School Outcomes and School Costs:
The Cost Function Approach

Timothy J. Gronberg
Dennis W. Jansen
Lori L. Taylor
Kevin Booker
Texas A&M University*

Introduction

Any change in school funding structures or funding strategies will impact not only patterns of taxation and revenue, but also patterns of student performance. Historically, studies and political discussions have focused primarily on the revenue and spending implications of school finance reforms. While such issues are certainly important, the student performance impacts are no less critical, particularly in light of rising concerns about school accountability and increased attention to outcome-based evaluations of schools.

Texas has been at the forefront of the transition from process or input-based evaluation of schools to outcome- or performance-based assessment. Since 1995, Texas has used the Texas Assessment of Academic Skills (TAAS) test results to establish accountability standards in the form of school report cards. The link between school funding structure and school accountability, however, is lacking. William Duncombe and John Yinger have argued that in the new world of educational performance standards, a fair and effective funding system must integrate the performance standards into the funding structure.[1] In this report, we develop and illustrate a cost function-based approach to implementing an outcome-based school finance formula.

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* The views expressed are those of the authors and do not necessarily represent the views of Texas A&M University, any other Texas state agency, or the Joint Select Committee on Public School Finance.

The key element of an outcome-based finance system is a set of reasonable estimates of the costs for individual school districts to reach a particular performance standard. In turn, such estimates rest on clearly defined standards of performance and on appropriate adjustments for factors that make the cost of achieving any given standard higher in some districts than in others. We adopt a cost function approach to developing the required estimates. A cost function relates district spending to student performance, prices of inputs, student characteristics, and other relevant characteristics of districts. The estimated cost function is used to predict the level of spending needed to reach a particular performance standard, given prices, student characteristics and other district characteristics. Differences in predicted spending provide insight into the extent to which factors outside of a district's control affect the cost of education. Such insights can be particularly helpful to policymakers interested in integrating performance standards into the school finance formula, and ensuring that school districts have the resources needed to meet those standards.

While the cost function approach is in our opinion the most appropriate to the task of informing the policy debate, it is important to recognize that any estimation–statistical or not–rests on extrapolation from historical experience. The estimates obtained from historical data are best used for estimation of future relationships when the relevant structures and institutions remain the same in the future as they were in the historical sample period and when the policy changes under analysis are modest. This is of heightened importance when using an estimated model to make inferences about the future impact of policy actions, especially policy actions that alter the incentives facing individuals. In the case of schools, it is conceivable that the cost of achieving any given performance level could decline–or rise–substantially due to changes in teacher and administrator incentives.

Advantages of a Cost Function Approach

Scholars have used a variety of tools to assess the impact of alternative funding structures and funding strategies on student outcomes.[2] There are several advantages to using a cost function approach rather than one of the major alternative methodologies currently employed in school finance studies. Three important advantages are identified by William Duncombe in a study of educational costs in New York.[3] The cost function offers a sound statistical approach to estimating the variation in required spending across districts, which is particularly important in states with large variations in district environments like Texas. It uses actual data on factors affecting spending to develop estimates of the costs of performance standards. Furthermore, the cost function allows a relatively straightforward calculation of alternative cost indices for policy analysis.

The cost function approach has a number of desirable technical properties. It is reasonable to expect that schools will be evaluated with respect to multiple outcomes, and the cost function framework accommodates this requirement handily. Some other statistical approaches, such as estimation of an education production function, are not as readily adapted to a multiple outcome situation. Second, the cost function approach is applicable as long as firms are minimizing costs. Public schools may attempt to provide education services at minimum cost, but they are certainly not profit maximizing as must be presumed in some other methodologies. Hence a cost function approach has often been employed in studies of nonprofit institutions, both in the public sector and in the private sector.

Finally, a cost function-based approach encourages or even forces researchers and policy analysts to be explicit about what outcomes are being studied and what inputs are being considered, as well as what assumptions are being made regarding behavior of decision makers at the school or district under analysis. One criticism of cost functions and similar approaches is that these lengthy lists of assumptions are too restrictive. Alternative methodologies, however, must make assumptions about outcomes and inputs under consideration, often without the rigor of making these explicit.

Criticisms of a Cost Function Approach

Realizing these benefits , however, requires good data and an appropriate statistical model. If the data are poor measures of the relevant outcomes, prices, and environment of a district, then it is hard "to make a silk purse out of a sow's ear." In developing measures used in the study, we have relied primarily on published and unpublished data produced by the Texas Education Agency (TEA). Texas is generally viewed as one of the best workshops for statistical analysis of education because of the availability and quality of the TEA data. However, the TEA data are not perfect. Some outcomes that districts and policy makers consider important—such as music or science—are not measured. Data on the full set of potentially important input prices for school districts is impossible to obtain.

If the estimation model is poorly specified, then the statistical results may—even with the best of data—provide a distorted picture of the true cost relationships. The cost function approach is subject to many, if not all, of the usual econometric concerns, from the possibility of simultaneous equations bias to concerns about misspecification and structural change. We use best-practice techniques in an attempt to posit a good working model. Details will be available in the Technical Appendix.

At its theoretical foundation, the cost function approach presumes that school districts are attempting to provide the designated outcomes at minimum cost. Statistical methods allow us accommodate school districts that are inefficient, but even this approach requires that school districts are trying to minimize costs. If school districts are not trying to minimize costs, then cost function analysis may be misleading.

The cost function approach has been criticized because its technical complexity makes it difficult to communicate to the policy-making community. A number of judgments and assumptions must be made by a researcher attempting to estimate an education cost model. The basis for and importance of these choices may, indeed, be less than transparent to the policy audience. In our view,[4] a singular focus upon transparency is a poor policy lens. The primary objective should be to use the approach which can provide the most accurate policy information. Simplicity, bought at a price of significant inaccuracy, is a poor bargain. Another related criticism of the cost function approach is that the cost function does not directly inform how school districts should spend their money.. This is a relevant observation about the cost approach, but we don't see it as a fatal criticism The cost function approach provides a predicted cost, for a district to achieve given outcomes standards, given district-specific conditions, given available technology, and given a target level of efficiency. It, indeed, does not identify what districts need to do to reach those performance standards The "how to" question is left up to the local district decision makers—those best positioned to form local strategic responses. In fact, the cost function can be used to identify relatively efficient districts, which can form a basis for additional study of best practices.

Cost Function Fundamentals

The underlying assumption of our analysis is that school districts produce education outcomes—quantity and quality—using an education process that combines input factors that are purchased (for example, teachers and other personnel) with environmental input factors that are not purchased (for example, student skills acquired in an earlier grade). Thus, school district cost is a function of the outcomes produced, the prices of inputs, the characteristics of students and parents that directly influence the education production process, and other features that influence the educational process, such as school district size.

There exists a sizeable literature which finds that school districts do not all operate in an efficient, cost-minimizing fashion and that the degree of inefficiency varies considerably across districts. We will use a stochastic frontier cost function model[5] to address this potential for inefficiency.

District Expenditures

Our model will be a district-level cost function. The underlying assumption is that cost and resource allocation decisions are largely made at the district level, where district administrators allocate funds across campuses and across physical facilities and instructional programs.

We will measure district costs as average operating expenditures per pupil, regardless of funding source. Therefore, our cost measure includes federal, state, and local dollars. However, as is common in education cost studies, we exclude debt service and transportation expenditures on the grounds that they are unlikely to be explained by the same factors that explain student performance, and therefore that they add unnecessary noise to the analysis. We exclude food expenditures on similar grounds, and because it is not clear how to value the butter, eggs and other in-kind subsidies that school lunch programs receive.

Education Outcomes/Performance Measures

The *No Child Left Behind Act of 2001* mandates assessment testing of all children in grades three through eight. Performance standards based upon these test scores will be one key component of any incentive-oriented school finance formula. If funding allocations and/or costly sanctions are going to be tied to a school or district's test performance, it is imperative that test performance be a meaningful indicator of school performance.

Measuring student performance is a challenging and controversial task. Even if one ignores the non-academic aspects of the problem, choosing a single test-based measure of academic performance is a formidable assignment. A variety of test score measures have been used by scholars analyzing the determinants of student achievement. A variety of test score measures have also been adopted by the policy community for use in the evaluation of the performance of students and of schools. The various competing measures can be classified into two generic categories: (1) those that focus on levels of scores and (2) those that focus upon changes in scores. The score levels reveal something about where we are, and the changes in score levels reveal something about where we are headed. In economic parlance, the score levels reflect information about the current stock of achievement, and the changes in score levels reflect information about the current flow of achievement. Since output is, fundamentally, a flow concept, there is a conceptual appeal to using the changes in score levels as a performance measurement.

In addition to the appealing match between test score changes and the concept of output flows, the use of score changes rather than score levels may allow for better identification of school contributions to student outcomes. As is well known, at least since the time of the Coleman Report (1966), student achievement levels reflect the effects of both school and non-school provided inputs.[6] Indeed, in the Coleman Report, the socioeconomic characteristics of students explained the lion's share of the measured differences in educational achievement. Furthermore, the cumulative effects of school and non-school inputs determine current achievement. Thus, level indicators of student achievement reflect not only the contribution of the current school, but also the contributions of the students themselves, their families, the communities in which they live, and the previous schools they have attended.

If the objective is to isolate the role of current school inputs, there is an advantage to looking at changes in achievement levels, thus controlling for the effects of historical inputs. This approach is basically value-added, measuring the additional contribution of the school to the skills and knowledge a student already possesses. Instead of giving a school credit for a student's high performance level when that performance level may be due to a superior home environment, we ask how the school helped improve a student's performance over and above what was already expected.

In this report, we use a value-added measure of education outcomes that is based on changes in passing rates on the TAAS.[7] Until 2003, the TAAS was administered to all students in grades three through eight and in grade 10 who are not exempt due to limited English proficiency (LEP) or to an "admission, review, and dismissal" committee exemption (primarily for special education students).

Changes in passing rates are a particularly attractive measure of value added because they can also be interpreted as measuring the yearly progress required under No Child Left Behind. However, because a change in a student's test scores from year to year is due to both the quality of the schooling and to the quality of the home environment, changes in scores or changes in passing rates—while free of historical effects—are still impure measures of school performance.[8]

TEA provided math and reading scores for each of the nearly 1,000,000 students in grades three through eight attending traditional public schools in Texas between the1993-94 and 2001-02 school years, as well as data on students in grade 10. We calculated the percentage of students in each district who passed the TAAS this year and compared it to the percentage of those same students who passed two years previously.[9] Our value-added measure is the average increase in the district passing rate for elementary and high school students (grades five through eight and grade 10).

In building a cost function based on value-added measures, there is a concern regarding control for the level of achievement. We need to provide a control for the effect summarized in the following question: Does the current level of student achievement in a district make it more or less difficult to achieve a given percentage point increase in passing rates? To address this concern we introduce a lagged level of the TAAS passing rate for students in grades three through six. The two-year lag matches well with our two-year changes used as our value-added performance measure.

In a series of recent papers, Thomas Kane and Douglas Staiger have identified a critical and largely unrecognized consideration in designing school accountability systems—the inherent volatility of test score measures.[10] In the rush to introduce education accountability systems based on student achievement, states have not fully investigated the statistical properties of the various performance measures employed. Using data from North Carolina, Kane and Staiger illustrate the potential value and appropriate techniques for such investigation. In a previous study (2003), we applied the Kane and Staiger methodology to Texas data, and found volatility in test score measures similar to those in the North Carolina data. Although more complex adjustments are possible, we will adopt the simple strategy of using three-year averages of our value-added output measures as one measure of reducing the noise (or uninformative volatility) in these output measures.

One criticism of the TAAS is that it is a test of minimum performance. To capture the cost impact of higher levels of performance, we also consider two other district performance indicators: (1) the percentage of students who perform "above criterion" on the SAT or ACT tests and (2) the percentage of students who complete an advanced course. The percentage of students performing above criterion on the SAT or ACT is the product of multiplying the percentage of students taking the SAT or ACT times the percentage of test-takers who score above criterion. These two indicators are specifically directed at high achieving students in high school.

Table 1 summarizes the district education outcome measures. The average increase in passing rates for students in grades five through eight and 10 is 2.85, indicating that the average across districts of the percent passing math and reading in these grades increased by 2.85 percentage points every two years. The minimum value observed in our sample was -2.07 percent, the maximum value 14.2 percent. Extreme values of this statistic are generated by small districts in which a small change in the number passing can lead to a large percentage change.

As mentioned above, we considered two non-TAAS-based measures of district quality. First is the percentage of students completing at least one advanced course. The list of qualified advanced courses consists almost entirely of Advanced Placement or International Baccalaureate courses, and 17.6 percent of students pass at least one of the designated courses in the average district.[11] Here the range of the variable is quite large, with a minimum value of 0.9 percent and a maximum value of 60.7 percent.

The second non-TAAS-based measure is the percentage of students in the district who achieved a score at or above the criterion established by the TEA on the SAT or ACT test. (These criterion scores are a SAT I score of 1100 or an ACT score of 24.) For this measure we calculated the percent of students meeting these criterion relative to the eligible student body (and not just as a percent of students taking the SAT or ACT). In the average district, 13.4 percent of students meet these criterion scores, and again the range is large, with a minimum of 0 percent and a maximum of 50.6 percent. For both of these measures, we calculated three-year moving averages in order to reduce the noise in the measure.

One outcome measure that we would ideally have included in our cost function is a measure of the completion rates of students or a measure of the dropout rate. We examined the TEA measures for this variable, but in the end found this variable not to be useful. The basic problem is that the TEA variable indicates a very low dropout rate, one so low as to not be believable. In practice, this shows up as a variable having a negligible or perverse impact on cost. Alternative measures of the completion rate over the time span of our data were not available to us.

Scale

There are few dimensions on which Texas school districts differ more than scale. The five largest Texas districts have average daily attendance of more than 65,000 students; the five smallest Texas districts have average daily attendance of less than 30 students. Moreover, the smaller school districts are often located in regions where the population density is low, so that these districts may already be geographically large. These features mean that one solution to the economies of scale issue—consolidation—is often not possible or practical. Scale effects are currently a key element in the Texas funding formula.

We will measure district scale as average daily attendance, and specifically TEA' s calculation of refined average daily attendance.

Input Prices

A second class of explanatory factors in our cost model is input prices. We wish to include the market prices for the major inputs employed in producing educational services.

The education sector is labor-intensive, with three major sources of cost—teachers, administrators, and auxiliary personnel. As our measure of teacher price, we use the average salary of teachers with less than three years of experience. The average wage of beginning teachers is a better measure of the wage level in a district than the average wage paid to all teachers because beginning teacher wages are less influenced by differenced in the experience profiles of districts.

Administrator salaries respond to local market conditions in much the same way that teacher salaries do. While administrators clearly earn more than beginning teachers, the differential between administrator wages and beginning teacher wages is very consistent across districts. Thus, principal salaries track very closely with teacher salaries. Because the two compensation measures are highly correlated with one another, the administrator salaries did not add much information to the cost function estimation and we do not include them in the final estimating equation.

Teachers and administrators may have very similar salary profiles across districts, but there is little reason to expect that the price of teacher would be a good proxy for the price of teacher aides and other school district personnel. Variations in teacher wages can explain less than one third of the variation in the average salary of auxiliaries and teacher aides. Therefore, we also included the average salary of auxiliaries and teacher aides.

While actual salary averages are an appropriate measure of price for estimation of a cost function, they are not appropriate for construction of a cost index. Only uncontrollable variations in compensation should be used to measure the cost of providing educational services. Therefore, when we calculate the cost function index, we use a teacher cost index instead of beginning teacher wages, and a comparably estimated auxiliary cost index instead of actual auxiliary wages. The teacher cost index and the auxiliary cost index use an individual fixed effects methodology to separate variations in compensation that arise from uncontrollable local characteristics (such as the average price of single-family housing) from variations in compensation that arise from school district choices about the characteristics of their personnel.[12] For more on teacher cost indexes, see the companion report "Adjusting for Geographic Variations in Teacher Compensation: Updating the Texas CEI". For information on the auxiliary cost index, see the forthcoming Technical Appendix.

Prices for instructional equipment and materials would ideally be included in our cost function but were not available to us. However, since prices for computer equipment and other instructional equipment and materials are, largely, set in a national market, it is not likely that they vary much among school districts. Hence their exclusion may not exert much impact on the relative cost calculations among districts.

Environmental Factors

We consider several environmental factors that influence district cost but which are not purchased inputs. In principle, a range of student, family, and neighborhood characteristics would be included in the cost model. In practice, school district matched socioeconomic variables are hard to come by in non-Census years. To capture variations in costs that derive from variations in student needs, we incorporated into our analysis the percentages of students in each district who had certain characteristics. These characteristics were:

- Classification as special education
- Classification as LEP
- Participation in the National School Lunch Program
- Enrollment in high school (versus primary school)

For LEP, special education, and high school students, the required resource intensity per student is increased (for example, specialized teachers and supplies, smaller required class sizes), thus driving up per pupil costs relative to regular students. The free lunch measure is chosen to account for the lower level of home inputs which are expected to obtain, on average, in households in official poverty status and in migrant households. The importance of home inputs in the production of student achievement is quite well established, and districts will have to increase other inputs to substitute for lower levels of parental-supplied inputs in order to produce any given quality of output.

Special Education Measure

An important spending category, and one receiving special attention in the current Texas school funding formula, is the support for services to students with special resource requirements, otherwise known as special education. Students are classified as special education students due to the presence of either physical or mental disabilities (or both). These disabilities are categorized into 11 categories, with considerable variation in the severity of condition across categories. For our analysis, we group learning disabled and speech disabled students into one group (less severe), and the remaining special education students into a second group (more severe). Our two special education measures allow us to assess the effect on school district expenditures per pupil of the percent of special education students, allowing for differential effects of less severely and more severely disabled cases.

Poverty Measure

An important factor in the relationship between the cost of education and student achievement is the economic status of a student and his or her family. Students in an economically disadvantaged situation have an increased likelihood of a paucity of educational resources at home. In fact, poverty is a variable frequently identified as a predictor of relative student performance.

Ideally a measure of student poverty would be constructed from individual family data, but such detail is not available to us (nor to many researchers involved in studies of education). In its place, a frequently used indicator of poverty is student participation in the National School Lunch Program, the U.S. Department of Agriculture program that reimburses individual school districts for all or part of their lunch (and often breakfast) depending on their level of eligibility. It is important to note that parents must apply for this program, and school districts with similar student poverty may differ in program participation, depending upon school approaches to signing up eligible families. Parents in various settings may also vary in their willingness to apply to this program. Because there is anecdotal evidence that high school students are reluctant to identify themselves as needy, we use the share of non-high school students who are fully subsidized by the school lunch program as our indicator of poverty in a district.[13]

Limited English Proficiency Measure

Texas is home to a large immigrant population. There is considerable diversity in English language proficiency across immigrant households, but a significant number of children of immigrant parents face extra challenges in school attributable to home language and cultural differences. The programmatic response of school districts is to provide English as a Second Language (ESL) or bilingual programs for these students. The resources invested in children in these programs may be higher than for non-program kids, and the cost of education in districts with larger LEP populations will be consequently higher. We use the share of non-high school students classified as limited English proficient as our LEP measure. We limit the measure to the non-high school LEP student population share due to concerns that much of the variation in high school LEP student shares reflects variation in dropouts, an endogenous/controllable outcome, rather than variation in an exogenous/uncontrollable student population characteristic.

Geography

We include a measure of geographic isolation—the distance to the nearest major metropolitan area—in order to proxy for some of the variation in non-teacher input prices. We hypothesize that a lack of access to suppliers or increased shipping costs may leave geographically separated districts facing higher costs, perhaps in the form of higher prices for some educational inputs.

Capital

At this time, we do not have access to a school district capital stock data series, so we do not include physical capital in our cost function analysis.

Efficiency

Finally, we explicitly allow for the possibility that some districts fail to minimize costs. We do so by estimating a stochastic frontier form of the cost function. This allows us to estimate how much of observed costs can be attributable to measured cost factors, and how much is attributable to “unnecessary" costs due to deviations from minimum-cost or best practices. The stochastic frontier approach allows for some districts to be successfully minimizing costs while other districts are further from the cost frontier. This methodology allows us both to estimate the cost frontier and to recognize that some districts may be inside the frontier, in other words producing educational services of a given quality at a higher cost than “necessary."

Districts inside the frontier would be less efficient than districts on the frontier, and the distance from the frontier can be measured and labeled as relative efficiency. The ratio of the predicted minimum cost of a district to its actual cost provides this measure of the district inefficiency. A district with a one-to-one ratio of predicted minimum cost to actual cost is considered efficient. As the predicted minimum cost falls below actual cost, a district's relative efficiency falls.

These relative efficiency measures need to be interpreted with caution, as does the separation of spending differences into those due to cost factor differences and those due to relative efficiency.

The measurement of efficiency in producing a set of outcomes is directly linked to the particular set of performance measures that are included in the cost model and the particular set of input measures. For example, if only a math and reading performance measure is included in the estimated cost function model, but a district devotes significant resources to music and athletic programs (and if those programs have little impact on math and reading) then this district will be identified as inefficient, even if all of its programs were being produced as efficiently as possible.

Unobserved variation in important unmeasured quasi-fixed factors could also muddy the interpretation of the efficiency estimates. In particular, if capital varies widely across districts, and if increased capital leads to increased educational achievement, then two otherwise identical districts that vary in the size of their capital stock will show one district realizing higher levels of educational achievement.

Finally, we would point out that the best-practice frontier estimated here is based upon observed district decisions made within the incentive environment in place at the time of observation. Changes in the institutional environment, with associated changes in fundamental incentive structures, would be expected to shift the frontier, both actual and estimated. Changes in the incentive environment would also be expected to impact how far the districts are located from the frontier.

Cost Function Estimation

We estimate the cost model using the method of multiple regression. This method allows the researcher to determine how a particular independent variable impacts the dependent variable, while controlling for other factors that affect the dependent variable. In our analysis, the dependent variable is actual spending per pupil by school districts, and the independent variables are the various cost factors described above. Table 2 reports summary statistics for variables included in our model.

We estimate our district cost model annually for academic years 1998-99 through 2001-02 using a variant of the translog model.[14] Due to concerns about cost function differences among districts with different service scope, we focus on districts that offer K-12 education. There are 975 of these in Texas, out of a total of 1041 traditional districts. The 975 are further reduced because 274 are missing one or more explanatory variables (mainly the outcome variables) and six are excluded because they have no tax base and therefore face a different incentive environment than other districts.

In the estimation, we explicitly allow for the possibility that some districts fail to minimize costs. This stochastic frontier approach allows us to estimate how much of observed costs can be attributable to measured cost factors, and how much is attributable to “unexplained" costs due to deviations from minimum cost practices. As noted above, unexplained cost could arise because the district is not minimizing its costs of providing the measured outputs or because the district is producing other costly, unmeasured outputs or from some combination of the two. The stochastic frontier approach provides estimated values of the efficiency measure for each school district in our sample.

Model Estimates

The core model results will be reported in the Technical Appendix. The parameter estimates from the translog model are used to calculate the implied marginal effects on expenditures per pupil from a change in one of the explanatory variables. In our modified translog model these marginal effects depend not only on the estimated model parameters but also on the values of the explanatory variables themselves. One implication is that these marginal effects will, in general, differ for each district. The common, accepted practice is to evaluate the marginal effects at the mean of the values of the explanatory variables. As an example, when evaluated at the sample mean values for all explanatory variables, a one student increase in the number of high school students (holding the total number of students constant) is associated with an estimated $3,726 increase in predicted cost. In other words, at the mean, an additional high school student adds $3,726 more to district cost than does an additional non high school student (all other things equal).

The estimated marginal effects are mostly statistically significant and agree with our expectations for the sign of the effect. In other words, the fundamental economic relationship between cost, outputs, and input prices hold for our model. This provides a minimum level of support for the reasonableness of our specification. For example, the model indicates that it costs more to produce higher levels of the outputs, both in terms of changes in passing rates and in the percent of students taking advanced courses or scoring above some criterion level on the SAT or ACT. This is a critical finding for this study, since the student outcome results will be used in estimating the cost of meeting alternative performance standards. We find that districts that must offer higher wages have higher per pupil costs. It also costs districts more to operate in environments that require a more resource intensive instructional technology, such as when the percentage of special education students is high or when districts are relatively remote from large metropolitan areas.

A central issue of concern, discussion, and debate among education researchers is the existence and extent of economies to student population size or scale. The scale economies issue can be explored at alternative levels of aggregation (classroom, school, district) and with alternative methodologies (for example, production functions or cost functions), depending upon the question being addressed. Here we are providing evidence as to the nature of cost economies (or diseconomies) of scale evaluated at the school district level. We provide a picture of the estimated scale economies in figure 1, which plots predicted expenditures per pupil against enrollment. The predicted expenditures are generated for a hypothetical district with all cost factors except for scale held constant at state mean values. This is the appropriate calculation of the pure (other factors fixed) estimated scale properties of the education technology.

Three features of this figure stand out. First, there are very significant estimated cost savings when moving from a very small district (500 or fewer pupils) to a small district (1,600 or fewer pupils). The estimated elasticity (responsiveness) of cost to enrollment when going from the minimum enrollment of 75 to an enrollment of 1,600 is 0.283.[15] In other words, a 100 percent increase in enrollment in this range is associated with a predicted 28.3 percent decline in per pupil costs, all else remaining the same.

Second, most of the scale economies are realized when district enrollment reaches 25,000. The corresponding cost elasticity for a change in enrollment from 25,000 to 210,670 is only 0.003.

Third, although the scale economies are largely exhausted at 25,000, the per-student costs do continue to decline at 210,670. We do not find evidence for diseconomies of scale for the large urban districts in our sample.

Our stochastic frontier model generates efficiency estimates for each district in our sample. In figure 2, we show the distribution of estimated efficiency values. The distribution is heavily skewed, with observations piling up between 90 and 98 percent efficiency and a long left tail of observations extending to a minimum value of 72 percent efficiency. The average level of efficiency is 93 percent.

Do size and efficiency go hand in hand? We plot the relationship between efficiency and enrollment in figure 3. Although it is the case that the very lowest efficiency values are concentrated smaller districts, the graph reveals considerable dispersion within enrollment size classes across the size distribution. It is also the case that being very large is not associated with being very inefficient. Dallas and Houston are average (to slightly above average) efficiency districts.

The information in Table 3 reinforces these points. Average efficiency is fairly uniform across the size categories in the last three columns, and across the urban/rural division. The range of values is greater (25 percentage points) among the small districts than it is among the large districts (17 percentage points), and the two smaller district size categories contain the districts with the lowest efficiency measures. However, at even the tenth percentile of the efficiency distribution we see that the small, medium and large size categories have very nearly the same efficiency measure, and this feature holds true for the entire range of the distribution.

Thus the range or dispersion of efficiency measures is related to district size, with the smallest sized districts containing the districts with the lowest efficiency measure, but inefficient districts are as common among large districts as they are among small districts.

Table 4 provides information on the characteristics of districts at the high and low ends of the efficiency distribution. The lowest efficiency districts spend more and have lower enrollments than the comparable state averages, while the highest efficiency districts spend less and have higher enrollments than the comparable state averages.

Estimating an Education Cost Index

Once the education cost function has been estimated, education cost indices can be generated. These cost indices, which indicate how much more it costs to meet the performance standard in Austin than in Amarillo, are the primary product of the cost function approach. The development of the indices involves several steps. For the three student performance measures, the objective is to evaluate districts at a common outcome standard. This effectively holds these factors constant across school districts. For the other factors, which are treated as uncontrollable, the cost model is evaluated at the actual value for these variables in each district.

Setting the Standard

Until 2003, Texas policy makers had in place a system for evaluating and ranking school districts in Texas that focused primarily upon student performance on the TAAS. In 2003, Texas replaced the TAAS with the Texas Assessment of Knowledge and Skills (TAKS). The TAKS is widely recognized as a more challenging test than the TAAS. Furthermore, the TAKS is expected to become even more challenging over the next few years as TEA ratchets up the passing standard on the new, harder test.

Ideally we would have just used the TAKS data for estimation and evaluation. However, the TAKS data is only available for one year, making it impossible to compute our value added measure using TAKS data. Furthermore, in that initial year TAKS was administered in a pilot program without consequences to students or district for their performance on that test. The scores required to meet standards were not known when the TAKS was administered, making it very difficult for districts to allocate resources efficiently. Cost function analysis on the basis of 2003 data would have been very problematic.

The change of testing regime forces us to adopt a methodology for mapping TAAS performance results into a TAKS regime. Obviously this step needs to be looked at with a healthy dose of skepticism, and the resulting calculations considered with caution, as best estimates but still uncertain guides to policy.

The TEA developed a conversion schedule that relates TAAS performance to expected TAKS performance. For example, the schedule indicates that where a Texas learning index (TLI) score of 70 would have been high enough to pass the TAAS, a third grader would need to have scored a 74 to have passed the math test at the TAKS level in 2003, and an 82 to pass the math test at the TAKS standard that will be in place for 2005. Actual performance in 2003 exceeded expectations that were based on this conversion, so the schedule may overestimate the TAAS scores needed to meet the TAKS standards. Nevertheless, this conversion is the best available data for spanning the transition between TAAS and TAKS.

We re-graded each TAAS test using the passing standards given in the conversion table, and using these re-graded exams, calculated the effective passing rate for each district at the 2003 TAKS standard and at the 2005 TAKS standard. (The 2005 standard is the panel recommendation.) District effective passing rates at the 2003 TAKS standard range from 29 percent to 93 percent, with an average of 70 percent. Using the higher 2005 conversion schedule, district effective passing rates range from 19 percent to 88 percent, with an average of 53 percent.

Texas's Consolidated State Application Accountability Workbook details the state's plans for compliance with the No Child Left Behind law. The workbook sets out a progression of increasing passing rates on the TAKS. The designated goal for 2005-06 is that the percent of students in all grades and demographic categories passing the TAKS be 53.5 percent for reading/language arts, and 41.7 percent for math. Similarly, the Accountability Rating Standards for 2002 required that academically acceptable districts have 55 percent passing in all subjects and demographic categories. Given these figures, it seems plausible to evaluate the cost of having 55 percent of students passing TAAS at the TAKS level. Therefore, for each conversion we calculated the gain in passing rates each district must produce in order to bring its effective passing rate up to 55 percent. These two estimates of the performance gap (one based on the 2003 conversion schedule, one based on the 2005 conversion schedule) represent upper and lower bounds on the value added districts must produce to meet the performance standards. For each bound, we calculate the cost of producing at least the state average value added, plus whatever additional value added is required to close the performance gap.

There is no similar guidance on an appropriate performance level for our two remaining outcomes measures—percent taking advanced courses and percent scoring above criterion on the SAT/ACT. Therefore, we evaluate these outcomes measures at the state mean.

The Level of Inefficiency

These evaluations generate a predicted per pupil spending amount for each district to attain a common student performance standard, assuming a common level of efficiency.   For purposes of this exercise, we assigned to each district the average level of efficiency obtained by school districts in Texas.

The Average Cost of Meeting the Standard

The model predicts that total federal, state, and local expenditure per pupil in the average district would need to be between $5,748 and $5,840 (in 2002 dollars). Total expenditures per pupil would need to be $4,806 in the least-cost district, and $13,309 in the highest-cost district. (Coincidentally, both the highest-cost district and the least-cost district have no performance gap to close under either grading scale. Therefore predicted costs are the same either way.)

Cost Index Results

We estimated the cost index for each district by dividing the predicted spending level for each district by the predicted spending level in a district with average characteristics. The index values so generated provide a measure of the cost in a district due to its uncontrollable factors relative to the cost in a district with state average characteristics for the uncontrollable factors. For example, an index value of 1.5 indicates that a district is predicted to require 50 percent more dollars per pupil to achieve the standardized output levels than a district with average uncontrollable characteristics.

Figure 4 illustrates the frequency distribution of the lower-bound cost index, labeled the Education Cost Index or ECI. The graph illustrates the range of the resulting cost index, which is from 0.80 to 2.23.

The mean of the ECI is 1.11, and half the districts have ECI values between .98 and 1.19, indicating that half the districts have costs of achieving the standardized level of educational outputs, given their district-specific uncontrollable factors, that are between 98 percent and 119 percent of the cost of achieving the standardized level of educational outputs with state average values of the uncontrollable factors. The ECI distribution is rather heavily skewed, with a long right tail of districts with ECI values greater than 1.50. Still, these extreme values of the ECI distribution are outliers. Fully eighty percent of districts have an index value between 0.92 and 1.36, and only ten percent have values of more than 1.36.

What factors are driving the significant dispersion in the estimated cost index values? Part of the variation is due to the variation in the student characteristic mix across districts. The estimated additional costs associated with a student in a specific category (eg. economically disadvantaged) are displayed in table 5.

The cost differential associated with an economically disadvantaged student is estimated to be $1,825. Predicted costs, the basis for the index calculation, for districts with above average numbers of economically disadvantaged students are adjusted upwards by this cost adjustment factor. Predicted costs for districts with below average numbers of economically disadvantaged students are adjusted downward by this factor.

For example, consider two districts with 200 students. If one had the state average share of 39.5 percent students receiving free lunches from the National School lunch program, then it would have 79 economically disadvantaged students. An otherwise equal district with 80 students who are economically disadvantaged would have predicted costs $1,825 higher than the district with 79 economically disadvantaged students. Conversely, an otherwise equal district that had 78 economically disadvantaged students would have predicted costs $1,825 below the district with the average share of economically disadvantaged students.

Two of the values in table 5 warrant additional commentary. First, the estimated additional costs associated with the more severely disabled students should be viewed with caution. The needs of these students are being addressed using very different educational techniques, and the outcomes by which their progress is evaluated are, in many cases, not the outcomes included in this study. The methodology used here may, therefore, not provide an accurate assessment of the costs associated with these students.

Second, the significantly higher costs associated with high school students may reflect more than just the predictably higher resource intensity required to service these students. It is also possible that a portion of the variation in the percentage of students in high school may reflect variation in dropout rates. This potential mixture of an input effect (more resources required per student) and an outcomes effect (higher retention rates) could be inflating the estimated high school effect in our analysis. This is particularly problematic because we have no (good) measure of dropout rates or retention rates.

Table 6 provides information on the urban/rural and district size (enrollment) distributions of the cost index values. The column labeled "All Districts" summarizes the ECI distribution for all districts. The columns labeled "Urban Districts" and "Rural Districts" divide the sample into urban and rural subsets.

As table 6 shows, the distribution of ECI values has a higher mean and is more spread out for rural districts. In fact, while the highest ECI value for any urban district is 1.98, the highest value for any rural district is 2.23. The mean of the ECI for urban districts is 1.01 with a standard deviation of 0.12, while the mean of the ECI for rural districts is 1.18 with a standard deviation of 0.18.

Perhaps the most striking feature of the ECI is the strong inverse relationship between the cost function index values and district enrollment. The columns labeled "Districts Under 1,600

ADA," "Districts 1,600 – 5,000 ADA," and "Districts Over 5,000 ADA" provide a good view of this feature. Districts over 5,000 ADA have an average ECI value of 0.94 and a standard deviation of 0.06. Districts with ADA between 1,600 and 5,000 have essentially the same standard deviation but a higher average, 0.99. Finally, districts with ADA below 1,600 have an average ECI of 1.20 and a standard deviation of 0.19.

An alternative view of the dispersion of ECI values with enrollment is found by looking at other characteristics of the distribution divided into district size categories. The highest ECI value for the largest districts with over 5,000 ADA is 1.14. For the medium size districts with ADA between 1,600 and 5,000 the highest ECI value is 1.17. For the smallest size districts, with ADA below 1,600, the highest ECI value is 2.23. Another way to state this is that, for the largest districts, more than 75 percent have ECI values *below* 1.00, while for the smallest districts, 90 percent have values *above* 1.00.

We further illustrate the relationship between ECI and enrollment in figure 5, which plots ECI values against district enrollment.

Figure 5 makes clear that the ECI distribution is, to a large degree, driven by district size. Further, these ECI calculations give strong indication of the importance of compensating for district size in calculating required expenditure per pupil for Texas schools.

We provide further insight into the relative importance of size and the relationship of size to other cost factors in table 7, where we tabulate the values of various uncontrollable factors for the 10 percent of districts with the highest ECI values and the 10 percent of districts with the lowest ECI values. The various columns report, for the highest ECI and lowest ECI districts, the mean and standard deviation of expenditures per pupil; predicted teacher wage; district enrollment; percent of students classified as economically disadvantaged, limited English proficient, or special education; the percent of the student body in high school; and our geographic remoteness measure.

High ECI districts tend to have higher expenditures per pupil but a lower predicted teacher salary, and a much lower enrollment, than low ECI districts. High ECI districts tend to have a much higher percentage of students labeled economically disadvantaged, a much higher percent of students labeled limited English proficient, and a higher percent of students in special education. High ECI districts also tend to have a higher percentage of students enrolled in high school. Finally, high ECI districts tend to be further from major metropolitan areas.

Estimating the Total Cost of Performance

Given the estimates of average cost per pupil and the district-specific cost differentials, it is natural to ask how this all stacks up for the state as a whole. For each district, we multiplied the average per pupil cost in 2002 by the rate of inflation between 2002 and 2004 to get an inflation adjusted estimate of per pupil cost.[16] For the state average, we estimate that the per-pupil cost of meeting the performance standard is between $6,172 and $6,271 in 2004 dollars. Average per pupil revenue in 2004—which includes federal, state and local dollars—was $6,503.[17]

Summing up across enrollments for 2004 yields an estimate of total costs.[18] Our best estimate of the total cost of meeting the performance standard is between $26.2 billion and $26.6 billion. Total actual revenues were $27.6 billion.

A major reason for the difference between actual revenues and predicted cost is that many districts are outperforming the standard upon which the cost estimates are based. Therefore, it might be more appropriate to ask what increase in total funding is required to bring all districts up to the standard without reducing the spending of any district. We estimate that it would cost between $226 million and $408 million per year to bring the districts up to at least the passing standard on TAKS and at least the state average share of students taking advanced courses and scoring above criterion on the SAT/ACT.

Conclusions

The cost of producing education outcomes depends on district size, the cost of inputs (such as teacher salaries), and on the environment in which education outcomes are being produced. More difficult environments (such as higher proportions of special education students or higher proportions of students in poverty) lead to higher costs of achieving any given level of student performance. The cost at which a school district can achieve a specified level of student performance thus depends on the performance level itself, but also on the wages of district teachers and other personnel, the characteristics of students and their parents, district size and remoteness. Many of these factors are largely, or even totally, beyond a district's direct control, and thus are factors to consider in determining the cost a district will face in achieving specific outcome targets.

The cost function we estimate suggests that there are significant cost differentials associated with student need. After adjusting for inflation, we estimate that, for an economically disadvantaged student, the estimated cost differential is $1,960 (in 2004 dollars). Thus, it costs $1,960 more to educate an economically disadvantaged students than to educate a student who is not economically disadvantaged, and average predicted cost must be adjusted upward for districts with above-average shares of economically disadvantaged students and adjusted downwards for districts with below-average shares of such students. For a limited English proficient student, the estimated cost differential is $1,248 (in 2004 dollars). For a special education student with relatively less severe challenges, the estimated cost differential is $3,695 and for a special education student with relatively more severe challenges, the estimated cost differential is $5,306 (both in 2004 dollars). Finally, we estimate that for a high school student, the estimated cost differential is $4,001 (in 2004 dollars).[19]

All of the above estimates have considerable uncertainty attached to the precise value of the estimated cost, as detailed in the text. Further there are reasons to believe that there is additional unquantified uncertainty due to what is called model uncertainty, the uncertainty that accompanies use of a model that, by definition, can only approximate reality.

Our estimated cost function allows us to calculate the aggregate cost of meeting performance standards. Presuming that no cut in funding for any district, we estimate that it would cost between $226 million and $408 million more per year to meet the average performance standard required to comply with the No Child Left Behind Act and to bring up to the state average the share of students taking advanced courses and scoring above criterion on the SAT/ACT.

It is important to realize that predicted cost of achieving various education performance targets based on the estimated cost function is strictly valid only when the institutional structure and incentives that held over the period for which the cost function was estimated continue to hold over the prediction period. Changes in the institutional structure (including changes in the measuring rod of performance, such as changing to the TAKS test) make prediction, a task that intrinsically involves uncertainty, even less certain. Further, changes in the incentive structure facing school district personnel such as administrators and teachers may well alter the cost of achieving a given set of performance standards. In fact, it may well be that the most cost-effective way of achieving higher student performance targets is to alter the incentive world facing administrators and teachers instead of simply expending additional resources within the extant incentive environment. Such an inference is, however, beyond the scope of cost function estimation, a methodology that does not provide specific insights into how districts should organize their resources to produce outcomes effectively and efficiently.

Figure 1 Estimated Scale Factor vs. Enrollment

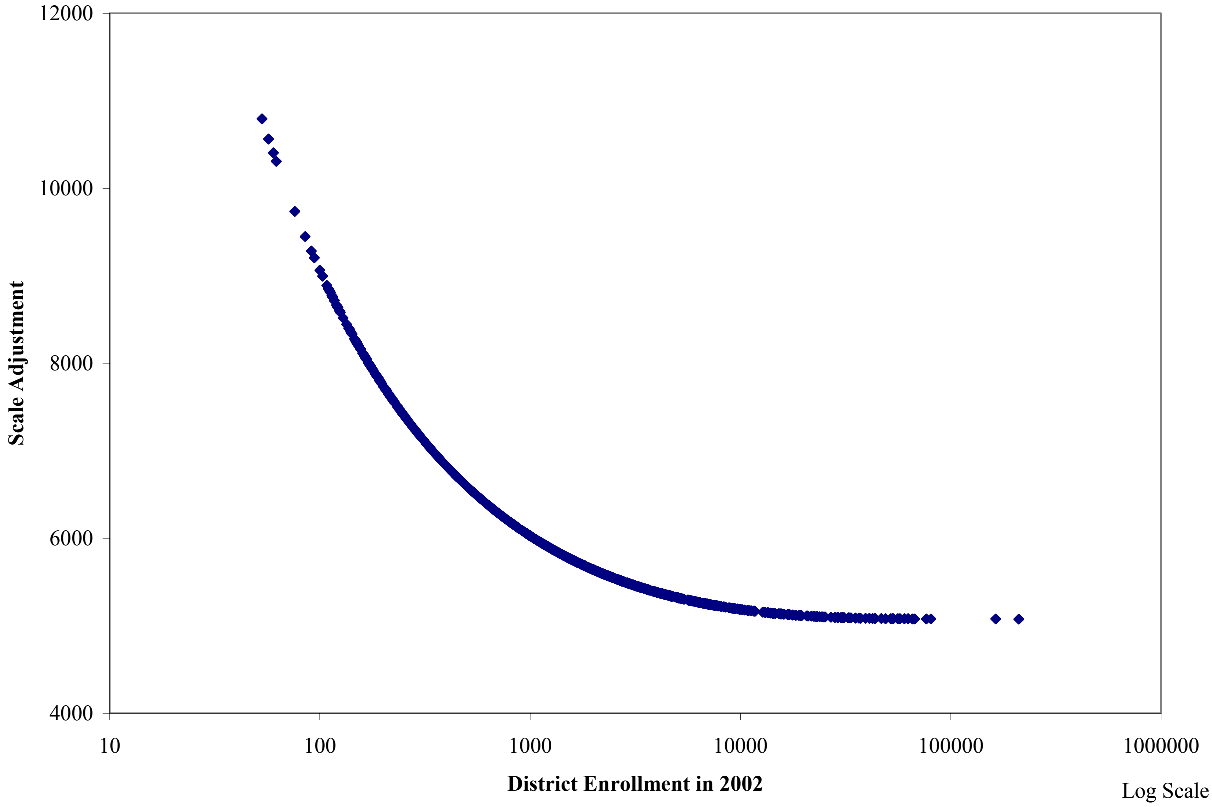

Figure 2 Efficiency Distribution

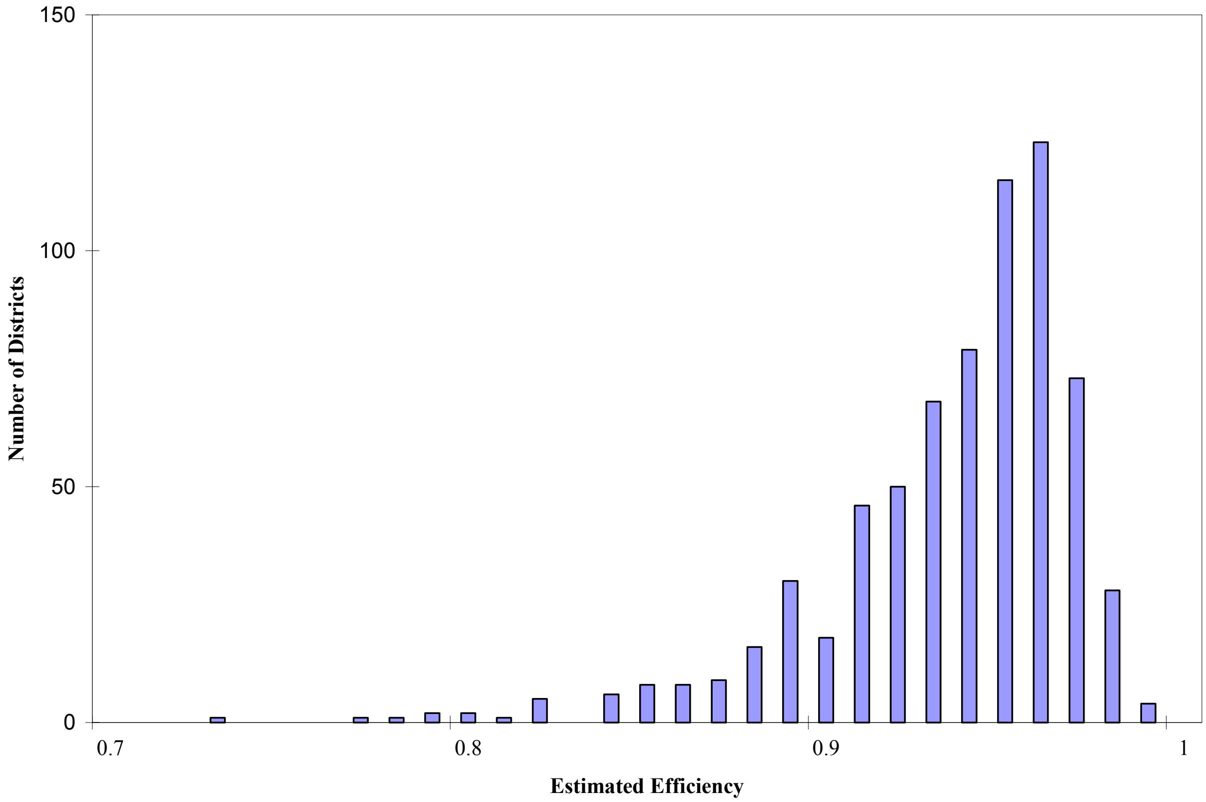

Figure 3 Efficiency vs. Enrollment

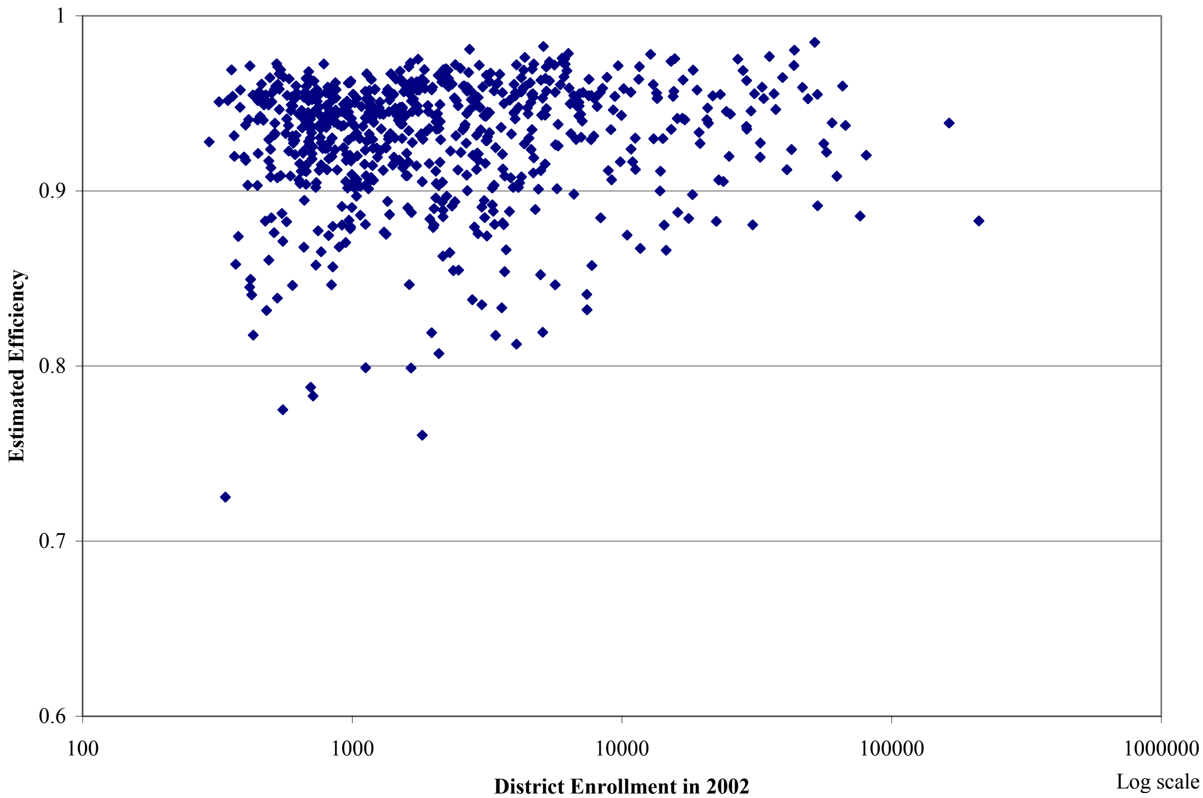

Figure 4 Distribution of ECI

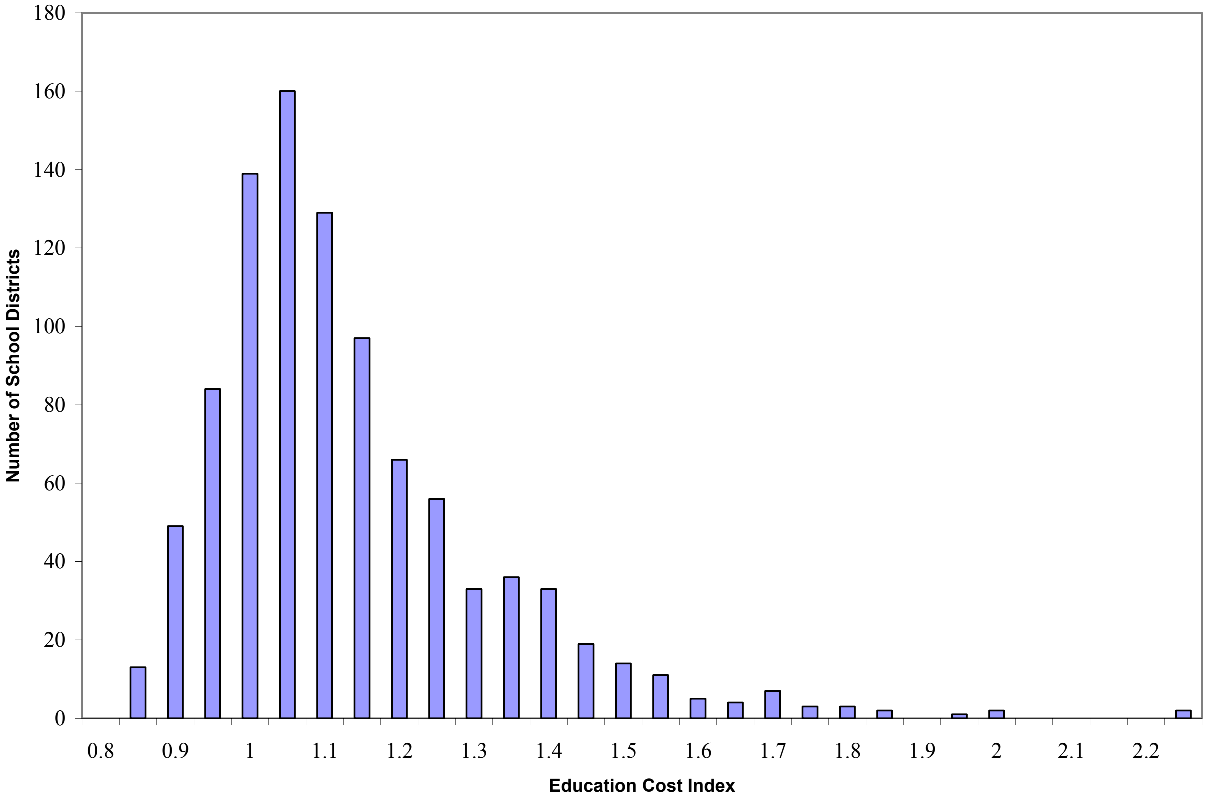

Figure 5 ECI vs. Enrollment

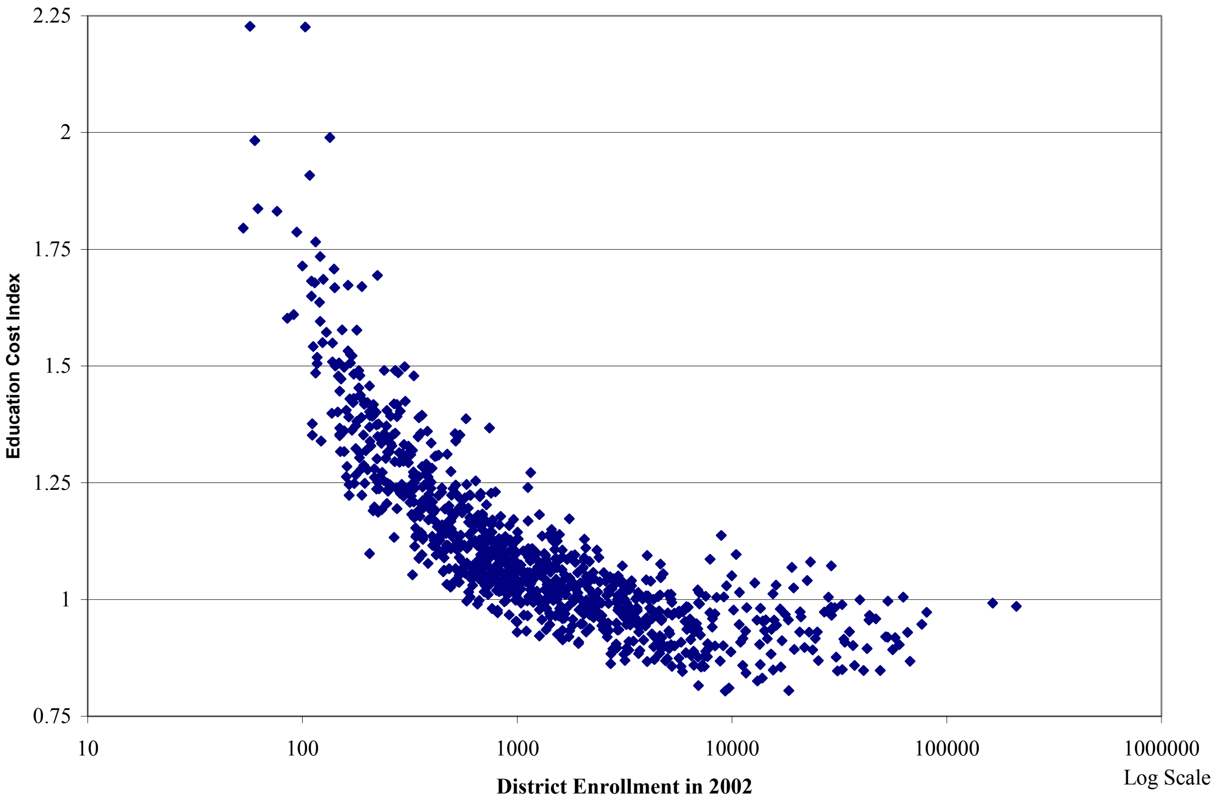

Table 1 Summary of Outcome Measures

	5-8th and 10th grade TAAS math and reading passing rate change	Percent completing at least one advanced course	Percent of graduates above criterion on SAT/ACT
Average	2.85	17.6	13.4
Standard Deviation	2.00	6.5	7.4
Minimum	-2.07	0.9	0.0
25th Percentile	1.60	13.4	8.4
Median	2.56	16.9	12.4
75th Percentile	3.73	20.5	17.0
Maximum	14.20	60.70	50.6

Table 2 Averages for Variables in Cost Model (for the 695 districts in the estimation)

	Monthly New Teacher Salaries	Monthly Auxiliary Worker Salary	Average Enrollment	Free Lunch Percent	LEP Percent	Special Ed (less severe) Percent	Special Ed (more severe) Percent	Percent in High School
Average	$2,838	$1,410	5,723	39.5%	8.8%	10.5%	3.2%	29.3%
Standard Deviation	$310	$165	14,197	16.9%	11.0%	2.9%	1.4%	2.8%
Minimum	$2,424	$1,089	295	0%	0%	4.0%	0.7%	19.9%
25th Percentile	$2,590	$1,293	837	27.5%	2.2%	8.4%	2.4%	27.6%
Median	$2,737	$1,391	1,635	39.1%	5.3%	10.3%	3.1%	29.3%
75th Percentile	$3,045	$1,499	4,248	50.8%	11.1%	12.3%	3.8%	31.0%
Maximum	$3,698	$2,136	210,670	91.6%	70.3%	23.9%	19.2%	43.3%

Table 3 Summary Statistics of Estimated Efficiency Measure

Summary Statistics	All districts	Urban districts	Rural districts	Districts under 1600 ADA	Districts 1600-5000 ADA	Districts over 5000 ADA
Mean efficiency	93.0	93.3	92.7	92.8	92.7	93.8
Standard deviation	3.6	3.4	3.7	3.4	3.9	3.2
Maximum	98.5	98.5	97.8	97.3	98.1	98.5
Minimum	72.5	78.3	72.5	72.5	76.1	81.9
Number of districts	694	358	336	338	205	151
Percentiles						
10%	88.3	88.5	88.0	88.2	87.9	88.8
25%	91.4	91.7	91.2	91.6	90.5	92.4
50%	93.9	94.3	93.7	93.8	93.6	94.6
75%	95.5	95.6	95.2	95.1	95.8	95.9
90%	96.4	96.6	96.2	95.8	96.6	97.2

Table 4 Characteristics of High and Low Efficiency Districts

	10% of Districts with Lowest Efficiency		10% of Districts with Highest Efficiency	
Variable	**Mean**	**% of State Average**	**Mean**	**% of State Average**
Expenditures per pupil	$7783	124.4%	$5348	85.5%
New teacher wage	$2814	99.1%	$2930	103.2%
District enrollment	3329	58.2%	7635	133.4%
Percent free lunch	38.9%	98.4%	38.9%	98.4%
Percent LEP	9.0%	101.3%	10.5%	118.8%
Percent Special Ed. (less severe)	10.6%	100.6%	9.7%	92.3%
Percent Special Ed. (more severe)	2.9%	90.5%	3.3%	103.9%
Percent High School	29.1%	99.3%	28.8%	98.4%
Miles to major metro	116	120.1%	92	94.9%
Proposed CFI	1.05	101.2%	1.01	97.1%
Efficiency	85.1	88.3%	97.0	104.3%

Table 5 The Differential Costs Associated with Student Need

Student Characteristic	Differential Cost (in $2002)	
	Estimate	Confidence Interval
Free Lunch	$1,825	$1,573 - $2,077
Limited English Proficiency	$1,162	$616 - $1,707
Special Ed (less severe)	$3,441	$2,414 - $4,468
Special Ed (more severe)	$4,941	$2,446 - $7,433
High School	$3,726	$2,717 - $4,736

Table 6 Summary Statistics of Cost Function-based ECI

Summary Statistics	All districts	Urban districts	Rural districts	Districts under 1600 ADA	Districts 1600-5000 ADA	Districts over 5000 ADA
Mean ECI	1.11	1.01	1.18	1.20	0.99	0.94
Standard deviation	0.19	0.12	0.19	0.19	0.06	0.06
Maximum	2.23	1.98	2.23	2.23	1.17	1.14
Minimum	0.80	0.80	0.88	0.92	0.86	0.80
Number of districts	968	401	567	607	207	154
Percentiles						
10%	0.92	0.88	0.99	1.02	0.91	0.86
25%	0.98	0.93	1.04	1.07	0.95	0.89
50%	1.06	0.99	1.13	1.14	0.98	0.94
75%	1.19	1.06	1.28	1.28	1.03	0.98
90%	1.36	1.13	1.42	1.42	1.06	1.01

Table 7 Characteristics of High and Low ECI Districts

	10% of Districts with Highest ECI		10% of Districts with Lowest ECI	
Variable	**Mean**	**Percent of State Average**	**Mean**	**Percent of State Average**
Expenditures per pupil	$8,990	133.9%	$5,730	85.3%
New teacher wage	$2,609	93.7%	$3,177	114.1%
District enrollment	186	4.4%	13,871	328.9%
Percent free lunch	50.5%	125.9%	17.8%	44.4%
Percent LEP	6.9%	86.6%	8.2%	103.0%
Percent Special Ed (less severe)	13.6%	123.0%	7.9%	99.4%
Percent Special Ed (more severe)	3.7%	117.2%	3.2%	103.0%
Percent High School	34.7%	115.7%	28.6%	95.3%
Miles to major metro	153	141.5%	54	50.0%
Proposed ECI	1.53	137.5%	88.4	79.6%

Notes

[1] William D. Duncombe and John M. Yinger, "Performance Standards and Educational Cost Indexes: You Can't Have One Without the Other," in Equity and Adequacy in Education Finance, Helen F. Lad, Rosemary Chalk, and Janet S. Hansen, Editors: National Academy Press, Washington, D.C. 1999, pp. 260-97.

2. For a review of the literature on adequacy studies, see "Measuring Educational Adequacy in Public Schools" by Bruce D. Baker, Lori L. Taylor and Arnold Vedlitz.

[3] William Duncombe, "Estimating the Cost of an Adequate Education in New York", Center for Policy Research Working Paper, No. 44, Center for Policy Research, Maxwell School of Citizenship and Public Affairs, Syracuse University, February 2002. We have drawn insights from this paper which we utilize throughout our report.

[4] A position also strongly argued by Duncombe, ibid.

[5] Stochastic frontier estimation modifies the traditional assumption about the error term by assuming it has two parts, a standard two-sided term to capture random unmodeled differences across districts and a one-sided term to capture inefficiencies measured by distance (in dollars) to the cost frontier. Estimation of the stochastic frontier version is more complicated than simple ordinary least squares but is easily implemented using any of a number of standard econometric statistical programs, such as STATA.

[6]James Coleman, and others, Equality of Educational Opportunity, U.S. Department of Health, Education, and Welfare, Office of Education, 1966.

7. It is most common in the literature to use a measure based on standardized test scores, but dropout rates, honors program enrollment rates, college enrollment rates, and labor market experiences have all been used in one form or another.

8. Regression-based value-added models have been developed, which attempt to control for the contributions of non-school factors on the growth in student achievement. In addition to standard statistical issues surrounding such regressions, there exists an appropriate concern about the transparency of such performance measures to relevant parties such as school administrators, families, and education policy setters.

9. Our value-added student performance measures are the percentage of students scoring above criterion on the combined math and reading test. In our study, we will actually use the Texas Learning Index or TLI scores, a transformation of TAAS scores normalized to a reference

population with 70 as the passing rate. The passing rate is a threshold measure, and only changes in scores across the threshold affect movements in the passing rate. The use of the passing rate as the outcomes measure creates incentives to focus resources on students who score around the passing rate cutoff score. This resource focus could come at the expense of consistently highest achieving and consistently lowest achieving students.

[10] Thomas J. Kane and Douglas O. Staiger, “Improving School Accountability Measures,” NBER Working Paper No. 8156, March, 2001; Thomas J. Kane and Douglas O. Staiger, “Volatility in School Test Scores: Implications for Test-Based Accountability Systems,” in Brookings Papers on Education Policy, 2002. Diane Ravitch, ed. Washington, D.C.: Brookings Institution, pp. 235-83; and Thomas J. Kane and Douglas O. Staiger, “The Promise and Pitfalls of Using Imprecise School Accountability Measures,” Journal of Economic Perspectives, Fall, 2002, pp. 91-114.

[11] See http://www.tea.state.tx.us/perfreport/aeis/2003/glossary.html#appendc for a list of advanced courses.

[12] To be precise, we use the wage level estimates upon which the indexes are based.

[13] Note that we used the stricter definition of eligibility for free lunch rather than free or reduced lunch.

14. We employ a modified translog cost function with multiple output measures (number of students educated plus measures of output quality), one or more input prices, and a multitude of environmental factors or quasi-fixed factors of production. The main modification is that we did not transform variables measured as percentages by taking natural logarithms, but instead entered these variables as percentage terms directly in the estimated cost function. A primary advantage of the translog is its flexibility. The primary disadvantage is its increased complexity in evaluating marginal effects, and the statistical concerns with multi-collinearity and over-parameterization due to the presence of many interaction terms involving the explanatory cost factors.

[15] The elasticity is calculated as an arc elasticity, i.e. from the midpoint of the range.

[16] We use the US employment cost index as the inflation rate. The employment cost index was used to make inflation adjustments prior to the estimation of the cost function. The ECI indicates that employment costs increased 7.4 percent between fourth quarter 2001 and fourth-quarter 2003. The consumer price indexes for both Dallas and Houston show much lower estimates of inflation.

[17] These estimates come from preliminary budgeted figures reported to TEA. Only districts that reported budget data to TEA are included in this estimate. Also, because actual federal revenues

are not yet available, the revenue estimate presumes no increase in federal funding between 2003 and 2004.

[18] Some districts are not included in this total. For example, districts that did not provide TEA with budget data are excluded, as are districts for which we lacked the data necessary to generate cost index values. Over 99 percent of Texas enrollment is included.

[19] While such a figure may seem high, recall that the cost differential reflects not only the incremental resource needs of high school students, but also the cost of keeping such students in school while holding high school outcomes unchanged.