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SDT 302

**EVIDENCE OF NEIGHBORHOOD
EFFECTS ON EDUCATIONAL
PERFORMANCE IN THE CHILEAN
SCHOOL VOUCHER SYSTEM**

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Evidence of neighborhood effects on educational performance in the chilean school voucher system

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Abstract

This paper uses alternative measures of neighborhood quality to study its impact on student performance in school. The Chilean voucher-based education system allows us to test separately for neighborhood and traditional in-classroom peer effects, which have been traditionally emphasized by the literature. We use the Human Development Index reported by United Nations, and the relative number of books in public libraries at the county level, to measure neighborhood quality. We find that a 5 basis point increase in the HDI Index, is related to an increase of 1 to 4 points in the SIMCE test, depending on the specification. The effect is equivalent to half a year increase in mothers education (one additional year achieves a 7 point increase in SIMCE scores). Interestingly, the effect remains when we look at the sample of *random* movers.

Key words: social networks, neighborhood effects, public policies.
JEL classifications: O18, Z13, J18.

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1 Introduction

Inequity in educational quality continues to be one of the most important public policy issues in contemporary Chile. It is a country that has traditionally stood out among emerging markets for the quality of its public policies, but that seems to persistently under-perform in educational indicators. For countries with similar economic development, Chile has the worst educational results in international tests. For example, the TIMSS 2003 International Mathematics Report, ranks Chile in 39th place among 45 countries. Chile's human development level is similar to Lithuania and Hungary, however they obtain 35 and 62 additional points in the TIMSS results (the international average of the test is 467 points).¹ The poor results in the national test have also been documented by Mizala and Romaguera (2002), McEwan and Carnoy (Fall 2000), Elacqua (2009), Contreras, Larrañaga, Flores, Lobato, and Macías (2005) and by the study of Hsieh and Urquiola (2006).

In 1981, Chile made a deep reform to the educational system that established three types of service providers: (i) public school financed with a public subsidy per student attending classes and under the county administration; (ii) voucher schools with private administration and financed through a portable public subsidy per student, that may also require some payments from the family, against a reduction in the public subsidy; and (iii) private paid schools with private funding and administration.

The voucher schools have covered around 45% of the set of potential students, another 45% study in public schools and the remaining 10% study in private schools. Unfortunately the system has not delivered the expected results. Performance gaps between public and private schools has continued to grow, and this phenomenon seems to be independent of the school's being totally public or financed through vouchers. What is interesting is that these results vanish once they control for socioeconomic conditions of the parental house, which indicates a worrying irrelevance of the financing system and apparent social predestination of academic performance Hsieh and Urquiola (2006).

Additional investigation has been done to control for individual and school characteristics and has obtained the same results. These results have driven public policy makers to introduce additional financing (both through the voucher and public systems) conditional on socioeconomic and vulnerability indicators of the students. There has been extensive research on peer effects, that is, the effect on school performance of the other members of the class.² Therefore, starting in 2008 there is an additional subsidy for students classified as *vulnerable* and also depending on the concentration of this type of students in each class.

However, the results we observe may also be driven by social interactions

¹Data obtained from Gonzales, Guzman, Partelow, Pahlke, Jocelyn, Kastberg, and Williams (2004) and Carcedo and Fernández (2005).

²Some examples in the Chilean case are McEwan (2003) and Pavez (2004).

that do not necessarily depend on the amount of the public subsidy or the interactions that may occur inside the classroom. For example, there might be a kind of peer effect outside school, where the place where the student lives or the people with whom the student relates outside campus, affect his knowledge and academic performance.

This paper adds an important factor by introducing a measure of social interaction and therefore highlights the relevance of it on student performance. The main objective is to determine the importance of the neighborhood in which the student lives, on school performance, after controlling by individual, school and family characteristics. The idea is to capture the effect of surrounding human development levels on academic performance by subsidized students.

Finding a large neighborhood effect on school performance could help to emphasize the complementarities of educational and social policies. Separated policies could have lower returns than coordinated interventions that exploit complementarities and scope economies. Finding large effects would suggest that differentiated education policy should move from an individual focus (such as the differentiated voucher policy) to a more collective approach directed towards communities. It should also move education policy from an approach that has the school as its main instrument to one that uses a more comprehensive public education approach.

Using data from the Standardized Test of Educational Quality (SIMCE) of 4th graders (2002) and the Human Development Index (HDI) computed by the United Nations at the county level, this study finds that social interactions have a statistically significant effect on academic performance. A 5 basis-point increase (one standard deviation) in the HDI of the neighborhood of the student generates a 1 to 4 point increase in SIMCE language scores (0.03 standard deviations).

In order to identify the neighborhood effect, we exploit the characteristics of the Chilean Educational System. Considering there is no limitation upon studying in a different county than one's home county and the previous findings on the school choice patterns (McEwan, 2003), we look at the additional effect on the sample of public school *movers*.³ Considering that our measure of social interaction continues to be statistically significant, we are more confident of a causal effect of neighborhood quality. However further research is needed on this topic.

The remainder of the paper is organized as follows. Section 2 reviews the strategies used in previous research done on peer effect and social interaction on educational performance. Section 3 describes the empirical strategy in order to address endogeneity problems. In this section alternative robustness checks used in this study are explained. Section 4 describes the data set used, and presents the main descriptive statistics for the analysis. Section 5 presents the main results with the whole sample, and the alternative

³Students that attend school in a different county from where they live.

robustness check. Finally, section 6 summarizes the main findings.

2 The Literature of Peer Effects and Social Interactions

There are a significant number of studies relating social interaction to labor market and schooling outcomes. Durlauf (2003) is a good survey of the role of neighborhood effects on different socioeconomic outcomes. Most of the literature has analyzed the impact of neighborhood on individual behavior as well as neighborhood composition. A major concern is the potential bias on the estimated neighborhood effect due to omitted variables. It is possible they are finding a positive neighborhood effect because they are capturing other unobservable individual characteristics or family background. Therefore, there are a series of studies that use alternative identification strategies to overcome this potential bias. We can distinguish between a group of studies that exploits the advantage of random assignment to different neighborhoods (mobility experiments), a second group that tries to reconstruct the moving patterns of families using longitudinal data, and a third group of studies that uses cultural similarity (ethnic or language) as network proxy, rather than neighborhood.

Among the first group, for example, Rosenbaum (1995) uses the random assignment of 7,000 families into different neighborhoods in Chicago. Comparing the outcomes of families that moved to middle-income White suburbs versus Black inner-city neighborhoods, he finds higher employment rates for the first group. He also documents higher chances of finishing high school and attending college for the children who moved to the suburbs. Katz, Kling, and Liebman (2000) use data of 540 families enrolled in the Moving to Opportunity (MTO) program in Boston. Even though they do not find significant impact on employment, earnings or welfare receipt of household heads, they find improvements in safety and health status of the heads of household and behavior of the children during the first three years after placement. Angrist and Lang (2004) use the Metropolitan Council for Educational Opportunity (METCO) desegregation program to analyze the impact of peer effects on the scores of white non-METCO Students. This program pays for the student's expenditure as well as transportation costs. In 2000 the program placed around 3,200 students in 32 suburban districts. Using Brookline (MA) micro data, the authors do not find an impact on students in the receiving districts. Their results suggest that if there is some negative effect on the scores of minority girls, it is modest and short-lived. Some studies have even measured the long-run impact of exogenous changes. This is the case of Gould, Lavy, and Paserman (2008) who look at the differential labor market outcomes after almost 60 years of a mostly random allocation of 50,000 Yemenite immigrants. The authors are able to relate

the quality of the childhood environment with behavior at adult ages. Additionally, they are able to find a positive effect on the educational outcomes of the following generation. Of course this type of study is limited by the availability of random movements.

The second group of studies exploits the advantage of longitudinal data in order to relate characteristics of the environment (neighborhood) where the children grew up and their current socioeconomic outcomes. In the US case we find studies using the intergenerational data Panel Study of Income Dynamics (PSID). For example, Corcoran, Gordon, Laren, and Solon (1992) use the intergenerational PSID data to analyze the relation between the characteristics of families and neighborhood where the child grew up and its economic status as adults. They argue that community influences could operate through peer influences, role modeling, social norms or neighborhood institutions. They find a significant positive association between a son's economics status and his family of origin income, and a negative relation with the Black race and family welfare income. On the other hand, they do not find any significant effect of parent's education once they control for other characteristics. Vartanian and Gleason (1999) relate the educational level a person has at age 25 with the neighborhood where they lived when he/she was a teenager, finding a significant correlation. They also use the PSID to measure background characteristics and Census Data to characterize neighborhoods in which the person lived between age 14 and 18. They find a negative effect of neighborhood quality on Black youth high school drop-outs, and a positive effect on White youths' probability of college graduation. Aaronson (1998) uses the siblings of the PSID sample of 742 families to estimate the neighborhood effect. He finds a negative impact of neighborhood poverty levels on high school dropouts and teenage pregnancy, even after controlling for family fixed effects. Garner and Raudenbush (1991) link survey data for 2,500 students that left school between 1984 and 1986 in a given district in Scotland with Census Data of 1981, to estimate a hierarchical linear regression model. They find a significant negative relation between neighborhood deprivation and educational attainment after controlling for child ability, family background and schooling characteristics. They also find a negative relation between a measure of local deprivation and school outcomes. Using a propensity score matching, Harding (2003), looked at the effect of neighborhood on school dropouts. He compares teenagers that were identical in observable variables at age 10, but grew up in different neighborhoods during adolescence. The results show that people living in poorer neighborhoods are more likely to leave high school and have teenage pregnancies.

The third group uses alternative identification strategies. For example, Borjas (1995) shows that the earnings of the children are not only affected by parental earnings, but also by the mean earnings of the ethnic group in the parents' generation. He studies the relation between geography and eth-

nic externalities, determining how the ethnic groups segregate in particular neighborhoods in the United States. The author argues that ethnic capital is an excellent proxy for the socioeconomic background of the neighborhood, providing an alternative way of capturing neighborhood effects. The impact of ethnicity remains even after controlling for parental and neighborhood effects. Similarly, Bertrand, Luttmer, and Mullainathan (2000) use the language spoken at home as a proxy of social networks and examine the role of those social networks in welfare participation. Using the number of people in the local area that speak the same language as a measure of contact availability and the average use of welfare of that language group, they find a strong positive effect of the network on welfare use.

For Chile, McEwan (2003) finds a positive and significant peer effect within the classroom using the average education of the mothers in the classroom as an indicator of the quality of classmates. He also finds that lower average income is related with worse results. Pavez (2004) relates better school outcomes with higher income, wider coverage of public schools, and higher student attendance, as well as higher average outcomes in the county. However, we are not aware of other studies intending on measuring neighborhood quality impact on schooling outcomes.

The Chilean educational system provides a unique opportunity to identify neighborhood effect. In many countries, public school options are limited by the place of residence, which implies that there are technological restrictions that do not allow the parents to separate the decision of residence from the school decision. This means that it is generally not possible to separate the “within” class peer effect from the more general peer effect indicated by neighborhood quality. However, in Chile there are no such restrictions, providing an opportunity for extracting the neighborhood effect.

3 Empirical Strategy

In order to measure the relevance of the different determinants on school performance, we will use a production-function approach for academic outcomes of subsidized students. We will build on the literature by estimating a classical linear production function such as:

$$Test_{ig} = \alpha + \beta X_{ig} + \gamma School_{ig} + \delta Family_{ig} + \rho Peer_{ig} + \theta Group_{ig} + \mu_{ig} \quad (1)$$

where:

- *Test* is the result in a standardized test of student *i* in neighborhood *g*;
- *X* are individual characteristics of the student (Gender);
- *School* are school characteristics (Type of School);

- *Family* are family characteristics (parents education, availability of books at home, HH Income);
- *Peer* are characteristics of the peer at school (% of mothers with HS or College in the classroom);
- *Group* are neighborhood characteristics (HDI or Books per habitant in county g); and
- μ are unobservable characteristics of the family or student

The innovation of this paper is the attempt to disentangle the effect of the *Group* indicator of the traditional *Peer* effect. As we have emphasized above, this type of estimation is not frequent in international literature and has never been attempted with Chilean data. Even though this is a kind of peer effect, the objective is to obtain estimates of the marginal effects of neighborhood characteristics on student achievement that are separate from the traditional “within classroom” peer effects.

The Chilean case gives us a unique opportunity for this type of estimation, because there is a high heterogeneity across counties in social indicators. For example, the access to public goods and poverty rates vary across counties. This variation allows us to obtain more precise estimates of the separated peer effects.

In order to identify the neighborhood effect on student test performance we will regress the evaluation results $Test_{ig}$ on individual, school, peer effect, family and neighborhood quality measures.

The main technical issue is that there might be a potential bias due to the correlation between the neighborhood measure and the unobservable characteristics that are determining the school performance that is, $Cov(Group_{ig}, \mu_{ig}) \neq 0$. For example, the neighborhood measure might be capturing part of the peer effect or individual characteristics. Hence, finding a positive coefficient does not assure us a causal effect. Considering that the estimated parameters could be biased, we look for an identification strategy.

We take advantage of the Chilean schooling system, since there is no legal requirement to attend only schools in the same county in which the family lives. As reported by McEwan (2003) most of the parents choose schools close to their home. Similarly, Elacqua and Buckley (2006), reports on the search behavior of parents in the Metropolitan Region, examining how they construct their school-choice sets and comparing this to what they say they are seeking in choosing schools. The data indicates that parental decisions are mainly influenced by closeness to home. If there is a school from a different county that is closer to your home, you are free to attend it. The descriptive statistics of the first study that uses geo-coding to measure real distance between home and school addresses (Chumacero, Gómez and Paredes, 2008) shows that, on average, voucher school students walk 2 km, while students attending private schools walk 4 km.

This means that we are able to observe children that live in the same county, and therefore share the same neighborhood indicators, but some of them attend school in the same county (*stayers*), while others go to a different one (*movers*). If attending school in a different county is random, we should observe a lower coefficient on the neighborhood characteristics of the home county for *movers*. Even though there should be a lower correlation between neighborhood and peer characteristics when a student goes to school in a different county than where he lives, there might be some unobservable characteristics that may induce parents to look for a school in a different county.

Therefore, despite the patterns for school choice observed in parents' surveys and reported by McEwan (2003) and Elacqua and Buckley (2006) we will perform some exogeneity test on the decision to attend school in a different county and look at the determinants of the probability of moving. A first test is to check the predictive power of the neighborhood indicator on the observable family characteristics of *movers* and *stayers*. Hence we will run a regression of the type:

$$Y_{ig} = \alpha + \beta X_{ig} + \mu_{ig} \quad (2)$$

where:

- Y is any of the observed family characteristics (mother's or father's education and household income);
- X is the HDI in the home county of the student, g ; and
- μ are unobservable characteristics of the student.

Afterwards we test if

$$\beta_{movers} = \beta_{stayer} \quad (3)$$

The second approach is to test if any observable characteristic is able to predict the decision to study in a different county (the decision to move). In this case we estimate:

$$Pr(Mover_i) = \beta X_i + \mu_i \quad (4)$$

If the decision to move is random, we should expect $\beta = 0$.

Both tests are performed for the whole sample and for the sample of students attending public schools. As mentioned in Section 1, we have three types of schools in the Chilean education system. Among the private paid schools, there is an explicit selection of students. This policy prevents families from freely choosing the school for their children, and therefore restricts the possibility of disentangling the different peer effects. Among the voucher schools with private administration we have a mix of schools totally financed with the subsidy, and schools that charge a co-payment. Their selection policy varies depending on the values and principles of the administrator. However, primary public schools are not allowed to select their students.

Therefore, we only expect random movement among students in the public school sample where selection on the school side is not likely.

Once we make the argument of random *movers*, we compare the magnitude of the neighborhood effect between *movers* and *stayers*. In order to be confident we are capturing a true neighborhood effect (instead of unobserved family characteristics) we should observe $\theta_{movers} \leq \theta_{stayer}$.

An alternative specification would be to estimate:

$$Test_{ig} = \alpha + \beta X_{ig} + \gamma School_{ig} + \delta Family_{ig} + \rho Peer_{ig} + \theta Group_{ig} + \eta Group_{ig} Mover_i + \mu_{ig} \quad (5)$$

and verify if $\eta \leq 0$, since it captures the additional effect on *movers*.

We exploit the fact that the parents' survey conducted with the Standardized Test of Education Quality, inquires about household county. Given the school system characteristics described in Section 1, we will concentrate on the publicly managed schools. This will allow us to considerably reduce the endogeneity of school choice.

An additional strategy to reduce the potential bias due to unobservable parents' characteristics on neighborhood choice and child outcomes, is to run the same regression for a sub-sample of only lower income families. The underlying assumption is that poor families do not have many choices with respect to the place where they live so that their location is exogenous. This is consistent with the finding of residential segregation in Chile (Larrañaga and Sanhueza, 2007).

Finally, we test the relative importance of the neighborhood of students' home county with respect to the neighborhood of the students' school county. Therefore, the estimated regression becomes:

$$Test_{ig} = \alpha + \beta X_{ig} + \gamma School_{ig} + \delta Family_{ig} + \rho Peer_{ig} + \theta_1 GroupHome_{ig} Mover_i + \theta_2 GroupHome_{ig} Stayer_i + \theta_3 GroupSchool_{ig} Mover_i + \mu_{ig} \quad (6)$$

4 Data and Stylized Facts

4.1 Data

The data is obtained from the 2002 Standardized Test of Educational Quality (SIMCE) of 4th graders (9 years old). This test is taken by all students of a given school grade in math and language. This census has been conducted by the Ministry of Education since 1997, testing different grades every year. Starting in 2005, the test on 4th grade has been taken every year. In the sample we have 7,600 schools tests with approximately 250,000 students tested in each grade at the national level. In addition, the application process

includes a survey for parents that provides background information on the household composition and characteristics. This questionnaire varies from year to year. In particular, the sample we are using allows us to control for parents' education and socioeconomic status, as well as home and school location. To our best knowledge, the household county was only part of the parents questionnaire in 2002 and 2003.⁴

The census has individual performance of 274,861 students in math and language. From this data set we can identify: student performance, the school in which he/she studies and his/her classmates. From the parents' questionnaire we obtain parental education, household income, and a proxy of household background through the availability of books at home. Unfortunately there are some missing parents' questionnaires and we are unable to recover the household county for approximately 10 percent of the sample, either because the parents did not report it or because they wrote down the street address instead of the county. There are also some missing data on student performance and parents education. Therefore the final sample has 195,910 observations.

Our dependent variable is either the results in the math or language test. We use student gender as a control for individual characteristics of the student. The school characteristic is captured by the administrative dependence of the school. To control for family characteristics we consider the parent' years of education, the household income, and the availability of books at home. The measure of peer effect considers the percentage of mothers with high school and college education of the students classmates.

Finally, we have two alternative measure of neighborhood effects. The first one is obtained from the data set of the Human Development Index (HDI) reported by the United Nation Development Program.⁵ This index takes into account schooling, income and health measures. Among the schooling measures it has the average years of schooling, percentage of the counties' population that can read and write, and percentage of the counties' population between 4 and 25 years that attends an educational facility. The income dimension takes into account the average autonomous income of the county and the percentage of the population under the poverty line. Finally, the health dimension considers the rate of lost years for every 1,000 habitants in the county. The data set contains the index for 341 counties in the country.

An alternative measure of neighborhood quality is the number of books in the public library of each county per habitant. This data is taken from a database of the Ministry of Housing. The data are from year 2001, and are only available for 225 of the 341 municipalities. However over 95 percent of the students that took the 2002 test live in a county for which this information is available.

⁴We thank the Ministry of Education for the access to this data.

⁵UNDP (2004).

Table 1: Characteristics of test takers and their households

	Whole Sample		Male		Female	
	Mean	St Dev	Mean	St Dev	Mean	St Dev
Math Test	250.91	53.50	252.59	54.09	249.17	52.84
Language Test	255.05	53.03	250.81	54.60	259.41	51.00
Mother's education (years)	9.16	4.58	9.17	4.57	9.14	4.58
Father's education (years)	9.23	4.62	9.24	4.61	9.22	4.64
HDIIndex 2003	0.73	0.06	0.75	0.06	0.76	0.06
Female dummy	49.08%		0.00%		100.00%	
0-10 books at home	32.86%		32.79%		32.94%	
11-50 books	41.40%		41.51%		41.29%	
51-100 books	12.42%		12.47%		12.36%	
101-200 books	7.19%		7.22%		7.16%	
More than 200 books	5.09%		4.99%		5.19%	
Rural Area	10.05%		10.12%		9.98%	
High income Household	5.62%		5.51%		5.74%	
Low income Household	47.74%		48.07%		47.41%	
Voucher School	41.18%		40.62%		41.77%	
Private School	7.76%		7.73%		7.78%	
Number of observations	195,910		99,425		96,485	

Source: Author's calculations based on SIMCE 2002 data.

4.2 Descriptive Analysis

Table 1 shows some descriptive statistics of the variables used in this study. As it is well known, boys tend to perform better in math examinations and girls in language tests. The availability of books in their houses is low. Only 30 percent of the households report to have more than 50 books at home. Parents have an average of 9 years of education, so they have not finished high school. Over 50% of students are attending voucher schools, leaving public education with a 38% of enrollment.

One of our identifying strategies considers the separate analysis of students that live and study in the same county where they go to school and those that do not. Therefore, in Table 2 we present the descriptive statics for both samples. We observe that, on average, students that live and study in a different county, *movers*, perform better in the tests, have more educated parents, and have a higher availability of books at home. Additionally, they tend to belong to households with higher incomes.

However, as we can observe in Table 3, most of the apparent advantages among *movers*, is driven by the higher proportion of them attending non-public schools. Among students in voucher schools, 17% attend school in a different county, while among private schools it increases to almost 40%. As mentioned in Section 1, there is a considerable gap between the achievement of students attending public and private schools. We additionally observe a very strong difference in the socioeconomic composition of private school students. Over a 60% belong to high income families, compared with 1% and

Table 2: Characteristics of *movers* and *stayers*

	Live and study in the same county		Live and study in a different county	
	Mean	St Dev	Mean	St Dev
Math Test	249.24	53.15	260.575	54.52
Language Test	253.32	52.74	265.08	53.59
Mother's education	9.01	4.54	9.98	4.72
Father's education	9.08	4.57	10.07	4.82
HDIndex 2003	0.72	0.05	0.74	0.07
Books per habitant	1.10	2.66	3.28	6.66
Female dummy	49.17%		49.68%	
0-10 books at home	34.10%		25.18%	
11-50 books	41.83%		38.88%	
51-100 books	11.90%		15.43%	
101-200 books	6.62%		10.54%	
More than 200 books	4.46%		8.73%	
Rural Area	10.42%		7.92%	
High income Household	4.21%		13.81%	
Low income Household	49.09%		39.97%	
Voucher School	40.00%		48.04%	
Private School	5.67%		19.87%	
Number of observations	167,084		28,826	

Source: Author's calculations based on SIMCE 2002 data.

2% among public and voucher schools, respectively.

Table 3: Characteristics of *movers* attending different types of schools

	Public Schools		Voucher Schools		Private Schools	
	Mean	St Dev	Mean	St Dev	Mean	St Dev
Math Test	237.96	52.30	258.75	51.34	301.51	40.73
Language Test	241.91	51.50	264.77	51.17	303.11	39.11
Mother's education	7.52	4.74	10.14	4.29	13.50	2.95
Father's education	7.62	4.73	10.04	4.29	14.09	3.21
HDIndex 2003	0.71	0.06	0.74	0.07	0.82	0.09
Books per habitant	2.96	6.48	3.11	6.99	4.19	6.02
Female dummy	48.52%		50.46%		49.68%	
0-10 books at home	43.27%		22.17%		3.21%	
11-50 books	37.96%		44.91%		25.77%	
51-100 books	9.21%		16.44%		23.07%	
101-200 books	4.78%		9.57%		22.19%	
More than 200 books	2.86%		5.85%		25.16%	
Rural Area	18.07%		3.62%		1.96%	
High income Household	1.17%		2.30%		62.06%	
Low income Household	47.04%		50.57%		2.92%	
Number of observations	9,251		13,848		5,727	

Source: Author's calculations based on SIMCE 2002 data.

Considering all the characteristics previously described, we restrict the sample to students attending public schools. As we observe in Table 4, the mean values of test scores are slightly higher for students that live and study in the same county. The main difference appears on the income level variable. There is a higher proportion of families with high income (over 2,000 US Dollars) when students live and study in a different county.

Table 4: Characteristics of test takers attending public schools

	Live and study in the same county		Live and study in a different county	
	Mean	St Dev	Mean	St Dev
Math Test	238.52	51.77	237.96	52.30
Language Test	242.03	51.22	241.91	51.50
Mother's education	7.88	4.45	7.52	4.74
Father's education	7.92	4.46	7.62	4.73
HDIndex 2003	0.71	0.05	0.71	0.06
Books per habitant	0.98	2.31	2.96	6.48
Female dummy	48.68%		48.52%	
0-10 books at home	44.04%		43.27%	
11-50 books	40.07%		37.96%	
51-100 books	8.34%		9.21%	
101-200 books	4.01%		4.78%	
More than 200 books	2.36%		2.86%	
Rural Area	16.05%		18.07%	
High income Household	0.62%		1.17%	
Low income Household	50.24%		47.04%	
Number of observations	90,780		9,251	

Source: Author's calculations based on SIMCE 2002 data.

5 Results

5.1 Full Sample Estimates

The results for students attending the school system in Chile show a positive impact of the neighborhood in which they live. Table 5 shows the estimated effect on language performance of all the different variables mentioned before.⁶ The magnitudes and signs are consistent with previous findings. On average, girls have higher scores in the language test and there are positive and statistically significant effects of having more educated parents and major availability of books at home. However, belonging to a low income household reduces the test scores. Attending a private school apparently only matters for girls, but is not statistically significant for boys.

⁶All estimations correct for possible heteroscedasticity, consider regional dummies and cluster at the county level.

The interesting fact is that when we control for neighborhood effects, as measured by the Human Development Index, we find a positive and significant effect. The significance of this Index suggests that the environment in which the student lives affects the academic performance, even after controlling for other observable characteristics. The significance and magnitude of previous controls remain. In order to be sure that we are measuring truly local effects with the neighborhood indicators, we re-estimate the effect for different samples.

Table 5: Estimated effect on Language performance

	Model 1	Model 2	Model 3
Female==1	0.16 (33.06)***	0.16 (32.74)***	0.15 (32.08)***
Mother's Education	0.03 (39.44)***	0.02 (39.60)***	0.02 (39.11)***
Father's Education	0.02 (29.86)***	0.02 (29.27)***	0.02 (28.53)***
0-10 books at home	0.10 (4.36)***	0.10 (4.38)***	0.10 (4.16)***
11-50 books at home	0.25 (10.53)***	0.25 (10.50)***	0.25 (9.99)***
51-100 books at home	0.37 (15.39)***	0.37 (15.36)***	0.37 (14.56)***
101-200 books at home	0.42 (16.29)***	0.42 (16.18)***	0.41 (15.37)***
More than 200 books at home	0.45 (17.45)***	0.45 (17.39)***	0.45 (16.57)***
High Income HH	0.10 (6.45)***	0.08 (6.51)***	0.10 (6.50)***
Low Income HH	-0.17 (17.55)***	-0.17 (17.57)***	-0.17 (17.64)***
Very low Income HH	-0.32 (25.13)***	-0.32 (25.70)***	-0.32 (25.88)***
Voucher School	0.17 (9.34)***	0.17 (9.41)***	0.18 (9.62)***
Private School	0.57 (18.24)***	0.55 (17.41)***	0.57 (18.34)***
Rural Area==1	0.05 (2.38)**	0.06 (2.79)***	0.05 (2.28)**
Peer Effects			
% of mother's with High School	0.48 (8.66)***	0.47 (8.72)***	0.49 (8.65)***
% of mother's with College Education	1.63 (7.19)***	1.46 (6.17)***	1.57 (6.66)***
Neighborhood Effects			
HDIndex 2003		0.53 (3.29)***	
Libros por habitante en la comuna			0.01 (6.44)***
Constant	-1.06 (20.72)***	-1.45 (11.77)***	-1.08 (20.38)***
Observations	194936	194936	187415
Adjusted R-squared	0.208	0.208	0.210

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

5.2 Exogeneity Tests

In order to reduce the potential endogeneity problem in the decision to attend a school in a different county, we reduce the sample only to public schools. As mentioned in Section 1, there is lower selection among public schools, and a very high percentage of parents mention closeness to school as the most relevant factor in the school choice. However, a way to be more confident of the school choice exogeneity is to verify that the neighborhood measure (HDI) explains, as well, the observed characteristics of *movers* and *stayers*.

The estimated coefficients are presented in Table 6. We cannot reject that the measure of neighborhood effect has the same predictive power for *movers* and *stayers* on parents' education or household income. Therefore, we are more confident that there is no significant bias due to the sample chosen.

Table 6: Estimated effect of HDI on observed characteristics for *movers* and *stayers*

	Live and study in the same county		Live and study in a different county	
Mother's Education	18.86	***	18.53	***
	(1.07)		(1.42)	
Father's Education	20.91	***	20.85	***
	(1.12)		(1.39)	
HH Income	1.39	***	1.27	***
	(0.04)		(0.60)	

Standard Errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

An additional method to look if *movers* and *stayers* are not randomly selected is to see which variables are relevant in predicting the *movers*' decision. As we can see in Table 7, mother's and father's education appear as good predictors of the decision to live and study in a different county, while the neighborhood measure and household income are not good predictors. However, when we restrict the sample to public schools, none of those variables appear statistically significant. Therefore, this is our preferred sample.

Considering that Larrañaga and Sanhueza (2007) showed there is important residential segregation in Chile, it looks like some poor people are stacked in their neighborhood and these might be affecting there long run achievement. Therefore, we perform an additional test by looking only at students belonging to the poorest families, expecting that any neighborhood characteristic will be less related with other individual choices they can make. However, we observe that among this restricted sample most of the observed family characteristics help predict the decision to move. Hence our preferred sample continues to be students attending public schools.

Table 7: Probit estimate for the decision of moving to a different municipality

	Full Sample	Public Schools	Public School and poor HH
HDIndex 2003	0.86 (0.20)	3.56 (1.13)	5.45 (2.11)**
Mother's Education	0.01 (4.39)***	-0.00 (1.19)	-0.02 (5.22)***
Father's Education	0.01 (4.00)***	-0.00 (0.54)	-0.00 (1.32)
HH Income	-0.90 (0.31)	-3.53 (1.64)	-5.40 (2.88)***
Rural Area==1	0.06 (0.79)	0.10 (1.39)	0.14 (2.15)**
Constant	-3.04 (2.13)**	-2.86 (2.38)**	-3.00 (2.85)***
Observations	195,213	99,935	38,951

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

5.3 Estimates for Public Schools

To check the robustness of the results founded in the previous subsection, we will look with more detail at the sample of students attending public schools. We continue finding a positive and statistically significant effect of the neighborhood in which the kid lives on language performance. We split the sample between *movers* and *stayers* to replicate the regressions. As shown in Table 8, family characteristics captured by parents' education and household income, and the traditional peer effect are as significant for both samples. However the neighborhood effect, measured through the HDI Index, vanishes for *stayers* while it remains strongly significant for *movers*. This raises the possibility that we are only able to identify a real neighborhood effect when we look at *random* movers. Among *stayers* both effects are more correlated and therefore we cannot identify them separately. Considering the second indicator of neighborhood quality, relative number of books per habitant in the county, the effect is not statistically different between *movers* and *stayers*.

5.4 Estimates with Math Test

To make an additional test on the robustness of the results presented, we replicate the complete set of regressions with the scores obtained in the math test. Consistent with the descriptive statistics and international literature, boys tend to perform better than girls in this test. Otherwise, similar results hold. The detailed regressions are in Tables A.2 to A.6.

The point estimates are lower with the math test. However the same pattern holds, showing a more significant effect for students living and studying

Table 8: Estimated effect on language performance for students attending public school

	Live and study in the same county		Live and study in the different county	
Mother's Education	0.02 (22.97)***	0.02 (21.48)***	0.02 (6.48)***	0.02 (6.29)***
Father's Education	0.02 (20.02)***	0.02 (19.06)***	0.02 (8.18)***	0.02 (8.14)***
High Income HH	-0.09 (1.99)**	-0.10 (2.12)**	0.01 (0.12)	0.02 (0.18)
Low Income HH	-0.10 (6.79)***	-0.10 (6.48)***	-0.08 (2.78)***	-0.11 (3.40)***
Very low Income HH	-0.23 (14.83)***	-0.23 (13.56)***	-0.23 (5.69)***	-0.25 (6.20)***
Peer Effects				
% of mothers with High School	0.70 (12.59)***	0.75 (13.92)***	0.58 (4.77)***	0.60 (4.15)***
% of mothers with College	2.78 (1.97)**	3.37 (2.50)**	2.03 (0.88)	5.41 (2.07)**
Neighborhood Effects				
HDIndex 2003	0.36 (1.09)		1.57 (4.28)***	
Book per habitant		0.01 (3.71)***		0.01 (3.06)***
Constant	-1.50 (6.01)***	-1.26 (12.60)***	-2.45 (8.10)***	-1.26 (8.52)***
Observations	90,308	84,235	9,185	8,626
Adjusted R-squared	0.114	0.115	0.129	0.132

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

in different municipalities (*movers*).

5.5 Other robustness checks

Additionally we test the effect of considering the partial components of the Human Development Index. A summary is presented in Tables 10 and 11. We can observe that the effect captured by the Human Development Index can equally well be explained by the educational or income component. However, the health component does not appear a significant explanatory variable.

5.6 Relevance of Home and School County Indicators

Finally, we test the relative importance of the home county neighborhood indicators, with respect to the school county one. Table 12 reports the coefficients of interest. We can observe that, within the sample of students

Table 9: Estimated effect on language for *poor* students attending public schools

	Live and study in the same county		Live and study in the different county	
Mother's Education	0.16 (15.16)***	0.15 (13.69)***	0.16 (5.14)***	0.15 (4.78)***
Father's Education	0.02 (11.64)***	0.02 (10.57)***	0.01 (1.52)	0.01 (1.85)*
High Income HH	0.01 (9.86)***	0.01 (9.39)***	0.02 (4.53)***	0.02 (4.21)***
Peer Effects				
% of mothers with High School	0.73 (13.93)***	0.75 (13.12)***	0.68 (6.05)***	0.76 (6.53)***
% of mothers with College Education	-0.85 (0.57)	-1.37 (0.88)	1.25 (0.99)	0.49 (0.24)
Neighborhood Effects				
HDIndex 2003	-0.21 (0.75)		1.66 (3.38)***	
Book per habitant		0.01 (1.85)*		0.01 (1.50)
Constant	-1.23 (5.58)***	-1.40 (19.97)***	-2.80 (5.63)***	-1.66 (4.88)***
Observations	35,247	31,965	3,476	3,141
Adjusted R-squared	0.071	0.073	0.055	0.057

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10: Estimates with HDI and the components with Language test

	Movers		Stayers	
Whole sample				
HDIndex 2003	28.68 (2.72)***		28.67 (3.24)***	
Health Dimension		7.12 (0.81)		-0.29 (0.03)
Income Dimension		24.94 (3.28)***		21.74 (3.58)***
Schooling Dimension			23.02 (2.30)**	36.34 (4.14)***
Public Schools				
HDIndex 2003	19.07 (1.09)		84.00 (4.28)***	
Health Dimension		4.12 (0.31)		6.13 (0.32)
Income Dimension		17.12 (1.33)		64.82 (5.36)***
Schooling Dimension			10.56 (0.71)	87.95 (5.23)***

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

attending public schools, the Home County HDI is non-significant for *stayers* consistent with the results reported in the previous specifications. With respect to the effect found for public school *movers*, this specification shows us that the school county neighborhood indicator is positive and significant, while the home county indicator appears as non-significant. Therefore we

Table 11: Estimates with HDI and the components with Math test

	Movers		Stayers	
Whole sample				
HDIndex 2003	0.36 (1.82)*		0.36 (2.17)**	
Health Dimension	0.10 (0.54)		-0.14 (0.60)	
Income Dimension		0.31 (2.22)**		0.31 (3.17)***
Schooling Dimension		0.25 (1.39)		0.48 (3.65)***
Public Schools				
HDIndex 2003	0.07 (0.24)		1.06 (2.81)***	
Health Dimension	0.01 (0.05)		-0.22 (0.63)	
Income Dimension		0.10 (0.43)		0.93 (4.44)***
Schooling Dimension		-0.08 (0.32)		1.22 (4.04)***

Robust z statistics in parentheses
 * significant at 10%; ** significant at 5%; *** significant at 1%

can clearly state a positive neighborhood effect for the sample of *movers*, among whom we can separately identify school and home county peer effect.

Table 12: Estimates on home and school neighborhood indicators

Home County HDI*mover	Home County HDI*stayer	School County HDI*mover
-0.45 (1.12)	0.54 (1.63)	0.98 (1.73)*

Robust t statistics in parentheses
 * significant at 10%; ** significant at 5%; *** significant at 1%

6 Conclusions

Several studies have measured the impact of peers in educational outcome. An important set of studies has been able to relate the background or quality of early childhood environment to educational and labor outcomes. We exploit characteristics of the Chilean educational system to show that there is an important neighborhood effect. The result suggests that a 5-basis point increase in the HDI Index is related to an increase of 1 to 4 points in the SIMCE test, depending on the specification. These results are consistent with different measures of neighborhood quality and robustness checks. The fact that the effects remain when we look at the sample of *random movers* made us more confident of a causal effect. However, the final specification shows that the school county neighborhood indicator remains significant, while the home county indicator appears to be non-significant. Hence, it looks like the home county indicator is also picking up the school county characteristics when we look at *stayers* and we are only able to estimate it separately for *random movers*.

This paper highlights the relevance of properly identifying the neighborhood effect, since it has important implication for the design of social policies. The positive effect of the neighborhood indicator we find on student performance emphasize the complementarities of educational and social policies. If we continue to design separated policies, we could have lower returns than with coordinated interventions that exploit complementarities and scope economies. The evidence suggest that the education policy should move from an individual focus (such as the differentiated voucher policy) to a more collective approach directed towards communities.

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7 Appendix

Table A.1: Average eighth-grade mathematics scores by country: 2003

Ranking	Country	Average Score	Standard errors	Ranking	Country	Average Score	Standard errors
1	Singapore	605	(3.6)	24	Serbia	477	(2.6)
2	Korea, Republic	589	(2.2)	25	Bulgaria	476	(4.3)
3	Hong Kong, SAR	586	(3.3)	26	Romania	475	(4.8)
4	Chinese Taipei	585	(4.6)	27	Norway	461	(2.5)
5	Japan	570	(2.1)	28	Moldova	460	(4.0)
6	Belgium (Flemish)	537	(2.8)	29	Cyprus	459	(1.7)
7	Netherlands	536	(3.8)	30	Macedonia, Republic of	435	(3.5)
8	Estonia	531	(3.0)	31	Lebanon	433	(3.1)
9	Hungary	529	(3.2)	32	Jordan	424	(4.1)
10	Malaysia	508	(4.1)	33	Iran, Islamic Rep. of	411	(2.4)
11	Latvia	508	(3.2)	34	Indonesia	411	(4.8)
12	Russian Federation	508	(3.7)	35	Tunisia	410	(2.2)
13	Slovak Republic	508	(3.3)	36	Egypt	406	(3.5)
14	Australia	505	(4.6)	37	Bahrain	401	(1.7)
15	United States	504	(3.3)	38	Palestinian Nat. Aut.	390	(3.1)
16	Lithuania	502	(2.5)	39	Chile	387	(3.3)
17	Sweden	499	(2.6)	40	Morocco	387	(2.5)
18	Scotland	498	(3.7)	41	Philippines	378	(5.2)
19	Israel	496	(3.4)	42	Botswana	366	(2.6)
20	New Zealand	494	(5.3)	43	Saudi Arabia	332	(4.6)
21	Slovenia	493	(2.2)	44	Ghana	276	(4.7)
22	Italy	484	(3.2)	45	South Africa	264	(5.5)
23	Armenia	478	(3.0)				

Source: TIMSS 2003 International Mathematics Report

Table A.2: Estimated effect on Language performance of students attending public schools

	Public Schools Same Municipality			Public Schools Other Municipality		
Female==1	0.16 (21.36)***	0.16 (21.33)***	0.15 (20.05)***	0.15 (7.39)***	0.15 (7.36)***	0.16 (7.05)***
Mother's Education	0.02 (22.92)***	0.02 (22.97)***	0.02 (21.48)***	0.02 (6.60)***	0.02 (6.48)***	0.02 (6.29)***
Father's Education	0.02 (20.14)***	0.02 (20.02)***	0.02 (19.06)***	0.02 (8.43)***	0.02 (8.18)***	0.02 (8.14)***
0-10 books at home	0.12 (4.34)***	0.12 (4.35)***	0.11 (4.01)***	0.09 (1.43)	0.09 (1.44)	0.11 (1.65)*
11-50 books at home	0.26 (9.30)***	0.25 (9.28)***	0.25 (8.74)***	0.24 (4.13)***	0.24 (4.06)***	0.25 (4.06)***
51-100 books at home	0.38 (13.89)***	0.38 (13.87)***	0.37 (13.16)***	0.41 (5.71)***	0.40 (5.54)***	0.41 (5.40)***
101-200 books at home	0.41 (14.14)***	0.41 (14.25)***	0.40 (13.43)***	0.36 (4.37)***	0.34 (4.22)***	0.36 (4.16)***
More than 200 books at home	0.46 (13.18)***	0.46 (13.28)***	0.46 (12.59)***	0.43 (4.85)***	0.41 (4.52)***	0.44 (4.77)***
High Income HH	-0.09 (1.87)*	-0.09 (1.99)**	-0.10 (2.12)**	0.03 (0.34)	0.01 (0.12)	0.02 (0.18)
Low Income HH	-0.10 (6.58)***	-0.10 (6.79)***	-0.10 (6.48)***	-0.11 (3.42)***	-0.08 (2.78)***	-0.11 (3.40)***
Very low Income HH	-0.23 (13.91)***	-0.23 (14.83)***	-0.23 (13.56)***	-0.26 (6.04)***	-0.23 (5.69)***	-0.25 (6.20)***
Rural Area==1	0.13 (6.04)***	0.13 (6.32)***	0.14 (5.83)***	0.10 (2.24)**	0.11 (2.64)***	0.12 (2.72)***
% of mothers with High School	0.72 (14.33)***	0.70 (12.59)***	0.75 (13.92)***	0.55 (3.87)***	0.58 (4.77)***	0.60 (4.15)***
% of mothers with College	2.89 (2.02)**	2.78 (1.97)**	3.37 (2.50)**	2.32 (0.91)	2.03 (0.88)	5.41 (2.07)**
HDIndex 2003		0.36 (1.09)			1.57 (4.28)***	
Book per habitant			0.01 (3.71)***			0.01 (3.06)***
Constant	-1.24 (12.99)***	-1.50 (6.01)***	-1.26 (12.60)***	-1.28 (7.47)***	-2.45 (8.10)***	-1.26 (8.52)***
Observations	90,308	90,308	84,235	9,185	9,185	8,626
Adjusted R-squared	0.113	0.114	0.115	0.124	0.129	0.132

Robust t statistics in parentheses

* significant at 10%

** significant at 5%

*** significant at 1%

Table A.3: Estimated effect on Language performance of *poor* students attending public schools

	Public Schools Same Municipality			Public Schools Other Municipality		
Female==1	0.16 (15.13)***	0.16 (15.16)***	0.15 (13.69)***	0.16 (5.20)***	0.16 (5.14)***	0.15 (4.78)***
Mother's Education	0.02 (11.61)***	0.02 (11.64)***	0.02 (10.57)***	0.01 (1.64)	0.01 (1.52)	0.01 (1.85)*
Father's Education	0.01 (9.86)***	0.01 (9.86)***	0.01 (9.39)***	0.02 (4.57)***	0.02 (4.53)***	0.02 (4.21)***
0-10 books at home	0.15 (3.94)***	0.15 (3.94)***	0.15 (3.82)***	0.06 (0.67)	0.07 (0.69)	0.09 (0.82)
11-50 books at home	0.28 (7.58)***	0.28 (7.60)***	0.29 (7.31)***	0.17 (1.71)*	0.18 (1.75)*	0.18 (1.62)
51-100 books at home	0.38 (7.88)***	0.38 (7.90)***	0.38 (7.51)***	0.32 (2.28)**	0.31 (2.25)**	0.34 (2.25)**
101-200 books at home	0.45 (8.37)***	0.45 (8.43)***	0.45 (7.98)***	0.37 (2.25)**	0.36 (2.20)**	0.39 (2.24)**
More than 200 books at home	0.40 (5.60)***	0.40 (5.64)***	0.41 (5.41)***	0.62 (2.97)***	0.59 (2.80)***	0.69 (3.46)***
High Income HH	0.14 (6.39)***	0.14 (6.25)***	0.15 (6.21)***	0.17 (3.49)***	0.17 (3.54)***	0.19 (3.56)***
% of mothers with High School	0.72 (13.51)***	0.73 (13.93)***	0.75 (13.12)***	0.69 (6.06)***	0.68 (6.05)***	0.76 (6.53)***
% of mothers with College	-0.85 (0.57)	-0.85 (0.57)	-1.37 (0.88)	1.32 (1.03)	1.25 (0.99)	0.49 (0.24)
HDIndex 2003		-0.21 (0.75)			1.66 (3.38)***	
Book per habitant			0.01 (1.85)*			0.01 (1.50)
Constant	-1.38 (20.50)***	-1.23 (5.58)***	-1.40 (19.97)***	-1.60 (4.96)***	-2.80 (5.63)***	-1.66 (4.88)***
Observations	35,247	35,247	31,965	3,476	3,476	3,141
Adjusted R-squared	0.071	0.071	0.073	0.052	0.055	0.057

Robust t statistics in parentheses

* significant at 10%

** significant at 5%

*** significant at 1%

Table A.4: Estimated effect on Math performance

Female==1	-0.07 (12.69)***	-0.07 (12.70)***	-0.07 (12.96)***
Mother's Education	0.03 (40.15)***	0.03 (40.20)***	0.03 (40.62)***
Father's Education	0.02 (28.78)***	0.02 (28.43)***	0.02 (27.38)***
0-10 books at home	0.07 (3.36)***	0.07 (3.36)***	0.08 (3.44)***
11-50 books at home	0.22 (9.87)***	0.22 (9.82)***	0.22 (9.57)***
51-100 books at home	0.34 (15.01)***	0.33 (14.94)***	0.34 (14.41)***
101-200 books at home	0.38 (16.01)***	0.38 (15.85)***	0.38 (15.36)***
More than 200 books at home	0.42 (18.30)***	0.42 (18.19)***	0.42 (17.48)***
High Income HH	0.14 (7.88)***	0.13 (8.87)***	0.14 (7.80)***
Low Income HH	-0.15 (15.85)***	-0.15 (15.80)***	-0.15 (15.91)***
Very low Income HH	-0.30 (24.21)***	-0.29 (24.24)***	-0.30 (24.50)***
Voucher School	0.14 (7.38)***	0.14 (7.42)***	0.15 (7.70)***
Private School	0.58 (17.08)***	0.56 (16.67)***	0.58 (17.27)***
Rural Area==1	-0.03 (1.62)	-0.03 (1.34)	-0.03 (1.47)
% of mothers with High School	0.45 (8.12)***	0.45 (8.10)***	0.47 (8.22)***
% of mothers with College	1.62 (5.56)***	1.51 (5.02)***	1.58 (5.16)***
HDIndex 2003		0.36 (2.20)**	
Books per habitant			0.01 (7.09)***
Constant	-0.86 (16.87)***	-1.12 (9.14)***	-0.88 (16.69)***
Observations	195,910	195,910	188,357
Adjusted R-squared	0.199	0.199	0.202

Robust t statistics in parentheses

* significant at 10%

** significant at 5%

*** significant at 1%

Table A.5: Estimated effect on Math performance of students attending public schools

	Public Schools Same Municipality			Public Schools Other Municipality		
Female==1	-0.06 (8.23)***	-0.06 (8.24)***	-0.07 (8.47)***	-0.08 (4.13)***	-0.08 (4.14)***	-0.07 (3.68)***
Mother's Education	0.02 (24.94)***	0.02 (24.89)***	0.02 (23.40)***	0.03 (7.72)***	0.03 (7.54)***	0.03 (7.31)***
Father's Education	0.02 (20.41)***	0.02 (20.33)***	0.02 (19.67)***	0.02 (6.14)***	0.02 (5.97)***	0.02 (5.83)***
0-10 books at home	0.08 (2.71)***	0.08 (2.71)***	0.08 (2.62)***	0.05 (0.67)	0.05 (0.68)	0.08 (1.11)
11-50 books at home	0.21 (7.16)***	0.21 (7.14)***	0.21 (6.87)***	0.19 (2.77)***	0.19 (2.73)***	0.21 (2.94)***
51-100 books at home	0.32 (11.16)***	0.32 (11.10)***	0.32 (10.61)***	0.32 (3.85)***	0.31 (3.75)***	0.32 (3.93)***
101-200 books at home	0.37 (11.74)***	0.36 (11.73)***	0.36 (11.23)***	0.31 (4.00)***	0.30 (3.83)***	0.30 (3.98)***
More than 200 books at home	0.37 (10.70)***	0.37 (10.68)***	0.37 (10.25)***	0.40 (4.36)***	0.38 (4.13)***	0.41 (4.33)***
High Income HH	-0.10 (2.36)**	-0.10 (2.41)**	-0.11 (2.56)**	-0.02 (0.20)	-0.03 (0.37)	-0.03 (0.34)
Low Income HH	-0.07 (4.66)***	-0.07 (4.75)***	-0.08 (4.69)***	-0.10 (2.87)***	-0.08 (2.46)**	-0.09 (2.77)***
Very low Income HH	-0.20 (12.25)***	-0.20 (12.68)***	-0.21 (11.85)***	-0.26 (6.78)***	-0.24 (6.52)***	-0.25 (6.96)***
Rural Area==1	0.03 (1.52)	0.03 (1.59)	0.04 (1.73)*	-0.01 (0.15)	0.00 (0.05)	0.01 (0.13)
% of mothers with High School	0.67 (12.51)***	0.66 (11.36)***	0.71 (12.68)***	0.46 (3.75)***	0.48 (4.34)***	0.52 (4.34)***
% of mothers with College	2.65 (1.86)*	2.62 (1.84)*	3.12 (2.20)**	1.66 (0.72)	1.47 (0.68)	4.54 (2.48)**
HDIndex 2003		0.07 (0.24)			1.06 (2.81)***	
Book per habitant			0.01 (2.48)**			0.01 (3.97)***
Constant	-1.00 (12.08)***	-1.05 (4.53)***	-1.02 (11.70)***	-1.00 (4.15)***	-1.79 (5.10)***	-1.03 (4.25)***
Observations	90,780	90,780	84,683	9,251	9,251	8,692
Adjusted R-squared	0.104	0.104	0.106	0.120	0.122	0.131

Robust t statistics in parentheses

* significant at 10%

** significant at 5%

*** significant at 1%

Table A.6: Estimated effect on Math for *poor* students attending public schools

	Public Schools Same Municipality			Public Schools Other Municipality		
	Female==1	-0.07 (6.97)***	-0.07 (6.97)***	-0.08 (7.25)***	-0.10 (3.29)***	-0.10 (3.31)***
Mother's Education	0.02 (12.69)***	0.02 (12.64)***	0.02 (11.35)***	0.02 (3.98)***	0.02 (3.90)***	0.02 (4.02)***
Father's Education	0.01 (9.27)***	0.01 (9.26)***	0.01 (8.91)***	0.02 (3.23)***	0.02 (3.20)***	0.02 (3.05)***
0-10 books at home	0.11 (3.02)***	0.11 (3.02)***	0.10 (2.76)***	-0.05 (0.53)	-0.05 (0.51)	0.00 (0.04)
11-50 books at home	0.23 (6.13)***	0.23 (6.17)***	0.23 (5.77)***	0.08 (0.77)	0.08 (0.81)	0.12 (1.04)
51-100 books at home	0.33 (7.88)***	0.33 (7.92)***	0.32 (7.40)***	0.13 (1.01)	0.13 (0.97)	0.17 (1.19)
101-200 books at home	0.40 (7.86)***	0.41 (7.93)***	0.40 (7.51)***	0.23 (1.63)	0.22 (1.58)	0.26 (1.73)*
More than 200 books at home	0.32 (4.65)***	0.32 (4.69)***	0.31 (4.30)***	0.31 (1.39)	0.28 (1.25)	0.33 (1.41)
High Income HH	0.05 (2.21)**	0.04 (1.98)**	0.06 (2.41)**	0.07 (1.36)	0.07 (1.47)	0.08 (1.45)
% of mothers with High School	0.65 (10.68)***	0.67 (11.02)***	0.69 (10.87)***	0.64 (5.37)***	0.63 (5.35)***	0.75 (6.17)***
% of mothers with College	-0.19 (0.13)	-0.19 (0.12)	-0.04 (0.03)	1.82 (1.45)	1.76 (1.39)	0.58 (0.28)
HDIndex 2003		-0.48 (1.75)*			1.52 (3.09)***	
Book per habitant			0.01 (1.83)*			0.01 (1.65)
Constant	-1.08 (16.98)***	-0.74 (3.57)***	-1.10 (16.45)***	-1.70 (4.96)***	-2.79 (5.55)***	-1.79 (4.94)***
Observations	35,450	35,450	32,157	3,502	3,502	3,167
Adjusted R-squared	0.057	0.057	0.060	0.045	0.048	0.051

Robust t statistics in parentheses

* significant at 10%

** significant at 5%

*** significant at 1%