

Monitoring Inefficiency in Public Education – A Value-Added Approach

Kalyan Chakraborty, Lamar University,

Department of Accounting, Finance, and Economics, COB, Lamar University, GB 249, P.O. Box 10025, Beaumont TX, 77710. E:kalchak1103@gmail.com

Abstract

This study examines the inefficiency of public secondary schools in Texas using value-added and data envelopment analysis (DEA). The empirical application uses four-year panel data from 410 school districts and applied seemingly unrelated regression (SUR) to determine the effect of socioeconomic and environmental factors on students test scores. Next, the raw test scores are adjusted using predicted residuals from the SUR regression model and applied as outputs in an output-oriented DEA model. Several school characteristics are used as inputs in the DEA model that generates school specific (in)efficiency scores. The study found the secondary schools in Texas are mostly efficiency, the average efficiency across all schools and for all years is 91.3 percent. However, the Malmquist productivity index found the total factor productivity (TFP) slightly decreased over the time. The study found dropout rate, poverty, low English proficiency, disability, and local area college education generally affect test scores negatively; and the cohort test score from the prior year affect current year test scores positively. To our knowledge this is the first effort to measure efficiency of secondary school in Texas using robust mythology. This study provides valuable insights to policymakers, education researchers, and parents to make informed decisions on school choice.

JEL Code: D2, I21, I24, R0

Keywords: Efficiency, Education, Value-added, Productivity, Data Envelopment Analysis, Seemingly Unrelated Regression

Disclosure Interest – No interest to declare.

Declaration of Funding – This research is funded by the Office of the Provost, Lamar university via FUND: 140134 – College of Business IDC / ORGN: 20605 – COB IDC/PROG: 200 – Research Centers.

Acknowledgement - I would like to thank Ms. Sai Vindhya Mekala, a Graduate Research Assistant, MIS Department, COB. for her excellent research assistance. She wrote the computer programs to retrieve and organize the entire dataset after we received them from the TEA. The original data files sent to us by the Texas Education Agency, Austin, TX.

Data Availability Statement – This study used proprietary data from the Texas Education Agency, State of Texas, United States, at cost. Data may be shared with researchers upon request and written consent.

We would like the thank the editor and an unknow reviewer of this journal for their valuable and insightful comments and suggestions. The quality of this paper is significantly improved by their comments.

1.Introduction

Education is positively related to economic growth. Since education has social and external benefits it justifies its public provision. Hanushek and Woessmann (2008) found in a cross-country study that each additional year of schooling raises long-run GDP growth 0.56 percent, 0.32 percent when regional differences are considered (Johnes et al., 2017). According to Education Recovery Scorecard (2025), a joint venture between Harvard and Stanford University, the U.S. students were half a grade level behind in both math and reading in spring 2024 compared with achievement levels before pandemic. In brief, students from 3rd through 8th grade are still performing worse than students in same grades in 2019.

The Nation's Report Card for 2024 published by National Center for Education Statistics (NCES, 2025) found that for Texas, 39 percent of the students in 4th graders scored 'at or above' proficient level in math and 33 percent in reading. For 8th Graders, math is 28 percent, and reading is 30 percent 'at or above' the proficient level. As per the accountability rating published in 2025, out of 8,553 campuses (1,193 Districts) evaluated in Texas, more than 5,000 schools received 'A or B' (665 ISD), for student achievement outcomes and growth, however about 2,141 schools received a 'C' and more than 1,313 schools received 'D or F,' and 531 schools 'Not Rated.' One in 6 schools in Texas got a D or F rating under the new performance standard. Almost 86 percent of the schools not rated are in the state's poorest communities. Struggling schools represent a decades-long problem of two policy failures, i.e., lack of adequate funds for schools in poorer communities and lack of policy to attract and retain experienced and high-quality teachers in those schools. Extreme poverty districts are more likely to hire inexperienced and alternatively certified teachers.

The state funding system ranks among the bottom five for providing adequate resources to high-poverty school districts. Texas is one of the six states that does not allocate specific dollars to educate students living in poverty. Under the current formula each district is allocated money weighted by factors such as enrollment number, inflation, their grade level participation to programs like gifted, after school, special education, and bilingual students. The Weighted Student Funding Formula has some elements of equity, but it fails to fulfill the goal of equity because the weights are likely to be inappropriate, and the method fails to account for the substantial number of challenge-to-educate students and its effect on the distribution of teachers. The main argument provided by the education researchers is that equality of inputs need not require every school to be the same. When equity is defined in terms of 'equality of outcome' a distributionally equitable education system should be the one in which all schools have sufficient resources to achieve similar education outcomes. Hence, equality of outcomes requires inequality of inputs.

This study attempts to answer the following two vital research questions: (a) What combination of resources would achieve higher student performance in Secondary schools after controlling student demographic and environmental factors; and (b) identify the best performing school in terms of managing their resources while delivering the state mandated educational outcomes. To our knowledge, there is no

comprehensive study that used longitudinal data from Texas secondary school and applied value-added approach to measure school districts' productive efficiency. The current study fills the void and measures the productive efficiency index for 410 secondary schools in Texas using 4-year panel data.

The value-added method has been used in the production economics literature where it measures the amount by which the value of a product is enhanced in each stage of production process (Koedel, et al, 2015). The idea for its application to education production function is that if each student's level of achievement up to the prior school year is known then it is possible to estimate how the inputs applied during the current year contribute to the growth of achievement. Among the early researchers, Jencks et al. (1972) found that race, poverty, parental education, family structure, language status, parenting skill, and neighborhood factors account 80-90 percent of students' achievement. Value-added studies are more common in economics of education literature but for efficiency of education literature, it is rare (Johnes, et al, 2017). Following, Grosskopf et al. (1997, 2001); Chakraborty (2009), and Saito and McIntosh (2003), this study uses value-added residuals techniques to control students' socio-economic factors exogenous to the school districts. In this approach students test scores at the specific grade levels/years are assumed to be dependent on their socioeconomic status and past test scores. The value-added method attempts to measure differential progress made by the students with different socioeconomic backgrounds, remaining all other school inputs constant. The results would be interesting to the policymakers since they could use the information to determine if additional resources are needed for the low achieving school districts to improve their efficiency and students' test scores. The results would help the parents to identify the high-achieving school districts in their localities and make their decisions about which public schools they would prefer to send their children to for education.

The next we discuss the background for this research, followed by the construction of an education production and cost functions, the fourth section defines the model and methodology. The fifth section discusses the data and the results, and the conclusions are in the last section.

2. Education Production Function

It is recognized in the education economics literature that there are difficulties in measuring productivity in education due to confusion about how to define productivity and how to interpret productivity changes over time (Hanushek and Ettema, 2017). The educational production function is built upon the premise that each school district uses various school and non-school inputs to produce multiple outputs that are assumed to be measurable by the students' achievement test scores. Inputs that are controlled by the school and/or district administrators and assumed to be associated with achievement scores, are measured by the student-teacher ratio, educational background of the teachers, teaching experience, and various instructional and non-instructional expenditures per student (Chakraborty 2003, 2009). Non-school inputs include student

socioeconomic status and other environmental factors influencing students' performance. Variables identifying socioeconomic status of the students are commonly measured as economic background, number of parents in the family, and parental education. Environmental factors are often measured as dropout rate, graduation rate, percent of students with special education, geographic location (e.g., rural vs. urban), and low English proficiency. A technically efficient school district is one that produces the maximum level of student achievement scores (outcomes) from given resources, or conversely, uses minimum resources to produce a given level of student outcomes. Outputs for educational production function in this study are measured as average test scores from STAAR test administered to all ISDs (integrated school district) in Texas. The test scores for mathematics and science at 8th grade; algebra and English at 9th grade; and algebra and English at 10th grade.

In this study a non-parametric linear programming technique (data envelopment analysis, DEA) is used to construct the best practice production frontier. In this construction, the relative performance of a district is evaluated in terms of its ability to either reduce an input vector or expand an output vector subject to the restrictions imposed by the best-observed practices and is measured as a ratio between actual observed output and maximal potential output. One of the major advantages of DEA is that it can model multi-output multi-input technologies and is free from restrictive assumption on the structure of the production function. The DEA has been extensively used in educational production function literature (Thompson, et al. 2021; Rassouli-Currier, 2007; Chakraborty, 2003).

One other advantage of using DEA method for panel data analysis is that the efficiency changes and total factor productivity growth across districts and over the time is measurable. This study calculates the Malmquist productivity index as a measure of changes in total factor productivity. The advantage of the constructing Malmquist productivity index is that it can be decomposed into two components: an index of technical change and efficiency change. The Malmquist productivity index, defined as output produced per unit of input over two different time periods, the method was first proposed by Caves et al. (1982) using a distance function approach. Fare et al. (1989, 1994) provided a modified version of the Malmquist productivity index that uses output distance functions, which are reciprocal to Farrell's output-based technical efficiency measures.

3. Theoretical Background

In the context of school districts efficiency analysis, school value-added models were developed initially for the purpose of measuring the effectiveness of school policies and practices (Mortimore et al. 1988; Sammons et al, 1997; Reynolds et al. 2014). The most common approach to value-added method is to fit a linear regression of student's current achievement on student's prior achievement, where the school efforts are at the school means of the predicted residual (Goldstein, 1997). The rational approach to value-added

method is that students' prior achievement can be used as sufficient statistic for the history of prior inputs (or endowment). This facilitates the estimation of the marginal contribution of contemporaneous inputs, where prior achievement is the key conditioning variable (Koedel et al. 2015).

In the context of school districts efficiency analysis, identifying high spending schools with low performance is a challenging task, because not every dollar spent by the district administration transforms into students' test scores. Some studies found increase in funding is associated with positive student outcomes (Hyman, 2017; Jacson et al. 2015; Lafortune et al. 2018). Lafortune et al (2018) found increased spending in low-income school districts are associated with large increases in student test scores. Henson (2026) argues that it is not easy to evaluate how much we are getting from the massive investment in education. Though there is plenty of data on K-12 education, empirical analysis on how the funds is managed is hardly available. The author contends that per-student expenditure can tell what a system costs, but it does not say what the system delivers.

A fair system of performance measures should account for the differences due to favorable and unfavorable conditions. Any measure of school performance should include not only the student outcomes but also the level of efficiency with which school officials transform school resources into outcomes. Studies in the past provided compelling evidence that there are 'school effects' i.e., certain schools have better schooling outcomes than others when student and family background and other value-added entry level preparations are controlled (Williams, 2010). Sirin (2005) found that socioeconomic status is not only linked to academic achievement, but also indirectly linked to it via other interaction terms such as, students racial and ethnic background, grade level, and school and neighborhood location.

There is a lack of study on school districts efficiency analysis using value-added method for public Secondary education in Texas. Most of the studies done in Texas are related to school funding issues. To measure the cost of providing state mandated accountability for 300 school districts in Texas, a study by Imazeki and Reschovsky (2005) found those school districts need \$2 billion additional funding. To determine the additional funding the authors measured Herfindahl Index of efficiency for each school district and concluded districts with higher efficiency levels would have lower spending per student. On a similar line of research, using data from large urban school districts researchers found the spending among school districts in the metropolitan areas is progressively distributed in accordance with the poverty tax rates (Baker, 2012). Taylor et al. (2014) used five-year panel data from five large school districts located in five large counties such as, Bexar, Dallas, Harris, Tarrant, and Travis and estimated a stochastic frontier cost function. The authors also created the Herfindahl Index for each school district to estimate inefficiency and used simulation to estimate the savings on cost per student for proposed consolidation of campuses for those school districts.

Carter (2012) used DEA to estimate efficiency for 931 school districts in Texas using one year data, and used a Tobit regression to examine the effect of selected non-discretionary factors on efficiency scores. The study found all the non-discretionary factors are statistically significant. Thompson et al. (2021) extended the study by Carter (2012) and used the DEA methodology and estimated efficiency for 1015 school districts in Texas for school year 2014-15. The study found on average Texas schools are 48.3 percent efficient and most efficient districts are in metropolitan fast-growing areas. The regression results found enrollment has a positive, and non-white and economically disadvantaged student population have negative and significant impact on efficiency scores.

Texas has many public charter schools, and those school districts are not limited to the compliance of the same rules and regulations as typical public schools. Some of these schools have small enrollment. Several researchers used Texas charter schools and public schools' data separately to compare the cost and outcome relationships. For example, Gronberg et al. (2012) estimated cost efficiency using a cost frontier for charter schools and compared them to cost efficiency estimated for traditional public schools in Texas. Using 5-year panel data the study found charter schools produced educational outcomes at lower cost than traditional public schools, probably because they operate under fewer regulations. However, those schools are not consistently more efficient than traditional public schools. DeAngelis (2019) used school level data from 5,472 schools for 2017-18 school year, including 432 public charter schools, and found that charter schools spend 28 percent less than district-run public schools. The study also found cost per student is positively related to state testing outcome for public charter schools, but not for the district-run public schools. To our knowledge this is a first attempt to measure productive efficiency of public Secondary schools in Texas using value-added approach.

4. Model and Methodology

Consistent with the education production function literature it is assumed in this study that the goal of public education is to maximize the educational value added to students – measured by the achievement test scores given school and non-school inputs. The concept of value-added output measure in education recognizes the fact that family and other environmental factors, beyond the control of the school districts, have significant influence on students' achievement (Hanushek, 1986; Hanushek et al., 1996; Loeb and Bound, 1995; Chakraborty, 2009; Chakraborty and Harper 2017). Use of a simple DEA model or stochastic frontier model to estimate inefficiency fails to account for the influence of such fixed or quasi-fixed factors. This problem does not arise in a two-stage DEA model. In two-stage DEA model efficiency scores obtained from the first stage DEA are regressed on some socio-economic and environmental factors using a Tobit regression at the second stage to determine the influence of such factors. (McCarty and Yaisawrang, 1993; Ruggiero and Vitaliano, 1999; Chakraborty et al., 2001, 2002). Instead of using raw achievement test scores

as a measure of educational outputs this study generates ‘value-added test scores from a seemingly unrelated regression (SUR) model and applied it as the final output in the DEA model.

Following, Grosskopf et al. (1997, 2001), Saito and McIntosh (2003), and Chakraborty (2009), this study uses value added residuals technique to control students’ socio-economic factors exogenous to the school districts. In this approach students test scores at the specific grade levels/years are assumed to be dependent on their socioeconomic status and past test scores. Without using time dimension this relationship may be written as:

$$MATH9(2017)_{s,g} = \delta_{1,g} + \sum_{i=2}^4 \delta_{i,g} SES + \delta_{5,g} TCOHORT(2016)_{s,g-1} + \varepsilon_{s,g} \quad (1)$$

Where s = school districts (1, 2, ..., 410); g = grade levels (9, 10); $MATH(2017)$ is the math test scores for 9th graders in 2017; SES is the socioeconomic status of the students for grade g , school district s ; $TCOHORT(2016)$ is the average Math scores for the same cohort one year previously (8th grade); the residual $\varepsilon_{s,g}$ represents the average value-added for school district s .

Math scores for 9th and 10th graders and reading scores for 9th and 10th graders are used as dependent variables for four regression equations that estimated four sets of value-added residuals using seemingly unrelated regression (SUR) using LIMDEP software. The residuals estimated from the above equations assumed to be representing the deviations of the value-added scores in school district ‘ s ’ from the state mean. Districts that add less value from the state average will have negative residuals, hence, negative outputs. Because DEA uses distance function approach which cannot handle negative outputs generated from the value-added residuals, a method like Grosskopf et al. (1997, 2001) and Chakraborty (2009), is applied in this study. The value-added residuals obtained from the regression equations are added to the average test scores for those grades to generate tractable per district output measures for each year. Per-student output measures are then transformed into total output measure for that grade by multiplying it to the grade level enrollments using the equation below:

$$VAOUTPUT_{s,g} = [AvgTEST_{s,g} + \varepsilon_{s,g}] * ENROL_{s,g} \quad (2)$$

In the DEA model these value-added test scores are used as outputs for the educational production function. It is assumed that each school district transforms its unique educational input into outputs given its budget constraints and available technology. This study estimates technical efficiency of the school districts from an output-oriented DEA model. An output-oriented DEA measure of technical efficiency seeks a proportionate increase in its output level given its input usage, while remaining on the same production frontier. In the measure of technical efficiency, a school district is defined as technically efficient if it is observed to produce the maximum level of output from a given number of resources used or, conversely, uses minimum resources to produce a given level of output.

This measure of performance is relative in the sense that efficiency in each school district is evaluated against the most efficient district and measured by the ratio of actual observed output to maximal potential output. The major advantage of DEA is that it can model multi-output multi-input technologies and is free from restrictive assumption on the structure of the production function. The output distance function allows estimation of multiple-input, multiple-output technology. We used output-oriented DEA because in the production of education school districts try to maximize outputs (students' test scores) given the inputs (resources). Output distance function (Fare et al., 1989) is used in in this study to measure efficiency and productivity. Assume there are $k = 1, \dots, K$ observations using $n = 1, \dots, N$ inputs denoted by $x_n^{k,t}$ in each time period $t = 1, \dots, T$ to produce $m = 1, \dots, M$ outputs denoted by $y_m^{k,t}$. If the production possibilities set for output requirement set is defined as $P^t(x^t)$ then it gives all possible combinations of y^t that can be produced from input vector x^t and is written as:

$$\begin{aligned} P^t(x^t) = y^t: y_m^t &\leq \sum_{k=1}^K z^{k,t} y_m^{k,t}, \quad m = 1, \dots, M; \\ \sum_{k=1}^K z^{k,t} x_n^{k,t} &\leq x_n^{k,t}, \quad n = 1, \dots, N; \quad z^{k,t} \geq 0, \quad k = 1, \dots, K. \end{aligned} \quad (3)$$

Where $z^{k,t}$ is an intensity variable indicating at what intensity a particular activity is conducted.

Since output distance function is equal to the reciprocal of Farrell's output-oriented measure of technical efficiency, the distance function of k^{th} district at time t is defined as:

$$[D_o^t(x^{k,t}, y^{k,t})]^{-1} = \max \theta \quad (4)$$

$$\text{subject to:} \quad \theta y_m^{k,t} \leq \sum_{k=1}^K z^{k,t} y_m^{k,t}, \quad m = 1, 2, \dots, M;$$

$$\sum_{k=1}^K z^{k,t} x_n^{k,t} \leq x_n^{k,t}, \quad n = 1, 2, \dots, N; \quad z^{k,t} \geq 0, \quad k = 1, 2, \dots, K.$$

The solution value of θ implies the output distance function, which is the reciprocal of the ratio of observed output to maximum potential output. In other words, the estimate of θ is the maximum proportional expansion of output. Two of the distance functions used in the construction of Malmquist productivity index require information from two different time periods. For example, the distance function $D_o^t(x^{k,t+1}, y^{k,t+1})$ in equation (5) evaluates data from period $t+1$ based on technology available in time t and may take value greater than one. The estimate of $D_o^t(x^{k,t+1}, y^{k,t+1})$ can be either greater than one if technical progress has occurred, or less than one if technical regress has occurred. Following is the linear program for the above-mentioned mixed period distance function.

$$[D_o^t(x^{k,t+1}, y^{k,t+1})]^{-1} = \max \theta \quad (5)$$

$$\text{subject to:} \quad \theta y_m^{k,t+1} \leq \sum_{k=1}^K z^{k,t} y_m^{k,t}, \quad m = 1, 2, \dots, M;$$

$$\sum_{k=1}^K z^{k,t} x_n^{k,t} \leq x_n^{k,t+1}, \quad n = 1, 2, \dots, N;$$

$$z^{k,t} \geq 0, \quad k = 1, 2, \dots, K.$$

Fare et al. (1994) decomposed the Malmquist productivity index for i th district in $t+1$ period as the product of an efficiency change index and technological progress and is expressed as:

$$MALM_o^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \right] * \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} * \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \quad (6)$$

where D_o is the output-oriented distance function, x^t and y^t and are the input and output set in time t . The first term on the right side measures the change in output-oriented measure of Farrell's measure of technical efficiency between year t and $t+1$. The second term on the right side is the geometric mean of two ratios, which captures the shift in technology between two periods evaluated at the input level x^{t+1} and x^t . Improvements in total factor productivity are associated with Malmquist index being greater than unity, and the deterioration in performance over time is associated with a value less than unity. The efficiency changes and technological change indexes have the same interpretation.

5. The Dataset

The data for this study came from the Texas Education Agency (TEA). The data comprised 410 ISD, for school year 2017-21, except for the year 2019-20 (Covid Year). Since student assessment data are the major component for this study the assessment data (outputs) are not available for Covid year, we excluded school year 2019-20 from this study. Hence, the study uses 4-year panel data. Since this study uses value-added approach for students test score data, we only selected those ISDs that provide consisted test score data for all four years. Hence, we had to make a compromise on the final selection of variables and the ISDs for inclusion in the study. We finally selected 20 variables and 410 ISDs, which are observed for 4 years (2017-21), (except for the Covid year 2019-20). The descriptive statistics for the data are provided on Table 1. I grouped the variables into three, (a) Educational Outputs; (b) Inputs under the control of the ISDs; (c) Inputs beyond the control of the ISDs.

Table 1: Descriptive statistics and the definitions of the variables

Year 2018-21: Observations 1640				
Variables	Mean	S.D	Min	Max
Outputs				
Mathematics - Gr 8	1615.68	44.74	1492	1827
Science - Gr 8	3872.82	212.96	3111	4733
Mathematics - Gr-9	3636.68	186.24	3244	4500
English – Gr-9	3689.85	129.52	3270	4331
Mathematics - Gr-10	3467.15	108.05	3175	4410
English - Gr-10	3552.24	88.62	3205	4003
Inputs under the control of the school district				
Student-Teacher Ratio (STR)	14.40	1.78	8.10	40.60

Teacher with Experience 10+ yrs (%)	46.14	9.69	0	79.50
Teachers with MA/PHD degree (%)	21.23	6.87	0.60	48.10
Average teacher salary (\$)	53,854	4,769	42,460	76,678
Average professional staff salary (\$)	60,720	7,013	26,583	99,258
Average admin. Staff salary (\$)	76,487	8,067	50,514	115,028
Enrollment for Grade 8, 9, 10	1748	3084	31	13,320
Socioeconomic input variables				
Real expenditure per student (\$)	10,477	2,766	7201	102,138
Total enrollment for USD	9,809	14,517	207	87,233
Dropout rate (DROP%)	1.17	1.15	0	8.50
Free or subsidized lunch (POV %)	62.14	19.37	5.90	100
Low English Proficiency (ELP %)	14.30	12.42	0	79.80
Needing special assistance (DIS %)	10.27	2.50	4.44	40.61
Local unemployment rate (UNEMP%)	4.67	1.58	2.10	15.2
Local college educated rate (COLL%)	15.83	6.34	3.9	33.6

For assessment data, instead of “percent of students at or above the proficiency level,” we used “Scaled Scores” for subjects. The TEA has changed and replaced the assessment questions and methods over time, hence Scaled Scores for each subject are comparable across different sets of test questions. All variables on Table 1 are self-explanatory. Annual student enrollment data has the maximum enrollment number for Harris County (215,408), and the minimum number for King County (90). We found among our initial 414 ISDs, there are 4 very large school districts that enrolled 100,000 students. The use of data representing the averages of district characteristics, with such a wide variability in district enrollment, would create a problem of heteroskedasticity for the econometric models. Further, since DEA analysis is prone to outlier observations which can create quite different and inconsistent efficiency scores, we deleted those 4 ISDs from our sample that reduced our sample size to 410 per year. Hence, to avoid this problem, we excluded ISDs with enrollment of 100,000 and above.

6. Analysis of Results

The empirical results are based on estimation of the following equations.

$$MATH9_{2017,s} = \delta_0 + \delta_1 DROP_s + \delta_2 DIS_s + \delta_3 POV_s + \delta_4 LEPS + \delta_5 MATH8_{2016,s} + \varepsilon_{s,g} \quad (7)$$

$$\text{Value-Added Output: } VAMATH9_{s,g} = (AvgMATH8 + \varepsilon_{s,g}) * ENROL_{s,g} \quad (8)$$

DEA Production Function, where $g = 8, 9, 10$; $s = 1, 2, \dots, 410$

$$VAMATH9_{s,g} = f(STR, SAR, EXPR, MAPHD, TSAL, PSAL, ADMSAL, EXPD)_{s,g} \quad (9)$$

As discussed in the model section, the value-added output used in production function (7) above is generated from a SUR model based on equations (1) and (2). Since all test scores (Math 8th, Math 9th, Math 10th, and Sci 8th, Read 9th, and Read 10th) share the common regressors, there is a possibility for contemporaneous correlation in the error term, hence use of SUR generates the most efficient estimator

(Marlow, 2000; Saito and McIntosh, 2003). This two-step procedure generates a consistent and asymptotically efficient estimator for equation (4) above. Results are reported in Table-2.

Table 2: Parameter Estimates from the Seemingly Unrelated Regression – Dependent Variable : Grade Level Test Scores (Observations, 1640)

Variables	Equation 1 Math 9 th Grade	Equation 2 English 9 th Grade	Equation 3 Math 10 th Grade	Equation 4 English 10 th Grade
Intercept	2128.510*** (10.46)	3267.241*** (46.00)	3480.69*** (61.39)	3181.73*** (44.92)
Dropout rate (%) (DROP)	-38.861*** (-9.80)	-29.236*** (-11.73)	-3.451*** (-5.30)	-9.067*** (-4.62)
Poverty rate (%) (POV)	-1.315*** (-3.95)	-1.833*** (-8.06)	-1.135*** (-5.60)	-1.038*** (-6.43)
Low Proficiency English (%) (LEP)	-0.006 (-0.01)	-0.682*** (-2.39)	1.806*** (6.44)	0.066 (0.31)
Disability (%) (DIS)	-0.973 (-0.54)	3.655*** (3.24)	-2.262 (-0.23)	0.492 (0.57)
Unemployment % (UNEMP)	-3.930 (-1.29)	5.710*** (2.94)	0.919 (0.49)	2.442 (1.67)
College Education % (COLL)	-5.436*** (-6.20)	-2.279*** (-4.05)	0.062 (0.11)	0.612 (1.43)
Lag Test score for the Cohort (TCOHORT)	0.090*** (8.96)	0.142*** (8.62)	0.012 (0.86)	0.114*** (6.39)
R-squared	0.2217	0.3674	0.0780	0.1981
F-statistics	66.01	137.00	19.7	57.6
Durbin-Watson	2.001	1.988	1.996	2.003
Autocorrelation	0.008	0.099	0.041	0.981

Z-statics are in parenthesis: *** - significant at 1% level; ** - significant at 5% level; * - significant at 10% level

Most of the socioeconomic variables have expected signs and are mostly statistically significant (except for disability). Socioeconomic variables included in the model are mostly negatively related to the student outcomes, measured by grade level test scores. For example, dropout rate, percent of students belonging to poverty, low English language proficiency, and disability affect test scores negatively. The coefficient for the local unemployment rate is mostly insignificant, except for equation 2, however the positive sign is contrary to our expectation, meaning higher unemployment is associated with higher test scores. The same is true for the college education variable. Significant and negative signs on this variable for equation 1 and 2, implies children from college educated families will produce lower test scores. An intuitive explanation could be that these two variables are not directly associated with the student population in the school district, rather they are used as proxy for local labor market condition and parental education. Positive and significant coefficient in *TCOHORT* implies higher achievement in the past, contributes positively to students' current performance. For equations 1 and 2, *TCOHORT* represents the math and reading test scores for the 8th graders. For equations 3 and 4, *TCOHORT* represents the math and reading test scores for the 9th graders. Test statistics (i.e., Durbin-Watson and autocorrelation) show no signs of autocorrelation in the model. Residuals from SUR model are used to generate four sets of value-added test scores based on

equation (8). Although R-squares have low explanatory power, the individual coefficients are significant (with mostly correct signs), and other test statistics for the model are significant. The overall results are comparable to similar studies in literature (Grosskopf, et al, 1997; Sato and McIntosh, 2003; and Chakraborty, 2009).

The value-added test scores are used as outputs in equation (9) to estimate inefficiency scores running a linear program number of times the sample size. The mean efficiencies from Model-1 for year 2017, 2018, 2019, and 2021 are 0.905, 0.908, 0.900, and 0.897, respectively. The mean efficiency for the entire study period is 91.3 percent implying production of test scores could be increased by 8.7 percent if all school districts operate at 100 percent efficiency. Summary of the technical efficiency scores (VRS) from value-added DEA; and the three Malmquist productivity indexes (EFFCH, TECHCH, TFPCH) are reported in Table 3. Out of 410 districts only 14 districts are fully efficient. Efficiency for 82 districts is between 100 and 99.5 percent, and majority of the districts are between 99.4 and 95.0 efficiency (226 districts). More than half of the school districts in Texas are operating at an efficiency level 90.0 percent or above. Column 3, 4, and 5 of Table 3 present the summary of the indexes for efficiency change (EFFCH), technological change (TECHCH), and total factor productivity change (TFPCH), the detailed results are not reported in the paper. For any of these ratios a value less than one implies deterioration or decrease, and greater than one denotes growth or improvement over the study period.

Table 3: Malmquist Productivity Index: Summary of selected Indexes
(Total USD = 414; Years 2017-21)

Index Measure	Technical Efficiency Under VRS	Efficiency Change EFFCH	Technological Change TECHCH	Total Factor Productivity Change TFPCH
Above 1:000	14	313	29	123
1.000 – 0.995	82	55	381	283
0.994 – 0.990	109	23	0	4
0.989 – 0.950	117	20	0	0
0.949 – 0.900	68	8	0	0
Blow 0.900	20	0	0	0
Sample Average	0.913	1.004	0.992	0.997

On average the annual decrease in total factor productivity for districts in Texas is 0.3 percent (1.000-0.997). The cause of the decrease in total factor productivity may be further analyzed by breaking it into indexes of technological change and efficiency change. For example, the decrease in total productivity (-0.3 percent) is the net effect of technological change (-0.8 percent) and growth in efficiency change (+0.4 percent). Hence when rounded up, $[+0.4 - 0.8] = -0.4 \sim -0.3$. Negative technological change can occur due to net migration/retirement of skilled and trained teachers from the state or region, high performing students change the school (use education vouchers), causing inward shift of production possibility frontier. In addition, sudden state funding cuts, deteriorating physical or digital learning environments

that reduce overall capacity to deliver effective instructions. The other explanation could be measurement error for input and output variables used in the study, or presence of outliers in the data (Chakraborty, 2009; Aparicio et al, 2021).

To check for the robustness of the model results, we used a sensitivity test and estimated a DEA-Tobit model and applied to the same data set. We used a two-stage DEA-Tobit model and the results are remarkably similar to the main results reported in this study. In the first stage we estimated technical efficiency running four DEA models using each test score as output and the same set of 8 school related variables as inputs. The overall efficiency score is very similar but slightly lower (0.988) than the value-added efficiency score (0.913). One reasonable explanation for the efficiency difference between standard DEA (0.988) and value-added DEA (0.913), is that the former measure did not account for the socioeconomic conditions while the later method did it via SUR residuals adjustment. In the sensitivity analysis the impact of socioeconomic variables is re-examined using 4 Tobit model using 4-set of efficiency scores as dependent variables and socioeconomic variables as independent variables. We use random effect Tobit model because efficiency scores from DEA lie between (0, 10. The results are reported in the Appendix Table A. The results show each socioeconomic variable is highly significant and have mostly negative impact on efficiency scores. Which is consistent with the results from the SUR model reported in Table 3. The test statistics are highly significant. These results suggest that the value-added model used in the study is appropriate for the analysis of Texas school district data.

To further explore the relationship between efficiency scores and the raw data on socioeconomic variables across years, these variables are reported against the average efficiency scores by district sizes in Table 4. It is hypothesized that expenditure per student is higher for small rural school districts and lower for city/urban and large metropolitan districts, hence the districts are grouped into five sizes based on enrollments.

Table 4: Efficiency scores vis-a-vis selected socioeconomic characteristics, grouped by School District Sizes (2017-2021)

Enrollment Sizes	Efficiency	Expenditure/ student (\$)	POV (%)	ELP (%)	DIS (%)	UNEM (%)	COLL (%)	USD
Small <1000	0.823	12758	69.94	9.63	11.58	4.88	11.31	30
Medium 1000 - 2000	0.865	11176	65.89	9.89	10.54	4.87	12.97	88
Large-A: 2000 - 5000	0.886	10250	62.71	13.39	10.39	4.62	14.88	122
Large -B: 5,000 – 10,000	0.907	9856	59.53	15.10	9.78	4.58	16.95	64
Large-C: 10,000 – 20,000	0.943	9835	58.24	17.71	9.78	4.72	18.59	47
X-Large 20,000 – 50,000	0.970	9940	58.99	21.46	9.94	4.56	19.99	44
Very Large >50,000	0.996	9909	52.56	21.98	9.77	4.20	23.73	15
Sample Average	0.913	10532	61.12	15.59	10.26	4.63	16.92	410

It is observed that the efficiency score for small (<1000) districts is the lowest (82.3 percent) and the expenditure per student is the highest. However, they have high poverty and disability level. Rouse and

Barrow (2006) find smaller class size and higher expenditure does not necessarily imply better quality for those school districts where most of its students come from low-income families. Because these schools may have a larger share of special education or English-Language-Learner students than schools serving more privileged children that have fewer special education classrooms. Very large school districts (>50,000) have the highest efficiency level (99.6 percent), have the lowest poverty and disability, but have very large low English language proficiency, and dropout rates. Figures 1, 2, and 3 depict the relationship between enrollment and the raw data on three major socio-economic characteristics.

Figure 1: Average Efficiency Scores and the Poverty Levels (%)

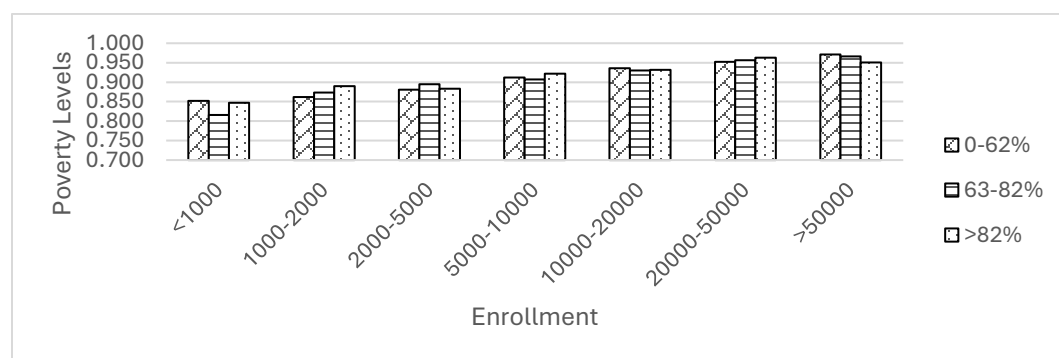


Figure 2: Average Efficiency Scores and Low English Proficiency Levels (%)

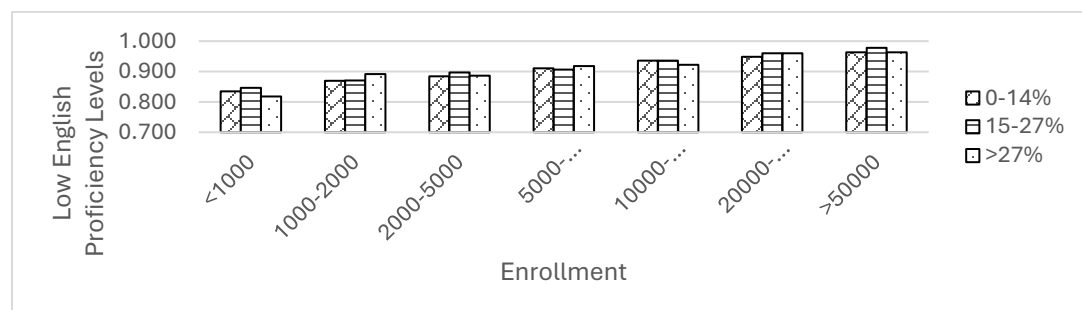
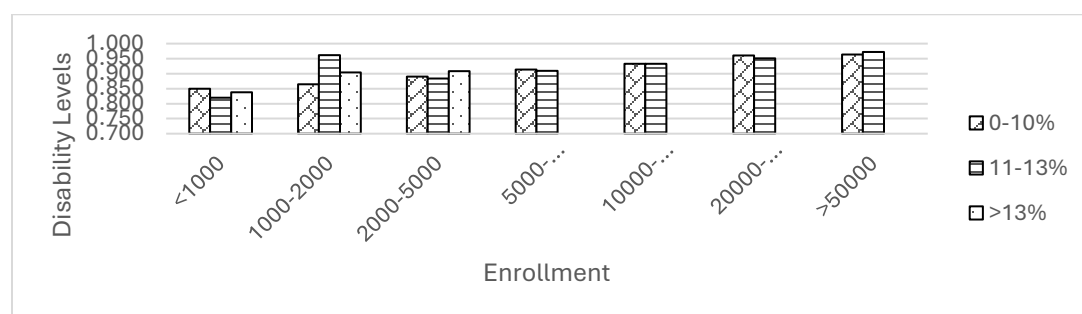


Figure 3: Average Efficiency Scores and Disability Levels (%)



Lastly, we further explored to what extent changes in selected socioeconomic factors affect efficiency. Table 5 reports the raw data on socioeconomic variables against efficiency scores grouped by the intensity of each

factor. The percentage of students in poverty, low English proficiency, disability and college and above education are divided into three sub-groups – Group-1 (below the mean), Group-2 (mean + one standard deviation), and Group-3 (above mean + one standard deviation).

Efficiency scores are consistently higher for the lowest levels of ‘poverty,’ ‘low English proficiency,’ and ‘disability’ across all district sizes except for college degree and higher. It is also evident from the SUR model, that higher percentage of college education negatively affects test scores, hence efficiency. One interesting observation from this table is that if the level of POV is raised from the mean to (mean + 1SD), the efficiency scores marginally increased for all sizes (except for small <1000), suggesting there could be a threshold beyond which the impact of increased levels of POV affect efficiency positively.

Table 5: Efficiency scores via-a-vis changes in Poverty (POV), Low English Proficiency (LEP), Disability (DIS), and College education (COLL) Grouped by District Sizes (2017-21)

District Sizes	Poverty (%)			Low English Proficiency (%)			Disability (%)			College and above (%)		
	< 62	63 - 82	> 82	<14	15 - 27	>27	<10	11 - 13	>13	<16	17 - 22	>22
Small <1000	0.852	0.798	0.821	0.827	0.819	0.775	0.835	0.814	0.814	0.828	0.758	0.838
Medium 1 - 2000	0.861	0.866	0.880	0.867	0.852	0.868	0.870	0.858	0.880	0.866	0.882	0.842
Large-A 2 - 5000	0.883	0.893	0.886	0.886	0.888	0.877	0.887	0.883	0.899	0.890	0.888	0.853
Large -B 5 – 10,000	0.909	0.905	0.911	0.907	0.904	0.913	0.911	0.903	---	0.917	0.899	0.903
X-large 10 – 20,000	0.947	0.940	0.948	0.950	0.935	0.938	0.945	0.942	---	0.948	0.940	0.942
2X-Large 20 – 50,000	0.926	0.973	0.968	0.975	0.969	0.965	0.969	0.972	---	0.979	0.966	0.970
3X Large >50,000	0.996	0.996	1.000	1.000	0.993	0.997	0.997	0.995	---	1.000	0.996	0.995

7. Conclusions

Studies measuring inefficiency in public education consistently found students’ socioeconomic factors play a far greater role than school inputs explaining variations in their achievement scores (Chakraborty, 2009, 2017). It is recognized that any measure of inefficiency that fails to account for the simultaneity in inputs, outputs, and socioeconomic factors would amount to inaccurate and unreliable estimates (Grosskopf et al, 2001; Saito and McIntosh, 2003; Klien, 2007). To address this issue, unlike past studies, the current study used a value-added DEA model that specifically addresses the importance of socio-economic factors in the measure of efficiency. Based on the results from this study overall Texas schools are 91.3 percent efficient, and the efficiency levels have decreased marginally over the study period. Average inefficiency of 8.7 percent implies given the current level of school expenditure, Texas school districts could have reduced

their expenditure by 8.7 percent and would still be producing same level of students' test score and be fully efficient. The phenomena observed for Texas school districts (i.e., higher expenditure and lower performance) is not very different from the studies done in other states and for the nation. As Henson (2026) points out that it is difficult to reconcile how the vast resources spent on New York K-12 public schools produce such a low return as measured by high school and college completion rate. His study found for K-12 for 2013-17 high school cohort, New York city spent \$250,000 per student (\$400,000 current dollars) as the growth of expenditures far outpaced the rate of overall inflation.

Nationwide, class sizes became smaller, teachers' educational level has increased, and expenditure per student has increased without any significant increase in student outcome. With a view to improving the quality of education government policy and proponents of education reform have increased school funding steadily over the years without any evidence that increased resources would improve performance (Hanushek, 2003). The four variables measuring socioeconomic factors (LEP, DIS, POV, COLL) are negatively related to test scores implying increase in any of these factors would reduce test scores for the school districts. The magnitude of these variables increased in general for all Texas school districts during study period. Hanushek (2003) finds nationwide percentage of students in minority, disability, and poverty and with single parents, children not speaking English at home, and percent of parents with less than high school education have increased between 1970 and 2000. As a result, part of the increased expenditure per student is spent on educating larger numbers of inadequately prepared or motivated students by raising their learning standard up to the average level.

It is recognized in the literature that efficiency estimates differ significantly depending upon the model used and how well the model addressed measurement error, omitted variables, and endogeneity. To formulate any policy for education reform based on efficiency analysis it is essential to consider several studies and not just what is observed from a single study. It is not always true that additional school funding will have no impact on students' performance. On the contrary additional resources can generate the desired outcome if the additional funding is used efficiently, for example to hire better quality teacher and formulate an effective incentive policy, such as 'merit-pay' for teachers, or rewarding the school for better performance of its students (Hanushek, 2003). Merit pays aims at motivating teachers and elevating student achievement. For example, Hoxby and Leigh (2003) found that the compensation of teaching wages is responsible for about three-quarters of the decline in teacher aptitude. One recent study by Hanushek et al. (2026) for Dallas (TX) school districts reform, replaced the dependence of teacher salary on experience and post-graduate degrees in a system with strong incentives for classroom effectiveness. This unconventional deviation from the personnel systems commonly used in the US school districts increased the math for

elementary students by 0.1 standard deviations. This finding confirms a long-standing recommendation for a closer connection between pay and performance.

However, it is important that one needs to use caution while interpreting the results from this study for the purpose of policy making. Our efficiency estimates from the DEA may be biased because DEA is sensitive to the choice of inputs and outputs and omitted variables. Since there is no unique set of educational inputs that is universally acceptable, the choice of input-set is mostly determined by the researchers and the availability of data. Further, variables considered under the control of the district administrators such as, teachers' salary, may not be controllable in the presence of strong teachers' union, prohibiting the administrators to exercise any control over the salary and benefit packages being offered, including the neighborhood characteristics.

APPENDIX

Table A: Parameter Estimates from the Random Effect Tobit Regression – Dependent Variable : Technical Efficiency Scores from Grade Level DEA Models (Observations, 1640)

Variables	Math 9 th Grade	English 9 th Grade	Math 10 th Grade	English 10 th Grade
Intercept	0.8680*** (30.71)	0.9761*** (27.90)	0.6625*** (9.64)	0.6669*** (24.82)
Dropout rate (%) (DROP)	-0.0006*** (-4.47)	-0.0001*** (-10.42)	-0.0015*** (-8.43)	-0.0003*** (-3.99)
Poverty rate (%) (POV)	-0.0001** (-2.37)	-0.0001*** (-2.30)	-0.0001 (-1.28)	0.0001 (1.41)
Low Proficiency English (%) (LEP)	-0.0001*** (-4.04)	0.0002*** (-6.04)	-0.0001*** (-4.83)	-0.0001*** (-6.13)
Disability (%) (DIS)	-0.0002** (-3.69)	0.0006*** (2.08)	-0.0002** (-2.45)	0.0001*** (-3.62)
Unemployment % (UNEMP)	-0.0001 (-0.15)	0.0001 (1.13)	-0.0001 (-0.18)	-0.0002*** (-2.81)
College Education % (COLL)	-0.0002*** (-6.70)	-0.0002*** (-7.01)	-0.0003*** (-8.00)	-0.0001*** (-5.32)
Lag Test score for the Cohort (TCOHORT)	0.0369*** (4.68)	0.0053 (0.55)	0.1043*** (4.89)	0.0926*** (12.41)
Sigma- v	0.0056*** (56.49)	0.0061*** (45.83)	0.0078*** (43.54)	0.0040*** (52.97)
Sigma- u	0.0028*** (13.57)	0.0023*** (8.88)	0.0019*** (4.46)	0.0009*** (4.76)
LLF	5158.49	5096.15	4709	5764.72
Chi-Squared	81.56	33.71	9.57	7.97

Z-statics are in parenthesis: *** - significant at 1% level; ** - significant at 5% level; * - significant at 10% level

References

- Aparicio, J., J. M. Cordsero, L. Lopez-Torres, and D. Satin. (2021). Comparing the performance of publicly funded private schools across EU countries: A Luenberger-type pseudo-panel approach. *Operation Research Spectrum*, 43(4), 1063–1097.
- Baker, B. D. (2012). Revisiting the age-old question: Does money matter in education? *Educational Researcher*, 41(3), 99–108.
- Carter, T. P. (2012). Measuring efficiency of Texas public school districts using data envelopment analysis. *Applied Economics Letters*, 19(15), 1447–1452.
- Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica*, 50(6), 1393–1414.
- Chakraborty, K. (2003). Efficiency and productivity of public-school districts: A DEA approach. *Socio-Economic Planning Sciences*, 37(4), 243–262.
- Chakraborty, K. (2009). Measuring school district efficiency: A value-added approach. *Applied Economics*, 41(17), 2227–2238.
- Chakraborty, K., Biswas, B., & Lewis, W. C. (2001). Measurement of technical efficiency in public education: A stochastic and nonstochastic analysis. *Southern Economic Journal*, 67(4), 889–905.
- Chakraborty, K., Biswas, B., & Lewis, W. C. (2002). Public education efficiency: A comparison of parametric and nonparametric methods. *Applied Economics*, 34(7), 917–925.
- Chakraborty, K., & Harper, E. (2017). Education production functions and efficiency analysis: A review. *Journal of Applied Economics*, 20(2), 173–200.
- DeAngelis, C. A. (2019). Charter school funding and spending in Texas. *Journal of School Choice*, 13(2), 225–248.
- Färe, R., Grosskopf, S., Lindgren, B., & Roos, P. (1989). Productivity developments in Swedish hospitals: A Malmquist output index approach. *Journal of the Operational Research Society*, 40(2), 119–135.
- Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review*, 84(1), 66–83.
- Goldstein, H. (1997). Methods in school effectiveness research. *School Effectiveness and School Improvement*, 8(4), 369–395.
- Gronberg, T. J., Jansen, D. W., & Taylor, L. L. (2012). The relative efficiency of charter schools: A cost frontier approach. *Economics of Education Review*, 31(2), 302–317.
- Grosskopf, S., K. Hayes, L.L. Taylor, and W. L. Weber (1997). Allocative efficiency and school competition. Working Paper, 97-08, Federal Reserve Bank of Dallas.
- Grosskopf, S., K. Hayes, L.L. Taylor, and W. L. Weber (2001). On the determination of school district efficiency: Competition and monitoring, *Journal of Urban Economics*, 49, 45–478.

- Hanushek, E. A. (1986). The economics of schooling: Production and efficiency in public schools. *Journal of Economic Literature*, 24(3), 1141–1177.
- Hanushek, E. A. (2003). The failure of input-based schooling policies. *Economic Journal*, 113(485), F64–F98.
- Hanushek, E. A., Rivkin, S. G., & Taylor, L. L. (1996). Aggregation and the estimated effects of school resources. *Review of Economics and Statistics*, 78(4), 611–627.
- Hanushek, E. A., & Woessmann, L. (2008). The role of cognitive skills in economic development. *Journal of Economic Literature*, 46(3), 607–668.
- Hanushek, E.A., and Ettema, E. (2017). Defining productivity in education: Issues and illustrations. *The American Economist*, 62(2), 165-183.
- Hanushek, E.A., Kuo, J., Morgan, A., Nguyen, M., Ost, B., Rivkin, S., (2026). The effect of comprehensive pay reform on achievement in urban schools. *Journal of Urban Economics*, 153, 1-14.
- Henson, W. (2026). If you can't measure it, can you improve it? Manhattan Institute. Report. Accessed April 26, 2026. <https://media.manhattan.institute/wp-content/uploads/if-you-cant-measure-it-can-you-improve-it.pdf>
- Hoxby, C. M., & Leigh, A. (2003). Pulled away or pushed out? Explaining the decline of teacher aptitude. *American Economic Review*, 93(2), 236–240.
- Hyman, J. (2017). Does money matter in the long run? Effects of school spending on educational attainment. *American Economic Journal: Economic Policy*, 9(4), 256–280.
- Imazeki, J., & Reschovsky, A. (2005). Assessing the use of econometric techniques in estimating the cost of meeting state education standards. *Public Finance Review*, 33(4), 391–447.
- Jackson, C. K., Johnson, R. C., & Persico, C. (2015). The effects of school spending on educational and economic outcomes. *Quarterly Journal of Economics*, 131(1), 157–218.
- Jencks, C., et al. (1972). *Inequality: A reexamination of the effect of family and schooling in America*. Basic Books.
- Johnes, J., Portela, M., & Thanassoulis, E. (2017). Efficiency in education. *Journal of the Operational Research Society*, 68(4), 331–338.
- Klein, R. (2007). Pitfalls in measuring school efficiency. *Education Economics*, 15(1), 1–20.
- Koedel, C., Mihaly, K., & Rockoff, J. E. (2015). Value-added modeling: A review. *Economics of Education Review*, 47, 180–195.
- Lafortune, J., Rothstein, J., & Schanzenbach, D. W. (2018). School finance reform and the distribution of student achievement. *American Economic Journal: Applied Economics*, 10(2), 1–26.
- Loeb, S., & Bound, J. (1995). The effect of measured school inputs on academic achievement. *Journal of Human Resources*, 31(1), 52–81.

- Marlow, M. L. (2000). Spending, school structure, and public education quality. *Journal of Policy Analysis and Management*, 19(1), 31–48.
- McCarty, T. A., & Yaisawrang, S. (1993). Technical efficiency in New Jersey school districts. *Public Finance Review*, 21(2), 271–284.
- Mortimore, P., et al. (1988). *School matters: The junior years*. Open Books.
- National Center for Education Statistics (2025), chrome-extension://efaidnbmninnibpcajpcglclefindmkaj/<https://nces.ed.gov/pubs2017/2017019.pdf>
Accessed July 30, 2026.
- Rassouli-Currier, R. (2007). School efficiency and productivity growth. *Journal of Educational Finance*, 32(4), 402–429.
- Reynolds, D., et al. (2014). Educational effectiveness research: A state-of-the-art review. *School Effectiveness and School Improvement*, 25(2), 197–230.
- Rouse, C. E., & Barrow, L. (2006). U.S. elementary and secondary schools: Equalizing opportunity or replicating the status quo? *The Future of Children*, 16(2), 99–123.
- Ruggiero, J., & Vitaliano, D. F. (1999). Assessing the efficiency of public schools. *Contemporary Economic Policy*, 17(3), 321–331.
- Saito, M., & McIntosh, W. (2003). Value-added models and education efficiency. *Applied Economics*, 35(2), 221–230.
- Sammons, P., Hillman, J., & Mortimore, P. (1997). *Key characteristics of effective schools*. Institute of Education.
- Sirin, S. R. (2005). Socioeconomic status and academic achievement. *Review of Educational Research*, 75(3), 417–453.
- Taylor, L. L., Ehlert, M., & Saultz, A. (2014). Measuring efficiency and cost savings in Texas school districts. *Educational Evaluation and Policy Analysis*, 36(2), 227–246.
- Thompson, J., Wood, R. C., & Hogan, T. (2021). Efficiency of Texas public school districts. *Applied Economics*, 53(9), 1015–1030.
- Williams, J. (2010). The role of school-effects in educational outcomes. *Oxford Review of Education*, 36(1), 69–87.