Neighborhood School Characteristics: What Signals Quality to Homebuyers?

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Analysis suggests that homebuyers and economists share the same definition of school quality.

Most people are familiar with the adage that real estate values are determined by three basic characteristics—location, location, location. Economists consider this cliché only a modest exaggeration because research suggests that locational characteristics can explain much of the variation in residential property values. Not surprisingly, home prices tend to be lower in communities with high property taxes and higher in communities with low crime rates. Home prices fall as the commute to the central business district increases and rise as the amount of air pollution decreases. Locations near a city park command a premium, while locations near the city dump sell at a discount.

Popular wisdom and economic research suggest that the quality of the neighborhood school should also be an important locational characteristic. Many researchers have found that property values are higher where school spending is higher (for example, Oates 1969; Sonstelie and Portney 1980; and Bradbury, Case, and Mayer 1995). Other researchers have found a positive relationship between housing values and the test performance of students at the corresponding school (for example, Jud and Watts 1981, Rosen and Fullerton 1977, and Walden 1990). However, the economic literature on school quality measurement argues that the appropriate measure of school quality is the school's marginal effect on students (see Hanushek 1986), and no one has examined the relationship between marginal school effects and housing values.[1] Thus, we have an incongruity in the literature: spending and test scores seem to influence property values, but economists who study schools would not generally consider these characteristics measures of school quality. Meanwhile, the literature has been silent on whether the economists' notion of school quality is a locational characteristic that matters to homebuyers.

In this article, we attempt to identify the influence of neighborhood schools on the value of residential homes. Using a hedonic model of home purchases and historical data on homes in the Dallas Independent School District (DISD), we demonstrate that school quality can be an important locational characteristic in determining housing values. We find evidence that property values in DISD reflect student test scores but not school expenditures. Interestingly, we also find that the relationship between test scores and property values arises from an underlying relationship between property values and the marginal effects of schools. Thus, our analysis suggests that homebuyers and economists share the same definition of school quality.

A simple model of housing values

A house is a collection of desirable characteristics such as shelter, comfort, and location. Therefore, the price that buyers are willing to pay for a house should be related to the prices they are willing to pay for its component characteristics. By treating a house as the sum of its parts, a hedonic housing model generates estimates of the consumer's willingness to pay for each component characteristic.

Our hedonic model of housing prices in a single labor market is adapted from Rosen (1974). In this simplified model, consumers attempt to maximize their own happiness, taking the housing stock as given. Consumers derive satisfaction from consuming all sorts of housing characteristics ($Z = z_1, z_2, \ldots z_n$) and a composite good (x). They earn an income (y) regardless of their chosen residence and can only consume combinations of Z and x that are affordable given that income. There are many types of consumers, and tastes for Z and x differ among those consumers according to socioeconomic characteristics (α) such as the person's age or educational attainment. In equilibrium, all consumers with identical preferences and income are able to achieve the same level of satisfaction.

After some manipulation, the individual consumer's decision-making can be described with a willingness-to-pay relationship or, more formally, a bid rent function:

$$(1) \qquad R = R(z_1, z_2 \ldots z_n; y, \alpha).$$

The value of the bid rent function represents the amount the consumer is willing to pay to rent a home with certain characteristics (Z), given the consumer's income level and socioeconomic type. Partial derivatives of the bid rent function with respect to housing characteristics represent the consumer's willingness to pay for those characteristics.

The price a potential buyer would be willing to pay for a house represents the present discounted value of the after-tax stream of bid rents.[2] If τ_R is the tax rate chosen by the jurisdiction for real estate,[3] θ represents the discounting factor, and housing is an infinitely lived asset, then the bid price of a house (P) would be

$$(2) \qquad P = \frac{R - \tau_R P}{\theta},$$

or equivalently,

$$(3) \qquad P = \frac{R(z_1, z_2 \ldots z_n; y, \alpha)}{\theta + \tau_R}.$$

The variation in incomes and socioeconomic characteristics generates a continuum of bid prices over a variety of types of homes.

In equilibrium, the sale price of any particular house equals the highest bid offered by potential consumers, regardless of their income or socioeconomic type. The hedonic price function describes this equilibrium.[4] The hedonic price function that we estimate describes the arm's length sales price as a function of the characteristics of the house and of its location.[5] The locational characteristics include neighborhood characteristics as well as local school characteristics.

The data

Data for this analysis come from three sources. Data on elementary school characteristics have been provided by DISD. Data on the characteristics of single-family homes in DISD come from the SREA Market Data Center's annual publication of residential property transactions. We restrict attention to the 288 DISD properties for which complete data are available that sold in July 1987 and were located in both the city and the county of Dallas. Data on nonschool locational characteristics come from the 1990 Census of Housing and Population.

DISD has provided data on student body characteristics, student achievement scores, and per-pupil expenditures for ninety-six elementary schools in its jurisdiction. From these data, we construct four possible indicators of school quality in 1987—current expenditures per pupil (*SPEND*), average sixth-grade achievement in mathematics on the Iowa Test of Basic Skills (*MATH687*), the marginal effect of the school on sixth-grade mathematics achievement (*SCHL687*), and the expected achievement of the student body in sixth-grade mathematics (*PEER687*). The first two of these indicators are common measures of school quality in the housing literature. The second two indicators represent a decomposition of average mathematics achievement into school effects and peer group effects (see the appendix). *SCHL687* measures the increase in student achievement in mathematics that can be attributed to the school. It corresponds to a common measure of school quality in the economics of education literature (see Hanushek and Taylor 1990, Aitkin and Longford 1986, and Boardman and Murnane 1979). *PEER687* is included as a possible indicator of school quality because research has shown that a high-achieving peer group in the school can have a positive effect on individual student performance (Summers and Wolfe 1977).

Table 1
Descriptive Statistics: A Tale of Two Cities

Variable	Northern Dallas Mean	Northern Dallas Standard deviation	Southern Dallas Mean	Southern Dallas Standard deviation
PRICE	$203,266	(204,301)	$82,502	(55,926)
SQFTLA	2,192	(1,026)	1,471	(568)
YRBUILT	58.3	(13.2)	53.5	(18.7)
POOL	.22	(.42)	.04	(.19)
FIREPL	.71	(.45)	.42	(.50)
DISTANCE	2.46	(.65)	2.11	(.86)
APARTMENTS	.18	(.20)	.26	(.23)
PRIVSCHL	.39	(.21)	.10	(.08)
NEIGHBORS	–1.47	(1.34)	1.59	(1.62)
MEDIAN INCOME	$52,819	(26,841)	$27,256	(7,735)
COLLEGE	.72	(.15)	.40	(.20)
BLUE-COLLAR	.11	(.09)	.31	(.13)
UNDER 12	.12	(.03)	.18	(.05)
OVER 65	.19	(.06)	.11	(.04)
HISPANIC	.10	(.12)	.32	(.25)
BLACK	.03	(.05)	.27	(.29)
SPEND	$2,498	(381)	$2,068	(232)
MATH687	76.97	(5.27)	69.56	(4.26)
SCHL687	29.55	(4.30)	26.86	(3.18)
PEER687	47.42	(3.21)	42.70	(3.07)
Number of observations	150		138	

The housing data used in this analysis include the log of the sale price of the property (*PRICE*), the year in which the home was built (*YRBUILT*), the number of square feet of living area in the structure (*SQFTLA*), and indicator variables that take on the value of one if the house has a swimming pool or a fireplace and zero otherwise (*POOL* and *FIREPL*, respectively). To capture potential nonlinearities in the relationship between the sale price and the age of the property, we also include interaction terms that take on the value of *YRBUILT* when the residence has a pool (*YR•POOL*) or fireplace (*YR•FIREPL*) and zero otherwise. We match the potential school quality indicators with housing characteristics using the SREA data on addresses and a Realtor's guide to DISD attendance zones (Positive Parents of Dallas et al. 1987).

The address data also permit us to merge in census tract characteristics from the 1990 Census of Housing and Population. The census tract data support three nonschool locational characteristics. These potential locational characteristics are the demographic characteristics of the neighborhood residents (*NEIGHBORS*),[6] the share of apartments in the neighborhood housing stock (*APARTMENTS*), and a proxy for the accessibility of private schools (the share of the elementary school population that is attending private school, denoted *PRIVSCHL*).

Finally, we used the address data to construct another nonschool locational characteristic—the linear distance to the central business district (*DISTANCE*)—and to divide the sample into two parts according to whether or not the property is located substantially north of downtown Dallas.[7]

Table 1 presents descriptive statistics for the data used in this analysis. As the table clearly indicates, there are significant differences between northern and southern Dallas.[8] On average, northern Dallas homes are more expensive, bigger, and more likely to have a pool or fireplace. Northern Dallas schools register higher on all our potential indicators of school quality. The average northern Dallas neighborhood has a smaller share of apartments in the housing stock and more access to private elementary schools than the average southern Dallas neighborhood. Meanwhile, the residents of southern Dallas neighborhoods are more likely than the residents of northern Dallas to be black or His-

Table 2
Estimates of the Hedonic Price Function

	Northern Dallas			Southern Dallas		
Variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
INTERCEPT	3.465**	3.123**	3.174**	3.163**	2.865**	2.867**
	(.334)	(.380)	(.391)	(.341)	(.592)	(.596)
SQFTLA	5.0E–4**	5.0E–4**	5.0E–4**	5.5E–4**	5.4E–4**	5.4E–4**
	(2.5E–5)	(2.5E–5)	(2.5E–5)	(5.7E–5)	(5.8E–5)	(5.9E–5)
YRBUILT	.007*	.006*	.007*	.008**	.008**	.008**
	(.004)	(.004)	(.004)	(.002)	(.002)	(.002)
YR•POOL	–.004	–.005	–.005	–.022**	–.023**	–.023**
	(.003)	(.003)	(.003)	(.011)	(.011)	(.011)
YR•FIREPL	–.007*	–.007*	–.007*	–.005	–.005	–.005
	(.004)	(.004)	(.004)	(.003)	(.003)	(.003)
POOL	.272	.289	.301	1.211**	1.255**	1.258**
	(.202)	(.201)	(.202)	(.571)	(.577)	(.581)
FIREPL	.448**	.433**	.441**	.431**	.419**	.420**
	(.205)	(.203)	(.204)	(.204)	(.205)	(.206)
DISTANCE	–.122**	–.146**	–.146**	–.137**	–.139**	–.138**
	(.039)	(.041)	(.041)	(.034)	(.034)	(.036)
APARTMENTS	.018	.007	.006	.074	.089	.088
	(.092)	(.092)	(.092)	(.121)	(.123)	(.124)
PRIVSCHL	.450**	.431**	.435**	1.073**	1.078**	1.075**
	(.142)	(.141)	(.141)	(.515)	(.516)	(.520)
NEIGHBORS	–.055**	–.042*	–.039*	–.042	–.041	–.041
	(.023)	(.024)	(.024)	(.029)	(.029)	(.030)
SPEND	3.3E–5	–7.8E–6	1.7E–5	–8.6E–6	–4.1E–6	–2.4E–6
	(7.0E–5)	(7.3E–5)	(8.3E–5)	(1.2E–4)	(1.2E–4)	(1.3E–4)
MATH687	—	.007*	—	—	.004	—
	—	(.004)	—	—	(.007)	—
SCHL687	—	—	.009*	—	—	.005
	—	—	(.005)	—	—	(.009)
PEER687	—	—	.004	—	—	.004
	—	—	(.007)	—	—	(.009)
Number of observations		150			138	

NOTE: Standard errors are in parentheses. The superscripts denote a coefficient that is significant at the 5-percent (**) or 10-percent (*) level.

panic, young, hold a blue-collar job, have a lower income, and to have not attended college.

The estimation and results

Because southern and northern Dallas differ so dramatically, we estimate the hedonic price function separately for the two areas using weighted least squares regression.[9] Furthermore, for comparison with the previous literature, we examine three models of the hedonic price function. In the first model, school quality is measured by per-pupil spending. In the second model, school quality is measured by both per-pupil spending and test scores. In the third model, which represents an unrestricted version of the second model, test scores are decomposed into school effects and peer group effects. We correct the standard errors from model 3 for the problem of estimated regressors (*SCHL687* and *PEER687*), using the technique suggested by Murphy and Topel (1985).[10] Table 2 presents our estimation results.

Despite the dramatic differences between northern and southern Dallas, Table 2 reveals striking similarities in the consumer's willingness to pay for housing characteristics. In both parts of the city, homebuyers pay a substantial premium for additional living space. Southern Dallas buyers tend to be slightly more sensitive to the age of the property, but homebuyers in both parts of the city have strong preferences for newer homes. Fireplaces add value to older homes, but the effect dissipates for newer homes.[11] After controlling for the age and size of the property and the presence of a fireplace, pools have a negligible effect on home prices.[12]

Northern and southern Dallas homebuyers are also similar in their willingness to pay for most nonschool locational characteristics. In both parts of the city, homebuyers are unwilling to pay for a change in the concentration of apartments (*APARTMENTS*) but are willing to pay for a shorter commute (*DISTANCE*) and greater access to private schools (*PRIVSCHL*). Furthermore, northern and southern Dallas homebuyers pay similar premiums for a shorter commute or greater access. Evaluated at the mean, a 1-percent decrease in the distance to the city center increases home prices by 0.36 percent in northern Dallas and 0.29 percent in southern Dallas, while a 1-percent increase in *PRIVSCHL* increases home prices by 0.17 percent in northern Dallas and 0.11 percent in southern Dallas.[13] Northern and southern Dallas homebuyers differ substantially in their willingness to pay for neighborhood demographics, however. Northern Dallas buyers seem willing to pay a premium for a change in resident characteristics, while southern Dallas buyers do not.

Another significant difference between northern and southern Dallas homebuyers appears in their willingness to pay for school quality. The data suggest that neither group considers school spending an indicator of school quality for which they are willing to pay. *SPEND* is insignificant across all of the model specifications for both northern and southern Dallas. However, the data indicate substantial differences in the willingness to pay for student achievement on standardized tests. As model 2 illustrates, homebuyers in northern Dallas pay a premium to live in the attendance zone of a school where students score well on standardized tests. Homebuyers in southern Dallas pay no such premium.

Given the desegregation efforts during the sample period, it is not particularly surprising that southern Dallas homebuyers were unwilling to pay a premium for the neighborhood schools.[14] Busing students away from the neighborhood school was much more common in southern Dallas than in northern Dallas (Linden 1995). Therefore, while homebuyers might have been able to rely on the attendance zone map in northern Dallas, they had less reason to expect that their choice of residence would guarantee a specific school in southern Dallas. Given the uncertainty about the stability of school attendance zones, it is more surprising that northern Dallas homebuyers were willing to pay a premium for school quality than that southern Dallas homebuyers were unwilling to pay such a premium.

One might suspect that northern Dallas homebuyers are willing to pay for school zones with good test scores because those scores indicate characteristics of the students who live in the area. If so, then the premium for test performance would arise from the attractiveness of the neighbors rather than the neighborhood school. However, as model 3 illustrates, the test score premium in northern Dallas arises from the marginal effects of the schools (*SCHL687*), not the characteristics of the student body (*PEER687*).[15] Evaluated at the mean, a 1-percent increase in *SCHL687* increases home prices by 0.26 percent. Of the characteristics that we are able to observe, only the size and age of the property and the distance from downtown have more influence than school effects on home prices in northern Dallas.

Conclusions

Using a hedonic model of property values, we examine the extent to which school quality is a locational characteristic that influences property values. We find that some homebuyers are not only cognizant of differences in school quality but also have revealed their preferences for higher quality schools by paying a premium for their home. Our analysis suggests that this premium for school quality can be among the most important determinants of housing prices.

Not all school characteristics appear to be indicators of school quality, however. We find no evidence that homebuyers are willing to pay for changes in school expenditures or student body characteristics. Instead, we find evidence that the school characteristic for which homebuyers pay a premium is the same characteristic that economists associate with school quality, namely, the marginal effect of the school on student performance.

A number of policy implications can be drawn from this research. The analysis suggests that policies that impact school effects can have a significant influence on residential property values. It also casts considerable doubt on policy analyses or policy initiatives that equate school spending with school quality. Finally, the analysis suggests that, at least as far as Dallas homebuyers are concerned, researchers are on target in trying to identify policy reforms that would increase the marginal effectiveness of schools.

Notes

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1 A few researchers, including Sonstelie and Portney (1980), have examined the relationship between property values and changes in test scores, but test score changes are generally considered a poor proxy for the marginal effects of schools.

2 This discussion ignores the differential tax treatment of renters and owners.

3 If assessment errors are randomly distributed, then all residences in a given government jurisdiction are taxed at the same expected rate. Restricting analysis to a single taxing jurisdiction eliminates the need to measure the potential capitalization of tax rate differentials and one can focus on estimating the hedonic price function for housing characteristics (Z).

4 For a further discussion of the hedonic price function, see Bartik and Smith (1987).

5 An arm's-length sales price can be considered an equilibrium house price for that time and location.

6 *NEIGHBORS* is a principal components index of resident characteristics. The demographic characteristics included in the index are median income of the census tract and the shares of the population that are black, Hispanic, over 65 years of age, under 12 years of age, employed in a blue-collar occupation, and college educated. The principal components index explains 65 percent of the variation in these variables. The index is negatively correlated with median income and the population shares of elderly and college educated individuals and positively correlated with the remaining demographic characteristics.

7 Residences north of a line along the southern border of Highland Park Independent School District were classified as being in northern Dallas. The remaining residences were classified as being in southern Dallas.

8 The means are significantly different at the 5-percent level for all of the characteristics.

9 The weight for northern Dallas is the reciprocal of the product of the square root of (*SQFTLA*) and the square root of (*1 – PRIVSCHL*); the weight for southern Dallas is the reciprocal of the product of the square root of (*1/YRBUILT*) and the square root of (*1 – PRIVSCHL*). Given these weights, the residuals are normally distributed and a Breusch–Pagan test can no longer detect heteroskedasticity at the 5-percent level of significance in either sample.

10 The Murphy–Topel error correction involves using the variance–covariance matrix of the first-stage estimation to inflate the standard errors that are used in hypothesis testing in the second stage. Parameter estimates are unaffected by the correction. Specifically, one tests hypotheses using the variance–covariance matrix

$$\hat{\Sigma}_{\text{corrected}} = \hat{\Sigma}_{\text{uncorrected}} + (Z'Z)^{-1}Z'F^*\hat{V}(\hat{\theta})F^{*\prime}Z(Z'Z)^{-1},$$

where Z is the matrix of second-stage regressors, F^* is a matrix of first-stage derivatives that is weighted by the estimated coefficients on the generated regressors from the second stage, and $\hat{V}(\hat{\theta})$ is the variance–covariance matrix from the first-stage regression. Murphy and Topel demonstrate that the second term in the above equation is a positive definite matrix.

11 It is unlikely that fireplaces, in and of themselves, have such large effects on property values. Rather, fireplaces likely proxy for other desirable home characteristics that we cannot observe in the data.

12 Pools appear to add value in southern Dallas, but the effect may be spurious because only five southern Dallas homes in our sample have pools.

13 These estimates come from model 3.

14 Of course, there are other possible explanations for not finding a relationship between school quality measures and property values in southern Dallas.

15 Omitting the potentially collinear *NEIGHBORS* from the estimation does not alter this result.

References

Aitkin, M., and N. Longford (1986), "Statistical Modeling Issues in School Effectiveness Studies," *Journal of the Royal Statistical Society*, A 149, pt. 1: 1–26.

Bartik, Timothy J., and V. Kerry Smith (1987), "Urban Amenities and Public Policy," in *Handbook of Regional and Urban Economics*, ed. Edwin S. Mills (Amsterdam: North Holland Press).

Boardman, Anthony E., and Richard J. Murnane (1979), "Using Panel Data to Improve Estimates of the Determinants of Educational Achievement," *Sociology of Education* 52 (April): 113–21.

Bradbury, Katherine L., Karl E. Case, and Christopher J. Mayer (1995), "School Quality, Local Budgets, and Property Values: A Re-Examination of Capitalization," manuscript.

Hanushek, Eric A. (1986), "The Economics of Schooling: Production and Efficiency in Public Schools," *Journal of Economic Literature* 24 (September): 1,141–76.

——— , and Lori L. Taylor (1990), "Alternative Assessments of the Performance of Schools," *Journal of Human Resources* 25 (Spring):179–201.

Jud, G. Donald, and James M. Watts (1981), "Schools and Housing Values," *Land Economics* 57 (August): 459–70.

Linden, Glenn M. (1995), *Desegregating Schools in Dallas: Four Decades in the Federal Courts* (Dallas: Three Forks Press).

Murphy, Kevin M., and Robert H. Topel (1985), "Estimation and Inference in Two-Step Econometric Models," *Journal of Business and Economic Statistics* 3 (October): 370–79.

Oates, Wallace E. (1969), "The Effects of Property Taxes and Local Spending on Property Values: An Empirical Study of Tax Capitalization and the Tiebout Hypothesis," *Journal of Political Economy* 77 (November/December): 957–71.

Positive Parents of Dallas, Dallas Chamber of Commerce, and Dallas Independent School District (1987), *All About DISD*.

Rosen, Harvey S., and David J. Fullerton (1977), "A Note on Local Tax Rates, Public Benefit Levels, and Property Values," *Journal of Political Economy* 85 (April): 433–40.

Rosen, Sherwin (1974), "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *Journal of Political Economy* 82 (January/February): 34–55.

Sonstelie, Jon C., and Paul R. Portney (1980), "Gross Rents and Market Values: Testing the Implications of Tiebout's Hypothesis," *Journal of Urban Economics* 7 (January): 102–18.

SREA Market Center Data Inc. (1987), *North Texas Annual 1987* (Atlanta: Damar Corp.).

Summers, Anita A., and Barbara L. Wolfe (1977), "Do Schools Make a Difference?" *American Economic Review* 67 (September): 639–52.

Walden, Michael L. (1990), "Magnet Schools and the Differential Impact of School Quality on Residential Property Values," *Journal of Real Estate Research* 5 (Summer): 221–30.

Appendix

We decompose average test scores into school effects and peer group effects, following the methodology outlined in Hanushek and Taylor (1990). Thus, we hypothesize that student achievement in period T is a function of the student's complete history of school (S) and student and family (F) characteristics. However, because the relationship is recursive, we can write

$$A_{iT} = \lambda A_{iT-1} + \beta_T F_{iT} + \sum_{k=1} q_{kT} S_{ikT} + \epsilon_{iT}, \tag{A.1}$$

where A_{iT} is the achievement of student i in period T, the S_{ikT} are dummy variables that equal one if the ith student attends school k in period T and equal zero otherwise, and F_{iT} represents student and family characteristics in period T. In this formulation, q_{kT} represents the value added by school k in period T and

$$\hat{A}_{iT} = \lambda A_{iT-1} + \beta_T F_{iT} \tag{A.2}$$

represents the level of student achievement that could be expected regardless of the school attended. Thus, q_{kT} is a measure of school effects, and the average $\hat{A}_{iT}$ for each school is a measure of peer group effects in that school.

Whenever student-level data are unavailable and the marginal effects of schools are independent of the student and family characteristics, equation A.1 can be estimated at the school level as

$$A_{kT} = \gamma + \tilde{\lambda} A_{kT-1} + \tilde{\beta}_T F_{kT} + \mu_{kT}. \tag{A.3}$$

In this equation, A_{kT} is average student achievement at school k in period T, F_{kT} represents average student and family characteristics at school k in period T, $\gamma + \mu_{kT} = q_{kT} + \varepsilon_{kT}$, and ε_{kT} represents the average estimation error for students at school k in period T. At this level of aggregation, $\gamma + \mu_{kT}$ is the best available proxy for school effects, and $P_{kT} = \tilde{\lambda} A_{kT-1} + \tilde{\beta}_T F_{kT}$ is the best available proxy for peer group effects. Because analysis at the school level incorporates error into the estimates of school and peer group effects, it is particularly important to treat these variables as estimated regressors in any subsequent analysis.

Table A.1
Estimating School and Peer Group Effects on Sixth-Grade Mathematics Achievement

	Parameter estimate	Standard error
INTERCEPT	26.767	6.301
MATH586	.740	.092
XCOHORT	–.083	.017
B&HISP	–.004	.002
SES	.004	.021
Number of observations	96	
R^2	.544	

DISD provided data on student body characteristics and student achievement scores for ninety-six primary schools in its jurisdiction for the years 1986 and 1987. The student body characteristics used in the analysis are the percentage of students who were black or Hispanic (*B&HISP*) and the percentage of students who were not receiving free or reduced-price lunches (the best available proxy for socioeconomic status, *SES*). The student achievement data used in the analysis are average scores on the Iowa Test of Basic Skills in mathematics. We use sixth-grade scores from 1987 (*MATH687*) and fifth-grade scores from 1986 (*MATH586*) as the measures of student achievement. The variable *XCOHORT* (the percentage increase in the number of students taking the exam) controls for changes in cohort size between 1986 and 1987.

From these data and the estimated coefficients in Table A.1, we construct measures of school and peer group effects for each of the ninety-six schools in our study. Thus, for each school, $SCHL687_k = 26.767 + \mu_{kT}$, and $PEER687_k = 0.740 \cdot MATH586_k - 0.083 \cdot XCOHORT_k - 0.004 \cdot B\&HISP_k + 0.004 \cdot SES_k$.