2011

Strategic Competition Over School Inputs and Outputs

Gary Richard Cohen
Oberlin College

Strategic Competition over School Inputs and Outputs

*Gary Richard Cohen**

Abstract

Although public schools are not generally subject to direct competition for students, it is commonly thought that they nonetheless face competition through parents' residential choice. Such competitive effects are likely to depend on the relative proximity of school districts if it is less costly to move short distances than long, or if parents are able to more easily send their children to nearby districts through open enrollment policies. Using panel data for 607 Ohio school districts from 1998 to 2007, I test for strategic interaction over teacher salaries and standardized test scores. I present evidence that Ohio public school districts act to 'follow their neighbors' – that is, that they attempt to exactly mirror changes in the inputs and outputs of nearby school districts – and I show that this result is robust to different definitions of 'neighbor.' I further show that conventional estimation of spatial autoregressive models via Maximum Likelihood or via poorly-instrumented General Method of Moments may create large biases in the estimated spatial autocorrelation coefficient. I suggest that this statistical phenomenon may explain some of the differences in estimated magnitudes of school competition across the spatial literature.

1 Introduction

Public education in the United States is highly decentralized compared to other developed countries, both in finance and in instruction methods. This creates great heterogeneity among school districts, so that even districts which are geographically near to one another may vary significantly in goals and performance. In Northeast Ohio, the districts of Richmond Heights and South Euclid-Lyndhurst sit less than three miles apart and have similar demographic characteristics. However, South Euclid-Lyndhurst schools are rated 'effective' by the Ohio Department of Education, meeting 15 of 26 state indicators (such as adequate performance on proficiency tests) and boasting a 96% on-time graduation rate; by contrast, Richmond Heights is rated a 'continuous improvement' district – meeting only 8 state indicators and graduating only 88% of their students on time.

In the past decade, addressing such inequalities became regarded as the purview of federal policymakers. However, federal reforms attempting to impose uniform standards on public schools – most infamously the No Child Left Behind Act of 2001 – have seen little success and large controversy. As those who craft education policy have increasingly begun to advocate 'school choice' programs as a means to introduce competitive discipline into the public school system, economists have increasingly turned their attention to understanding the mechanisms by which that competition occurs.

While nearby school districts do have the potential to vary widely in many respects, there is reason to believe that they exert important influences on one another. Although public schools do not need to compete

*I am indebted to Professor Hirschel Kasper for his guidance on both the structure and content of this work. I also owe special thanks to Professor Ron Cheung for his assistance with the spatial econometrics. Lastly, I would like to thank the rest of the Oberlin College Economics faculty and my two student discussants, Eric Hardy and Ian Walker, for their comments on the first draft of this paper.

directly for students in the way that private schools do, they are nonetheless accountable to parents to the extent that parents vote on school finances and are able to move between districts in order to send their children elsewhere.

These effects are further magnified in Ohio, where the 'property tax reduction factor' and the large proportion of schools that admit students under open enrollment give parents greater powers of voice and exit. When an Ohio school district passes a levy, its revenue is fixed until it can renew the levy or pass another; if property values rise, the tax rate automatically falls to compensate. This makes school districts more accountable to parents' wishes, as the only way out of a binding nominal revenue constraint is by popular vote. In addition, most districts allow students to apply to enroll in other schools or other districts without moving residency – neighboring districts in some cases, and any Ohio district in others. This drastically lowers the cost of exiting a poorly-performing district. Because parents are able to observe the actions and the particular advantages of other school districts – particularly those that are geographically close – they are likely to take these observations into account when voting or making attendance decisions about their local schools.[1]

Furthermore, there is reason to believe that these interactive effects between school districts are spatially dependent. It is reasonable to assume that parents taking advantage of open enrollment policies will be more likely to send their children to nearby schools, whether they are explicitly restricted to neighboring districts or whether they simply wish to avoid unreasonably long commutes for their children. It is also reasonable to assume that it is less costly for parents to move residence between nearby districts than between those that are far apart.

Because of this, spatial econometric methods may provide useful insight into the nature and degree of such interactions. By allowing for the identification of a causal 'spillover' effect between nearby school districts, a spatial econometric analysis is able to identify the ways in which school districts respond to the decisions of their neighbors.

Empirical work on strategic competition among schools is important because the predictions of theory are ambiguous. An increase in the observed quality of one school district may encourage nearby districts to respond strategically, making similar improvements in order to retain students and thus funding.[2] Absent strategic behavior, an increase in the quality of one school district will raise property values and thus the expected value of future taxes. It then may push those who place little value on public education to move to other districts with lower expected tax burdens, while attracting those who highly value public education. This would lead to some districts 'specializing' in having good schools, while others 'specialize' in having low tax costs.[3]

On the other hand, the spatial effects of school competition on teacher salaries are neither theoretically ambiguous nor untreated by quantitative research. Teachers compete in regional labor markets; an increase in salaries in one district creates pressure on nearby others to increase their own salaries in order to attract and retain teachers. Although tenure is far more important in the market for public school teachers than in others, previous empirical research has found large and significant (on the order of 64% to 100%)[4] spillover

[1] The average student mobility over the sample – defined as the number of students enrolled in a district for less than one year – is 8%, with a standard deviation of 5%. This translates to 1 in 12.5 with some variation, meaning that most parents probably choose districts before students start school but that there is some movement.

[2] See section 2 of Millimet and Rangaprasad (2007)

[3] See Nechyba (2003) for a formal model.

[4] Winters (2010) defines 'neighbor' as school districts within fifty miles and weights nearby districts more greatly than distant ones. He finds teacher salaries in a district increase about sixty-four cents for every dollar increase in a district's neighbors. Millimet and Rangaprasad (2007) consider districts neighbors if they are in the same county and find salary increases that match neighbors up to dollar-for-dollar parity.

effects from the spatially-weighted averages of neighboring districts.

The paper is organized as follows. Section 2 reviews some of the most relevant literature on public schools. Section 3 discusses the data and empirical methodology. Section 4 presents the empirical evidence drawn from spatial econometric analysis. Section 5 provides sensitivity analysis for the empirical results. The last section concludes and discusses possibilities for further study.

2 Review of the Literature

The assertion that schools compete is hardly new.[5] Though research into the economics of education has long considered competition between public schools through households' decisions to locate based on the costs and benefits of local public services,[6] only recently have explicit spatial econometric models been applied to competition between schools. Spatial econometric methods show much promise for the analysis of interactions between neighboring schools, allowing researchers to look beyond the overall effects of competition in educational markets and investigate the strength of competition between schools within a particular market. This may yield important insight into what factors make a strong environment for school competition.[7]

More technically, the presence of a spatial relationship among dependent variables can cause nonspatial estimates to be biased and inconsistent.[8] Thus, the discovery of such a relationship casts doubt on the other estimators and in particular may result in finding artificially significant effects for nonspatial estimators. The presence of spatial correlation between the error terms may also be a concern; if shocks from one unit of observation spill over to others, or if unobservable characteristics are correlated across spatial units larger than the unit of observation, failing to account for these correlations may result in inconsistently-estimated standard errors.[9]

The literature examining strategic competition through spatial econometric methods is young but growing quickly. Blair and Staley (1995) examine a subset of Ohio school districts and find that a school increases its test scores by half a point for each one point increase in the test scores of neighboring districts, hypothesizing that schools compete on quality. Wagner and Porter (2000) and Greenbaum (2002) examine Ohio and Pennsylvania respectively and find that teacher salaries in a district are positively influenced by teacher salaries in nearby districts, so that an increase of one dollar in neighboring district teacher salaries increases one's own teacher salaries by fifty six to ninety six cents. Ghosh (2010) studies Massachusetts public schools under open enrollment and finds evidence of spillovers in per student expenditures, although his point estimates are significantly less than one.

A few recent studies take more care to establish causality through instrumented General Method of Moments (GMM) estimation and find larger spillovers seemingly indicative of stronger competition. I will show in Section 5 that this may be thanks to their use of exogenous instruments for competition versus naïve Maximum Likelihood estimates. Babcock, Engberg and Greenbaum (2005) and Millimet and Rangaprasad (2007) find evidence of teacher salary spillovers in Pennsylvania and spillovers in multiple school inputs[10] in Illinois; Babcock, Engberg and Greenbaum find that a one dollar increase in teacher salaries in districts on

[5] See, e.g. Zanzig (1997) and Hoxby (2000)

[6] Tiebout (1956)

[7] For example, Millimet and Rangaprasad (2007) find that Illinois schools only compete under periods of binding revenue constraint or 'tax caps' by evaluating constrained versus unconstrained counties.

[8] Anselin (1988)

[9] See, e.g. Kelenkoski and Lacombe (2008), who show that controlling for spatial correlation significantly changes their results.

[10] 'Inputs' include teacher salary, the student-teacher ratio, total per-student expenditure, per-student capital expenditure, and school size.

a union's comparison list increases teacher salaries by about eighty four to ninety one cents – a larger effect than in Greenbaum's earlier study of the same state – while Millimet and Rangaprasad define 'neighbors' as districts in the same county and find spillovers in salary of about fifty six cents to a dollar per neighboring dollar. Winters (2010) applies a general spatial model (SAC) to a national sample of public schools and finds spillover effects on the order of sixty four cents per neighboring dollar of teacher salary using a distance-based weighting scheme.

Nonetheless, there is appreciable need for further research. My work most closely follows from Millimet and Rangaprasad (2007), who perform the most careful estimation and instrumentation out of any study examining multiple inputs. They assert that strategic competition between school districts only occurs during periods of revenue constraint caused by tax caps; Ohio's 'property tax reduction factor' thus makes it a strong case for such competition. However, they restrict the effects of strategic competition to districts within the same county. This imposes a somewhat arbitrary structure on the data, sharply delineating the bounds of an educational market where reality may well be more complex. Their failure to provide robustness testing for the structure of the spatial weights matrix is not unusual in spatial econometric research, but it nonetheless introduces the possibility that their results are idiosyncratic to their particular choice of spatial weights.[11]

This paper contributes to the existing body of literature by providing the first treatment of spatial dependence in school outputs (i.e. test scores) where competition is treated as endogenous. It also joins the small number of state-level studies employing spatial panel data, allowing for more accurate estimates in the presence of unobservable, time- or district-invariant heterogeneity. In addition, I employ careful robustness testing for the form of the weighting matrix and Instrumental Variables (IV) estimation of the spatially lagged dependent variable (transforming the Spatial Autoregressive (SAR) model into a reduced-form Spatial Lag of X (SLX) model) to provide greater confidence that the results are real.[12]

3 Data and Methodology

Following the existing literature and the brief theory outlined in the introduction, I assume that my dependent variables are correlated across space after controlling for other determinants.[13] After verifying this assumption with statistical tests, I turn to regression analysis to determine whether the relationship is causal – that is, whether there are spillovers between neighboring school districts in teacher salaries and student achievement. The structural model estimated in this paper can thus be represented by a Spatial Autoregressive (SAR) model:

$$(1) \quad Y_{it} = C + \rho W Y_{it} + X_{it}\beta + \varepsilon_{it}$$

where C is the constant term, and W is a $nt \times nt$ weights matrix that specifies the structure of the spatial correlation for the dependent variable. Because the spatial weights are assumed invariant across years, W is a concatenation of t identical $n \times n$ matrices along its diagonal; observations in each year interact with one another, but observations in different years are given relative weights of zero. Because W is an $nt \times nt$ matrix and Y is a $nt \times 1$ vector, WY is a $nt \times 1$ vector and WY_{it} is a scalar representing a spatially-weighted sum of

[11] See Plümper and Neumayer (2010) for a look at problems relating to misspecification of the weighting matrices.

[12] See Gibbons and Overman (2010) for a very good overview of endogeneity and identification issues in spatial econometric research.

[13] I test for this formally with robust LM tests derived by Elhorst (2009). I find very strong evidence of spatial autocorrelation in both dependent variables.

neighboring Y values to district i in year t. The coefficient ρ measures the extent of spatial autocorrelation in the dependent variable, and ε is a mean zero error term that is independent and identically distributed across observations.

Because of the presence of Y on the right-hand side of the SAR model, attempts at direct estimation suffer from obvious endogeneity problems.[14] To overcome these problems, I instrument for Y by estimating a Spatial (lag of) X (SLX) reduced-form of (1):

$$(2) \quad Y_{it} = C + WZ_{it}\gamma + X_{it}\beta + \varepsilon_{it}$$

Where γ is a vector of coefficients, Z is a $nt \times k$ matrix of exogenous instruments and $WZ\gamma$ is used to instrument for ρWY. In addition to increasing the strength of the argument for a causal effect from ρWY, Instrumental Variables estimation is consistent in the presence of spatially-correlated error terms.[15]

I conduct several diagnostic tests for the validity of the IV estimates. First, I report the Kleibergen-Paap (2006) rk LM statistic, an underidentification test for the relevance of the instruments. Second, I report the Kleibergen-Paap (2006) rk Wald F statistic for the strength of the instruments, using the conventional rule-of-thumb value of 10. Finally, I report Hansen's J statistic, an overidentification test for the validity of the instruments.

I produce the spatial weights matrix as follows: each element w_{ij} of W is the inverse of the distance between the centers of school districts i and j, with a 50-mile cutoff so that districts further than 50 miles from district i are given zero weight. The matrix is then normalized so that its rows sum to one in order to act as a set of weights and let any multiplicative effect emerge in ρ. Diagonal elements are set equal to zero so that no district is its own neighbor. Thus, each element of the vector WY is a distance-weighted average of Y across all other districts within 50 miles. The theoretical justification for the choice of inverse distance weights is the assumption that parents find it less costly to observe, move to or send their children to nearby districts than those that are far. The justification for the 50 mile radius is that school districts on one side of a large metropolitan area should still consider as neighbors school districts on the other side; when parents do move long distances within a metropolitan area, they are likely to move from suburbs into other suburbs rather than into the nearer city center. While I believe these are defensible assumptions, I provide robustness testing for the structure of the spatial weights matrix in Section 5.

I estimate two empirical models in this paper, each a problem unto itself. The first seeks to uncover spillovers in teacher salaries. Because the data does not include a measure of average teacher salary, I define it as a district's total expenditures on teacher salaries divided by the number of full-time equivalent (FTE) teachers. The explanatory variables fall into two categories: labor demand factors and labor supply factors. Among the factors influencing school districts' demand for labor are district size[16] (measured here by the number of schools in a district, the total enrollment, and the total number of teachers), the county unemployment rate,[17] and the value of the property tax base.[18] Among the factors influencing labor supply are mostly compensating differentials – Martin (forthcoming) suggests that teachers require higher salaries to teach students from disadvantaged backgrounds, so I control for the share of minority students and the share of low-income students as measured by eligibility for free and reduced-price lunch. Because Vedder and Hall (2000) report that teachers prefer a low student-teacher ratio, I include the student-teacher

[14] Again, see Gibbons and Overman (2010) for a full discussion.
[15] Kelejian and Prucha (1998)
[16] Walden and Newmark (1995)
[17] Taylor (forthcoming)
[18] e.g. Lentz (1998) and Winters (2009)

ratio. Because teachers are also likely to require compensating differentials for most any type of work above basic, elementary-level classroom teaching, I also include the proportion of secondary teachers,[19] the proportions of kindergarten and prekindergarten teachers, the proportion of ungraded teachers, the proportion of students in individualized education programs (IEP), and the proportion of students who are 'limited English proficient/English language learners' (LEP/ELL). Ohio is somewhat unique in allowing school districts to collect residence-based income taxes in addition to property taxes; I thus include a dummy variable for whether a district uses an income tax to control for any systematic differences that may cause or arise from the adoption of such a tax. Unfortunately, the data lacks measures of union activity. Because teacher unions exert significant upward pressure on teacher wages,[20] I expect to find bias in explanatory variables correlated with union activity. However, because changes in the union status of Ohio school districts are particularly rare, I expect a good deal of the effects of unionization to be absorbed by school district fixed effects.

The second model tests for spillover effects in achievement test scores, examining proficiency rates on the five sections of the 10th-grade Ohio Graduation Test (OGT). Explanatory variables related to this educational output largely involve uncontrollable student inputs and controllable institutional inputs. On the institutional side, there is some evidence[21] that school districts benefit from increasing returns to scale in education production – so I include the number of schools in a district as well as the total enrollment. It is also pertinent to consider average teacher salary as a proxy for teacher quality.[22] Although there is mixed empirical evidence on the effectiveness of a small student-teacher ratio in increasing test scores[23] there is enough popular discussion of this question that it is worth allowing for a possible effect. On the student side, students' race and socio-economic status – the latter which I proxy for here by median income and free lunch status – have been shown to influence test scores.[24] In addition, it is likely that students' ability to learn in a traditional, English-speaking classroom will influence test scores, so it is reasonable to control for the proportion of students in IEP's and students who are LEP/ELL. Following some more recent work demonstrating that female students perform better on average than males,[25] I control for the proportion of female students. Some plausibly relevant variables are omitted from the study for lack of data. It might be important to know, for example, the experience and education of teachers and administrators. Fortunately, there is some debate as to whether these variables are actually significant in predicting student achievement.[26]

I employ different techniques to control for the non-stationarity of each time series. Much of the variation in teacher salaries appears to stem from random fluctuation – while teachers rarely experience nominal pay cuts, real wages can fall from year to year if nominal wages remain fixed or increase slowly. Therefore, it is appropriate to use fixed effects to account for the time-invariant differences between districts as well as any year-to-year differences that may arise from changes in education finance at the state level. On the other hand, the state proficiency tests are frequently rewritten in such a fashion that yearly fixed effects are insufficient to explain some of the jumps in student performance. Because these changes are likely to capture more of the state's attitude towards testing than any school district's quality, I use a first differences model for test scores. This allows me to attempt to tease out a measure of quality by examining which districts

[19] Walden and Sogutlu (2001)
[20] See, e.g. Hoxby (1996)
[21] e.g. Alesina, Baqir and Hoxby (2004), Bradley and Taylor (1998)
[22] Figlio (1997)
[23] See Hanushek (2003) for a discussion of the effectiveness of many educational inputs.
[24] See Geller et al. (2006)
[25] Such as U.S. Department of Education (2004)
[26] See, e.g. Rivkin, Hanushek and Kain (2005)

performed better or worse relative to the overall change in 'performance' when the Ohio Department of Education changes the tests.

Table 1: Summary Statistics and Data Sources

Variable	Mean	Std. Dev	Min	Max	Source
Left-Hand Side					
% Proficient on Ohio Graduation Test – Average	89.50%	7.22%	44.68%	100%	ODE
% Proficient on OGT – Reading	94.28%	5.32%	59.20%	100%	ODE
% Proficient on OGT – Writing	93.61%	6.28%	49.10%	100%	ODE
% Proficient on OGT – Mathematics	86.07%	8.73%	12.00%	100%	ODE
% Proficient on OGT – Science	85.12%	10.63%	25.80%	100%	ODE
% Proficient on OGT – Social Studies	88.40%	8.86%	36.00%	100%	ODE
Average Teacher Salary	$44,677	$6,426	$16,800	$76,099	CCD
Right-Hand Side					
Number of Schools	6.05	9.44	1	153	CCD
Total Enrollment	2,941	4,892	22	76,559	CCD
FTE Teachers	182.7	338.2	18	6670.7	CCD
Median Income	$28,032	$6,362	$15,775	$65,666	ODE
Students per Teacher	16.86	2.11	3.67	26.44	CCD
Teachers per Student	0.061	0.008	0.043	0.270	CCD
Average Property Value per Teacher	$1,688,105	$808,250	$294,660	$8,667,604	ODT
County Unemployment Rate	5.46%	1.34%	1.8%	14.4%	BLS
Proportion Prekindergarten Teachers	0.53%	0.95%	0%	14.08%	CCD
Proportion Kindergarten Teachers	4.25%	1.69%	0%	18.44%	CCD
Proportion Secondary Teachers	34.22%	8.19%	4.15%	95.59%	CCD
Proportion Ungraded Teachers	0.85%	2.48%	0%	67.01%	CCD
% Non-White	7.69%	14.85%	0%	100%	CCD
% Asian and Pacific Islander	0.78%	1.27%	0%	14.87%	CCD
% Black	5.44%	13.96%	0%	99.91%	CCD
% Hispanic	1.41%	3.04%	0%	38.93%	CCD
% Female	47.75%	2.07%	14.62%	59%	CCD
% Limited English Proficient	0.44%	2.20%	0%	59.02%	CCD
% Individualized Education Program	13%	3.34%	1.68%	29.56%	CCD
% Free and Reduced-Price Lunch	24.18%	15.57%	0%	86.2%	CCD
Does the District Use an Income Tax?	.2466	.4311	0	1	CCD

Note: All monetary values in 1998 dollars.

I use the same exogenous instruments for both models. These are the percentage of female students enrolled in a school district, the median income for a school district, and the unemployment rate for the county. The latter two are defensibly exogenous to average teacher salaries and test scores because they are determined by broader economic forces; although higher student achievement has been linked by many researchers to better labor market outcomes, such effects are neither likely to be significant on the time scale of the sample nor be confined to a particular school district. They are defensibly relevant to average teacher salaries and test scores because they partially determine both the labor market conditions facing prospective teachers and the expected return to education for students. The percentage of female students is defensibly exogenous to average teacher salaries and test scores because the proportion of female students enrolled in a particular school in a given year is essentially random; though the influence of all-female or all-male private schools may be of concern, it is unlikely to be large enough to offset the number of families with children in public schools. The percentage of female students is defensibly relevant to both instruments because female students are easier to teach and because they perform better than male students on standardized tests. Following Kelejian and Prucha (1998), I instrument for WY with the first and second-order spatial lags of these three variables.

The data – which describe the population of Ohio public school districts – are drawn from four sources. The first is the U.S. Department of Education Common Core of Data (CCD), which is available from the National Center for Education Statistics. The CCD provides annual data for all Local Education Agencies in the United States, including traditional local school districts as well as regional education services agencies and public charter school agencies. In particular, the CCD provides some important data on students and staffing – including enrollment by gender, ethnicity, and proxies for socioeconomic status as well as staff breakdowns by occupation – and richly-detailed breakdowns of annual revenue and expenditures. The second data source is the Ohio Department of Education (ODE)'s interactive Local Report Card, which provides district-level, annual data on such diverse measures as median incomes, proficiency test scores, on-time graduation rates and disciplinary incidents. The third is the Ohio Department of Taxation (ODT)'s Tax Data Series, which provides annual school district level data on property values, taxes levied and tax rates. The fourth source of data is the Bureau of Labor Statistics (BLS), which provides county-level data on unemployment rates and the Midwest Consumer Price Index I use to control for inflation.

I restrict the sample along two lines. First, I remove the two school districts that came into existence during the sample period of 1998-2007. Second, I remove five other districts – the four Lake Erie island schools and the College Corner school district (which is jointly administered by the Indiana Department of Education) – for missing data, enrollments of zero, and similar irregularities. After paring away these districts, I am left with a balanced panel of 607 school districts across 10 years, for a total of 6070 observations. I provide summary statistics in Table 1.

4 Empirical Findings

The main results for teacher salaries and test scores, respectively, are presented in Tables 2 and 3. I first note that each specification fares extremely well in terms of the identification tests; the Kleibergen-Paap statistics provide evidence that the instruments are relevant and strong, while the Hansen J test fails to reject the null hypothesis of instrument validity at any reasonable significance level.

I turn my attention first to teacher salaries. Because the dependent variable is presented in logged form, the coefficients on the logged independent variables can be interpreted as elasticities. For example, the estimated marginal effect of a 1% increase in the number of schools in a district is a 0.028% increase in average teacher salaries in that district. For the independent variables that are proportions or percentages, the coefficients report the effect of an increase of 100 percentage points (from 0 to 1). Therefore, a one percentage point increase in the unemployment rate in a district is expected to decrease average teacher salaries by 0.448%.

The results tend to agree with expectations and with previous studies, but there are a few notable differences. Firstly, there is a strong relationship between student enrollment, teacher employment and teacher salaries. These coefficients should be interpreted with a degree of caution; it is unlikely that enrolling one percent more students increases teacher salaries by 0.4%, or that employing one percent more teachers decreases teacher salaries by 0.5%, but rather that these variables tend to increase or decrease together to smaller net effect. I also find that teachers who teach minority students are paid less, not more. This relationship is likely non-linear and likely due to the extremely skewed distribution of minority students in

Table 2: Strategic interaction over average teacher salaries

W*Ln(Average Teacher Salaries)	0.985**
	(0.202)
Ln(Number of Schools)	0.028
	(0.007)
Ln(Total Enrollment)	0.399***
	(0.022)
Ln(Full Time Equivalent Teachers)	-0.499***
	(0.027)
% Non-White	-0.118***
	(0.042)
% Free and Reduced-Price Lunch	0.021
	(0.019)
% Individualized Education Program	0.080*
	(0.048)
% Limited English Proficient	0.109***
	(0.031)
Ln (Students per Teacher)	0.177***
	(0.015)
Proportion Prekindergarten Teachers	-0.324***
	(0.105)
Proportion Kindergarten Teachers	0.158***
	(0.059)
Proportion Secondary Teachers	0.040***
	(0.015)
Proportion Ungraded Teachers	0.031
	(0.040)
Ln(Median Income)	0.046
	(0.221)
County Unemployment Rate	-0.448***
	(0.109)
Ln(Average Property Value per Teacher)	0.037***
	(0.009)
School District Income Tax Dummy	-0.005
	(0.004)
Kleibergen-Paap rk LM statistic (underidentification test)	[$p = 0.000$]
Kleibergen-Paap rk Wald F statistic (weak identification test)	28.30
Hansen J statistic (overidentification test)	[$p = 0.812$]

Notes: The dependent variable is the natural log of the average salary for all teachers in a school district. Estimation is by GMM. The instrument set for the spatially lagged dependent variable comprises the first- and second-order spatial lags of the county unemployment rate, the natural log of the school district's median income, and the percentage of female students in the district. Additional controls include school district and year fixed effects. Standard errors in parentheses are robust to arbitrary heteroskedasticity.
* Significant at 10%; ** Significant at 5%; *** Significant at 1%

Ohio; when the dependent variable is taken as a level instead of a log, the coefficient changes sign. However, there is some reason to be more confident in the insignificance of free lunch status in determining teacher salary. Because Southeast Ohio is both the poorest area in the state and the area with the fewest minority students – and because Ohio's rural areas in general have fewer minority students and lower incomes than the

Table 3: Strategic interaction over state standardized test scores

W*Standardized Test Scores	1.058***
	(0.093)
Ln(Number of Schools)	0.001
	(0.008)
Ln(Total Enrollment)	-0.015
	(0.023)
Ln(Average Teacher Salary)	-0.004
	(0.017)
Ln(Median Income)	0.099
	(0.155)
Ln(Teachers per Student)	-0.001
	(0.018)
% Asian and Pacific Islander	0.066
	(0.270)
% Black	-0.207**
	(0.104)
% Hispanic	-0.125
	(0.185)
% Individualized Education Program	-0.017
	(0.050)
% Limited English Proficient	-0.022
	(0.031)
% Free and Reduced-Price Lunch	-0.002
	(0.028)
% Female	-0.025
	(0.029)
Kleibergen-Paap rk LM statistic (underidentification test)	[$p = 0.000$]
Kleibergen-Paap rk Wald F statistic (weak identification test)	39.94
Hansen J statistic (overidentification test)	[$p = 0.733$]

Notes: The dependent variable is the one-year (i.e. first) difference of the average percentage of students scoring 'proficient' or higher across all five sections of the Ohio Graduation Test (Reading, Writing, Mathematics, Science, Social Studies). Estimation is via GMM, and all independent variables are also first differences. The instrument set for the spatially lagged dependent variable comprises the first differences of the first- and second-order spatial lags of the county unemployment rate, the natural log of the school district's median income, and the percentage of female students in the district. Standard errors in parentheses are robust to arbitrary heteroskedasticity.
* Significant at 10%; ** Significant at 5%; *** Significant at 1%

suburbs – Ohio is a good case for examining poverty independent of race. It may be that teachers truly do not require compensating differentials to teach poor students, but that previous studies conflate the effects of student race and poverty. Finally, I find no impact on teacher salaries from the use of a school district income tax. These taxes are sometimes financially motivated but sometimes politically motivated (because they are less regressive than property taxes), and may not be a good overall indicator or determinant of a district's revenue.

The coefficient on the lagged dependent variable bears a little more interpretation. Though it also represents an elasticity – and an elasticity very close to one – the variable itself is a distance-weighted sum of the logged average teacher salaries in all school districts within a 50 mile radius. Therefore, a 1% increase in teacher salaries in all other school districts within 50 miles would be expected to increase teacher salaries by 0.985% in the district in question. An increase of more than 1% in districts that are near and less than 1% in districts that are far will also be expected to increase teacher salaries in the district of interest by about 0.985%. However, we should expect a 1% increase in the average teacher salary in a single particular district to raise teacher salaries in nearby districts by some fraction of 0.985%, because school districts under this weighting scheme have many neighbors. Therefore, we should only expect to see large changes in salary when many school districts are affected by exogenous shocks to the labor market.

Next, I turn to the evidence from proficiency tests. Note that here the dependent variable is presented in level form; therefore, the interpretations of the estimated coefficients should be as percentage points and not percentages. For example, a 1% annual increase in the median income in a district might be expected to increase the proportion of students earning 'proficient' or higher on the Ohio Graduation Test by just one thousandth of a percentage point over the previous year (although of course the effect is not significant). The interpretation for an independent variable in level form is as above – its coefficient represents the effect of an increase from 0% to 100%. Therefore, an increase of one percentage point in the proportion of black students is expected to result in a decrease in the proportion of students earning 'proficient' or higher on the OGT by 0.2 percentage points versus the previous year.

Overall, I find that little besides the strategic effect is significant; it is likely that the levels of the independent variables matter more for overall student achievement than the year-to-year differences matter for year-to-year changes in achievement. The caveat for interpreting the spatial autoregressive term is the same: though a school district is expected to increase its scores by around 1.058 percentage points for each one percentage point increase in the test scores of all neighboring districts, the spillover from any one school district to its neighbors will be smaller. The overall implications of an estimate of 1.058 are that school districts will respond in small ways to changes in each neighboring district so that they maintain parity with their neighbors overall – or, at least, that they do not fall further behind.

Although these results are strong and the tests confirm the validity of the instruments, some concern may linger about the directionality of these simultaneously-determined inputs and outputs. Therefore I turn to the lagged specifications in Table 4. The lagged models allow me to establish a clearer direction of causation – because a district's behavior this year cannot change what its neighbors did last year – and to establish some sort of 'window' within which strategic competition occurs.

Table 4: Strategic interaction across time

Dependent Variable	Ln (Average Teacher Salary)					Average OGT Performance				
Time Lag (Years)	0	1	2	3	4	0	1	2	3	4
W*Dependent Variable	0.985***	1.309**	0.790**	0.373	-0.267	1.086***	1.184***	1.337***	1.052***	-0.648
	(0.202)	(0.335)	(0.375)	(0.268)	(0.395)	(0.159)	(0.201)	(0.237)	(0.281)	(0.458)
Number of Observations	6070	5463	4856	4249	3642	6070	5463	4856	4249	3642
Underidentification Test	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Weak Identification Test	28.30	11.60	13.23	41.90	25.33	58.03	42.71	33.03	26.28	26.67
Overidentification Test	[0.812]	[0.429]	[0.019]	[0.000]	[0.000]	[0.633]	[0.011]	[0.001]	[0.000]	[0.000]

Note: Estimation is via GMM. The instrument set for the spatially lagged dependent variable comprises the first- and second-order spatial lags of the county unemployment rate, the natural log of the school district's median income, and the percentage of female students in the district. Additional controls include school district and year fixed effects. Tests reported are the same as in Tables 2 and 3, with p-values in brackets. Standard errors in parentheses are robust to arbitrary heteroskedasticity.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

The results are striking; in both models, the point estimates for the one year lag on strategic competition are greater than their contemporaneous counterparts (although neither is significantly different from one). The point estimates for the elasticity of strategic competition range between 0.79 and 1.337, and appear to follow an inverted 'U' shape. This evidence weakly suggests that districts may be better able to respond to neighbors' behavior as they have observed it in the past than what they expect it to be in the present. In both cases, lags are not significant beyond three years, suggesting that districts respond more immediately.

However, these results come with two important caveats. First, I use a fixed effects model instead of a first differences model for the standardized test scores. While I am unsure that fixed effects can appropriately model the frequent changes to the Ohio Graduation Test, using first differences makes it impossible to gain any meaningful information from a lagged regression.[27] Second, the regression diagnostics raise some concern about the validity of the results; specifically, most of the lagged results reject the null hypothesis of instrument validity in the Hansen J test. In addition, the J statistic grows with the time lag. I selected the instrumental variables – the unemployment rate, median income, and percentage of female students – for their plausible, intuitive exogeneity. There is no similarly intuitive reason to suspect reverse causation between teacher salaries today and, for instance, the unemployment rate two years ago. Regardless, the lagged results should be viewed with some amount of caution for these two reasons.

5 Sensitivity Analysis

Sensitivity analysis is important (though often neglected) for spatial econometrics, because the structure of the spatial weights is decided arbitrarily by the researcher and not estimated from the data. It is therefore possible to obtain results that are idiosyncratic to a particular choice of weights matrix and that disappear when alternative weights are used. To attempt to banish such concerns, I estimate the full, contemporaneous-time model using a variety of spatial weights matrices. Although I tested a great many different specifications, I present a representative few in Table 5.

Table 5: Robustness of spatial weights matrix

Dependent Variable	Ln(Average Teacher Salary)				Average OGT Performance			
Weights Type	Binary Distance	Inverse Distance	Inverse Squared Distance	4 Nearest Neigh-bors	Binary Distance	Inverse Distance	Inverse Squared Distance	4 Nearest Neigh-bors
Cutoff Distance	50 mi.	25 mi.	75 mi.	N/A	50 mi.	25 mi.	75 mi.	N/A
W*Dependent Variable	1.145***	1.396	0.748*	1.386**	1.049***	1.047***	1.052***	1.059***
	(0.134)	(0.850)	(0.442)	(0.651)	(0.092)	(0.108)	(0.100)	(0.132)
Underidentification Test	[0.000]	[0.235]	[0.008]	[0.302]	[0.000]	[0.000]	[0.000]	[0.000]
Weak Identification Test	169.36	1.35	3.05	1.19	64.55	23.28	29.44	12.76
Overidentification Test	[0.278]	[0.193]	[0.054]	[0.968]	[0.211]	[0.986]	[0.642]	[0.859]

Note: Estimation is via GMM. The instrument set for the spatially lagged dependent variable comprises the first- and second-order spatial lags of the county unemployment rate, the natural log of the school district's median income, and the percentage of female students in the district. For the test score results, these instruments (like the dependent variable) are first differences. Percentage female instruments were dropped for the binary distance regressions, as the full instrument set was overidentified. Additional controls are as in Tables 2 and 3. Tests reported are the same as in Tables 2 and 3, with p-values in brackets. Standard errors in parentheses are robust to arbitrary heteroskedasticity.
* Significant at 10%; ** Significant at 5%; *** Significant at 1%

The first robustness test involves changing the weighting scheme – though I maintain the cutoff at fifty miles, I change the distance weighting to a 'binary' scheme to that all districts within fifty miles receive equal weight. The second alternative specification weights by inverse distance like the primary models, but uses a twenty-five mile cutoff to reduce the distance at which districts can be considered neighbors at all. The

[27] The difference between test scores last year and two years ago should be independent of the difference between this year and last year. Indeed, lagged difference regressions were all insignificant.

third weights structure changes both the weights and the cutoff distance, allowing districts to be considered neighbors out to a radius of seventy-five miles but weighting them by the square of the inverse distance to increase the relative weight given to nearby districts. The final weights matrix does something entirely different, choosing the four nearest districts and giving them each a weight of one quarter.

The results support the validity of the primary regressions, though the evidence is a great deal more robust for test scores than for teacher salaries. While the diagnostics generally support the exogeneity of the instruments, the teacher salary regressions suffer from weak instrument and/or instrument relevance problems for three of the four matrices. This is likely a function of the data available, rather than the validity of the theory; the most significant instrumental variable affecting teacher salaries is the unemployment rate, where data is only available at the county level. Because the twenty five mile cutoff, the squared inverse distance weights, and the four nearest neighbors weights all place great weight on observations which are likely to be in the same county, they suffer from a lack of variation in the values of that exogenous instrument. In particular, the fifty mile binary weight matrix – which puts greater relative weight on distant districts than the inverse distance matrix – benefits from more variation in the unemployment rate and thus appears to identify the strategic effect more strongly than the primary specification.

In addition to the sensitivity analysis for the weights structure, I perform one final set of regressions – comparing the primary results to those obtained from non-spatial Ordinary Least Squares (OLS), from Maximum Likelihood (ML), and from a poorly-instrumented GMM that uses all of WX and W^2X as instruments. As mentioned in Section I, the presence of spatial dependence can cause non-spatial estimates to be biased and inconsistent. Though ML estimation is often used in the spatial econometrics literature, the endogeneity of WY creates a far larger problem for the estimates than the "spurious precision" (Gibbons and Overman 2010) of ML is worth. And though Kelejian and Prucha (1998) have confirmed that $\{X, WX, W^2X, \ldots\}$ are valid instruments for estimating spatial autoregressive models by Two Stage Least Squares or GMM, a number of applied researchers performing spatial econometrics simply include all of these 'instruments' without considering that several variables in X are likely to be endogenous. Therefore it is worthwhile to examine the possible biases caused by these errors in estimation. These results are presented in Tables 6 and 7.

The non-spatial estimates in Table 6 appear to suffer from some slight biases and errors; the well-instrumented regression finds stronger evidence than the others that teachers who teach minority students are paid less, and weaker evidence that teachers who teach IEP students are paid more. Overall, the problems that incorrectly estimating the spatial autoregressive term inflicts on the non-spatial estimates are minor – even for the OLS regression that simply ignores spatial dependence. On the other hand, the estimates for the spatial autocorrelation coefficient ρ suffer from severe biases when improperly estimated. Not only do ML estimation and poor GMM instrumentation significantly underestimate the effects of strategic competition, they also provide the aforementioned "spurious precision"; the standard errors for poorly-instrumented GMM and ML are roughly one-quarter and one-tenth the size of those for the properly instrumented regression. Rather than providing roughly correct coefficient estimates, these methods produce estimates that are precisely wrong.

Table 6: Strategic interaction over average teacher salaries – model comparison

Model	Nonspatial OLS	Maximum Likelihood	GMM – 'Bad' Instrument Set	GMM – 'Good' Instrument Set
W*Ln(Average Teacher Salaries)		0.314***	0.433***	0.985***
		(0.017)	(0.053)	(0.202)
Ln(Number of Schools)	0.028***	0.028***	0.028***	0.028***
	(0.005)	(0.005)	(0.007)	(0.007)
Ln(Total Enrollment)	0.425***	0.417***	0.392***	0.399***
	(0.013)	(0.013)	(0.020)	(0.022)
Ln(Full Time Equivalent Teachers)	-0.502***	-0.501***	-0.479***	-0.499***
	(0.017)	(0.016)	(0.024)	(0.027)
% Non-White	-0.062*	-0.080**	-0.055	-0.118***
	(0.035)	(0.033)	(0.038)	(0.042)
% Free and Reduced-Price Lunch	0.012	0.015	-0.010	0.021
	(0.016)	(0.015)	(0.018)	(0.019)
%Individualized Education Program	0.107**	0.098**	0.126***	0.080*
	(0.043)	(0.040)	(0.046)	(0.048)
% Limited English Proficient	0.119***	0.115***	0.105***	0.109***
	(0.038)	(0.036)	(0.031)	(0.031)
Ln(Students per Teacher)	0.181***	0.180***	0.175***	0.177***
	(0.014)	(0.013)	(0.015)	(0.015)
Proportion Prekindergarten Teachers	-0.307***	-0.315***	-0.340***	-0.324***
	(0.101)	(0.095)	(0.102)	(0.105)
Proportion Kindergarten Teachers	0.103**	0.122**	0.108*	0.158***
	(0.052)	(0.049)	(0.057)	(0.059)
Proportion Secondary Teachers	0.039***	0.040***	0.037**	0.040***
	(0.014)	(0.013)	(0015)	(0.015)
Proportion Ungraded Teachers	0.016	0.022	0.012	0.031
	(0.031)	(0.030)	(0.037)	(0.040)
Ln(Median Income)	0.040	0.047	0.010	0.046
	(0.193)	(0.182)	(0.209)	(0.221)
County Unemployment Rate	-0.510***	-0.489***	-0.464***	-0.448***
	(0.111)	(0.105)	(0.105)	(0.109)
Ln(Average Property Value per Teacher)	0.048***	0.044***	0.038***	0.037***
	(0.008)	(0.008)	(0.009)	(0.009)
School District Income Tax Dummy	-0.006	-0.005	-0.005	-0.005
	(0.004)	(0.003)	(0.003)	(0.004)
Robust to Arbitrary Heteroskedasticity	NO	NO	YES	YES
Underidentification Test			[$p = 0.000$]	[$p = 0.000$]
Weak Identification Test			485.02	28.30
Overidentification Test			[$p = 0.000$]	[$p = 0.812$]

Notes: The dependent variable is the natural log of the average salary for all teachers in a school district. The 'good' instrument set for the spatially lagged dependent variable comprises the first- and second-order spatial lags of the county unemployment rate, the natural log of the school district's median income, and the percentage of female students in the district. The 'bad' instrument set for the spatially lagged dependent variable comprises the first- and second-order spatial lags of all right hand side variables in the model. Additional controls are school district and year fixed effects. Tests reported are the same as in Tables 2 and 3, with p-values in brackets.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

Table 7: Strategic interaction over state standardized test scores – model comparison

Model	Nonspatial OLS	Maximum Likelihood	GMM – 'Bad' Instrument Set	GMM – 'Good' Instrument Set
W*Standardized Test Scores		0.920***	1.014***	1.059***
		(0.017)	(0.031)	(0.093)
Ln(Number of Schools)	0.003	0.002	0.004	0.001
	(0.008)	(0.006)	(0.008)	(0.007)
Ln(Total Enrollment)	0.083***	-0.004	-0.004	-0.015
	(0.026)	(0.019)	(0.021)	(0.023)
Ln(Average Teacher Salary)	0.107***	0.006	0.0003	-0.004
	(0.018)	(0.013)	(0.015)	(0.017)
Ln(Median Income)	-1.413***	0.0004	0.047	0.099
	(0.117)	(0.025)	(0.090)	(0.155)
Ln(Teachers per Student)	0.122***	0.013	0.006	-0.001
	(0.018)	(0.013)	(0.015)	(0.018)
% Asian and Pacific Islander	-0.441	-0.010	0.046	0.066
	(0.404)	(0.302)	(0.266)	(0.270)
% Black	-0.180	-0.210**	-0.220**	-0.207**
	(0.118)	(0.089)	(0.105)	(0.104)
% Hispanic	-0.217	-0.145	-0.072	-0.125
	(0.201)	(0.151)	(0.185)	(0.185)
% Individualized Education Program	0.066	-0.020	-0.008	-0.017
	(0.060)	(0.044)	(0.049)	(0.050)
% Limited English Proficient	0.005	-0.025	-0.018	-0.022
	(0.074)	(0.055)	(0.036)	(0.031)
% Free and Reduced-Price Lunch	-0.048**	-0.010	-0.003	-0.003
	(0.020)	(0.015)	(0.018)	(0.018)
% Female	-0.012	-0.021	-0.035	-0.025
	(0.044)	(0.033)	(0.029)	(0.029)
Robust to Arbitrary Heteroskedasticity	NO	NO	YES	YES
Underidentification Test			[p = 0.000]	[p = 0.000]
Weak Identification Test			159.92	39.94
Overidentification Test			[p = 0.581]	[p = 0.733]

Notes: The dependent variable is the one-year (i.e. first) difference of the average percentage of students scoring 'proficient' or higher across all five sections of the Ohio Graduation Test (Reading, Writing, Mathematics, Science, Social Studies). Estimation is via GMM, and all independent variables are also first differences. The 'good' instrument set for the spatially lagged dependent variable comprises the first differences of the first- and second-order spatial lags of the county unemployment rate, the natural log of the school district's median income, and the percentage of female students in the district. The 'bad' instrument set for the spatially lagged dependent variable comprises the first- and second-order spatial lags of all right hand side variables in the model. Tests reported are the same as in Tables 2 and 3, with p-values in brackets.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

The case for test scores is different: the biases in the spatial autocorrelation coefficient are relatively minor compared to those for teacher salaries. While the ML regression estimates the strategic effect to be significantly less than one – again, partially due to artificial precision in the standard errors – the poorly-instrumented GMM finds results that are not significantly different from those of the well-instrumented model and which still pass the statistical test for instrument validity.[28] The most striking differences are now between the spatial and non-spatial models. The non-spatial OLS model makes serious errors of both types – including the confusing conclusion that a 1% increase in a school district's median income will

[28] The poorly-instrumented model is likely 'saved' here by the lack of information in the largely insignificant control variables that comprise its instrument set.

decrease test scores by about 1.4 points. These results highlight the importance of testing and controlling for spatial autocorrelation even in non–spatially minded work.

6 Conclusion

Invoking a broad theoretical and empirical foundation of strategic competition between local schools, I employ a spatial autoregressive model to examine the extent of such competition between public school districts in Ohio. Building upon previous results which provide evidence that school districts behave strategically when setting input levels, I extend the field of competition to outputs and find a significant competitive effect whose magnitude suggests schools act to maintain parity with their neighbors. I show that the significance and magnitude of this competitive effect is robust to various definitions of 'neighbor', and provide evidence that these strategic effects persist within a two to three year window. I further provide suggestive evidence that the true magnitude of competition may be larger than found in some previous studies due to the biases induced by treating such competition as exogenous.

The policy implications of these findings are reassuring; a defensibly causal estimate of parity for the spatial autocorrelation parameter suggests that school districts actively 'keep up' with their neighbors. Therefore, fruitful innovations undertaken at just a few schools may spread to others over time. This provides some support for the 'bottom-up', experimental paradigm of school reform; it suggests that uniform standards may not be necessary for uniform improvement. However, because the spatial autocorrelation parameter is not significantly greater than one, the results suggest that schools will make no such improvements without some form of impetus.

The results presented in this paper open up several avenues for further research. Empirical analysis to confirm the robustness of the relationship – particularly in other states – is necessary. Because charter schools are often regarded as the champions of the experimental paradigm of school reform, it would be worthwhile to investigate whether traditional public schools also respond to the decisions of nontraditional public or private schools. This study also presents a 'black box' view of competition in educational outputs. Are spillovers in test scores merely a function of spillovers in inputs such as teacher salaries and capital expenditures? Or is there a significant unobservable component, perhaps the adoption of successful curricula or teaching methods? A multidimensional model allowing for cross-policy effects like that used by Millimet and Rangaprasad (2007) may be able to answer this question, but it is beyond the scope of this paper.

That said, my findings contribute to the growing pool of evidence suggesting that competition can alter the behavior of public schools, and also provide reassurance that spillovers in school inputs found in previous studies carry over to the case of outputs – that competition among public schools provides real benefits to students.

References

[1] Anselin, Luc. 1988. *Spatial econometrics: Methods and Models*. Dordrecht: Kluwer Academic Publishers.

[2] Anselin, Luc, Anil K. Bera, Raymond Florax, and Mann J. Moon. 1996. "Simple Diagnostic Tests for Spatial Dependence." *Regional Science and Urban Economics*, Vol. 26, No. 1, pp. 77-104.

[3] Babcock, Linda C., John B. Engberg, and Robert T. Greenbaum. 2005. "Wage Spillovers in Public Sector Contract Negotiations: The Importance of Social Comparisons." *Regional Science and Urban Economics*, Vol. 35, No. 4, pp. 395-416.

[4] Baum, Christopher F., Mark E. Schaffer and Steven Stillman. 2002. "IVREG2: Stata module for extended instrumental variables/2SLS and GMM estimation," Statistical Software Components S425401, Boston College Department of Economics, revised 30 Jan 2011.

[5] Bradley, Steve and Jim Taylor. 1998. "The Effect of School Size on Exam Performance in Secondary Schools," *Oxford Bulletin of Economics and Statistics*, Department of Economics, University of Oxford, vol. 60, No. 3, pp. 291-324.

[6] Elhorst, JP. 2009. "Spatial Panel Data Models." In Fischer MM, Getis A (Eds.) *Handbook of Applied Spatial Analysis*, pp. 377-407. Springer: Berlin Heidelberg New York.

[7] Figlio, David N. 1997. "Teacher Salaries and Teacher Quality." *Economic Letters*, Vol. 55, No. 2, pp. 267-271.

[8] Geller, C. R., D.L. Sjoquist and M. B. Walker. 2006. The Effect of Private School Competition on Public School Performance in Georgia. *Public Finance Review*, vol. 34, No. 1, pp. 4-32.

[9] Ghosh, Soma. 2010. "Strategic Interaction among Public School Districts: Evidence on Spatial Interdependence in School Inputs." *Economics of Education Review* vol. 29, No. 3. pp. 440-450.

[10] Gibbons, S. and H.G Overman. 2010. "Mostly pointless spatial econometrics", Spatial Economics Research Centre DP0061.

[11] Greenbaum, Robert T. 2002. "A Spatial Study of Teachers' Salaries in Pennsylvania School Districts." *Journal of Labor Research*, Vol. 23, No. 1, pp. 69-86.

[12] Hanushek, Eric A. 2003. "The Failure of Input-Based Schooling Policies," *Economic Journal*, Royal Economic Society, vol. 113, No. 485, pages F64-F98.

[13] Hoxby, Caroline M. 1996. "How Teachers' Unions Affect Education Production." *Quarterly Journal of Economics*, Vol. 111, No. 3, pp. 671-718.

[14] Hoxby, Caroline M. 2000. "Does Competition among Public Schools Benefit Students and Taxpayers?" *American Economic Review*, vol. 90, No. 5, pp. 1209-1238.

[15] Jeanty, P. Wilner. 2010. "SPWMATRIX: Stata module to generate, import, and export spatial weights," Statistical Software Components S457111, Boston College Department of Economics, revised 11 Mar 2010.

[16] Kalenkoski, Charlene M. and Donald J. Lacombe. 2008. "Effects of Minimum Wages on Youth Employment: The Importance of Accounting for Spatial Correlation." *Journal of Labor Research*, Vol. 29, No. 4, pp. 303-317.

[17] Kelejian, Harry H. and Ingmar R. Prucha. 1998. "A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances." *Journal of Real Estate Finance and Economics* vol. 17, No. 1, pp. 99–121.

[18] Kleibergen, Frank and Richard Paap. 2006. "Generalized reduced rank tests using the singular value decomposition," *Journal of Econometrics*, Elsevier, vol. 133, No. 1, pp. 97-126.

[19] Kleibergen, Frank and Mark E. Schaffer. 2007. "RANKTEST: Stata module to test the rank of a matrix using the Kleibergen-Paap rk statistic," Statistical Software Components S456865, Boston College Department of Economics, revised 25 Apr 2010.

[20] Lentz, Corliss. 1998. "Why Some Communities Pay More than Others? The Example of Illinois Teachers." *Public Administration Review*, Vol. 58, No. 2, pp. 137-144.

[21] Martin, Stephanie. Forthcoming. "Are Public School Teacher Salaries Paid Compensating Wage Differentials for Student Racial and Ethnic Characteristics?" *Education Economics.*

[22] Millimet, Daniel L. and Vasudha Rangaprasad. 2007. "Strategic Competition amongst Public Schools." *Regional Science and Urban Economics*, Vol. 37, No. 2, pp. 199-219.

[23] Nechyba, Thomas. 2003. "School finance, spatial income segregation, and the nature of communities" *Journal of Urban Economics* vol. 54, No. 1, pp. 61-88

[24] Ohio Department of Education. 2008. Interactive Local Report Card data files: School Years 1998-1999 through 2007-2008 (Computer File). Ohio Department of Education, Columbus.

[25] Ohio Department of Taxation. 2008. Taxable Property Values by School District, Taxes Levied and Tax Rates for Current Expenses, and Average Property Values per Pupil: Tax Years 1998 through 2007 (Computer File). Ohio Department of Taxation, Columbus.

[26] Plümper, Thomas and Eric Neumayer. 2010. "Model specification in the analysis of spatial dependence." *European Journal of Political Research*, vol. 49, No. 3, pp. 418-442.

[27] Rivkin, S. G., E. A. Hanushek., and J. F. Kain. 2005. "Teachers, Schools, and Academic Achievement." *Econometrica*, vol. 73, No. 2, pp. 417-458.

[28] Schaffer, Mark E., 2005. "XTIVREG2: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models," Statistical Software Components S456501, Boston College Department of Economics, revised 28 Jun 2010.

[29] Taylor, Lori L. Forthcoming. "Competition and Teacher Pay." *Economic Inquiry.*

[30] Tiebout, Charles M. 1956. "A Pure Theory of Local Expenditures." *The Journal of Political Economy*, vol. 64, No. 5, pp. 416-424.

[31] U.S. Department of Education, 2004. Trends in Educational Equity of Girls & Women: 2004. National Center for Education Statistics, Washington D.C.

[32] U.S. Department of Education, 2008. Common Core of Data: School Years 1998–1999 Through 2007-2008 (Computer File). National Center for Education Statistics, Washington D.C.

[33] U.S. Department of Labor, 2008. Local Area Unemployment Statistics for Ohio Counties: Years 1998 to 2007. Bureau of Labor Statistics, Washington D.C.

[34] U.S. Department of Labor, 2008. Midwest Region Consumer Price Index – Years 1998 to 2007. Bureau of Labor Statistics, Washington D.C.

[35] Vedder, Richard and Joshua Hall. 2000. "Private School Competition and Public School Teacher Salaries." *Journal of Labor Research*, vol. 21, No. 1, pp. 161-168.

[36] Wagner, Gary A. and Tod S. Porter. 2000. "Location Effects and the Determination of Beginning Teacher Salaries: Evidence from Ohio." *Education Economics*, vol. 8, No. 2, pp. 109- 127.

[37] Walden, Michael L. and Craig M. Newmark. 1995. "Interstate Variation in Teacher Salaries." *Economics of Education Review*, vol. 14, No. 4, pp. 395-402.

[38] Walden, Michael L. and Zulal Sogutlu. 2001. "Determinants of Intrastate Variation in Teacher Salaries." *Economics of Education Review*, vol. 20, No. 1, pp. 63-70.

[39] Winters, John V. 2009. "Variation in Teacher Salaries in Georgia: Does the Property Tax Base Matter?" *Journal of Education Finance*, vol. 35, No. 2, pp. 157-171.

[40] Winters, John V. 2010. "Teacher Salaries and Teacher Unions: A Spatial Econometric Approach." Working Paper 2010-1-1, W.J. Usery Workplace Research Group Paper Series. Downloadable from http://ayps.gsu.edu/usery/Papers.html

[41] Zanzig, Blair. R. 1997. "Measuring the Impact of Competition in Local Government Education Markets on the Cognitive Achievement of Students." *Economics of Education Review.* 16 (October), 431-44