
	(0.61)	(0.90)

Between 20 and 80 %	0.32	0.78***
	(1.39)	(3.47)
More than 80%	0.72***	0.59***
	(4.94)	(4.08)
Percentage of Owners (Base Category = More than 80%)		
Between 20 and 40 %	0.31	0.16
	(0.95)	(0.51)
Between 40 and 60 %	0.41*	0.21
	(1.78)	(0.95)
Between 20 and 80 %	-0.19	0.016
	(-1.18)	(0.10)
More than 80%	-0.12	-0.050
	(-1.13)	(-0.46)
Percentage of females with high school	0.48***	0.40***
	(5.94)	(5.24)
Median Income	0.32***	0.39***
	(4.93)	(5.99)
Constant	49.0***	47.9***
	(218)	(217)
Observations	44411	45538

Note: *z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1:[*

Source*: Elaboration based on ECLS-K.*

Table A-20
Sensitivity Analysis Model 2- Dummy for Missing
Effect of Covariates – Mathematics

	Mathematics
Individual Factors	
Male	0.79***
	(10.7)
Ethnicity (Base Category = White)	
Black	-3.88***
	(-26.4)
Hispanic	-2.65***
	(-20.2)
Asian	1.10***
	(6.09)
Other	-1.45***
	(-7.24)
SES (Base Category= Quintile 1)	
Quintile 2	2.05***
	(15.7)
Quintile 3	3.60***
	(26.8)
Quintile 4	4.87***
	(35.4)
Quintile 5	6.65***
	(45.8)
Number of Siblings	-0.28***
	(-8.71)
School Factors	
Public School	-0.76***
	(-5.56)
Title 1	-0.66***
	(-5.78)
Percentage Hispanic	-0.021
	(-0.35)
Neighborhood Factors	
Deprivation	
Percentage of Poor Population (Base Category less than 10%)	
Between 10 and 20 %	-0.40**
	(-2.50)
Between 20 and 30 %	-0.32
	(-1.30)
Between 30 and 50 %	-1.52***
	(-4.62)
More than 50%	0.20
	(0.30)
Percentage of Male Unemployed	-0.039
	(-1.24)
Affluence	
Urban Percentage (Base Category = Less than 20%)	
Between 20 and 40 %	0.022
	(0.056)
Between 40 and 60 %	0.45
	(1.51)

Between 20 and 80 %	0.80***
	(2.79)
More than 80%	0.60***
	(3.10)
Percentage of Owners (Base Category = More than 80%)	
Between 20 and 40 %	-0.33
	(-0.95)
Between 40 and 60 %	-0.27
	(-1.12)
Between 20 and 80 %	-0.24
	(-1.33)
More than 80%	-0.18
	(-1.36)
Percentage of females with high school	0.43***
	(4.54)
Median Income	0.74***
	(8.81)
Constant	48.9***
	(197)
Observations	71421

Note: *z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1:[*
Source*: Elaboration based on ECLS-K.*

Table A-21
Sensitivity Analysis Model 2: Dummy for Missing
ICC - Mathematics

	Empty	Full
Random Effect		
Child	52.79	48.15
School	12.13	4.39
Neighborhood	11.88	4.51
Residual	17.41	17.8
ICC		
Child	0.560	0.643
School	0.129	0.059
Neighborhood	0.126	0.060
School + Neighborhood	0.255	0.119

Note*: All Random Effects are significant for a p-value < 0.01.*
Source: *Elaboration based on ECLS-K.*

Table A-22
Sensitivity Analysis Model 1: Balanced Panel
Effect of Covariates - Mathematics

	Mathematics
Individual Factors	
Male	1.16***
	(8.96)
Ethnicity (Base Category = White)	
Black	-4.10***
	(-15.1)
Hispanic	-2.25***
	(-8.67)
Asian	0.38
	(1.11)
Other	-1.81***
	(-4.60)
SES (Base Category= Quintile 1)	
Quintile 2	1.97***
	(8.32)
Quintile 3	3.75***
	(15.3)
Quintile 4	5.39***
	(21.6)
Quintile 5	7.52***
	(28.7)
Number of Siblings	-0.19***
	(-3.38)
School Factors	
Public School	-0.096
	(-0.41)
Title 1	-1.06***
	(-5.49)
Percentage Hispanic	-0.25**
	(-2.26)
Neighborhood Factors	
Deprivation	
Percentage of Poor Population (Base Category less than 10%)	
Between 10 and 20 %	-0.30
	(-1.11)
Between 20 and 30 %	-0.33
	(-0.75)
Between 30 and 50 %	-2.31***
	(-3.86)
More than 50%	0.56
	(0.47)
Percentage of Male Unemployed	-0.041
	(-0.81)
Affluence	
Urban Percentage (Base Category = Less than 20%)	
Between 20 and 40 %	0.44
	(1.33)
Between 40 and 60 %	0.20
	(0.90)

Between 20 and 80 %	0.78***
	(3.47)
More than 80%	0.59***
	(4.08)
Percentage of Owners (Base Category = More than 80%)	
Between 20 and 40 %	-0.0038
	(-0.0064)
Between 40 and 60 %	0.47
	(1.11)
Between 20 and 80 %	0.86**
	(2.13)
More than 80%	0.67**
	(2.38)
Percentage of females with high school	
	0.39
Median Income	(0.61)
	-0.28
Constant	(-0.64)
	-0.0092
Observations	45538

Note: *z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1:[*
Source*: Elaboration based on ECLS-K.*

Table A-23
Sensitivity Analysis Model 1: Balanced Panel
ICC - Mathematics

	Empty	Full
Random Effect		
Child	51.71	46.43
School	16.95	6
Neighborhood	4.67	1.64
Residual	16.31	16.43
ICC		
Child	0.577	0.659
School	0.189	0.085
Neighborhood	0.052	0.023
School + Neighborhood	0.241	0.108

Note: *z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1:[*
Source*: Elaboration based on ECLS-K.*

Table A-24
Fixed Effect Model - Mathematics

Individual Factors	
Male	0.83***
	(8.25)
Ethnicity (Base Category = White)	
Black	-3.51***
	(-15.5)
Hispanic	-2.49***
	(-13.1)
Asian	0.94***
	(3.52)
Other	-1.22***
	(-4.37)
SES (Base Category= Quintile 1)	
Quintile 2	2.18***
	(13.6)
Quintile 3	3.90***
	(23.3)
Quintile 4	5.20***
	(29.8)
Quintile 5	7.18***
	(36.9)
Number of Siblings	-0.18***
	(-4.13)
School Factors	
Public School	-0.56**
	(-2.24)
Title 1	-0.53***
	(-3.18)
Percentage Hispanic	-0.15*
	(-1.87)
Neighborhood Factors	
Deprivation	
Percentage of Poor Population (Base Category less than 10%)	
Between 10 and 20 %	-0.35*
	(-1.73)
Between 20 and 30 %	-0.53
	(-1.61)
Between 30 and 50 %	-2.10***
	(-4.41)
More than 50%	-0.20
	(-0.21)
Percentage of Male Unemployed	0.024
	(0.63)
Affluence	
Urban Percentage (Base Category = Less than 20%)	
Between 20 and 40 %	0.28
	(0.63)
Between 40 and 60 %	0.47
	(1.41)
Between 20 and 80 %	0.65**
	(2.03)
More than 80%	0.57**
	(2.50)
Percentage of Owners (Base Category = More than 80%)	
Between 20 and 40 %	-0.10
	(-0.21)
Between 40 and 60 %	-0.18

	(-0.52)
Between 20 and 80 %	-0.15
	(-0.61)
More than 80%	-0.27*
	(-1.65)
Percentage of females with high school	0.11
	(0.67)
Median Income	0.37**
	(2.50)
School Fixed Effects	
Male	0.059
	(0.16)
Black	0.16
	(0.35)
Hispanic	1.08**
	(2.16)
Asian	0.55
	(0.82)
Other	-1.20
	(-1.49)
SES	1.85***
	(7.42)
Number of Siblings	-0.15
	(-1.04)
Poverty Percentage	3.65
	(1.61)
Unemployment	0.23
	(0.12)
Percentage of Owners	0.96
	(1.18)
Percentage of females with high school	2.16
	(1.33)
Median Income	-0.000018**
	(-2.10)
Neighborhood Fixed Effects	
Male	-0.056
	(-0.21)
Black	-0.56
	(-1.41)
Hispanic	-0.20
	(-0.49)
Asian	-0.75
	(-1.33)
Other	-0.81
	(-1.29)
SES	0.31*
	(1.69)
Number of Siblings	-0.10
	(-0.89)
School Public	1.24***
	(4.28)
Title 1	-0.053
	(-0.21)
Percentage of Hispanic	0.11
	(1.07)
Constant	45.7***
Observations	45538

Note: *z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1:;* ***Source****: Elaboration based on ECLS-K.*

Figure A-3
Q plot Level 1 residuals

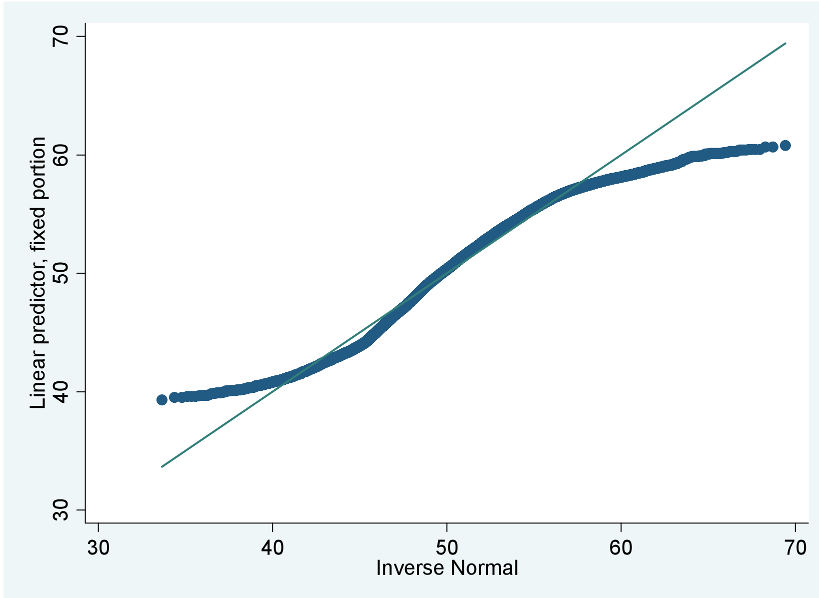


Figure A-4
Predicted Random Effects - Child

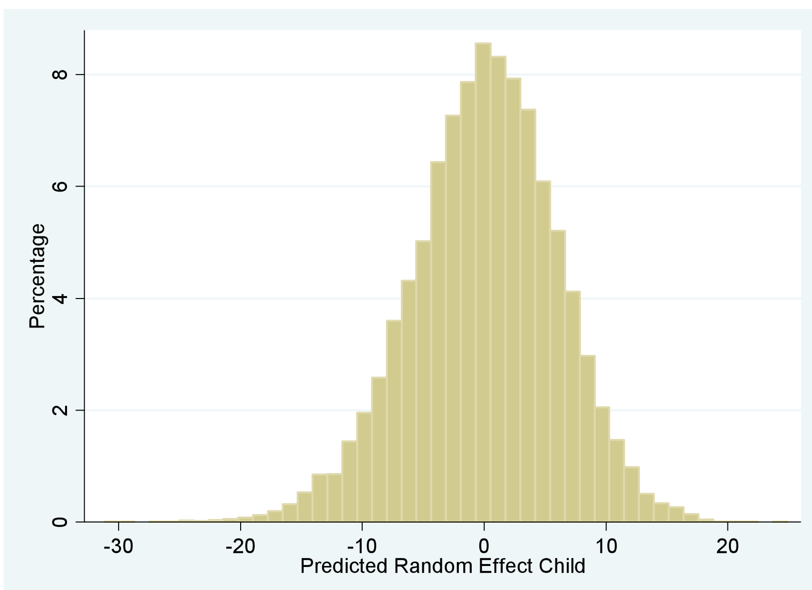


Figure A-5
Predicted Random Effects - Neighborhood

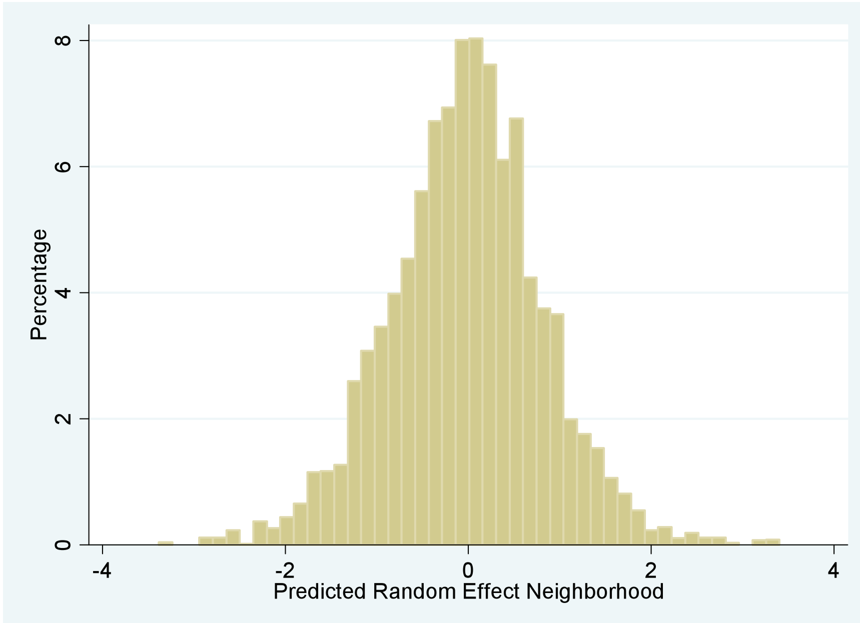
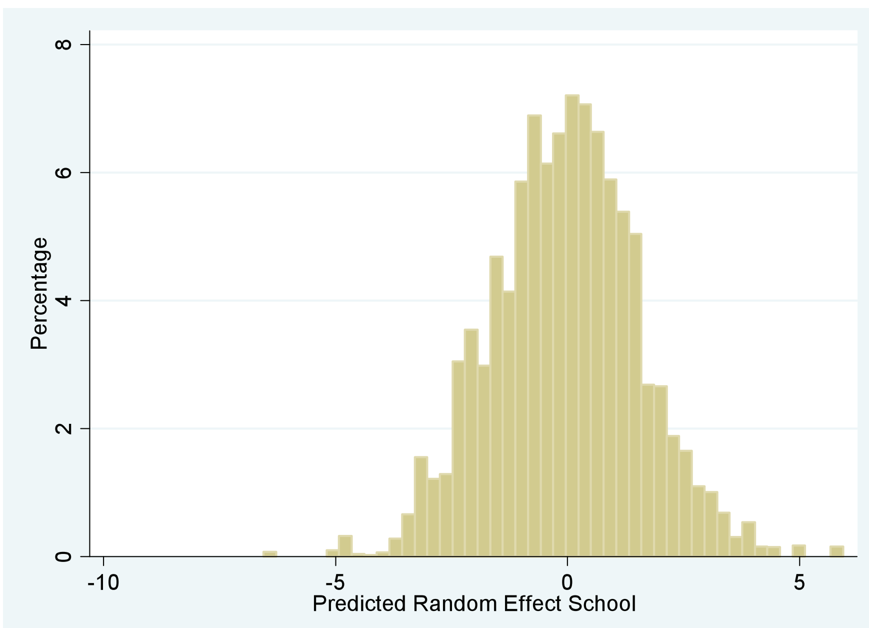


Figure A-6
Predicted Random Effects – School



2. Institutional Appendix to Chapter 3: The North Carolina School District

The North Carolina Department of Public Instruction is the area in charge of implementing the State's public school laws and policies. Among the issues under the Department supervision are the Curriculum Content and the Assessment System, usually referred as the ABCs of Public Education.

A.1. Curriculum Content: the Standard Course of Study

The definition of the basic education program for the State has two aspects. The first is the Basic Education Program for North Carolina's Public Schools which outlines the general guidelines that should be provided in all schools throughout the state. The second one, the North Carolina Standard Course of Study (NCSCS) sets the content standards and describes the curriculum. Curriculum and assessment are aligned: while the *Standard Course of Study* sets content standards for what students should know, the ABCs Accountability measures them.

The NCSCS started in the 1890's being as a guide which outlined the curriculum for the public schools. The NCSCS is reviewed every five to seven years to keep pace with the needs of students. Since the original one, it has evolved from a very detailed curriculum to a flexible guide that emphasizes what students should know through various levels of proficiency[88]. Local school districts, schools, and teachers can develop and adapt curricular units to students needs. As many public schools in the state presently offer an even more comprehensive curriculum than the minimum set by the NCSCS, elective course are also included in the NCSCS[89].

A.1.1. Honors Courses

Honors mathematics courses are designed for students who have demonstrated an advanced level of interest and/or achievement in mathematics. The rationale for honors courses is to offer challenging, higher level courses for students who aspire to an advanced level of learning. Honors mathematics courses are distinguished from regular courses by a difference in

[88] The Elementary and Secondary Reform Act, passed in June 1984, mandates this role to the Department of Public Instruction.

[89] http://www.dpi.state.nc.us/curriculum/introduction.

the quality of the work expected rather than merely by the quantity of the work required[90]. Local districts determine the criteria for placement in Honors Courses.

A.2. Assessment and Accountability Program

The statewide testing program, known as the ABCs of Public Education, was implemented in elementary and middle schools in 1996-97 for the first time with a high school model in 1997-98. In 1998-99 the two accountability models were combined into one comprehensive ABCs model for elementary, middle and high schools. The ABCs accountability model sets growth and performance standards for each elementary, middle, and high school in the state. End-of-grade (EOG) and end-of-course (EOC) test results and selected other components are used to measure the schools' growth and performance. Table A-25 describes the current ABC system.

Table A-25
North Carolina Assessment System

Grade	Area
3	Grade 3 Pretest in Reading and Math and EOG Test in Reading and Math
4	EOG Test in Reading and Math, Writing Assessment, Open-Ended Assessment in Reading and Math
5	EOG Test in Reading and Math
6	EOG Test in Reading and Math
7	EOG Test in Reading and Math Writing Assessment
8	EOG Test in Reading and Math Open-ended assessment in Reading and Math Computer Skills
9	EOC Tests in Algebra 1
10	EOC Tests in Geometry , Competency Test in Reading and Math; HSCT
11	EOC Tests in Algebra 2

Note*: Only Mathematics EOC tests are listed.*
Source: *Elaboration based on North Carolina ABCs System.*

The ABCs define the statewide testing program on the basic academic skills which should be mastered by all students. Four achievement or mastery levels are defined: Insufficient Mastery, Inconsistent Mastery, Consistent Mastery and Superior Performance[91]. Students need to perform Level III or above to pass the test.

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[90] North Carolina Honors Course Standards and Honors Course Implementation Guide. Online at: http://www.dpi.state.nc.us/curriculum/honorsguide.

[91] The use of the mastery levels allows the comparison of student and group performance to standards based on what is expected in each subject at each grade level.

A.2.1. The High School Comprehensive Test

The North Carolina HSCT in Reading and Mathematics is a component of the ABCs accountability model for high schools. The high school comprehensive test consists on a multiple-choice test developed to measure growth in student achievement in Reading and Mathematics from grade 8 to grade. Although the test is curriculum-based, the content measured is not course specific. All students officially classified as tenth graders by the school principal participate in the test administration unless specifically exempted.

The test was first administered to all students in grade 10 during the 1997-98 school year. The test was eliminated, due to budget constraints in 2001, but reinstated in 2002-2003. In the school year 2004-2005, the HSCT was changed from a universal to a sample basis and used to calculate AYP for NCLB requirements.

A.3. Graduation Requirements

To graduate high school students are expected to meet specific course and credit requirements, testing standards and performance requirements in order to receive a high school diploma. Graduation requirements vary according to the four possible courses of study. North Carolina has four possible courses of study: Career Prep, College Prep and College University Prep and Occupational. The latter, the Occupational Course of Study, is intended to meet the needs of a small group of students with disabilities who require a different curriculum.

Requirements for graduation differ depending on when students entered ninth grade for the first time, the course of study. Students should meet Local Educational Authority (LEA) requirements, as well. Table A-26 describes the graduation requirement for ninth graders entering from 2000-2008 as well as the courses that count towards graduation requirements.

Algebra 1 counts towards graduation independent of the course of study and is only not necessary in the Occupational Course of Study that is aimed at a low fraction of the enrollment. According to the NCSCS, schools districts can decide locally to offer courses that they develop. In general, NC schools districts have opted for either offer a preparatory class (Pre-Algebra or Introductory Algebra) and/or split the Algebra 1 contents in a two sequence courses (Algebra 1A and 1B). For instance, Pre-Algebra, Algebra 1A, and Algebra 1B are not courses outlined in the North Carolina Standard Course of Study. If Algebra 1 is offered in parts students may only receive 1/2 credit for each part.

Table A-26
Graduation Requirements Mathematics
Cohort entering 9th grade in 2000-2008

Course of Study			
Career Prep	**College Prep**	**College University Prep**	**Occupational**
3 Credits Including Algebra I	**3 Credits*** Algebra I, Geometry, Algebra II, OR Algebra I, Technical Math I & II	**4 Credits** Algebra I, Algebra II, Geometry, and higher level math course with Algebra II.	**3 Credits** Occupational Mathematics I, II, III

***Source**: Elaboration based on North Carolina State Board of Education.*

In terms of curriculum content, in many situations the objectives for Pre-Algebra may be the same as the standards for 8th grade algebra. However, there are no guidelines that say that this is the case. If Algebra I were taken in parts, the student must take and pass the Algebra 1 EOC at the end of Algebra 1B in order to receive credit for Algebra 1 for the graduation requirement. Depending on local and school offer, students may take Algebra 1 as early as 7th grade. The middle school students must take both the EOG for their grade level and the EOC for the particular high school course.

Locally developed courses, such as Pre-Algebra, are counted as a math credit only in the Career Prep Course of Study. In contrast, if a student is following the College Tech Prep or College/University Prep courses of study, a locally developed course is considered an elective, not a math credit.

3. Methodological Appendix to Chapter 3: Bandwidth Selection

Non parametric models have the advantage of not making assumptions about the process generating the data. Similar to parametric regression, a weighted sum of the *y* observations is used to obtain the fitted values. Instead of using equal weights (as in ordinary least squares) or weights proportional to the inverse of variance (often the case in weighted least squares), the choice of weights in nonparametric methods follow other criteria, mostly related to the use of alternative weighting schemes.

Non parametric estimates are possible only by reducing the number of points in the data. Thus, non parametric methods are local average methods which results depend on the bandwidth, *h* (Cameron and Trivedi, 2008:295). The bandwidth determines how fast the weights decrease as the distance from x_0 increases. For instance, the observations with the most information about $f(x_0)$ should be those at locations x_i closest to x_0. Thus, the rate at which the weights decrease relative to the locations of the x_i's controls the smoothness of the resulting estimate of $f(x)$.

The choice of the bandwidth *h* is decisive to solve the trade-off between bias and variance as well[92]. Kernel estimators of the type of equation (6) are biased as they use information that could be far from x_0 (Heckman, Ichimura and Tood, 1997; Hahn, 1998). Observations closer to x_0 imply lower bias but larger variance. In practice, there are alternative to define the optimal bandwidth, *h*. In our estimate we follow Silverman (1986) which use as rule of thumb to choose the bandwidth (*h*) for densities that are close to normal:

$$h = b * \min \left\{ SD_x, \frac{InterquantileRange}{1{,}34} \right\} * n^{-1/5}$$

where b depends upon the kernel used[93].

---

[92] The difference with the classical histogram is that the function f(x) is evaluated at more point given a smoother curve.

[93] Gaussian: 1.06, Epachenikov: 2, 34.

Table A-27
Optimal Bandwidth Selection

	Kernel Density	
	Gaussian	**Epanechnikov**
b	1.06	2.34
min	0.26	0.26
SDx	0.26	0.26
IQR/IRQ Norm	0.802	0.802
IQR	1.075	1.075
IQR Norm	1.34	1.34
Sample Size	0.114	0.114
N	52003	52003
power	-0.2	-0.2
Optimal Bandwidth	**0.0314**	**0.0693**

Source: *Elaboration based on NCPSDB.*

4. Data Appendix to Chapter 3

Table A-28
Descriptive Statistics

Variable	Mean	SD	Min	Max
Individual Variables				
Male	0.46	0.5	0	1
White	0.68	0.46	0	1
Black	0.24	0.43	0	1
Hispanic	0.02	0.14	0	1
Asian	0.02	0.14	0	1
Other	0.03	0.17	0	1
Parent's Education	1.63	0.74	0	3
7th Grade Reading Score	0.36	0.84	3.23	3.55
7th Grade Math Score	0.32	0.79	3.56	2.71
6th Grade Reading Score	0.36	0.78	3.21	2.77
6th Grade Math Score	0.32	0.79	2.99	2.82
Contextual Variables				
Single Parents	22.18	6.34	0	51.1.
Poverty	16.48	4.93	0	34
Parents Without High School	16.3	5.99	0	32.7
Drop Out 7-12	3.12	0.87	0	38.44
Drop Out 9-12	4.61	1.24	0	38.44
AYP Targets Met	0.012	0.11	0	1
Highly Qualified Teachers	0.88	0.09	0	1
Local Per Pupil Spending	1731	579	0	4130
Federal Per Pupil Spending	801	284	410	2284
Percentage of Black Students	0.30	0.18	0	0.97
Year 2004	0.66	0.47	0	1

Notes: *N= 69913*
Source: *Elaboration based on NCPSDB.*

Table A-29
Correlation between Explanatory and Outcome Variable

Variable	Correlation
Male	0.06*
White	0.31*
Black	-0.32*
Hispanic	-0.05*
Asian	0.03*
Other	-0.03*
Parent's Education	0.25*
7th Grade Reading Score	0.62*
7th Grade Math Score	0.79*
6th Grade Reading Score	0.60*
6th Grade Math Score	0.73*
Single Parents	-0.15*
Poverty	-0.11*
Parents Without High School	-0.07*
Drop Out 7-12	-0.08*
Drop Out 9-12	-0.07*
AYP Targets Met	0.12*
Highly Qualified Teachers	0.02*
Local Per Pupil Spending	0.06*
Federal Per Pupil Spending	-0.04*
Percentage of Black Students	-0.15*

Note: ** significant for a p-value < 0.05*
Source: *Elaboration based on NCPSDB.*

Table A-30
Correlation between Family and Background Factors

	Male	White	Black	Hisp.	Asian	Other	Parents Education	7th Grade Reading	7th Grade Math	6th Grade Reading	6th Grade Math
Male	1.00										
White	0.03*	1.00									
Black	-0.04*	-0.84*	1.00								
Hispanic	0.00	-0.24*	-0.09*	1.00							
Asian	0.03*	-0.21*	-0.08*	-.026*	1.00						
Other	0.00	-0.24*	-0.09*	-.026*	-.023*	1.00					
Parent's Education	0.04*	0.14*	-.081*	-.14*	-.04*	-0.02*	1.00				
7th Grade Reading Score	-0.02*	0.32*	-0.06*	-0.06*	-0.03*	-0.04*	0.24*	1.00			
7th Grade Math Score	0.07*	0.34*	-0.34*	-0.06*	0.00	-0.03*	0.24*	0.69*	1.00		
6th Grade Reading Score	-0.03*	0.31*	-0.28*	-0.07*	-0.04*	-0.04*	0.23*	0.77*	0.66*	1.00	
6th Grade Math Score	* 0.06*	0.33*	-0.32*	-0.06*	-0.00	-0.03*	0.21*	0.63*	0.81*	0.70*	1.00

Note: ** significant for a p-value < 0.05*
Source: *Elaboration based on NCPSDB.*

Table A-31
Correlation between Contextual Variables

	Students at or above Level 3	Populatio n 5-17 Below the Poverty Line	Students Living in a Single Parent Family	Parents Without High School	Drop-Out 7-12	Drop-Out 9-12	AYP Targets Met	Highly Qual. Teacher	Local Spend.	Fed. Sp.	Perc. Black Students
Students at or above Level 3	1.00										
Population 5-17 Below the Poverty Line	-.078*	1.00									
Students Living in a Single Parent Family	-0.18*	0.74*	1.00								
Parents Without High School	-.023*	0.49*	0.24*	1.00							
Drop Out 7-12	-0.25*	0.37*	0.29*	0.44*	1.00						
Drop Out 9-12	-0.24*	0.39*	0.28*	0.48*	0.98*	1.00					
AYP Targets Met	0.15*	0.05*	-0.06*	-0.02*	-0.028*	-0.02*	1.00				
Highly Qualified Teachers	0.82*	0.17*	0.14*	0.18*	-.006*	-0.05*	0.13*	1.00			
Local Per Pupil Spending	0.36*	-.32*	-0.01	-0.52*	-0.38*	-0.41*	0.01*	0.13*	1.00		
Federal Per Pupil Spending	-0.66	0.87*	0.72*	0.47*	0.36*	0.36*	-0.00	-0.29*	-0.41*	1.00	
Percentage of Black Students	-0.29*	* 0.51*	0.82*	0.07*	0.05*	0.01*	-0.10*	-0.00	0.11*	0.54*	1.00

Note: ** significant for a p-value < 0.05*
Source: *Elaboration based on NCPSDB.*

Table A-32
Correlation in Prior Ability Variables

A) Math

7th Grade				
0.856	6th Grade			
0.822	0.846	5th Grade		
0.787	0.808	0.834	4th Grade	
0.747	0.766	0.784	0.803	3rd Grade

B) Reading

7th Grade				
0.835	6th Grade			
0.810	0.834	5th Grade		
0.788	0.815	0.827	4th Grade	
0.757	0.786	0.795	0.817	3rd Grade

Note: ** significant for a p-value < 0.00.*
Source: *Elaboration based on NCPSDB.*

Table A-33
Percentage of Missing by Selected Characteristics
(as % of total)

	Missing
Individual and Family Factors	
Gender	0
Race	0
Parent's Education	0.81
7th Grade Scores	0
6th Grade Scores	5.32
5th Grade Scores	**10.24**
4th Grade Scores	**14.45**
3rd Grade Scores	**19.10**
Percent of Students at or above Level 3	0.93
Percent of District Population Aged 5 to 17 Living Below the Poverty Line	0.93
Percent of Public School Students Living in a Single Parent Family	0.93
Percent of Public School Students Who Have At Least One Parent With Less Than a High School Education	0.93
Percent of AYP targets met by LEA	0.93
Percent of Classes Taught by Highly Qualified Teachers*	0.93
Percent of Students Identified as Black	0.93
Amount spent per student from local sources	0.93
Amount spent per student from state sources	0.93
Dropout Rate, Grades 7-12	0.23
Dropout Rate, Grades 9-12	0.23

Source: *Elaboration based on NCPSDB.*

Table A-34
Composition of Missing Groups for Outcome Variable
T-Test

Variable	P value of the Difference <0.05	
	Significant	**Not Significant**
Parents' Education	X	

Source: *Elaboration based on NCPSDB.*

Table A-35
Composition of Treatment and Control Group
Contextual Variables

	Control	Treatment
Percent of District Population Aged 5-17 Below the Poverty Line	16.60	16.04
Percent of Public School Students Living in a Single Parent Family	22.10	22.44
Percent of Public School Students Who Have At Least One Parent With Less Than a High School	16.61	15.19
Percent of AYP targets met by LEA	0.82	0.81
Percent of Classes Taught by Highly Qualified Teachers*	0.88	0.88
Percent of Students Identified as Black	0.29	0.32
Amount spent per student from local sources (in current dollars)	1692	1866
Amount spent per student from state sources (in current dollars)	4724	4670
Dropout Rate, Grades 7-12	3.14	3.06
Dropout Rate, Grades 9-12	4.64	4.50

Note: *T-test significant for a p-value <0.05*
Source: *Author's elaboration based on NCPSDB.*

Table A-36
Probability of Treatment: Odds Ratio

Year 2004	1.139***
	(0.0291)
Male	0.720***
	(0.0171)
African American	1.266***
	(0.0427)
Latinos	1.052
	(0.0926)
Asian American	2.092***
	(0.172)
Other Races	1.367***
	(0.108)
Parents with High School	1.285***
	(0.0959)
Parents with College	1.506***
	(0.112)
Parents with Graduate Education	1.939***
	(0.153)
7th Grade Standardized Reading Scale	1.340***
	(0.0356)
7th Grade Standardized Math Scale	4.009***
	(0.110)
6th Grade Standardized Reading Scale	1.164***
	(0.0316)
6th[h] Grade Standardized Math Scale	2.497***
	(0.0747)
Percent of Students at or above Level 3	0.976***
	(0.00566)
Percent of Public School Students Living in a Single Parent Family	0.980***
	(0.00508)
Percent of District Population Aged 5 to 17 Living Below the Poverty Line	0.971***
	(0.00586)
Percent of Public School Students Who Have At Least One Parent With Less Than HS	1.010***
	(0.00360)
Dropout Rate, Grades 7-12	3.517***
	(0.335)
Dropout Rate, Grades 9-12	0.453***
	(0.0301)
Percent of AYP targets met by LEA	0.352***
	(0.0662)
Percent of Classes Taught by Highly Qualified Teachers	0.732
	(0.227)
Amount spent per student from local sources	1.001***
	(3.02e-05)
Amount spent per student from state sources	1.000*
	(3.99e-05)
Percent of Students Identified as Black	15.15***
	(2.562)

Note: *z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1*
Source: *Elaboration based on NCPSDB.*

Table A-37
Distribution of On- and Off-Support Cases

PS Decile	Number of Units		
		Control	Treatment
1	Off-Support	6389	17
	On-Support	**705**	**14**
2	Off-Support	874	4
	On-Support	**5924**	**45**
3	Off-Support	1047	9
	On-Support	**5548**	**129**
4	Off-Support	722	4
	On-Support	**5980**	**265**
5	Off-Support	278	9
	On-Support	**6151**	**526**
6	Off-Support	199	12
	On-Support	**5756**	**1005**
7	Off-Support	136	25
	On-Support	**5137**	**1637**
8	Off-Support	93	46
	On-Support	***4139***	**2694**
9	Off-Support	66	226
	On-Support	**2816**	**3860**
10	Off-Support	57	553
	On-Support	**1388**	**4973**

Note: *Bootstrapped standard error in parenthesis. Nearest Neighbor Algorithm*
Off Support: *student's PS do not match**; On Support:*** *observations that find a student in the control group whose propensity score is comparable within a caliper of +/-0.005 of the propensity score.*
Source: *Elaboration based on NCPSDB.*

Table A-38
T-test after Balancing

Variable	All	Deciles of the Propensity Score									
		1	2	3	4	5	6	7	8	9	10
Male	Yes	No	No	No	No	No	No	No	Yes	No	No
White	Yes	No	Yes	Yes	Yes	No	No	No	No	No	Yes
Black	Yes	No	Yes	Yes	No	No	No	No	No	No	Yes
Hispanic	Yes	No	No	No	Yes	No	No	No	No	No	No
Asian	Yes	-	No	-	Yes	No	No	Yes	No	No	No
Other	Yes	No	No	Yes	Yes	Yes	No	No	No	No	No
Less than HS	Yes	No	No	No	No	Yes	No	No	No	No	Yes
High School	Yes	No	No	Yes	No	No	No	No	No	Yes	Yes
College	Yes	No	No	Yes	Yes	No	No	No	No	No	No
Graduate	Yes	No	No	No	Yes	No	Yes	No	No	Yes	Yes
Prior Math Score	Yes	No	No	No	No	No	No	No	No	Yes	Yes
Prior Reading Score	Yes	No	No	No	No	Yes	Yes	Yes	Yes	No	No

Note: *Yes if balanced is achieved for a p-value <0.05, No otherwise; - : No observations*
Source: *Elaboration based on NCPSDB.*

Table A-39
Characteristics of Student with Negative Treatment Effect
(in %)

	Negative	*Positive*
Male	0.41	0.49
White	0.61	0.74
Black	0.31	0.18
Parents' Education	1.58	1.54

Note: *T-test significant in all cases for a p-value <0.05*
Source: *Elaboration based on NCPSDB.*

Table A-40
ATT by Group

Category	**Effect Size**
Gender	
Male	0.20
	(0.017)
Female	0.15
	(0.012)
Race	
White	0.16
	(0.012)
Black	0.17
	(0.029)
Parents' Education	
No High School	0.11
	(0.064)
High School	0.17
	(0.017)
College	0.149
	(0.014)
Graduate	*0. 149*
	(0.026)

Note: *Bootstrapped standard error in parenthesis; Kernel Matching Algorithm*
Source: *Elaboration based on NCPSDB.*

5. Methodological Appendix to Chapter 4:

Kernel Density

A kernel function is a non parametric function that produces smooth estimates of a density at a certain score by using the frequency of the scores in the model. The function is continuous, symmetric around zero and has the advantage of not making assumptions about the process generating the data. Similar to parametric regression, a weighted sum of the *y* observations is used to obtain the fitted values. Instead of using equal weights (as in ordinary least squares) or weights proportional to the inverse of variance (often the case in weighted least squares), the choice of weights in nonparametric methods follow other criteria, mostly related to the use of alternative weighting schemes.

$$F_k = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x_i - x_0}{h}\right)$$

Where K (.) is a kernel function, x is the score for which we want to estimate the kernel and *h* is the bandwidth parameter.

The kernel function, as all non parametric methods, is a local average method which results depend on the bandwidth, *h* (Cameron and Trivedi, 2008:295). The bandwidth determines how fast the weights decrease as the distance from x_0 increases. For instance, the observations with the most information about $f(x_0)$ should be those at locations x_i closest to x_0. Thus, the rate at which the weights decrease relative to the locations of the x_is controls the smoothness of the resulting estimate of $f(x)$.

The choice of the bandwidth *h* is decisive to solve the trade-off between bias and variance as well[94]. Kernel estimators of the type of equation (6) are biased as they use information that could be far from x_0 (Heckman, Ichimura and Tood, 1997; Hahn, 1998). Observations closer to x_0 imply lower bias but larger variance. In practice, there are alternative to define the optimal bandwidth, *h*. In our estimate we follow Silverman (1986) which use as rule of thumb to choose the bandwidth (*h*) for densities that are close to normal:

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[94] The difference with the classical histogram is that the function f(x) is evaluated at more point given a smoother curve.

$$h = b * \min \left\{ SD_x, \frac{InterquantileRange}{1,34} \right\} * n^{-1/5}$$

where b depends upon the kernel used[95].

We use as alternative to the Gaussian (normal) the Epachelnikov kernel function that is the most efficient in minimizing the mean integrated error.

Table A-41
Optimal Bandwidth Selection

	Kernel Density - Epanechnikov		
	White	**Hispanic**	**Black**
b	2.34	2.34	2.34
min	0.84	0.76	0.76
SDx	0.85	0.8	0.79
IQR/IRQ Norm	0.84	0.761	0.76
IQR	1.13	1.02	1.02
IQR Norm	1.34	1.34	1.34
Sample Size	0.114	0.189	0.130
N	52767	4171	26901
power	-0.2	-0.2	-0.2
Optimal Bandwidth	**0.2242**	**0.3363**	**0.2316**

Source: *Elaboration based on NCPSDB.*

Relative Distribution

To compare the two groups score distribution we use the whole distribution instead the usual summary measures such as the mean, the median or the mode. We utilize the relative probability density function (pdf) and cumulati ve density function (cdf) function to synthesize the differences in the two distributions. The method consists on expressing the values of group A as positions in the distribution of group B (Jann, 2008:5), and analyze the distribution of the relative rank[96].

Let A_0 be the outcome variable of the reference group (White) and A the outcome variable of the comparison group (either Hispanic of Black). The relative ranks are

$$R = F_0(Y), \qquad R \in [0,1]$$

---

[95] Epachenikov: 2, 34.

[96] The relative ranking is independent of monotone transformations and is closely related to the approach utilized by Di Nardo, Fortin and Lemieuz (1996).

Where F_0 is the cdf of the reference group (White). The cumulative distribution function of the relative data is

$$G(r) = F(F_0^{-1}(r)), \qquad 0 \le r \le 1$$

Where F_0^{-1} is the quantile function, the inverse of F. The relative density is the ratio of the densities of the two groups evaluated at the quantiles of the reference group as follows:

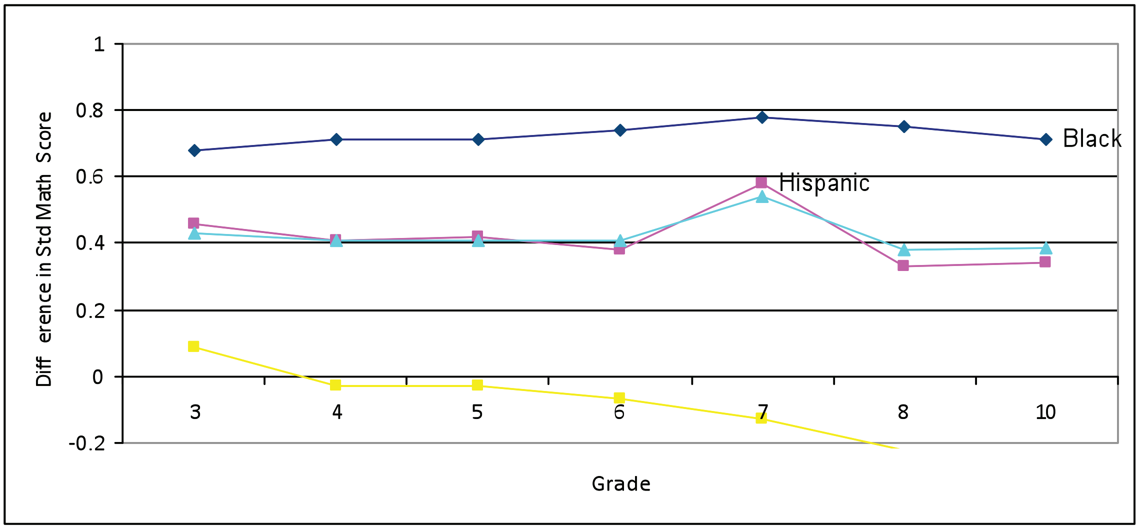
$$g(r) = \frac{f(F_0^{-1}(r))}{f_0(F_0^{-1}(r))} \qquad 0 \le r \le 1$$

Due to the inaccuracy of approximation formulas for the variance in finite sample, standard errors (and, consequently confidence intervals) were estimated using the bootstrapping.

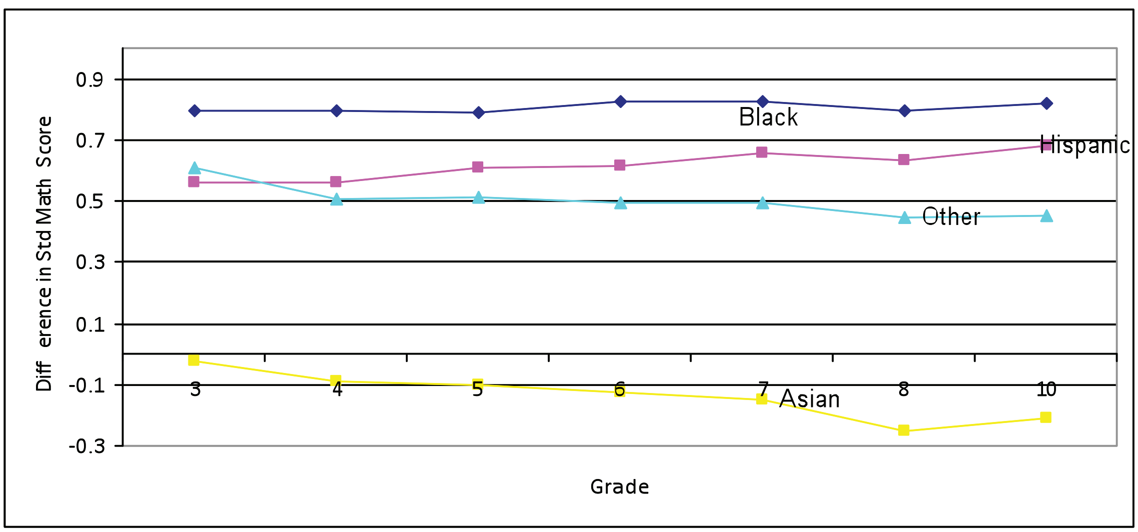
6. Data Appendix to Chapter 4

Figure A-7
White-"Race" Achievement Gap - Math

A) Intact Cohort



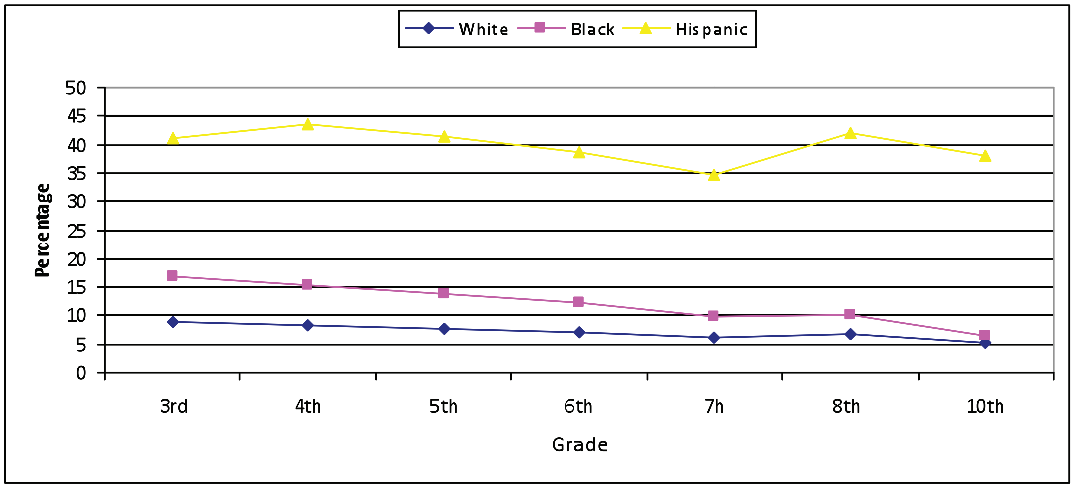
B) Complete Cohort



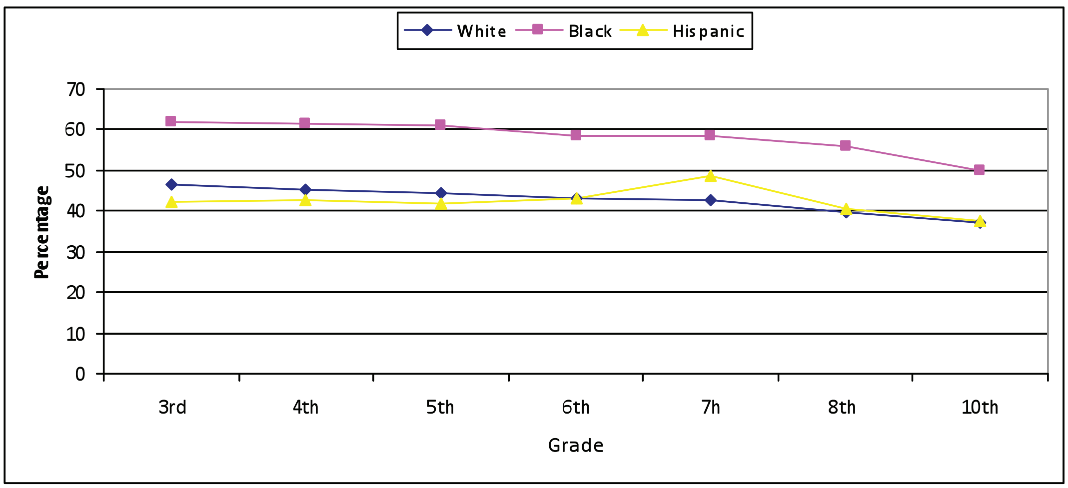
Source: *Elaboration based on NCPSDB.*

Figure A-8
Average Parental Education - Complete Cohort

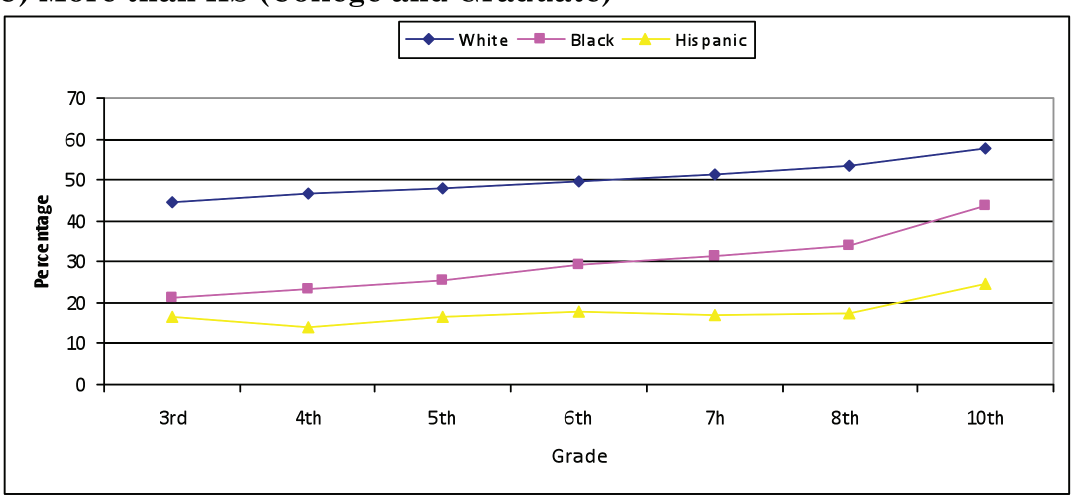
A) Less than HS



B) Only HS

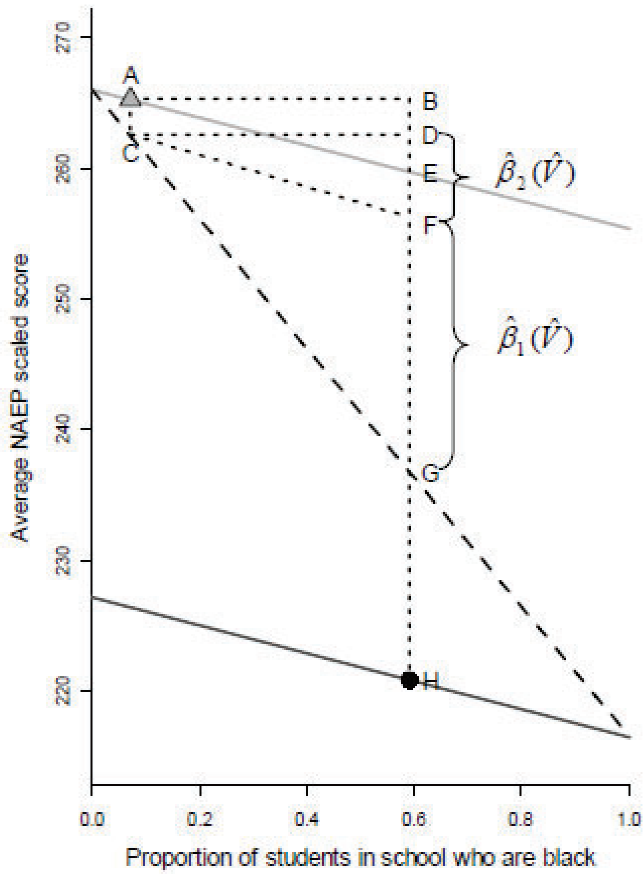


C) More than HS (College and Graduate)



Source*: Elaboration based on NCPSDB.*

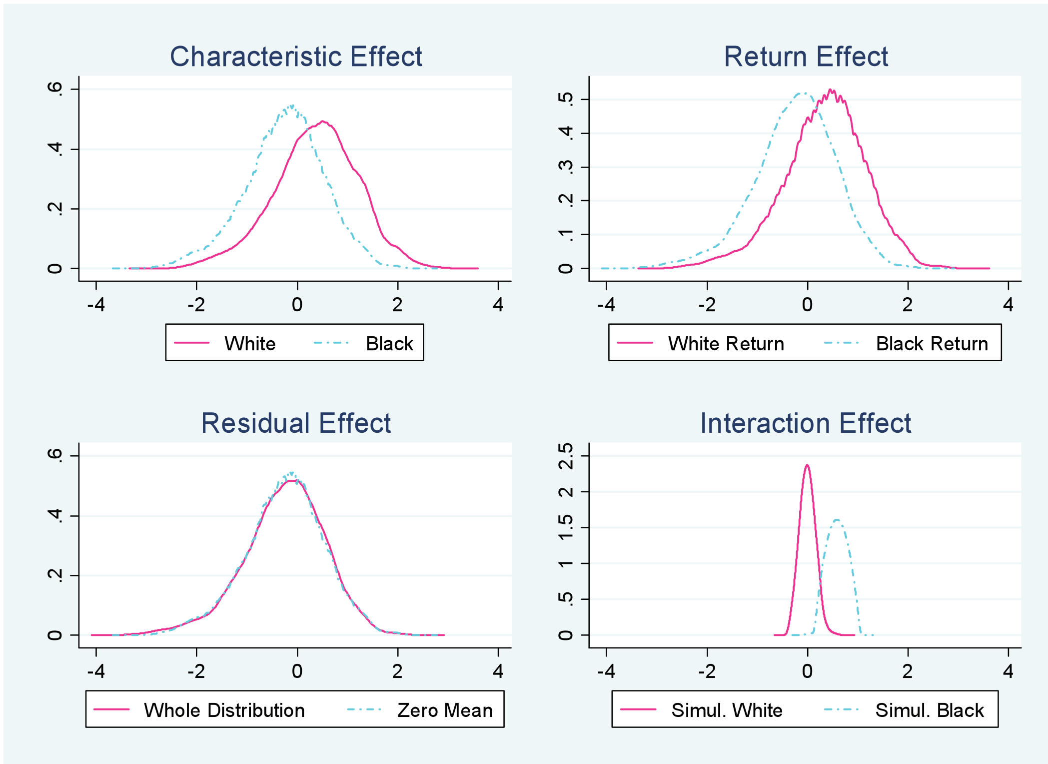
Figure A-9
Graphical Decomposition of Racial Achievement



Note: *Triangle A is the average achievement of white students and average racial make-up while circle H represents the average prediction for Black student and the average racial make-up. The average Black-White achievement,* $\hat{\delta}$*, is the net vertical distance while the Variance index of segregation is the net vertical distance between A and H.* $\hat{\beta}_2\left(\hat{V}\right)$ *is the between school component, the segments AC and GH (equivalent to* $\hat{\beta}_1\left(1-\hat{V}\right)$*) are the within school component while* $\hat{\beta}_1\left(\hat{V}\right)$ *is ambiguous.*

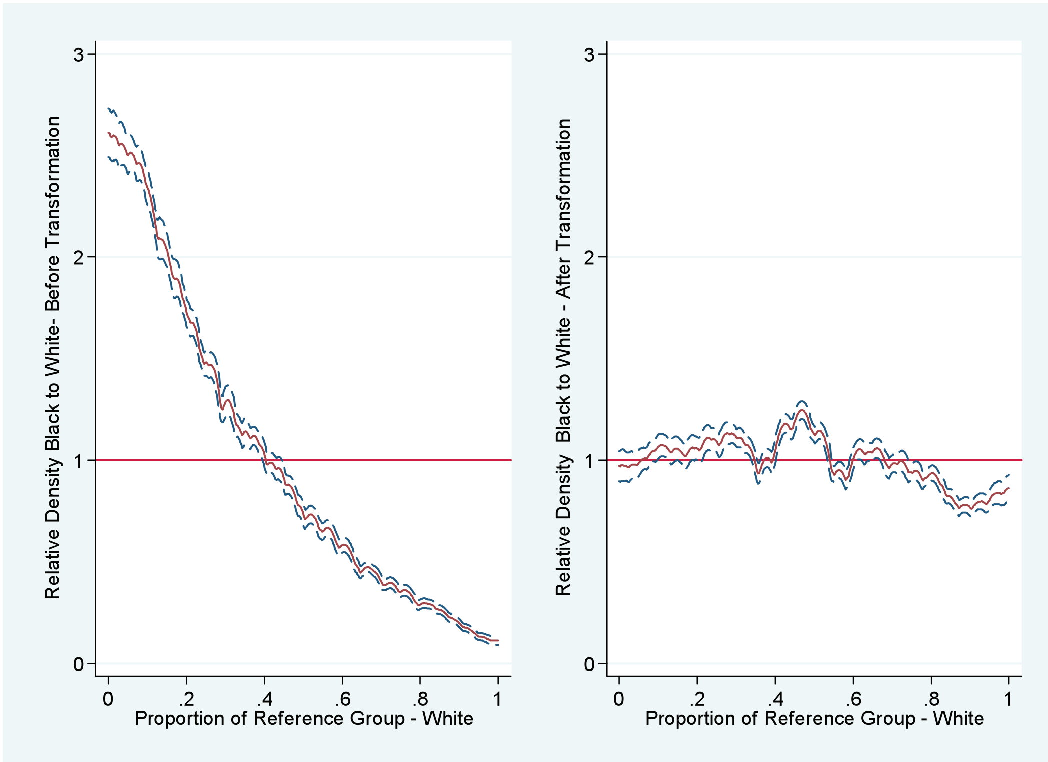
Source: *Murnane et al (2008).*

Figure A-10
Hypothetical Reading Score Distribution - Black



Source: *Elaboration based on NCPSDB*

Figure A-11
Relative Distribution
Black and White Production Function



Note: *Dotted Lines: Confidence Intervals, bootstrapped SE.*
Source: *Elaboration based on NCPSDB*

Table A-42
Outcomes Mean and SD

Grade	Mean	SD	Min	Max
Reading				
3rd Grade				
Intact	0.26	0.88	-2.67	2.73
Complete	0	1	-2.88	2.73
10th Grade				
Intact	0.19	0.88	-3.45	3.44
Complete	0	1	-3.45	3.43

Source: *Elaboration based on NCPSDB*

Table A-43
Descriptive Statistics – 10th Grade

Variable	N	Mean	SD	Max	Min
A) Intact Cohort					
Male	51934	0.46	0.5	0	1
White	51934	0.68	0.47	0	1
Hispanic	51934	0.27	0.13	0	1
Black	51934	0.026	0.44	0	1
Asian	51934	0.013	0.01	0	1
Other	51934	0.02	0.02	0	1
No High School	51934	0.05	0.22	0	1
High School	51934	0.40	0.49	0	1
College	51934	0.44	0.50	0	1
Graduate	51934	0.11	0.31	0	1
B) Complete Cohort					
Male	92196	0.49	0.50	0	1
White	92196	0.62	0.48	0	1
Hispanic	92196	0.05	0.21	0	1
Black	92196	0.29	0.45	0	1
Asian	92196	0.02	0.14	0	1
Other	92196	0.03	0.16	0	1
No High School	89699	0.07	0.79	0	1
High School	89699	0.41	0.49	0	1
College	89699	0.40	0.49	0	1
Graduate	89699	0.11	0.32	0	1

Source: *Elaboration based on NCPSDB*

Table A-44
Correlation Table - Reading

Standardized Reading Scale							
0.333 0.00	white						
-0.309 0.00	-0.814 0.00	black					
-0.099 0.00	-0.273 0.00	-0.134 0.00	hispanic				
0.022 0.00	-0.190 0.00	-0.093 0.00	-0.031 0.00	asian			
-0.030 0.00	-0.212 0.00	-0.104 0.00	-0.035 0.00	-0.024 0.00	other		
-0.117 0.00	0.010 0.00	-0.017 0.00	0.006 0.08	0.011 0.00	-0.002 0.54	male	
0.274 0.00	0.138 0.00	-0.094 0.00	-0.110 0.00	0.003 0.31	-0.019 0.00	0.020 0.00	morethanHS

Standardized Reading Scale						
-0.117 0.00	propblack					
-0.014 0.00	0.052 0.00	prophispanic				
0.082 0.00	0.021 0.00	0.159 0.00	propasian			
-0.057 0.00	-0.018 0.00	-0.120 0.00	-0.105 0.00	propother		
-0.029 0.00	0.010 0.00	0.118 0.00	-0.035 0.00	-0.078 0.00	propmale	
0.153 0.00	-0.091 0.00	0.071 0.00	0.520 0.00	-0.161 0.00	-0.036 0.00	propmorethanHS

Source: *Elaboration based on NCPSDB*

Table A-45
Missing Data

Variable	N	Percentage
A) Intact Cohort		
Male	1	0.000
Race	1	0.000
Parents' Education	385	0.007
B) Complete Cohort		
Male	42	0.0005
Race	42	0.0005
Parents' Education	2539	0.0275

Source: *Elaboration based on NCPSDB*

Table A-46
T-test on Missing Values
Composition of Missing Groups for Outcome Variable
T-Test

Variable	P value of the Difference <0.05	
	Significant	Not Significant
Parents' Education	X	

Source: *Elaboration based on NCPSDB.*

Table A-47
Peers Racial Make-Up All Races

A) Intact Cohort

Race Classmates	White	Black	Hispanic	Asian	Racial Make-Up
3rd Grade					
White	0.70	0.64	0.66	0.65	0.68
Black	0.25	0.31	0.28	0.28	0.27
Hispanic	0.02	0.02	0.03	0.02	0.016
Asian	0.01	0.01	0.02	0.03	0.013
Other	0.02	0.02	0.02	0.02	0.024
10th Grade					
White	0.72	0.60	0.68	0.66	0.68
Black	0.23	0.35	0.26	0.28	0.27
Hispanic	0.02	0.02	0.02	0.02	0.016
Asian	0.01	0.01	0.01	0.03	0.013
Other	0.02	0.02	0.02	0.02	0.024

B) Complete Cohort

Race Classmates	White	Black	Hispanic	Asian	Racial Make-Up
3rd Grade					
White	0.63	0.52	0.55	0.54	0.64
Black	0.31	0.42	0.37	0.38	0.30
Hispanic	0.02	0.02	0.04	0.03	0.021
Asian	0.02	0.02	0.02	0.04	0.013
Other	0.02	0.02	0.02	0.02	0.02
10th Grade					
White	0.65	0.54	0.60	0.59	0.62
Black	0.26	0.37	0.30	0.30	0.29
Hispanic	0.04	0.05	0.06	0.05	0.045
Asian	0.02	0.02	0.02	0.04	0.021
Other	0.02	0.03	0.02	0.02	0.026

Source: *Elaboration based on NCPSDB*

Table A-48
Decomposition of Racial Gap – All Factors
Mathematics

A) Intact

	Black	Hispanic	Black	Hispanic
	3rd Grade		10th Grade	
Total Gap	**-0.81**	**-0.62**	**-0.86**	**-0.50**
School				
Within	-0.26	-0.34	-0.45	-0.20
Ambiguous	-0.38	-0.03	-0.21	-0.02
Between	-0.05	0.00	-0.02	-0.14
Characteristics				
Gender	-0.02	-0.03	-0.01	-0.01
Education	-0.15	-0.22	-0.19	-0.27
Peers				
Black		0.00		0.00
Hispanic	0.00		0.00	
Asian	0.00	0.00	0.00	0.00
Other	0.00	0.00	0.00	0.00

B) Complete

	Black	Hispanic	Black	Hispanic
	3rd Grade		10th Grade	
Total Gap	**-1.00**	**-0.79**	**-0.92**	**-0.79**
School				
Within	-0.44	-0.36	-0.51	-0.47
Ambiguous	-0.21	-0.03	-0.23	-0.05
Between	-0.05	0.06	-0.03	-0.06
Characteristics				
Gender	0.02	0.03	0.01	0.02
Education	-0.35	-0.45	-0.20	-0.29
Peers				
Black		0.00		0.00
Hispanic	0.00		0.00	
Asian	0.00	0.00	0.00	0.00
Other	0.00	0.00	0.00	0.00

Source: *Elaboration based on NCPSDB*

Table A-49
Regression Results - Reading

Variable	Intact		Complete	
	3rd Grade	10th Grade	3rd Grade	10th Grade
Black	-0.60***	-0.58***	-0.58***	-0.68***
	(-71.1)	(-67.2)	(-86.2)	(-94.7)
Hispanic	-0.42***	-0.22***	-0.43***	-0.56***
	(-14.8)	(-7.90)	(-21.2)	(-37.2)
Asian	-0.22***	0.014	-0.074***	-0.13***
	(-6.98)	(0.46)	(-2.87)	(-6.06)
Other	-0.35***	-0.27***	-0.46***	-0.31***
	(-15.0)	(-10.7)	(-21.6)	(-15.3)
Proportion Black	0.024	-0.0015	-0.042	-0.026
	(0.68)	(-0.058)	(-1.39)	(-1.17)
Proportion Hispanic	0.013	-0.39	0.15	-0.24*
	(0.040)	(-1.16)	(0.54)	(-1.69)
Proportion Asian	-0.49**	1.96***	-0.94***	0.99***
	(-1.96)	(7.78)	(-3.89)	(5.33)
Proportion Other	-0.48***	-0.33***	-0.43***	-0.41***
	(-2.89)	(-5.03)	(-3.08)	(-7.12)
Male	-0.10***	-0.17***	-0.20***	-0.25***
	(-14.5)	(-24.1)	(-34.0)	(-41.4)
Proportion of Male	0.24**	-0.18	0.37***	-0.69***
	(2.16)	(-1.37)	(2.96)	(-5.90)
More Than HS	0.33***	0.34***	0.62***	0.45***
	(45.0)	(47.3)	(97.5)	(72.2)
Proportion More Than HS	0.67***	0.96***	0.30***	0.99***
	(14.4)	(22.5)	(10.5)	(26.6)
Missing Indicator	-0.29***	-0.58***	-0.61***	-0.79***
	(-6.81)	(-14.1)	(-20.4)	(-28.9)
Constant	-0.17***	-0.22***	-0.21***	-0.052
	(-2.87)	(-3.43)	(-3.15)	(-0.85)
Observations	51894	51894	92368	89501
R-squared	0.150	0.169	0.217	0.207

Note: *t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.*
Source: *Elaboration based on NCPSDB.*

Table A-50
Regression Results - Math

Variable	Intact		Complete	
	3rd Grade	10th Grade	3rd Grade	10th Grade
Black	-0.64***	-0.66***	-0.65***	-0.74***
	(-78.6)	(-73.7)	(-96.6)	(-103)
Hispanic	-0.37***	-0.22***	-0.39***	-0.52***
	(-13.3)	(-7.55)	(-19.1)	(-34.6)
Asian	-0.086***	0.20***	0.042	0.19***
	(-2.83)	(6.24)	(1.64)	(9.13)
Other	-0.38***	-0.28***	-0.48***	-0.33***
	(-16.6)	(-10.6)	(-22.6)	(-16.7)
Proportion Black	-0.085**	-0.061**	-0.17***	-0.11***
	(-2.42)	(-2.22)	(-5.70)	(-4.85)
Proportion Hispanic	0.40	-1.67***	0.65**	-0.58***
	(1.32)	(-4.78)	(2.36)	(-4.18)
Proportion Asian	-0.49**	1.79***	-1.07***	1.04***
	(-2.01)	(6.81)	(-4.41)	(5.61)
Proportion Other	-0.29*	-0.19***	-0.30**	-0.25***
	(-1.80)	(-2.77)	(-2.14)	(-4.33)
Male	0.047***	0.024***	-0.049***	-0.041***
	(6.70)	(3.29)	(-8.33)	(-6.95)
Proportion of Male	0.11	0.018	0.23*	-0.39***
	(1.02)	(0.13)	(1.84)	(-3.39)
More Than HS	0.30***	0.37***	0.58***	0.45***
	(42.2)	(48.5)	(91.1)	(72.4)
Proportion More Than HS	0.53***	0.96***	0.22***	0.90***
	(11.8)	(21.6)	(7.59)	(24.4)
Missing Indicator	-0.37***	-0.62***	-0.62***	-0.77***
	(-9.01)	(-14.3)	(-20.7)	(-28.7)
Constant	-0.049	-0.34***	-0.12*	-0.21***
	(-0.87)	(-5.19)	(-1.80)	(-3.46)
Observations	51881	51816	92437	89461
R-squared	0.164	0.184	0.217	0.213

Note: *t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.*
Source: *Elaboration based on NCPSDB.*

Table A-51
Oaxaca-Blinder Decomposition
All Factors – Reading

Variable	**Three-fold Decomposition**					
	Endowments		**Coefficients**		**Interaction**	
	Hispanic	**Black**	**Hispanic**	**Black**	**Hispanic**	**Black**
Proportion Black	0.002***	0.007***	-0.024	-0.036*	0.0033	-0.014*
	(0.001)	*(0.004)*	*(0.03)*	*(0.012)*	*(0.004)*	*(0.005)*
Proportion Hispanic	-0.002	-0.0002	-0.108*	0.002***	-0.029*	0.001
	(0.002)	*(0.000)*	*(0.031)*	*(0.013)*	*(0.008)*	*(0.000)*
Proportion Asian	0.002*	0.001*	-0.04***	-0.03*	-0.033***	-0.001***
	(0.000)	*(0.000)*	*(0.02)*	*(0.01)*	*(0.001)*	*(0.000)*
Proportion Other	-0.000	-0.000	-0.001	-0.002	-0.000	-0.000
	(0.000)	*(0.000)*	*(0.01)*	*(0.004)*	*(0.002)*	*(0.000)*
Male	-0.002	-0.003*	0.035*	-0.037*	0.000	0.001*
	(0.001)	*(0.001)*	*(0.015)*	*(0.007)*	*(0.000)*	*(0.000)*
Proportion of Male	-0.001*	-0.000	0.276	-0.044	0.000	0.000
	(0.000)	*(0.000)*	*(0.374)*	*(0.125)*	*(0.001)*	*(0.001)*
More Than HS	-0.156*	-0.064*	-0.025	-0.107*	0.012	0.023*
	(0.004)	*(0.002)*	*(0.021)*	*(0.008)*	*(0.011)*	*(0.002)*
Proportion More Than HS	0.002	-0.001	-0.169	-0.315*	-0.001	0.003*
	(0.002)	*(0.000)*	*(0.11)*	*(0.044)*	*(0.001)*	*(0.001)*
Constant			*-0.472*	*-0.149*		
			(0.392)	*(0.132)*		
Total	-0.169*	-0.07*	-0.53*	-0.694*	-0.023***	0.013*
	(0.006)	*(0.004)*	*(0.021)*	*(0.008)*	*(0.014)*	*(0.005)*

Note: *Bootstrapped standard error in parentheses; *** p<0.01, ** p<0.05, * p<0.1.*
Source: *Elaboration based on NCPSDB.*