DEPARTMENT OF ECONOMICS WORKING PAPER SERIES

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Working Paper 2005-04
http://www.bus.lsu.edu/economics/papers/pap05_04.pdf

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January 7, 2005

ABSTRACT

We decompose school proficiency test scores into their parent, peer group, and school input components to see which are valued by the housing market. The value-added model proposes that only locationally fixed district-specific factors such as inputs to schooling and the characteristics of student peers are capitalized into house prices. This model claims that portable inputs to student outcomes, such as parental contributions, are not capitalized. A competing model argues that value-added is not easily observed; rather, educational outcomes such as proficiency test scores are easily observed and are capitalized into house prices. Based on our study of 123 school districts and 27,000 house transactions, we find little support for the value-added model. Instead, we find that households value a district's average proficiency test scores. The primary component of the proficiency test score that is capitalized into house prices is the parental input component. The peer group component is also valued, but less strongly. The school input component is not valued.

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JEL Classifications: I2, N3, R21, R00

Keywords: house prices, hedonic model, capitalization, school quality, value-added, achievement test scores

*A spinoff of this paper became "Educational Outcomes and House Values: A Test of the Value-Added Approach," which is under second review at *Journal of Regional Science*. The spinoff paper does not decompose school quality into its component parts, it uses a different data set, and it emphasizes spatial statistics.

Capitalization of Parent, School, and Peer Group Components of School Quality into House Price

"From this year, we will be including in the tables measures of the value added by schools so that more sophisticated data is available," –Department for Education and Skills of the United Kingdom (Gledhill, 2002)

It is widely accepted that local amenities affect neighborhood house prices, the amount of capitalization depending on the demand and supply of the amenity. Local public school quality is among the most important local amenities and it is clear that public school quality varies spatially by significant amounts. A large body of literature investigates the relationship between house prices and public school quality. Over the years, proficiency tests have replaced expenditures as the most widely accepted measure of school quality in house price hedonic regressions. But education and labor economists increasingly claim that school achievement is not the proper measure of school quality. Instead, the literature increasingly looks to growth over time in student achievement or value-added to measure the quality of a school.

According to Meyer (1997),

> "The indicators commonly used to assess school performance-average and median test scores-are highly flawed. They tend to be contaminated by student mobility and by nonschool factors that contribute to student achievement (e.g. student, family, and community characteristics and prior achievement)…The conceptually-appropriate indicator of school performance is the value-added indicator. The value-added indicator measures school performance using a statistical model that includes, to the extent possible, all of the nonschool factors that contribute to growth in student achievement. The objective is to statistically isolate the contribution of schools to student achievement growth from these other factors."

The value-added approach argues that a school is responsible for the additional knowledge that it imparts to its students. It is not responsible for the students' innate aptitudes or their parents' characteristics. Therefore, "good" schools are not necessarily the ones with the highest test scores, because high levels of achievement may simply

reflect parents' characteristics. Instead, a good school is one with a high value-added: a school that takes the students it is given and adds significantly to their knowledge.

Many researchers in the labor and education economics literatures have adopted the value-added approach. Among the early works in the area are Boardman and Murnane (1979) and Aitkin and Longford (1986). More recent works in this expanding line of research include Hanushek and Taylor (1990), Hanushek (1992), Gomes-Neto et al. (1997), Hunt-McCool and Bishop (1998), and Figlio (1999). State governments are increasingly focusing on the value-added of schools by measuring the gain in student test scores, including South Carolina, Tennessee, California, Texas and Kentucky.[1] Some states have begun to provide financial incentives to schools that score well on these measures.

Even if public policy and large portions of the education and labor economics literatures adopt value-added measures, we question whether households care more about value-added than about levels of school achievement. The housing market can help decide this question, and it can also reveal the relative importance of peers, parents, and the school-specific component of public school quality. However, little work has been done in this area.

Capitalization of school quality into house prices affects many households. In the fourth quarter of 2001, 68.0 percent of U.S. households were homeowners (U.S. HUD 2002, Table 27) and there were over 73 million owner-occupied housing units. We find that house prices vary by about 20% when comparing a school district with student achievement that is one standard deviation below the mean to a district with achievement that is one standard deviation above the mean. This variation in house price has a substantial impact on household wealth. Assuming an average house value of $185,000, a two standard deviation increase in school quality implies an increase in the average homeowner's wealth by $37,000.[2] Thus, the issue about capitalization of

school quality into house prices affects many U.S. households and the size of the impact is substantial. Further study of what aspects of school quality are capitalized is needed.

We decompose student achievement into a parent component, a peer component, and a school input component. Using a data set of 27,000 housing transactions in the state of Ohio, we include these three components of school quality in a hedonic house price regression. We find that house prices are affected most by the impact of a community's parental characteristics on school achievement. School specific peer effects also influence house prices, but to a much smaller degree. Variations in purchased inputs across school districts have little impact on student performance and we find, correspondingly, that they have little effect on house prices. We therefore find very little support for the use of value-added measures of school quality when explaining spatial variation in house prices.

I. Literature

Early studies of the relationship between house prices and the quality of local education used public school expenditures per pupil as the key school characteristic, probably because outcome measures such as test scores were not available (e.g., Oates 1969). Rosen and Fullerton (1977) argued that proficiency test scores are a better measure of school output. Subsequent research generally uses K-12 student achievement measures in studies of house value capitalization.[3] Haurin and Brasington (1996) use the pass rate on a ninth grade statewide proficiency test to measure student achievement.

Another reason for the change from using expenditures per pupil to student outcomes as the key measure of school quality was that the education production function literature found that school inputs have little or no impact on student outcomes (Hanushek 1986, 1997). The consensus opinion is that parental inputs are the dominant

factor in determining K-12 academic outcomes. The impact of a third input, peer group effects, continues to be debated in the literature (Betts 1996), but most evidence suggests peer effects occur in grades K-12.[4] Recently, Zimmer and Toma (2000) found strong evidence of peer effects in five countries in a study of math achievement.

Hayes and Taylor (1996) argue that the impact of school quality on house values derives from the marginal effect of schools on educational outcomes; that is, the value-added of a school. Using Dallas data, they test three models: one based on per pupil expenditures, the second based on average achievement in the sixth grade, and the third based on the marginal impact of schools' value-added on achievement. Their value-added model decomposes observed average achievement at time t in the j-th school district (A_{jt}) into the expected effect derived from parental inputs and a school district specific residual:

(1) $A_{jt} = b_o + b_1P_j + b_2A_{jt-1} + e_j$

where P_j represents parental characteristics, A_{jt-1} is the prior year's achievement, and e_j is the random error in district j.[5] Hayes and Taylor assume the value-added by a district is the sum of the estimated value of the constant and the predicted value of the district's error term. They claim that these terms capture all nonparental inputs to school outcomes.[6] Using a small sample of 288 observations of house prices, they first test whether school expenditures affect house values, but they find no impact. They also test for the impact of average school achievement on house values and find a statistically significant effect. However, when they decompose school achievement into "value-added" and the expected achievement based on P_j and A_{jt-1}, they find that only value-added has an impact on house prices. They conclude that homeowners are not willing to pay for residing in the same district as parents or students with a particular set of characteristics; rather, they are only willing to pay for school-specific attributes.

Hayes and Taylor's study raises a key question: do households value levels of K-12 student achievement or do they value only the district's value-added to student outcomes? The answer is important to all studies of house prices because controlling for variations in school quality is important. Hayes and Taylor claim that only value-added is important, but this claim can be criticized in a number of ways. First, their sample size of house prices is quite small. Second, their measure of value-added is, in essence, the random error in the school achievement regression for a single year. While this term contains components of the school-specific value-added to education, it also contains the impact of other omitted variables and the truly random component of school achievement. Third, they include past achievement levels as an explanatory variable in the house value estimation, but past achievement levels may be the result of school-specific effects that should be included in the measure of value-added.[7] Fourth, they claim that school-specific peer group effects are not part of a school's value-added. However, this claim is inconsistent with their argument that value-added includes all nonportable school-specific factors.

Predating Hayes and Taylor was a study of house prices by Dubin and Goodman (1982). Dubin and Goodman studied the impact of crime and education on house prices in Baltimore. Beginning with 21 school characteristics, they used principal components analysis to narrow the list to five school attributes for city schools and six for suburban schools. Although they did not discuss the value-added hypothesis, two of their education components are value-added measures. In their hedonic estimation, they find that neither value-added measure significantly affects city house prices, and suburban house prices are only marginally affected by one of the value-added measures.

Downes and Zabel (2002) use a sample of 1,173 house price observations in the Chicago metropolitan area to test alternative models of the impact of school quality on house prices. In contrast to Hayes and Taylor, they find that higher average levels of

school achievement raise house values, but their measure of a school district's value-added does not. Downes and Zabel argue that even if value-added is the theoretically preferred measure, what is important is the attribute of school quality that households value. Their empirical tests confirm that the housing market values achievement test outcomes, one of the most readily available measures of school quality. A limitation of their study is that they do not fully decompose school achievement into its component parts, this point elaborated in our model of school achievement. Their measure of value added is an 8th grade proficiency test, holding constant 6th grade proficiency test results from two years prior. However, this measure of value added captures only part of the value added by a school district. For example, if a district's programs substantially raised students' test scores between 1st and 6th grades, but scores fell slightly between 6th and 8th grades, then the Downes and Zabel measure penalizes the district for its improvements in scores in the elementary school years. Our measure of value added avoids this potential problem.

Brasington (1999) also studies which measure of educational outcomes is capitalized into house prices. He compares 37 measures of school quality, including expenditures per pupil, proficiency test results, and ad-hoc value-added measures. Using a standard hedonic housing estimation, he finds that significant explanatory variables include proficiency test results and expenditures per pupil, but not the value-added measures.[8]

In contrast to Hayes and Taylor (1996), Brasington's and Downes and Zabel's results argue for the possibility that households use easily observed indicators of school district achievement when bidding for houses. However, none of these studies addresses the underlying econometric theory needed to test the value-added model. The measures of value-added are ad hoc and peer group effects are not accounted for.

Numerous other recent studies measure the extent of capitalization of school quality into house prices. Nearly all use a measure of average student achievement rather than value-added. Goodman and Thibodeau (1998) use third through fifth grade proficiency test results as a control variable in testing for segmentation in the housing market and they find that the impact on house prices of the test's pass rate is positive, significant, and large. Bogart and Cromwell (2000) find mixed and sometimes perverse results for Shaker Heights OH; however, they attribute their results to a lack of within-jurisdiction variation in test scores and unobserved heterogeneity within school catchment areas. Black (1999) finds a positive relationship between house prices and the average of fourth grade Massachusetts reading and math proficiency test scores. Brasington (2000) finds that Ohio proficiency test scores are positively capitalized into house prices. Sieg et al. (1999) find that math proficiency test scores are positively related to the price of California housing in 1987-1995.

II. A Model of House Prices and K-12 Public School Outcomes with Peer Group Effects

Our basic model assumes that house prices reflect the market values of structural attributes of housing, neighborhood characteristics, and selected aspects of a community's K-12 public education (Rosen 1974). We assume a standard form for the empirical hedonic house price function:

(2) $\ln H_{ij} = c_{H0} + c_{HX}X_{ij} + c_{HY}Y_j$

where $\ln H_{ij}$ is the natural logarithm of house value for the i-th house and household in the j-th school district, X_{ij} represents house characteristics including quality of neighborhood indicators, and Y_j is the set of educational outcomes or inputs that are valued by households. Candidates for measures of Y_j include the average level of

educational attainment by children in the district (A_j), or the value-added by the district (V_j).

We adopt the education production function approach and initially assume that educational attainment is produced with parental inputs (P_i), school inputs (S_j), innate child factors (F_i), and peer effects (R_j). We assume the production function's form is additively separable, implying that parental inputs have the same impact on attainment no matter which school district is selected.[9]

(3) $A_{ij} = a_{A0} + a_{AP}P_i + a_{AS}S_j + a_{AF}F_i + a_{AR}R_j$

When a household selects a school district, the set of peers in the district is exogenous, thus peers take on the attribute of a district-specific fixed effect. The value-added hypothesis, now expanded to include all district-specific effects, argues that house values are influenced by both a district's purchased inputs and the educational impact of a district's group of student peers; that is, $V_j = a_{AS}S_j + a_{AR}R_j$.

Testing the hedonic price model requires observations of house prices, house and neighborhood characteristics, and a school district's educational outcomes, inputs, and peer effects. Although V_j is not directly observed, it can be estimated from (3). While our data set reports individual house prices and characteristics, our data on student outcomes, parent characteristics, and school inputs is at the school district level.[10] Students' innate abilities and peer effects are unobserved.

Aggregating (3) to the district level implies:

(4) $A_j = a_{A0} + a_{AP} P_j + a_{AS}S_j + a_{AF}F_j + a_{AR}R_j$

where A_j is average student achievement, P_j is the average of parental inputs, and F_j is the average of innate abilities of children in the district.[11]

Addressing the lack of observations of innate student abilities requires an assumption about the distribution of ability among students. Omitting F_j from an estimation based on (4) results in omitted variable bias (Hanushek 1979) and is

generally assumed to upward bias the coefficients of the parental characteristics variables (Zimmer and Toma 2000). We note that parents and their children are jointly mobile, and neither is part of the value-added of a school. This observation allows us to assume that students' innate abilities are a stochastic linear function of parental characteristics, with no loss of generality in terms of testing our focal hypothesis. We replace F_j in (4) by a constant, a linear term in P_j, and a random error ε_j, yielding:

(5) $A_j = a_{A0} + a_{AP}P_j + a_{AS}S_j + a_{AR}R_j + \varepsilon_j$

with a_{A0} and a_{AP} appropriately redefined.

While the above assumption addresses the problem of unobserved innate characteristics, a possible problem is that parents select a school district based on the innate abilities of their children, inducing a correlation between F_j and S_j or R_j. We argue that this behavior is unlikely. Utility maximizing parents will optimize their choice of schools by selecting the best school district they can afford given the market's implicit price for the educational quality of the locality.[12] Also, parents rarely send children of differing ability to different schools providing evidence that parents are not sorting among school districts based on their children's innate abilities.[13]

The quality of peers may be correlated with other factors explaining student achievement; specifically, with average parental characteristics or with a school district's purchased inputs. In general, we assume the statistical relationship can be described as follows:

(6) $R_j = d_{R0} + d_{RP}P_j + d_{RS}S_j + e_{Rj}$

where R_j measures peer effects and e_R is a mean zero random error.

Knowing the values for parental, school, and peer inputs to education, we substitute into the house price function (2), yielding:

(7) $\ln H_{ij} = c_{H0} + c_{HX}X_{ij} + c_{HP}\, P_j^* + c_{HS}\, S_j^* + c_{HR}\, R_j^* + \eta_{ij}$.

The variables P_j^*, S_j^*, and R_j^* represent measures of the impact of P_j, S_j, and R_j on student achievement; they are not the raw values of these variables. That is,

(8) $P_j^* = \hat{a}_{AP}P_j$; $S_j^* = \hat{a}_{AS}S_j$; $R_j^* = \hat{a}_{AR}R_j$.

Peer effects are difficult to observe and if R* is omitted from (5) or (7), the remaining coefficients may be biased.[14] The consequences for tests of our hypotheses are twofold. First, the expected values of the coefficients of P and S in the education production function when R is omitted are $E(\hat{a}_{AS}) = a_{AS} + a_{AR}\, d_{RS}$ and $E(\hat{a}_{AP}) = a_{AP} + a_{AR}\, d_{RP}$ (Kmenta, 1986: 450). It is plausible that $a_{AR} > 0$, $d_{RS} > 0$, and $d_{RP} \geq 0$, yielding upward bias in the coefficients of P and S in (5). This bias causes measurement errors in P* and S* as shown by inspecting (8). However, these measurement errors are the same multiple for all observations, thus the t-statistics and goodness of fit measure of these variables when inserted in the house value equation are unaffected; only the coefficients' values are affected. In addition, testing described later suggests that, for our sample, any bias that has been introduced by omitting peer effects is small. The implications of the omission of peer group effects from (7) for interpretation of the house value estimation are more serious. Even if P* and S* are measured without error, the expected values of the key coefficients in (7) would be biased: $E(\hat{c}_{HS}) = c_{HS} + c_{HR}d_{RS}$ and $E(\hat{c}_{HP}) = c_{HP} + c_{HR}d_{RP}$.

We address the issue of unobserved peer effects by using multiple observations of each district's educational outcome, with n designating the n-th observation in district j, n = 1…N. Instead of (5) we estimate:

(9) $A_{jn} = a_{A0} + a_{AP}P_j + a_{AS}S_j + \varepsilon_{jn}$.

Because all the observations of test scores in a district occur at the same time, the values of P_j and S_j do not vary over n. Another implication of the invariance of P_j and S_j

across the multiple observations for a district is that a fixed effects model cannot be estimated using this data set.

Using (5) and (6), we find that the estimation residual for the n-th observation of district j in (9) is:

(10) $A_{jn} - \hat{A}_{jn} = a_{AR}\, e_{Rj} + \varepsilon_{jn}$.

The first term on the right hand side of (10) is the coefficient of the peer group effect in the educational attainment equation multiplied by the random error of equation (6). The second term is the random error in the education production function. Of course, the expected value of $A_{jn} - \hat{A}_{jn}$ in the full sample is 0; however, the expected value of $A_{jn} - \hat{A}_{jn}$ in the j-th school district is $a_{AR}\, e_{Rj} \neq 0$. This nonzero value occurs because e_{Rj} in (9) is common to all N observations of the j-th district. The key point is that, for each district, we have multiple observations of the component of the peer group effect in (6) that is not correlated with either parental influences or district inputs. We define $R' = a_{AR}\, e_{Rj}$ and discuss its estimation in the next section of the paper.

Next, we substitute R' for R* in the house value equation (7):

(11) $\ln H_{ij} = c_{H0} + c_{HX}X_{ij} + c_{HP}\, P_j^* + c_{HS}\, S_j^* + c_{HR}\, R'_j + \eta_{ij}$.

Because, by construction, R' is uncorrelated with P and S, its inclusion does not affect the expected value of the estimates of $\hat{c}_{HP}$ and $\hat{c}_{HS}$, thus they may be biased. However, the coefficient of R' is an unbiased estimator of the coefficient of R* yielding an estimate, $\hat{c}_{HR}$, of the impact of K-12 public school peer groups on house values. If $\hat{c}_{HR} = 0$, student peers do not affect house values, and in this case, the coefficients of P* and S* in (11) are unbiased. Otherwise, some bias may be present depending on the size of the coefficient of R'.

The value-added model argues that both school inputs and peers affect house values. It also argues that parental effects on student achievement have no effect on

house values. Our analysis of biases indicates that the coefficient of P* in (10) may be nonzero even if there are no underlying parental effects. Thus, our key tests for the value-added hypothesis are of the values of c_{HS} and c_{HR}. Support for the value added hypothesis requires these coefficients to be positive, statistically significant, and reasonably large.

Downes and Zabel (2002) and Brasington (1999) find that average achievement levels are significant when explaining house values while their measures of value-added are not. We modify (11) to test the hypothesis that households use average student achievement to determine their bids for housing:

(12) $\ln H_{ij} = \forall_{H0} + c_{HX}X_{ij} + \forall_{HA} A_j + \eta_{Aij}$.

III. Data and Estimation

House price observations are based on transaction data for 1991 and are drawn from six urban areas in Ohio (Amerestate 1991). We eliminate central city school districts from the sample, leaving 123 suburban districts. A total of 27,232 house prices are observed. We use three measures of K-12 educational attainment in Ohio: the percentage of students passing all parts of the fourth, ninth, and twelfth grade proficiency tests administered to public schools students.[15] The average pass rate differs for the three tests because of differences in difficulty and in the minimum score for passing, so we measure the results as deviations from each test's mean.[16]

The hedonic house price equation includes vectors of house attributes contained in the Amerestate data and variables that measure amenities and disamenities across local governments (Office of Criminal Justice Services 1994; MESA Group 1994). Explanatory variables in the education production function are drawn from various sources including the Ohio Department of Education (1995) and the School District Data

Book (MESA Group 1994). These variables are similar to those in Haurin and Brasington (1996), who list detailed definitions in their data appendix.

Measures of school inputs in the education production function include the teacher-pupil ratio, teacher education (percent with MA degrees, percent with more education than a BA but less than a MA), teacher experience, the dropout rate, the attendance rate, and expenditures per pupil. Measures of parental inputs include their education (percent not finishing high school, percent completing high school but no further education), percent in poverty, average real income, percent two-parent families, percent Black, percent Hispanic, percent resident in the community for less than six years, and the percent homeowners.

House characteristics include lot size and its square, number of rooms and its square, garage size, number of full and half baths, house age and its square, and dummy variables for the presence of pools, decks, fireplaces, and air conditioning. Neighborhood variables include average household income, the crime rate, the percentage of minority households, and the effective property tax rate. House values tend to vary throughout the year so we include quarterly seasonal variables, omitting spring. We also include five dummy variables for the six major urban areas in Ohio that are the source of our data (Cleveland, Cincinnati, Columbus, Akron, and Dayton, omitting Toledo).

We first estimate the education production function in (9) for 123 districts and three test score results and calculate the residuals following (10). The average residual for each district is our estimate of R', the peer effect.[17] We then create P_j* and S_j* based on the estimation results. Finally, we estimate the house price equations (11) and (12), after correcting for heteroskedasticity.[18]

IV. Results

The estimation results for the reduced-form education production function are in Table 1. Due to the cross-sectional nature of the data, fixed and random effects models are inapplicable. However, the results of a Bera and Jarque (1980) test and correlation of regressors with residuals suggest that ordinary least squares is appropriate in this instance. The Bera and Jarque test cannot reject the null hypothesis of normally distributed errors for two of our three test grades, and previous education production functions using a similar data set have also passed this test for an absence of omitted variable bias (Brasington, 2002b).[19] As a further check, we note that omitted variable bias is a problem of the error term being correlated with included regressors. The correlation with least squares residuals is less than 0.10 in absolute value for all explanatory variables in all test sections, further suggesting that ordinary least squares will provide relatively unbiased parameter estimates.

All else constant, we find that the greater the percentage of parents with less than a high school degree or with only a high school degree, the lower are student test scores. The higher the percentage of parents in the district that are Black or Hispanic, the lower are average test scores. The greater the mobility rate in the district, the lower are test scores. Among the school input variables, the only significant findings are that the dropout rate is negatively related to test passage and that student attendance is positively related to test passage. Variations in real expenditures per pupil do not have a significant impact on test scores.

[INSERT TABLE 1 ABOUT HERE]

The estimate of the baseline hedonic house price equation in (11) is presented in Table 2. The coefficients of house and neighborhood characteristics all have the expected signs and their sizes are plausible. The key coefficients are those of P*, S*, and R'. All are positive and statistically significant. Because they are measured in the

same units (test score points), the coefficients can be directly compared. A Wald test confirms that they differ substantially in size.[20] The impact of the component of test scores attributable to parental characteristics is much larger than that of school inputs or peer effects. The relatively small size of the peer group coefficient suggests that the bias in the coefficient of P* is not serious.

[INSERT TABLE 2 ABOUT HERE]

The critical observation derived from Table 2 is that the value-added model is not supported. Very little value is attached to school inputs and peer effects. The impact of average parental attributes on house prices is much larger. Changing the parents' component from one standard deviation below the mean to one above the mean raises house values by 20 percent. The same change for the peer effect raises house values by only 1.3 percent.

[INSERT TABLE 3 ABOUT HERE]

Table 3 reports selected estimation results for an alternative model, which argues that only the aggregate level of achievement influences house prices. When A_j is substituted for the three components of average achievement, it has a positive and highly significant coefficient, and the adjusted R^2 falls by only a small amount. This result suggests that proficiency test results may be the key variable that bidders uses when determining offers for houses.

Spatial Statistics Approach

It is of course possible that our regressions omit factors important to the explanation of house prices. Downes and Zabel (2002) find that failing to account for unobserved effects does not bias the parameter estimates of the school quality variables, and our baseline model has included MSA dummies to capture any omitted influences that differ across urban areas. Still, Downes and Zabel's finding may be

specific to their data set, and MSA dummies may be inadequate controls for omitted variable bias. Therefore we employ spatial statistics as a more sophisticated technique for addressing omitted variable bias.

House price hedonic regressions with individual sale prices tend not to be statistically independent. In fact, tests for statistical independence often show spatial autocorrelation in the residuals. Such spatial autocorrelation is to be expected: the price of a given house is similar to the price of nearby houses, and this similarity diminishes with distance. Moreover, non-housing determinants of house value are not fully captured by the variables included in the hedonic regressions (LeSage 1997, 1998). Estimating a house price hedonic with ordinary least squares does not account for spatial dependence between observations, which may lead to biased, inefficient and inconsistent parameter estimates (Anselin, 1988, p. 58-59). A study by He and Winder (1999) demonstrates bi-directional price causality between three adjacent housing markets in Virginia, illustrating a case of spatial dependence in housing markets.

The spatial Durbin model can address the problem of spatial dependence in house value regressions (Pace and Barry, 1997a).[21] The spatial Durbin model includes a spatial lag of the dependent variable v as well as spatial lags of the explanatory variables in X:

(13) $v = \rho Wv + X\beta + W\underline{X}\alpha + \varepsilon$

where $\varepsilon \sim N(0,\sigma^2 I_n)$. In (13) the scalar term ρ is the spatial autoregressive parameter. It measures the degree of spatial dependence between the values of nearby houses in the sample. The W term is an n by n spatial weight matrix. It has non-zero entries in the i,jth position, reflecting houses that are nearest neighbors to each of the i homes in the sample. In this manner the spatial weight matrix W summarizes the spatial configuration of the houses in the sample.[22] Next, $\underline{X}$ is the explanatory variable matrix X with the

intercept excluded, and α is the parameter associated with the spatial lag of the explanatory variables.

The Wv term in (13) captures the extent to which the price of each house is affected by the price of neighboring houses (Bolduc et al., 1995; Griffith, 1988, p.82-83). For example, when a house is put on the market, the offer price is often set with the knowledge of the selling price of similar houses in the neighborhood. Multiple listing services publish offer prices and newspapers publish sale prices, thus offers and bids on houses are be influenced by offers and bids on nearby houses.

The $W\underline{X}\alpha$ term in (13) allows the structural characteristics of neighboring houses to influence the price of each house. A common saying in real estate is to never own the largest (or the smallest) house on the block: the market will force such a house to sell at a discount, an example of the type of impact captured by $W\underline{X}\alpha$. The $W\underline{X}\alpha$ term allows other structural characteristics of neighboring houses to affect the sale price of each house. Glower, et al. (1998) find that the degree that a house is atypical influences its time on the market and sale price, so it may be important to incorporate the structural characteristics of neighboring houses into the house price hedonic.

The $W\underline{X}\alpha$ term also captures the influence that the neighborhood characteristics of nearby houses have on the sale price of each house. Crime may impose negative externalities and therefore spill over across city boundaries. In addition, the tax competition literature suggests that the tax rate charged by a neighboring taxing jurisdiction will affect the tax rate chosen by the home jurisdiction, which may in turn affect house prices. The $W\underline{X}\alpha$ term allows for these types of spillovers.

The log-likelihood for the model in (13), concentrated with respect to the parameters β and σ, takes the following form (Anselin, 1988, p. 181; Pace and Barry, 1997a):

(14) $\ln L = C + \ln |I_n - \rho W| - (n/2)\ln(e'e)$

where: $e = e_o - \rho e_d$, $e_o = v - Z\beta_o$, $e_d = Wv - Z\beta_d$, $\beta_o = (Z'Z)^{-1}Z'v$, $\beta_d = (Z'Z)^{-1}Z'Wv$,

$Z = [X\ WXI_n]$, and C is a constant term that does not involve the parameters.

The need to compute the log-determinant of the n by n matrix $(I_n - \rho W)$ makes it computationally difficult to solve the maximum likelihood problem in (14). Operation counts for computing this determinant grow with the cube of n for dense matrices. However, the matrix W is sparse. The sparsity of W may be exploited (Pace, 1997; Pace and Barry, 1997a) so that a personal computer can handle the 27,233-observation regression with computational ease. The Cholesky decomposition is used in Barry and Pace's (1999) Monte Carlo estimator to compute the log-determinant over a grid of values for ρ restricted to the interval [0,1].

The sparse spatial Durbin procedure has been demonstrated to greatly improve cross-sectional regression estimates that are spatial in nature (Pace, 1998; Pace and Barry, 1997b). Part of the improvement stems from incorporating the influence of omitted variables (Anselin, 1988, p.103; Pace, Barry and Sirmans, 1998). Alternative methods to address the problem include using highly aggregated dummy variables, focusing on narrow geographic areas where many influences are already controlled, or including a very large number of explanatory variables. Still, using aggregate dummy variables does little to capture localized sources of omitted variable bias. Studies with limited geographic coverage have limited appeal, and structural characteristics may be similar within small areas so that multicollinearity problems are exacerbated. In addition, no matter how large the number of explanatory variables, regressions may still omit important influences like air quality, landscaping quality, and proximity to parks. Because it incorporates the influence of omitted variables, spatial statistics can improve explanatory power and reduce the parameter estimate bias that generally results from

omitting a relevant variable. A detailed proof of how spatial statistics achieves consistent and unbiased parameter estimates, unbiased estimates of the standard errors, and efficient parameter estimates where least squares may not, is available in Griffith (1988, p. 94-107).

The results for the spatial model are reported in the lower panel of Table 3. The adjusted R-squared has risen from 0.66 in the least squares model to 0.95 in the spatial model. The 0.77 estimate of ρ suggests strong spatial dependence in the data, possibly stemming from the captured influence of spillovers and omitted variable bias. We find that the coefficient of the school input component of student achievement becomes negative and loses its statistical significance. Even more than the least squares model, the spatial model suggests little role for a school's value added. There also is evidence of the upward bias in the parent component: the non-spatial model had a coefficient estimate of 0.019, while in the spatial model the estimate drops to 0.014. However, the coefficient of the parent component continues to be much larger than that of the peer effect.

V. Conclusions

Our results reject the hypothesis that the market price of housing reflects the value added to student achievement by a school district. We find that the coefficient of the variable measuring the impact of school inputs on student achievement is small and it is not consistently statistically different than zero in house value regressions, particularly in regressions that control for the effects of omitted variables.

We find evidence that households value the quality of peer group influences in a school district; however, the impact is small. A change in the peer effect from one standard deviation above the mean to one standard deviation below the mean lowers house values by 1.3 percent, this equaling about $1,100 in our sample.

We find that positive parental influences on student achievement are highly valued in the housing market. A change in the parental influence measure from one standard deviation below the mean to one standard deviation above the mean implies a 20 percent increase in house value. We also find that the average level of student achievement performs nearly as well as a decomposition of student achievement into peer, parental, and school effects in the house price estimation.

These findings must be interpreted in the context of the hedonic price model. We know from Rosen's 1974 analysis that the coefficients in the hedonic housing price equation reflect market values, not supply or demand. Interpretations of why the housing market values particular inputs or outputs are speculative. Still, it is tempting to suggest that average student achievement affects house prices because it is readily observable. Peer effects and school effects are less easily observed, so households seem to use more easily observed parental characteristics (race and education) or proficiency test outcomes as the key factor in comparing public school quality among school districts.

From an empirical perspective, it is much easier to include a district's proficiency test scores in a hedonic house price estimation than to include a set of school inputs and proxies for peer group effects or parental characteristics. Thus, we find support for the increasingly common practice of including K-12 test scores as a control variable in hedonic house price equations.

If the own-parent impact on the education of a child is portable among school districts, why are parents' attributes valued in the housing market even when controlling for racial composition, crime rates, household income, and tax rates? Perhaps parental characteristics, such as high levels of education, are valued because these parents continually apply pressure to school administrators for better performance and for delivery of a high quality education. Using Rosen's underlying framework for hedonic

models as guidance, the results suggest that the set of communities with favorable parent characteristics may be in short supply compared with household demand, bidding up their market price.

Our results suggest that the school-specific component of school quality, that is, the value-added of a school, is not highly valued by the housing market. If the housing market provides a valid assessment of the value-added approach to measuring school quality, our results question the use of value-added in the education and labor economics literatures. However, our results do not necessarily make value-added an inappropriate measure of school quality for policymakers. Policymakers may wish to reward schools for improvement, rather than for absolute levels of achievement. Still, our results suggest that the value-added of a school is not the measure of school quality that homeowners use when they decide which house to buy.

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Table 1: Estimation of the Education Production Function: Dependent Variable is Student Test Score[1]

Variable	Coefficient	t-statistic	Mean
Constant	-59.52	1.16	
% With Both Parents	-1.58	0.16	0.79
% Parents with Education less than H.S. Diploma	-23.94	2.47	0.11
% Parent with Education of only H.S. Diploma	-32.63	5.36	0.34
% Parents in Poverty	14.37	0.78	0.06
Average Household Real Income ($000)	-0.01	0.25	39.21
% Homeowners	1.57	0.25	0.74
% Black Households	-19.30	5.56	0.08
% Hispanic Households	-41.36	2.42	0.01
% Households Residing in Locality for Less than 6 Years	-15.49	2.17	0.44
Teacher-Pupil Ratio	-143.30	1.52	0.06
% Teachers with Education > BA but < Masters Degree	-1.98	0.33	0.29
% Teachers with Education > Masters Degree	5.51	0.91	0.48
Average Teacher Experience in Years	-0.10	0.48	15.48
Student Attendance Rate	0.92	1.71	94.75
Student Drop Out Rate	-0.67	2.50	2.86
Real Expenditures per Pupil ($000)	0.89	1.28	4.99
Sample Size	369		
Adjusted R-square	0.63		

[1] The mean test score (normed) is 0.0 with standard deviation of 10.9.

Table 2: Estimates of Log of House Prices[1]

Variable	Coefficient	t-statistic	Mean
Intercept	10.137	91.17	
Achievement: Parents' Component (P*)	0.019	21.65	
Achievement: School Component (S*)	0.004	3.16	
Achievement: Peer Group Component (R')	0.002	3.30	
Air Conditioning	0.079	17.23	0.43
Fireplace	0.126	28.12	0.45
Lot Size (0000)	0.119	17.63	1.24
Lot Size-squared	-0.014	10.35	2.53
Age (10)	-0.028	9.31	3.54
Age-squared	-0.001	5.33	17.58
Number of Rooms	0.122	10.45	6.29
Number of Rooms-squared	-0.004	4.02	41.25
Garage	0.146	23.69	0.90
Number of Full Baths	0.136	27.32	1.38
Number of Partial Baths	0.101	22.74	0.42
Deck	0.055	9.89	0.14
Pool	0.060	4.10	0.02
2nd Quarter	0.052	9.61	0.31
3rd Quarter	0.055	9.95	0.28
4th Quarter	0.055	9.52	0.23
Akron	-0.049	4.68	0.08
Cincinnati	-0.009	1.02	0.17
Cleveland	0.063	7.15	0.39
Columbus	-0.033	3.75	0.13
Dayton	0.013	1.44	0.17
Crime Rate	-1.500	5.65	0.01
% Minority Households	-0.090	2.96	0.08
Average Real Household Income (000)	0.003	8.27	38.98
Effective Property Tax Rate	0.373	0.98	0.03
Sample Size	27,233		
Adjusted R-square	0.658		

[1]The mean of the log of house price is 11.23.

Table 3: Comparative Results for other House Price Estimations[1]

Variable	Coefficient		t-statistic
Average Achievement Only			
Average Student Achievement	0.008		17.94
Adjusted R-square	0.653		
			Likelihood Ratio
Spatial Model			
Achievement: Parents' Component (P*)	0.014		128.8
Achievement: School Component (S*)	-0.005		4.2[a]
Achievement: Peer Group Component (R')	0.003		5.2
Adjusted R-square	0.95		
Estimated spatial autocorrelation coefficient	0.77		

[1] Dependent variable is log house prices. All estimations include the complete set of control variables. To conserve space, we present only the results for our focal variables. Full regression results are available upon request.
[a]Fails to exceed the critical likelihood ratio of 4.61 at the 0.10 level of significance.

ENDNOTES

[1] While not necessarily the most appropriate measure of value-added, improvement in test scores is a type of value-added measure (Hanushek and Taylor 1990). Some states' accountability for improvement lies at the school level, such as Kentucky, while other states such as Tennessee hold individual teachers and students accountable for improvement.

[2] The wealth increase for the owner of the median valued home would be about $29,500.

[3] Early studies using K-12 test scores in house price estimations include Sonstelie and Portney (1980), Li and Brown (1980), and Jud and Watts (1981). All find that test scores positively affect house prices.

[4] Support for the hypothesis that peers influence student achievement is found in Summers and Wolfe (1977), Henderson et al. (1978), and Betts and Morell (1999). Evans et al. (1992), in a study of teenage pregnancy, finds evidence of peer effects in a single equation estimation, but when parental sorting among localities is accounted for in a 2SLS estimation, the peer effects tend to disappear.

[5] Their model is closely based on Hanushek and Taylor (1990).

[6] Hayes and Taylor (1996) refer to the component of achievement that is not a school effect as a peer effect. Their definition of peer effects includes family effects on educational attainment, but peers and own-families have different impacts on achievement. Also, it is curious that they do not expect peer groups (which are school-specific) to affect house values in the same way that school inputs affect house values.

[7] Hayes and Taylor (1996) identify school-specific effects based on one-year changes in educational outcomes (fifth to sixth grade). However, the housing market should value school-specific effects for all grade levels. These prior effects are imbedded in their A_{jt-1}

variable and its contribution is not counted as part of their measure of school-specific value-added.

[8] Brasington (1999) also uses a spatial autocorrelation model to estimate house prices and still finds proficiency levels more consistently capitalized, but the results are weaker.

[9] Our assumed form of educational production function is the same as that made by Zimmer and Toma (2000).

[10] Only twelve of our 123 school districts have more than one high school, so the 9th and 12th grade outcomes are observed at the individual school level for over 90% of the sample.

[11] We assume that children are distributed equally among households in the district.

[12] Epple and Romano (1998) discuss the evidence about the differential impact of peers on students of differing innate ability levels. They conclude that there is no compelling empirical evidence supporting any particular differential impact.

[13] Altonji and Dunn (1996) find no evidence that siblings of differing motivation level and ability attend different schools. Only 20% of their sibling sample attended different schools, and most of those cases involved relocation and divorce. In only five percent of their sample did one sibling attend private school while another did not. Other studies assume that omitted ability of a child does not bias parameter estimates because innate ability may be "unknown to parents, or, if known, may not be acknowledged in the decision process [of parents]" (Rosenzweig and Wolpin, 1994, p. 678).

[14] Although we assume that R_j* represents peer effects, it also captures other unobserved district-specific fixed effects that influence educational attainment and are valued by home buyers.

[15] The tests include reading, math, citizenship, science, and writing components.

[16] The standard deviations of the three tests are similar: 3.14, 3.31, and 3.43 for the fourth, ninth, and twelfth grade tests.

[17] The range of R' is from -10.32 to 12.93. The standard deviation is 4.09.

[18] We test for heteroskedasticity using White's test. With a critical value of 49.6 at the 1% level of significance, our calculated test statistic of 1008.0 rejects the null of homoskedasticity. Possible generated regressor bias and heteroskedasticity are addressed using an appropriate weighting scheme, as detailed in Brasington (2002a).

[19] With a critical LM of 9.21, the 4th, 9th, and 12th grade tests show calculated LM values of 13.2, 6.5, and 3.95. Brasington (2002b) uses an education production function based on 1992 Ohio math proficiency test outcomes and cannot reject the null for either his urban or rural samples.

[20] The Wald F for the test of equality of the three coefficients is 143, substantially greater than the 1% critical value of 4.6.

[21] The spatial Durbin model is also known as the unrestricted version of the mixed regressive spatially autoregressive model with common factor specification.

[22] LeSage (1997) presents an intuitive discussion of the spatial weight matrix and of spatial statistics in general.