Int Adv Econ Res (2008) 14:228–241
DOI 10.1007/s11294-008-9137-z

Efficiency and Equity in School Funding: A Case Study for Kansas

Kalyan Chakraborty · John Poggio

Published online: 8 February 2008

Abstract This study measures cost inefficiency of Kansas public school districts and applied both mathematical programming and stochastic frontier approach. The empirical study uses two-stage data envelopment analysis model and the cost inefficiency effects model proposed by Battese and Coelli (Empirical Economics 24:325–332, 1995) and applied to a panel data. The results found mean inefficiencies from these two models are very close. The results indicate that Kansas school districts, on average, exhibit cost inefficiency in their operations, however, there is a tendency for inefficiencies to decline over time. The study does not find any strong evidence for lower efficiency due to lower expenditure per-pupil. Instead, we found inconclusive evidences where lower efficiency for certain school districts could be assigned to unfavorable environmental cost conditions.

Keywords Cost inefficiency · Stochastic cost frontier · Function · Public education

JEL Code D2 · I2 · R0

Introduction

In recent years, several states have faced challenges to their K-12 school funding systems on the basis of equity and inadequacy. Kansas has a long history of litigation related to school funding. Since 1972, state courts have declared the state school funding system unconstitutional five times (Green 2005). Equity in school funding became one of the most important issues before the Kansas legislature since

Presented at the 61st IAES Conference Berlin, Germany, March 15–19, 2006

K. Chakraborty (✉)
Emporia State University AIS, Box 4057, 1200 Commercial Street, Emporia, KS 66801, USA
e-mail: kchakrab@emporia.edu

J. Poggio
Department of Psychology & Research, Center for Educational Testing and Evaluation,
University of Kansas, 1122 West Campus Road, 738 Pearson Hall, Lawrence, KS 66045-3101, USA
e-mail: jpoggio@ku.edu

the summer of 2005 when Kansas Supreme Court declared in *Montoy vs Kansas* that the current system of school financing violated the Education Article [Article 6] of the Kansas Constitution. The current ruling is the outcome of a lawsuit filed in 1999 where the plaintiffs in the Dodge City and Salina school districts alleged that the state school finance system was flawed and that districts with the largest number of at-risk students were receiving inadequate funds to address the special needs of those students. In the summer of 2005, the Kansas Supreme Court ordered the Kansas legislature to provide and a total of $285 million by July 1, 2005 for public school financing.

The recent court ruling has necessitated a critical examination about how school districts are managing their resources for educational services. Except the studies by Chakraborty (2003, 2005), no study has made an effort to uncover the causes of low performance for some school districts in Kansas by applying sound economic theory and advanced tools of econometric analysis. Our interest in measuring cost efficiency is motivated by the question that has been raised recently in the public policy arena: “Are the school districts in Kansas minimizing cost while trying to achieve state mandated educational standards?” We addressed this issue by measuring cost efficiency for school districts using 5-year panel data applied to parametric and non-parametric methods. The major objectives of the current study are: (1) to identify the districts that are inefficiently managing their resources while delivering the state mandated educational outcome; and (2) to identify the factors which account for efficiency differential among school districts. We have also made an effort to identify the sources of low performance for plaintiffs’ districts vis-à-vis all other districts in the sample.

To achieve our first objective, we defined and estimated an educational cost function and constructed a cost inefficiency index for all school districts in Kansas. In order to achieve our second objective, we conducted a regression analysis capturing the relationship between the inefficiency index and the environmental cost factors affecting inefficiency. We have applied an econometric model that captures the impact of environmental factors on school district inefficiency more rigorously than the models used in past public education literature. We consider this approach as novel and unique, and it will add to the existing body of knowledge.

In the next section, we have provided the background for this study including a brief survey of the studies done in the literature. Both educational cost function and the model are defined in the third section, which is followed by a section on the dataset. The fifth section discusses the results. The summary and conclusions are in the concluding section.

Background

Efficiency and equity in school finance has remained the major issue over the past 25 years. Most states are experiencing growth in per-pupil expenditure while student achievement score remains stagnant (Hanushek and Rivkin 2004). In June 2005 before the Supreme Court ruling, the state independently conducted two separate studies and investigated the relationship between school funding and student achievement for all Kansas school districts (Poggio 2001; Glasnapp and Poggio

2003). Both of these studies used simple statistical analysis and concluded that expenditure per-pupil is not a “powerful” determining factor for student achievement. In general, research in public school finance mostly initiated in response to lawsuits or court rulings in the U.S. (McCarty and Yaisawarang 1993; Downes and Pouge 1994; Noulas and Ketkar 1998; Duncombe and Yinger 2000; and Ruggiero 2001).

A recent study by Duncombe and Yinger (2005) estimated the base cost per student for Kansas school districts and developed a cost index for inclusion into the school finance formula. Similar studies were found in the literature using data from other states (Ruggeiro 2001; Duncombe and Yinger 1998; Downs and Pouge 1994). Although revising the state funding formula based on base cost and/or cost index makes funding more transparent and equitable, it does not guarantee improved cost efficiency for districts. Researchers found that budgetary reforms to equalize expenditure could actually increase the inequality of student achievement (Grosskopf et al. 1997; Husted and Kenny 2000).

Most past studies estimated an educational production function using stochastic and/or non-stochastic methods and measured technical efficiency index (McCarty and Yaisawarang 1993; Grosskopf et al. 1997; Chakraborty 2001, 2003, 2005). Some studies that used two-stage data envelopment analysis (TSDEA) and stochastic frontier approach (SFA) to measure two sets of efficiency scores found the rank correlation between this two sets of efficiency scores is close to one (i.e., they are highly correlated) (Ruggerio and Vitaliano 1999; Chakraborty et al. 2001). Contrary to those studies, this study found no rank order correlation between the two sets of efficiency estimates in our data, although the mean efficiencies are very close. One possible reason might be the use of panel data because data envelopment analysis (DEA) models are not panel model. Another reason might be that DEA estimates in the first step fails to take into account the relevant factors that determine inefficiency hence, it is likely to be quite off. We argue that the reason for no correlation between these two sets of efficiency estimates is that the model we used treated the exogenous socio-economic variables differently from the models commonly used in a stochastic frontier framework. Considering the significant influence of socio-economic variables on students’ learning, these variables need special treatment/attention and, as a result, the econometric model used in this study is more appropriate for that purpose.

Educational Cost Function and Model

Stochastic frontier cost function estimation is superior to production function because it can handle multiple inputs and outputs, and it is an input oriented measure as a result, the approach can differentiate between variable and quasi-fixed inputs measuring efficiency (Kumbhakar and Sarker 2005). However, the cost function approach imposes the restrictive behavioral assumption that each school district minimizes its cost of providing educational services, given its input prices and the environmental cost factors.

We have developed an educational cost function following the model proposed by Ruggerio and Vitaliano (1999) and Ruggerio (2001). Assume each school district employs various instructional and non-instructional inputs to produce multiple educational outputs commonly measured by educational outcome (y), given the input prices (w) and environmental cost conditions (z). Assume district administrators seek to minimize the total cost (c) for providing such educational services given the exogenous input prices (w) and environmental factors (z). Hence, the observed expenditure (E) is written as:

$$E = c(y|\, w, z)/CE \tag{1}$$

We assume that the observed total expenditure (E) is the minimum cost $c(.)$ without any inefficiency; when CE is the overall cost efficiency; $w=(w_1,\ldots w_K)$ are the prices of inputs ($x_1\ldots x_K$). Then the observed cost is the minimum cost if CE=1 and cost inefficiency implies 0<CE≤1. If we further assume CE=δ, then $E = \frac{1}{\delta}c(y|\, w, z)$.

If school districts are cost inefficient, then actual expenditure will be greater than the minimum cost of providing the observed outcomes. As a result, the empirical expenditure function is derived as:

$$E(z, w) = [(y, E)|E] \geq c(y|\, z, w)] \tag{2}$$

Eq. 2 shows minimum cost for each school district, which depends on the input prices and the social and economic environment within which the school district operates.

The DEA Method

In DEA, the observed expenditure of each school district is compared to the best practice frontier to determine its relative status. School districts with unfavorable cost environments are expected to lie below the frontier. Assume y_{ik} and E_i are the kth outcome and observed expenditure for the ith school district, respectively. Hence the linear program for our cost minimizing expenditure may be written as:

$$CE_i = Min\lambda \tag{3}$$

$$s.t. \sum_{J=1}^{N} \theta_j E_j \leq \lambda_i E_i; \sum_{J=1}^{N} \theta_j y_{k,j} \geq y_{kj} \ \ \forall k = 1, 2, \ldots, K; \ \ \sum \theta_j = 1; \theta_j \geq 0;$$
$$\forall j = 1, \ldots, N$$

where N is the number of school districts, K is the number of student outcomes, and θ is the optimal weight for the individual school district. The CE_i index, obtained from the solution of the above linear program, is a ratio of the cost minimizing to the observed expenditure, therefore, a measure of inefficiency. However, this measure of inefficiency assumes all school districts face the same favorable cost environment which is contradictory.

In order to measure cost efficiency conditioned on the differential cost environment faced by the school districts, the most commonly used technique is to apply a regression analysis (ordinary least square, OLS, or tobit) in the second-stage. In this method, the efficiency index obtained from the first-stage DEA model is regressed on the environmental cost factors in the second-stage, and the residuals (from OLS) or the predicted efficiencies (from tobit) obtained from the regression are adjusted to obtain 'pure' cost efficiency (Ray 1991; McCarty and Yaisawrang 1993; Linna 1998; Duncombe and Yinger 1997; Kirjavainen and Loikkanen 1998; Noulas and Ketkar 1998; Ruggiero and Vitaliano 1999; Ruggiero 2001; and Chakraborty et al. 2001). However, researchers have shown that the efficiency estimates obtained from the first-stage DEA model are truncated at [0, 1], hence parameter estimates using ordinary least squares would be biased and inconsistent (McCarty and Yaisawrang 1993).

Unlike past studies, this study used a random effect tobit model and applied it to a panel data to estimate 'pure' cost efficiency. Assuming that the efficiency index from the DEA model is uncorrelated with the environmental cost factors, the standard random effect tobit model for panel data may be written as:

$$y_{it}^{*} = z'_{it}\beta + \varepsilon_{it} + u_i \tag{4}$$

$$y_i = y_i^{*} \text{ if } y_i^{*} > 0;\ y_i = 0 \text{ otherwise}$$

where y_i^{*} is a latent variable which can be viewed as a threshold beyond which the environmental variables (z_i) must affect y_i to be seen from a value 0 to a positive value. Cost efficiency index (CE_i) is viewed as a continuous variable limited by (0, 1), z_i' is the vector of environmental factors, and ε_{it}, u_i ~ bivariate normal with mean (0, 0) and variances (σ^2, ω^2) and correlation 0. The basic assumptions are that the random effect is the same for every period, and the unique effect ε_{it} is uncorrelated across periods. All effects are uncorrelated across individuals (Greene 2002a).

Stochastic Frontier Approach (SFA)

Stochastic production frontier was developed and extended by Aigner et al. (1977), Meeusen and van den Broeck (1977), and Jondrow et al. (1982). The basic idea behind the stochastic frontier model is that the error term is composed of two parts: (1) the systematic component (i.e., a traditional random error) that captures the effect of measurement error, other statistical noise, and random shocks; and (2) the one-sided component that captures the effects of inefficiency. Several extensions of the stochastic frontier models have been proposed over the years (Battese and Coelli 1995; Kumbhakar and Lovell 2000; Greene 2001, 2002a, b).

This study uses the model proposed by Battese and Coelli (1995) (inefficiency effects model) to explain cost inefficiency with a panel data context. The log-linear structure of the model may be written as:

$$LnE_i = Lnc(w_{it}, y_{it}; \beta) + v_{it} + u_{it} \tag{5}$$

$$U_{it} = \delta' Z_{it} + C_{it} \tag{6}$$

where v_{it} represents the random noise of the ith school district in tth period and u_{it} captures the effect of cost inefficiency that has a systematic component $\delta' z_{it}$ associated with the environmental factors (exogenous variables) and a random component c_{it}.

Where $E_i = \sum W_{Ni} X_N$ is the observed expenditure incurred by the ith school district, $y_i = (y_{1i}, y_{2i}, \ldots, y_{Mi}) \geq 0$ is a vector of M outcomes produced by ith school district, $w_i = (w_{1i}, w_{2i}, \ldots, w_{Ni}) > 0$ is the vector of input prices, $c(w_i, y_i; \beta)$ is the cost frontier common to all school districts, $\boldsymbol{\beta}$ is the vector of technology parameters to be estimated, and u_i is the percentage increase in cost due to inefficiency (Kumbhakar and Sarker 2005).

The empirical estimation of the model is done by maximum likelihood estimation (MLE) technique using a computer program FRONTIER 4.1 by Coelli (1996). The MLE is conducted after re-parameterization of the variance parameters (i.e., σ_v^2 and σ_c^2) as:

$$\sigma^2 = \sigma_c^2 + \sigma_v^2 \text{ and } \gamma = \frac{\sigma_c^2}{\sigma_c^2 + \sigma_v^2}$$

The parameter γ represents the share of inefficiency in the overall residual variance and ranges between 0 and 1. A value of 1 suggests the existence of a deterministic frontier, and a value of 0 suggests that ordinary least square would generate similar results without any effect of structural inefficiency in the model.

The Dataset

The information on inputs and outputs were obtained from the Kansas State Department of Education. Information on standardized test scores in math and reading were collected from the Center for Educational Testing and Evaluation, University of Kansas, Lawrence. Math tests are administered in all districts at the 4th, 7th, and 10th grades, and reading tests at grades 5th, 8th, and 11th. Test score data is available at the school level, but information on most of the other variables used in this study is available only at the district level. For consistency, test score data are aggregated at the district level.

School and non-school inputs used in this study are measured as operating expenditure per-pupil (FTE), student–teacher ratio, student–administrative staff ratio, average contract salary for teachers and administrative staff, and district enrollment (FTE). Full time equivalent student (FTE) is based on the percent of time a student is enrolled in grades K-12. Operating expenditure includes expenditure for instruction, administration, and plant maintenance and operation and does not include capital and debt services. Variables measuring teachers' quality are measured as percent of teachers (FTE) with MA and/or PhD degrees and percent of teachers (FTE) with ten or above years of teaching experience. Variables used to control for the school district cost environment are percent of students belonging to a minority, percent of students enrolled in a special-ed program, and percent of students qualified for free and subsidized lunches.

Initially, we collected information for all 304 school districts, starting from the school year 2000–01 but, due to merger and consolidation, some of the districts did not exist across the entire study period (2001 to 2005). Further, non-availability of test score data for all six output measures for some districts prohibits their inclusion in our dataset. Hence, this study used a balanced panel data for 283 districts, observed for 5 years. Table 1 presents descriptive statistics for each of these variables.

Table 1 Descriptive statistics of the variables used in the study (5-year average) (Obs. 1415 USD)

Description of the Variables	Mean	Standard Deviation	Maximum	Minimum
Outputs (Y)				
Fourth grade math score (M4)	61.20	7.95	88.10	32.80
Seventh grade math score (M7)	54.89	7.29	78.50	31.20
Tenth grade math score (M10)	49.23	6.13	73.20	33.55
Fifth grade reading score (R5)	83.10	3.56	94.60	68.90
Eighth grade reading score (R8)	82.87	3.01	90.91	66.40
Eleventh grade reading score (R11)	80.38	3.21	89.80	60.70
Variable inputs (X)				
Student–teacher ratio (STR)	13.30	2.41	22.40	6.50
Student–administrative staff ratio (SAR)	81.52	26.06	386.25	21.18
Percent of teachers with ten or more years of experience (EXPR)	63.35	1.55	98.86	28.23
Percent of teachers with MA and/or PhD degree (MAPH)	35.71	13.59	98.52	2.23
Input prices (W)				
Average contract salary of the teachers ($) (TSAL)	39,694	3,414	73,749	29,071
Average contract salary of the administrative staff ($) (PSAL)	63,518	16,709	99,974	33,349
Environmental factors (Z)				
Percent of students belongs to minority (MIN)	10.50	12.61	80.77	0.00
Percent of students with disabilities (DIS)	14.21	3.95	56.91	3.09
Percent of students receiving free or reduced lunches (POV)	35.62	12.72	80.65	1.62
Other variables				
Operating expenditure per student ($) (EXP)	9,295	1,498	17,580	6,119
Enrollment (FTE) (ENROL)	1,636	4,140	48,760	123

Empirical Results

Results from TSDEA—Model

We estimated the cost/expenditure function (2) using a linear program (3) for each of 283 school districts in the first-stage DEA model. In this construct, we used six output (y) measures (M4, M7, M10, R5, R8, and R11), two input measures (x) (student–teacher ratio, student–administrative staff ratio), and three input prices (w) (TSAL, PSAL, and OEXP). The variable ‘OEXP’ represents expenditure per-pupil other than salary for the teacher and administrative personnel. This method constructs a reference set of efficient districts that uses lowest quantity of inputs for observed set of outputs, given the input prices. The mean efficiency from DEA is 0.638, implying school districts are 63.8% cost efficient. For a fully efficient district $\delta=1$, hence, mean cost inefficiency is $1/\delta=1.56$, or on the average, school districts are 56% inefficient.

However, this measure of inefficiency does not control for the differential cost environment, and therefore does not reflect the true cost inefficiency. In order to adjust δ, we ran a tobit regression in the second-stage using Eq. 4. In tobit regression, the cost efficiency index obtained from the first-stage DEA model is used as the dependent variable and the environmental variables (z) as explanatory variables. The parameter estimates are presented in Table 2. The overall results are consistent with the literature. Except for the variable MIN, all other variables have

Table 2 Estimated parameters of the random effect Tobit model using educational cost function

Variables	Coefficient	Marginal Effects	t-statistics
Intercept	1.1147	1.0899	24.200[a]
Percent of student belongs to minority (MIN)	0.0005	0.0005	0.868
Percent of students with disabilities (DIS)	0.0085	0.0083	6.219[a]
Percent of students receiving Free and reduced lunch (POV)	−0.0025	−0.0025	−4.702[a]
Ln(Student enrollment) (ENROL)	−0.0762	−0.0745	−13.122[a]
Sigm	0.1852		7.279[a]
Log of the Likelihood Function	179.989		
Chi-squared	21.046		

Dep-variable: Efficiency Estimates from DEA Model (Obs. 1415)
[a] Significant at 95%

correct signs and are significant at 5% or below. Theoretically, the magnitude of the coefficients from a random effect tobit model should be similar to marginal effects as suggested by Greene (1999). Positive and highly significant coefficient on the variable percent of students with disabilities implies cost efficiency increases with a higher percentage of student enrollments in special-ed program.

For further investigation, we reported the raw data on environmental variables and adjusted efficiency scores obtained from TSDEA model (including efficiency scores from SFA model) in Table 5. We found average efficiency is higher for districts that have higher percentage of special-ed students. We believe that the school districts with a larger percentage of special-ed students tend to spend their money more efficiently in terms of hiring more teachers, requiring smaller class size, building more classrooms, and purchasing more equipment than other districts.

Residual variance (σ_u^2) in the tobit regression captures the cost inefficiency unexplained by environmental factors because (σ_v^2) is zero by assumption. The adjusted mean efficiency from tobit regression is 0.831[1]. Mean cost efficiency is 83.1%, which implies, when controlled for the environmental factors the mean cost efficiency estimate significantly increases. In order to estimate adjusted efficiency estimates for the individual school districts, we needed to add (0.831–0.638 =) 0.193 to the predicted efficiency scores from the tobit regression. Cost efficiency estimates from the TSDEA are reported in the upper half of Table 4.

Instead of individual school district efficiency scores, we reported average efficiency levels divided into six sub-groups. In TSDEA model, 13 out of 283 districts have efficiency scores between 100–95%. It is interesting to note that the average enrollment for this group is the lowest (column 2) and expenditure per-pupil is the highest (column 3), contrary to the 18 least efficient school districts that have the highest average enrollment and the lowest average expenditure per student. The main reason for difference in efficiency level between these two groups is the percentage of minority students and poverty are higher for the second group than the first.

[1] Following Greene (1995) and Ruggiero and Vitaliano (1999), $\frac{1}{\delta} = e^u = e^{0.18528} = 1.20355; \delta = 0.830$

Results from SFA—Model

We estimated the stochastic cost frontier Eq. 5 in log-linear specification[2]. In this model, the dependent variable is operating cost per-pupil and explanatory variables are: variables measuring outputs (y), controllable inputs (x), and input prices (w). Variables used for the inefficiency function (6) represent the three environmental factors (z), and all variables are in natural units. Results are reported in Table 3. The *Year* variable in stochastic frontier Eq. 5 represents Hicks-neutral technological change, and for the inefficiency function Eq. 6, it represents whether inefficiency effects change over time (Battese and Coelli 1995). Positive and significant coefficient on *Year* in stochastic frontier equation (Table 3) suggests cost per pupil has increased significantly over time for the study period. The negative and significant coefficient on *Year* in inefficiency function suggests inefficiency for Kansas school districts has decreased over time. For the stochastic cost function, 10 out of 14 parameters are highly significant, and all coefficients have expected signs. For example, parameter estimates for all six output variables are positive, implying it costs more to produce higher achievement scores. However, four out of the six output parameters are insignificant, implying a weak relationship between cost per-pupil and output, which is consistent with the literature (Hanushek 1993; Ruggiero and Vitaliano 1999). With the functional form being log-linear, the estimated coefficients represent elasticity. For example, a 1% increase in teachers' salary or enrollment would increase cost per-pupil by 0.035%, or decrease cost per-pupil by 0.028%, respectively.

For the inefficiency-effect Eq. 6, all of the estimated parameters (Table 3) have correct sign and are significant. For example, a 1% increase in minority, disability, or poverty would increase inefficiency by 0.005, 0.009, and 0.002% respectively. Likelihood ratio statistic is highly significant, implying stochastic frontier specification is appropriate. The estimated value of the variance parameter γ is close to one and is highly significant. This implies environmental cost factors in the inefficiency function are able to explain a "substantial" part of the unconditional variance of the one-sided error term (Kumbhakar and Sarkar, 2005)[3]. The lower half of Table 4 presents the average school district efficiency scores divided into six sub-groups.

There are two school districts with efficiency score above 95% and 8 districts with efficiency scores below 70%. A comparison between these two sub-groups (the most and least efficient districts) reveals that the most efficient districts have higher enrollment and lower expenditure per-pupil compared to the least efficient districts, although they all operate under similar environmental cost factors. From this, we conclude that higher expenditure per-pupil generally transforms into higher inefficiency for Kansas schools. In order to determine which of the two models captures the impact of non-controllable environmental factors more accurately, we compared the selected school district profiles against the cost efficiency scores obtained from the two models (Table 4). With all other things remaining similar, we

[2] Trans-log functional form was also tested but the current specification fits the data best.

[3] The null hypothesis in the inefficiency function is the absence of district specific inefficiencies i.e., H_o: $\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$ where δ's are the parameters associated with z variables.

Table 3 Estimated parameters of the stochastic cost function and time varying inefficiency

Variable	Coefficient	t-statistics
Intercept	6.0925	10.472[a]
Ln(Forth grade math score)	0.0237	1.107
Ln(Seventh grade math score)	0.0107	0.447
Ln(Tenth grade math score)	0.0222	0.897
Ln(Fifth grade reading score)	0.1491	2.088[a]
Ln(Eighth grade reading score)	0.2143	2.447[a]
Ln(Eleventh grade reading score)	0.0349	0.447
Ln(Student–teacher ratio)	−0.4218	−17.324[a]
Ln(Student–administrative staff ratio)	−0.1262	−13.244[a]
Ln(Percent of teachers with ten or more years of experience)	−0.0915	−6.158[a]
Ln(Percent of teachers with an MA and/or PhD degree)	0.0357	5.370[a]
Ln(Average contract salary of the teachers) ($'000)	0.1393	3.422[a]
Ln(Average contract salary for the administrative personnel) ($'000)	0.1263	4.772[a]
Ln(Student enrollment) (FTE)	−0.0289	−5.594[a]
Time	0.0512	16.392[a]
Intercept	−0.2458	−2.212[a]
Percent of students belonging to minority	0.0052	5.349[a]
Percent of student with disabilities	0.0090	3.824[a]
Percent of students receiving free or subsidized lunches	0.0019	2.022[a]
Time	−0.0335	−2.989[a]
Sigma squared	0.0274	5.050[a]
Gamma	0.8924	41.314[a]
Log Likelihood	1,356.22	
LR for one-sided error	205.30	

Function Based on Battese and Coelli Model (1995). Dep-Variable: Ln(Operating Expenditure per-pupil)
[a] Significant at 5%

found 65 (13+52) school districts with efficiency scores of 90% or above in TSDEA model have significantly lower enrollment and less minority students compared to 29 (2+27) comparable districts in the SFA model. We argue that the cost efficiency measure under TSDEA model inappropriately identified several districts as working under favorable environment when, in reality, they were not. As a result, when SFA model is applied to the same dataset, it constructed the "best practice" frontier well above the so called efficient districts, reducing their efficiency scores significantly. That is why in SFA model we have only 29 districts with efficiency level 90% and above. This implies that the specific structure of the SFA model used in this study (Battese and Coelli 1995) captures the impact of environmental factors more precisely and outperforms the TSDEA model for our data.

One of our objectives in this study was to identify the sources of inefficiency for the plaintiffs' school districts. To that effect, Table 5 reports the raw data on environmental variables and expenditure per-pupil vis-à-vis efficiency scores obtained from the two models. The first four columns are divided into sub-groups based on the range of student enrollment, column 5 reports sample average, and the last two columns report information on the Salina and Dodge City school districts[4]. We followed a recent report published by the legislative division of post audit, Kansas (LPA 2006) and grouped the school districts accordingly. It is evident from

[4] Out of three school districts in Saline county, we only chose Salina (USD 305) for comparison.

Table 4 Profile of environmental cost factors for school districts grouped by efficiency levels (2001–2005)

Efficiency Level	Enrollment (FTE)	Per Student Expenditure ($)	Minority Percent	Disability Percent	Poverty Percent	Total USD
TSDEA—mean efficiency (0.8308)						
1.000–0.950	239	10,774	4.63	19.71	38.92	13
0.949–0.900	311	9,225	5.52	16.44	36.02	52
0.899–0.850	457	9,496	7.14	14.15	35.70	76
0.849–0.800	851	9,216	16.18	12.97	33.18	66
0.799–0.700	2,069	8,345	12.45	12.85	34.57	58
Below 0.700	11,657	8,837	36.55	12.99	44.05	18
SFA—mean efficiency (0.8292)						
Above 0.950	2,069	7,096	10.96	12.13	34.75	2
0.950–0.900	1,124	7,988	7.19	14.22	35.87	27
0.899–0.850	1,498	8,854	10.16	14.03	35.58	87
0.849–0.800	838	9,451	8.36	14.19	34.53	83
0.799–0.700	2,520	10,200	13.30	14.55	36.44	76
Below 0.700	1,776	12,238	16.46	13.64	38.91	8

All variables are at group mean.

the table that the medium and the large size districts are most efficient for SFA model (83.6%) and face similar cost environment except for the "minority" variable. Extra-large districts are the least efficient for both models and have less than average expenditure per-pupil.

Based on student enrollment, both Salina and Dodge City school districts are comparable to large size USDs whose mean enrollment is 7,796. Considering the environmental factors, the large size districts and Salina operate under similar conditions except Salina has a larger percentage of student population from "poverty" (10% higher). It is noticeable that although expenditure per student for Salina is similar to the large USDs, the efficiency scores for Salina are much lower both from TSDEA and SFA model (0.654, 0.675) than the large size USDs (0.728, 0.836), respectively. We would like to argue that cost inefficiency for Salina is primarily due to its higher percentage of "poverty" rather than "disability." Dodge

Table 5 Cost efficiency vis-à-vis environmental cost factors grouped by district size (2001–2005)

Variables	Small <400	Medium 401–1,730	Large[a] 1,731–9,999	Ex-Large >10,000	Sample Average	Salina[b]	Dodge City[c]
Minority (%)	7.44	8.36	19.09	36.49	10.37	21.75	64.57
Disability (%)	15.01	14.10	13.17	12.86	14.21	14.79	12.27
Poverty (%)	39.53	34.05	32.69	36.83	35.62	42.76	64.50
Expenditure ($)	10,142	9,062	8,387	9,136	9,296	8,787	9,296
TSDEA	0.910	0.839	0.728	0.575	0.838	0.654	0.620
SFA	0.817	0.836	0.836	0.786	0.829	0.675	0.787
Total USD	89	143	45	6	NA	NA	NA

[a] Average size for large districts is 7,796

[b] Salina (USD-305) 5-year average enrollment (FTE) is 7,620

[c] Dodge City (USD-443) 5-year average enrollment (FTE) 5,797

City school district has one of the highest percentages of student population from "minority" and "poverty" in the sample. Although Dodge City has higher expenditure per student compared to large USDs, presumably a major part of its expenditure is due to the high cost of serving underprivileged and English language learner students. We would argue that the cost inefficiency for Dodge City (TSDEA 0.620 and SFA 0.787) is primarily due to its unfavorable cost conditions. Based on the results from the SFA model, we can infer that we do not find any direct relationship between cost efficiency and expenditure per student in our dataset.

Summary and Conclusions

This study applied both stochastic and non-stochastic cost function approach to evaluate the cost efficiency of Kansas school districts over a 5 year period from 2001–2005. We estimated the stochastic cost function using Battese and Coelli (1995) inefficiency-effect model which is novel in the public education literature and is more appropriate for controlling the effect of environmental factors. Our results indicate that, on average, Kansas school districts exhibit the presence of cost inefficiency in their operations; however, there is a tendency for inefficiencies to decline over time. Results also indicate that we do not find any strong evidence for lower efficiency due to lower expenditure per-pupil (SFA model). Rather, we found inconclusive evidences where lower efficiency could be assigned to unfavorable environmental conditions. For Salina, we found inefficiency is primarily due to a higher percentage of "poverty" students, while for Dodge City both "minority" and "poverty" probably are the two major causes for its low efficiency.

One of the major limitations of our study is that we did not look into the productive efficiency of the districts. School districts could be productively efficient, implying producing maximum possible outcomes given the inputs, but could still be cost inefficient. This is because, in reality, district administrators may not have any incentive to minimize the cost, and hence could become cost inefficient but could produce high achievement scores. Thus, one has to use caution when interpreting the results from this study for policy making. Our efficiency estimates from TSDEA model could be biased because the model is sensitive to variable selection (inputs and outputs used). Further, the variables used as input prices in this model are often determined endogenously. Lastly, we recognize that the use of additional environmental variables, such as low English proficiency and parental education that influence student innate abilities and achievement scores (including the efficiency index), are absent from our model. Future research should be directed toward measuring both cost and production efficiency for all school districts in Kansas using a longer panel data.

References

Aigner, D. J., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*, 1–37.

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production for panel data. *Empirical Economics*, *24*, 325–332.

Chakraborty, K. (2003). Measuring productive efficiency and cost of public education. *Southwestern Economic Review*, *30*(1), 23–33.

Chakraborty, K. (2005). Cost of Improving Efficiency and Students' Performance in Public Schools: An Empirical Analysis. Working Paper, School of Business, Emporia State University, Emporia, Kansas.

Chakraborty, K., Biswas, B., & Lewis, W. C. (2001). Measurement of technical efficiency in public education: A stochastic and Nonstochastic production function approach. *Southern Economic Journal*, *67*(4), 889–905.

Coelli, T. J. (1996).*A guide to frontier version 4.1: a computer program for stochastic frontier production and cost function estimation*. Armidale: Centre for Efficiency and Productivity Analysis, University of New England.

Downes, T., & Pogue, T. (1994). Adjusting school aid formulas for the higher cost of educating disadvantaged students. *National Tax Journal*, *47*, 89–110.

Duncombe, W., & Yinger, J. (1997). Why is it so hard to help central city schools? *Journal of Policy Analysis and Management*, *16*(1), 85–113.

Duncombe, W., & Yinger, J. (1998). School finance reform: aid formulas and equity objectives. *National Tax Journal*, *51*, 239–262.

Duncombe, W., & Yinger, J. (2000). Financing higher student performance standards: the case of New York State. *Economics of Education Review*, *19*, 363–386.

Duncombe, W., & Yinger, J. (2005). Estimating the Costs of Meeting Student Performance Outcomes Adopted by the Kansas State Board of Education—Report Prepared for the Kansas Legislative Division of Post Audit. Education Finance and Accountability Program, Center for Policy Research, Syracuse University. Syracuse, NY.

Glasnapp, D. R., & Poggio, J. P. (2003). An Empirical Evaluation of Disparate Impact on Student Achievement — Expert Report in Robinson v. Kansas, mimeo, Center for Educational Testing and Evaluation, School of Education, University of Kansas, Lawrence, Kansas.

Green, P. C. (2005). School finance litigation in Kansas: Judicial mandate, legislative defiance, and legal innovation. *Kansas Policy Review*, *27*(2), 7–21.

Greene, W. (1995). The econometric approach to effeciency analysis. In H. Fried, K. Lovell, & S. Schmidt (Eds.), *The measurement of productive efficiency.* Oxford: Oxford University Press.

Greene, W. (1999). Marginal effects in censored regression model. *Economics Letters*, *64*(1), 43–49.

Greene, W. (2001). New Developments in the Estimation of Stochastic Frontier Models with Panel Data. Paper Presented at the 7th European Workshop on Efficiency and Productivity Analysis, University of Oviedo, Spain. Sept 25.

Greene, W. (2002a). Alternative Panel Data Estimators for the Stochastic Frontier Models Working Paper, Department of Economics, Stern School of Business, New York University.

Greene, W. (2002b). Fixed and Random Effects in Stochastic Frontier Models. Working Paper, Department of Economics, Stern School of Business, New York University.

Grosskopf, S., Hays, K. J., Taylor, L. L., & Weber, W. L. (1997). Budget-constrained frontier measures of fiscal equality and efficiency in schooling. *Review of Economics and Statistics*, *79*(1), 116–124.

Hanushek, E. A. (1993). Can equity be separated from efficiency in school finance debates. In E. P. Hoffman (Ed.) *Essays on the economics of education*. Kalamazoo: The Upjohn Institute.

Hanushek, E. A., & Rivkin, S. (2004). Understanding the 20th century explosion in U.S. school costs, mimeo. University of Rochester and Amherst College.

Husted, T. A., & Kenny, L. W. (2000). Evidence on the impact of state government on primary and secondary education and equity–efficiency trade-off. *Journal of Law and Economics*, *XIII*, 285–307 (Apr).

Jondrow, J., Lovell, C. A. K., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, *19*, 233–238.

Kirjavainen, T., & Loikkanen, H. A. (1998). Efficiency differences of finnish senior secondary schools: an application of DEA and Tobit analysis. *Economics of Education Review*, *17*(4), 377–394.

Kumbhakar, S. C., & Lovell, C. A. K. (2000). *Stochastic frontier analysis*. Cambridge: Cambridge University Press.

Kumbhakar, S. C., & Sarkar, S. (2005). Deregulation, ownership, efficiency change in Indian banking: An application of stochastic frontier analysis. In R. C. GhoshNeogi (Ed.) *Theory and application of productivity and efficiency—econometric and DEA approach*. New York: McMillan India Ltd.

Legislative Division of Post Audit (2006). Cost study analysis: Elementary and Secondary Education in Kansas—Estimating The Cost of K-12 Education Using Two Approaches. 05PA19. January.

Linna, M. (1998). Measuring hospital cost efficiency with panel data models. *Health Economics*, *7*, 415–427.

McCarty, R., & Yaisawarng, S. (1993). Technical efficiency in New Jersey school districts. In H. Fried, K. Lovell, & S. Schmidt (Eds.) *Measurement of productive efficiency*. London: Oxford University Press.

Meeusen, W., & van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas Production Frontiers with Composed Error. *International Economic Review*, *18*, 435–444.

Noulas, A. G., & Ketkar, K. W. (1998). Efficient utilization of resources in public schools: A case study of New Jersey. *Applied Economics*, *30*, 1299–1306.

Poggio, J. P. (2001). *Adequacy of educational programs and opportunities in Kansas, mimeo, center for educational testing and evaluation, school of education*. Lawrence: University of Kansas.

Ray, S. C. (1991). Resource-use efficiency in public schools: A study of Connecticut data. *Management Science*, *37*, 1621–1628.

Ruggiero, J. (2001). Determining the base cost of education: An analysis of Ohio school districts. *Contemporary Economic Policy*, *19*(3), 268–279, July.

Ruggiero, J., & Vitaliano, D. F. (1999). Assessing the efficiency of public schools using data envelopment analysis and frontier regression. *Contemporary Economic Policy*, *17*(3), 321–331, July.