Which Measures of School Quality Does the Housing Market Value?

*David M. Brasington**

Abstract. **This study explores which measures of public school quality the housing market values. Both a traditional hedonic house price estimation and a hedonic corrected for spatial autocorrelation are used. Proficiency tests, expenditure per pupil and the pupil/teacher ratio are consistently capitalized into housing prices. Teacher salary and student attendance rates are also valued, but these results are sensitive to the estimation technique employed. Value-added measures, the graduation rate, teacher experience levels and teacher education levels are not consistently positively related to housing prices, so researchers should probably avoid using them as public education quality measures.**

Introduction

Economists have long been interested in the contribution of school quality to constant-quality house price. After all, over 80% of Americans will be homeowners during some point in their lifetime (Simmons Market Research, 1994). Many studies have confirmed the magnitude of public school quality's contribution to house prices. An important question to ask when estimating the capitalization of school quality into house price is: Which is the most appropriate measure of school quality? Although housing economists have generally settled on proficiency test scores to measure school quality, there is almost no empirical evidence comparing proficiency tests to other potential school quality measures. In addition, the increasing popularity of a new school quality measure, called the value-added approach, makes re-examination of the appropriate school quality measure a worthy topic to investigate.

Using housing transactions from the major metropolitan areas of the state of Ohio, a variety of school quality measures is included in a hedonic analysis to determine which ones are capitalized into housing market values. The housing market most consistently rewards high proficiency test passage rates, expenditures per pupil and a low pupil/teacher ratio. It is probably not a coincidence that these three measures are widely publicized and readily available to homebuyers. Average teacher salary and the student attendance rate are also consistently valued by the housing market; however, this consistency depends on whether a traditional least squares estimation or a spatial autocorrelation model is estimated. Value-added school quality measures are not very highly esteemed by the housing market, and teacher education levels not at all. Finally, teacher experience levels and student graduation rates are unreliable

*Tulane University, New Orleans, LA 70118 or dbrasin@mailhost.tcs.tulane.edu.

proxies for school quality in hedonic regressions because their signs swing somewhat dramatically depending on whether the traditional least squares estimation or the mixed regressive spatially autoregressive estimation technique is used.

Literature Review

Public school quality is one of the most important determinants of house price (Haurin and Brasington, 1996; and Goodman and Thibodeau, 1998); even today, though, many researchers include no such measure to help explain house price (Jud and Seaks, 1994; Benjamin and Sirmans, 1996; and Des Rosiers and Theriault, 1996). The researchers who do account for public school quality capitalization use many different measures. Perhaps the first to include school quality was Oates (1969), who used school expenditures. Other researchers have also used expenditure per pupil with varying degrees of success (Edel and Sclar, 1974; Gustely, 1976; Sonstelie and Portney, 1980; and Bradbury, Case and Mayer, 1995). Linneman (1980) uses a dummy variable for whether community residents believe school quality is bad, while Grether and Mieszkowksi (1974) and Harrison and Rubinfeld (1978) and use the pupil/teacher ratio. Rosen and Fullerton (1977) criticize the use of expenditures to measure school outcomes. Instead, they suggest that proficiency test scores, an outcome of the schooling process, may better reflect school quality than expenditures, an input to education. Most of the subsequent research has followed Rosen and Fullerton's advice (Jud and Watts, 1981; Jud, 1985; Walden, 1990; Haurin and Brasington, 1996; Brasington, 1999; and Goodman and Thibodeau, 1998). However, the switch to proficiency tests was not based on any empirical analysis comparing proficiency test scores to previously popular school quality measures.

In the intervening period, a new technique for measuring school quality has emerged and gained popularity in the education production function literature. Called the value-added approach, it measures school quality not by student outcomes at the end of a process, but by the change in outcomes over a period of time. For instance, a school district takes children with a given set of parents, neighborhood qualities, and innate intelligence and work ethic, and attempts to add to their knowledge. Value added is the improvement in academic achievement the district manages to give the students over and above their starting values. In this way, a poor inner-city school district may have low proficiency test passage rates, but it may have actually taught its students a great deal more than a wealthy suburban school district has taught its pupils. Researchers who have seen merit in the value-added approach include Summers and Wolfe (1977), Aitkin and Longford (1986), Boardman and Murnane (1979) and Hanushek and Taylor (1990). For a detailed review of the education production function literature and the value-added approach, see Marquis (1996).

Very little has been done in the housing market literature to test the validity of the value-added approach. 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 effect of schools. Hayes and Taylor (1996) is similar to the current analysis in that they use a hedonic analysis to examine which school quality measures are and are not valued by the housing market. Their measures of school quality are expenditures per pupil, the average level of sixth-grade achievement on the math portion of a standardized test, the value-added of the school, and, to capture peer group effects, the expected achievement of the sixth-grade student body on the math proficiency test. They find expenditures per pupil and peer group effects are insignificant, while the value added and level of proficiency in math are capitalized into the Northern Dallas submarket, but not into the less prosperous Southern Dallas submarket.

This study differs from Hayes and Taylor (1996) in many important ways. First, Hayes and Taylor use only four school performance measures, while this study uses thirty-seven. Second, this study's sample is significantly larger and contains more MSAs, more housing transactions, more housing submarkets, more neighborhood characteristics and more structural housing characteristics. Third, whereas Hayes and Taylor use census-tract neighborhood data and school outcomes, this study uses school district-level neighborhood data and school district outcomes. Fourth, this study uses not only a traditional hedonic regression but also a model that accounts for spatial autocorrelation. Fifth, this study uses a different value-added measure of public school quality.

Measure of Value-added

The measure used here does not completely fit the letter of the value-added approach. The value-added approach is best measured at the individual student level (Marquis, 1996); Hayes and Taylor (1996) use a school-level measure, and this study uses school district-level data. In addition, the value-added approach ideally measures the same students' improvement over time on the same test. While Hayes and Taylor use only one cohort of sixth-grade scores, and while Sonstelie and Portney (1980) use a change in test scores, this study measures value-added differently. It starts with the percentage of fourth-grade students in each school district who pass various sections of the 1996 Ohio fourth-grade proficiency test. This is the earliest proficiency test given by the state of Ohio. Ideally, kindergarten proficiency tests would be the baseline measure, but even in fourth grade, it is likely that parent characteristics are the underlying factors behind student performance. With fourth-grade achievement, there is a baseline measure to examine how the school district enhances the academic performance of the students it is given. The baseline measure is calculated according to the following formula:

$$d_{ij4} = p_{ij4} - \mu_{j4}. \tag{1}$$

In Equation (1), i is a school district subscript, j is a test section subscript, the 4 subscript denotes the fourth-grade test, p is the percentage of fourth-graders who pass each section of the test and μ is the statewide average for the percentage of students who pass the test section. Therefore, d is the difference between the school district in question and the statewide average. This number could be positive or negative. If it is positive, it is because the district starts with students who have above-average socioeconomic backgrounds. If it is negative, it is because the district is endowed with students who have unfavorable socioeconomic circumstances.

To see how each district performs with the students it is given, it is necessary to have a final outcome measure. There are two such available measures. The state of Ohio administers ninth and twelfth-grade proficiency tests. Ordinarily the twelfth-grade test would be the preferred measure for what the school system does for students; however, there are not yet consequences for students who fail this test. On the other hand, the ninth-grade test must be passed in order for each student to receive a full high school diploma. Students who cannot pass all sections of the ninth-grade proficiency test but still successfully complete their coursework receive a certificate of attendance instead of a high school diploma. Therefore, two measures of final school system output are constructed as follows:

$$d_{ij9} = p_{ij9} - \mu_{j9}, \tag{2}$$

$$d_{ij12} = p_{ij12} - \mu_{j12}, \tag{3}$$

where the subscripts 9 and 12 denote the grade level of the proficiency test. The interpretation for d is how the district's final output compares to that of the mean school district. The next step is to calculate the trend in relative performance:

$$\mathit{VALUE\ ADDED\ 9} = d_{ij9} - d_{ij4}. \tag{4}$$

$$\mathit{VALUE\ ADDED\ 12} = d_{ij12} - d_{ij4}. \tag{5}$$

Therefore, the value-added measures employed in this article assess the gain or fall in relative standing among the school districts from grade four outcomes to grade nine or twelve outcomes. For example, if a district has d_{ij4} of -12.0 for the science section of the proficiency test, it means the district passes 12% less students than the average district. However, if this same district has d_{ij9} of -3.0 for science, it has improved from fourth grade to ninth grade relative to other school districts, and its *VALUE ADDED 9* is negative 3.0 minus negative 12.0, which equals positive 9.0. On the other hand, a district that starts with strong socio-demographics may have a d_{ij4} of 23.0 for the science section. If its d_{ij9} is 10.0, which is still above the average, its *VALUE ADDED 9* is -13.0. It has taken students with high potential and pulled them back toward the average.

An important question is, then, which does the housing market value: levels of proficiency test passage or the value added of the school system? There are twelve value-added measures and eighteen traditional proficiency passage rate variables. These include measures from all sections of the test individually (writing, reading, math, citizenship and science) and composite calculations using grades four, nine and twelve proficiency test passage rates.

It is equally important to assess the relative merit of previous school quality measures that have been employed in the hedonic house price literature. Therefore, expenditure per pupil, the pupil/teacher ratio, average teacher salary, teacher education levels, teacher experience levels, student attendance rates, and the graduation rate are also employed. Variables are defined and sources and hedonic variables' means are provided in Exhibit 1.

Exhibit 1
Definitions, Sources and Means of Variables

Variable Name	Definition	Mean	Std. Dev.
LOG HOUSE PRICE	House transaction price for 1991 sales, deflated by MSA and logged (1)	11.2	0.51
AIR CONDITIONING	Air conditioning dummy (1)	0.45	0.50
FIREPLACE	Fireplace dummy (1)	0.47	0.50
LOT SIZE	Size of lot in hundreds of thousands of square feet (1)	0.12	0.20
AGE	Age of house in hundreds of years (1)	0.34	0.22
ROOMS	Total number of rooms in house (1)	6.31	1.31
GARAGE	Garage dummy (1)	0.90	0.30
FULL BATHROOMS	Number of full bathrooms (1)	1.40	0.54
PART BATHROOMS	Number of partial bathrooms (1)	0.44	0.52
DECK	Deck dummy (1)	0.15	0.35
POOL	Pool dummy (1)	0.02	0.14
Q2, Q3, Q4	Quarter of sale dummy (1)	0.29	0.46
TAX RATE	Property tax rate in mills; property tax collections from school taxes on all real Class 1 (residential) properties, divided by total real Class 1 property valuation (2)	35.5	6.55
MEDIAN INCOME	Median community income, deflated by MSA, in hundreds of thousands of dollars (3)	0.39	0.13
DISTANCE	Distance of centroid of school district from MSA's CBD in miles	12.3	5.77
PERCENT MINORITY	Percentage of school district residents who are not white (3)	0.09	0.12
CRIME	Serious crimes including murder, forcible rape, robbery, aggravated assault, motor vehicle theft, and arson, per 100,000 residents (4)	0.69	0.81
EXPENDITURE PER PUPIL	Expenditure per pupil in thousands of MSA-deflated dollars (2)	4.87	0.86
TEACHER MASTERS PLUS	Percentage of teachers with a master's degree or more (2)	49.1	9.48
TEACHER SALARY	Deflated average teacher salary in tens of thousands of dollars (2)	3.70	0.28
STUDENT/TEACHER RATIO	Number of enrolled pupils per classroom teacher (2)	18.4	1.8
AVERAGE TEACHER EXPERIENCE	Average number of years of teaching experience (2)	15.4	1.91
GRADUATION RATE	One minus the attrition rate for the current school year (2)	96.9	2.2
ATTENDANCE RATE	School district's attendance rate (2)	94.6	1.4

Exhibit 1 (continued)
Definitions, Sources and Means of Variables

Variable Name	Definition	Mean	Std. Dev.
VALUE ADDED (SECTION) *9* and *12*	Change in relative ranking among school districts of passage rate of students from the section of the test in fourth grade to the section of the test in ninth and twelfth grade; it is a measure of how well a school district does with the students it is endowed with (2)	—	—
VALUE ADDED ALL 9 and *12*	Summation of the value added to writing, reading, math, citizenship, and science sections of the ninth and twelfth grade tests; it is a composite measure of how well a school district does with the students it is endowed with (2)	—	—
(SECTION) *4, 9* and *12*	Percentage of students passing the section of the fourth, ninth or twelfth grade proficiency test; a traditional proficiency test measure of public school quality (2)	—	—
ALL 4, 9 and *12*	Mean of passage rates of all five proficiency test sections (2)	—	—

Sources: (1) Amerestate 1991 housing transaction tape; (2) Ohio Department of Education, Division of Education Management Information Services; (3) *School District Data Book* (MESA Group, 1994), (4) Office of Criminal Justice Services of the State of Ohio. Means of proficiency and value-added school quality measures are shown in Exhibit 4. 27,440 observations except for *TAX RATE* and *PERCENT MINORITY*, which have 22,489 observations because these variables were omitted from Cincinnati.

The correlation between *VALUE ADDED SCIENCE 9* and *SCIENCE 9* is 0.41; however, the correlation between *VALUE ADDED SCIENCE 9* and *SCIENCE 4* is −0.23. This pattern of correlations is consistent across test sections. To the extent that the fourth grade measures demographic endowment, it seems that schools with favorable socio-demographic characteristics have lower value added. For the purposes of this study, it is gratifying to note that the value-added and traditional measures seem to be distinct assessments of school system performance. Therefore, the housing market may reveal a difference in valuation for each type of school quality measure.

Data

The primary source of data for the hedonic regression is a tape of housing purchases that occurred during 1991 in the six largest metropolitan areas of Ohio (Amerestate, 1991). The dataset consists of 27,440 houses in 128 communities, and the mean deflated house value is $76,115. The *School District Data Book* (MESA Group, 1994), the Ohio Department of Education, and the Office of Criminal Justice Services of Ohio provide the remainder of the explanatory variables used.

Estimation Techniques

A series of Chow tests suggests that each of the major metropolitan areas in Ohio represents a distinct housing submarket; therefore, a separate hedonic regression is run for each MSA. In addition, Haurin and Brasington (1996) suggest that central cities represent a distinct housing market; however, central cities are excluded from the analysis because there are not enough of them to run a separate hedonic.

Two forms of hedonic estimations will be attempted. The first is a version of the traditional least squares hedonic estimation. The second technique will correct for spatial autocorrelation and use a maximum likelihood estimation. The results of both statistical techniques are shown for the following reasons. First, using a traditional hedonic estimation will allow the results to be more directly compared with results from other traditional hedonic studies. Second, having a side-by-side comparison of the traditional hedonic technique and a spatial autocorrelation estimation will allow readers to see to what degree the estimation results differ by using the newer, more sophisticated regression technique.

The traditional regression technique of Haurin and Brasington (1996) is presented first. In notation form, the following equation will be estimated:

$$\ln v_{ij} = \beta X_{ij} + \delta J_j + \varepsilon_{ij}. \tag{6}$$

In this equation, v stands for house value, the subscript i refers to house i, the subscript j refers to school district j, X represents structural house and land characteristics, δ represents the percentage deviations of an average house price in district j from that of a constant-quality house in the reference district and J is a dummy variable for each jurisdiction. The second step of the estimation takes the premium of each district, δ, and explains it as a function of community-level variables:

$$\delta_j = \gamma Z_j + \mu_j. \tag{7}$$

In Equation (7), Z is a vector of community-level variables. Equation (7) is a test of the capitalization of community-level variables into house price. The community-level variables are the same for all MSAs except Cincinnati, in which the tax rate and racial composition are omitted.

There is a problem with regressing Equations (6) and (7) as they appear: the dependent variable in the second equation is a parameter estimate from the first-stage regression. Each estimate has a standard error and the estimates are also correlated. Therefore, a GLS technique must be used to estimate the second equation. Following Haurin and Brasington (1996), substitute Equation (7) into Equation (6) to create Equation (8):

$$\ln v_{ij} = \beta X_{ij} + \delta Z_j + \varepsilon_{ij} + \mu_j. \quad (8)$$

Assuming the errors in Equations (6) and (7) are uncorrelated, the variance of the error in Equation (8) is $\tau^2 + \sigma^2$, where τ^2 is the variance of μ_j and σ^2 is the variance of ε_{ij}. These variances are estimated in auxiliary regressions of Equations (6) and (7) where the dependent variable of Equation (7) is the vector of estimated values of the coefficient of J_j in Equation (6). Finally, using these estimated variances, Equation (8) can be estimated. In the absence of spatial effects, the parameter estimates will be consistent and asymptotically efficient. Results will be discussed in the next section.

The second regression technique is now described. As before, the traditional hedonic approach is the following:

$$\ln v_i = \beta X_i + \varepsilon_i. \quad (9)$$

In this equation, v stands for house value, the subscript i refers to house i, X represents structural house and land characteristics as well as community-level variables, and ϵ is the error term.

However, LeSage (1997) explains why using ordinary least squares (OLS) to estimate housing transaction prices from multiple neighboring locations may produce biased and inconsistent parameter estimates. The problem essentially is that each house price influences other nearby house prices, but ordinary regression techniques do not account for this interplay. This problem is called spatial autocorrelation, and the literature suggests that in addition to being biased and inconsistent, OLS estimates may also be inefficient, lead to incorrect inference, and misstate R^2 (Anselin, 1988).

In the presence of spatial autocorrelation, OLS is inappropriate. An instrumental variables technique may be used, but most attempts to adjust for spatial autocorrelation have been based on maximum likelihood (Anselin and Hudak, 1992). One solution is to set up a spatial autoregressive model (LeSage, 1997) of the following form:

$$\ln v_i = \rho W^* \ln v_i + \beta X_i + \varepsilon_i, \quad (10)$$

where ρ is a spatial autoregressive parameter and W is the spatial weight matrix that tells how much influence neighboring observations have on the observation in question.[1] Griffith (1988) provides actual SAS programming code with which to perform a spatial autoregressive estimation of the form in Equation (10). Unfortunately, even the smallest regression exceeded the mainframe computer's capacity by at least a factor of six. Instead, a mixed regressive spatially autoregressive model with common factor specification (Pace and Barry, 1997a; and Anselin, 1988) of the following form is used:

$$\ln v_i = \rho W^* \ln v_i + \beta X_i + W X_i + \varepsilon_i. \quad (11)$$

Equation (11) has the following concentrated log-likelihood function:

$$L(\rho) = \log|I - \rho W| - (n/2)^*\log(SSE(\rho)), \tag{12}$$

where I is the identity matrix, n is the number of observations and $SSE(\rho)$ is the sum of squared errors associated with a given value of ρ. In this format, the scarcity of the spatial weight matrix W may be exploited (Pace, 1997; and Pace and Barry, 1997a, b) so that a personal computer can handle the large data set estimations with computational ease.[2] This procedure has been demonstrated to greatly improve cross-sectional regression estimates that are spatial in nature (Pace and Barry, 1997c, d; Pace, 1998a, b; and Pace, Barry, Clapp and Rodriguez, 1998).

Results

This study examines thirty-seven school quality measures for six metropolitan areas, requiring 222 regressions. This exercise is performed for a traditional least squares technique and is repeated for a spatial autocorrelation estimation technique. The extraordinary number of regressions prevents a full disclosure of results.[3] An example of each type of regression will be shown, and the remainder of the results will be summarized.

The traditional hedonic estimation results are discussed first. Exhibit 2 presents results from a typical regression that uses the percentage of fourth-grade students in each district who pass the reading portion of the 1996 proficiency test to measure school quality.

The signs and significance of the structural house characteristics and community characteristics are generally as expected and do not vary much when different educational outcome measures are used. However, the choice of public school quality measure matters. Exhibit 2 shows that fourth-grade reading scores are positively related to house value in three regressions and negatively related to house value in two regressions. The sixth regression has a positive coefficient, but a low t-ratio means there is insufficient precision in the estimate to indicate a positive association.

Estimation results using the mixed regressive spatially autoregressive technique are now discussed. Exhibit 3 shows how fourth-grade reading scores and house prices are related when correcting for spatial effects.

Again, the housing characteristics have the expected relationship with price, although the parameter estimates are somewhat different in magnitude than those in the traditional hedonic. This is particularly true for the community-level characteristics, which only have on average $128 \div 6 \approx 23$ values that they can take. Fourth-grade reading scores are positively related to house price in four of the six regressions and negatively related in the other two regressions. This is similar to the results achieved using non-spatial least squares. The parameter estimates are generally much larger in the maximum likelihood spatial model than in the traditional estimation, though, suggesting that school quality may be an even more important determinant of house price than studies based on least squares suggest. Further research is required before this claim can be substantiated, however.

Exhibit 2
Traditional Hedonic House Price Regression Example

Variable	Cleveland	Columbus	Akron	Cincinnati	Dayton	Toledo
Intercept	10.2*	9.80*	9.76*	10.3*	10.6*	7.83*
	0.09	0.13	0.64	0.16	0.15	0.41
AIR CONDITIONING	0.06*	0.05*	0.09*	0.11*	0.09*	0.07*
	0.01	0.01	0.02	0.01	0.01	0.02
FIREPLACE	0.11*	0.10*	0.15*	0.15*	0.11*	0.12*
	0.01	0.01	0.02	0.01	0.01	0.02
LOT SIZE	15.3*	21.3*	2.43	17.4*	14.8*	17.1*
	1.13	2.07	2.69	1.54	1.61	2.84
LOT SIZE SQUARED	−183*	−241*	−8.93	−192*	−155*	−193*
	20.00	41.7	52.3	30.9	35.8	62.9
AGE	−0.62*	−0.51*	−0.83*	−0.39*	−0.79*	−1.07*
	0.06	0.07	0.12	0.07	0.06	0.11
AGE SQUARED	0.13*	0.31*	0.12	−0.12*	0.45*	0.60*
	0.05	0.08	0.11	0.06	0.06	0.10
ROOMS	0.08*	0.07*	0.25*	0.04	0.20*	0.17*
	0.02	0.03	0.05	0.03	0.02	0.04
ROOMS SQUARED	<−0.01	<0.01	−0.01*	<0.01	−0.01*	−0.01*
	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
GARAGE	0.12*	0.05*	0.22*	0.15*	0.19*	0.18*
	0.01	0.01	0.02	0.01	0.01	0.03
FULL BATHROOMS	0.12*	0.15*	0.15*	0.12*	0.13*	0.19*
	0.01	0.01	0.02	0.01	0.01	0.02
PART BATHROOMS	0.11*	0.08*	0.11*	0.03*	0.11*	0.12*
	0.01	0.01	0.02	0.01	0.01	0.02
DECK	0.06*	0.03*	0.03	0.04*	0.06*	0.03
	0.01	0.01	0.03	0.01	0.01	0.02
POOL	0.06*	0.09*	0.11	0.04	0.09*	0.08*
	0.03	0.04	0.09	0.02	0.03	0.03
Q2	0.06*	0.05*	0.05*	0.05*	0.05*	0.02
	0.01	0.01	0.02	0.01	0.01	0.02
Q3	0.07*	0.04*	0.04*	0.06*	0.06*	0.03*
	0.01	0.01	0.02	0.01	0.01	0.02
Q4	0.09*	0.04*	0.07*	0.08*	0.06*	0.06*
	0.01	0.01	0.02	0.01	0.01	0.02
TAX RATE	<−0.01	<−0.01*	−0.01*	—	<0.01*	0.01*
	<0.01	<0.01	<0.01	—	<0.01	<0.01
MEDIAN INCOME	0.71*	0.80*	0.43*	0.67*	0.81*	0.19*
	0.05	0.06	0.23	0.06	0.04	0.08
READING 4	<0.01*	0.01*	<0.01	<−0.01*	−0.01*	0.02*
	<0.01	<0.01	0.01	<0.01	<0.01	<0.01
DISTANCE	−0.02*	−0.03*	−0.01*	−0.01*	−0.02*	<−0.01
	<0.01	<0.01	<0.01	<0.01	<0.01	0.01
PERCENT MINORITY	−0.40*	−0.53*	−4.57*	—	−1.19*	0.92*
	0.04	0.25	0.91	—	0.09	0.54
CRIME	−0.01*	−0.03*	−0.13*	−0.03*	−0.05*	0.01
	<0.01	0.01	0.03	0.01	0.01	0.02
Number of observations	9951	4016	1971	4951	4734	1817
R^2	0.64	0.67	0.60	0.72	0.72	0.75

Parameter estimates are shown with standard errors below. Dependent variable is *LOG HOUSE PRICE*. School quality measure is *READING 4*.
* Significant at .1.

Exhibit 3
Mixed Regressive Spatial Autoregressive Example

Variable	Cleveland	Columbus	Akron	Cincinnati	Dayton	Toledo
Intercept	6.08*	5.84*	5.58*	5.56*	5.92*	4.51*
	−34,833.8	−11,180.0	−5,482.8	−14,039.9	−13,257.9	−4,387.6
AIR CONDITIONING	0.04*	0.05*	0.06*	0.07*	0.05*	0.05*
	−35,406.8	−11,432.1	−5,531.7	−14,761.1	−13,586.8	−4,427.8
FIREPLACE	0.05*	0.07*	0.09*	0.09*	0.06*	0.09*
	−35,416.0	−11,440.0	−5,543.4	−14,765.3	−13,594.6	−4,439.7
LOT SIZE	0.94*	0.96*	0.24*	1.08*	0.87*	1.25*
	−35,435.7	−11,442.4	−5,529.8	−14,768.0	−13,582.2	−4,439.5
LOT SIZE SQUARED	−0.82*	−0.36*	0.07	−0.89*	−0.67*	−0.75*
	−35,413.9	−11,428.5	−5,528.0	−14,741.3	−13,568.6	−4,425.3
AGE	−1.05*	−1.00*	−1.22*	−0.84*	−0.97*	−1.08*
	−35,599.3	−11,458.3	−5,585.3	−14,810.7	−13,645.0	−4,470.7
AGE SQUARED	0.00	0.00	0.00	0.00	0.00	0.00
	−35,513.6	−11,436.9	−5,544.8	−14,768.1	−13,591.8	−4,440.6
ROOMS	0.22*	0.26*	0.25*	0.22*	0.27*	0.24*
	−35,994.4	−11,704.0	−5,549.5	−14,878.7	−13,772.4	−4,465.2
ROOMS SQUARED	−0.01*	−0.01*	−0.02*	−0.01*	−0.02*	−0.01*
	−35,909.2	−11,662.6	−5,542.0	−14,844.9	−13,731.6	−4,453.7
GARAGE	0.11*	0.05*	0.18*	0.08*	0.12*	0.17*
	−35,451.6	−11,430.1	−5,561.3	−14,751.5	−13,610.5	−4,449.7
FULL BATHROOMS	0.10*	0.09*	0.13*	0.12*	0.10*	0.14*
	35,497.3	−11,456.2	−5,553.6	−14,791.5	−13,628.5	−4,458.3
PART BATHROOMS	0.08*	0.04*	0.09*	0.02*	0.09*	0.08*
	−35,451.7	−11,429.4	−5,540.4	−14,733.6	−13,610.5	−4,437.3
DECK	0.04*	0.02*	0.05	0.04*	0.05*	0.03*
	−35,407.6	−11,424.2	−5,528.4	−14,737.0	−13,628.7	−4,425.2
POOL	0.04*	0.09*	0.09	0.05*	0.08*	0.09*
	−35,394.3	−11,423.5	−5,527.1	−14,732.9	−13,569.4	−4,427.1

Exhibit 3 (continued)
Mixed Regressive Spatial Autoregressive Example

Variable	Cleveland	Columbus	Akron	Cincinnati	Dayton	Toledo
Q2	0.07*	0.06*	0.04*	0.04*	0.05*	0.03*
	−35,420.8	−11,434.4	−5,529.3	−14,733.5	−13,576.1	−4,425.7
Q3	0.08*	0.04*	0.03	0.06*	0.05*	0.04*
	−35,433.0	−11,427.6	−5,528.3	−14,740.5	−13,577.7	−4,427.0
Q4	0.07*	0.04*	0.05*	0.06*	0.03*	0.06*
	−35,423.0	−11,427.2	−5,530.2	−14,740.0	−13,569.4	−4,429.3
TAX RATE	<-0.01*	−0.01	−0.02*	—	<0.01*	−0.01*
	−35,397.3	−11,421.5	−5,536.0	—	−13,571.1	−4,427.2
MEDIAN INCOME	0.39*	0.15	−2.45*	0.57*	0.62*	1.20*
	−35,396.2	−11,422.8	−5,534.0	−14,742.1	−13,568.3	−4,430.2
DISTANCE	−0.01*	−0.06*	−0.05*	<−0.01	−0.03*	0.04*
	−35,394.7	−11,425.7	−5,537.8	−14,727.7	−13,580.4	−4,425.3
PERCENT MINORITY	0.08	1.68*	−1.62*	—	−0.92*	5.15*
	−35,392.7	−11,426.8	−5,537.9	—	−13,585.9	−4,437.6
CRIME	−0.10	0.01	−0.04*	0.12*	−0.03*	0.26*
	−35,393.0	−11,422.9	−5,531.7	−14,735.7	−13,579.9	−4,437.3
READING 4	<0.01*	0.02*	0.04*	−0.02*	−0.02*	0.03*
	−35,447.1	−11,436.2	−5,594.7	−14,815.6	−13,657.9	−4,479.2
LAG AIR CONDITIONING	<−0.01	−0.04	0.01	<−0.01	0.02	−0.01
LAG FIREPLACE	−0.06	−0.05	0.06	−0.08	−0.05	<−0.01
LAG LOT SIZE	−0.53	−0.21	−0.93	−0.51	−0.91	−0.68
LAG LOT SIZE SQUARED	0.41	−1.31	0.93	0.45	0.78	0.66
LAG AGE	1.86	1.11	1.52	1.40	1.23	1.15
LAG AGE SQUARED	0.00	0.00	0.00	0.00	0.00	0.00
LAG ROOMS	0.66	0.66	0.14	0.37	0.40	0.38
LAG ROOMS SQUARED	−0.05	−0.05	−0.01	−0.03	−0.03	−0.03
LAG GARAGE	0.13	−0.04	0.06	0.01	−0.01	−0.02
LAG FULL BATHROOMS	0.08	−0.02	0.02	−0.01	−0.10	0.06
LAG PART BATHROOMS	−0.05	−0.06	−0.02	−0.04	−0.04	<−0.01

Exhibit 3 (continued)
Mixed Regressive Spatial Autoregressive Example

Variable	Cleveland	Columbus	Akron	Cincinnati	Dayton	Toledo
LAG DECK	0.04	−0.03	−0.02	0.01	−0.03	0.05
LAG POOL	−0.08	−0.07	0.04	−0.09	−0.07	−0.02
LAG Q2	0.02	0.02	−0.06	<−0.01	0.01	−0.06
LAG Q3	0.02	−0.01	−0.07	−0.03	0.03	−0.07
LAG Q4	0.03	0.01	−0.08	−0.01	<0.01	−0.06
LAG TAX RATE	<−0.01	0.01	0.03	—	−0.01	0.02
LAG MEDIAN INCOME	−0.43	−0.04	3.14	−0.78	−0.63	−1.31
LAG DISTANCE	0.01	0.05	0.03	<0.01	0.03	−0.04
LAG PERCENT MINORITY	−0.05	−0.87	4.66	—	1.39	−2.85
LAG CRIME	0.01	−0.03	−0.06	−0.09	0.09	−0.18
LAG READING 4	<0.01	−0.01	<−0.01	0.03	0.03	0.00
Number of observations	9,951	4,016	1,971	4,951	4,734	1,817
Unrestricted optimal log likelihood	−35,392.3	−11,421.1	−5,526.3	−14,727.6	−13,563.9	−4,422.8
Optimal lag coefficient (ρ)	0.62	0.64	0.48	0.65	0.66	0.49
SSE	795.99	233.53	88.04	346.27	250.76	55.96
R^2	0.71	0.73	0.83	0.76	0.75	0.89

Parameter estimates are shown with optimal restricted log likelihood shown below, where the restricted model is without the variable in question and its lagged value. Optimal restricted log likelihood for lagged variables is the same as for the explanatory variables themselves; therefore, these values are not shown below the lagged variables. The dependent variable is *LOG HOUSE PRICE*. School quality measure is *READING 4*. *AGE SQUARED* and its lag have zero coefficients reported because, using Spacestatpack, an insufficient number of decimal places is reported. Likelihood ratio statistics for each variable may be constructed according to the following formula: LR = −2(optimal unrestricted log likelihood–optimal restricted log likelihood), which is asymptotically distributed as chi-square with degrees of freedom equal to the number of restrictions (two in this case: the variable and its lag are set to zero in the restricted model).
*Significant at .1.

The mixed regressive spatially autoregressive model yields significantly larger R^2 values compared to least squares, although it is unclear whether this is an artifact of the maximum likelihood procedure or whether it is due to the spatial effects. For instance, the optimal spatial lag coefficients for Akron and Toledo are only 0.48 and 0.49. This indicates fairly mild spatial autocorrelation. R^2 showed the most improvement for Akron and Toledo. On the other hand, Cincinnati, Cleveland, Columbus and Dayton have optimal spatial lag coefficients ranging from 0.62 to 0.66, suggesting a non-trivial amount of spatial autocorrelation.

The lagged variables in Exhibit 3 essentially indicate how far off estimates would be if the spatial lag were not included. For example, consider *MEDIAN INCOME* for Cincinnati in Exhibit 3. It has a coefficient of 0.571. *LAG MEDIAN INCOME* has a coefficient of -0.776. Because Cincinnati's optimal spatial lag is fairly large, *MEDIAN INCOME* is fairly highly spatially correlated. That is, it is fairly highly correlated with the spatial *LAG MEDIAN INCOME*. If only income were included without its spatial lag in the regression, because of the high correlation the coefficient of *MEDIAN INCOME* might have been negative ($0.571 - 0.776 < 0$).

Exhibit 4 portrays a complete summary listing of the regression results for each school outcome variable using both the traditional least squares technique and the mixed regressive spatially autoregressive technique.

There are multiple ways to summarize how the housing market values each type of educational measure in Exhibit 4. Finding the ratio of positive to negative relationships with constant-quality house price is one reasonable way.

Using the traditional least squares hedonic method, the value-added measures have a positive to negative ratio of 1.23. This means that slightly more than half the time the housing market looks favorably on high value added in a school district. In contrast, the positive-to-negative ratio for the traditional proficiency test measures is 5.23. This suggests that the housing market resoundingly values high levels of student achievement, while it does not place as high a value on the ability of a school system to improve the academic achievement of the students it is given.

The additional measures of school quality using least squares reveal mixed success. Expenditure per pupil has been a popular proxy for school quality in the hedonic literature. The results suggest that expenditure per pupil is highly valued in the housing market. Controlling for community income levels, the tax rate, and racial composition, the higher is expenditure per pupil, the higher is house value in all six regressions. Average teacher salary, which has a 0.55 correlation with expenditure per pupil, also works well as a proxy for school quality. On the other hand, high teacher education levels and student graduation rates are not valued by the housing market. Average teacher experience and the attendance rate fall somewhere in the middle: while they are not significantly negatively related to constant-quality house value in any regression, they are only positively significantly related to house value in two of the six MSAs.

Exhibit 4
Summary of Hedonic Education Measures

Education Measure	Mean	Std. Dev.	Spatial +	Spatial −	Spatial 0	Traditional +	Traditional −	Traditional 0
VALUE ADDED WRITING 9	−12.8	13.1	2	0	4	2	2	2
VALUE ADDED WRITING 12	0.7	9.6	3	2	1	2	1	3
VALUE ADDED READING 9	−19.7	12.5	2	3	1	3	2	1
VALUE ADDED READING 12	0.6	5.4	2	1	3	3	2	1
VALUE ADDED MATH 9	−16.2	9.7	3	1	2	3	1	2
VALUE ADDED MATH 12	1.2	8.4	2	2	2	1	3	2
VALUE ADDED CITIZENSHIP 9	−24.6	9.3	3	2	1	3	1	2
VALUE ADDED CITIZENSHIP 12	0.4	7.9	4	1	1	2	2	2
VALUE ADDED SCIENCE 9	2.4	8.3	2	2	2	2	2	2
VALUE ADDED SCIENCE 12	1.1	8.6	2	2	2	1	2	3
VALUE ADDED ALL 9	−71.0	36.8	2	1	3	3	2	1
VALUE ADDED ALL 12	3.9	32.5	2	1	3	2	2	2
WRITING 12	72.7	11.2	3	2	1	3	0	3
WRITING 9	41.3	15.1	2	1	3	2	1	3
WRITING 4	84.7	7.8	3	2	1	4	0	2
READING 12	83.8	7.0	4	1	1	5	1	0
READING 9	43.7	13.4	4	1	1	3	1	2
READING 4	88.2	7.5	4	2	0	3	1	2
MATH 12	67.5	12.7	3	1	2	3	2	1
MATH 9	23.9	10.2	4	0	2	5	0	1
MATH 4	80.3	11.3	6	0	0	5	1	0
CITIZENSHIP 12	73.3	11.0	4	0	2	5	1	0
CITIZENSHIP 9	19.3	8.3	4	1	1	3	0	3
CITIZENSHIP 4	90.8	7.2	2	2	2	4	1	1
SCIENCE 12	60.0	12.4	3	1	2	4	1	1
SCIENCE 9	58.5	14.8	5	0	1	3	0	3
SCIENCE 4	68.1	13.9	2	2	2	4	1	1
ALL 4	82.4	9.2	3	2	1	5	1	0
ALL 9	37.3	9.8	4	0	2	3	0	3
ALL 12	71.5	10.2	3	1	2	4	1	1
EXPENDITURE PER PUPIL	4.9	0.9	3	2	1	6	0	0
STUDENT/TEACHER RATIO	18.4	1.8	2	4	0	0	4	2
TEACHER SALARY	3.7	0.3	3	3	0	4	0	2
TEACHER MASTERS PLUS	49.1	9.5	1	1	4	0	2	4
AVERAGE TEACHER EXPERIENCE	15.4	1.9	1	3	2	2	0	4
ATTENDANCE RATE	94.6	1.4	5	0	1	2	0	4
GRADUATION RATE	96.9	2.2	5	0	1	1	2	3

Summary of results of mixed regressive spatial autoregressive estimation and traditional least squares hedonic regressions using each of the variables in column 1 to measure public school quality. Positive (+) means the education measure was positive and statistically significant, negative (-) means it was negative and statistically significant, and zero (0) means it was statistically insignificant that many times out of the six MSA regressions. Statistical significance is based on the t-ratio for the traditional least squares hedonic and the likelihood ratio for the spatial autocorrelation model. Number of observations is 27,440.

Turning to the spatial autocorrelation model, a slightly different summary of results emerges. The ratio of positive to negative education measures for the value-added measures is 1.61, slightly higher than with the traditional hedonic. This means that house price has a positive relationship with value-added school quality measures almost twice as often as it has a negative relationship with them. The ratio of positives to negatives for proficiency test level education measures is 3.31, which is lower than 5.23 but still indicates that a positive relationship with house price is more than three times as common as a negative relationship.

The spatial autocorrelation results differ somewhat from the traditional hedonic estimation for the other measures of school quality. Expenditures per pupil are still valued in the spatially corrected model, but not as consistently as for the traditional approach. Teacher salary, which the traditional approach valued highly, is no longer consistently positively related to house price. On the other hand, student attendance rates are even more consistently valued. A higher student-to-teacher ratio is still penalized in the housing market, and teacher education levels are still not related to constant-quality house price, but average teacher experience levels have gone from weakly positive to fairly strongly negative. The most striking change is that, contrary to the results of the traditional method, the spatial regression overwhelmingly values student graduation rates.

Conclusion

Numerous measures of public school quality have been examined to determine which are highly valued by the housing market. This study has used a more extensive sample than previous studies, and it has constructed a wider variety of appropriate measures of public school quality than prior studies. The focus has been to compare the current academic standard, proficiency test scores, to other school quality measures.

The results suggest that the housing market values proficiency test passage rates but not value added by a school district. Therefore, it may be that parents do not choose schooling based on which school districts are best able to improve students' academic achievement; instead, they appear to choose school systems based on peer group effects, valuing they type of children who attend the school district. This is consistent with the Tiebout (1956) hypothesis that households sort based on preferences, and that preferences are driven by socio-demographic characteristics. Therefore, while the value-added approach may be a legitimate measure of improvement in students' academic achievement, it is probably not useful for measuring school quality in housing market studies.

The results also suggest that expenditure per pupil, which used to be the most popular measure of school quality in a house price hedonic, seems to be valued by the housing market after all. It is therefore an appropriate substitute for proficiency test scores in hedonic regressions. Another useful proxy for school quality seems to be the pupil/teacher ratio. High values of this variable are fairly consistently penalized in the housing market. Additionally, average teacher salary, which is a major component of school expenditures, is also valued by the housing market, but the results are more consistent using a spatially corrected model than a traditional hedonic model. The same is true for student attendance rates.

On the other hand, teacher education levels are not highly valued by the housing market and therefore are inappropriate proxies for school quality in house price hedonics. Teacher experience levels and student graduation rates show a schizophrenic behavior: their relationship with constant-quality house price greatly hinges on the estimation technique.

This study could be extended in many ways. The most important way would be to construct a superior measure of value added by a school system. This would involve a micro dataset that follows a true cohort of students over time, instead of measuring the change in relative standing of the school district on various test sections from the fourth-grade test to the ninth or twelfth-grade tests.

This study examines which of the many ways to measure school quality works best in housing studies. The following measures of school quality are most consistently positively related to house prices: proficiency tests, expenditure per pupil and the student-to-teacher ratio. Average teacher salary and student attendance rates are also fairly consistent measures of public school quality, but they are sensitive to changes in statistical technique. Value added is not very highly valued, and the graduation rate, teacher experience levels and teacher education levels seem to be bad ways to measure school quality in housing studies.

Notes

[1] See LeSage (1997) for an excellent intuitive discussion of the spatial weight matrix.

[2] Many thanks to Kelley Pace (1998c) for providing Spacestatpack.

[3] The full set of results is available from the author upon request.

References

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

Amerestate, *PaceNet Data Set*, Cincinnati, 1991.

Anselin, L., *Spatial Econometrics*: *Methods and Models*, Kluwer Academic Publishing: London and Dordrecht, 1988.

Anselin, L. and S. Hudak, Spatial Econometrics in Practice: A Review of the Software Options, *Regional Science and Urban Economics*, 1992, 22, 509–36.

Benjamin, J. D. and G. S. Sirmans, Mass Transportation, Apartment Rent and Property Values, *Journal of Real Estate Research*, 1996, 12, 1–8.

Boardman, A. E. and R. J. Murnane, Using Panel Data Estimates to Improve Estimates of the Determinants of Educational Achievement, *Sociology of Education*, 1979, 52, 113–21.

Bradbury, K. L., K. E. Case and C. J. Mayer, School Quality, Local Budgets, and Property Values: A Re-Examination of Capitalization, Working paper, 1995.

Brasington, D. M., Demand and Supply of Public School Quality in Metropolitan Areas; The Role of Private Schools, Working paper, Tulane University, 1999.

Des Rosiers, F. and M. Theriault, Rental Amenities and the Stability of Hedonic Prices: A Comparative Analysis of Five Market Segments, *Journal of Real Estate Research*, 1996, 12, 17–36.

Edel, M. and E. Sclar, Taxes, Spending, and Property Values: Supply Adjustment in a Tiebout-Oates Model, *Journal of Political Economy*, 1974, 82, 941–54.

Goodman, A. C. and T. G. Thibodeau, Housing Market Segmentation, *Journal of Housing Economics*, 1998, 7, 121–143.

Grether, D. M. and P. Mieszkowski, Determinants of Real Estate Values, *Journal of Urban Economics*, 1974, 1, 127–46.

Griffith, D. A., Estimating Spatial Autoregressive Model Parameters with Commercial Software Packages, *Geographical Analysis*, 1988, 20, 176–86.

Gustely, R. D., Local Taxes, Expenditures, and Urban Housing: A Reassessment of the Evidence, *Southern Economic Journal*, 1976, 42, 659–65.

Hanushek, E. A. and L. L. Taylor, Alternative Assessments of the Performance of Schools: Measurement of State Variations in Achievement, *Journal of Human Resources*, 1990, 25, 179–201.

Harrison, D. Jr. and D. L. Rubinfeld, Hedonic Housing Prices and the Demand for Clean Air, *Journal of Environmental Economics and Management*, 1978, 5, 81–102.

Haurin, D. R. and D. M. Brasington, The Impact of School Quality on Real House Prices: Interjurisdictional Effects, *Journal of Housing Economics*, 1996, 5, 351–68.

Hayes, K. J. and L. L. Taylor, Neighborhood School Characteristics: What Signals Quality to Homebuyers?, *Federal Reserve Bank of Dallas Economic Review*, 1996, 3, 2–9.

Jud, G. D., A Further Note on Schools and Housing Values, *Journal of the American Real Estate and Urban Economics Association*, 1985, 13, 452–61.

Jud, G. D. and T. G. Seaks, Sample Selection Bias in Estimating Housing Prices, *Journal of Real Estate Research*, 1994, 9, 289–98.

Jud, G. D. and J. M. Watts, Schools and Housing Values, *Land Economics*, 1981, 57, 459–70.

LeSage, J. P., Regression Analysis of Spatial Data, *Journal of Regional Analysis and Policy*, 1997, 27, 83–94.

Linneman, P., Some Empirical Results on the Nature of the Hedonic Price Function for the Urban Housing Market, *Journal of Urban Economics*, 1980, 8, 47–68.

Marquis, W., What Schools Contribute to Education: A Comparative Study of Catholic and Public High School Students Using a Value Added Approach, Doctoral dissertation, Ohio State University, 1996.

MESA Group, *School District Data Book*, National Center for Education Statistics, U.S. Department of Education, Washington, DC, 1994.

Oates, W. E., The Effects of Property Taxes and Local Public Spending on Property Values: An Empirical Study of Tax Capitalization and the Tiebout Hypothesis, *Journal of Political Economy*, 1969, 77, 957–71.

Office of Criminal Justice Services, *Crime by County 1993*, Columbus, OH, State of Ohio, 1994, 1–15.

Ohio Department of Education, http://www.ode.ohio.gov/www/ims, 1997.

Pace, R. K., Total Grid Estimation, *Journal of Real Estate Research*, 1998a, 15, 101–14.

——, Appraisal Using Generalized Additive Models, *Journal of Real Estate Research*, 1998b, 15, 77–99.

——, Spacestatpack: A Spatial Statistics Package in Fortran 90 (with PC executable code) (version α), http://finance.lsu.edu/re/kelleyresume.html, 1998c.

——, Performing Large Spatial Regressions and Autoregressions, *Economics Letters*, 1997, 54, 283–91.

Pace, R. K. and R. Barry, Quick Computation of Spatial Autoregressive Estimators, *Geographical Analysis*, 1997a, 29, 232–47.

——, Sparse Spatial Autoregressions, *Statistics and Probability Letters*, 1997b, 33, 291–97.

——, Using the Spatial Configuration of the Data to Improve Estimation, *Journal of Real Estate Finance and Economics*, 1997c, 14, 333–40.

——, Fast Spatial Estimation, *Applied Economics Letters*, 1997d, 4, 337–41.

Pace, R. K., R. Barry, J. Clapp and M. Rodriguez, Spatiotemporal Autoregressive Models of Neighborhood Effects, *Journal of Real Estate Finance and Economics*, 1998, 17, 15–33.

Rosen, H. S. and D. J. Fullerton, A Note on Local Tax Rates, Public Benefit Levels, and Property Values, *Journal of Political Economy*, 1977, 85, 433–40.

Simmons Market Research Bureau, Inc., *Simmons Study of Media and Markets: Multi-Media Audiences: Adults*, USA, 1994, 290.

Sonstelie, J. C. and P. R. Portney, Gross Rents and Market Values: Testing the Implications of Tiebout's Hypothesis, *Journal of Urban Economics*, 1980, 7, 102–18.

Summers, A. A. and B. L. Wolfe, Do Schools Make a Difference?, *American Economic Review*, 1977, 67, 639–52.

Tiebout, C., A Pure Theory of Local Expenditures, *Journal of Political Economy*, 1956, 64, 416–24.

Walden, M. L., Magnet Schools and the Differential Impact of School Quality on Residential Property Values, *Journal of Real Estate Research*, 1990, 5, 221–30.