NEIGHBORHOODS ATTRIBUTES AS DETERMINANTS OF CHILDREN'S ACADEMIC ACHIEVEMENT

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Resumen

Los estudios sobre los efectos del vecindario sobre los logros educativos han confirmado la existencia de estos efectos particularmente en la adolescencia. Una deficiencia común de la investigación empírica hasta la fecha, la falta de información en múltiples contextos, se aborda en este trabajo mediante el uso de encuestas escolares de datos para obtener una mayor comprensión sobre el efecto de la pobreza en los niños que cursan el nivel primario de enseñanza en los EE.UU. Este trabajo propone la utilización de un modelo jerárquico lineal de clasificación cruzada para tomar en cuenta en forma apropiada la estructura anidada de la información ya que los niños pertenecen simultáneamente a los dos grupos, el barrio y la escuela.
Los resultados que se presentan, basados en la encuesta ECLS-K, una muestra de más de 20000 niños en aproximadamente 1.000 vecindarios y 1200 escuelas 1200, pone de manifiesto la asociación entre la composición socioeconómica del vecindario y los resultados académicos de los estudiantes. Este estudio proporciona evidencia a favor de las teorías de la socialización y epidémica. La presencia de adultos con buen nivel educativo en el vecindario así como la mediana de ingresos tienen impacto positivo en el logro del estudiante. De la misma forma, elevados niveles de pobreza tienen una influencia significativa, pero negativa en los resultados académicos. Sin embargo, el impacto se produce cuando se supera el umbral de 30% de hogares pobres en el vecindario. Los resultados agregados son invariantes a distintas especificaciones en términos de variables, esto no sucede cuando se analizan subgrupos clasificados según su origen étnico, género y estatus socio-económico.

Palabras clave: Vecindarios - Multinivel

Abstract

Studies of neighborhood effect 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. The paper proposes a cross-classified hierarchical linear model to account for the nested structure of the samples of individuals in neighborhoods and schools.
Our results, based on the ECLS-K survey, a sample of more than 20000 children in approximately 1,000 neighborhoods and 1,200 schools, highlights the association between neighborhood's socioeconomic composition and student's outcomes. This study provides evidence in favor of both socialization and epidemic theories. The presences of well-educated adults in the neighborhood and the median income have a positive impact on student's achievement. High levels of poverty have a significant influence but negative influence on student's tests scores. Nevertheless, the impact occurs when a threshold of 30% of poor households in the neighborhood 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 socio economic status is challenged. Neighborhoods have a larger impact on some subgroups (Black and Hispanics, for instance) than on the whole sample.

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Keywords: Neighborhoods - Multilevel

JEL Classification: I21, I24, Z13.

I. Introduction

During the last decades, there has been growing interest in the role of the social environment on shaping children's development. 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. The first one, the school effectiveness approach, tries to isolate the impact of school and classroom resources on children's outcomes; the second one, 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, 2006). 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 analyze simultaneously both sources of influence, school and neighborhood.

Identification of neighborhood effects faces conceptual and empirical obstacles. From the theoretical point of view, there are several potential ways neighborhoods may affects individuals' outcomes 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 a first issue to solve. Although census units are generally used as synonymous of neighborhood, they do not necessarily coincide with the idea of "community of influence". Additional obstacles include simultaneity, selectivity and omitted variables bias. Most of the empirical literature refers to neighborhood influence effects found as the upper bound of neighborhood's influence. Last but not least, empirical findings have not translated 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 explore 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. Our contribution to the literature consists on 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.

Our 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 source of influence. The findings of the study provide evidence in favor of both socialization and epidemic theories. The presences of well-educated adults in the neighborhood and the median income have positive impact on 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, discusses methodological problems and reviews 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 youth's attitudes, norms and values (Jencks and Mayer, 1990; Brooks-Gunn et al, 1997; Ginther, Haveman and Wolfe, 2000; Sampson et al, 2008; Kirk, 2009). 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).

Literature has proposed several hypothetical links between neighborhood characteristics and individual outcomes (Vigdor, 2006). For instance, Duncan and Raudenbusch (2001) 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, 1999b; Oberwittler, 2007); 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].

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 been difficulties in implementation and measurement.

Neighborhood literature has taken a variety of approaches to define neighborhood (Sampson et al, 2002: 445). 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 (Durlauf, 2004). As census's units are not perfect indicators of either residential neighborhoods or functional communities, the use of census tract may introduce measurement error (Duncan et al, 1997).

II.1 Methodological challenges in the identification of "neighborhoods effects"

The 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.

[1] The policy implications of each theory are different. See Duncan and Raudenbusch (2001) for a discussion.

II. 1.1. 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 and 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 selection both into neighborhood and outcomes (Ginther et al, 2000; Kauppinen, 2008).

II. 1.2. Simultaneity

A second problem comes from reflection. 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[2]. 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)[3]. The isolationendogenous, contextual and correlated effect has important policy implications: there are some feedbacks in case of endogenous effects which are not present in contextual and correlated effects.

II. 1.3. 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). In that sense, Sampson et al (2002) report inconsistencies across studies in the operationalization of neighborhood processes and mechanisms.

II. 1.4. Omitted Variable Bias

Omitted variables bias (OVB) may be an issue if individual or contextual characteristics which are relevant to the analysis are neglected. In 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, the bias come in most empirical studies from the use of only one or two variables to represent all neighborhood's relevant characteristics and processes (Duncan and Raudenbush, 2001: 5).

Another type of omitted variable problem which may lead to bias in the estimates of neighborhood effects: 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 (Durlauf, 2004).

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).

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

[3] 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.

II. 1.5. Specification bias: non linearity and heterogeneity

A somehow interrelated issue to the former arises from miss-specification bias due to the existence of non-linearity. A few papers have explored the existence of some kind of tipping and/or threshold points for the contextual factor to have either positive or negative influence. Tipping may occur either along racial or socio-economic lines (Vigdor, 2006). 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.

Heterogeneity in contextual effects may raise, as well some specification issues as long as some variables or thresholds may operate in opposite ways according to population grouping criteria. In that sense, some literature has documented non-homogenous influence of context in Black and males, for instance.

II. 1.6. Empirical finding on the impact of neighborhoods on Educational Outcomes

There are many reviews and thorough analysis in the empirical literature on neighborhoods effects such as 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 (Caughy and O'Campo, 2006; Garner and Raudenbush, 1991; Sampson et al, 2008; Sastry and Pebley, 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 (Durlauf, 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 et al (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, 2006; Card and Rothstein, 2007; Sastry and Pebley, 2008).

European-based research, on the other hand, has identified some effect of neighborhood characteristics on student's scores despite the lower neighborhood differentiation that characterizes European settings (compared to the US's) (Brannstorm, 2007; Kaupinnen, 2008; Garner and Raudebusch, 1991). 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.

Regarding the neighborhood attributes that matter there 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).

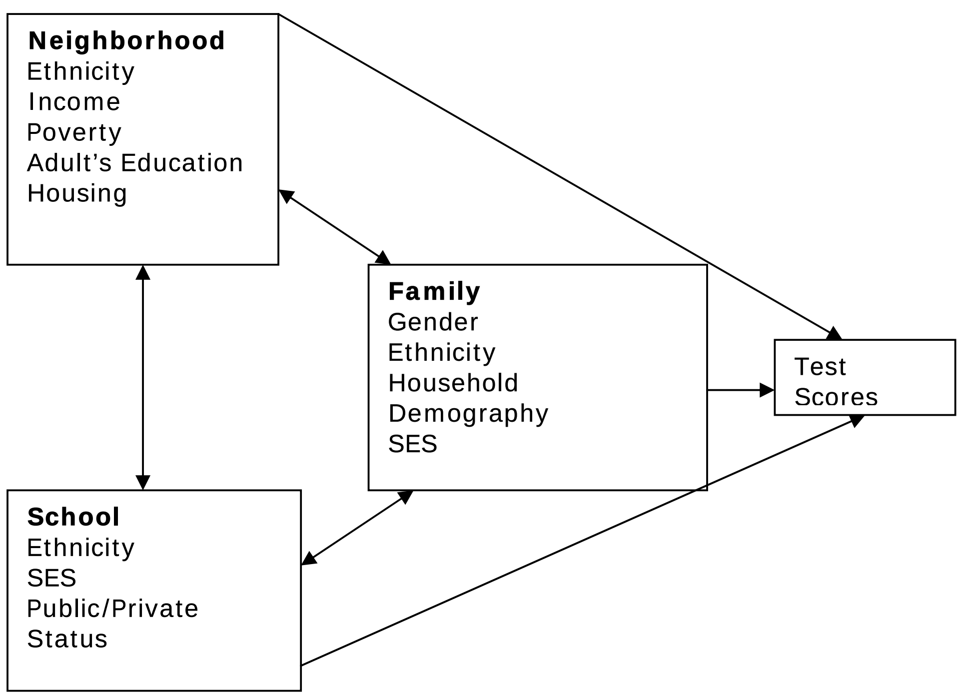
Vigdor (2006) points out four general conclusions of research on neighborhood effects: a) neighborhood effects are modest; b) neighborhood effects are heterogeneous: they are stronger among females, White, and children of early school age[4]; c) difficulties to model the possible mechanisms linking neighbors and individual outcomes; d) absence of specific policy recommendations associated with research.

III. Analytic Framework and Research Hypotheses

As a conceptual framework we use the social ecological model (Bronfenbrenner, 1979 and 1994; Arum, 2000), which encompasses the interrelationships that exist between the individual and his environment. This conceptualization recognizes that, although learning outcomes are determined 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 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).

Figure 1
Conceptual Model



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

[4] This problem might be related to the existence of non-linearities.

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, adult's high-school completion and female-headed households. 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; Sampson e al, 1999a).

We include educational level of the adult population to control for "reflection" and assume 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 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 five percent of the total variance in student's achievement.

Research Question #2. Which neighborhood-level factors are the most strongly associated with 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

Data 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[5]. School administrators and teachers are asked about school/classroom facilities and characteristics.

ECLS-K was merged with the 2000 Census using child's home census tract identification. that contains information of 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 attachment. In this paper, we use the administrative approach and define neighborhood as "the one corresponding to the census tract[6] where the house the child lives is located".

[5] Non-cognitive skills include child's competence and interest in academics as well as social skills.
[6] 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).

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 1^{st} 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 for the final model.

The summary in Table 1 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.

Table 1
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**
	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**
	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.*

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 of neighborhood 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. Fortunately, the proportion of kids who have same school and neighborhood remains no larger than a third of the remaining sample in all waves[7].

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; Figlio and Page, 2000; Sampson et al, 2008).

IV.4 Explanatory Variables

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.

[7] Homogeneity of families within neighborhoods may represent as well an issue in terms of identification. The analysis of the data shows that, except for few neighborhoods, whose SD of the SES is zero; there is enough variance in the sample within and between neighborhoods.

Individual- and family-background variables as well as school variables 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; Ginther et al, 2000). The variables are split into two groups. The first contains the factors related to concentration of disadvantage. ; 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. The second group encompasses the 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), an educational variable of the adult population was included to to address the potential biases "reflection" may create, the percentage of adult women that completed at least High School.

The selected background and explanatory variables described in Table 2 were re-coded when necessary. Categorical variables were converted to a set of dummy variables[8]. Correlations between explanatory variables and outcomes are in all cases correlations significant for a p-value < 0.01.. Only six of the 36 correlation coefficient between contextual variables between the contextual variables are around 0.70 which rules out collinearity concerns[9].

Table 2
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-1 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 and 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.

[8] 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.
[9] Correlation tables could be provided under request.

V. Methods

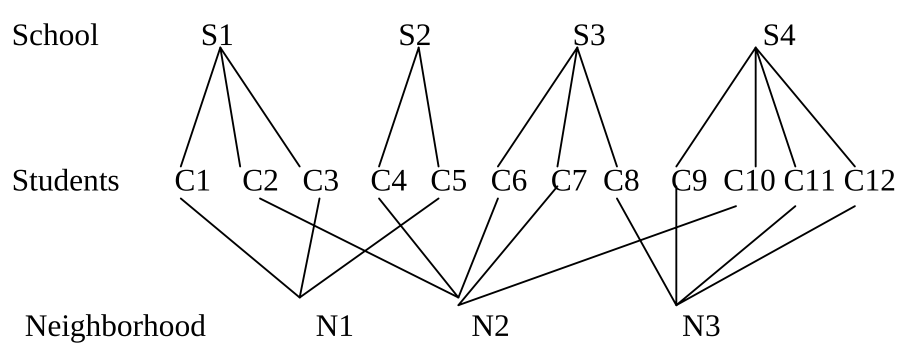
From the empirical point of view, the setup is straightforward: factors explaining students' outcomes can be approximated through the estimation of a simple education production function (Hanushek, 1979). The only relative novelty is the extension of the "classical" education production function to consider 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 nth (Y_i) as a function of a set inputs that include individual, family, school and neighborhood characteristics. The model is formulated as follows:

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

Our interest in 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.

Figure 2
Cross Classified Structure



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, occasioning correlation in the residuals at the individual level. Ignoring the importance of group effects will violate one of the basic assumption linear regression models: the independence between student outcomes.

To make the specification more concrete, and adding the time dimension, the specification turns to be a three level model, *t* for time, *i* for individual and (*s,n*) for school and neighborhood:

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

$$\beta_{0i(s,n)} = \beta_{00(s,n)} + \beta_{0\,i(s,n)}\, X_{i(s,n)} + \mu_{child} \qquad (3)$$

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

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)) 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) 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.1 Intra-Class Correlation Coefficients

The intra-class correlation coefficient (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). We can define three ICCs as follows:

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

$$\rho = \frac{\sigma^2_{\mu S}}{\sigma^2_{\mu S} + \sigma^2_{\mu N} + \sigma^2_{\varepsilon}} \qquad (5)$$

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

$$\rho = \frac{\sigma^2_{\mu N}}{\sigma^2_{\mu S} + \sigma^2_{\mu N} + \sigma^2_{\varepsilon}} \qquad (6)$$

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

$$\rho = \frac{\sigma^2_{\mu S} + \sigma^2_{\mu N}}{\sigma^2_{\mu S} + \sigma^2_{\mu N} + \sigma^2_{\varepsilon}} \qquad (7)$$

V.2 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[10]. Alternative models, empty and explanatory in the different version are tested using the likelihood ratio test and information criteria, AIC and BIC.

[10] Unrecognized level-one heteroskedasticity may lead to high variance at level 2 (Sneijders and Berkhof, 2008).

V.3 Location of the Xs

All individual continuos background variables are centered on the grand mean. 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 variables included in the model.

V.4 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 (2006) and Pfefferman et al, 2006.

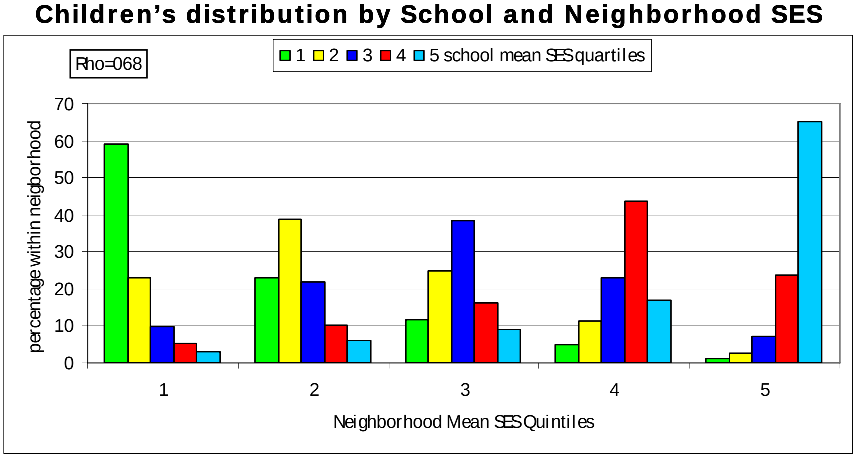
V.5 Software and Maximization Algorithm

Estimation of the Cross Classified Hierarchical Linear Models was conducted in STATA 10 using the xtmixed package (StataCorp. 2007. Stata Statistical Software: Release 10. College Station, TX: StataCorp LP).

VI. Results

There is a considerable variation between neighborhood-level and school-level social composition. Figure 3 depicts how students from different levels of neighborhood SES are allocated to schools of different levels of SES, both measured as student' average parental SES[11]. Even though the correlation between mean family SES at the neighborhood and school level is high and significant (0.68) is not perfect. More than half of the students living in a very low mean family SES at the neighborhood level (first quintile) attend also 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.

Figure 3
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.*

[11] 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.

Social segregation of students seems to be higher on the school level than on the neighborhood level (Gorard, 2009). Figure 4 suggests 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 to live into high SES neighborhoods. The strong association between school SES and individual SES (Rho=0.63 and 0.58 respectively) suggests that both school and neighborhood may reinforce home disparities. Although is difficult to sustain that this were the case, as long as low SES kids do better in low SES schools than high SES schools, results point out the need of further investigation.

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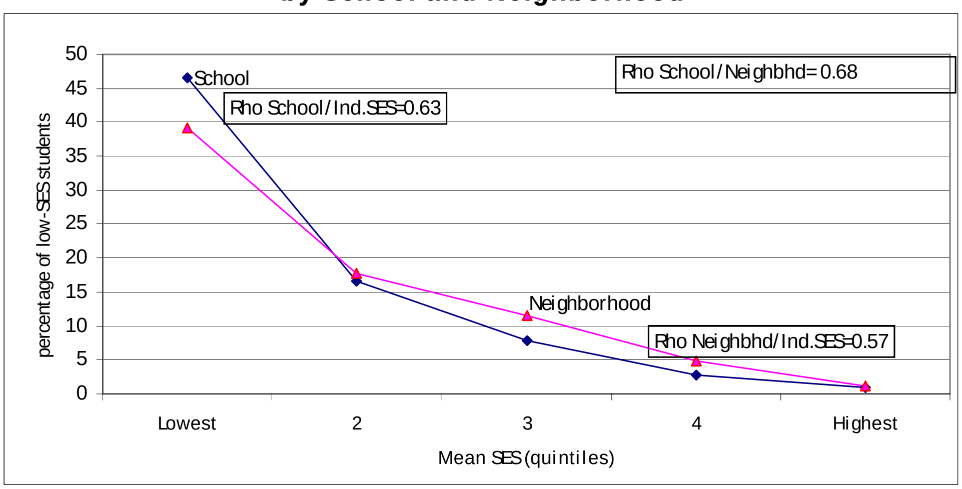
Some previous empirical evidence suggests that the concentration of social disadvantage within particular schools contributes to lower school performance which translates into barriers to school improvement. In this scenario, the classical policy recommendation, of improving school's physical and monetary resources does not work[12]. There is no much to be done when the reputation of failing school is installed, no matter the quality of their educational offerings.

Figure 4
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.*

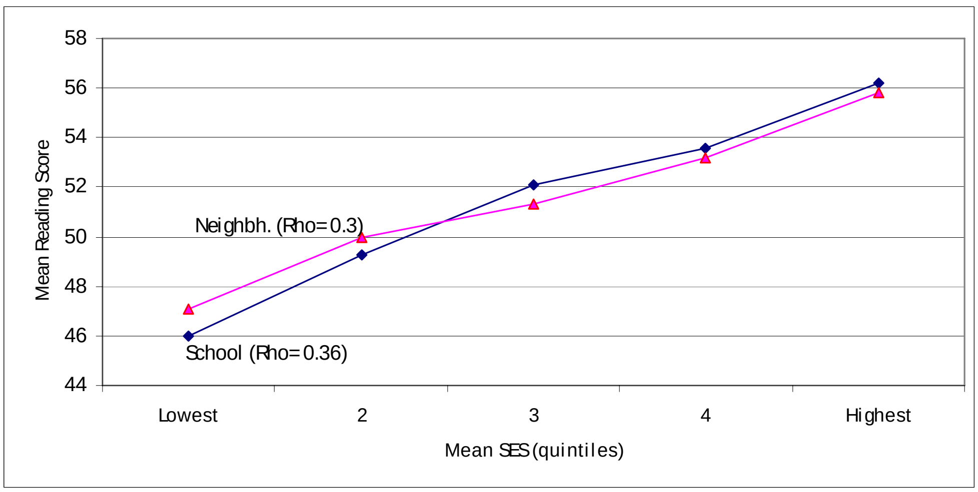
As "low achieving schools" tend to be located in neighborhood with a high proportion of minorities (Black, Hispanic and/or immigrants) and White population tends to avoid this neighborhoods and schools. This pattern has been document in various countries; in Germany people from German heritage avoid schools dominated by non-German background (especially Turkish) children; in the U.S., middle-class parents maximize

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

educational advantage for their children by avoiding non-middle-class and non-White children (Andre-Bechely, 2007; Holme, 2002). Some scholars argue that parents move to the 'catchment areas' of good schools or “close neighbors” (Crane, 1991, Croft, 2004; Goux and Maurin, 2006). 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 people’s response to the enactment of those types of policies was moving out while districts “required” U$ per student to “voluntary” engage in some desegregation[13].

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 development. Figure 5 approximates a first answer. Despite the high correlation between mean parental SES at the school and neighborhood levels, Mathematics achievement is strongly associated to individual SES with a higher correlation on the school level (0.37) than on the neighborhood level (0.30). However, SES is not the only factor which is associated to student’s outcomes. We essay alternative answers to the question in the following section by including more controls and using a cross-classified multilevel model.

Figure 5
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 separates estimation for selected population subgroups. Table 4 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 2 level cross classified specification. As a second step we investigate the impact of introducing individual and contextual variables one step at a time. We explore also 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 estimated alternative specifications are summarized in Table 4.

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

Table 4
Alternative Specifications

	Explanatory Variables Included			
	Family	**School**	**Neighborhood**	**Slope**
Empty				
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 5 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).

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 the percentage of 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 5
Neighborhood-level variance and ICC before and after adding explanatory variables

	Empty Model			Random Intercept		
	School (1)	**Neighbhorh. (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; Table A-2 reports the model comparison.*
Source: *Elaboration based on ECLS-K.*

Table 6 illustrates the effects of the family-background variables on mathematics and reading scores. All the variables included are significant and have a large impact in explaining academic achievement. The effects of SES and race are strong, specially 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 interpretation is straightforward: a child whose family is in the fifth quintile of the SES has almost ten 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.

Summarizing, we find that family background variables have a strong influence in educational achievement but, per Table 5 we know that they only explain half of the between-neighborhoods variance. The analysis which includes contextual variables follows.

Table 6
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 5, columns (5) and (6) described. Table 7, 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 as reflecting 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 statistically non 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 7
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 them with whom they socialize (and likely accept as role models) but by neighborhood's social capital quality. 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[14].

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 neighborhood 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 8 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[15]. Second, the influence of the context is not homogenous and varies across neighborhoods.

Table 8
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 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 6): White children are underrepresented in the lowest half of the population in contrast to to the overrepresentation of Hispanic and Black children. Likewise, and not surprisingly, students classified by race are distributed unequally by quintiles of student's achievement with Hispanics and White overrepresented again in the lowest quintiles of performance (Figure 7). These results are consistent with the students' performance varying along racial lines depicted in Table 6 for mathematics[16].

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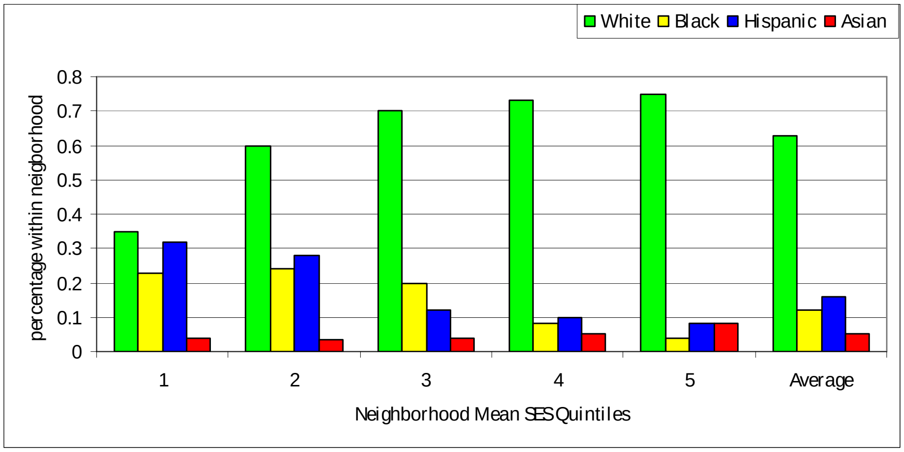
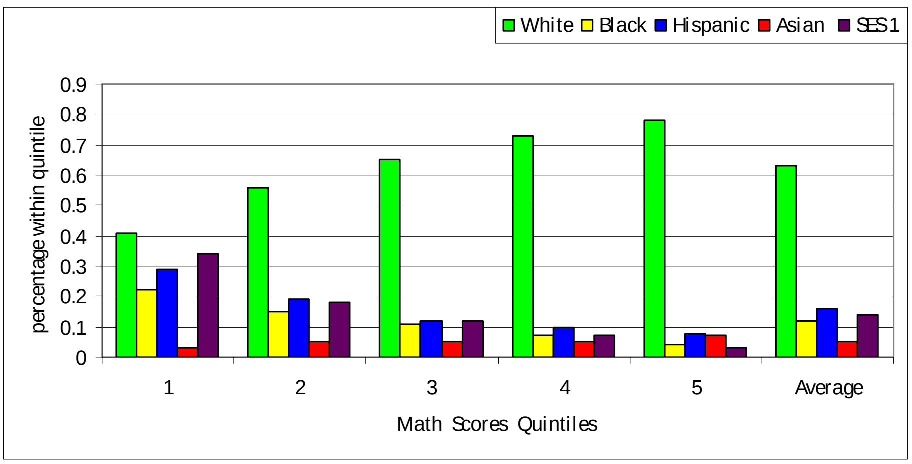
[14] Many empirical work in education points out the differences in provision, facilities and teaching along different dimensions (Hanushek, 1997).
[15] Details of the size of each random effect for math are reported in Tables A-3 through A-6 in the Appendix. Full model results are available under request
[16] Results for Reading are available under request.

Figure 6
Distribution of Selected Population Groups by Neighborhood Quintiles of Average Family SES



Source: *Elaboration based on ECLS-K.*

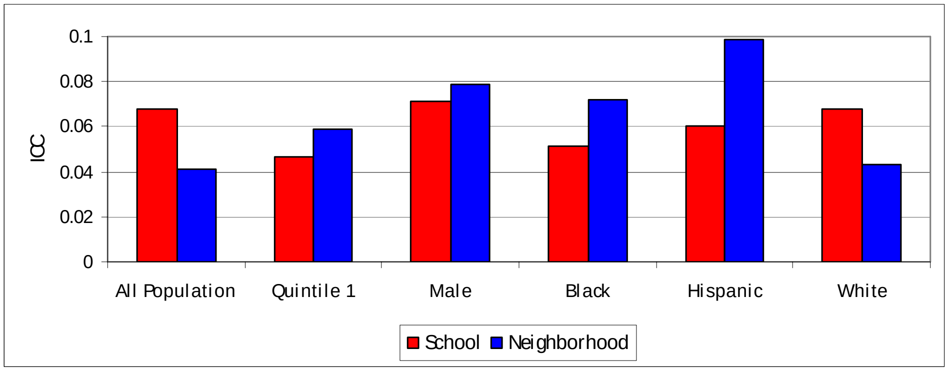
Figure 7
Distribution of Students by Quintiles of Achievement by Selected Population Groups



Source: *Elaboration based on ECLS-K.*

The estimate of the HLM for subgroups summarized in Figure 8 suggests that ICC for the whole population varies across subgroups. For instance, there is a huge jump in the influence of context for SES Quintile 1, Male, Black, Hispanic but not for White children. This evidence suggest that the estimate for the while sample may bias downward the impact of the context perhaps by a very large amount. The impact for Hispanic, for instance, is more than the double of the corresponding to the whole sample.

Figure 8
ICC in Selected Population Groups



Source: *Elaboration based on ECLS-K.*

A complementary analysis of the influence of the same explanatory variables utilized before and available under request confirms that the effect of the covariates vary in size and significance as well. 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 human capital in tract are much larger (and significant) for White and lowest quintile-children than for the average population. Finally, the impact of median income is double than for the average for Black children and nil for Hispanics. Overall, these findings provide strong support for the epidemic theory.

VI.5 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. Like with 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 lower SES children and ethnic composition on school achievement. These effect works on individual achievement through *peers* and was captured by three covariates: school public status, Title I status and ethnic composition of the school measured by percentage of Hispanic peers.[17]

All estimates show that all three covariates have a negative and significant impact on student's individual scores. Nevertheless, Public and Title 1 status are more significant in size (negative) than ethnic composition. The latter, even being statistically significant does have an effect of around a fifth of a SD on student's scores.

Nevertheless, again the most interesting results come from the subgroup analysis. 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.

VI.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, the fixed effect. Statistically, the choice of random versus fixed coefficients depends on the assumptions

[17] We explored 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. We explored as well the Percentage of Black students at school with the same criteria.

made on the random coefficients: zero expectations, homoskedasticity and normal distribution[18]. 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. Unbiased estimates of the fixed effect could be obtained through the random effect model provided that the group means are included (Schneider and Berkhof, 2008).

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 as the ones estimated by the consistent fixed effects estimator. The results summarized in Table 9 below confirm the goodness of fit of the random effects specification.

A second problem may come from heteroskedasticity: if the variance of residuals is not constant the t test will not be reliable but will not affect the point estimates. Heteroskedasticity may be a source of bias only if it is associated with omitted variables[19]. We explored potential heteroskedasticity by analyzing kurtosis, skewness and 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 the plot reported in Figure A-1 in the Appendix.

Table 9
Specification Tests

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

Source: *Elaboration based on ECLS-K.*

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-2 through A4 in the Appendix does not suggest non normality[20].

VI.7 Model Robustness

The substantial variation in data and model specification among the studies to date of children's attainment raises some concern about the robustness of the estimates which appear to be very sensitive to model specification. For this reason we report alternative specifications. In order to test the robustness of our final specifications we estimated the same final model over different samples as Table 10 reflects. These alternatives samples varied with the inclusion of a dummy for missing values.

[18] Homoskedasticity is closest to the assumption that the level 2 units are a random sample of the population (Sneijders and Berkhof, 2008).
[19] 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.
[20] Random effects were checked upwards following Sneijders and Boskhorf (2008).

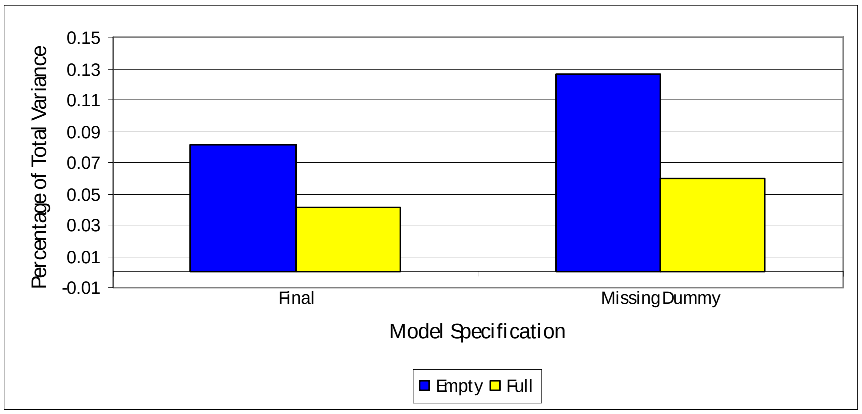
Table 10
Sensitivity Analysis

Model	Dummy For Missing	Kids who Change School	Waves
Final	No	Yes	1-7
Model 2 –Dummy for Missing	Yes	Yes	1-7

Source: *Elaboration based on ECLS-K.*

Figure 9 reports the results of the simulation exercise. The size and significance of the explanatory variables does not changed dramatically across specifications[21]. The ICCs at the neighborhood level decrease always by a half when individual and contextual variables are included.

Figure 9
Neighborhood Variance as Percentage of Total Model



Source: *Elaboration based on ECLS-K.*

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 in the last decades. This paper has presented empirical evidence for the existence of neighborhood and school effects on students' academic achievement.

Using a cross-classified hierarchical linear model, we found 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 ethnicity the outstanding 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 either Black or Hispanic is associated as well with lower scores in both mathematics and reading.

The concentration of poverty and deprivation has a negative and significant impact on child's test scores. The effect of disadvantage offsets the positive influence associated to the concentration of affluent and educated people -measured respectively by median income and females over 25 years oldwho have completed at least high school- in the neighborhood. 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

[21] The full model for the simulation is available under request.

et al (1993) and Kaupinnen (2008) that emphasizes 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 presents non-linearity and shows a big jump at the 30% threshold. This phenomenon implies that social problems increase with certain characteristics but not at a constant rate multiplying the constraint on progress for individuals who already have problems.

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 ethnicity, gender and socio economic status is challenged. Consistently with previous findings in other fields,[22] 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 by gender, ethnicity and SES. Neighborhoods appear to have higher impact on Black and Hispanics than on the whole sample[23].

The results of this study indicate the presence of two types of effects: contextual and endogenous effects[24]. As long as we have confirmed that some neighbors' characteristics are associated (either positively or negatively with the outcome), we expect lower achievement in poor, minority populated neighborhoods. The reminder non-explained variance implies the existence of of positive and negative peer's influence (or endogenous effects in Manski's terminology) and which we hypothesize is takes place once certain thresholds for the contextual variables have been reached. Our research design, however, does not allow the precise identification.

In terms lines 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, among others with the aim of improving the whole community. 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. Furthermore, given that family's spatial locations depend in part on educational policies there is an interrelation between neighborhood and school decisions that calls for policies which address simultaneously neighborhood and school conditions[25].

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 U.S., most initiatives taken during the Clinton's administration such as

[22] For instance, see evidence on crime and violence in Oberwittler (2007) and Sampson et al (2008).
[23] 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).
[24] We could assimilate the effects we found to Raudenbusch and Wilms (1995)'s Type A and Type B effect. Type A effect comprises both school practices and the contextual influences; 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.
[25] 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).

Empowerment Zones and Enterprise Communities Program (EZ/EC) were implemented along with anti-poverty and transportation measures[26].

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 either targeted or universal; the presence of peer contagion effects generate feedback in the student's group of peers adding an indirect impact to the direct impact on the student[27].

The main threat to the modeling strategy adopted may be the endogeneity control. Like in most 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)[28].

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, there are many lines for further research we can envision. 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 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[29]. 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 has 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.

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

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

[28] 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).

[29] 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.

VIII. Appendix

Table A-1
Explanatory Variables Definition

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-2
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-3
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-4
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-5
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-6
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.*

Table A-7
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.*

Figure A-1
Q plot Level 1 residuals

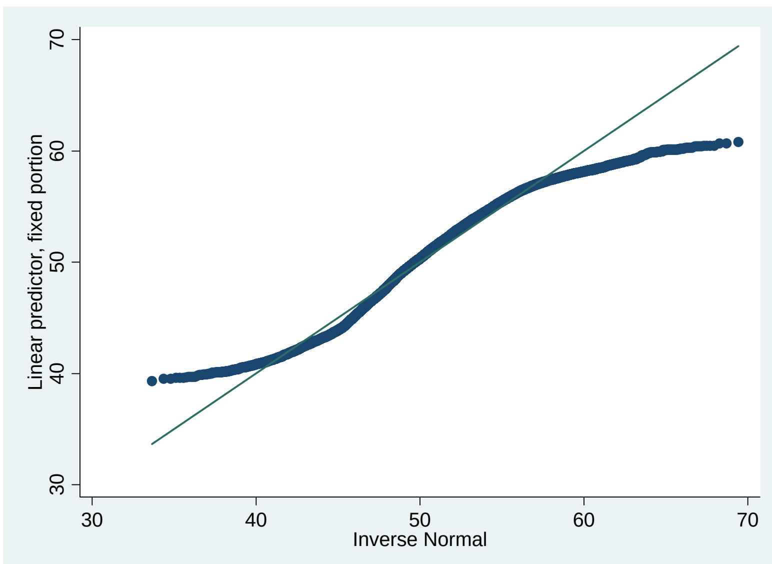


Figure A-2
Predicted Random Effects - Child

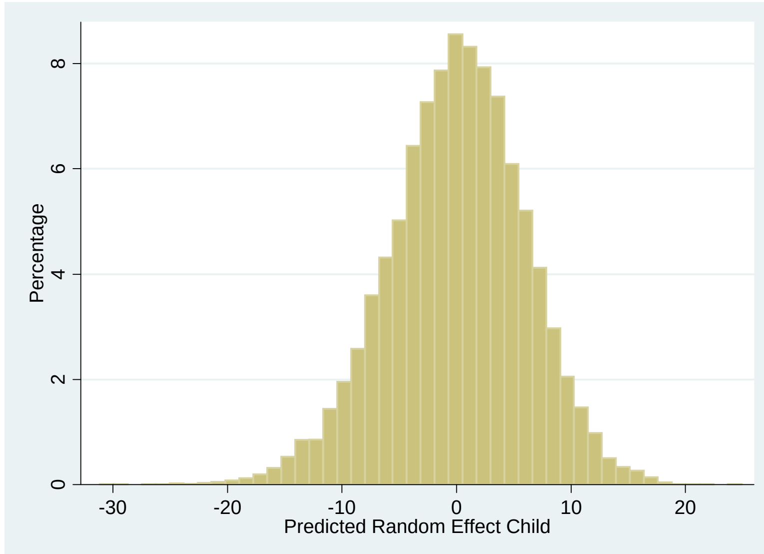


Figure A-3
Predicted Random Effects - Neighborhood

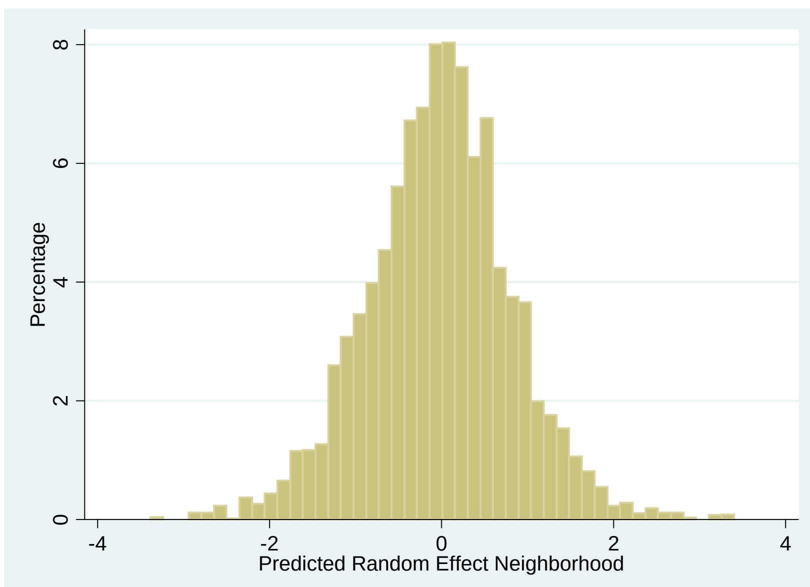
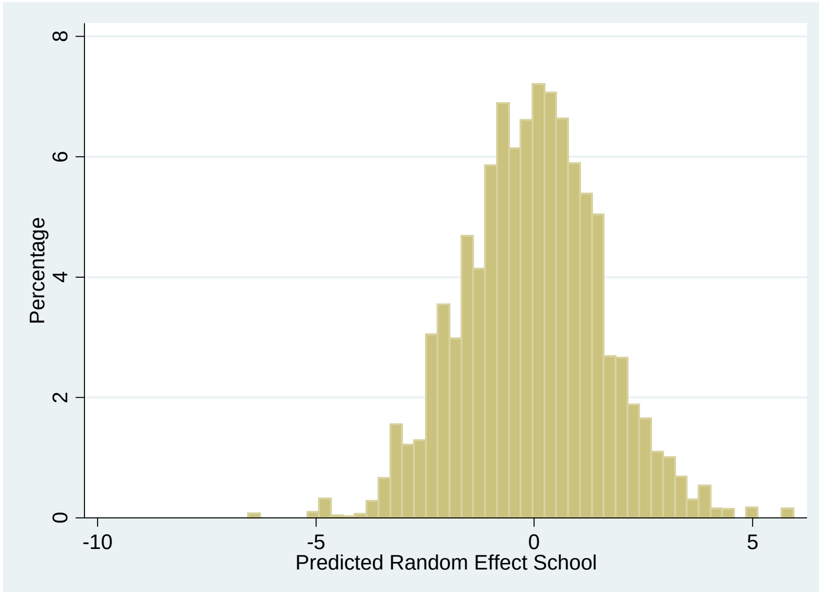


Figure A-4
Predicted Random Effects – School



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