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ABSTRACT

We use house price hedonics to compare the extent that homeowners value traditional measures of school quality or the “value added” of schooling. Unlike other studies, we use spatial statistics as an identification strategy. Based on our study of 310 school districts and 77,000 house transactions, we find little support for the value added model. Instead, we find that households consistently value a district’s average proficiency test scores and expenditures. The elasticity of house prices with respect to school expenditures is 0.49 and an increase in test scores by one standard deviation, ceteris paribus, raises house prices by 7.1%.

Educational Outcomes and House Values: A Test of the Value added Approach

"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)

A large body of literature investigates the relation between house prices and public school quality. Over the years, proficiency test results have replaced expenditures as the most widely accepted measure of school quality in hedonic house price regressions. But education and labor economists increasingly claim that school achievement is not the proper measure of school quality. Instead, this 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 and teachers whose students 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. Information derived from the housing market can help decide this question. However, little work has been done in this area.

Capitalization of school quality into house prices affects many households. In the second quarter of 2004, 69.2 percent of U.S. households were homeowners, and there were over 73 million owner-occupied housing units (U.S. HUD 2004). We find that house prices vary by about 14% 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 nearly $26,000. Thus, the issue about capitalization of school quality into house prices affects many U.S. households and the size of the impact is substantial.

We measure the amount of capitalization of various schooling measures into 77,000 houses sold in 2000 in Ohio. We find strong support for the capitalization of student proficiency tests and school expenditures into house values but, using a variety of formulations, we find little evidence of capitalization of value added measures. Therefore, regardless of how much better value added may be as a measure of the performance of school inputs, only the levels of test scores and expenditures are capitalized. This apparent contradiction can be reconciled by recognizing that households' choices determine capitalization and that their choices are influenced by the information available to them. In our sample, more information is available about test score outcomes than about any value added measure of school quality. We discuss the various strategies used in the literature to account for omitted neighborhood variables. Our approach is to include neighborhood controls and use spatial statistical estimation methods.

1. 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.[2] For example, 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.[3]

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 ($\mathbf{A}_{jt}$) into the expected effect derived from parental inputs and a school district specific residual:

$$\mathbf{A}_{jt} = \mathbf{b}_o + \mathbf{b}_1\mathbf{P}_j + \mathbf{b}_2\mathbf{A}_{jt-1} + \mathbf{e}_j \tag{1}$$

where $\mathbf{P}_j$ represents parental characteristics, $\mathbf{A}_{jt-1}$ is the prior year's achievement, and $\mathbf{e}_j$ is the random error in district *j*.[4] 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 non-parental inputs to school outcomes.[5] Using a sample of only 288 houses, 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 $\mathbf{P}_j$ and $\mathbf{A}_{jt-1}$, 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 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.[6]

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. 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. Ries and Somerville (2004) criticize Downes and Zabel for their reliance on the American Housing Survey, which means they cannot match houses precisely to census tracts, school districts, or municipalities.

Brasington (1999) also studies which measures of educational outcomes are capitalized into house prices. He compares 37 measures of school quality, including expenditures per pupil, proficiency test results, and value added measures. Running 444 standard hedonic housing estimations, he finds that significant explanatory variables include proficiency test results and expenditures per pupil, but not the value added measures.[7] Brasington's value added measures capture changes in a school district's performance relative to other school districts in the state, which follows the spirit of value added. But Brasington's value added measures track performance changes relative to the entire state, not the urban area of each school district, which is the more relevant measure. Further, Brasington's value added measures are calculated using only a single year's (1996) proficiency test data. The failure to follow a cohort over time means the 4th, 9th and 12th grade students in 1996 may have different demographic characteristics, which Brasington's value added measures do not control 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. Figlio and Lucas (2004) find that proficiency tests and state-assigned grades for elementary school are capitalized into the price of Florida houses in 1999-2001. Brasington (2000) finds that Ohio proficiency test scores are positively capitalized into 1991 house prices. Sieg et al. (1999) find that math proficiency test scores are positively related to the price of California housing in 1987-1995.

Despite the rising interest in value added and the recent use of proficiency tests scores in house price studies, some studies continue to use expenditures to measure school quality. Examples include Bradbury et al. (2001), Hilber and Mayer (2002), and Brasington (1999). In fact, Brasington (1999) finds expenditures per pupil are consistently capitalized into house prices, although he includes no regression in which proficiency tests and expenditures appear simultaneously.

Much attention has been devoted to the identification of school quality effects in house price hedonics. Black (1999) advocates the "boundary fixed effects approach", which has been applied to school quality capitalization studies since Gill (1983) and Cushing (1984). This approach compares the relation between house prices and school quality on two sides of a single school district's attendance borders (catchment zones). Black assumes that the neighborhood characteristics do not change across the border, this being an important, but somewhat questionable, assumption. Houses near both sides of a border are assigned the same value for a dummy variable that indicates a boundary between schools. Black argues that this dummy variable captures the observed and unobserved neighborhood characteristics shared by houses on either side of the border. Thus, any remaining difference in house price is attributable to differences in school quality. House price regressions include as explanatory variables the observable house characteristics and the boundary dummy variables. Black estimates regressions that follow both the standard approach and the boundary approach and finds a lower rate of capitalization of school quality into house prices using the boundary approach, although the effect remains statistically significant and large. This result suggests that studies that do not control for omitted neighborhood characteristics overestimate the relationship between house prices and school quality.

Recently, the boundary fixed effects approach has come under attack. Clapp, et al. (2004) criticize the boundary approach on three grounds: (1) attendance zones change (Cheshire and Sheppard, 2002), (2) capitalization is weaker toward the edge of an urban area (Brasington, 2002a), and (3) household sorting is not controlled because buyer characteristics are omitted. Furthermore, while Black (1999) assumes no or very gradual change in neighborhood characteristics across school attendance borders, Kane, et al. (2003) find a discontinuous change in income levels, building quality index, square footage and other characteristics at the school boundaries. Even when the boundary changes, discontinuities in income levels and building quality appear along the new boundary, making it problematic to use the boundary fixed effect approach to identify school quality. Another problem with Black's approach is one of sample size. In order to better control for neighborhood quality and have the sample match the assumption of equal neighborhood quality on either side of a school boundary, houses farther away from school boundaries are excluded from the sample. The tighter the limit on distance to the boundary, the smaller is the sample. That is, Black's (1999) approach disregards thousands of observations because they are not near a school catchment area's boundary.

Other research specifically compares the boundary fixed effect approach to other methods and finds that estimates derived from using the boundary approach are biased (Chiodo, et al., 2004) or have a theoretically incorrect sign (Lacombe, 2004). Clapp, et al. (2004) use panel data methods to measure the effect of test scores on house prices. They find that school quality capitalization effects are smaller than that found using the standard method when fixed effects dummies control for omitted neighborhood characteristics.

Dills (2004) examines many aspects of school quality capitalization. Her house price data are aggregated to the district level, this problematic for a study of capitalization. She finds in a cross sectional regression that levels of proficiency test scores are capitalized; however, she finds that changes in test scores are not related to changes in levels of aggregate house value. Dills also finds that the relation between school quality and house values disappears when a fixed effects panel is estimated.

Ries and Somerville (2004) use data from a natural experiment to test for capitalization. In their case, catchment areas were changed by the school district and thus can be interpreted as a permanent change in school quality for the affected set of houses. They also argue that temporal variations in school quality measures have a significant component of random variation, a claim we agree with. Even if the change in scores over time accurately reflects quality, households may perceive these short term changes as random fluctuations and thus not value them. Ries and Somerville (2004) correctly note that this measurement error in school quality that is present in typical panel data sets will downwards bias the estimate of the effect of school quality. In their preliminary regressions they find results generally similar to Black: without controlling for fixed effects, there is a very strong relationship between house prices and school quality, and it diminishes but remains significant when fixed effects dummies or boundary dummies are included. Next they use a panel data approach with their unique data set and find that changes in school quality affect house prices, but only for changes in secondary school quality.

In summary, the literature through 1999 found a strong positive relationship between house prices and school quality as measured by test scores. Since then, there has been recognition that omitting neighborhood factors may bias the results. Recent empirical studies using the boundary fixed effects method found that use of simple cross-sectional OLS methods results in upwards bias of the size of the house price-test score relationship. Findings using the boundary method generally remain positive and significant. However, the latest generation of studies suggests there is no consensus about the best method for accounting for omitted neighborhood effects.

2. A MODEL OF HOUSE PRICES AND K-12 PUBLIC SCHOOL OUTCOMES

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:

$$\ln \mathbf{H}_{ij} = \mathbf{c}_{H0} + \mathbf{c}_{HX}\mathbf{X}_{ij} + \mathbf{c}_{HY}\mathbf{Y}_j + \varepsilon_{ij} \tag{2}$$

where $\ln \mathbf{H}_{ij}$ is the natural logarithm of house value for the *i*-th house and household in the *j*-th school district, $\mathbf{X}_{ij}$ represents house characteristics including quality of neighborhood indicators, and $\mathbf{Y}_j$ is the set of educational outcomes or inputs that are valued by households. Candidates for measures of $\mathbf{Y}_j$ include the average level of educational attainment by children in the district ($\mathbf{A}_j$), per-pupil expenditures ($\mathbf{\$}_j$), or the value added by the district ($\mathbf{V}_j$).

3. DATA DESCRIPTION

House price observations are based on transaction data for the year 2000 and are drawn from seven urban areas in Ohio (FARES 2002). A total of 77,578 house prices are observed, spanning 310 school districts. School quality is measured by expenditures per pupil, proficiency tests, and value added.[8] Our proficiency test measures are the percentage of students passing all parts of the fourth and ninth grade proficiency tests administered to public schools students.[9] The average pass rate differs for the tests because of differences in the test's difficulty and in the minimum score for passing, so we measure the results as deviations from each test's mean.[10]

The hedonic house price equation includes vectors of house attributes contained in the housing data. House characteristics include the age of the house and its square, the number of full and partial bathrooms, the number of fireplaces, square footage of the house and acres of land, and dummy variables for one-story houses and the presence of decks and central air conditioning. Neighborhood variables include air quality, the property tax rate, a measure of racial heterogeneity, income levels, and the crime rate.

Measures of parental inputs in the education production include marital status, racial composition, education levels, income levels, occupation type, and the percent homeowners. Variable definitions, sources, and means for all house price hedonic and education production function variables are given in Table 1.

[INSERT TABLE 1 ABOUT HERE]

4. CREATING THE HAYES AND TAYLOR VALUE ADDED MEASURE

We must estimate an education production function to derive the value added measure of Hayes and Taylor (1996). The estimation results for the reduced-form education production function are in Table 2. 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, and previous education production functions using a similar data set also have passed this test for the absence of omitted variable bias (Brasington, 2002b).[11] 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, further suggesting that ordinary least squares will provide relatively unbiased parameter estimates.

Following Equation (1), we regress year 2000 ninth grade proficiency test passage rates as a function of a variety of parental controls and fourth grade proficiency test passage for the same cohort of students; that is, this cohort's passage rate for 1995. The results are shown in Table 2. All else constant, fourth grade proficiency passage explains most of the variation in ninth grade proficiency passage. The only other statistically significant findings are a negative relation between the percentage of single-parent households and test passage, and a positive relation between percent white and test passage. The residuals from this regression capture the value added of a school district in the style of Hayes and Taylor (1996).

[INSERT TABLE 2 ABOUT HERE]

It is possible that fourth grade test scores have significant interactions with parent characteristics. For example, highly educated parents who are disappointed with fourth grade test results may exert additional effort to improve student performance by the ninth grade. If so, the value added measure of Hayes and Taylor should be based on a regression that includes these interaction terms. The results of this alternative education production function are shown in the final column of Table 2. Three of the interaction terms are statistically significant, but a test for joint significance fails to reject the null hypothesis of no significance at the 1% level.[12] Throughout the study, we use the

HAYES-TAYLOR VA measure based on the first regression, although nearly identical results are achieved with the alternate measure.

5. RESULTS: NON-SPATIAL FULL SAMPLE HOUSE PRICE HEDONICS

We first estimate a house price hedonic in Equation (2) that takes the following form:

$$\ln \mathbf{H}_{ij} = \mathbf{c}_{H0} + \mathbf{c}_{HX}\mathbf{X}_{ij} + \mathbf{c}_{HA}\mathbf{A}_{j} + \mathbf{c}_{H\$}\mathbf{\$}_{j} + \varepsilon_{ij} \tag{3}$$

where $\mathbf{A}_j$ is achievement in school district *j*, measured by PROFICIENCY 9, and $\mathbf{\$}_j$ is EXPENDITURES per pupil. The first column of results in Table 3 shows the regression results with no attempt to control for neighborhood characteristics.

[INSERT TABLE 3 ABOUT HERE]

The No Controls column of Table 3 shows both test scores and expenditure per pupil are valued by the housing market when no attempt is made to control for neighborhood characteristics.[13] Black (1999), Clapp et al. (2004), Dills (2004) and Ries and Somerville (2004) all find that the value of school quality falls when neighborhood controls are taken into account.[14] The latter three papers use fixed effects dummy variables to control for neighborhood characteristics. We include county fixed effect dummy variables in our regression and re-estimate Equation (3). The parameter estimate of PROFICIENCY 9 drops slightly from 0.0059 to 0.0055, while EXPENDITURES drops markedly from 0.063 to 0.035. Thus, we also find that controls for omitted variables reduce the estimated size of school quality capitalization.

Gujarati (2003, p. 646) notes that fixed effects models can introduce multicollinearity problems, which may greatly affect the validity of regression results. Instead of using the fixed effects approach, we first include a set of neighborhood controls that vary within a county.[15] In the Neighborhood Controls column of Table 3, we include explanatory variables for air quality, racial composition, income levels, the tax rate, and the crime rate, these measured at more localized levels down to the census block group. The school quality parameter estimate drops from 0.0059 in the No Controls regression to 0.0037, and the expenditures parameter estimate drops from 0.063 to 0.052.[16] The change in coefficients suggests that omitted neighborhood characteristics bias school quality parameters upwards. However, both parameter estimates remain statistically significant. Below, we augment this technique with a more theoretically appealing identification strategy, spatial statistics.

6. SPATIAL STATISTICS APPROACH TO HOUSE PRICE HEDONIC ESTIMATION

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, determinants of house value are not fully captured by the variables included in the hedonic regressions (LeSage 1997, 1999). Estimating a house price hedonic with ordinary least squares does not account for the spatial dependence between observations, which may lead to biased, inefficient, and inconsistent parameter estimates (Anselin, 1988, p. 58-59).

The spatial autoregressive model can address the problem of spatial dependence in house value regressions. The spatial autoregressive model includes as explanatory variables a "spatial lag" of house price **H** along with the explanatory variables in **X**:

$$\mathbf{H} = \rho\mathbf{W}\mathbf{H} + \mathbf{X}\beta + \varepsilon \tag{4}$$

where the error term $\varepsilon \sim N(0, \sigma^2\mathbf{I}_n)$. In Equation (4) 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. The spatial weight matrix **W** summarizes the spatial configuration of the houses in the sample.[17]

The $\rho\mathbf{WH}$ term in Equation (4) captures the extent to which the price of each house is related to 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 log-likelihood for the model in Equation (4) takes the following form (LeSage, 1999, p. 64):

$$\ln L = -(n/2) \ln (1/n) (\mathbf{e}_o - \rho\mathbf{e}_L)' (\mathbf{e}_o - \rho\mathbf{e}_L) + \ln |\mathbf{I}_n - \rho\mathbf{W}| \tag{5}$$

$$\mathbf{e}_o = \mathbf{H} - \mathbf{X}\hat{\beta}_o \tag{6}$$

$$\mathbf{e}_L = \mathbf{H} - \mathbf{X}\hat{\beta}_L \tag{7}$$

where n is the number of observations, $\hat{\beta}_o$ in Equation (6) is the matrix of parameter estimates from an ordinary least squares regression $\mathbf{H} = \mathbf{X}\hat{\beta}_o + \varepsilon_o$, and $\hat{\beta}_L$ in Equation (7) is the matrix of parameter estimates from an ordinary least squares regression $\mathbf{WH} = \mathbf{X}\hat{\beta}_L + \varepsilon_L$.

The need to compute the log-determinant of the n by n matrix $(\mathbf{I}_n - \rho\mathbf{W})$ makes it computationally difficult to solve the maximum likelihood problem in Equation (5). Operation counts for computing this determinant grow with the cube of n for dense matrices, so that most papers using spatial statistics are limited to a few thousand observations. However, the matrix **W** is sparse. The sparseness of **W** may be exploited (Pace, 1997; Pace and Barry, 1997) so that a personal computer can handle the 77,578 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 autoregressive model has been demonstrated to greatly improve cross-sectional regression estimates that are spatial in nature.

Of importance to our analysis is the improvement in the estimation that stems from incorporating the influence of omitted variables (Anselin, 1988, p.103; Pace, Barry and Sirmans, 1998). The identification strategies of Dills (2004), Black (1999), Ries and Somerville (2004), and Clapp, et al. (2004) all involve the use of dummy variables. Specifically, Dills (2004) uses school district dummy variables, Ries and Somerville (2004) use east-west, neighborhood, and border dummy variables, and Clapp, et al. (2004) use town and Census tract dummy variables. The spatial autoregressive term $\rho\mathbf{WH}$ from Equation (4) acts like a highly localized dummy variable capturing highly localized influences common to just the nearest neighbors of each house, such as the presence of an abandoned house nearby, while still capturing county-wide, school district-wide, and Census tract-wide influences. Thus, the spatial technique has advantages over many traditional fixed effect models.

The border dummy variables used by Black (1999), Gill (1983) and Cushing (1984) deserve special comparison. The borders upon which border dummies are based have only as much width as the researcher allows, typically between 0.25 to one mile on either side of the border, potentially capturing even more localized influences than spatial statistics. On the other hand, school attendance borders can be several miles long. A neighborhood can change dramatically over several miles, but the border dummies average these neighborhood influences over these several miles.[18] Because of the small geographic area covered, spatial autoregressive models that use nearest neighbors capture something close to an individual fixed effect for cross-sectional data. An alternative, intuitive explanation of how spatial statistics absorbs omitted variables may be found in Brasington and Hite (2004); a detailed mathematical proof is available in Griffith (1988, p. 94-107). In a direct comparison, Lacombe (2004) finds that spatial statistics gives more theoretically consistent results than the borders approach.

7. RESULTS: SPATIAL HOUSE PRICE HEDONICS

The spatial autoregressive model of Equation (4) is estimated, retaining the neighborhood control variables. The results for the spatial model are reported in the Spatial Plus Neighborhood column of Table 3. The spatial autoregressive term is statistically significant, but the parameter estimate of ρ is 0.013, suggesting that the neighborhood controls already absorb a good deal of spatial influence.[19] The spatial model reduces the PROFICIENCY 9 parameter estimate imperceptibly from 0.0037 to 0.0036 and the EXPENDITURES parameter estimate rises from 0.052 to 0.061. Our results suggest that the housing market values higher levels of both school expenditures and proficiency test passage. At the mean value of expenditures, the elasticity of house prices is 0.49. An increase in the test score of one standard deviation (19.8) raises house prices by 7.1%, ceteris paribus.[20]

Does the housing market capitalize measures of the value added of schooling? The first measure of value added we examine is HAYES-TAYLOR VA. The first two columns of results in Table 4 summarize the results. When we include only the HAYES-TAYLOR VA measure (as well as all the control variables), the coefficient of the value added measure is positive and statistically significant.[21] However, in a head to head competition with the level of test scores, we find their measure of value added is not capitalized by the housing market. In fact, all else constant, higher levels of HAYES-TAYLOR VA are associated with declining house prices.[22]

[INSERT TABLE 4 ABOUT HERE]

The next value added measure we examine is that of Downes and Zabel (2002). Their value added measure controls for past performance and asks how current performance by the same cohort is related to house prices. The results of the full-sample, spatial hedonic are found in the Downes-Zabel VA column of Table 4, where both the test score outcome for fourth and ninth grades are found to be positive and significant. Downes and Zabel (2002) state that in their formulation, if value added is capitalized rather than current performance, then the coefficient of the lagged score should be negative and that of the current score will equal the negative of lagged score.[23] In neither their results nor ours is this true.[24]

The final value added measure is based on Brasington (1999). However, unlike the measure used by Brasington (1999), the value added measure used here is based on a comparison of a single cohort across time. It also tracks changes in performance relative to the metropolitan area, not the state. Even with these corrections, BRASINGTON VA is negative in the final column of Table 4. The results suggest that Brasington's (1999) measure of value added does not signal school quality for home buyers, and that households do not value improvements in school achievement between grades 4 and 9 relative to their neighbors.

The consistency of the results can be seen by moving from the full sample regression to separate regressions for each metropolitan area: Akron, Cincinnati, Cleveland, Columbus, Dayton, Toledo, and Youngstown. Each regression uses the spatial autoregressive model with the neighborhood controls. The first experiment is to always include EXPENDITURES and PROFICIENCY 9, and to also include one of the value added measures.[25] The results are summarized in Table 5.

[INSERT TABLE 5 ABOUT HERE]

The first two columns report the results for each MSA when both EXPENDITURES and PROFICIENCY 9 are included, but no other school quality measure. PROFICIENCY 9 is positive and significant in all metropolitan areas, while EXPENDITURES is positive and significant in five, negative and significant in one, and insignificant in one. We then include one of the competing value added variables in the estimation with results reported in the next three columns. The value added measure of Hayes and Taylor (1996) is never positive and significant. The value added measure of Downes and Zabel (2002) varies widely. The Brasington (1999) measure is negative in five of the seven regressions, and statistically insignificant in the other two. None of the value added measures perform better than the proficiency test score in the head-to-head competition.

The next experiment is to include only one measure of school quality at a time, which alleviates any multicollinearity with the expenditures and proficiency test measures. The full set of neighborhood controls and the spatial autoregressive model are used. The results are summarized in Table 6.

[INSERT TABLE 6 ABOUT HERE]

The value added measure of Hayes and Taylor (1996) performs better alone than when it competes with other school quality measures, but it has a positive, significant relation with house prices in only four out of seven metropolitan area regressions and it is negative in two. Results for the Downes and Zabel and Brasington variables are very mixed with no consistent evidence that they represent measures that are valued by the population. When entered solely by itself, the performance of expenditures per pupil has worsened, now showing a positive association with house prices in only four of seven MSAs. But proficiency test scores remain significant and positively related to house prices in all seven metropolitan areas.

8. CONCLUSIONS

Our results reject the hypothesis that the market price of housing reflects the value added to student achievement by a school district. We calculated value added by tracking the achievement of a cohort of students over time, from fourth to ninth grade. We find that the value added of schools is not consistently capitalized into house prices regardless of what measure is used.[26] This result occurs both for the full sample and for samples from seven metropolitan areas.

We find greater support for the capitalization of school expenditures and proficiency test scores. The most consistently valued measure of school quality is proficiency test score. It is positive and significant when entered alone or with per pupil expenditures for the full sample and all metropolitan area samples. It is positive and significant in all 21 regressions. An increase in test scores by one standard deviation, ceteris paribus, raises house prices by 7.1%. Expenditures have a positive and significant relationship with house prices in 16 of the 21 regressions. The elasticity of house prices with respect to per-pupil expenditures of 0.49. In contrast, no value added measures are consistently related to house prices. The measures of Hayes and Taylor have the expected sign in only five out of 16 regressions, and those of Downes and Zabel and of Brasington have the expected sign in three out of 16 regressions each.

A number of caveats must be listed. First, the 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. Thus, interpretations of why the housing market values neighborhood characteristics are speculative. Still, it is tempting to suggest that households value average student achievement because these data are readily observable, while valued added is difficult to determine. Another caveat is that household sorting among districts is not accounted for in hedonic house price estimation, reinforcing the statement that our results do not represent solely demand relationships. Finally, the lack of significance of our value added measures could be due to measurement errors. Further testing and refinement of the concept is appropriate.

From an empirical perspective, it is much easier to include a district's proficiency test scores in a house price hedonic estimation than to include a set of school inputs in the form of a value added measure of school quality. Thus, we find support for the increasingly common practice of including K-12 test scores as a control variable in hedonic house price equations. And while expenditures also appear to be valued by the housing market, the use of school expenditures in a hedonic house price estimation should be viewed as a supplement to proficiency test data, not a substitute.

Our results raise the question of whether public policy makers should focus on proficiency test score outcomes or on value added measures of school quality. Our finding that households value the level of scores does not mean that the value added concept should be abandoned. Educational policy makers should focus on educational outcomes and the eventual labor market outcomes, not the impact of schools on house prices. Perhaps value added is the correct measure for this task. However, these policy makers cannot ignore the impact of test scores on house prices because their policies are often evaluated by the public in school tax referenda or in elections for school board membership.

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TABLE 1: Variable Definitions, Sources, and Means[a]

Variable Name	Definition (Source)	Full Sample Means (σ)
HOUSE PRICE	Sale price of house in 2000 in U.S. dollars (1); natural log is used in hedonic regressions, but the actual mean sales price is shown	126,926 (83,713)
ONESTORY	Dummy variable = 1 if house is one story (1)	0.47 (0.50)
AIR CONDITIONING	Dummy variable = 1 if house has central air conditioning (1)	0.27 (0.44)
FIREPLACES	Number of fireplaces the house has (1)	0.48 (0.58)
FULLBATHS	Number of full bathrooms (toilet plus shower) the house has (1)	1.40 (0.60)
PARTBATHS	Number of partial bathrooms the house has (1)	0.42 (0.53)
AGE	Age of house in hundreds of years (1)	0.46 (0.30)
HOUSE SIZE	Thousands of square feet of building size (1)	1.58 (0.68)
YARD SIZE	Natural log of size of yard of house in acres (1)	-1.41 (0.90)
DECK	Dummy variable = 1 if house has a deck (1)	0.10 (0.30)
TAX RATE	Tax year 2000 class 1 (agricultural and residential) tax rate in school district in effective mills (2)	32.3 (6.2)
AIR POLLUTION	Natural log of all air releases in Census tract of the house in thousands of pounds (3)	-1.21 (2.05)
RACIAL HETEROGENEITY	Leik (1966) index of racial heterogeneity of Census block group of the house, where 0 is racially homogeneous, 1 is racially heterogeneous (4)	0.11 (0.10)
INCOME	Median income of households in census block group in thousands of U.S. dollars, where a household is the householder and other individuals age 15+ living in the household, and income is wages, salaries, net self-employment, interest, dividends, net rental or royalty income, or income from estates or trusts, social security or railroad retirement income, Supplemental Security Income, public assistance or welfare payments, retirement, survivor or disability pensions (4)	50.8 (21.1)
CRIME RATE	Total actual offenses in the police district per thousands of persons in police district (5)	54.6 (52.7)
EXPENDITURES	Total expenditure per pupil in public school district in thousands of U.S. dollars, for 2000-2001 school year (6)	8.0 (1.2)
PROFICIENCY 9	Difference between percentage of students in a school district who passed all five sections of the 2000-2001 Ohio 9th grade proficiency test and the average passage rate in the relevant metropolitan area (6)	0.06 (19.8)

PROFICIENCY 4	Difference between percentage of students in a school district who passed all five sections of the 1995-1996 Ohio 4th grade proficiency test and the average passage rate in the relevant metropolitan area (6)	-0.04 (19.2)
HAYES-TAYLOR VA	Hayes and Taylor (1996) value added measure; residuals from regression of 322 school districts with dependent variable PROFICIENCY 9 and explanatory variables PROFICIENCY 4 and parent characteristics as shown in Table 2	-3.3 (6.9)
BRASINGTON VA	Brasington (1999) value added measure; PROFICIENCY 9 minus PROFICIENCY 4 (6)	0.10 (6.34)
TWO WAGE EARNERS	Percent of married couples in a school district that are two-wage earner couples, for 1999 income tax returns (7)	70.0 (4.2)
SINGLE PARENTS	Single-parent returns as a percentage of total returns in school district, for 1999 income tax returns (7)	24.8 (9.3)
%WHITE	Percentage of the population in census block group that is white, non-Hispanic (4)	92.0 (11.0)
%NO HIGH SCHOOL	Percentage of persons 25 years or older in census block group whose highest educational attainment is less than a high school degree or equivalent (4)	14.6 (6.8)
%HIGH SCHOOL	Percentage of persons 25 years or older in census block group whose highest educational attainment is a high school diploma, including equivalency (4)	31.8 (12.2)
BLUE COLLAR	Percentage of employed civilian population age 16+ in census block group with blue collar jobs, encompassing the following occupations: farming, protective services, food preparation, fishing and forestry, construction, extraction and maintenance, production, transportation, and material moving (4)	35.5 (11.6)
HOME OWNERSHIP	Percent of occupied housing units in census block group that are occupied by owners rather than renters (4)	79.9 (8.5)
Sources: (1) First American Real Estate Solutions (2002); (2) Ohio Department of Taxation (2003); (3) U.S. Environmental Protection Agency (2002); (4) GeoLytics CensusCD 2000 (2002); (5) GeoLytics Crime Reports CD (2000); (6) Ohio Department of Education (2002); (7) Ohio Department of Taxation (2002)		

[a]Means for the full sample are shown. Means by metropolitan area are available from the authors by request.

TABLE 2: Education Production Function to Create Hayes-Taylor Value Added: Dependent Variable is PROFICIENCY 9

Explanatory Variable	No Interactions	With Interactions
PROFICIENCY 4	0.45** (10.0)	3.34** (3.5)
TWO WAGE EARNERS	-0.014 (0.1)	-0.060 (0.52)
TWO WAGE EARNERS* PROFICIENCY 4	- -	-0.020** (2.7)
SINGLE PARENTS	-0.66** (3.2)	-0.65** (2.5)
SINGLE PARENTS* PROFICIENCY 4	- -	-0.011 (0.9)
%WHITE	0.23** (3.9)	0.33** (3.9)
%WHITE* PROFICIENCY 4	- -	0.005 (1.4)
%NO HIGH SCHOOL	-0.062 (0.5)	-0.042 (0.3)
%NO HIGH SCHOOL* PROFICIENCY 4	- -	-0.007 (0.7)
%HIGH SCHOOL	0.042 (0.4)	-0.010 (0.1)
%HIGH SCHOOL* PROFICIENCY 4	- -	-0.006 (0.7)
BLUE COLLAR	-0.15 (1.4)	-0.13 (1.2)
BLUE COLLAR* PROFICIENCY 4	- -	-0.006 (0.8)
INCOME	0.00003 (0.5)	0.00006 (0.7)
INCOME* PROFICIENCY 4	- -	$-0.9\text{x}10^{-5}$* (2.0)
HOME OWNERSHIP	-0.00002 (0.0)	-0.036 (0.5)
HOME OWNERSHIP* PROFICIENCY 4	- -	-0.011* (2.3)
INTERCEPT	-10.96 (0.9)	-14.38 (1.1)
Adjusted *R*-squared	0.73	0.75
Number of observations = 322 school districts. Parameter estimates shown with absolute value of *t*-ratio in parentheses below. *=statistically significant at the 5% level, **= statistically significant at 1% level. Hayes and Taylor's (1996) value added measure is the residual from this regression.		

TABLE 3: Full Sample House Price Hedonics
Dependent Variable is Natural Log of House Prices

Explanatory Variables	No Controls	County Dummies	Neighborhood Controls	Spatial Plus Neighborhood
PROFICIENCY 9	0.0059** (85.7)	0.0055** (80.3)	0.0037** (46.6)	0.0036** (33.7)
EXPENDITURES	0.063** (59.5)	0.035** (27.4)	0.052** (45.5)	0.061** (43.0)
ONESTORY	0.017** (6.4)	0.021** (7.9)	0.013** (5.1)	0.013** (6.5)
AIR CONDITIONING	0.019** (7.1)	0.054** (15.5)	0.013** (4.8)	0.028** (9.4)
FIREPLACES	0.096** (42.1)	0.099** (45.0)	0.076** (34.6)	0.074** (35.3)
FULLBATHS	0.078** (29.7)	0.071** (27.4)	0.064** (25.4)	0.063** (26.4)
PARTBATHS	0.069** (27.2)	0.064** (26.2)	0.059** (24.1)	0.058** (23.8)
AGE	-0.509** (39.1)	-0.414** (31.2)	-0.472** (37.2)	-0.505** (39.4)
AGE SQUARED	0.166** (16.8)	0.109** (10.8)	0.184** (19.1)	0.200** (20.4)
HOUSE SIZE	0.376** (111.6)	0.371** (113.3)	0.332** (101.4)	0.328** (112.3)
HOUSE SIZE SQUARED	-0.011** (38.0)	-0.011** (38.7)	-0.010** (34.9)	-0.009** (37.4)
YARD SIZE	0.064** (45.0)	0.076** (51.3)	0.054** (39.2)	0.061** (41.2)
DECK	0.068** (18.3)	0.061** (16.0)	0.062** (17.4)	0.058** (16.2)
TAX RATE	- -	- -	0.0006** (2.8)	0.003** (11.1)
AIR POLLUTION	- -	- -	-0.008** (15.4)	-0.007** (12.3)
RACIAL HETEROGENEITY	- -	- -	-0.322** (28.9)	-0.269** (20.1)
INCOME	- -	- -	0.005** (70.5)	0.005** (59.3)
CRIME RATE	- -	- -	0.00011** (4.2)	0.00006* (1.8)
INTERCEPT	10.6** (1064.4)	10.8** (760.9)	10.5** (1068.3)	10.2** (13,119.0)
Adjusted *R*-Squared	0.69	0.71	0.71	0.72
Spatial autoregressive term ρ estimate	-	-	-	0.013** (11.5)
Number of observations is 77,578 houses. Parameter estimates shown with absolute value of t-ratio in parentheses below; they are asymptotic t-ratios for spatial models (LeSage, 1999, p. 49). *=statistically significant at 10% level, **= at 1% level.				

TABLE 4: Full Sample Value Added Spatial House Price Hedonics
Dependent Variable is Natural Log of House Prices

Variable	Hayes-Taylor VA	Hayes-Taylor VA	Downes-Zabel VA	Brasington VA
PROFICIENCY 9	- -	0.0048** (47.6)	0.0025** (14.2)	0.0037** (45.8)
EXPENDITURES	- -	0.051** (49.0)	0.050** (40.3)	0.050** (48.0)
HAYES-TAYLOR VA	0.0014** (8.2)	-0.0042** (18.8)	- -	- -
PROFICIENCY 4	- -	- -	0.0012** (6.7)	- -
BRASINGTON VA	- -	- -	- -	-0.0012** (6.8)

Number of observations is 77,578 houses. Parameter estimates shown with absolute value of t-ratio in parentheses below; they are asymptotic t-ratios for spatial models (LeSage, 1999, p. 49). *=statistically significant at 10% level, **= statistically significant at 1% level. All models use the spatial autoregressive model of Equation (4). Full complement of explanatory variables listed in Table 3 “Spatial Plus Neighborhood” column are used, but only focus variables’ results are shown.

TABLE 5: Coefficient Signs for Metropolitan Area Samples:
School Quality Measures Compete with Expenditures and Proficiency 9
Dependent Variable is the Natural Log of House Prices

Metropolitan Area	Expenditures	Proficiency 9	Hayes-Taylor VA	Downes-Zabel VA	Brasington VA
Akron	+	+	-	-	-
Cincinnati	+	+	-	0	-
Cleveland	+	+	-	+	-
Columbus	+	+	-	+	-
Dayton	0	+	-	+	0
Toledo	+	+	-	0	-
Youngstown	-	+	0	+	0

The values in the table are the sign of the coefficient estimate for a spatial autoregressive model when EXPENDITURES, PROFICIENCY 9, and only one of the other listed school quality measures appear in the house price hedonic for the metropolitan area. A negative sign (-) means the variable was negative and statistically significant at the 0.10 level, a positive sign (+) means the variable was positive and statistically significant at the 0.10 level, and a zero (0) means the variable was not statistically significant at the 0.10 level. Other control variables from “Spatial Plus Neighborhood” column of Table 3 also are included.

TABLE 6: Coefficient Signs for Metropolitan Areas:
School Quality Measures Entered Separately
Dependent Variable is Natural Log of House Prices

Metropolitan Area	Hayes-Taylor VA	Downes-Zabel VA	Brasington VA	Expenditures	Proficiency 9
Akron	-	-	-	0	+
Cincinnati	-	-	-	+	+
Cleveland	+	+	+	+	+
Columbus	+	0	-	+	+
Dayton	+	+	+	-	+
Toledo	0	+	0	+	+
Youngstown	+	+	+	-	+

Sign of parameter estimate for spatial autoregressive model when only the listed school quality measure appears in the house price hedonic for the metropolitan area. A negative sign (-) means the variable was negative and statistically significant at the 0.10 level, a positive sign (+) means the variable was positive and statistically significant at the 0.10 level, and a zero (0) means the variable was not statistically significant at the 0.10 level. Other control variables from “Spatial Plus Hood” column of Table 3 are also used.

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] Many of these studies are cited later in the article, but an excellent review of the literature has been written by Ross and Yinger (1999).

[3] 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). Zimmer and Toma (2000) find strong evidence of peer effects in five countries in a study of math achievement.

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

[5] 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 unclear why they do not expect peer groups (which are school-specific) to affect house values in the same way that school inputs affect house values.

[6] 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 $\mathbf{A}_{jt-1}$ variable and its contribution is not counted as part of their measure of school-specific value added.

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

[8] A referee notes that expenditures per pupil may be valued by parents and homeowners even if they have no direct impact on students' academic performance. Examples range from the quality of sports' uniforms to the quality of sports teams to the quality of the music program.

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

[10] The standard deviations of the tests are similar: 3.14 for the fourth and 3.31 for the ninth grade tests.

[11] With a critical *LM* of 9.21, the test shows a calculated *LM* value of 5.73. 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.

[12] With a critical *F* value of 4.90 at the 1% level, the calculated *F* statistic is 4.09.

[13] A standard error correction for clustering of residuals yielded negligible changes in *t*-ratios, so the *t*-ratios presented throughout the study are uncorrected. In fact, Brasington (2002c) suggested that such a correction was unnecessary, and Clapp, et al. (2004) do not adjust standard errors in their assessed value models either.

[14] Incidentally, the cross-sectional regression of Clapp, et al. (2004) that includes fixed effects yields a 0.006 parameter estimate for test scores. This 0.006 parameter estimate is identical and directly comparable to the impact we find without neighborhood controls.

[15] It also appears to be true that while omitting neighborhood variables biases the OLS estimate of the effect of school quality on price upwards, the fixed effect approach biases it downwards substantially when there are random intertemporal fluctuations in quality that are not valued by households, but only a single measure of quality is observed. This conjecture is the topic of future research by the authors.

[16] The strength of the relation also varies by housing supply elasticity, as discovered by Brasington (2002a). In an unreported regression, being in a school district characterized

by rapid new housing construction weakens the rate of capitalization of both EXPENDITURES and PROFICIENCY 9.

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

[18] For unclear reasons, Black (1999) includes either border dummies or Census block group characteristics, never both simultaneously.

[19] While the influence of using the spatial statistics approach is marginal in the current situation, its use is warranted on theoretical grounds, and spatial dependence is present, as evidenced by a significant spatial autoregressive term that retains its statistical significance in every specification.

[20] The experiment is to increase in test scores only in one district, holding constant the other scores in the MSA.

[21] A one standard deviation increase in the Hayes-Taylor measure (6.9) raises house prices by 9.7%.

[22] The negative relation could be driven by multicollinearity, as the correlation between HAYES-TAYLOR VA and PROFICIENCY 9 is 0.72. We examine this possibility further in Table 6.

[23] Their house price hedonic (and our replication) includes both the current test score outcome and the lagged outcome: $c_1\mathbf{A}_{jt} + c_2\mathbf{A}_{it-1}$. Rewrite this expression as $(c_1\text{-}c_2)\ \mathbf{A}_{jt}$ - $c_2(\mathbf{A}_{it}\ \text{-}\mathbf{A}_{jt-1})$. Value added is measured in the second term, thus if it is capitalized, then $-c_2$ will be positive (the negative of c_2) and if current scores are not valued, then $c_1 = -c_2$.

[24] Referring to footnote 23, we find $c_1 = 0.0025$ and c_2=0.0012. The implications are that current achievement is positively valued (0.0025-0.0012 = 0.0013), but the measure of value added is not (-0.0012).

[25] That is, every model contains EXPENDITURES and PROFICIENCY 9. The first two columns of results are from regressions containing only the school quality measures EXPENDITURES and PROFICIENCY 9.

[26] In unreported regressions, the same lack of support for value added is found using value added measures based upon changes in achievement between grades 6 and 9. The same pattern of results is also found when the spatial error model and spatial Durbin model are used instead of the spatial autoregressive model.