Neighborhood effects in Education*

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Abstract

We use an individual level education production function model, with spatial dependence, to isolate the role of geographic neighborhood on educational outcomes. After controlling for observed individual, teacher and school effects the estimates suggest a strong and consistent effect from the performance of neighbors. Several counter-factual models suggest that the effect really is due to geography-a finding with startling policy conclusions.

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1 Introduction

To the extent that peers influence educational outcomes, it makes sense to hypothesize a role for geographic proximity in a child's education production function. Children that live close to each other may play and experience neighborhood conditions together, causing geographic-specific effects outside of the influences of peers at school. Neighborhood conditions such as demographics, existence of parks, sidewalks, etc. and safety conceivably foster geographic effects and may even work directly on education production.

Since researchers usually observe educational outcomes through schools, there is not a lot of research on geographic-specific[1] peer effects. Zimmer and Toma (2000) use zip code level characteristics to account for neighborhoods. In a study using data from Boston's Metco Program, Angrist and Lang (2004) find modest and transient peer effects[2]. Jargowsky and El-Komi (2009) consider the impact of neighborhood on educational outcomes of students in Texas by using US Census information on Census tracts around schools. However, they are unable to estimate the direct effect of neighbors because they do not know the specific geographic location of the students. Our approach utilizes the location of the students to directly test for an effect due to geographic peers by adding nearby students' outcomes as inputs to the education production function.

Several studies consider the effects of classroom peers on educational outcomes (see for example Hoxby (2000); Hanushek et al. (2003); Figlio (2007))[3]. Lazear (2001) for instance, outlines the theoretical implications of a disruptive peer in terms of the production of education. Bramoullé et al. (2009) and Calvó-Armengol et al. (2009) look at peers in terms of network. While their model is similar to the spatial specification

[1] In most of the research, this is aggregated at a level where neighborhoods may not necessarily be neighboring. One exception is Solon et al. (2000) which essentially finds no correlation in outcomes of children growing up within a few blocks of each other. Apart from other differences from this paper, it is not clear if neighborhood changes when neighbors do not.

[2] Sobel (2006) suggests potential problems with generalizability of these results.

[3] Papers that have considered neighborhood peer effect outside of classroom have analyzed it only in context for friends (Ryan, 2001) or have focused on neighborhood defined in context of on-campus housing location (Foster, 2006; Stinebrickner and Stinebrickner, 2006; Sacerdote, 2001).

employed here, our focus is on geography. Moreover, a social network may not necessarily be exogenous. Insofar as parents choose neighborhoods while students choose their friends, this is mitigated in our analysis. And as noted above, we directly account for the *presence* of neighbors of different abilities[4]. We, therefore, account for the effects of neighbors even if they are not in the social network of a particular individual.

In this paper, we use a series of "spatial lag" models (Lesage and Pace, 2009) to test for a direct effect of neighbors *even after controlling for classroom and school peer effects*. Our findings generally indicate the existence of such effects. If true, these results suggest a new line of policy options for improving educational outcomes; i.e. , rather than spend additional dollars through schools, consider redirecting marginal dollars to neighborhoods so as to capitalize on these effects.

2 Hypotheses

The value (or lack thereof) of neighbors is well recognized. For instance, the research on housing prices and crime both consider the role of surrounding residential quality. Similarly, medical research is now recognizing the role of neighborhood condition in health outcomes. Augmenting this reasoning with what is known as Tobler's first law of geography (*Everything is related to everything else, but near things are more related than distant things*), would imply that neighbors that are close by are likely to have a stronger (positive or negative) impact. If this extension holds for the educational outcomes as well, it is reasonable to assume that students are likely to interact with other students who live in the neighborhood. One implication of this is that spatial 'closeness' can be thought of in terms of mobility options. For instance, a nine year old may not be able to interact with nine year old's in neighborhoods that are, say a half-mile away. Older

[4]It is possible that neighbors who do well in school or stay out of trouble may lead to conforming behavior, etc.

kids may have access to bicycle or even cars that are less constraining. Thus for high school students, 'nearby' neighbors may not have as strong an impact. These, then, lead to the following hypotheses.

Primary Hypothesis: Educational outcomes of geographic neighbors affect educational outcomes.

Hypothesis 1: For high school students 'nearby' neighbor will not be as influential.

So far the analysis has not incorporated the idea of neighboring grades. As far as residential neighbors are concerned, interactions are not necessarily restricted to only those who share the same grade or even same age. In a non-school setting, similar physical (think sports) or other such factors may over-ride detailed sorting by age. It would then be relevant to understand impact of these on educational outcomes. It is feasible that being in the same grade and also in the same neighborhood reinforces the impact.

Hypothesis 2: Neighbors who are in same grade matter more than those that are not.

It is likely that individual sorting behavior[5] brings similar individuals together in geographic space. Insofar as similar students (either high or low scoring) cluster, geographic neighbors will have similar attributes. As opposed to testing for evidence of similar neighbors, we test for the *impact*[6] of neighbors. This is a subtle but significant distinction. The research question posed in this paper is valuable irrespective of neighbors being similar. In other words, even if a neighborhood does not have individuals with similar attributes, there *may* be an impact of individuals in that neighborhood on

[5]Such as that suggested by Tiebout (1956). Moreover, it is worth noting that sorting *may* be a pre-condition for (at least positive) externality.

[6]For our purposes, we define impact as the relationship between neighbors' educational performance.

their neighbors. Similar to knowledge spillover that occurs among school peers, in dense urban areas, geographic neighbors may also be a possible source of externality.

3 Method

The empirical specification relies on the notion of an education production function. The idea is that learning is produced with various inputs such as parenting, teaching, learning of classmates, individual-specific inputs such as age and gender, and school structures. Our goal is to add an additional input– the learning of geographic neighbors. The empirical strategy entails two stages. In the first stage, dummy variables are used to purge the dependent variable of the inputs that operate through teachers and school. Here, the analysis is similar to that of Rivkin et al. (2005) and Addonizio (2009)[7]. Let learning be measured by the change in score of two consecutive time periods (ΔM)[8]. Then, ΔM is regressed on dummies for school, teacher and grade in order to capture the residuals for the second stage. In the second stage, we use a spatial econometric framework to estimate the impact of geographic neighbors net of the school-level effects.

More specifically, let

$$\Delta M_i = \delta T_i + \gamma G_i + \psi S_i + \eta_i \tag{1}$$

denote the first stage model where T, G and S are teacher, grade and school dummies, respectively. η_i is a stochastic error term. The residuals then, arguably, maintain variation that is purged of effects that operate primarily through the schools. One assumption made here is the invariance of individual ability in consecutive years so that this effect is differenced away (Todd and Wolpin, 2003). Similarly, parent behavior is also assumed to be unchanging over the two consecutive time periods. For the latter, it is feasible that

[7]Rivkin et al. (2005) disentangle teacher effect from that of family effect. The focus here is on effects that operate outside of school mechanism.

[8]Math scale scores are used. See Data section below and appendix for details.

a change in location may be parent behavioral response, which we are able to control for (see section on Estimation). The residuals from (1) are the dependent variable (y_i) in the second stage of estimation, which is the spatial lag specification. While estimation in the first stage relies on least squares, the method in the second stage relies on maximum likelihood since the lag term is endogenous by definition.

The absence of interaction effects in (1) is not an oversight. They would be crucial, for instance, if teachers teach several grades (within the same school) or if schools emphasize the outcomes of one grade over another. However, in our case, the richness of the data-set renders these interaction effects redundant[9]. The effect of teacher, school and grade is controlled for at the individual level rather than at class, school or grade level. In addition, for purposes of this paper, it is acceptable that controls capture several other unobserved factors. For instance, it is possible that neighborhood effects that are mediated through school is captured in the above estimates of school/classroom effect (Kauppinen, 2008). This, if true, would imply that our estimates give a lower bound estimate of neighborhood effect.

Moreover, in equation (1), the direction of bias from plausible omitted variables – for example, parental inputs that changed over the two periods– again favors a conservative interpretation of our estimates. To see this, consider the unobservable changes in score in the prior year. A negative change in score likely induces parental intervention that is positively correlated with the school/teacher variables as parents become more involved. On the other hand, a positive gain would imply either less involvement at least at the school level or a continuation of positive involvement (i.e., doing what works). The former implies no correlation with school variables while the latter essentially amounts to no change in parent behavior. Thus any correlation that does not operate at neighborhood level is likely to be correlated, if at all, positively [10] with school. The estimates can

[9]Each teacher associated with a student is identified.

[10]It is possible that that the there may be no correlation i.e. parents do not react to scores in which case there is no omitted variable bias.

then be expected to have, if any at all, a positive bias. In other words, with this approach, estimates of neighborhood effect from the residual would again only be more conservative.

Yet another concern would be about students choosing teachers. For instance, parents/students may have additional information on teachers that makes an individual more likely to chose a particular teacher or class. This however turns to be precisely the sort of behavior that is of interest. For when such individuals do choose teachers or class, they would to do so to improve educational outcomes. The analysis here attempts to estimate the 'publicness' (i.e. positive externality) of these students upon their neighbors.

In the second stage, a spatial econometric model is used to model nearby neighbors change in conditional score. The idea here is similar to that of peer effect in classroom which recognizes the fact that individuals are affected by, and also affect, their peers themselves. Among several spatial models[11], the spatial lag model is a natural choice. In its basic form this is:

$$y_i = \rho W y_i + \beta X + \xi_i \tag{2}$$

where W is the spatial weights matrix, X is set of controls and ρ the spatial coefficient. The weight matrix is an integral part of spatial analysis. As described below, we use the notion of nearest neighbor. The identification is through the inherent non-linearity. An important point to note is that the spatial term is different from the expected term in the linear-in-means model[12]. Each individual in a specific neighborhood has a different residential peer variable. The dependent variable is the purged change in educational attainment change and the spatial term on the right hand side is the geographically weighted purged educational attainment change of neighbors. Hence, the coefficient ρ

[11] A SARAR(1) model which includes both the lag as well as an error model also gives significant value of ρ for all grades. As expected the magnitude goes down.

[12] This is an important criticism of linear-in-means models.

captures the direct impact of neighbor on individual[13].

4 Data

A total of 34,453 observations on unique individuals from six grades are available. These remain after those data points which had either missing educational outcomes or could not be geocoded[14] were deleted. Blacks and Hispanics constitute approximately 30 and 65 percent of the data. This pattern is more or less[15] consistent across grades. Of the total sample, eighty percent belong to low socio-economics status (ses). Less than 0.1 percent of these have a change in score in either of the two extreme deciles of educational change. Within ethnic groups, the change in score in consecutive years is the greatest for Asians and the lowest for Hispanics (see Figure 1). Small change is indicative of consistency across the two periods and not necessarily of a deterioration or improvement. The initial math score shows similar average ability across groups. This in combination with change in score suggests that while both Asians and Blacks have built up on their initial scores, the other groups have not.

[Figure 1 about here]

The dependent variable for the initial specification is the change in math scale scores[16]. Scaled scores are especially useful in comparability across learning outcome of students. The dependent variable used in the analysis is change in TAKS (Texas Assessment of Knowledge and Skills) scale score for Math. This is different from using raw scores (which is the total number of right response) as it accounts for the level of

[13]The full impact is $(I-\rho)^{-1}$.

[14]This analysis does not deal with the question of randomness of missing observations.

[15]The percentage of Hispanics in data declines in grade 11 before increasing again but it never goes below 59.95 percent

[16]Future research will incorporate reading scores as well.

difficulty of the question. Horizontal scale score as used in this analysis is actually more appropriate for comparing within a grade rather than across. Recent developments [17] will move towards using vertical scale score which can be used directly to compare across grades.

However, for this analysis, change in score is reasonable given that even with horizontal scale score, the "met standard" levels remain same through different grades (set at 2100 since 2005). The dependent variable used here can thus be interpreted as the distance from "met standard". Thus a positive value of the dependent variable would imply the student has moved closer or gone further beyond the "met standard" [18]. It is then, in this sense, interpreted as achievement gain/loss.

As shown in Table 1, there is considerable variation for this variable by grade. This sinusoidal pattern is difficult to interpret although one possible explanation is that drop outs generally appear after the transition from middle school . The increasing pattern later may indicate increased motivation of those that decide to stay in school.

[Table 1 about here]

Control variables include sex, ethnicity, initial score, initial score of neighbors [19], and dummy variables for recent change in residential location , for low socio-economic status and for those who reside in apartments. Table 2 [20] displays some of the summary statistics for the relevant variables.

[Table 2 about here]

The distributions of the purged residuals; i.e. the dependent variables in the spatial models are shown in Figure 2. The graphs suggests normal distributions. Moreover,

[17] In 2007 the Texas legislature passed a bill that required Texas to use a vertical scale for English TAKS reading and mathematics in grades 3 through 8 starting in spring 2009.

[18] See Appendix for details.

[19] Results for variable of interest were robust with or without the initial score of neighbors

[20] see Tables section for summary statistics by grades.

there does not seem to be any visual evidence of a ceiling effect.

[Figure 2 about here]

There are 67 distinct schools in the data-set. The data are fairly evenly distributed across grades 7 through 11. Grade 12 students comprise of only about 4 percent of the data-set. In all, there are 4519 teachers associated with the full set of students from grades 7 through 12.

The weights matrix specifies who is a neighbor for an individual i. For the purpose of this paper, we use the nearest neighbors. From a residential point of view, those closest are most likely to be influential [21]. Neighbors of a particular individual are given a different weight if they are 'very close' (defined as less than a 1000 feet away). This follows the reasoning noted above that those, for instance, sharing a same apartment building, have greater connectivity. Again, the weighting is with actual neighbors unlike calculating expectations within a group. The spatial weight matrix (W) multiplied with the initial score is the weighted average of the neighbors initial score, i.e. it can be a proxy for quality of neighbors [22].

5 Results

The first step of analysis uses dummies for teachers, grades and school to get purged residuals. As illustrated in Table 3, each teacher associated with every individual student is identified. The model has an adjusted R-square of 0.29. This accounts for the variation between groups, where dummy variables denote the groups. The residuals will maintain the within group variation. It is worth pointing out again that the framework above controls for teachers within schools as well. This is important in light of research

[21] This assumption is relaxed - see below.

[22] This was a crucial factor in analysis by Kauppinen (2007).

emphasizing the importance of teachers in educational outcomes (Rivkin et al., 2005).

[Table 3 about here]

The spatial analysis starts with a baseline spatial lag model (SAR – or simultaneous auto-regression). The variable of primary interest is ρ. This captures the spatial effect of neighbors educational outcome on a particular individual. The baseline model (model 1) in table 4 shows a typical result for this regression based on just the seventh grade students. The spatial term is significant across the models and a similar pattern emerges for the other grades as well (see Table 5).

[Table 4 about here]

To exercise the model, we augment it in several ways. First, neighbors' initial scores are added (Model 2). This controls for the learning that neighborhood began with. Subsequently, controls for apartment dwellers and those that have moved recently are added (models 3 and 4, respectively) as displayed in Table 4.

In model 3 we see that the apartment dummy is positive but insignificant. The results from grades 8 through 12 also indicate an insignificant effect for apartment dwellers, although the signs are negative throughout. Regarding movers (model 4), the estimate is negative and significant and this result is consistent for all grades. The pattern of coefficients provides limited support for hypothesis 1; i.e. , neighbors matter more for lower grades. Although the largest value of ρ is for seventh grade and the estimate is insignificant for twelfth grade, the pattern in between is un-affected. In fact the magnitude increases from eighth through eleventh grade. To highlight the spatial effects (captured by ρ), we present the estimates for ρ for all grades and all models in Table 5.

[Table 5 about here]

To consider hypothesis 2, which posits that same grade neighbors matter more, we consider groups of grade 7, 8 and 9. If similar age groups are important, then the estimate of ρ (which captures impact of neighbor's score) should be approximately the same or greater in magnitude than when we consider these grades clubbed together together. However, if only same grade neighbors matters more than ρ should be greater in magnitude when geographic neighbors are constrained to be in the same grade.

The estimates presented in Table 6 suggest that same grade neighbors are not as important as similar grade neighbors i.e. neighbors of similar age. For instance, consider grades 7, 8 and 9. Estimates of ρ are 0.092 0.032 and 0.064 respectively (Table 5). If we consider grade 7 and 8 (grade 8 and 9) to be one group, estimate of ρ is 0.076 (and 0.082). Incorporating grade 9 as well gives an even bigger estimate of ρ than that of each individual grade.

Finally, we give all eighth graders neighbors who are seventh and ninth graders. That is, our dependent variable has purged scores of only eighth grader only while the explanatory variable contains purged scores of seventh and ninth graders that are neighbors with the eighth graders. We get an estimate of 0.072 for ρ. Clearly, the evidence suggests impact of similar age neighbor to be considerable and significant. Thus we do not find evidence and therefore reject the second hypothesis.

[Table 6 about here]

6 Discussion

We now modify the definition for the geographic neighbor. We posit that if neighborhood effects are truly due to geographic neighbors, other neighbors should not have strong effect. Two approaches are used. In the first, the weight matrix captures those neighbors that are the furthest. Next, we select neighbors at random. As shown in Table 7, these counter examples suggest that we are indeed capturing neighborhood effects. In most cases, the effects fall ten fold [23].

[Table 7 about here]

Another concern could be that the geographic neighborhood effect could be operating solely through some unobserved sorting behavior. In the terminology of Manski (1993), it may be argued that the above analysis may be capturing 'correlated effects'. This posits that outcomes and behaviors of neighbors are similar in unobserved characteristics and therefore correlated. We take two approaches to this issue. It is reasonable to assume that if individuals sort, for example, on the basis some unobserved factors that are related to school quality then that sorting process could be expected to work across all grades. Thus the same factor that sorts individuals of say, the 7^{th} grade would influence the 10^{th} neighbors. Therefore, in the final specification considered above(Model 4), we include the initial score for 10^{th} grade neighbors of 7^{th} grade students. This reduces the value of ρ by about 40 percent of its initial value (model II in table 8). However, ρ remains significant and the magnitude, even after this reduction, remains substantial. Two points are worth reiterating. First, the dependent variable at this stage is residuals that has been purged of school based inputs. Therefore, these effects are not negligible. Second, given the simultaneity present within neighborhood, this paper suggests that

[23] Exceptions are grade 10 and 12.

processes, such as sorting (and possibly other processes), may very well facilitate and enable the externality effects observed.

The second strategy entails using information on housing characteristics of students within our data. The basic idea is to use type of housing (such as single family residence) and their value to proxy for family income. To do this, we merge the school data with housing data from Dallas Central Appraisal District (DCAD). Over ninety percent of the student level data could be matched with housing data. We introduce two variables in our final specification (model 4). The first is an indicator variable for Single Family Residence. We interact this with the housing value of the residence. Results show (model I of table 8) very little change in ρ, the variable of interest. Interestingly the coefficient on single family residence is negative and remains negative and significant even when it is interacted with log of house values. The log of median value of single family residence is close to 7 (PUT Exact number here) and therefore for several students, living in a single family resident does not seem to have a substantial effect on the educational outcome. Moreover, the housing value seems to be proxying for race. The results therefore are consistent with the notion of spatial geographic spillover that may not be substantially captured via the specific measure of housing type used here and seem to be uncorrelated with the effect of geographic neighbors.

[Table 8 about here]

It is important to state several limitation associated with using administrative data as is used here. One such limitation is to recognize that high stakes tests, justly or unjustifiably, emphasize certain aspects of learning which are deemed requisite. Thus, the analysis may be capturing the learning focused exclusively at acing the high stakes exams as opposed to 'education', however that may be defined [24]. The teacher analog

[24] Mark Twain's "I never let my schooling interfere with my education" comes to mind.

of this behavior— "teaching to test"—is then certainly another possibility. Other unintended consequences of high stakes test as well could impact the analysis. For instance, schools may exclude low-scoring students from taking the tests. The results here would then be driven by this spatial behavior of schools.

A point worth making here is that the contagion effect need not necessarily operate for and through low scorers only. Seen in that light it has policy implications.

The results of this analysis pertains to a dense and large urban district and characteristics associated with it thereof. Therefore, the usual caution is warranted in applicability of these results to other sub-populations. In addition, this analysis does not consider whether effects are short lived or if there is a diminishing effect. Moreover, given that peers are defined in terms of distance, it possible that the peer effects are more akin to impact of exposure as opposed to interaction. This is augmented by the fact that we do not find[25] substantial decrease in effects as we move our measure of neighborhood from, for example, 500 feet to 800 or even 1500 feet[26]. This is consistent with the notion of spatial features being an important aspect of a neighborhood and its evolution. Finally, the effects are differential, albeit generally high, among different grades.

We have not estimated the multiplier effect as the focus has been testing for a spatial process wherein geographic neighbors have any impact at all as far as the educational outcome in middle and high school is concerned. Our analysis shows an unignorable effect. It may then be crucial for policy makers to be cognizant of this fact more so given the continued outpouring of resources in schools while remaining unaware of influences *other* than those of and by school.

Even though similar in observables; groups may be different in unobservables. For instance - students may have more pro-active parents, etc. It is true to a great extend, this and similar factors may have a significant role to play in the mechanisms through which

[25] Results available upon request from authors.

[26] This is only indicative and not conclusive as interaction need not diminish by distance, although likely to be more so for lower grades - CHECK THIS in results.

the geographic neighbors influence educational outcomes. After all, immediate family and siblings are usually the closest neighbors (though not peers). This paper concerns itself with establishing the presence of such a student's educational attainments impact on his neighbor's. More research is essential to understand what helps the mechanism of these multiplier terms. In addition, it is also important to evaluate how, if at all, these effects change over time.

Future research would first incorporate geographic features of the landscape. The idea there being on the same lines as that of 'broken-window' theory in crime (Wilson and Kelling, 1982). Additional information regarding family, especially parent characteristics, would enable estimation of neighborhood effects that are not attenuated by parental input effects that work through the neighborhood.

Although the production of education recognizes the impact of both peer in the classroom as well as parental impact in home environment, peers associated with home environment, especially related to geography has been overlooked. This paper draws attention to it and underscores the need for further research to understand their impact.

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Appendix

Using Scale scores

This paper uses scale score and interprets it as *distance* from either 'met standard' or 'commendation' as the case may be. This is best understood using an example. Consider first, that a student scores 1800 in time period t-1 and scores 2000 in time period t. Then the change in score equals (positive) 200 which says the student moved closer to meeting standard. Similar interpretation follows if the student scores above 2100 in both years. If the years are reversed, the change would be a negative number specifying how far the student has moved from meeting the standard.

Consider now, a student whose score was above and below 2100 in the two time periods. Lets assume it was 2100 in time period t-1 and scores 1900 in time period t. The change in score is now (negative) 200. Thus the student has moved 200 points away from meeting the 'standard'. Following the same logic, if the scores for the two time periods was reversed, the student would then move closer to meeting the 'standard'.

Table 1: Change in Math Scale Score by Grades

grade	**mean**	**std dev**	**min**	**max**
7	-63.704	159.077	-682.000	617.000
8	11.158	122.184	-791.000	747.000
9	-20.890	128.816	-997.000	700.000
10	6.447	117.014	-699.000	839.000
11	73.385	105.475	-610.000	661.000
12	49.707	88.210	-741.000	441.000
All grades	-0.127	134.245	-997.000	839.000

Source: DISD

Table 2: Summary statistics Grades 7 through 12

Variable	**Mean**	**Std. Dev.**
Math Score Change	-0.127	134.245
Init Math score	2154.431	200.245
Low SES	0.801	0.399
Female	0.523	0.499
Black	0.296	0.456
Asian	0.01	0.097
Hisp	0.646	0.478
Ind	0.002	0.048
White	0.046	0.21
Special Ed	0.025	0.156
No. of observations		34453

Table 3: Estimation results : School, Teacher and Grade dummies

Variable	Coefficient	(Std. Err.)
teacher1	-15.476	(125.830)
teacher2	0.595	(41.617)
teacher3	9.541	(130.117)
teacher4	-11.535	(41.462)
teacher5	47.915	(32.775)
⋮		
school66	153.2153	(265.561)
school67	-61.504	(258.692)
⋮		
class2	158.549	(179.416)
class3	153.569	(169.711)
class4	-50.763**	(7.962)
class5	-40.400**	(7.411)
class6	14.528**	(6.906)
Intercept	-94.276	(229.275)
N	34453	
R^2	0.290	
$F_{(3781,30671)}$	3.32	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 4: SAR (models 1-4) for Grade 7

Variable	Model 1	Model 2	Model 3	Model 4
Constant	1107.530861	950.749017	951.486079	949.242419
	(112.899769)	(121.121212)	(122.035149)	(122.66973)
ses	-21.613964	-20.276613	-20.204345	-19.867234
	(-4.949548)	(-4.668578)	(-4.636165)	(-4.558666)
age	-19.989349	-20.206958	-20.159383	-19.882155
	(-97.374832)	(-14.304804)	(-14.096617)	(-13.958746)
female	2.116535	1.937395	1.937056	2.004970
	(0.786766)	(0.721715)	(0.721554)	(0.747180)
Black	-40.826497	-36.053519	-35.973076	-35.473920
	(-5.437471)	(-4.814835)	(-4.793897)	(-4.727956)
Asian	20.894481	22.534825	22.616278	22.722383
	(1.353779)	(1.466104)	(1.470680)	(1.478235)
Hisp	-17.249575	-16.786559	-16.757486	-16.698872
	(-2.348079)	(-2.281498)	(-2.276665)	(-2.269530)
Ind	-3.051873	-4.536586	-4.432681	-3.234041
	(-0.086368)	(-0.129014)	(-0.126039)	(-0.091989)
sped	-29.643783	-29.955128	-29.981960	-29.759425
	(-3.699272)	(-3.759959)	(-3.763016)	(-3.736508)
init	-0.359492	-0.366323	-0.366369	-0.367233
	(-66.707369)	(-62.759340)	(-62.723978)	(-62.746928)
neighinit		0.077185	0.076671	0.077157
		(10.068867)	(9.936665)	(9.983507)
apt			-0.675711	0.210540
			(-0.229815)	(0.071045)
moved				-7.981500
				(-2.326848)
rho	0.091948	0.143975	0.142991	0.143989
	(6.424213)	(21.964093)	(21.900117)	(21.980351)

t-statistics in brackets

For ethnicity, the base category is white.

Table 5: Estimates of ρ (SAR model) for all Grades

Grade	Model-1	Model-2	Model-3	Model-4
7	0.091948	0.143975	0.142991	0.143989
	(6.424213)	(21.964093)	(21.900117)	(21.980351)
8	0.031986	0.029995	0.032969	0.029968
	(2.422391)	(2.371688)	(2.444165)	(2.370816)
9	0.063992	0.061986	0.063980	0.062948
	(16.640800)	(16.369753)	(16.641459)	(16.509640)
10	0.059987	0.075976	0.071984	0.076992
	(14.463790)	(5.173476)	(5.051954)	(5.203500)
11	0.078996	0.080956	0.079982	0.080974
	(4.772858)	(4.813649)	(4.788807)	(4.815117)
12	0.060993	0.049976	0.044962	0.045998
	(7.563245)	(6.839606)	(1.427479)	(1.444878)

t-statistics in brackets

Table 6: Estimates of ρ (SAR models) for all Grades pooled
and Grades 7-8-9 combinations Pooled

Grades	Model-1	Model-2	Model-3	Model-4
7-8	0.075999	0.104958	0.097992	0.096989
	(7.601205)	(26.955166)	(26.011554)	(25.871261)
8-9	0.081981	00.079968	0.080966	0.078973
	(7.898885)	(7.798728)	(7.843030)	(7.752571)
7-8-9	0.103967	0.120967	0.114966	0.114965
	(33.681066)	(14.746480)	(35.476764)	(35.473703)
8 with 7 & 9*	0.071982	0.072985	0.073989	0.073967
	(5.149404)	(5.175469)	(5.203796)	(5.203925)

t-statistics in brackets

** Only with grade 7 or 9 neighbors*

Tables

Table 7: Estimates of ρ (SAR model 4 with nearest, furthest and random neighbors) for all Grades

Grade	**Nearest**	**Random**	**Furthest**
7	0.143989	0.015982	0.049960
	(21.980351)	(7.584802)	(13.383026)
8	0.029968	-0.002989	0.003986
	(2.370816)	(-0.128598)	(1.461698)
9	0.062948	-0.000975	-0.007967
	(16.509640)	(-0.045066)	(-0.188439)
10	0.076992	0.008963	0.026979
	(5.203500)	(4.953632)	(2.072494)
11	0.080974	0.012969	-0.002993
	(4.815117)	(6.197025)	(-0.053843)
12	0.045998	0.011977	-0.035978
	(1.444878)	(3.338259)	(-5.861765)
7-8-9	0.114965	-0.005954	0.019972
	(35.473703)	(-0.469841)	(14.980712)

t-statistics in brackets.

Table 8: SAR (models I-IV) for Grade 7 with residential and other grade controls

Variable	Model I	Model II	Model III	Model IV
Constant	949.909483	747.684667	955.051836	750.987
	(148.736493)	(73.825809)	(163.305345)	(80.040487)
ses	-19.67418	-11.947676	-17.329518	-10.215
	(-4.46236)	(-3.565849)	(-3.890899)	(-3.02535)
age	-19.463377	-12.873849	-19.618464	-12.882
	(-12.141995)	(-17.634514)	(-12.152291)	(-17.552636)
female	1.828107	0.493293	1.946235	0.787
	(0.673404)	(0.194366)	(0.717446)	(0.31025)
Black	-36.070304	-30.926564	-30.738395	-25.515
	(-4.736809)	(-4.975206)	(-3.952968)	(-3.936758)
Asian	25.911962	22.915744	26.958403	24.902
	(1.665622)	(1.660455)	(1.734049)	(1.804137)
Hisp	-17.299807	-16.383069	-13.676879	-12.302
	(-2.317055)	(-2.711934)	(-1.814426)	(-1.988103)
Ind	-8.297838	-8.836653	-3.643893	-4.097
	(-0.223651)	(-0.256587)	(-0.098245)	(-0.119045)
sped	-29.042657	-22.066409	-29.367323	-23.420
	(-3.554167)	(-2.564179)	(-3.596782)	(-2.722912)
init	-0.366328	-0.279151	-0.367157	-0.280
	(-61.887199)	(-46.908235)	(-62.045057)	(-47.070822)
gr7init	0.073694	0.03918	0.070693	0.033
	(8.927407)	(10.01113)	(8.420941)	(7.911479)
apt	-0.319576	-0.854831	-1.231861	3.297
	(-0.105665)	(-0.300055)	(-0.284899)	(0.811654)
moved	-7.913517	-4.801694	-7.889477	-4.758
	(-2.281771)	(-1.511042)	(-2.276273)	(-1.498846)
sfresid	-0.366328		-89.321919	-84.270
	(-61.887199)	(-)	(-3.553274)	(-3.558981)
sfxval			9.196844	9.418
	(-)	(-)	(3.59121)	(3.916963)
gr10init		-0.002052		-0.002
	(-)	(-0.764468)	()	(-0.80953)
rho	0.137979	0.085991	0.13598	0.082
	(9.236397)	(5.740549)	(9.128131)	(5.59066)

t-statistics in brackets

For ethnicity, the base category is white.

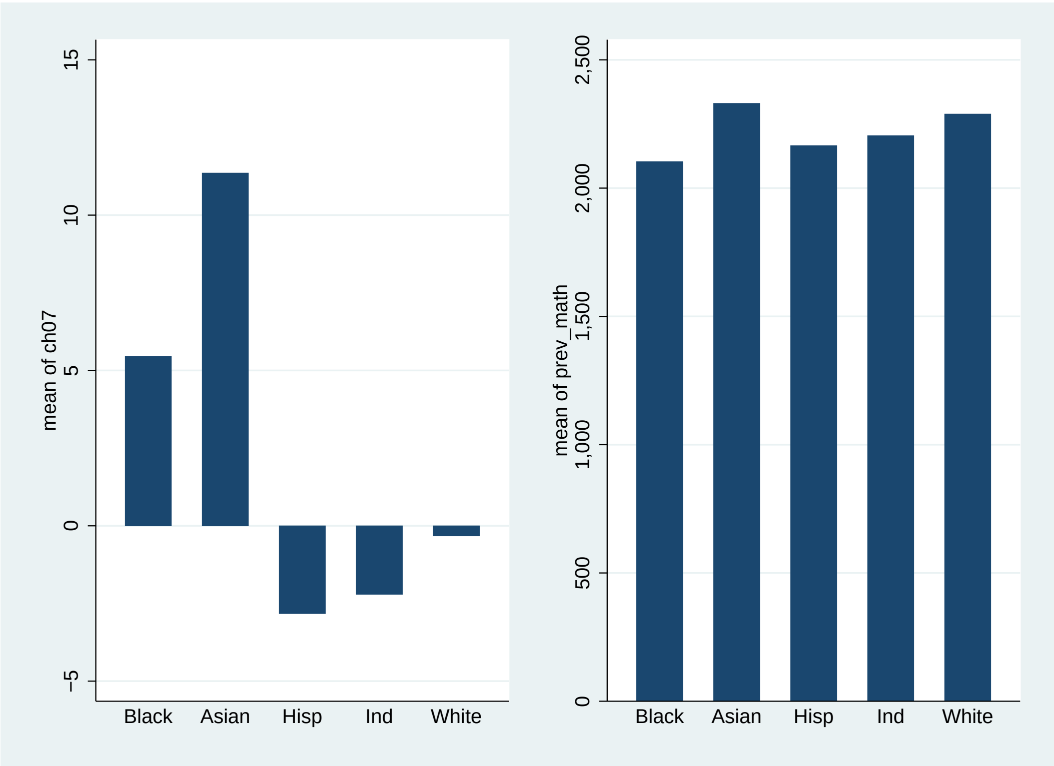

Figure 1: Change in score and Initial math score by ethnicity

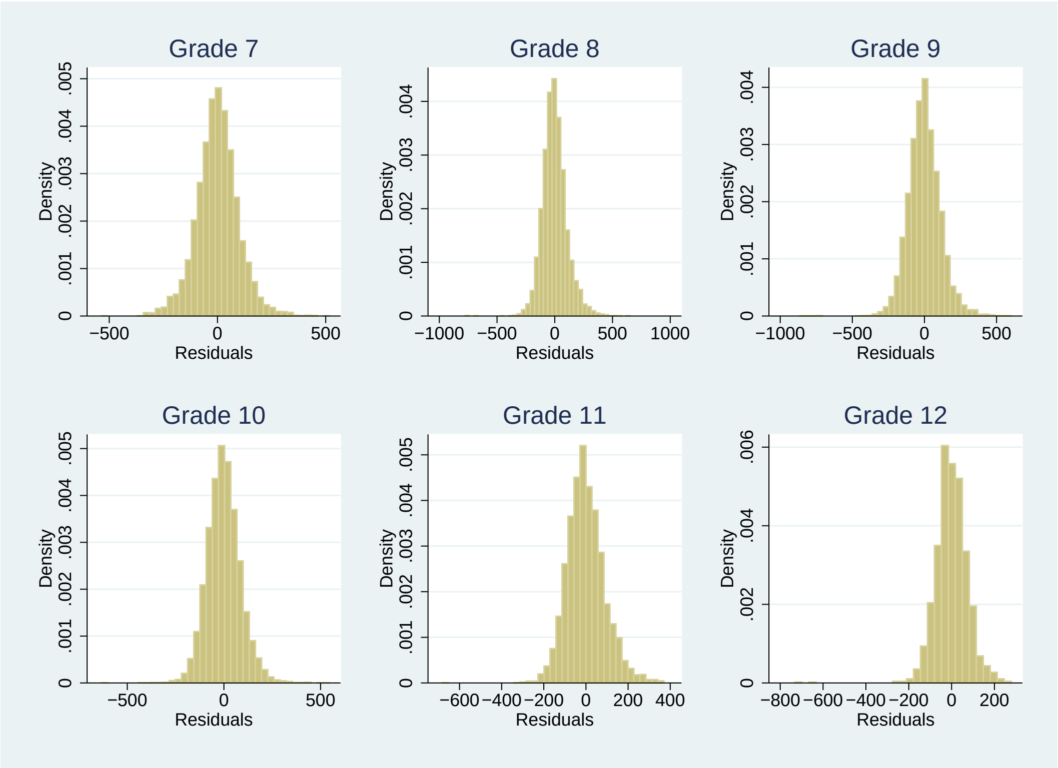

Figure 2: Change in score for grades 7 through 12