DEPARTMENT OF ECONOMICS WORKING PAPER SERIES

Public and Private School Competition: The Spatial Education Production Function

David M. Brasington
Louisiana State University

Working Paper 2005-09
http://www.bus.lsu.edu/economics/papers/pap05_09.pdf

Department of Economics
Louisiana State University
Baton Rouge, LA 70803-6306
http://www.bus.lsu.edu/economics/

Public and Private School Competition: The Spatial Education Production Function

Abstract

School vouchers may increase the competition public school districts face. Greater competition may spur public schools to improve student outcomes, which reliably predict labor market productivity and earnings. Previous school competition studies do not use spatial statistics; they fail to incorporate spillovers and the effect of omitted variables into their education production functions. Significant spatial effects are found in all regressions, and spatial statistics improves adjusted R-squared. There seems to be no consistent association between private school attendance rates and public school achievement, or between the number of public school districts in a county and public school performance. Competitive effects, which seem plausible in non-spatial regressions, dissipate when spatial statistics is used. When school inputs appeared statistically significant in non-spatial regressions, the spatial regressions generally made the significance disappear. Poverty appeared to depress reading and writing passage rates, but this effect disappeared in the spatial models.

JEL Classification codes: J24, I21, H40, D62

Keywords: spillovers, human capital formation, spatial statistics, school vouchers, private and public school competition

David M. Brasington, Economics Department, Louisiana State University, Baton Rouge, LA 70803; Phone: (225) 578-7822, Fax: (225) 578-3807, dbrasin@lsu.edu

May 2, 2005

1. Introduction

Economists care about schooling because school quality, as measured by proficiency test scores, is an important predictor of labor market productivity and earnings (Sander, 1996; Bishop, 1989; Loury and Garman, 1995; Murnane, Willett and Levy 1995). Whatever improves school quality might also improve labor market productivity and earnings.

The private sector and the government both provide primary and secondary schooling. The dual provision of schooling has inevitably lead to comparisons between private and public schools, with many charging that private schools do a better job with less money. Some economists speculate that private schools must compete for students and must therefore deliver a high-quality product at low cost to survive. Public school systems, which have local monopoly power, are under less competitive pressure to deliver high-quality and efficient services (e.g., Couch, Shughart and Williams, 1993).

School vouchers are often proposed to increase competition. Under the current system, students are assigned to tax-funded (public) schools based on their residence. If students attend the schools they are assigned to, they pay no extra tuition. But if students want to attend private schools or a tax-funded school other than the one they are assigned to, parents must continue to pay taxes for their assigned public school, and they also have to pay full tuition at the school they attend.

A voucher program would lower the cost of attending another school. Under a voucher program, parents receive a voucher--a check from the government--that can be redeemed at the assigned school or another school. Some voucher plans restrict voucher use to public schools only, while other voucher plans allow recipients to use the voucher at any public or private school. A flurry of recent research uses education production functions to investigate the extent to which public schools respond to competition from other public schools and private schools. Knowing whether public schools respond more to competition from other public schools or private schools, the most effective voucher policy may be designed. If vouchers increase school competition, student outcomes may improve, and the labor force of the future may be more productive.

Previous research fails to address some important econometric issues. Public schooling is often thought to have positive spillovers over some spatial subgroup. Traditional education production functions ignore the possibility of spillovers. Furthermore, even the most careful education production functions are subject to omitted variable bias. Because of the public policy importance of the voucher issue, estimates of school competition must be as unbiased and efficient as possible.

The current study introduces the spatial education production function. The spatial education production function uses spatial statistics--estimation that accounts for the spatial layout of the data--to address spillovers and omitted variable bias. The study finds spatial effects in all sections of the Ohio proficiency test and in all 15 spatial regressions. Therefore, education production functions that do not account for the spatial configuration of the data are vulnerable to biased, inefficient and inconsistent parameter estimates (Anselin, 1988). The specific spatial models used are designed to be insensitive to outliers and for this reason are expected to have lower adjusted R-squared than non-spatial models; nevertheless, the spatial education production functions have higher adjusted R-square than their non-spatial counterparts, suggesting that spatial statistics adds to explanatory power.

Most of the non-spatial regressions show a positive relationship between public school outcomes and the number of public school districts in the county. Once spatial statistics is used to address spillovers and omitted variables, only 13% of the regressions show a relationship. The magnitude of the effect is trivial: the elasticity of test passage with respect to the number of public school districts is 0.026.[1] Overall, the current study provides weak evidence that public schools respond a little bit to competition from other public schools. The results are more similar to Rothstein (2005), who finds no effect, than to Hoxby (2000), who finds large competitive effects.

A comparison of spatial and non-spatial estimation methods fails to support the assertion that traditional regressions bias the parameter estimate of private school competition downward (Hoxby, 1998). Neither the traditional nor the spatial education production functions indicate a consistent public school response to competition from private schools. The response is more prevalent in the non-spatial regressions (40%) than the spatial regressions (20%), suggesting that once spatial effects are considered, the correlation between private school attendance and public school outcomes is weakened. In fact, when the result is significant, it is almost always negative. The implications for allowing vouchers at private schools are discussed.

2. Theoretical model of school competition

The main contribution of the paper is its novel application of an empirical technique and the results it yields about school competition; still, some researchers find it useful to couch empirical work in a theoretical framework that motivates the statistical test. A theoretical model of the production of education with spillovers is now presented.

It is based on Murdoch, Rahmatian and Thayer (1993) but deviates in several respects.[2] The model abstracts from many of the complex issues involved in education; its purpose is to motivate the use of spatial statistics in the empirical section by showing that there may be spillovers between school districts.

Each school district i undertakes an activity α, the provision of schooling, which is measured by proficiency test passage rates. Production takes the following form:

$$\alpha_i = \alpha_i(d_i, \ \Psi_i, \ b_i) \tag{1}$$

where d is a vector of student and parent demographic characteristics, Ψ is a vector of community demographic characteristics, and b is school board administrative efficiency and effectiveness. In turn,

$$b_i = b_i(k_i, \ e_i(k_i), \ s_i) \tag{2}$$

where k is a vector of variables related to competition in the schooling market, e is enrollment, and s is a vector of inputs chosen by the school board such as teacher quality and the pupil/teacher ratio. Vector s is chosen in a framework outside the current model, but it is flexible enough to incorporate either rent-seeking or output-maximizing behavior by the administration.

Education is assumed to exhibit positive externalities (Wyckoff, 1984); therefore, although the median voter chooses α, the total amount of schooling consumption γ is the following:

$$\gamma_i = \alpha_i + \omega_i \tag{3}$$

where ω are spill-ins from public schooling provision in neighboring communities. The median voter's utility is a function of the total amount of schooling consumption, regardless of its source. Therefore,

$$U_i = U_i(n_i, \gamma_i) \tag{4}$$

Equation (4) portrays the median voter's utility as a function of consumption of a numeraire good n as well as public schooling. The utility function is assumed to be strictly quasi-concave, twice continuously differentiable, and a monotonically increasing function of its arguments.

School district i not only receives spill-ins from neighboring communities; it generates them as well. When the median voter chooses α, part of that provision is privately consumed. Another part is the pure public portion of schooling, consumed by the community in question as well as by its neighbors. Formally,

$$\alpha_i = t_i + p_i \tag{5}$$

where t is the community's own provision of the public aspect of schooling, and p is consumption of the pure private portion of schooling.

The proportion of a community's provision of public schooling that stays in the community and the proportion that spills over into neighboring school districts is described by the following joint product technology:

$$p_i = \theta_i * \alpha_i \tag{6}$$

$$t_i = \phi_i * \alpha_i \tag{7}$$

where θ is the proportion of own provision of schooling that is privately consumed and ϕ is the fraction that is a pure public good. Equation (7) holds for all school districts, so

$$\omega_i = \sum_{r \neq i} \phi_r * \alpha_r \tag{8}$$

where ϕ_r is the fraction of activity in school district r that spills in to jurisdiction i as a public good. Because $\gamma_i = t_i + p_i + \omega_i$, equation (4) may be rewritten as

$$U_i = U_i(n_i, t_i + p_i + \omega_i) \tag{9}$$

The median voter maximizes (9) subject to the following budget constraint:

$$y_i = n_i + \tau_i\alpha_i \tag{10}$$

In equation (10), y is income and τ is the per-unit cost of education faced by the median voter. The median voter chooses α taking other districts' schooling decisions as given. Constrained maximization proceeds by setting up the Lagrangian,

$$L = U_i(n_i, \phi_i * \alpha_i + \theta_i * \alpha_i + \sum_{r \neq i} \phi_r * \alpha_r) + \lambda(y_i - n_i - \tau_i\alpha_i) \tag{11}$$

where λ is the Lagrange multiplier. Partial differentiation yields the following first-order conditions, along with the budget constraint:

$$\frac{\partial U_i}{\partial n_i} - \lambda = 0 \tag{12}$$

$$\frac{\partial U_i}{\partial \alpha_i}(\theta_i + \phi_i) - \tau_i\lambda = 0 \tag{13}$$

so that the ratio of the marginal rates of substitution of the numeraire good and own contribution of schooling are equated to the tax price:

$$\frac{\partial U_i}{\partial \alpha_i} / \frac{\partial U_i}{\partial n_i} = \tau_i \tag{14}$$

The theoretical model has shown how spillovers may be involved in the production of education and how the spillovers enter communities' choice of schooling levels. The theoretical model contains variables representing student and parent characteristics, community characteristics and school-specific inputs. The following section discusses the inputs to education in greater detail to justify the choice of variables in the empirical section.

3. Literature review and choice of education production function variables

Education is produced using the following inputs: students and parents, the community, and school-specific factors. Each input group is discussed in turn. Every attempt is made to include the typical set of education production function variables as well as variables related to competition.

Student and parent characteristics are typically strongly related to public school outcomes. One such characteristic is the presence of a two-parent household. A single-parent household may not devote as much attention to its children; therefore, %BOTH PARENTS is expected to be positively related to student outcomes. Another theoretically important household characteristic is income. PARENT INCOME is expected to be positively related to student achievement. On the other hand, low parent education levels may imply that parents are less able to help their children with their homework or that they do not value education highly. %NO DIPLOMA and %HS DIPLOMA ONLY are therefore likely to be negatively related to student outcomes, compared with higher levels of parent education. The proportion of nonwhite students, %MINORITY, is also included; it has been found negatively related to school outcomes in many education production functions.

Characteristics of the community include demographic factors and variables related to competition. The proportion of school district residents who are living in poverty, %POVERTY, is expected to be negatively related to school outcomes. Competitive pressures may also influence the supply of public school quality. Competition may come from private schools as well as from other public schools. Each of these possibilities is discussed in turn.

Theoretical models have found positive (Falkinger, 1994), negative (Epple and Romano, 1998) and ambiguous (Ireland, 1990) effects of increased private school enrollment on public school performance. Empirical studies have shown more consistent results. Couch, Shughart and Williams (1993) find the percentage of students in a public school district who attend private schools has a positive relationship with standardized algebra test scores in North Carolina's public schools; public schools seem to respond to competition from private schools. Borland and Howsen (1996) extend Couch, Shughart and Williams' analysis to include the effect of both public and private school competition on public school performance. This competition from both sources is captured in a single Herfindahl index, which is positively related to public school performance. Hoxby (1998, 1997) also finds competition from private schools is positively related to higher public school achievement. Dee (1998) shows that competition from private schools has a positive and statistically significant impact on high school graduation rates of neighboring public schools. In contrast, Zanzig (1997) finds a negative relationship between public school math test scores and the percentage of students in the county who attend private schools. %PRIVATE is included in the current study to capture the relationship between private school competition and public school performance.

There may also be competition between public schools. Hoxby (1998, 1996) says such competition should exist because efficient and high-quality education providers are rewarded with higher budgets. An increase in quality causes an increase in house prices, which increases the tax base, tax collections, and the size of the school budget. In addition, Hoxby suggests schools are more responsive to parents' desires as opposed to school staff desires when there are many public school districts in the area. Hoxby further asserts that when parents have more choice among districts, they are more involved in their children's schooling. One may expect a positive relationship between the number of school districts and public school outcomes, then. Indeed, Hoxby (1998, 2000) finds such a relationship. Using a Herfindahl index to measure competition, she finds an increase in competition is associated with a small but statistically significant increase in achievement. In contrast, when Rothstein (2005) uses Hoxby's (2000) data with different instruments, he finds no statistically significant results. Rothstein further suggests that Hoxby's failure to control for private school attendance led to her finding about public school competition. Zanzig (1997) generally finds that the number of public school districts in a county has a positive effect on public school performance until a threshold of three or four districts is reached. Beyond this threshold additional public schools depress performance. Based on the literature, the number of public school districts in each of Ohio's eighty-eight counties, #DISTRICTS, is included to capture public school competition.

Finally, the characteristics of the schools themselves may influence student achievement. There are dissenters (Ornstein, 1993; Fowler and Walberg, 1991; Jewell, 1989), but considerable evidence suggests that larger school districts are consistently negatively related to student outcomes, although the magnitude is small (Haller, 1992; Stern, 1989; Friedkin and Necochea, 1988; Brasington, 1997). Therefore, COHORT SIZE is included in the education production function; a negative relationship with student performance is anticipated. Other school-specific characteristics include TEACHER SALARY, TEACHER EXPERIENCE, and TEACHER EDUCATION levels, as well as the PUPIL/TEACHER RATIO. Although the debate continues as to the significance of these factors, no education production function is complete without them. Data on per pupil expenditures is also available, but this variable is highly correlated with TEACHER SALARY (0.81) and PUPIL/TEACHER RATIO (-0.89) and seems to cause multicollinearity problems.

The student outcomes are now described. Ohio's high school students must pass a ninth-grade proficiency test to receive a full high school diploma. Students who do not pass this test by the end of twelfth grade but pass their coursework receive a certificate of attendance instead. All students must take the test, so sample selection bias is not an issue (Hanushek and Taylor, 1990).[3] The 1993 proficiency test contains four sections: writing, reading, math, and citizenship. The measures of school outcome employed are the proportion of ninth-graders in each district who pass each portion of the ninth-grade proficiency test in 1993. Of the 611 Ohio school districts, 605 reported their 1993 proficiency test results.

The recent education production literature includes studies that use levels of outcomes (Hoxby, 1996; Sander, 1996; Kennedy and Siegfried, 1997; Zanzig, 1997; Dee, 1998; Couch, Shughart and Williams, 1993; Borland and Howsen, 1996) as well as the value-added approach (Meyer, 1996; Hanushek, 1992; Gomes-Neto, Hanushek, Leite and Frota-Bezzera, 1997; Figlio, 1999). Two ways of implementing value added were tried. The value added approach of Meyer (1996) yielded no additional insights; the approach of Hayes and Taylor (1996) yielded an adjusted R-squared of 0.01. The current study therefore restricts its attention to variation in the level of outcomes, rather than value added. The results of the current study complement Brasington and Haurin (2005), who find that levels of proficiency are valued by the housing market, while measures of the value added of a school are not. Variables' definitions, sources and means are shown in Table 1.

(Insert Table 1 about here)

4. Traditional, non-spatial estimation

Theory provides no guide as to the functional form the education production function should take (Figlio, 1999). Furthermore, a Davidson and MacKinnon (1981) test for linearity versus loglinearity yields inconclusive results; the linear functional form is adopted by default.

It is only in the last few years that the economics of education literature has addressed endogeneity in education production functions (Akerhielm, 1995; Sander, 1999; Hoxby, 1998). From the school district's point of view, TEACHER SALARY and PUPIL/TEACHER RATIO are choice variables and should be treated endogenously. TEACHER EXPERIENCE and TEACHER EDUCATION are related to how long a teacher has been in the school district. These variables are likely simultaneously determined with student achievement and are therefore treated endogenously.

Hoxby (1998) suggests that #DISTRICTS is endogenous to school quality, and the number of streams in the area should be used as an instrument. Hoxby also suggests that %PRIVATE is endogenous to public school quality. However, there is some evidence that school district consolidation is not a function of public school quality (Brasington, 1999); therefore, the number of school districts in an area is not a function of school quality. In addition, a Hausman test reveals that both #DISTRICTS and

%PRIVATE may be treated exogenously in the education production function.[4] Rothstein (2005) also argues in favor of treating #DISTRICTS as an exogenous variable.

5. The spatial education production function

The theoretical model of school district competition includes educational spillovers. In fact, a good deal of research has investigated spillovers in public good provision.[5] A natural way to account for externalities is to incorporate spatial autocorrelation in the statistical estimation: rarely do economic theory and statistical technique complement each other so naturally.[6]

When each school district affects the performance of neighboring school districts, spatial autocorrelation may exist (LeSage, 1997a). Ordinary least squares does not account for the interplay between spatially close observations, which may lead to biased, inefficient and inconsistent parameter estimates (Anselin, 1988). Neighboring school districts affect each other more than school districts far away from each other (Wyckoff, 1984); consequently, a spatial weights matrix must be constructed to summarize the spatial configuration of the observations. The traditional education production function takes the following form:

$$t_{ij} = \beta x_i + \varepsilon_i \tag{15}$$

where t represents test passage, i is school district i, j is test section j, x is the set of student, parent, community and school-specific factors related to test passage, and ε is the error term.

But the traditional education production function ignores spillovers and other forms of spatial dependence. We first employ the Bayesian spatial error model of

LeSage (1997b) to address heteroskedasticity, outliers, and omitted variables. It is the same as the traditional model in Equation (15), but with a more complex error term:

$$t_{ij} = \beta x_i + \varepsilon_i \tag{16}$$

$$\varepsilon = \lambda W \varepsilon + \mu,\ \mu \sim N(0, \sigma^2 V)$$

$$V = diag(v_1, v_2, \ldots, v_n)$$

$$r/v_i \sim \chi^2(r) / r$$

$$1/\sigma^2 \sim \Gamma(\eta, \delta)$$

In Equation (16), ε is a spatial autoregressive error term that says the error term for each observation is related to the error terms of the neighboring observations. Unlike time series, where an autoregressive lag represents nearby time periods, the λWε is an autoregressive lag based on nearby observations in space. The W in the autoregressive term is a spatial weight matrix (LeSage, 1997a) that summarizes the spatial layout of the data on a map. It tells who the nearest school districts are for each observation. The spatial weights matrix W in the current study is constructed so that the five nearest neighbors are allowed to influence each school district. With 605 school districts in the sample, W is a 605x605 matrix. Row 1 represents school district 1. For each column y in row 1 we must ask, "Is school district y one of the five nearest to school district 1?" If the answer is yes, the column gets a 1; if not, the column gets a 0.[7] Each row has five 1's, then. A common procedure in the spatial statistics literature is to make the sum of each row equal unity, so with five neighbors each neighbor is assigned a weight of 1/5 = 0.2.

The λ in Equation (16) is the spatial autoregressive parameter to be estimated. It tells the degree to which the error terms of our observation and its neighbors are related. Finally, μ is a white noise error term.

The first two terms in Equation (16) describe a spatial error model.[8] The remaining terms distinguish the Bayesian model from the non-Bayesian spatial error model. The additional characterization of the error term helps correct for heteroskedasticity and outliers, and is discussed in greater detail in LeSage (1999), but a brief discussion is provided here. A big difference between Bayesian and non-Bayesian estimation is the use of prior information. We allow diffuse priors for λ, β, and σ^2. Ordinarily, the term r in Equation (16) would be distributed gamma with two parameters. Instead, following LeSage (1999, p. 121), we use an informative prior on v_i of $r = 4$. This particular prior yields relatively constant estimates of v_i in the presence of homoskedasticity, while at the same time accommodating non-constant error variances in the presence of heteroskedasticity and outliers.[9] Computational tricks by Barry and Pace (1999) and Pace and Barry (1998) are used to allow the sample to run in a reasonable amount of time.[10]

The spatial error model captures the influence of omitted variables that vary across space. Any omitted influence that varies across space will be subsumed in the error term, and the spatial autoregressive term will capture these influences. The income of parents and race of the students are included, but the education production functions do not measure the income and racial characteristics of the neighborhood. These community characteristics may affect student performance above and beyond the influence from the parents, perhaps through volunteering efforts and tax levy passage.

Neighborhood crime rates are also omitted, and the accompanying feeling of security could affect student performance. These omitted influences will be subsumed in the error term, and normally might adversely influence parameter estimates. But the second term in Equation (16) recognizes the correlation between the error terms of neighboring school districts. If people live in areas with similar people, then income, race, and crime rates will be similar across space, and change character gradually from school district to school district. If the error term for school district A is affected by income, race, and crime rates, the error term for nearby school district B is affected to a similar degree. The correlation between the error terms is captured by the spatial model. In this manner the spatial error model addresses the influence of omitted variables in the house price hedonic. A more complete intuitive explanation of how spatial statistics addresses omitted variables is found in Brasington and Hite (2005). A mathematical proof is available in Griffith (1988, p. 94-107).

The Bayesian spatial error model in Equation (16) depends on having a large number of draws to converge to the true joint posterior distribution of the parameters. With insufficient draws, parameter estimates cannot be trusted. Although convergence diagnostics are available, the true test of convergence is when the estimates don't change with added draws. A model with 300 draws (with 30 additional burn-in draws) achieves similar results to a model with 1000 draws (with 100 additional burn-in draws), suggesting that 300 draws is sufficient.

There are other ways in which spatial statistics can capture the influence of omitted variables. One of these is a Bayesian spatial autoregressive model (LeSage, 1997b):

$$t_{ij} = \rho W\, t_{ij} + \beta x_i + \varepsilon_i \tag{17}$$

$$\varepsilon \sim N(0, \sigma^2 V)$$

$$V = diag(v_1, v_2, \ldots, v_n)$$

$$r/v_i \sim \chi^2(r) / r$$

$$\sigma^2 \sim \Gamma(\eta, \delta)$$

$$\rho \sim uniform(-1,1)$$

In the above equation, ρWt_{ij} is the spatial autoregressive term. It is the term that captures the essence of public good spillovers, allowing the educational production of each school district to depend on the educational production of its neighboring school districts. The theoretical section modeled spillovers as part of a joint product technology, but there may be an additional justification for the ρWt_{ij} term. School district administrators may keep their eyes on neighboring school districts and try to compete with them academically, so the outcomes of neighboring school districts may affect the administrative effort of a school district, which in turn may affect school district outcomes. Administrators care less about the performance of far-away school districts.

Compared to the Bayesian spatial error model of Equation (16), the Bayesian spatial autoregressive model of Equation (17) takes the influence of unobserved variables out of the error term ε and controls for them with the ρWt_{ij} term. While the spatial error model guards against inefficient parameter estimates, the spatial autoregressive model guards against biased parameter estimates. If the ρWt_{ij} term is significant, and if it were omitted as in a traditional education production function, the matrix of parameter estimates β would suffer from bias and hypothesis testing would be invalid.

A final way spatial dependence is captured in the education production functions is through a spatial Durbin model (LeSage, 1997b):

$$(I - \rho W)t_{ij} = \alpha + \beta_1 x_i + W\beta_2 x_i + \varepsilon_i \quad (18)$$

$$\varepsilon \sim N(0,\sigma^2 V)$$

$$V = diag(v_1, v_2, \ldots, v_n)$$

$$r/v_i \sim \chi^2(r) / r$$

$$\sigma^2 \sim \Gamma(\eta,\delta)$$

$$\rho \sim uniform(-1,1)$$

As in the spatial autoregressive model of Equation (17), the spatial Durbin model of Equation (18) also contains a spatial autoregressive term ρWt_{ij} and the education production function controls x_i. Unlike the spatial autoregressive model, the spatial Durbin model contains the education production function controls for our neighbors Wx_i as well. While the β terms are different for x_i and Wx_i, the same W is used in two places in Equation (18). Some research (e.g., Anselin (1988)) claims the ρ and β_2 are not identified, but Kelejian and Prucha (2004) prove they are.[11]

The Wx_i term captures spillovers in a different way than the ρWt_{ij} term. School quality may be more than a function of its own inputs and neighboring districts' school quality. It may also be a function of demographic influences in neighboring districts. Children who live on the border of two school districts may play with each other, so that peer group effects may spill across school district boundaries. Churches, Rotary Clubs, and country clubs may draw members from different (but probably nearby) school districts; parents at these social organizations may discuss schooling with each other and form attitudes about schooling quality, dress codes, and homework levels, which may influence the schooling decisions they make. Wx_i allows the characteristics of neighboring school districts to affect outcomes in each school district. These spillover effects may be stronger across schools than across school districts, but if they are present across school districts then they are likely to be present across schools within a district.[12]

6. Estimation results

The first set of regression results uses %PASS ALL, the percentage of students passing all four sections of the proficiency test, as the dependent variable. The first set of results in Table 2 is the non-spatial instrumental variables model.

(Insert Table 2 about here)

The results of the instrumental variables model are generally consistent with expectations. Proficiency test passage is higher, all else constant, in school districts where children come from two-parent families, with high incomes, with a low proportion of minority students, and in communities with low poverty rates and higher-educated citizens. The sign of COHORT SIZE is negative, but fails to achieve statistical significance at the 0.10 level. Most of the school-specific inputs show a significant relationship with student achievement, but two of these are of theoretically inconsistent sign. While school districts with better-paid teachers have higher passage rates, the results suggest the school districts with higher teacher education levels have lower passage rates, and a higher student/teacher ratio raises passage rates. A correlation matrix suggests the results are not an artifact of multicollinearity. Consistent with competitive effects, #DISTRICTS is positively related to passage rates. However,

%PRIVATE is negatively related to passage rates in public school districts, a result in contrast with most of the literature, but consistent with Zanzig (1997).

But the preceding analysis does not address spillovers or omitted variables. The results of the first spatial education production functions are reported in the remaining columns of Table 2.[13]

Testing for spatial effects is of supreme importance. The spatial error lag has a parameter estimate of 0.36 and is statistically significant. In fact, the spatial parameter estimates are all positive and statistically significant throughout the paper, suggesting that the use of spatial statistics is warranted. The 0.36 estimate means the error terms have on average a 0.36 spatial correlation with each other: the unmeasured things in our education production function are somewhat similar to the unmeasured things of our neighbors. The next model, the spatial autoregressive model, suggests that the average correlation between one school district's passage rate and its neighbors' passage rates is 0.26, and the spatial Durbin model suggests this correlation is 0.28.[14] The spatial Durbin model also finds that three of the explanatory variables of our neighbors help explain the proficiency passage rate of our school district. It is difficult to compare the results of Millimet and Rangaprasad (2005) because 1) they do not use proficiency tests as measures of school quality, and 2) they do not use the same spatial models and so have no estimates of λ or β_2. Millimet and Rangaprasad report the estimates of ρ when the measures of school quality are the pupil/teacher ratio, expenditures per pupil, capital expenditures per pupil, teacher salary, and school size, but the results are not comparable to the estimate of ρ for the proficiency test passage variables used in the current study.

Their estimates vary from specification to specification, as well, ranging from small and negative to large and positive.

Explanatory power is higher in the spatial models. Adjusted R-squared is 0.49 in the non-spatial models, while it is 0.54, 0.54, and 0.56 in the spatial models. The Bayesian component of the spatial models purposefully tries not to fit outliers, which depresses adjusted R-squared. If the spatial models had fit outliers like the non-spatial model, the difference in adjusted R-squared might be even larger. Even if the improvement is modest, the larger adjusted R-squared is found in all spatial models throughout the study.

Perhaps the most significant finding in Table 2 is that the spatial models eliminate the statistical significance of all the school-specific inputs. Failure to incorporate spatial dependence seems to have attributed too much explanatory power to teacher salary, the pupil/teacher ratio, and teacher education levels. The lack of significance is consistent with Hanushek (1986) and much of the recent literature.

The other major differences concern the school competition variables. Hoxby (1998) argues that the parameter estimate of %PRIVATE is biased downward, but the spatial models that address the influence of omitted variables suggest otherwise. The non-spatial model's parameter estimate was -0.19, but the parameter estimates of the spatial models range from -0.15 to -0.12, suggesting (if anything) an upward bias to least squares. And while the non-spatial model showed a significant relationship for %PRIVATE, only one of the three spatial models shows a statistically significant relationship, and that barely reaches the 0.10 level of significance. In any case, even the largest parameter estimate -0.19 yields an elasticity of -0.02, so regardless of statistical significance, the economic significance of competitive effects from private schools is negligible.

The results for the relationship between public school competition are similar to those for private school competition. While the instrumental variables regression shows a positive, significant relationship, the spatial models generally find no relationship. Again, the only spatial model showing a significant relationship is the spatial autoregressive model. And again, the magnitude of the parameter estimate, even for the largest parameter estimate, shows a trivial elasticity of test passage with respect to the number of school districts of 0.04.

The enrollment of each grade is negatively related to test passage in two of the three spatial models and approaches significance in the third; it was insignificant in the non-spatial model. The elasticity is -0.03, and is almost exclusively found when %PASS ALL is used, findings consistent with Brasington (1997).

Table 3 shows the results of regressions when the percentage of students passing the math section is the dependent variable.

(Insert Table 3 about here)

Passage rates on the math section are lower than for other sections, so it is not surprising that the results are similar to the %PASS ALL results: if a student failed any section, it most likely was the math section. But while parent income was related to %PASS ALL in three of four regressions, it is not related to %PASS MATH in any regression. The only role for parent income is found in the spatial Durbin model, where LAG PARENT INCOME is positively related to %PASS MATH. The parameter estimate (not shown) is 0.29, suggesting that the elasticity of our own math passage rate with respect to our neighbors' income levels is 0.16. If neighboring school districts' incomes are 10% higher, our math passage is 1.6% higher. The evidence for competitive effects is stronger for the math model than for any other test section: five out of eight parameter estimates are statistically significant. But, as before, the magnitude of the effects is trivial. And, as before, the parameter estimate of %PRIVATE is weaker in the spatial models than in the non-spatial model.

As before, the non-spatial model shows significant effects for three of four school inputs, and two of these have an unexpected sign. As before, incorporating spatial dependence kills off the statistical significance of TEACHER EDUCATION and PUPIL/TEACHER RATIO. However, TEACHER SALARY remains positive and statistically significant in two of the three spatial models. The median elasticity from the spatial models is 0.29, suggesting that a 10% rise in teacher salary is associated with a 2.9% rise in math passage rates. In other words, a ten percent rise in teacher salaries might raise the average district's passage rate from 0.61 to 0.628.

COHORT SIZE is not significant in any regression, spatial or not, and %POVERTY, while significant in the non-spatial model, is insignificant in all spatial models. The magnitude of the spatial parameters ranges from 0.23 to 0.31.

The results of the %PASS CITIZENSHIP regression are easily summarized.

(Insert Table 4 about here)

Competitive effects are almost completely absent. As in the math section, the incomes of neighbors seem to spill over and positively affect citizenship passage rates, but no direct relationship between parental incomes and passage rates is found. No school input is statistically significant, either in the spatial or non-spatial models. The magnitude of the spatial parameters ranges from 0.17 to 0.23. Adjusted R-squared shows its largest leap by going from 0.44 in the non-spatial model to 0.55 in the spatial Durbin model.

The results of the %PASS READING model are similar to those of the %PASS CITIZENSHIP model.

(Insert Table 5 about here)

There is no evidence of competitive effects or of the importance of any school input to test passage rates. Parent income shows up insignificant in the non-spatial model, but becomes statistically significant in all spatial models. And while %POVERTY is statistically significant in the non-spatial model, when spatial dependence is addressed, it loses its significance. The spatial parameters range from 0.17 to 0.26.

The model with %PASS WRITING shows almost nothing of statistical significance.

(Insert Table 6 about here)

Adjusted R-squared ranges from 0.21 in the non-spatial model to 0.25 in the spatial Durbin model. The lack of significance and low adjusted R-squared may stem from the way the writing section is graded. Unlike the other test sections, the writing section is not a multiple choice test. The tests are sent out of state and hand-graded. The passage rates are high: the average passage rate of this section is 0.87, and the standard deviation is 0.08. The lack of variation contributes to the lack of statistically significant findings. Still, the spatial parameters range from 0.17 to 0.20, similar to those of the other test sections, and three spatial lags are significant in the spatial Durbin model. And, as in the reading section, %POVERTY appears significant until spatial dependence is addressed.

7. Conclusion

Educational spillovers have been discussed theoretically for a long time, but no one has accounted for them in empirical estimations of local public schooling provision.[15] Significant spatial effects are present in all fifteen spatial education production functions, with spatial parameter estimates that range from 0.17 to 0.36. Researchers who ignore the spatial nature of the data run the risk of having biased, inefficient and inconsistent parameter estimates (Anselin, 1988). Researchers should account for spillovers in the production of education and omitted variable bias by incorporating spatial statistics. In addition to more accurate parameter estimates, the spatial models add to the explanatory power of education production functions. Despite the use of spatial Bayesian techniques that mitigate the fitting of outliers, average adjusted R-squared improves from 0.42 to 0.46.

The influence of competition on public school performance is the focus of the education production functions. Most recent education production function studies find that public schools respond to competition from private schools (Hoxby 1998, 1997; Dee, 1998; Couch, Shughart and Williams 1993; Borland and Howsen, 1996). The current study disagrees. There seems to be no consistent association between private school attendance rates and public school achievement. Furthermore, although there is always a positive relationship between the number of public school districts in a county and public school test scores, it is only statistically significant in eight of the twenty regressions. The magnitude of its effect is paltry, too, never exceeding 0.05.[16]

At first glance, such slight competitive effects suggest that school vouchers will not markedly improve public school performance; consequently, vouchers will probably not improve labor force productivity or earnings either. If so, vouchers may only serve to subsidize rich parents. Willms and Echols (1992) find that Scottish parents with high socio-economic status were the ones who took advantage of Britain's school voucher system. If only rich parents use the vouchers, the vouchers will be used to make tuition at other schools more affordable for those most able to afford it.

But these findings must be interpreted carefully. The data are real. As such, they represent the current competitive environment in education. And, as the results of the current study confirm, the current environment can hardly be described as competitive. To the extent that they can afford it, parents choose where to live in part based on the quality of school their house is assigned to. But other considerations are involved: taxes, convenience to work, pollution, availability of parks, and quality of housing stock all may be more important to parents than school quality. And the quality of schools may change over time, but high moving costs inhibit relocation. Residents whose children graduate may stop volunteering at the schools and approving school tax levies. And the tax laws make it costly to attend private schools or schools outside the attendance zone, since a parent must forego his tax contribution and pay full tuition at the new school as well. What's more, private school competition consists predominantly of Catholic schools. School vouchers would make private schools more affordable, which would elicit a supply response that may open up a wide variety of attractive choices to parents (Merrifield, 2002). So that parents who are not particularly interested in sending their children to Catholic schools may be more interested in sending them to a Montessori school that emphasizes African American culture.

Public economists sometimes think of education as a merit good: a pure private good that is funded by taxation and provided by the local government. Being private, its benefits are confined to the area in which it is produced. The significant spatial parameter estimates of the current study imply that some of the benefits of schooling spill over into neighboring areas. Schooling is not a merit good, then, and the presence of externalities means a non-optimal amount may be consumed.

Failure to incorporate spatial statistics may lead to misleading parameter estimates. Six of the eight parameter estimates for school inputs were statistically significant in the %PASS ALL and %PASS MATH regressions, but five of the six effects disappeared in the spatial models. Poverty appeared to depress reading and writing passage rates, but this effect disappeared in the spatial models. And spatial statistics uncovered other provocative findings, like the finding that having richer neighbors increases math and citizenship passage rates in our own school district.

Having found evidence of spillovers in education production functions, labor and education economists are exhorted to use spatial statistics in their estimations. Public and urban economists who deal with schooling in estimations are encouraged to do the same. Furthermore, significant spatial effects may be present in the demand for and supply of other publicly provided commodities like crime prevention, pollution abatement, garbage collection, libraries, and parks. Additional research is required. Pending these investigations, much of the empirical economic literature of the last thirty years may need to be redone to address the spatial nature of the data.

Table 1 Variable Definitions, Sources, and Means		
Variable	Definition and Source	Mean (σ)
%PASS ALL	Proportion of ninth-grade students passing all sections of the ninth-grade proficiency test (math, citizenship, reading and writing) in each school district in 1993 (1)	0.51 (0.14)
%PASS MATH	Proportion of ninth-grade students passing the math section of the ninth-grade proficiency test in each school district in 1993 (1)	0.61 (0.14)
%PASS CITIZENSHIP	Proportion of ninth-grade students passing the citizenship section of the ninth-grade proficiency test in each school district in 1993 (1)	0.72 (0.12)
%PASS READING	Proportion of ninth-grade students passing the reading section of the ninth-grade proficiency test in each school district in 1993 (1)	0.87 (0.07)
%PASS WRITING	Proportion of ninth-grade students passing the writing section of the ninth-grade proficiency test in each school district in 1993 (1)	0.87 (0.08)
%BOTH PARENTS	Proportion of students in each school district living with two parents in 1990 (2)	0.81 (0.09)
PARENT INCOME	Average parental income of students in each school district, in hundreds of thousands of dollars in 1990 (2)	0.33 (0.11)
%PRIVATE	Proportion of students in grades nine through twelve living in each public school district who attend non-public schools in 1990 (2)	0.06 (0.07)
%MINORITY	Proportion of students in each school district who are nonwhite in 1993 (1)	0.06 (0.12)
COHORT SIZE	Average number of students in each grade in each high school in 1993 in thousands; school district fall average daily membership divided by the number of grade levels the school district serves, divided by the number of high schools the district has, divided by 1000 (1,3)	0.19 (0.14)
TEACHER SALARY	Average teacher salary in each school district in hundreds of thousands of dollars in 1993 (1)	0.33 (0.05)
TEACHER EXPERIENCE	Average teacher experience in each school district in hundreds of years in 1993 (1)	0.15 (0.02)
PUPIL/TEACHER RATIO	Total average daily membership in each school district divided by the total number of classroom teachers, in hundreds of students per teacher in 1993 (1)	0.19 (0.02)
TEACHER EDUCATION	Number of teachers with a Masters degree divided by the total number of regular teachers in each school district in 1993 (1)	0.33 (0.05)
%POVERTY	Proportion of persons in each school district living	0.10

	under the official poverty income level in 1990 (2)	(0.07)
#DISTRICTS	Number of school districts in each county in 1993, in hundreds of districts (4)	0.10 (0.07)
%NO DIPLOMA	Proportion of parents of school-age children in each school district in 1990 who do not have a high school diploma (2)	0.16 (0.08)
%HS DIPLOMA ONLY	Proportion of parents of school-age children in each school district in 1990 who have a high school diploma but have not attended college (2)	0.45 (0.11)
LAG ---	Spatial lag Wx of the variable in question for the spatial Durbin model of Equation (18)	- -

Notes: Means are shown with standard deviation in parentheses below. Number of observations is 605. Sources: (1) Ohio Department of Education, Information Management Services, (2) *School District Data Book* (MESA Group, 1994), (3) *Ohio Educational Directory: 1992-1993 School Year*, (4) Ohio Department of Education, *Maps of Ohio School Districts: City, Exempted, Local*.

Table 2
Regression Results Using %PASS ALL

	Instrumental Variables Model	Spatial Error Model	Spatial Autoregressive Model	Spatial Durbin Model
%BOTH PARENTS	0.29** (4.09)	0.27** (2.68)	0.34** (3.56)	0.23* (2.55)
PARENT INCOME	0.40** (4.53)	0.15 (1.61)	0.17* (2.19)	0.15* (2.05)
%PRIVATE	-0.19* (2.47)	-0.15 (1.57)	-0.14* (1.65)	-0.12 (1.43)
%MINORITY	-0.15** (2.91)	-0.19** (3.26)	-0.19** (3.65)	-0.21** (3.71)
COHORT SIZE	-0.053 (1.18)	-0.070 (1.50)	-0.080* (1.92)	-0.077* (1.86)
TEACHER SALARY	0.58* (2.42)	0.32 (1.19)	0.23 (0.99)	0.20 (0.83)
TEACHER EXPERIENCE	-0.30 (0.94)	-0.05 (0.13)	-0.11 (0.35)	-0.16 (0.48)
PUPIL/TEACHER RATIO	0.74* (2.13)	0.56 (1.41)	0.48 (1.35)	0.56 (1.48)
TEACHER EDUCATION	-0.49* (2.00)	-0.20 (0.73)	-0.16 (0.71)	-0.13 (0.55)
%POVERTY	-0.24* (2.29)	-0.14 (1.08)	-0.06 (0.53)	-0.09 (0.74)
#DISTRICTS	0.20* (2.46)	0.13 (1.10)	0.14* (2.00)	0.26 (1.55)
%NO DIPLOMA	-0.49** (5.58)	-0.56** (5.44)	-0.51** (6.25)	-0.61** (6.59)
%HS DIPLOMA ONLY	-0.25** (3.95)	-0.34** (4.16)	-0.28** (4.47)	-0.38** (5.90)
LAG %BOTH PARENTS	- -	- -	- -	0.25 (1.48)
LAG PARENT INCOME	- -	- -	- -	0.17 (0.92)
LAG %PRIVATE	- -	- -	- -	0.23* (1.71)
LAG %MINORITY	- -	- -	- -	0.06 (0.65)
LAG COHORT SIZE	- -	- -	- -	0.041 (0.38)
LAG TEACHER SALARY	- -	- -	- -	0.26 (0.47)

LAG TEACHER EXPERIENCE	- -	- -	- -	-1.20* (1.82)
LAG PUPIL/TEACHER RATIO	- -	- -	- -	0.54 (0.73)
LAG TEACHER EDUCATION	- -	- -	- -	-0.60 (0.94)
LAG %POVERTY	- -	- -	- -	0.08 (0.40)
LAG #DISTRICTS	- -	- -	- -	0.028 (0.15)
LAG %NO DIPLOMA	- -	- -	- -	0.29 (1.64)
LAG %HS DIPLOMA ONLY	- -	- -	- -	0.36** (2.75)
CONSTANT	0.22* (1.73)	0.37** (2.75)	0.17 (1.43)	-0.00 (0.02)
Spatial Parameter Estimate ρ or λ	- -	0.36** (6.87)	0.26** (5.73)	0.28** (4.76)
Adjusted R-Square	0.49	0.54	0.54	0.56

Number of observations = 605. Parameter estimates shown with absolute value of t-statistic in parentheses below. ** = statistically significant at 0.01 level, * = statistically significant at 0.10 level. Spatial parameter is ρ for both Spatial Autoregressive Model and Spatial Durbin Model, and λ for Spatial Error Model. LAG --- is the estimate of the spatial lag parameter for Wx of each variable.

Table 3
Regression Results Using %PASS MATH

	Instrumental Variables Model	Spatial Error Model	Spatial Autoregressive Model	Spatial Durbin Model
%BOTH PARENTS	0.38** (4.30)	0.27** (2.72)	0.34** (3.93)	0.24* (2.50)
PARENT INCOME	0.09 (1.12)	0.05 (0.60)	0.10 (1.25)	0.05 (0.67)
%PRIVATE	-0.21** (2.81)	-0.16 (1.62)	-0.14* (1.70)	-0.11 (1.32)
%MINORITY	-0.22** (4.44)	-0.27** (4.20)	-0.26** (5.36)	-0.30** (5.15)
COHORT SIZE	-0.031 (0.70)	-0.046 (0.95)	-0.052 (1.17)	-0.06 (1.29)
TEACHER SALARY	0.79** (3.34)	0.58* (2.18)	0.49* (2.04)	0.37 (1.40)
TEACHER EXPERIENCE	-0.37 (1.17)	-0.04 (0.11)	-0.10 (0.30)	-0.04 (0.14)
PUPIL/TEACHER RATIO	0.88* (2.56)	0.65 (1.52)	0.57 (1.58)	0.49 (1.38)
TEACHER EDUCATION	-0.63** (2.60)	-0.38 (1.41)	-0.35 (1.42)	-0.23 (0.87)
%POVERTY	-0.26* (2.50)	-0.14 (1.04)	-0.08 (0.75)	-0.06 (0.48)
#DISTRICTS	0.16* (2.11)	0.15 (1.44)	0.15* (2.11)	0.31* (1.97)
%NO DIPLOMA	-0.56** (6.53)	-0.67** (6.95)	-0.59** (7.02)	-0.70** (7.93)
%HS DIPLOMA ONLY	-0.18** (2.87)	-0.22** (2.96)	-0.19** (2.94)	-0.29** (4.57)
CONSTANT	0.33** (2.62)	0.43** (3.08)	0.23* (1.74)	0.02 (0.05)
Spatial Parameter Estimate ρ or λ	- -	0.31** (5.07)	0.23** (5.48)	0.23** (4.04)
Adjusted R-square	0.49	0.53	0.53	0.55

Number of observations = 605. Parameter estimates shown with absolute value of t-statistic in parentheses below. ** = statistically significant at 0.01 level, * = statistically significant at 0.10 level. Spatial parameter is ρ for both Spatial Autoregressive Model and Spatial Durbin Model, and λ for Spatial Error Model. Spatial lags are included for Spatial Durbin Model but suppressed in output to save space: LAG PARENT INCOME, LAG %NO DIPLOMA, and LAG %HS DIPLOMA ONLY are positive.

Table 4
Regression Results Using %PASS CITIZENSHIP

	Instrumental Variables Model	Spatial Error Model	Spatial Autoregressive Model	Spatial Durbin Model
%BOTH PARENTS	0.28** (3.60)	0.27** (3.01)	0.28** (3.36)	0.24* (2.50)
PARENT INCOME	0.06 (0.87)	0.05 (0.70)	0.07 (0.98)	0.05 (0.67)
%PRIVATE	0.08 (1.22)	0.03 (0.38)	0.02 (0.26)	-0.11 (1.32)
%MINORITY	-0.16** (3.72)	-0.18** (3.41)	-0.18** (4.17)	-0.30** (5.15)
COHORT SIZE	-0.060 (1.54)	-0.051 (1.17)	-0.057 (1.57)	-0.06 (1.29)
TEACHER SALARY	0.25 (1.21)	0.22 (0.88)	0.22 (1.02)	0.37 (1.40)
TEACHER EXPERIENCE	0.07 (0.26)	0.26 (0.73)	0.18 (0.59)	-0.04 (0.14)
PUPIL/TEACHER RATIO	0.06 (0.19)	-0.05 (0.15)	-0.02 (0.06)	0.49 (1.38)
TEACHER EDUCATION	-0.14 (0.67)	-0.13 (0.53)	-0.14 (0.65)	-0.23 (0.87)
%POVERTY	-0.31** (3.30)	-0.27* (2.21)	-0.22* (2.57)	-0.06 (0.48)
#DISTRICTS	0.09 (1.37)	0.08 (0.78)	0.09 (1.31)	0.31* (1.97)
%NO DIPLOMA	-0.29** (3.84)	-0.33** (3.83)	-0.32** (3.84)	-0.70** (7.93)
%HS DIPLOMA ONLY	-0.17** (3.06)	-0.20** (3.07)	-0.18** (3.37)	-0.29** (4.57)
CONSTANT	0.58** (5.23)	0.61** (4.73)	0.46** (3.95)	0.02 (0.05)
Spatial Parameter Estimate ρ or λ	- -	0.22** (3.86)	0.17** (3.53)	0.23** (4.04)
Adjusted R-square	0.44	0.45	0.45	0.55

Number of observations = 605. Parameter estimates shown with absolute value of t-statistic in parentheses below. ** = statistically significant at 0.01 level, * = statistically significant at 0.10 level. Spatial parameter is ρ for both Spatial Autoregressive Model and Spatial Durbin Model, and λ for Spatial Error Model. Spatial lags are included for Spatial Durbin Model but suppressed in output to save space: LAG PARENT INCOME, LAG %NO DIPLOMA, and LAG %HS DIPLOMA ONLY are positive.

Table 5
Regression Results Using %PASS READING

	Instrumental Variables Model	Spatial Error Model	Spatial Autoregressive Model	Spatial Durbin Model
%BOTH PARENTS	0.19** (4.34)	0.13** (2.60)	0.14** (3.07)	0.10* (2.42)
PARENT INCOME	0.04 (1.07)	0.07* (1.79)	0.08* (2.54)	0.07* (2.08)
%PRIVATE	0.05 (1.38)	0.04 (0.97)	0.03 (0.63)	0.05 (1.50)
%MINORITY	-0.10** (4.14)	-0.13** (4.60)	-0.14** (5.76)	-0.15** (5.40)
COHORT SIZE	-0.038* (1.79)	-0.040 (1.63)	-0.030 (1.49)	-0.032* (1.70)
TEACHER SALARY	0.10 (0.89)	-0.01 (0.09)	-0.02 (0.19)	-0.03 (0.27)
TEACHER EXPERIENCE	0.09 (0.60)	0.16 (0.75)	0.17 (0.91)	0.13 (0.78)
PUPIL/TEACHER RATIO	0.10 (0.62)	0.07 (0.33)	0.05 (0.25)	0.06 (0.37)
TEACHER EDUCATION	-0.13 (1.08)	-0.03 (0.25)	-0.05 (0.37)	-0.04 (0.33)
%POVERTY	-0.12* (2.37)	-0.10 (1.50)	-0.08 (1.62)	-0.06 (0.95)
#DISTRICTS	0.09* (2.39)	0.05 (0.93)	0.06* (1.83)	0.05 (0.89)
%NO DIPLOMA	-0.25** (5.95)	-0.28** (5.30)	-0.28** (6.95)	-0.33** (6.94)
%HS DIPLOMA ONLY	-0.05 (1.46)	-0.04 (1.08)	-0.02 (0.70)	-0.06* (1.86)
CONSTANT	0.75** (12.40)	0.80** (10.86)	0.64** (9.49)	0.43** (3.36)
Spatial Parameter Estimate ρ or λ	- -	0.26** (4.55)	0.17** (4.02)	0.23** (4.48)
Adjusted R-square	0.47	0.50	0.49	0.51

Number of observations = 605. Parameter estimates shown with absolute value of t-statistic in parentheses below. ** = statistically significant at 0.01 level, * = statistically significant at 0.10 level. Spatial parameter is ρ for both Spatial Autoregressive Model and Spatial Durbin Model, and λ for Spatial Error Model. Spatial lags are included for Spatial Durbin Model but suppressed in output to save space: LAG %BOTH PARENTS, LAG %MINORITY, LAG COHORT SIZE, LAG TEACHER SALARY, and LAG %HS DIPLOMA ONLY are positive; LAG TEACHER EDUCATION is negative.

Table 6
Regression Results Using %PASS WRITING

	Instrumental Variables Model	Spatial Error Model	Spatial Autoregressive Model	Spatial Durbin Model
%BOTH PARENTS	0.21** (3.30)	0.18* (2.38)	0.20** (3.28)	0.15* (2.45)
PARENT INCOME	0.05 (0.77)	0.03 (0.51)	0.04 (0.66)	0.04 (0.69)
%PRIVATE	0.08 (1.43)	0.07 (1.23)	0.06 (1.20)	0.10* (1.74)
%MINORITY	-0.04 (1.09)	-0.06 (1.29)	0.05 (1.35)	-0.09* (2.24)
COHORT SIZE	-0.036 (1.14)	-0.037 (0.98)	-0.037 (1.22)	-0.039 (1.28)
TEACHER SALARY	0.01 (0.04)	0.05 (0.26)	0.05 (0.30)	0.02 (0.11)
TEACHER EXPERIENCE	-0.03 (0.15)	0.02 (0.06)	0.00 (0.02)	-0.07 (0.30)
PUPIL/TEACHER RATIO	0.15 (0.61)	0.16 (0.56)	0.14 (0.55)	0.23 (0.94)
TEACHER EDUCATION	0.00 (0.02)	-0.02 (0.09)	-0.03 (0.17)	-0.02 (0.12)
%POVERTY	-0.15* (2.02)	-0.15 (1.59)	-0.12 (1.57)	-0.12 (1.13)
#DISTRICTS	0.05 (0.87)	0.01 (0.18)	0.03 (0.53)	0.01 (0.12)
%NO DIPLOMA	-0.05 (0.75)	-0.06 (0.79)	-0.06 (0.94)	-0.07 (0.98)
%HS DIPLOMA ONLY	-0.11* (2.36)	-0.13** (2.69)	-0.11* (2.38)	-0.18** (3.89)
CONSTANT	0.73** (8.16)	0.77** (7.66)	0.59** (5.35)	0.50* (2.32)
Spatial Parameter Estimate ρ or λ	- -	0.20** (3.13)	0.17** (2.99)	0.18** (3.11)
Adjusted R-square	0.21	0.23	0.22	0.25

Number of observations = 605. Parameter estimates shown with absolute value of t-statistic in parentheses below. ** = statistically significant at 0.01 level, * = statistically significant at 0.10 level. Spatial parameter is ρ for both Spatial Autoregressive Model and Spatial Durbin Model, and λ for Spatial Error Model. Spatial lags are included for Spatial Durbin Model but suppressed in output to save space: LAG COHORT SIZE and LAG %HS DIPLOMA ONLY are positive; LAG TEACHER EDUCATION is negative.

References

Akerhielm, Karen. Does Class Size Matter? Economics of Education Review 14(3), September 1995, p. 229-241.

Anselin, Luc. *Spatial Econometrics: Methods and Models*. Kluwer Academic Publishing, London and Dodrecht: 1988, p. 35, 58-59, 103, 181.

Barry, Ronald and R. Kelley Pace. "A Monte Carlo Estimator of the Log Determinant of Large Sparse Matrices." Linear Algebra and its Applications 289(1-3), 1999, p. 41-54.

Bishop, John. Is the Test Score Decline Responsible for the Productivity Growth Decline? American Economic Review 79(1), March 1989, p. 178-197.

Borland, Melvin V. and Roy M. Howsen. Competition, Expenditures and Student Performance in Mathematics: A Comment on Couch et. al. Public Choice 87(3-4), June 1996, p. 395-400.

Bradford, David F. and Wallace E. Oates. Suburban Exploitation of Central Cities and Governmental Structure, in *Redistributions Through Public Choice*, H.M. Hochman and G.E. Peterson, eds, New York and London: 1974, p. 44-90.

Brasington, David M. Joint Provision of Public Schooling: The Consolidation of School Districts. Journal of Public Economics 73(3), September 1999, p.373-393.

Brasington, David M. School District Consolidation, Student Performance, and Housing Values. Journal of Regional Analysis and Policy 27(2), 1997, p. 43-54.

David M. Brasington and Donald R. Haurin. "Educational Outcomes and House Values: A Test of the Value-Added Approach," *Journal of Regional Science* (forthcoming).

Brasington, David M. and Diane Hite. "Demand for Environmental Quality: A Spatial Hedonic Analysis," Regional Science and Urban Economics 35(1), January 2005, p. 57-82.

Couch, Jim F. and William F. Shughart II and Al L. Williams. Private School Enrollment and Public School Performance. Public Choice 76(4), August 1993, p. 301-312.

Davidson, Russell and James G. MacKinnon. Several Tests for Model Specification in the Presence of Multiple Alternatives. Econometrica 49(3), May 1981, p. 781-793.

Dee, Thomas S. Competition and the Quality of Public Schools. Economics of Education Review 17(4), October 1998, p. 419-427.

Edwards, John H. Y. A Note on the Publicness of Local Goods: Evidence from New York State Municipalities. Canadian Journal of Economics 19(3), August 1986, p. 568-573.

Epple, Dennis and Richard E. Romano. Competition Between Private and Public Schools, Vouchers, and Peer-Group Effects. American Economic Review 88(1), March 1998, p. 33-62.

Falkinger, Josef. The Private Provision of Public Goods when the Relative Size of Contributions Matters. Finanzarchiv 51(3), 1994, p. 358-371.

Figlio, David N. Functional Form and the Estimated Effects of School Resources. Economics of Education Review 18(2), April 1999, p. 241-252.

Fowler, William J. Jr. and Herbert J. Walberg. School Size, Characteristics, and Outcomes. Educational Evaluation and Policy Analysis 13(2), 1991, p. 189-202.

Friedkin, Noah E. and Juan Necochea. School System Size and Performance: A Contingency Perspective. Educational Evaluation and Policy Analysis 10(3), 1988, p. 237-249.

Gomes-Neto, Joao Batista, Eric A. Hanushek, Raimundo Helio Leite, and Roberto Claudio Frota-Bezzera. Health and Schooling: Evidence and Policy Implications for Developing Countries. Economics of Education Review 16(3), June 1997, p. 271-282.

Griffith, Daniel A. 1988. Advanced Spatial Statistics: Special Topics in the Exploration of Quantitative Spatial Data Series. Kluwer Academic Publishers, Dordrecht.

Haller, Emil J. High School Size and Student Indiscipline: Another Aspect of the School Consolidation Issue? Educational Evaluation and Policy Analysis 14(2), 1992, p. 145-156.

Hanushek, Eric A. The Trade-Off Between Child Quantity and Quality. Journal of Political Economy 100(1), February 1992, p. 84-117.

Hanushek, Eric A. "The Economics of Schooling: Production and Efficiency in Public Schools." Journal of Economic Literature 24(3), September 1986, p. 1141-1177.

Hanushek, Eric A. and Lori L. Taylor. Alternative Assessments of the Performance of Schools: Measurement of State Variations in Achievement. Journal of Human Resources 25(2), 1990, p. 179-201.

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

Hoxby, Caroline Minter. Does Competition Among Public Schools Benefit Students and Taxpayers? American Economic Review 90(5), December 2000, p. 1209-1238.

Hoxby, Caroline Minter. What Do America's 'Traditional' Forms of School Choice Teach Us About School Choice Reforms? Federal Reserve Bank of New York Economic Policy Review 4(1), March 1998, p. 47-59.

Hoxby, Caroline Minter. Do Private Schools Provide Competition for Public Schools? Revision of NBER Working Paper no. 4978 (1994), 1997.

Hoxby, Caroline Minter. Are Efficiency and Equity in School Finance Substitutes or Complements? Journal of Economic Perspectives 10(4), Fall 1996, p. 51-72.

Ireland, Norman J. The Mix of Social and Private Provision of Goods and Services. Journal of Public Economics 43(2), November 1990, p. 201-219.

Jewell, Robert W. School and School District Size Relationships: Cost, Results, Minorities, and Private School Enrollments. Education and Urban Society 21(2), 1989, p. 140-153.

Kelejian, Harry H. and Ingmar R. Prucha. "Prediction Efficiencies in Spatial Models with Spatial Lags." University of Maryland, College Park, Economics Department working paper, October 8, 2004.

Kennedy, Peter E. and John J. Siegfried. Class Size and Achievement in Introductory Economics: Evidence from the TUCE III Data. Economics of Education Review 16(4), October 1997, p. 385-394.

Kennedy, Peter. *A Guide to Econometrics*. The MIT Press, Cambridge, MA:1998, p. 172.

Kennedy, Peter. *A Guide to Econometrics*. The MIT Press, Cambridge, MA:1992, p. 368.

LeSage, James P. "The Theory and Practice of Spatial Econometrics." February, 1999. www.spatial-econometrics.com.

LeSage, James P. Regression Analysis of Spatial Data. Journal of Regional Analysis and Policy 27(2), 1997a, p. 83-94.

LeSage, James P. "Bayesian Estimation of Spatial Autoregressive Models." International Regional Science Review 20(1-2), 1997b, p. 113-129.

Loury, Linda D. and David Garman. College Selectivity and Earnings. Journal of Labor Economics 13(2), April 1995, p. 289-308.

Maddala, G.S. *Introduction to Econometrics*. Prentice-Hall, Inc., USA: 1992, p. 395.

Merrifield, John. *School Choices: True and False*. The Independent Institute, Oakland, CA: 2002.

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

Meyer, Robert H. Value-Added Indicators of School Performance, in *Improving America's Schools: The Role of Incentives*, Eric A. Hanushek and Dale W. Jorgenson, eds, National Academy Press, Washington, D.C.: 1996, p. 197-223.

Millimet, Daniel L. and Vasudha Rangaprasad. "Strategic Competition Amongst Public Schools." Southern Methodist University Department of Economics working paper, April 2005.

Murdoch, James C., Morteza Rahmatian and Mark A. Thayer. A Spatially Autoregressive Median Voter Model of Recreational Expenditures. Public Finance Quarterly 21(3), July 1993, p. 334-350.

Murnane, Richard J., John B. Willett and Frank Levy. The Growing Importance of Cognitive Skills in Wage Determination. Review of Economics and Statistics 77(2), May 1995, p. 251-266.

Ohio Department of Education, Division of Information Management Services. http://www.ode.ohio.gov/www/ims/pregen_rept.html, 1999.

Ohio Department of Education, State Board of Education. *Ohio Educational Directory: 1992-1993 School Year*. Columbus, OH: 1993.

Ohio Department of Education. *Maps of Ohio School Districts: City, Exempted, Local*. Columbus, OH: 1985.

Ornstein, Allan C. School Consolidation vs. Decentralization: Trends, Issues, and Questions. The Urban Review 25(2), 1993, p. 167-174.

Pace, R. Kelley and Ronald P. Barry. "Simulating Mixed Regressive Spatially autoregressive Estimators." Computational Statistics 13, 1998, p. 397-418.

Ramanathan, Ramu. *Introductory Econometrics with Applications, 4th ed*. The Dryden Press, USA: 1998, p. 170.

Reiter, Michael and Alfons Weichenrieder. Are Public Goods Public? A Critical Survey of the Demand Estimates for Local Public Services. Finanzarchiv N.F. 54(3), 1997, p. 374-408.

Rothstein, Jesse. "Does Competition Among Public Schools Benefit Students and Taxpayers? A Comment on Hoxby (2000)." American Economic Review (forthcoming).

Sander, William. Catholic Grade Schools and Academic Achievement. Journal of Human Resources 31(3), Summer 1996, p. 540-548.

Sander, William. Endogenous Expenditures and Student Achievement. Economics Letters 64(2), August 1999, p. 223-231.

Stern, David. Educational Cost Factors and Student Achievement in Grades Three and Six: Some New Evidence. Economics of Education Review 8(2), 1989, p.149-158.

Voβ, W. Nutzen-Spillover-Effekte als Problem des Kommanalen Finanzausgleichs: Ein Beitrag zur Okonomischen Rationalitat des Ausgleichs Zentralitatsbedingten Finanzbedarfs, Frankfurt a.M., 1991.

Willms, J. Douglas and Frank Echols. Alert and Inert Clients: The Scottish Experience of Parental Choice of Schools. Economics of Education Review 11(4), December 1992, p. 339-350.

Wyckoff, James H. The Nonexcludable Publicness of Primary and Secondary Public Education. Journal of Public Economics 24(3), August 1984, p. 331-351.

Zanzig, Blair R. Measuring the Impact of Competition in Local Government Education Markets on the Cognitive Achievement of Students. Economics of Education Review 16(4), October 1997, p. 431-444.

---

[1] The number quoted is from the %PASS MATH results, the set of results with the highest proportion of statistically significant results. The median of the three significant parameter estimates is used (0.16), and the values of #DISTRICTS and %PASS MATH are evaluated at the sample means. All elasticities throughout the paper are evaluated at sample means.

[2] Among the main differences are 1) converting from expenditures to proficiency tests as an outcome measure, 2) including variables for student and parent demographic characteristics, community demographic characteristics, variables related to competition, school characteristics, enrollment, and school board administrative efficiency and effectiveness, and 3) deriving first-order conditions from the model.

[3] Only students assessed to have a learning disability are exempt. Only if a student's team leader determines that the student has a learning disability each year and exempts that student every year of his or her high school career will that student not be required to take the proficiency test.

[4] The form of the Hausman test is that detailed in Maddala (1992) and Ramanathan (1988). Specifically, education production functions are run with and without the predicted values of #DISTRICTS and %PRIVATE. The calculated F statistic is 1.89 compared to a critical value of 2.30 at the 0.10 level of significance, suggesting that #DISTRICTS and %PRIVATE may be treated exogenously. In unreported regressions, #DISTRICTS and %PRIVATE are treated endogenously, yielding somewhat larger parameter estimates for the two variables but no change in statistical significance

[5] See Bradford and Oates (1974), Voβ (1991), and Reiter and Weichenrieder (1997) for surveys. See also Murdoch, Rahmatian and Thayer (1993), Wyckoff (1984), and Edwards (1986).

[6] Murdoch, Rahmatian and Thayer (1993) use a spatial autoregressive model to capture spillovers in recreation expenditures in Los Angeles. Brasington and Hite (2005) use a spatial Durbin model to capture spillovers in environmental quality, and Millimet and Rangaprasad (2005) use spatial statistics to model spillovers in educational input hiring.

[7] The spatial statistics literature commonly assumes that an observation cannot be its own neighbor, so that the spatial weights matrix has a zero diagonal. Also, just like there is no consensus on functional form in traditional regressions there is no consensus on the

number of neighbors to use in spatial statistics, and the choice of the number of neighbors often affects estimation results. Five neighbors are chosen in the current study because, looking at a map of Ohio's school districts, it seems that on average each school district shares a border with five other school districts.

[8] If V is a matrix of ones, the first two terms of Equation (16) fully characterize a non-Bayesian spatial error model.

[9] An alternative is to set the two parameters of the gamma distribution for r to the informative priors of 8 and 2. Nearly identical estimates are achieved either way.

[10] For example, the Bayesian spatial error model with 300 draws and 30 burn-in draws, using %PASS MATH as dependent variable, took 629 seconds.

[11] Kelejian and Prucha (2004) prove this for a model with both a spatial autoregressive lag term ρWt and $\lambda W\varepsilon$, but the results should follow for the spatial Durbin model as well.

[12] School outcomes are not available in Ohio at the school level, just at the school district level. For high schools, this may not matter much, as most school districts have one high school. For example, even among the urban school districts only 24 of the 140 have more than one high school.

[13] Millimet and Rangaprasad (2005) also have a claim to being the first, since neither of our papers have been published. The first draft of this paper was completed August 5, 1999, which may precede theirs.

[14] This is much larger than the spatial effects Murdoch, Rahmatian and Thayer (1993) find for recreation expenditures. They find a very small (0.01) spatial autoregressive parameter estimate and statistically significant spillovers in only one of their two regressions.

[15] Except for the working paper by Millimet and Rangaprasad (2005).

[16] At the mean, the largest it reaches is 0.043 in the spatial Durbin model of the %PASS CITIZENSHIP regression.