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On the Determinants of School District Efficiency: Competition and Monitoring[1]

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A number of researchers have asserted that inefficiency in the U.S. school system arises from a lack of incentives for public schools to behave efficiently. This paper uses a Shephard input distance function to model educational production, and a switching-regressions estimation to explore the relationship between school district efficiency and two existing incentive mechanisms—competition and voter monitoring. We find evidence that ease of monitoring enhances both technical and allocative efficiency of urban school districts, and that increased competition reduces allocative inefficiency in communities above a competitive threshold. We find no evidence that competition is related to technical inefficiency. © 2001 Academic Press

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I. INTRODUCTION

Scores of educational production studies conclude that school expenditures are not systematically correlated with student performance (for surveys, see Hanushek [29] and Hanushek *et al*. [30]). Some interpret this lack of correlation as evidence that money doesn't matter in education. Others conclude that the underlying relationship between inputs and outputs is obscured by school inefficiency. For example, Hanushek argues that the lack of evidence that money matters ''implies a significant level of inefficiency in schools'' (Hanushek [28, p. 37]). Studies that directly model inefficiency such as cost function studies and frontier analyses of educational production have found substantial inefficiencies in the U.S. public school system and nearly all have found that, controlling for inefficiency, there is a positive relationship between school inputs and outputs (see, for example, Ruggiero [40], Cooper and Cohn [11], Ray and Mukherjee [39], Grosskopf *et al*. [22], and the discussion in Grosskopf *et al*. [23]).

A number of researchers have asserted that this inefficiency arises from a lack of incentives for public schools to behave efficiently. The literature identifies at least two existing mechanisms that could provide local governments with such incentives—competition and voter monitoring. Competition creates incentives for increased governmental efficiency by influencing the citizen's willingness to pay for public services or their willingness to stay in the jurisdiction. A number of researchers have found evidence that competition enhances government efficiency (e.g., Hayes *et al*. [33] and Grossman *et al*. [24]).

Voter monitoring creates incentives for increased efficiency primarily by influencing the probability that a government official will retain public office. Although voter monitoring is not directly observable, a number of researchers have argued that citizens are more likely to monitor where governments are more accessible and citizens are more likely to be personally affected by policy. For example, Davis and Hayes [13] argue that citizens may be more likely to monitor government activity where the tax price of government services is higher, and that homeowners may be more likely to monitor than renters because they receive a greater return to government efficiency. Proxies for increased monitoring such as tax rates and the degree of government centralization have been associated with smaller and/or more efficient governments (e.g., Grossman and West [25], Davis and Hayes [13], Hayes and Wood [34], and Hayes *et al*. [33]).

Extending and updating Grosskopf *et al*. [22], this paper explores the relationship between school district efficiency and these two incentive mechanisms.[2] We use a Shephard input distance function to model educational

[2] This paper builds on earlier work by Grosskopf *et al*. [22] which used a smaller sample from an earlier period and which focused exclusively on the relationship between allocative efficiency and competition.

production, and a switching-regressions estimation to examine the relationship between enrollment competition and school district efficiency. We examine two types of efficiency—technical efficiency and allocative efficiency. A technically efficient school district chooses its input quantities so that it could not proportionately decrease inputs without reducing outputs; an allocatively efficient school district chooses its mix of inputs so that all inputs have the same marginal product per dollar. We find evidence that monitoring enhances both technical and allocative efficiency of school districts, and that competition reduces allocative inefficiency in communities above a competitive threshold. We find no evidence that competition is related to technical inefficiency.

II. THE LITERATURE

A large and growing literature examines school competition. For example, Couch *et al*. [12], Dee [14], and Hoxby [35] find evidence that public school quality is lower when there is less competition from private schools. Zanzig [46] finds evidence that increased competition among public school districts enhanced student test scores in California; Borland and Howsen [8, 9] report similar results for Kentucky. Hoxby [36] examines the National Longitudinal Survey of Youth and finds evidence that educational attainment is higher and educational spending lower in communities with more competition among public schools. Grosskopf *et al*. [22] find evidence that school districts in concentrated markets are more than twice as allocatively inefficient as school districts in competitive metropolitan areas. Duncombe *et al*. [15] interpret increased private school enrollment as an indicator of increased competition and, contrary to their expectations, find that the cost efficiency of New York school districts is lower where competition is higher. Consistent with other implications of Tiebout competition, researchers have also found that private schools are less prevalent in metropolitan areas with more public school options (Martinez-Vazquez and Seaman [37] and Hoxby [36]), and that more variety among public schools in a metropolitan area leads, ceteris paribus, to increased homogeneity within local jurisdictions (Hamilton *et al*. [27], Eberts and Gronberg [16], Gramlich and Rubinfeld [19], Munley [38], Grubb [26], and Aaronson [4]).

The literature on monitoring and schools is much less extensive, but monitoring and efficiency in the production of public services have been examined in a variety of contexts. For example, Davis and Hayes [13] develop a model of optimal monitoring and present evidence that variations in monitoring activity —as proxied by tax rates, homeownership rates, and jurisdictional size—partially explain the pattern of police department inefficiency across 141 cities. Hayes and Wood [34] and Hayes *et al*. [33] find similar results for a broader sample of municipalities. In the context of public school education, Duncombe *et al*. [15] use DEA analysis to examine the cost efficiency of New York public schools and find mixed evidence that monitoring is associated with efficiency. Consistent with their expectations, they find that improved cost efficiency is associated with a greater percentage of college graduates in the population. However, contrary to their expectation that parents and homeowners should have particular incentives to monitor school district behavior, they find a negative relationship between these factors and school district efficiency.

III. THE DISTANCE FUNCTION

We use a Shephard [42] input distance function to model school production and generate measures of technical and allocative inefficiency. The input distance function can be readily used to analyze the performance of public enterprises: it is a natural measure of technical inefficiency, it explicitly includes multiple outputs, it is dual to the cost function, which facilitates identification of shadow prices to analyze allocative inefficiency, and it does not require data on output prices, which are typically unavailable in the public sector. Although the input distance function is dual to the cost function, it requires data on input quantities rather than input prices. Thus, the distance function is preferable in settings where prices do not vary, such as when making comparisons across schools within a single labor market. The distance function also has the advantage for our purposes of being ‘‘agnostic’’ with respect to the economic motivation of the decision maker, unlike the cost function which presumes cost minimizing behavior.[3]

More formally, the input distance function is a generalization of a production function to the multiple output setting. Given nonnegative input vectors $x = (x_1, x_2, \dots, x_N)$ and nonnegative output vectors $y = (y_1, y_2, \dots, y_M)$ the input distance function may be defined as

$$D(y, x) = \max\{\lambda:\ x/\lambda \text{ is an element in } L(y)\}, \tag{1}$$

where

$$L(y) = \{x:\ x \text{ can produce } y\}. \tag{2}$$

Thus, the distance function represents the greatest proportional contraction of inputs that is possible without reducing output.

The distance function satisfies fairly general regularity properties (see Färe and Grosskopf [17]). It is homogeneous of degree one in inputs, concave in inputs, convex in outputs, and non-decreasing in inputs.

The distance function is perhaps most easily understood with the aid of a diagram. Consider Fig. 1. In this figure, observation K employs the input bundle (x_i, x_j) to produce output level y. The distance function seeks the largest proportional contraction of that input bundle which allows production of the original output level y (which may be a vector). In this example, the value

[3] While the cost function assumes cost minimizing behavior, inefficiency can be allowed for in the cost function using techniques outlined by Schmidt and Sickles [41].

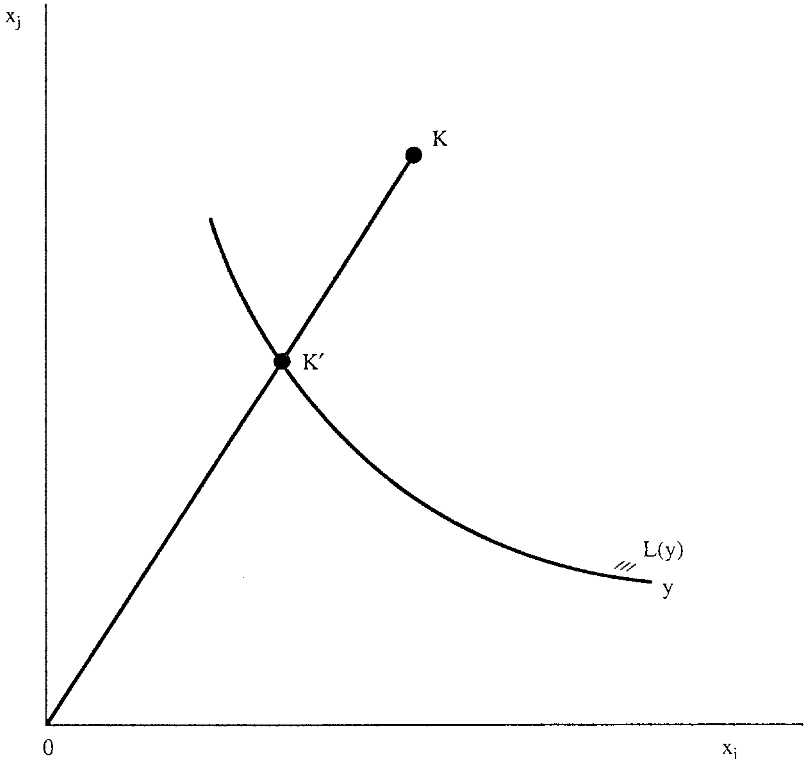

FIG. 1. Input distance function: $D(y^K, x^K) = 0K/0K'$.

of the distance function for observation K is OK/OK' which is greater than one. In fact, all feasible input vectors will yield values of the distance function greater than or equal to one, which means that the distance function completely describes the technology, i.e.,

$$D(y, x) \geq 1 \quad \Leftrightarrow \quad x \in L(y). \tag{3}$$

Furthermore, $D(y, x) = 1$ if and only if the input bundle is an element of the isoquant of $L(y)$.

The reciprocal of the value of the input distance function is the Farrell [18] input-saving measure of technical efficiency. We use it to measure variations in technical efficiency among school districts.

As discussed in Blackorby and Russell [6], the first derivatives of the input distance function with respect to input quantities yield (cost-deflated) shadow or support prices of those inputs.[4] We use these shadow prices to test for allocative efficiency. Let $w = (w_1, w_2, \ldots, w_N)$, where w is positive, be the vector of observed input prices. If a school district is allocatively efficient then the following holds:

$$D_i(y, x)/D_j(y, x) = w_i/w_j, \qquad \text{for all } i, j = 1, 2, \ldots, N. \tag{4}$$

D_i is the partial derivative of $D(y, x)$ with respect to input i and is interpreted as the virtual or shadow price of the ith input. Alternatively, we can define a measure κ_{ij} as the degree to which the shadow price ratio agrees with the actual price ratio, where the formulation in (5) follows the nonminimal cost literature,[5]

$$\kappa_{ij} = \frac{D_i(\cdot)/D_j(\cdot)}{w_i/w_j}. \tag{5}$$

See, for example, Toda [44] or Atkinson and Halvorsen [3].

If $\kappa_{ij} = 1$ for all i, j then the observation is said to be allocatively efficient. When $\kappa_{ij} \neq 1$ we can have the following non-optimal situations. If

$$\kappa_{ij} > 1, \tag{6}$$

factor i is underutilized relative to j at observed relative prices, and if

$$\kappa_{ij} < 1, \tag{7}$$

factor i is overutilized relative to j at observed relative prices. In Fig. 2, the school district is observed to employ input bundle $\bar{x}$. The observed relative price of the two inputs is given by the absolute value of the slope of the line ww. The relative shadow prices (ratio of marginal products) that support the input vector $\bar{x}$ are given by the absolute value of the slope $w^* w^*$. In this case the ratio of shadow prices is less than the ratio of observed prices implying that input i is overutilized relative to input j. That is, $\kappa_{ij} < 1$. Based on observed relative prices, allocative efficiency occurs at x', where the isoquant is tangent to the line $w'w'$ which is parallel to the line ww. Another way of interpreting the value of $\kappa_{ij} < 1$ is that the marginal product per dollar paid the input j

[4] This result follows from Shephard's (dual) lemma because the input distance function is dual to the cost function (see Färe and Grosskopf [17]).

[5] In this literature, firms are assumed to minimize (unobservable) shadow costs given (unobservable) shadow prices. This is achieved by introducing additional parameters in the cost function that essentially allow input prices to ''pivot.'' These parameters are used to construct the κ_{ij} in Eq. (5). Unlike the distance function methodology, this technique cannot identify firm-specific relative shadow prices.

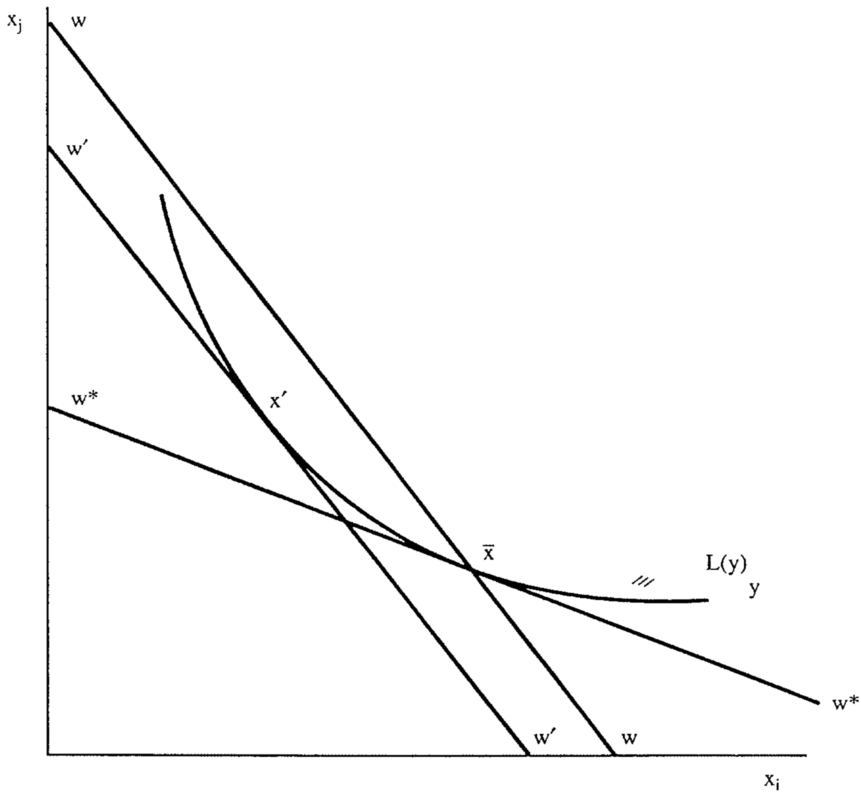

FIG. 2. Overutilization of x_i at $\bar{x}$.

exceeds the marginal product per dollar paid for input *i* at the observed input mix and prices.

IV. THE DATA

The Texas public school system is particularly well suited to analyses of the relationship between school efficiency and competition for students for a number of reasons. There are a large number of school districts in the state and the availability of detailed district-level data on school inputs and student performance supports credible estimates of school district efficiency. At the same time the school finance formula creates strong incentives for school districts to compete for students by directly tying state aid to enrollment.[6] Finally, data on enrollments in all public school districts and accredited private schools allow us to construct reasonable measures of the degree of competition for students.

Data for this analysis come primarily from the Texas Education Agency (TEA). The data include information by school district for the 1996–1997 school year on enrollment, the number of teachers, administrators, staff and teacher aides employed, the average salaries paid to each type of employee, and other school characteristics. The TEA also provided information by school district and grade level on average student achievement in reading and mathematics, the number of students taking the test battery, student ethnicity, and other student body characteristics. From these data, we construct measures of school outputs, student and family inputs, and school inputs for each school district. We construct our competition measures from TEA data on total enrollments in all public and accredited private schools in Texas. Additional demographic data come from the School District Data Book Profiles: 1989–1990.

Together, the combined sources provide complete information on 302 urban school districts with at least 50 students in both the 6th and 10th grades. We restrict our attention to school districts in metropolitan areas because the Tiebout model is more appropriate to urban areas. We restrict our attention to school districts with at least 50 students in each of the relevant grades to avoid sampling problems that might be introduced by a small number of students.

Output Measures

The literature on measuring school effects has reached a broad consensus that the most appropriate measure of school output is the marginal effect of the school on educational outcomes (see, for example, Hanushek [29], Hanushek and Taylor [31], Aitkin and Longford [1], or Boardman and Murnane [7]). We use student achievement on a battery of test scores as the relevant educational outcome and extract the marginal effect of schools by following the value-added residuals technique described in Hanushek and Taylor [31] and Aitkin and Longford [1].

Thus, we estimate school district output per pupil using Texas Assessment of Academic Skills (TAAS) scores in mathematics and reading, data on changes in cohort size, and demographic data on the racial and socio-economic composition of the student body. At both the primary (6th grade) and secondary (10th grade) levels, we estimate the per-pupil value added by the school district

[6] During the 1996–1997 school year, Texas had a complicated school finance formula that combined a foundation grant per pupil with a guaranteed yield per pupil for enrichment and a recapture provision. On average, state aid represented 53.3% of school district spending.

according to

$$\begin{aligned}\text{MATH97} = \alpha &+ \delta_1 \text{MATH95} + \delta_2 \text{READ95} \\ &+ \delta_3 \text{SES} + \sum_{j=4}^{6} \delta_j \text{ETHNICITY}_j \\ &+ \delta_7 \text{XCOHORTN} + \delta_8 \text{XSES} \\ &+ \sum_{j=9}^{11} \delta_j \text{XETHNICITY}_j + \epsilon,\end{aligned} \tag{8}$$

where observational and grade-level subscripts have been suppressed, MATH97 is the average TAAS mathematics score in 1997, MATH95 and READ95 are the average TAAS scores in mathematics and reading for the same cohort two years previously, ETHNICITY_j is the fraction of the grade cohort that is BLACK, HISPANIC, or ASIAN (respectively), SES is the fraction of the grade cohort that is not receiving free or reduced-price lunches (the best available proxy for socio-economic status), XCOHORTN is the percentage increase in cohort size between 1995 and 1997, XSES is the change in the share of students receiving free or reduced-price lunches, XETHNICITY_j is the change in the share of students in ethnic group j, and the estimated residual, ϵ, represents the average value added per pupil, plus an error term.[7] We focus on value added in mathematics because Bishop [5] suggests that mathematics skills are disproportionately valued in the labor market.

Estimating school outputs as equation residuals generates output measures that represent deviations from the state average. School districts that add less value than the state average have negative output measures. Since the distance function methodology is not designed for negative outputs, we generate tractable per-pupil output measures for grades six and ten by adding the value-added residuals for each grade level to the average 1997 mathematics test for that grade level. To further transform the per-pupil output measures into total output measures, we multiply by grade-level enrollment (ENROLL_g). Therefore,

$$\text{OUTPUT}_{sg} = \left(\overline{\text{MATH97}}_g + \epsilon_{sg}\right) \cdot \text{ENROLL}_{sg} \tag{9}$$

is our proxy for the output in grade g of school district s. It represents the total achievement level we would expect school district s to produce if it had the same grade-cohort characteristics as the sample average. Alternatively, one can think of OUTPUT_{sg} as the level of total student achievement purged of the

[7] We estimate the output measures simultaneously using the standard SAS package for seemingly unrelated regression (SUR). The estimation results are presented in the Appendix.

effect of home production and earlier achievement.[8] There are two outputs for each school district—value added in mathematics in grade 6 and value added in mathematics in grade 10.

Input Measures

As in Grosskopf *et al*. [22], the variable inputs which we consider to be within school district control are limited to instructional and administrative personnel. We define the quantity of instructional inputs per pupil as the weighted average of the number of teachers and teacher aides per pupil.[9] The quantity of administrative inputs per pupil is the weighted average of the number of administrators and support personnel per pupil.[10] In both cases, we derive weights from the average wages paid for the personnel categories in each metropolitan area.[11] To generate measures of total instructional (INST) and administrative (NINST) inputs, we multiply these per-pupil measures of variable input by the sum of the enrollments in grades 6 and 10 ($\text{ENROLL}_s = \text{ENROLL}_{s6} + \text{ENROLL}_{s10}$).

There are several important inputs that are beyond school district control, at least in the near term. As in Grosskopf *et al*. [22], we focus on two ''fixed'' inputs: non-labor school inputs and family inputs. Unfortunately, we have no direct measure for either of these inputs. Because the quantity of non-labor inputs should be highly correlated with expenditures on library books, furniture and equipment, physical plant maintenance, and general maintenance and operations, we use a principle components index of per-pupil expenditures in these four categories, multiplied by ENROLL_s, as our proxy for the quantity of non-labor inputs (CAPINPUT).[12] We use the predicted values from Eq. (8) multiplied by the corresponding grade-level enrollments (ENROLL_{sg}) to measure the contribution of home production at each grade level (STUINPUT_{sg}), yielding an index that depends on past achievement test scores, the ethnic and

[8] We note that this general technique for measuring educational quality was also employed by Grosskopf *et al*. [21–23] and Callan and Santerre [10]. However, Callan and Santerre did not have access to pretest information and therefore were unable to derive a value-added quality measure.

[9] Ideally, we would like to adjust the quantity numbers for variations in teacher quality. However, Hanushek [29] has demonstrated that observable teacher characteristics like salary, experience, and educational background do not indicate classroom effectiveness. Lacking a reliable indicator of teacher quality, we treat teachers as homogeneous.

[10] Support personnel include supervisors, counselors, librarians, nurses, physicians, and special service personnel.

[11] For example, if teacher aides are paid half the salary of teachers, on average, in the metropolitan area, then each teacher aide is counted as one-half of a teacher.

[12] $\text{CAPINPUT} = \text{ENROLL}_s \cdot (0.0173 \cdot \text{BOOKS} + 0.0022 \cdot \text{FURNITURE} + 0.0004 \cdot \text{PLANT} + 0.0002 \cdot \text{M \& O})$ where BOOKS is per-pupil expenditures on library books and media, FURNITURE is per-pupil expenditures for the purchase of furniture and equipment, PLANT is per-pupil expenditures on the physical plant, and M & O is per-pupil expenditures on maintenance and operations.

socio-economic composition of the school district, and the change in cohort characteristics. These estimates of student input are calculated for the primary and secondary grade levels for each school district.

Competition Measures

We construct two measures of the degree of competition for students. For both of our competition measures, we use data on enrollments in both public and accredited private schools (Texas Education Agency [43]). First, we construct four-firm concentration ratios (CR) for each metropolitan statistical area (MSA). The CR for a given market is the sum of enrollment shares for the four largest school ''districts'' (public or private) in that market. The CRs range from 45% for the Dallas and Houston MSAs to 99.8% in the Laredo MSA. Second, we construct Herfindahl indices (HI) of student enrollment for each MSA. The HI for a given market is the sum of the squared enrollment shares for all of the public and private school systems in that market. (For ease of exposition, we multiply HI by 100.) The HIs range from 9 in the Dallas MSA to nearly 68 in the San Angelo MSA.

Arguably, competition within school districts also affects district efficiency. We follow the literature and analyze competition at the district level for a number of reasons. First, we do not have access to campus level data for all private schools. Where a single accredited agency (such as the Catholic Diocese) runs multiple schools in a county, enrollments are reported only at a level analogous to a school district. We choose to treat public and private schools symmetrically in our measures of competition. Second, under the school finance formula school districts lose revenue if they lose enrollments, giving them strong incentives to compete for students. In contrast, campus revenues are controlled by school districts and could be unaffected by changes in enrollment. Therefore, district-level competition provides more direct incentives for efficiency. Campuses within a school district are also limited in their ability to differentiate themselves from one another because they share a common tax rate and central administration. Finally, because school districts control the number of campuses within their boundaries, intra-district competition is highly endogenous. Modeling that endogeneity is beyond the scope of this paper.

Indicators of Monitoring Activity

Theory does not dictate the appropriate indicators for monitoring activity. Davis and Hayes [13] postulate that monitoring activity is higher in communities with higher tax rates, smaller populations, and greater shares of owner occupied housing, and find significant relationships between these factors and governmental inefficiency that support the monitoring hypothesis.[13] Hayes and Wood [34] use similar monitoring arguments to hypothesize that governmental efficiency may also be related to the educational attainment of the community or its ethnic composition. They also find evidence that monitoring activity (as indicated by home ownership rates) is significant in explaining governmental inefficiency. Duncombe *et al*. [15] use similar measures as indicators of monitoring activity.

We include a number of potential indicators of monitoring activity in our analysis of school district efficiency. The monitoring indicators that we include are the school district's effective tax rate (TAX RATE), the share of occupied housing that is owner-occupied (OWNER), and the shares of the population over 20 that attended at least some college (COLLEGE) and that completed high school but did not attend college (HS_GRAD). To control for inefficiencies associated with school district size (which may arise either from difficulties associated with monitoring the behavior of large jurisdictions or from economies of scale in educational production) we include data on school district enrollment in all grades (ENROLL) and enrollment squared (ENROLL** 2). As in Duncombe *et al*. [15] we also include estimates of the share of households in the school district that have school-age children (W5TO17).

Table 1 presents descriptive statistics for the data used in this analysis.

V. ESTIMATION

We specify the following equation to identify the parameter estimates of $D(y, x)$,

$$1 = D(y, x) \cdot \exp(\upsilon), \tag{10}$$

where $D(y, x)$ is linearly homogeneous in x and υ is an error term. Taking the log of (10) yields

$$0 = \ln D(y, x) + \upsilon. \tag{11}$$

The translog cost function has a long history of use in estimating cost functions because of its flexibility and ability to nest various hypotheses within its structure. In this analysis we use a translog form for the distance function. Thus, Eq. (11) becomes

$$\begin{aligned} 0 = \alpha &+ \sum_j \beta_j \ln x_j + \tfrac{1}{2} \sum_j \sum_k \beta_{jk} \ln x_j \ln x_k + \sum_j \sum_m \rho_{jm} \ln x_j \ln y_m \\ &+ \sum_j \sum_r \gamma_{jr} \ln x_j \ln z_r + \sum_r \delta_r \ln z_r + \tfrac{1}{2} \sum_r \sum_j \delta_{rj} \ln z_r \ln z_j \\ &+ \sum_r \sum_m \nu_{rm} \ln z_r \ln y_m + \sum_m \lambda_m \ln y_m + \tfrac{1}{2} \sum_m \sum_n \lambda_{mn} \ln y_m \ln y_n + \upsilon, \end{aligned} \tag{12a}$$

[13] They also consider the possibility that variations in urbanicity or political institutions could impact government efficiency, but find that these structural differences had little explanatory power.

TABLE 1
Descriptive Statistics

	Mean	Std. dev.	Minimum	Maximum
10th grade				
$ENROLL_{10}$	595.25	965.27	52.00	8765.00
$MATH97_{10}$	76.17	3.90	61.01	85.44
SES_{10}	26.35	21.67	0.00	100.00
$ASIAN_{10}$	1.75	3.15	0.00	28.66
$BLACK_{10}$	10.23	14.09	0.00	87.79
$HISPANIC_{10}$	25.28	28.61	0.00	100.00
$MATH95_{8}$	70.75	4.97	52.39	82.31
$READ95_{8}$	78.83	4.37	62.47	89.75
$XSES_{10}$	−5.01	9.23	−44.95	99.56
$XASIAN_{10}$	0.27	0.82	−4.37	6.53
$XBLACK_{10}$	−0.04	2.04	−9.84	9.39
$XHISP_{10}$	0.15	2.56	−8.54	11.86
$XCOHORTN_{10}$	6.54	10.40	−35.09	35.25
6th grade				
$ENROLL_{6}$	668.44	1153.84	54.00	12031.00
$MATH97_{6}$	79.74	3.58	68.04	86.95
SES_{6}	39.07	23.02	0.00	99.20
$ASIAN_{6}$	1.45	2.42	0.00	18.58
$BLACK_{6}$	10.11	13.83	0.00	84.65
$HISPANIC_{6}$	26.61	28.63	0.00	100.00
$MATH95_{4}$	74.85	4.39	56.19	84.68
$READ95_{4}$	80.48	3.95	67.20	90.77
$XSES_{6}$	−1.19	8.24	−33.36	−99.20
$XASIAN_{6}$	0.13	0.59	−1.47	3.54
$XBLACK_{6}$	−0.07	2.13	−10.81	8.40
$XHISP_{6}$	1.95	3.33	−8.20	15.64
$XCOHORTN_{6}$	−8.01	14.15	−146.91	18.55
School district				
INSTR	83.88	131.98	8.36	1254.21
NINST	12.99	21.65	0.73	198.43
P	1.65	0.06	1.53	1.83
CAPINPUT	1294.11	2693.07	77.62	33316.15
Herfindahl Index	17.92	12.61	9.02	67.75
Concentration ratio	61.56	16.00	45.01	99.84
ENROLL	10.37	19.17	0.76	209.38
TAXRATE	1.56	0.15	1.15	2.10
OWNER	70.72	11.26	27.61	88.39
COLLEGE	42.91	14.32	8.47	90.97
HS_GRAD	28.87	6.19	6.64	45.75
W5TO17	37.36	7.62	18.06	69.66

where x_j is the quantity for discretionary inputs (INST and NINST), z_r is the quantity for non-discretionary inputs (STUINPUT_6, STUINPUT_{10}, and CAPINPUT), and the y_m are the output quantities (OUTPUT_6 and OUTPUT_{10}). We impose homogeneity in the discretionary inputs ($\sum \beta_j = 1$, $\sum \beta_{jk} = 0$, $\sum \rho_{jm} = 0$, $\sum \gamma_{jr} = 0$ where all of the sums are over values of j) as required by the definition of the input distance function (Färe and Grosskopf [17]).[14]

One advantage of the translog specification is that by Shephard's lemma the first derivative of (12a) with respect to $\ln x_1$ equals the expenditure share for input 1 ($S_1 = w_1 x_1/(w_1 x_1 + w_2 x_2)$). By estimating the distance function and the share equation together in a system of simultaneous equations we can improve the efficiency of the estimated parameters. We use the observed input quantities and the average prices for teachers and administrators ($P = w_2/w_1$) in each metropolitan area to define instructional expenditure shares ($S_1 = x_1/(x_1 + Px_2)$) for each observation. The relative price of administrators (P) is defined in terms of average prices rather than the observed prices because the observed prices may include rents.[15]

Thus, we estimate the following system of equations,

$$\begin{aligned}
0 = \alpha &+ \sum_j \beta_j \ln x_j + \tfrac{1}{2} \sum_j \sum_k \beta_{jk} \ln x_j \ln x_k + \sum_j \sum_m \rho_{jm} \ln x_j \ln y_m \\
&+ \sum_j \sum_r \gamma_{jr} \ln x_j \ln z_r + \sum_r \delta_r \ln z_r + \tfrac{1}{2} \sum_r \sum_j \delta_{rj} \ln z_r \ln z_j \\
&+ \sum_r \sum_m \nu_{rm} \ln z_r \ln y_m + \sum_m \lambda_m \ln y_m \qquad (12b) \\
&+ \tfrac{1}{2} \sum_m \sum_n \lambda_{mn} \ln y_m \ln y_n + \upsilon, \\
S_1 = \beta_1 &+ \beta_{11} \ln x_1 + \beta_{12} \ln x_2 + \sum_m \rho_{1m} \ln y_m + \sum_r \gamma_{1r} \ln z_r + \mu
\end{aligned}$$

using restricted least squares.[16]

By definition, the input distance function is bounded from below by one. However, the predicted values of the first equation in (12b) (the log of the

[14] In addition to the restrictions needed to satisfy the homogeneity conditions, we also impose symmetry (e.g., $\beta_{jk} = \beta_{kj}$).

[15] Implicity, this approach assumes that although wage levels may vary among school districts in a metropolitan area, teachers and administrators receive the same compensating differential (in percentage terms).

[16] Equation (12b) appears to not be estimable given the nonvariance of the left hand side of the first equation. However, such a system can be estimated by first imposing homogeneity restrictions and then using restricted least squares estimation. (See Hayes *et al.* [32].)

distance function) are distributed around zero. Therefore, we follow Greene [20] in adjusting the intercept term by adding the absolute value of the most negative residual ($|\min \hat{v}|$). The scaling yields estimated values of ln D in (12b) that are greater than or equal to zero, and estimated values for exp(ln D) that are greater than or equal to one. While all school districts are likely to exhibit at least some inefficiency relative to the true but unobserved technology, our method assigns one school district to be technically efficient in the best-practice sense. As mentioned above, inverting the value of the input distance function for each observation yields our measure of Farrell technical inefficiency:

$$\tau_s = \frac{1}{\exp\left(\ln \hat{D}(y, x) + |\min(\hat{v})|\right)}$$
$$= \frac{1}{\hat{D}(y, x) \cdot \exp(|\min(\hat{v})|)}.$$

Values of τ_s range from zero to one, with a value of one indicating that the school district is technically efficient (in the sense that the variable inputs cannot be proportionally reduced without reducing current output levels).

The predicted values from the instructional share equation (together with the variable input quantities and the ratios of average prices $P = w_2/w_1$) provide sufficient information to generate a point estimate of κ for each school district (κ_s).[17] If $\kappa_s > 1$ (< 1) then the wage-deflated marginal product of instructors is greater than (less than) the wage-deflated marginal product of administrative staff for school district s. We use the value of κ_s as our measure of allocative inefficiency: the farther κ_s is from one, the greater is the difference between the market price and the shadow price and the more allocatively inefficient is the school district.

To isolate the relationship between competition and inefficiency, we regress our measures of technical and allocative inefficiency against a measure of competition (either the four-firm concentration ratio or the Herfindahl Index) and the various indicators of monitoring activity (ENROLL, ENROLL**2, TAXRATE, OWNER, COLLEGE, HS_GRAD, and W5TO17). For the purposes of these regressions, allocative inefficiency is measured as the absolute

[17] With some rearrangement, the definition of κ_{12} given in Eq. (5) becomes

$$\kappa_s = \left(\frac{\partial D/\partial x_1}{\partial D/\partial x_2}\right) \Big/ \frac{w_1}{w_2} = \left(\frac{\partial D/\partial x_1}{\partial D/\partial x_2}\right) \cdot P,$$

where x_1 is INSTR and x_2 is NINST. Because there are only two variable inputs under consideration, we have dropped the subscripts on κ indicating input type.

value of $(\kappa_s - 1)$ and technical inefficiency is measured as the absolute value of $(\tau_s - 1)$.[18] After transformation, our measures of inefficiency ($|\kappa_s - 1|$ and $|\tau_s - 1|$) have been multiplied by 100 for ease of exposition. As $|\kappa_s - 1|^* 100$ increases, allocative inefficiency increases and as $|\tau_s - 1|^* 100$ increases, technical inefficiency increases.

We allow for non-linearities in the relationship between competition and inefficiency (as were found in Grosskopf *et al.* [22], Zanzig [46], and Borland and Howsen [8]) by following a ''switching regimes'' technique suggested by White [45] and Alexander [2]. The dummy variable (denoted DSwitch) takes on the value of one for market concentration measures that are greater than or equal to a critical value (z_0). We then search sequentially for the z_0 that maximizes the log likelihood function conditional on z_0.[19] For HI, we search over the range from 9 to 61.5 in one-half percentage point increments; for CR, we search over the range from 45 to 99 in one-half percentage point increments.

At this point we face several econometric problems: (1) the standard errors for (12b) will be incorrect because the regression includes generated regressors, (2) statistical significance cannot be determined for our measures of technical and allocative inefficiency because they represent transformations of the predicted values from (12b), and (3) we cannot obtain unconditional standard errors for the coefficients in the switching regressions because the critical value (z_0) is determined endogenously.

We address these problems by employing a nested bootstrap. Specifically, we create 250 data sets (of 302 observations each) based on random draws with replacement from the original data. Since we are drawing with replacement, some school districts will not be included in each sample while other school districts will be included more than once. We then replicate each stage of the analysis 250 times—one replication for each of the 250 data sets. Thus, Eq. (8) is re-estimated 250 times. In turn, the resulting OUTPUT_{sg} and STUINPUT_{sg} measures are used to re-estimate (12b). Appendix Tables 6 and 7 present information about the estimation of Eqs. (8) and (12b).

[18] Recall that allocative efficiency implies that $\kappa_s = 1$ while technical efficiency implies that $\tau_s = 1$.

[19] The log likelihood function is

$$\text{Log } L = -T\log(\sqrt{(2\pi)}) - \frac{T}{2} - \frac{T_1}{2}\log\left(\frac{\sum_{t=1}^{T_1} e_{it}^2}{T_1}\right) - \left(\frac{T - T_1}{2}\right)\log\left(\frac{\sum_{t=T_1+1}^{T} e_{it}^2}{T - T_1}\right),$$

where T_1 is the number of observations with concentration levels below the critical value z_0.

TABLE 2
Descriptive Statistics for κ_s and τ_s

	N. obs.	Mean	Std. dev.	Minimum	Maximum
Across all replications					
$\lvert\kappa_s - 1\rvert^* 100$	75,500	3.077	2.955	0.000	33.840
$\lvert\tau_s - 1\rvert^* 100$	75,500	19.523	6.978	0.000	44.078
Replication #5					
$\lvert\kappa_s - 1\rvert^* 100$	302	3.003	2.663	0.001	22.594
$\lvert\tau_s - 1\rvert^* 100$	302	20.322	6.002	0.000	41.431
Replication #123					
$\lvert\kappa_s - 1\rvert^* 100$	302	2.969	2.916	0.035	23.825
$\lvert\tau_s - 1\rvert^* 100$	302	20.595	6.232	0.000	42.508
Replication #190					
$\lvert\kappa_s - 1\rvert^* 100$	302	3.170	2.965	0.048	23.367
$\lvert\tau_s - 1\rvert^* 100$	302	22.500	6.470	0.000	41.372
Across replications at the sample mean of the original dataset					
$\lvert\kappa_s - 1\rvert^* 100$	250	0.959	0.374	0.047	1.947
$\lvert\tau_s - 1\rvert^* 100$	250	18.631	2.772	12.875	24.392

Each estimate of (12b) yields a distribution of τ_s and κ_s. Thus, we can use the switching regressions technique discussed above to estimate the relationship in each of our 250 replicated data sets between our estimates of inefficiency and our measures of competition. Using the replicated data sets in this way allows us to generate distributions not only of the coefficient estimates from the switching regressions, but also of the endogenous critical values (z_0).

VI. RESULTS

Table 2 presents a variety of descriptive statistics for our two measures of inefficiency. Because each of the 250 replications generates 302 estimates of τ_s and κ_s, there are 75,500 possible values for $|\kappa_s - 1|$ and $|\tau_s - 1|$. The first panel presents descriptive statistics on all of these estimates. The next three panels present descriptive statistics from randomly selected replications. The last panel presents the distribution of average efficiency estimates for each replication, where average efficiency is calculated by multiplying the replication coefficients by the means of the original sample (the values in Table 1).

As Table 2 illustrates, there is a wide range of inefficiency in Texas school districts. Consider first the estimates of allocative inefficiency. Evaluated at the mean, Texas school districts appear close to allocatively efficient (relative shadow prices deviate from relative market prices by less than one percent). However, many school districts display substantial allocative inefficiency. Relative shadow prices deviate from relative market prices by more than 5% in roughly 20% of the school districts in our sample.

The estimates of technical inefficiency are centered on 20% and have a rather straightforward interpretation. Relative to the best practice in the state, Texas school districts could reduce inputs by roughly 20% without reducing measured output.

Table 3 presents our results for three different models of school district efficiency. Model I excludes any measure of market concentration. Model II is a simple linear model including a market concentration variable (either HI or CR). Model III replaces the market concentration variable with an interaction term (DSwitch X market concentration). The interaction term takes on the value of the market concentration variable whenever market concentration equals or exceeds the critical value z_{r0} (and zero otherwise). Table 3a presents our technical efficiency results; Table 3b presents our allocative efficiency results. In all cases, the tables report median coefficient values from the 250 replications of the analysis, together with the fifth and ninety-fifth percentiles of the distribution of coefficients.

As Tables 3a and 3b illustrate, we find evidence that competition and monitoring activity have strikingly different relationships with allocative and technical inefficiency. Consistent with the hypothesis that monitoring creates incentives for increased governmental efficiency, we find that technical inefficiency is lower in school districts with higher proportions of homeowners, highly educated individuals, and households with school age children, and that allocative inefficiency is lower in school districts with higher tax rates. For example, evaluated at the means of the original sample, a 1% increase in the homeownership rate is associated with a 0.5% decrease in technical inefficiency while a 1% increase in the effective tax rate is associated with a 1% decrease in allocative inefficiency (see Table 4). Furthermore, the elasticities suggest that the efficiency loss associated with the higher costs of monitoring a large school district may be offset by economies of scale, particularly those arising from the indivisibility of some personnel inputs.

We also find systematic evidence that competition influences allocative inefficiency. Across the various specifications in Table 3b, the positive coefficient on the measure of market concentration indicates that allocative inefficiency rises with market concentration. For example, consider Model III. Ceteris paribus at the means of the original sample, moving from a educational market with 5 equally sized schools (CR = 80 and HI = 20) to a market with 4 equally sized schools (CR = 100 and HI = 25) would imply a 6−10% increase in allocative inefficiency, depending on the measure of market concentration (see Table 5).

As in our earlier analysis, the relationship between allocative inefficiency and market concentration is non-linear. The likelihood function is maximized with a switching point at a four-firm concentration ratio of 50 (or at a

Herfindahl index of 9.5). By these criteria, all of the metropolitan areas in Texas except for Dallas and Houston are highly concentrated markets.[20] However, we also note that the Dallas and Houston metropolitan areas contain more than one-third of Texas enrollment (urban and rural).

The switching-regimes regressions also suggest that school districts in highly concentrated markets are substantially more allocatively inefficient than school districts in competitive markets. The second row in Table 5 compares the predicted efficiency scores for school districts in highly concentrated markets (market concentration $\geq z_0$) with the predicted efficiency scores for otherwise equal school districts in competitive metropolitan areas (market concentration $< z_0$). Evaluating the models at the means of the other variables, we find that markets with CRs at or above the critical value have predicted inefficiency scores at least 50% higher than markets with CRs below the critical value. Markets with HIs above the critical ratio are at least 16% more allocatively inefficient than school districts in competitive metropolitan areas.

The nature of the allocative inefficiency also seems to differ between competitive and highly concentrated markets. Across all the metropolitan areas, the number of school districts that tend to overutilize administrators relative to instructors ($\kappa_s > 1$) is roughly equal to the number of school districts that overutilize instructors ($\kappa_s < 1$).[21] However, allocative inefficiency in the Dallas and Houston MSAs almost always takes the form of overutilizing administrators, while overutilizing administrators is much less common in highly concentrated markets. This pattern suggests that competition may be ineffective at limiting administrative bloat.

Interestingly, while allocative inefficiency appears to reflect competitive pressures, technical inefficiency does not. One possible explanation for this differential arises from a school district's role as both supplier of educational services and employer of educational personnel. In metropolitan areas where school districts have monopoly power in enrollments, they also may have monopsony power in the markets for teachers and administrators. Therefore, the market power of school districts in highly concentrated markets may be more likely to manifest in the misallocation of personnel rather than some other form of inefficiency.

[20] By the four-firm concentration ratio, both Dallas and Houston are not highly concentrated markets; by the Herfindahl index, only Dallas is not a highly concentrated market.

[21] A school district is said to overutilize administrators relative to teachers if the wage-deflated marginal product of teachers is greater than the wage-deflated marginal product of administrators ($\kappa_s > 1$) in at least 95% of the replications. Similarly, a school district overutilizes teachers if $\kappa_s < 1$ in at least 95% of the replications.

TABLE 3a
Technical Inefficiency

	Model I	Model II		Model III	
		CR	HI	CR	HI
Intercept	41.54	41.00	40.04	40.65	40.10
	(31.14, 51.84)	(29.80, 51.11)	(28.89, 50.18)	(28.24, 50.85)	(28.87, 49.71)
Market concentration	—	0.002	0.03	—	—
		(−0.03, 0.05)	(−0.03, 0.09)		
Dswitch X market concentration	—	—	—	0.01	0.04
				(−0.03, 0.04)	(−0.04, 0.15)
TAXRATE	2.38	2.41	3.07	2.56	3.06
	(−1.18, 6.92)	(−1.35, 7.15)	(−0.51, 7.94)	(−1.45, 7.83)	(−0.94, 8.42)
OWNER	−0.14	−0.14	−0.13	−0.13	−0.14
	(−0.20, −0.06)	(−0.20, −0.06)	(−0.20, −0.06)	(−0.20, −0.06)	(−0.20, −0.06)
W5TO17	−0.12	−0.12	−0.12	−0.12	−0.12
	(−0.22, −0.03)	(−0.22, −0.04)	(−0.23, −0.04)	(−0.23, −0.03)	(−0.22, −0.03)
COLLEGE	−0.13	−0.13	−0.13	−0.13	−0.13
	(−0.18, −0.09)	(−0.18, −0.09)	(−0.18, −0.09)	(−0.18, −0.09)	(−0.18, −0.09)
HS_SCHL	−0.20	−0.20	−0.19	−0.19	−0.20
	(−0.32, −0.08)	(−0.31, −0.08)	(−0.30, −0.08)	(−0.29, −0.09)	(−0.30, −0.08)
ENROLL	−0.02	−0.02	−0.02	−0.02	−0.02
	(−0.08, 0.06)	(−0.08, 0.06)	(−0.08, 0.06)	(−0.08, 0.07)	(−0.08, 0.06)
ENROLL** 2	−3E-4	−3E-4	−2E-4	−3E-4	−2E-4
	(−2E-3, 1E-4)	(−2E-3, 2E-4)	(−2E-3, 2E-4)	(−2E-3, 2E-4)	(−2E-3, 2E-4)
Log L	−971.7	−971.3	−970.8	−965.3	−965.1
	(−994.6, −947.6)	(−994.0, −947.2)	(−993.5, −947.0)	(−988.9, −940.8)	(−988.3, −941.7)
z_0	—	—	—	65.5	21.0
				(54.5, 97.0)	(10.5, 61.5)

Note. Median coefficient values. The 5th and 95th percentile values are in parentheses.

TABLE 3b

Allocative Inefficiency

	Model I	Model II		Model III	
		CR	HI	CR	HI
Intercept	10.50	5.55	7.43	7.62	7.91
	(6.22, 15.24)	(0.92, 10.73)	(3.41, 12.10)	(3.52, 12.28)	(4.01, 12.62)
Market concentration	—	0.04	0.05	—	—
		(0.02, 0.06)	(0.02, 0.07)		
DSwitch X market concentration	—	—	—	0.02	0.04
				(0.01, 0.05)	(0.01, 0.06)
TAXRATE	−3.25	−2.11	−2.21	−2.26	−2.30
	(−5.36, −1.26)	(−3.90, 0.01)	(−4.19, −0.09)	(−4.18, −0.19)	(−4.24, −0.23)
OWNER	−0.01	−0.01	−0.01	−0.01	−0.01
	(−0.05, 0.02)	(−0.05, 0.03)	(−0.05, 0.03)	(−0.05, 0.03)	(−0.05, 0.03)
W5TO17	0.02	0.004	0.01	0.01	0.01
	(−0.05, 0.07)	(−0.06, 0.05)	(−0.05, 0.06)	(−0.06, 0.06)	(−0.05, 0.06)
COLLEGE	−0.01	−0.01	−0.01	−0.01	−0.01
	(−0.04, 0.02)	(−0.04, 0.02)	(−0.04, 0.01)	(−0.04, 0.02)	(−0.04, 0.01)
HS_SCHL	−0.04	−0.02	−0.03	−0.03	−0.03
	(−0.11, 0.03)	(−0.09, 0.04)	(−0.10, 0.03)	(−0.09, 0.04)	(−0.10, 0.03)
ENROLL	−0.05	−0.04	−0.04	−0.04	−0.04
	(−0.11, −0.01)	(−0.12, −0.01)	(−0.12, −0.01)	(−0.12, −0.01)	(−0.12, −0.01)
ENROLL** 2	2E-4	2E-4	2E-4	2E-4	2E-4
	(−4E-6, 1E-3)	(2E-5, 1E-3)	(5E-6, 1E-3)	(2E-5, 1E-3)	(1E-5, 1E-3)
Log L	−737.6	−726.7	−730.3	−715.1	−701.9
	(−827.5, −662.6)	(−821.7, −648.6)	(−820.7, −649.1)	(−781.3, −636.6)	(−758.1, −639.2)
z_0	—	—	—	50.0	9.5
				(50.0, 97.0)	(9.5, 24.5)

Note. Median coefficient values. The 5th and 95th percentile values are in parentheses.

TABLE 4

Inefficiency and Monitoring—Selected Elasticities

	Model III	
	CR	HI
Technical inefficiency		
OWNER	−0.49	−0.48
	(−0.79, −0.21)	(−0.77, −0.21)
W5TO17	−0.23	−0.22
	(−0.46, −0.06)	(−0.43, −0.06)
COLLEGE	−0.29	−0.29
	(−0.43, −0.18)	(−0.42, −0.18)
HS_SCHL	−0.29	−0.28
	(−0.48, −0.12)	(−0.44, −0.11)
ENROLL	−0.01	−0.01
	(−0.04, 0.02)	(−0.05, 0.01)
Allocative inefficiency		
TAXRATE	−0.98	−1.14
	(−1.94, −0.09)	(−2.17, −0.12)
ENROLL	−0.11	−0.13
	(−0.26, −0.02)	(−0.29, −0.03)

Note. Median elasticities, calculated at the means of the original sample. The 5th and 95th percentiles are in parentheses.

TABLE 5

Allocative Inefficiency and Competition

	Model III	
	CR	HI
$\dfrac{\lvert\hat{\kappa}_s - 1\rvert_{four\ school\ market}}{\lvert\hat{\kappa}_s - 1\rvert_{five\ school\ market}}$	1.10 (1.05, 1.15)	1.06 (1.02, 1.09)
$\dfrac{\lvert\hat{\kappa}_s - 1\rvert_{z=z_0}}{\lvert\hat{\kappa}_s - 1\rvert_{z<z_0}}$	1.50 (1.14, 2.64)	1.16 (1.04, 1.53)
z_0	50.0 (50.0, 97.0)	9.5 (9.5, 24.5)

Note. Medians calculated at the means of the original sample. The 5th and 95th percentiles are in parentheses.

VII. CONCLUSIONS

Using an input distance function to model the relationship among the multiple inputs and multiple outputs of Texas school districts, we examine the effects of two incentive mechanisms for government efficiency—competition and monitoring. We find substantial evidence that increased competition for enrollments could enhance the allocative efficiency of school districts in concentrated markets. However, our analysis cannot detect a relationship between technical inefficiency and enrollment concentration. Furthermore, nearly one-third of the urban school districts in our sample are not located in concentrated markets. Thus, while our analysis offers support for the notion that increased school competition—fostered either by vouchers or charter schools—would improve school efficiency in some metropolitan areas, our analysis also suggests that increased competition is not a panacea. On the other hand, policies that enhance the public's ability to monitor the behavior of local school districts appear generally effective in increasing both technical and allocative efficiency.

APPENDIX

TABLE 6

Predicted Outcomes in Mathematics by Grade—1997

	6th grade			10th grade		
	5th percentile	Median	95th percentile	5th percentile	Median	95th percentile
Intercept	44.11	52.18	60.48	21.45	28.44	35.40
$MATH95_g$	0.15	0.31	0.47	0.18	0.30	0.42
$READ95_g$	−0.10	0.09	0.27	0.21	0.33	0.49
SES_g	−0.07	−0.05	−0.02	−0.03	−5E-5	0.04
$BLACK_g$	−0.08	−0.05	−0.02	−0.07	−0.05	−0.03
$HISPANIC_g$	−0.02	−0.002	0.02	−0.04	−0.01	0.01
$ASIAN_g$	−0.10	−0.02	0.08	−0.04	0.08	0.16
$XSES_g$	−0.03	0.001	0.03	−0.04	−0.01	0.05
$XBLACK_g$	−0.28	−0.13	−0.03	−0.24	−0.12	−0.02
$XHISP_g$	−0.21	−0.11	−0.02	−0.20	−0.11	−0.04
$XASIAN_g$	−0.32	0.13	0.55	−0.59	−0.26	0.22
$XCOHORT_g$	−0.002	0.02	0.05	0.05	0.07	0.09
R-square	0.5775	0.6347	0.6935	0.6530	0.7255	0.7794

TABLE 7
Estimates of the Translog Input Distance Function

	5th percentile	Median	95th percentile
Intercept	1.9610	3.6525	5.2579
$\ell X1$	0.4890	0.5039	0.5180
$\ell X2$	0.4820	0.4961	0.5110
$\ell Y1$	−2.0661	1.1397	4.6027
$\ell Y2$	−5.4206	−1.8087	2.1338
$\ell Z1$	−4.6570	−1.0454	2.2684
$\ell Z2$	−2.2439	1.6539	5.5228
$\ell Z3$	−0.8202	−0.3103	0.1414
$\ell X1 \ell X1/2$	0.1454	0.1527	0.1602
$\ell X1 \ell X2$	−0.1602	−0.1527	−0.1454
$\ell X1 \ell Y1$	−0.0146	0.0020	0.0163
$\ell X1 \ell Y2$	−0.0163	−0.0020	0.0146
$\ell X1 \ell Z1$	−0.0071	0.0058	0.0220
$\ell X1 \ell Z2$	−0.0199	−0.0045	0.0091
$\ell X1 \ell Z3$	−0.0040	−0.0021	−0.0002
$\ell X1 \ell X2/2$	0.1454	0.1527	0.1602
$\ell X2 \ell Y1$	−0.0163	−0.0020	0.0146
$\ell X2 \ell Y2$	−0.0146	0.0020	0.0163
$\ell X2 \ell Z1$	−0.0220	−0.0058	0.0071
$\ell X2 \ell Z2$	−0.0091	0.0045	0.0199
$\ell X2 \ell Z3$	0.0002	0.0021	0.0040
$\ell Y1 \ell Y1$	−5.0248	−1.8678	1.6384
$\ell Y1 \ell Y2$	−3.2631	2.2677	7.4129
$\ell Y1 \ell Z1$	−2.0906	5.1669	11.4758
$\ell Y1 \ell Z2$	−8.9071	−4.0145	2.2931
$\ell Y1 \ell Z3$	−0.5540	0.2709	0.9698
$\ell Y2 \ell Y2$	−3.0654	1.6560	5.6171
$\ell Y2 \ell Z1$	−8.5366	−3.4009	2.8345
$\ell Y2 \ell Z2$	−10.2134	−2.1029	7.6603
$\ell Y2 \ell Z3$	−1.3580	−0.3812	0.6890
$\ell Z1 \ell Z1$	−6.4032	−2.9141	0.5147
$\ell Z1 \ell Z2$	−2.0567	4.4382	10.0680
$\ell Z1 \ell Z3$	−1.0198	−0.2381	0.6257
$\ell Z2 \ell Z2$	−5.1768	0.7876	5.1329
$\ell Z2 \ell Z3$	−0.7148	0.3766	1.3187
$\ell Z3 \ell Z3$	−0.0433	0.0244	0.0729
$\partial \ln D/\partial X1$	0.794	0.795	0.796
$\partial \ln D/\partial X2$	0.204	0.205	0.206
$\partial \ln D/\partial Y1$	−0.776	−0.498	−0.186
$\partial \ln D/\partial Y2$	−1.114	−0.746	−0.374

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