The Bush School of Government & Public Service
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Is a Low Instructional Share an Indicator of School Inefficiency? Exploring the 65-Percent Solution

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Abstract

Policymakers throughout the nation are searching for policies that could increase school efficiency. One policy initiative that has at least superficial appeal is the so-called 65-percent solution–an administrative rule requiring that schools spend at least 65 percent of their budgets on instruction. Advocates argue that the 65-percent solution is needed because too few resources reach the classroom. Teachers' unions, parent-teacher organizations and other educator groups are nearly unanimous in their opposition.

This analysis uses data on students, staff and spending to estimate the relative efficiency of Texas public schools. The authors find no evidence that Texas public schools are administratively top-heavy. Instead, the analysis suggests that schools that spend a larger share of their budgets on instruction are significantly less efficient than other public schools.

Introduction

The No Child Left Behind Act of 2001 (NCLB) has had an enormous impact on the U.S. education system. NCLB requires all states to develop and administer student exams in math, reading, science and any other subjects the state deems appropriate. Importantly, states are required to publish the results at the state, district and school levels.[1] At all levels, the states must provide separate information on the performance of low-income students, minority students, special education students and students with limited English proficiency.

The flood of new data on student performance has revealed a profound disconnect between educational outlays and student performance, and has led parents and taxpayers to agitate for substantial improvements in school effectiveness. Meanwhile, states and school districts are facing severe financial penalties if they fail to make progress toward student proficiency. Under NCLB, the federal government can withhold Title 1 funding from school districts where students fail to make adequate yearly progress for three consecutive years. Facing voter pressure on the one hand, federal pressure on the other, and budgets that are still recovering from the fiscal crisis of 2003 (Braunstein 2004), state and local policymakers throughout the nation are scrambling to implement policy changes that will increase school efficiency.

One policy initiative that has at least superficial appeal is the so-called 65-percent solution. At the simplest, the 65-percent solution is an administrative rule requiring that schools spend at least 65 percent of their budgets on instruction. For example, Governor Rick Perry of Texas recently issued an executive order requiring that all Texas school districts spend at least 65 percent of their funds on instruction. Legislatures in three other states (Louisiana, Kansas and Georgia) have proposed similar rules, and advocacy groups are pushing for adoption of the 65-percent solution in at least 6 more states.

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[1] Science exams will become part of the report cards required by NCLB starting with the 2007-08 school year.

Advocates for the 65-percent solution argue that the policy is needed because too few resources reach the classroom. According to the Nation Center for Education Statistics (NCES) U.S. school districts devote just over 61 percent of their current operating expenditures to instruction, on average. Fans of the 65-percent solution interpret non-instructional expenditures as laden with bureaucratic overhead, and conclude that school districts with low instructional shares must be inefficient. By their reckoning, a policy that encouraged schools to shift resources toward instruction would increase school performance without any increase in overall spending.

Teachers' unions, parent-teacher organizations and other educator groups are nearly unanimous in their opposition to the 65-percent solution. Part of their opposition arises from dissatisfaction with the prevailing definition of instructional spending. The NCES defines instruction as "activities dealing directly with the interaction between teachers and students." (U.S. Department of Education 2003). By this definition, salaries and supplies for classroom teachers, instructional aides, band directors and football coaches are instruction expenditures, while salaries and supplies for counselors, librarians, curriculum specialists, nurses and other similar school personnel are not.[2] Educators deemed non-instructional are particularly vocal in their opposition to the proposal.[3]

Opponents also dislike the 65-percent solution because it does not increase the size of the educational pie. In the words of a state legislative policy specialist for the National Education Association (the nation's largest teacher's union) "sixty-five percent of inadequate is still inadequate."[4]

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[2] Tuition expenses for students educated in another setting are also considered instructional spending by the NCES.

[3] For example, see Weiss (2006).

[4] "65 Percent Solution: Gimmick or Gold Mine?" (2007).

Finally, opponents argue that the 65-percent solution is not supported by research. The only independent research cited by either side is a 2005 report by Standard and Poor's. The S&P report examines the relationship between instructional shares and student proficiency rates, and concludes that school districts with higher instructional shares are no more likely than other school districts to have high levels of student performance. (S&P 2005).

A lack of correlation between instructional shares and proficiency rates is not strong evidence against the 65-percent solution, however. Education researchers have long recognized that students from advantaged backgrounds can score well on standardized tests despite ineffective schools, while students from disadvantaged backgrounds can score poorly even when the schools are highly effective. Any analysis of student performance that does not control for student characteristics has questionable validity. The S&P analysis incorporates no such controls.

Furthermore, even if instructional shares are correlated with a theoretically sound measure of student performance, that does not necessarily imply that schools should increase the share of resources allocated to instruction. Identifying the efficient mix of instructional and non-instructional resources for any given school requires specifying the efficient resource allocation in the production of student outcomes, and then evaluating the school relative to that benchmark.

In this paper, we explore two inter-related questions. First, are the philosophical underpinnings of the 65-percent solution sound? Are schools systematically allocating too few resources to the classroom? And second, is the share of expenditures devoted to instruction a good indicator of school efficiency? Can the 65-percent solution improve public schools?

We use data on students, staff and spending to estimate the relative efficiency of Texas public schools. We find no evidence that Texas public schools are administratively top-heavy, and no evidence that increasing the share of the educational budget devoted to instruction would increase the efficiency of the public school system. Instead, our analysis suggests that schools that spend a larger share of their budgets on instruction are generally less efficient than other public schools.

Texas Public Schools

The Texas public school system is particularly well suited to an analysis of the relationship between instructional shares and school efficiency. There are nearly 8,000 public schools in Texas serving more than 4 million students each year. The state's long-established accountability system provides annual, student level data on student performance in grades three through eleven, making it possible to generate reliable measures of school output. The personnel and financial accounting systems support high quality estimates of educational inputs, prices and instructional shares.

Texas also is a state with a thriving charter school movement. (Since the first Texas charter school opened its doors in 1997, more than 300,000 students have attended charter schools in Texas.) Charter schools are publically supported schools that compete for enrollments with traditional public schools, but must comply with fewer rules and restrictions. As such, charter schools have stronger incentives to behave efficiently than do traditional public schools, and may have greater ability to behave efficiently. Including charter schools greatly enhances any analysis of public school efficiency because it allows researchers to examine both regulated and deregulated educational environments.

Finally, Texas is a state that has implemented the 65-percent solution. The Texas Education Agency (TEA) has incorporated two indicators of instructional share into its Financial Integrity Rating System of Texas (School FIRST). School FIRST is Texas' primary tool for managerial accountability among school districts. Each year, TEA assigns School FIRST ratings–which range from Substandard to Superior Achievement– to each school district based on an array of fiscal indicators.[5] Upon receipt of their final ratings, school districts must hold public meetings wherein they explain their ratings and their performance on each of the component indicators. In addition, the Commissioner of Education may apply unspecified sanctions to school districts that are assigned a Substandard rating.

One School FIRST indicator is a measure of instructional share that is based on the NCES definition. This indicator will be phased in over three years starting in 2007-08. After it is fully phased in, districts must spend at least 65 percent of their current operating expenditures on instruction, extracurricular activities or tuition payments to alternative schools. Another School FIRST indicator broadens the NCES definition to include librarians, nurses and counselors. Starting with the 2007-08 school year, districts must spend at least 65 percent of their current operating expenditures on instruction, broadly defined. School districts that fail to meet these indicators will find it very difficult–but not impossible–to meet the standards for Superior Achievement under the FIRST system.[6]

Measuring School Efficiency

Following Grosskopf et al. (2001), we use an input distance function to model school production and generate measures of school inefficiency. The input distance function is a dual to the cost function that requires data on input quantities rather than input prices, and is preferable to the cost function in cross-sectional settings where prices do not vary (such as when making comparisons across schools within a single labor market).

The input distance function can be most easily understood by examining figures 1 and 2. Assume that schools use two variable inputs to produce an array of educational outputs (y). In

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[5] In 2005-06, 91.2 percent of Texas school districts were rated Superior while 6.1 percent were rated Above Standard, 0.3 percent were rated Standard and 2.2 percent were rated Substandard (TEA 2007).

[6] Districts that publish their check register (excluding the payroll register) and their yearly payroll expenditures on the web will be considered in full compliance with these indicators.

figure 1, L(y) represents all of the efficient combinations of x_1 and x_2 that can produce y. At point K, a school district that is producing y is using too much of both inputs. A proportional reduction in input usage to K' would represent efficient usage levels. The value of the input distance function is OK/OK'. We measure the technical efficiency of school s (τ_s) as OK'/OK.[7] If $\tau_s = 1$, the school is technically efficient. If $\tau_s < 1$ then the school is technically inefficient. The smaller the level of τ_s, the greater the inefficiency.

In addition to technical inefficiency, the input distance function also allows us to estimate allocative inefficiency. The slope of L(y) at point K' represents the relative marginal product, or equivalently the relative shadow price, of the two inputs. The partial derivatives of the input distance function with respect to the inputs provides estimates of those shadow prices.[8] The slope of w*w* in figure 2 represents those relative shadow prices at point K'. A school is allocatively efficient (choosing the right mix of inputs) when the slope of L(y) –i.e. the slope of w*w* in figure 2–equals the slope of the school's actual budget constraint (which is the observed relative price of the two inputs, or the slope of w'w' in figure 2). We define κ_s as the degree to which the shadow relative prices match the observed relative prices for school s.

$$\kappa_s = \frac{\acute{w}_1 \;/\acute{w}2}{w*_1 \;/w*_2}. \tag{1}$$

If $\kappa_s = 1$ then the school is allocatively efficient. When $\kappa_s > 1$ then the marginal product per dollar paid for input 2 (w_2'/w_2*) is greater than the marginal product per dollar for input 1 (w_1'/w_1*) and input 1 is overutilized relative to input 2, given the observed relative prices. On the other hand, if $\kappa < 1$, then the marginal product per dollar for input 1 is greater than the marginal product per dollar for input 2, and input 1 is underutilized.

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[7] The reciprocal of the value of the input distance function is the Farrell (1957) input-reducing measure of technical efficiency.

[8] See Grosskopf et al. (2001).

Data and Model Specification

Analysis using the input distance function requires information on the quantity of school outputs, the quantity of school inputs and the relative prices of those inputs. Data for this analysis come from the Texas Education Agency (TEA) and Texas State Board for Educator Certification (SBEC). This analysis focuses on urban, public schools in Texas during the 2004-05 school year. Because our measures of school output–value added in mathematics and reading–come from student test scores in grades 4 through 11, only schools that served those grades are included in the analysis.[9] Complete data were available for 4,322 urban public schools fitting this description.

Output Measures

As part of its school accountability system, Texas administers annual examinations in reading and mathematics. Starting in 2003, students in grades 3 through 11 have taken the Texas Assessment of Knowledge and Skills (or TAKS) test. After the initial transition year (2003) TAKS scores have been used to identify high and low performing schools under the state's accountability system, and for NCLB purposes. Nearly 2 million Texas students took the TAKS in 2004 and again in 2005.

We measure school value added as the marginal effect of the school on student test scores, holding constant the observable characteristics of the students. Following Hanushek et al. (2007), we model the performance of student i in 2005 (year t) as a function of student performance in 2004 (year t-1), student characteristics, school effects, and district effects.

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[9] In the interests of student privacy, TEA censored the data it provided on small schools. Because charter schools tend to be smaller than traditional public schools, this censoring greatly limited the number of charter schools and small traditional schools for which we were able to generate output measures. In addition, we excluded as an outlier one school that served more than 35 percent special education students. The average Texas urban school serves 12 percent special education students.

$$y_{it} = y_{it-1}\beta + x_{it}\gamma_t + \sum_s \delta_{st} S_{ist} + \sum_d \gamma_{dt} D_{idt} + \varepsilon_{it} \qquad (2)$$

where y_{it} is the performance of student i in year t, $\mathbf{x}_{it}$ is a vector of student characteristics, S_{ist} is an indicator variable that equals one if student *i* attended school *s* in year *t* and is zero otherwise, and D_{idt} is an indicator variable that equals one if student *i* attended district *d* in year *t* and is zero otherwise. To ensure comparability across grade levels, both the test scores and the pre-test scores are standardized, and expressed as z-scores for the grade level and subject area. The student characteristics used in the analysis are indicator variables for grade level, and indicators for whether or not the student is limited English proficient, is in the school lunch program, is in special education, or has changed schooles since the previous test. In addition, the analysis includes interaction terms which allow the five student characteristics—PRETEST, LEP, SPECIAL, LOWSES and NEWCAMPUS—to vary across grade levels. Models for value added in mathematics and reading were estimated separately using data on 1.95 million students. Appendix table A1 presents the regression results.

The least-squares mean (or population marginal mean) for each school fixed effect is the predicted value of equation (2) holding all covariates at their means and assuming that schools are nested within their corresponding school districts. We measure average value added per pupil in reading and mathematics as the least-squares mean for each school fixed effect (i.e. the predicted z-score) plus the population mean test score.[10]

Because the efficiency analysis is based on total rather than per pupil output, we further transform these value-added measures into total output measures by multiplying each by school enrollment. In so doing, we implicitly assume that value added in the tested grades is

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[10] Schools where either output measure was based on fewer than 10 student-level observations are excluded from the efficiency analysis.

representative of the value added in the nontested grades. Table 1 presents descriptive statistics on the per-pupil and total output measures for the schools included in the efficiency analysis.

Input Measures

As in Grosskopf et al. (2001, 1997), labor is the only variable input in our analysis. We focus on two types of labor—instructional and non-instructional personnel. Our measure of instructional labor input is a weighted sum of the full-time-equivalent number of teachers and teacher aides employed in the school, where the weights are the relative predicted wages for the two groups (see below).[11] Thus, if salary models predict that teacher aides are paid half the salary of teachers in a school district, then each teacher aide in that school district is counted as one half of a teacher. Our measure of non-instructional labor input is a similarly weighted sum of the full-time-equivalent numbers of administrative, support and auxiliary personnel.[12] School district personnel who are not assigned to a specific school (e.g. central administrators or substitute teachers) are allocated to the schools on a per pupil basis. Thus, if a school contains one third of the students in the district it is also assigned one third of the unallocated personnel. Schools that use contract labor for instruction rather than employees have been excluded to ensure that our measure of instructional labor captures all labor inputs.

Ideally, we would like to have a direct measure of school capital as well as school labor. Unfortunately, there are no data on school capital stocks. However, non-labor, current expenditures should be a reasonable proxy for capital stocks. As do other researchers (e.g. Imazeki and Reschovsky, 2004), we exclude non-payroll expenditures for food and

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[11] Ideally, we would like to adjust the teaching personnel quantities for variations in quality. However, Hanushek (1986) has demonstrated that observable teacher characteristics like salary, experience and educational background do not indicate classroom effectiveness. Lacking a reliable indicator of quality, we treat teachers as homogeneous.

[12] Support personnel include supervisors, counselors, librarians, nurses, physicians and special service personnel. Auxiliary personnel are nonprofessional school personnel such as clerical, cafeteria and maintenance workers.

transportation from the current expenditures of each school when making this calculation. Any district expenditures in this category that are not allocated to specific schools are distributed among the schools on a per-pupil basis. We treat this measure of school capital stocks as a quasi-fixed input in our analysis.

Finally, the students themselves are inputs into the educational process. Therefore we also include the number of elementary and secondary students in each school as inputs that are outside of school control, at least in the short run.

Input prices

Estimating allocative efficiency involves comparing shadow relative prices with observed relative prices. Therefore, it is crucial to have reliable estimates of the relative price of instructional and non-instructional labor. Grosskopf et al. (2001) used average wages by labor market as the prices. However, subsequent research suggests that there can be both considerable variation in worker characteristics across labor markets, and considerable variation in predicted wages across school districts within labor markets (e.g. Taylor 2004, 2005, forthcoming). Therefore, we base our measures of relative wages on five labor cost models, one for each type of school employee (teachers, teacher aides, administrators, support staff, and auxiliaries).

The labor cost models are estimated from five-year panels of individual payroll records for everyone working in an urban public school in Texas.[13] The five-year panels cover the period from the 2000-2001 school year through the 2004-2005 school year.

The modeling strategy follows Taylor (2005). Full-time-equivalent monthly wages (in logs) are a function of labor market characteristics, worker characteristics and job characteristics. Fixed effects for metropolitan areas capture labor market characteristics, and individual fixed effects capture unobservable differences across workers. Time-varying worker characteristics

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[13] Incomplete and inconsistent records (such as records that indicate that full-time equivalent employees were paid less than the federal minimum wage) were excluded from the analysis.

such as years of experience, educational attainment, effective days worked (percent day times number of days employed) and tenure are included in all models. In addition, the teacher model includes indicators for teaching assignments (math, science, health and P.E., computer, special education, and secondary school) and for the percentage of time each individual spends teaching in a field for which he or she holds a Texas state teaching certificate, while the administrator and support staff models include indicators for occupation (principal, assistant principal, nurse, etcetera). To control for district-specific compensating differentials, all of the models also include student demographics (the percentage of students who are economically disadvantaged, limited English proficient, and Anglo), school district size (the log of enrollment, log of enrollment squared, and indicator variables for the Dallas and Houston Independent School Districts),[14] the average distance in miles from the center of the closest metropolitan area, and an indicator for whether or not the district is a charter school district. Appendix table A2 presents the labor models for instructional personnel; appendix table A3 presents the models for non-instructional personnel.

For each school district, the labor models generate predicted monthly salaries for each of the five types, holding worker characteristics constant at the statewide mean for that type. We interpret those salary predictions as the prices for those types of labor. Thus, the price of teachers in Spring Independent School District (ISD) is the monthly salary that Spring ISD would be expected to pay in 2004-2005 to a teacher with state average demographics.

The salary predictions are used to generate weights for aggregating the five worker categories into instructional and non-instructional personnel. For example, the average predicted salary for teachers is $4,195 per month while the average predicted salary for teacher aides is $1,653. Therefore, when calculating the number of full-time-equivalent instructional personnel, teacher aides represent 39 percent of a teacher on average (1,653/4,195). Across districts,

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[14] The Dallas and Houston Independent School Districts (ISDs) are notable outliers with 2004 enrollments of 160,000 and 211,000 students, respectively. The Dallas ISD is twice as large as the next largest school district in the state.

teacher aides represent as much as 63 percent and as little as 29 percent of a teacher. Similar calculations indicate that support staff represent 73 percent of an administrator while auxiliaries represent 33 percent of an administrator, on average.

Importantly, the relative price of non-instructional personnel is also used in calculating allocative efficiency. The relative price of non-instructional personnel is the ratio of predicted administrator wages to predicted teacher wages. The average administrator is paid 37 percent more per month than the average teacher so, on average, the relative price of non-instructional personnel is 1.37. It ranges from a low of 1.14 to a high of 1.54. Table 1 provides descriptive statistics on this variable as well.

Instructional Shares

Following the FIRST accountability standards, we define a school's NCES instructional share as spending on instruction, extracurricular activities and tuition payments divided by current operating expenditures. Similarly, we define a school's TEA instructional share as spending on NCES instruction plus instructional resources and media, guidance counseling and health services, again divided by current operating expenditures. Finally, because including extracurricular activities in the definition of instruction has raised eyebrows, we also construct a baseline instructional share indicator, which excludes extracurricular expenditures from the NCES definition.

Most school district expenditures are attributed by the districts to the specific schools within those districts. However, some districts have a large share of unallocated expenses. Most unallocated expenses are non-instructional costs (such as central administration expenditures), but some unallocated expenses (such as expenditures for substitute teachers) are instructional in nature. We distribute unallocated instructional and non-instructional expenditures to the schools in a district on a per student basis. Thus, if a school has 15 percent of the students in the district, we assign 15 percent of the unallocated spending (by category) to that school.

We find a wide variation in the share of resources devoted to instruction.[15] Using the narrowest definition of instructional share, schools at the 5th percentile allocate only 51 percent of current operating expenditures to instruction while schools at the 95th percentile allocate 64 percent. Intriguingly, charter schools spend a significantly lower share of their budgets on instruction. On average, charter schools in Texas spend 51 percent of their budgets on instruction while traditional public schools spend 58 percent. (The difference in means is significant at the 1 percent level.)

Most urban Texas schools spend only a small fraction of their budgets on extracurricular activities. Therefore, broadening the definition of instruction to include those activities increases the budget shares only slightly. Using the NCES definition of instruction, we find that charter schools spend 52 percent of their budgets on instruction while traditional public schools spend a significantly higher 60 percent.

Further broadening the definition of instruction to include librarians, counselors and nurses has a greater impact on estimates of the budget share devoted to instruction. By this measure, the average charter school spends 55 percent of its budget on instruction while the average traditional public school spends 66 percent. Again, the difference between the two types of schools is highly significant.

Previous researchers have concluded that there is no relationship between instructional shares and student performance (Standard & Poors 2005). In contrast, we find a statistically significant relationship between student performance and instructional shares, once student demographics are taken into account. Our measures of value added in math and reading are significantly and positively correlated with instructional shares, no matter how broad the definition (Table 2).

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[15] We exclude from the analysis schools with operating expenditures less than $3,000 per pupil or more than $34,000 per pupil.

Estimation

The translog cost function has a long history of use in estimating cost functions because of its flexibility and ability to nest various hypotheses within its structure. In this analysis we estimate a translog form for the input distance function. All of the independent variables are transformed into logs and then interacted with all of the other independent variables under analysis. There are two discretionary inputs (instructional personnel and non-instructional personnel), three non-discretionary inputs (non-labor expenditures, the number of elementary grade students and the number of secondary grade students)[16] and two outputs (mathematics output and reading output).[17] The dependent variable is the log of the input distance function, which by definition is set equal to zero.[18]

One advantage of the translog specification is that by Shephard's lemma the first derivative of the input distance function with respect to (the log of) instructional personnel equals the instructors' share of payroll expenditures. By estimating the distance function and the share equation together in a system of simultaneous equations we can improve the efficiency of the estimated parameters. We use the observed input quantities and the predicted salaries of teachers and administrators ($P=w_2/w_1$) in each district to define instructional payroll shares ($S_1= x_1 / (x_1 + Px_2)$) for each observation. We then estimate a system of two equations–one for the input distance function and the other for the share equation–using restricted least squares.

By definition, the input distance function is bounded from below by one. However, the predicted values of the log of the distance function are distributed around zero. Therefore, we follow Grosskopf et al (2001) in adjusting the intercept term by adding the absolute value of the

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[16] When the number of students in a grade level is zero, we re-code so that the log is zero.

[17] We impose homogeneity in the discretionary inputs as required by the definition of the input distance function. In addition, we also impose symmetry (e.g. $\beta_{12}=\beta_{21}$).

[18] While an equation with a constant dependent variable appears not to be estimable, it can be estimated by first imposing homogeneity restrictions and then using restricted least squares estimation. See Grosskopf et al. (2001) for details.

most negative residual. The scaling yields estimated values of the log of the distance function that are greater than or equal to zero, and estimated values for the input distance function that are greater than or equal to one. While all school districts are likely to exhibit at least some inefficiency relative to the true but unobserved technology, our method assigns one school district to be technically efficient in the best-practice sense. As mentioned above, inverting the value of the input distance function for each observation yields our measure of Farrell technical inefficiency, τ_s. Values of τ_s range from zero to one, with a value of one indicating that the school is technically efficient (in the sense that the variable inputs cannot be proportionally reduced without reducing current output levels).

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

At this point we face two estimation problems. Our first problem arises because the outputs and relative prices are known to be measured with error. Therefore, traditionally calculated standard errors for the estimated equations would be incorrect. Second, statistical significance can not be determined for our efficiency measures because they represent transformations of the predicted values from the estimated system of equations.

We address these problems by bootstrapping the outputs and prices. As the least-squares means from the output equation, each output measure has an associated standard error. Each salary prediction also has an associated standard error. Therefore, we replicate the original data set 100 times. For each observation in each replicated data set, mathematics (reading) output per pupil is set equal to the school's point estimate for mathematics (reading) output per pupil, plus a random error drawn from a normal distribution with a standard deviation equal to the standard error of the school's point estimate. Similarly, each predicted salary is set equal to the school's point-estimate prediction, plus a random error drawn from a normal distribution with a standard deviation equal to the standard error of the school's point estimate for the salary. Because the variable inputs are weighted averages of the labor types, with the weights based on the salary predictions, the variable input quantities are recalculated for each replication. We then re-estimate the system of equations 100 times—once for each of the 100 data sets.[19]

Results

Each of the 100 replications generates an estimate of τ_s and κ_s for each of the 4,322 schools under analysis. Table 3 presents the distribution of school-specific means for these efficiency measures. We use these school-specific means in all further analyses of efficiency.

As the table illustrates, there is a wide range of efficiency in Texas school districts. Consider first the estimates of technical efficiency. The estimates of technical efficiency are centered on 46 percent and have a rather straightforward interpretation. Relative to the best practice in the state, the average Texas school produces only 46 percent of its potential. In other words, the average public school in Texas could reduce their labor inputs by roughly 54 percent without reducing measured performance.

Interestingly, the distribution of technical efficiency suggests that charter schools are significantly more efficient than traditional public schools. The average technical efficiency of charter schools is 8 percentage points higher than the average technical efficiency of traditional public schools. A t-test of the difference in means indicates that the difference is statistically

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[19] Tables indicating the distribution of coefficient estimates are available from the authors.

significant at the 1 percent level. The greater technical efficiency of charter schools could indicate either that charters face greater incentives to behave efficiently, or that charter schools are more able to respond to such incentives, or both.

Schools where $\kappa_s = 1$ are allocatively efficient, so deviations from one in either direction indicate allocative inefficiency. On average, relative shadow prices diverge from market prices by 2.9 percent in traditional public schools and 14.3 percent in charter schools. The charter school mean is dominated by an outlier with an unusually high marginal product of non-instructional personnel. (The school has only one non-instructional staffer and an enrollment of nearly 200 students.) However, even after excluding this school, the average divergence for charter schools is more than 8.5 percent. Thus, the evidence suggests that charter schools are less allocatively efficient than traditional public schools.[20]

To explore the distribution of allocative inefficiency further, we divide the sample into three groups–schools that overuse administrators, schools that overuse instructors and allocatively efficient schools. Any school where 95 or more of the 100 iterations indicate that $\kappa_s > 1$ is considered a school that overuses administrative personnel (relative to instructional personnel). Similarly, any school where 95 or more of the iterations indicate that $\kappa_s < 1$ overuses instructional personnel. All other schools are deemed allocatively efficient.

If Texas public schools are systematically top-heavy–as is frequently alleged–then κ_s should be greater than one for most schools. However, as table 4 illustrates, most urban public schools in Texas are allocatively efficient. Nearly two-thirds of the charter schools, and more than 87 percent of the traditional public schools are choosing an efficient mix of instructional and non-instructional labor. Somewhat surprisingly, the evidence suggests that among the inefficient schools, charter schools have a strong tendency to overuse administrators (all but one of the allocatively inefficient charter schools overuse administrators) while traditional public schools have no such bias (half of the allocatively inefficient traditional public schools overuse

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[20] The differences are statistically significant at the one- percent level.

teachers). Excluding charter schools, there is no evidence that Texas public schools are systematically mis-allocating their personnel resources away from the classroom.

Table 5 illustrates the relationship between our efficiency measures and per pupil spending. Not surprisingly, spending per pupil is lowest among schools that are in the top quartile for technical efficiency and highest among schools in the bottom quartile.[21] (The correlation between technical efficiency and per pupil spending is -0.4782.) Schools that overuse teachers spend significantly more than allocatively efficient schools, while schools that overuse administrators spend about the same as allocatively efficient schools. There is no evidence that an over-reliance on administrative personnel in and of itself leads to unusually high spending by Texas public schools.

Table 6 presents the estimated coefficients arising from a regression of τ_s on each measure of instructional share. Because the residuals from two schools in the same school district need not be independent, the standard errors have been adjusted for clustering by school district.

As the table illustrates, we find a significant relationship between the share of current expenditures devoted to instruction and the technical efficiency of school districts. However, the nature of that relationship is unexpected. Contrary to the philosophical underpinnings of the 65-percent solution, we find that schools with a relatively high instructional share tend to be *less* technically efficient than other schools. Evaluated at the mean, a one percentage point increase in the spending share devoted to PURE instruction reduces technical efficiency by 0.44 percent. Similarly, a one percentage point increase in the NCES definition of instructional share reduces technical efficiency by 0.52 percent, while a one percentage point increase in the TEA definition of instructional share reduces technical efficiency by 0.67 percent. Thus, any increase in instructional share is associated with a reduction in technical efficiency, but the broader the

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[21] The differences are statistically significant at the one- percent level.

definition of instructional share, the greater the reduction in technical efficiency from a small increase in instructional spending.

Furthermore, the pattern persists even when charter schools are excluded from the analysis. As the remaining columns of Table 6 illustrate, instructional shares provide no information about the technical efficiency of charter schools, but traditional public schools with a higher instructional share tend to be less technically efficient than schools with a lower instructional share.

Table 7 presents the coefficient estimates arising from a regression of $|\kappa_s\text{-}1|$ on each measure of instructional share. As the table makes clear, regardless of the definition, there is no significant relationship between instructional shares and allocative efficiency. Schools with a low instructional share are no more allocatively inefficient than schools with a high instructional share.

Given these patterns, it is not surprising that the 65-percent threshold does not help to distinguish between efficient and inefficient schools. As Table 8 illustrates, schools that spend at least 65 percent of their budgets on the NCES definition of instruction are twice as likely to be in the bottom quartile of technical efficiency scores as in the top quartile. Using the other two definitions of instruction, the pattern is similar, if not quite as striking. Schools that spend more than 65 percent of their budgets on instruction by the broader TEA definition are 24 percent more likely to be in the least inefficient quartile than in the most efficient quartile, while schools that spend more than 65 percent of their budgets by the narrowest definition are 76 percent more likely to be in the least efficient quartile.

With respect to allocative efficiency (Table 9), the 65-percent threshold provides no information if instructional spending is narrowly defined.[22] Using either the NCES definition or the broader TEA definition, the 65-percent threshold has informational content, but the

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[22] The chi-squared statistic is 2.319 with 2 degrees of freedom. The probability of a greater chi-squared statistic is 0.314.

information is virtually useless for policy-making. No more than 10 percent of the schools below the threshold overuse administrators and could therefore be expected to benefit from increasing the share of personnel resources devoted to instruction. Most of the schools below the threshold are already allocatively efficient, and a significant fraction of schools below the threshold are underusing administrators. All told, there is no reason to believe that schools below the 65-percent threshold–however it is defined–should systematically re-allocate their resources to spend more on instruction. Indeed, given the negative correlation between instructional shares and technical efficiency, our analysis suggests that the 65-percent solution could reduce the efficiency of the Texas school system.

The Sensitivity of the Analysis to Charter Schools

Charter schools have a different efficiency profile and expenditure mix than traditional public schools. They tend to be more technically efficient but less allocatively efficient. Charters are also disproportionately likely to overuse administrators, and spend nearly twice as much per pupil on non-labor inputs. Conceivably, charter schools may have undue influence on the analysis. To address this concern, we re-estimated the distance function and share equation, using only data on traditional public schools.

As Table 10 shows, when charter schools (which tend to be more technically efficient) are excluded from the analysis, the relative technical efficiency of the system improves. Relative to the best practice of their traditional school peers, the average traditional public school produces 61 percent of its potential, whereas when compared to traditional and charter schools, the average traditional public school produces 46 percent of potential.

Nothing changes about the signaling value of instructional shares, however. Schools with higher instructional shares remain significantly less technically efficient than schools with lower instructional shares (Table 11). Across the three definitions of instructional share, a one percentage point increase in instructional share reduces efficiency by between 0.33 and 0.52

percent. The relationship between the degree of allocative inefficiency (| κ_s-1|) and instructional shares remains statistically insignificant.[23]

Excluding charter schools from the analysis increases the number of traditional public schools identified as allocatively efficient, and reduces the number of schools identified as overusing teachers (Table 12). However, once again most schools with instructional shares below 65-percent–by any definition–are allocatively efficient. In each case, schools below the 65-percent threshold are more likely to overuse administrators than to overuse teachers, but no more than 10 percent of the schools below the threshold overuse administrators and could therefore be expected to benefit from increasing the share of personnel resources devoted to instruction.

Regardless of whether charter schools are included in the estimation of school efficiency, we find no evidence that traditional public schools in Texas are administratively top-heavy, or that inducing schools to spend a greater share of their resources in the classroom would improve school efficiency.

The Sensitivity of the Analysis to the Definition of Labor Inputs

Our measure of instructional labor (the number of full-time-equivalent teachers plus a weighted count of full-time-equivalent teacher aides) treats teachers as homogeneous. Therefore, a school with 15 teachers has the same labor input whether they are 15 rookies with a bachelor's degree or 15 experienced teachers with a master's degree. Although the literature suggests that differences in a teacher's experience and educational attainment have little correlation with her effectiveness, this approach may understate the labor inputs of schools with highly qualified (and therefore highly compensated) teachers.

To address this concern, we replicated the analysis using estimates of the effective quantities of instructional and non-instructional inputs instead of the full-time-equivalent counts.

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[23] Coefficient estimates are available upon request from the authors.

We defined the effective quantity of instructional labor as the school's total payroll for teachers and teacher aides, divided by the predicted teacher wage. We similarly defined the effective quantity of non-instructional labor as the total non-instructional payroll divided by the predicted administrator wage. In so doing, we treat compensation as a direct indicator of educator quality. Schools that spend more on teachers are presumed to be using more teacher input than other schools.

As the bottom panel of table 10 illustrates, using effective labor quantities reduces the relative technical efficiency of the system. Where the baseline analysis indicates that the average public school produces 46 percent of potential, the analysis based on effective inputs indicates that the average public school produces 39 percent of potential. Charter schools remain systematically more efficient than traditional public schools, and the efficiency gap widens. Where the baseline analysis indicates that charter schools are 8 percentage points more efficient than traditional public schools, the analysis based on effective units indicates that charter schools are nearly 14 percentage points more efficient.

Relying on effective labor inputs strengthens the case against the 65-percent solution. The relationship between instructional share and technical efficiency becomes more negative (Table 11). Across the three definitions of instructional share, a one percentage point increase in instructional share reduces technical efficiency by between 0.71 and 1.15 percent. As with the baseline analysis, the broader the definition of instructional share, the greater the reduction in technical efficiency from a small increase in instructional share.

Increases in instructional share still do not signal increases in the degree of allocative efficiency. As with the other analyses, the relationship between $|\kappa_s-1|$ and any definition of instructional share is statistically insignificant.

Using effective input quantities reduces the number of schools identified as allocatively efficient, and increases the number of schools identified as overusing teachers (Table 12). Where the baseline analysis found a balance among traditional public schools between those that overuse administrators and those that overuse teachers, this alternative specifications suggests that traditional public schools are more likely to overuse teachers (392 schools) than to overuse administrators (336 schools).

As with the baseline analysis, charter schools tend to overuse administrators whether their instructional shares are above or below the 65-percent thresholds. Among traditional public schools, the analysis based on effective input quantities suggests that schools below each 65-percent threshold are at least as likely to overuse teachers as to overuse administrators. For example, using the NCES definition of instruction, we find that 83 percent of the traditional public schools below the 65-percent threshold are already allocatively efficient, 9 percent overuse teachers and 8 percent overuse administrators. Again, there is no evidence that increasing the share of educational budgets devoted to instruction would improve the allocative efficiency of traditional public schools, and considerable evidence that increasing instruction's share of the budget could reduce the technical efficiency of the public school system.

Conclusions

Our analysis of urban schools in Texas finds evidence of widespread technical efficiency. Based on the best practice of traditional public schools and charter schools in Texas, we estimate that Texas schools could cut their operating expenses by as much as 50 percent with no decrease in student performance. Therefore, Texas could benefit enormously from policies that encouraged school districts to use their resources more efficiently.

On the other hand, we find no evidence that inducing schools to spend a greater share of their budgets on instruction will lead to increased efficiency. Most urban public schools are choosing an efficient mix of instructional and non-instructional labor, and schools are as likely to be devoting too many personnel resources to the classroom as too few. Furthermore, our analysis suggests that schools spending a larger share of their budget on instruction are systematically less efficient than other schools.

The analysis presented here casts considerable doubt on the efficacy of the 65-percent solution, a policy prescription that has been widely touted as a cost effective strategy for inducing schools to become more efficient. Educators have questioned the efficacy of the 65-percent solution for some time, arguing that it lacked a foundation in research. Our analysis supports their position. Although we find evidence of substantial inefficiency, we find no evidence that requiring schools to increase the share of their budgets devoted to instruction would reduce that inefficiency. If anything, the 65-percent solution could increase inefficiency, particularly if schools respond by increasing instructional expenditures without any offsetting decrease in other spending.

Intriguingly, the 65-percent solution has direct parallels outside education. For example, the Better Business Bureau (BBB) publishes standards for charity accountability. One of those standards is that the charitable organization "shall spend at least 65 percent of its total expenses on program activities." (BBB 2007). Similarly, the American Institute of Philanthropy (2007) recommends that program expenses exceed 60 percent of total expenses. Arguably, the 65 percent solution is just an extension to the public sector of these well accepted standards for charitable organizations. To a certain extent, therefore, our analysis also casts doubt on the common practice of using budget shares as an indicator of fiscal responsibility among nonprofit organizations in general.

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Table 1. Descriptive Statistics

	N. Obs.	Mean	Standard Deviation	Minimum	Maximum
Traditional Public Schools					
Reading Output per Pupil	4,201	36.41	0.17	34.40	36.98
Mathematics Output per Pupil	4,201	36.43	0.21	34.54	37.18
Reading Output	4,201	26,553.17	17,986.31	1,527.75	169,206.20
Mathematics Output	4,201	26,557.34	17,951.21	1,509.85	168,934.50
Instructional Personnel	4,201	51.58	31.39	4.66	300.15
Non-instructional Personnel	4,201	20.32	13.26	2.16	135.83
Non-labor Expenditures	4,201	799.94	606.92	51.27	5,170.83
Secondary Students	4,201	312.19	606.24	1.00	4,658.00
Elementary Students	4,201	417.87	297.14	1.00	1,380.00
Relative Price of Admin.	4,201	1.37	0.05	1.14	1.52
Total Enrollment	4,201	729.23	494.21	42.00	4,658.00
Instructional Share	4,201	0.58	0.04	0.09	0.73
NCES Instructional Share	4,201	0.60	0.04	0.20	0.78
TEA Instructional Share	4,201	0.66	0.04	0.32	0.83
Charter Schools					
Reading Output per Pupil	121	36.22	0.30	35.31	36.94
Mathematics Output per Pupil	121	36.21	0.33	35.31	37.14
Reading Output	121	11,979.24	7,248.55	1,276.61	40,409.93
Mathematics Output	121	11,976.75	7,243.00	1,265.89	40,411.56
Instructional Personnel	121	22.47	14.97	3.75	95.65
Non-instructional Personnel	121	10.97	7.49	1.01	36.08
Non-labor Expenditures	121	724.12	493.73	77.34	2,747.34
Secondary Students	121	172.59	153.65	1.00	850.00
Elementary Students	121	158.51	188.92	1.00	732.00
Relative Price of Admin.	121	1.39	0.06	1.25	1.54
Total Enrollment	121	330.64	199.79	35.00	1,113.00
Instructional Share	121	0.51	0.11	0.18	0.75
NCES Instructional Share	121	0.52	0.11	0.18	0.75
TEA Instructional Share	121	0.55	0.11	0.23	0.77

Table 2. The Correlation between Value Added per Pupil and Instructional Shares

	Value Added in Math	Value Added in Reading
All Schools		
Instructional Share	0.286	0.296
NCES Instructional Share	0.197	0.277
TEA Instructional Share	0.229	0.304
Traditional Public Schools		
Instructional Share	0.266	0.240
NCES Instructional Share	0.150	0.206
TEA Instructional Share	0.183	0.233
Charter Schools		
Instructional Share	0.183	0.424
NCES Instructional Share	0.192	0.435
TEA Instructional Share	0.142[a]	0.398

There are 4,201traditional public school observations and 121 charter school observations.
[a] indicates that the correlation is not statistically significant at the 5 percent level.

Table 3. Descriptive Statistics for School Inefficiency

	N. Obs.	Mean	Standard Deviation	Minimum	Maximum
All Schools					
τ_s	4,322	0.457	0.054	0.216	0.996
κ_s	4,322	1.000	0.116	-6.088	1.577
$\lvert \kappa_s-1 \rvert$	4,322	0.030	0.112	0.000	7.088
Traditional Public Schools					
τ_s	4,201	0.455	0.047	0.216	0.721
κ_s	4,201	1.000	0.039	0.822	1.329
$\lvert \kappa_s-1 \rvert$	4,201	0.029	0.026	0.000	0.329
Charter Schools					
τ_s	121	0.536	0.146	0.262	0.996
κ_s	121	1.016	0.659	-6.088	1.577
$\lvert \kappa_s-1 \rvert$	121	0.143	0.643	0.001	7.088

Table 4. The Allocation of Labor Resources

	Efficient	Overuse Teachers	Overuse Administrators
Traditional	3667	267	267
Charter	79	1	41
Total	3746	268	308

Table 5. Per Pupil Spending by Efficiency Categories

	N. Obs.	Mean	Std. Dev.	Minimum	Maximum
Technical Efficiency					
Top 25%	1,081	6,636.36	949.73	3,933.10	12,401.13
Interquartile Range	2,161	7,177.87	922.53	3,471.43	18,959.48
Bottom 25%	1,080	8,213.39	1,683.09	3,935.27	25,396.19
Allocative Efficiency					
Allocatively Efficient	3,746	7,225.39	1,119.61	3,471.43	16,711.90
Overuse Teachers	268	8,426.99	2,539.71	3,935.27	25,396.19
Overuse Administrators	308	7,243.47	1,275.60	4,846.94	15,366.49

Table 6. The Relationship Between Instructional Shares and Technical Efficiency

Dependent Variable: Technical Efficiency (τ_s)

	All Urban Public Schools			Traditional Public Schools			Charter Schools		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Instructional Share	-0.203			-0.132			-0.145		
	(0.044)**			(0.043)**			(0.140)		
NCES Instructional Share		-0.238			-0.148			-0.165	
		(0.049)**			(0.053)**			(0.141)	
TEA Instructional Share			-0.308			-0.217			-0.217
			(0.048)**			(0.056)**			(0.140)
Constant	0.575	0.599	0.660	0.532	0.544	0.599	0.610	0.621	0.654
	(0.025)**	(0.030)**	(0.032)**	(0.025)**	(0.032)**	(0.038)**	(0.071)**	(0.072)**	(0.077)**
Charter Schools Included?	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Traditional Public Schools Included?	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Observations	4322	4322	4322	4201	4201	4201	121	121	121
R-squared	0.03	0.03	0.06	0.01	0.01	0.03	0.01	0.01	0.03
Pearson Correlation	-0.169	-0.186	-0.251	-0.112	-0.114	-0.167	-0.109	-0.122	-0.158

The robust standard errors (in parentheses) have been clustered by school district. * significant at 5%; ** significant at 1%.

Table 7. The Relationship Between Instructional Shares and Allocative Inefficiency

Dependent Variable: Allocative Inefficiency ($| \kappa_s - 1 |$)

	All Urban Public Schools			Traditional Public Schools			Charter Schools		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Instructional Share	-0.230			-0.036			-0.568		
	(0.145)			(0.029)			(0.546)		
NCES Instructional Share		-0.263			-0.013			-0.608	
		(0.180)			(0.033)			(0.589)	
TEA Instructional Share			-0.303			-0.047			-0.531
			(0.186)			(0.034)			(0.567)
Constant	0.165	0.189	0.231	0.049	0.036	0.059	0.432	0.457	0.433
	(0.086)	(0.109)	(0.124)	(0.017)**	(0.020)	(0.022)**	(0.334)	(0.361)	(0.366)
Charter Schools Included?	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Traditional Public Schools Included?	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Observations	4322	4322	4322	4201	4201	4201	121	121	121
R-squared	0.01	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.01
Pearson Correlation	-0.093	-0.100	-0.120	-0.055	-0.018	-0.065	-0.096	-0.102	-0.088

The robust standard errors (in parentheses) have been clustered by school district. * significant at 5%; ** significant at 1%.

Table 8. Technical Efficiency and the 65 Percent Solution

	Top Quartile	Interquartile Range	Bottom Quartile
Instructional Share Below 65%	1,052	2,113	1,029
Instructional Share Above 65%	29	48	51
NCES Instructional Share Below 65%	1,022	2,038	962
NCES Instructional Share Above 65%	59	123	118
TEA Instructional Share Below 65%	482	752	338
TEA Instructional Share Above 65%	599	1,409	742

Table 9. Allocative Efficiency and the 65 Percent Solution

	Efficient	Overuse Teachers	Overuse Administrators
Instructional Share Below 65%	3,635	257	302
Instructional Share Above 65%	111	11	6
NCES Instructional Share Below 65%	3,487	236	299
NCES Instructional Share Above 65%	259	32	9
TEA Instructional Share Below 65%	1,320	97	155
TEA Instructional Share Above 65%	2,426	171	153

Table 10. Descriptive Statistics for School Inefficiency, Alternative Specifications

	N. Obs.	Mean	Standard Deviation	Minimum	Maximum
Traditional Public Schools, Baseline Analysis					
τ_s	4,201	0.455	0.047	0.216	0.721
κ_s	4,201	1.000	0.039	0.822	1.329
$\lvert \kappa_s - 1 \rvert$	4,201	0.029	0.026	0.000	0.329
Traditional Public Schools, Charters Excluded from the Analysis					
τ_s	4,201	0.618	0.064	0.316	0.998
κ_s	4,201	1.001	0.038	0.822	1.295
$\lvert \kappa_s - 1 \rvert$	4,201	0.028	0.026	0.000	0.295
All Schools, Baseline Analysis					
τ_s	4,322	0.457	0.054	0.216	0.996
κ_s	4,322	1.000	0.116	-6.088	1.577
$\lvert \kappa_s - 1 \rvert$	4,322	0.030	0.112	0.000	7.088
All Schools, Effective Labor Inputs					
τ_s	4,322	0.393	0.056	0.172	0.986
κ_s	4,322	1.000	0.105	-5.188	2.055
$\lvert \kappa_s - 1 \rvert$	4,322	0.032	0.100	0.000	6.188

Table 11. The Relationship Between Instructional Shares and Technical Efficiency, Alternative Specifications

Dependent Variable: Technical Efficiency (τ_s)

	Excluding Charter Schools			Effective Labor Inputs		
	(10)	(11)	(12)	(13)	(14)	-15.00
Instructional Share	-0.222			-0.280		
	(0.060)**			(0.048)**		
NCES Instructional Share		-0.206			-0.357	
		(0.073)**			(0.051)**	
TEA Instructional Share			-0.318			-0.453
			(0.078)**			(0.050)**
Constant	0.747	0.741	0.829	0.555	0.606	0.691
	(0.034)**	(0.044)**	(0.052)**	(0.027)**	(0.031)**	(0.034)**
Charter Schools Included?	No	No	No	Yes	Yes	Yes
Traditional Public Schools Included?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,201	4,201	4,201	4,322	4322	4,322
R-squared	0.02	0.01	0.03	0.05	0.07	0.13
Pearson Correlation	-0.140	-0.118	-0.181	-0.228	-0.272	-0.360

The robust standard errors (in parentheses) have been clustered by school district.
* significant at 5%; ** significant at 1%.

Table 12. The Allocation of Labor Resources, Alternative Specifications

	Efficient	**Overuse Teachers**	**Overuse Administrators**
Traditional Public Schools, Baseline Analysis	3,667	267	267
Traditional Public Schools, Charters Excluded from the Analysis	3,631	249	321
All Schools, Baseline Analysis	3,746	268	308
All Schools, Effective Labor Inputs	3,555	394	373

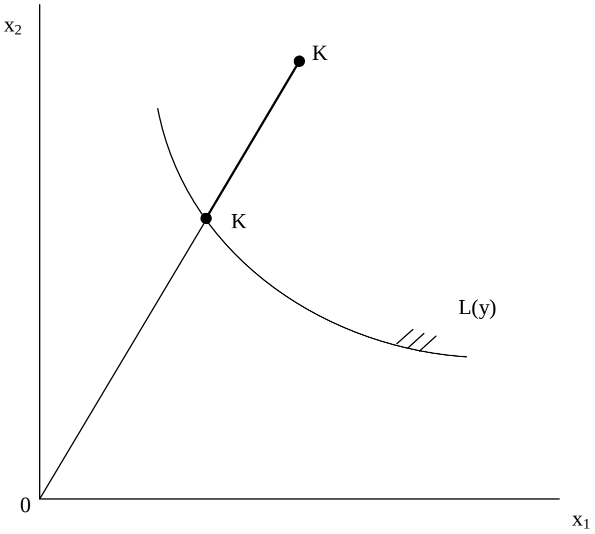

FIG.1. Input distance function: *D(*y^K*,* x^K*)=0K/0K'*.

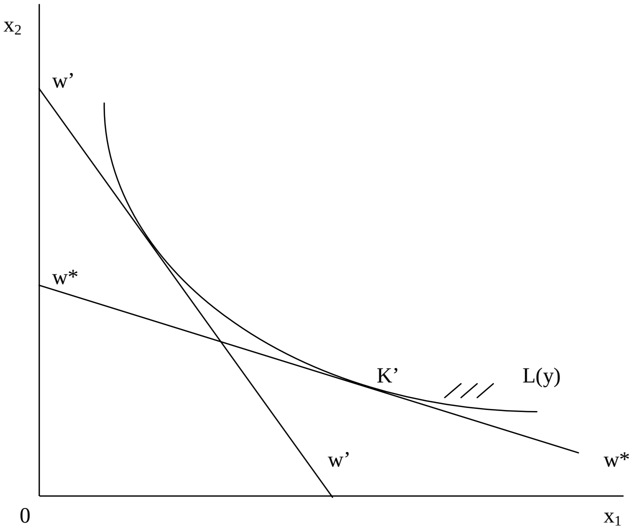

FIG.2. Overutilization of $\mathbf{x_1}$ **at K'**

Table A1. Estimating School Output, 2004-05

	Reading		Mathematics	
	Coefficient	Standard Error	Coefficient	Standard Error
PRETEST	0.625	0.002 ***	0.782	0.002 ***
LEP	-0.618	0.009 ***	-0.107	0.008 ***
LOWSES	-0.059	0.004 ***	-0.061	0.003 ***
SPECIAL	-0.320	0.008 ***	-0.178	0.008 ***
NEWCAMPUS	-0.051	0.007 ***	-0.060	0.007 ***
Grade 4	-0.037	0.009 ***	-0.125	0.008 ***
Grade 5	-0.020	0.009 **	-0.116	0.008 ***
Grade 6	0.097	0.009 ***	0.084	0.008 ***
Grade 7	0.093	0.008 ***	0.078	0.007 ***
Grade 8	0.076	0.008 ***	0.025	0.007 ***
Grade 9	0.245	0.011 ***	0.243	0.010 ***
Grade 10	0.052	0.003 ***	0.021	0.003 ***
LEP x Grade 4	0.509	0.012 ***	0.005	0.011
LEP x Grade 5	0.453	0.012 ***	-0.017	0.010
LEP x Grade 6	0.580	0.011 ***	0.000	0.010
LEP x Grade 7	0.433	0.011 ***	-0.011	0.010
LEP x Grade 8	0.169	0.012 ***	-0.013	0.011
LEP x Grade 9	0.271	0.012 ***	-0.001	0.011
LEP x Grade 10	-0.001	0.013	-0.037	0.011 ***
LOWSES x Grade 4	-0.110	0.005 ***	-0.083	0.005 ***
LOWSES x Grade 5	-0.107	0.005 ***	-0.050	0.005 ***
LOWSES x Grade 6	-0.046	0.005 ***	-0.046	0.004 ***
LOWSES x Grade 7	-0.025	0.005 ***	-0.034	0.004 ***
LOWSES x Grade 8	-0.033	0.005 ***	0.005	0.004
LOWSES x Grade 9	-0.059	0.004 ***	-0.056	0.004 ***
LOWSES x Grade 10	-0.077	0.005 ***	0.017	0.004 ***
SPECIAL x Grade 4	0.189	0.013 ***	0.068	0.013 ***
SPECIAL x Grade 5	0.105	0.013 ***	0.097	0.013 ***
SPECIAL x Grade 6	0.135	0.013 ***	0.022	0.013 *
SPECIAL x Grade 7	0.147	0.012 ***	0.037	0.012 ***
SPECIAL x Grade 8	0.104	0.011 ***	0.002	0.012
SPECIAL x Grade 9	0.020	0.011	0.057	0.011 ***
SPECIAL x Grade 10	-0.075	0.011 ***	0.014	0.012
NEWCAMPUS x Grade 4	-0.005	0.008	0.022	0.008 ***
NEWCAMPUS x Grade 5	0.036	0.008 ***	0.008	0.008
NEWCAMPUS x Grade 6	-0.019	0.009 **	-0.054	0.009 ***

NEWCAMPUS x Grade 7	-0.040	0.008 ***	-0.039	0.008 ***
NEWCAMPUS x Grade 8	0.010	0.009	0.003	0.008
NEWCAMPUS x Grade 9	-0.144	0.013 ***	-0.143	0.012 ***
NEWCAMPUS x Grade 10	0.009	0.009	0.009	0.008
PRETEST x Grade 4	-0.040	0.002 ***	-0.135	0.002 ***
PRETEST x Grade 5	0.000	0.002	-0.102	0.002 ***
PRETEST x Grade 6	0.038	0.002 ***	-0.085	0.002 ***
PRETEST x Grade 7	0.043	0.002 ***	-0.031	0.002 ***
PRETEST x Grade 8	0.011	0.002 ***	-0.033	0.002 ***
PRETEST x Grade 9	-0.081	0.002 ***	-0.028	0.002 ***
PRETEST x Grade 10	-0.053	0.002 ***	0.012	0.002 ***
Number of Observations		1.95 million		1.95 million
Number of Schools		5124.000		5109.000
Number of Districts		656.000		651.000

The school fixed effects are nested within the district effects. The notation '***', '**' and '*' indicates that the coefficient is significantly different from zero at the 1-percent, 5-percent and 10-percent levels, respectively.

Table A2: Salary Models for Instructional Staff

	Teachers		Teacher Aides	
	Coefficient	Robust Std. Error	Coefficient	Robust Std. Error
Charter School	-0.0727	0.0204 ***	0.2661	0.0608 ***
Enrollment (log)	0.0497	0.0184 **	0.0108	0.0598
Enrollment (log) squared	-0.0019	0.0009 **	0.0006	0.0034
Dallas ISD	-0.0019	0.0105	0.1252	0.0394 ***
Houston ISD	-0.0255	0.0083 ***	-0.0350	0.0414
Percent Low Income	-0.0098	0.0195	-0.0472	0.0883
Percent LEP	0.0417	0.0559	-0.1337	0.1299
Percent Anglo	-0.0196	0.0206	-0.0373	0.0865
Miles from Center of CBSA	-0.0013	0.0005 ***	-0.0019	0.0010 *
Years of Experience	0.0136	0.0011 ***	0.0019	0.0026
Experience Squared	-0.0004	0.0000 ***	-0.0001	0.0001
Experience Unknown	0.0564	0.0104 ***	0.0097	0.0024 ***
No Degree	0.0019	0.0068	-0.0468	0.0102 ***
MA	0.0261	0.0033 ***	0.0586	0.0347
Ph.D	0.0335	0.0079 ***	-0.0232	0.0313
Days worked	-0.1096	0.0255 ***	-0.1998	0.0416 ***
Teaching Assignment				
Math	-0.0005	0.0013		
Science	0.0000	0.0011		
Health and P.E.	-0.0026	0.0024		
Computer	0.0010	0.0025		
Special Education	0.0015	0.0008		
Secondary School	0.0034	0.0008 ***		
Percent Time in Field	0.0026	0.0008 ***		
New Hire	-0.0050	0.0020 **	-0.0149	0.0027 ***
fy2000	-0.1328	0.0056 ***	-0.1751	0.0119 ***
fy2001	-0.0996	0.0045 ***	-0.1259	0.0078 ***
fy2002	-0.0621	0.0035 ***	-0.0779	0.0064 ***
fy2003	-0.0143	0.0020 ***	-0.0236	0.0130 *
Adj. R-squared		0.9541		0.8748
Number of Observations		1120374		230116
Number of Individuals		320991		82273

All models also include individual fixed effects and 25 metropolitan-area fixed effects. The asterisks indicate coefficients that are significant at the 1-percent (***), 5-percent (**) and 10-percent (*) levels, respectively. All standard errors are corrected for clustering by metropolitan area.

Table A3: Salary Models for Non-instructional Staff

	Administrators		**Professional Support Staff**		**Auxiliary Staff**	
	Coefficient	Robust Std. Error	Coefficient	Robust Std. Error	Coefficient	Robust Std. Error
Charter School	0.0023	0.0471	0.0773	0.0417 *	0.2398	0.0864 **
Enrollment (log)	0.1943	0.0547 ***	0.0991	0.0391 **	-0.1066	0.1372
Enrollment (log) squared	-0.0094	0.0029 ***	-0.0050	0.0020 **	0.0081	0.0080
Dallas ISD	0.0162	0.0205	0.0103	0.0172	0.0496	0.0843
Houston ISD	-0.0619	0.0210 ***	0.0346	0.0188 *	-0.0461	0.0922
Percent Low Income	-0.0145	0.0399	0.0400	0.0402	-0.0670	0.0839
Percent LEP	0.1042	0.0998	0.0608	0.0830	-0.0108	0.3187
Percent Anglo	-0.0128	0.0381	0.0427	0.0363	-0.1648	0.1443
Miles from Center of CBSA	-0.0006	0.0004	-0.0014	0.0005 **	0.0009	0.0012
Years of Experience	0.0105	0.0009 ***	0.0092	0.0013 ***	0.0073	0.0024 ***
Experience Squared	-0.0003	0.0000 ***	-0.0003	0.0000 ***	-0.0003	0.0001 ***
Experience Unknown	0.0531	0.0118 ***	0.0254	0.0124 *	0.0173	0.0042 ***
No Degree	0.0188	0.0123	-0.0222	0.0134	-0.0121	0.0080
MA	0.0080	0.0034 **	0.0107	0.0049 **	0.0012	0.0125
Ph.D	0.0301	0.0085 ***	0.0266	0.0201	-0.0140	0.0090
Days worked	-0.1687	0.0325 ***	-0.1541	0.0334 ***	-0.3852	0.0794 ***
Occupation						
Principal	0.0141	0.0058 **				
Asst. Principal	-0.0675	0.0067 ***				
Asst. Superintendent	0.0615	0.0064 ***				
Superintendent	0.1737	0.0192 ***				
Counselor			0.0074	0.0071		
Educational Diagnostician			-0.0059	0.0059		
Instructional Officer	-0.0290	0.0116 **				
Nurse			-0.0187	0.0240		
Speech Pathologist			-0.0206	0.0250		
New Hire	0.0038	0.0017 **	-0.0046	0.0014 ***	-0.0392	0.0033 ***
fy2000	-0.1768	0.0079 ***	-0.1492	0.0086 ***	-0.1802	0.0097 ***
fy2001	-0.1280	0.0047 ***	-0.1075	0.0040 ***	-0.1348	0.0115 ***
fy2002	-0.0807	0.0046 ***	-0.0646	0.0043 ***	-0.0806	0.0105 ***
fy2003	-0.0361	0.0024 ***	-0.0272	0.0030 ***	-0.0192	0.0095 *
Adj. R-squared		0.8863		0.9551		0.8891
Number of Observations		77,825		189,251		631,984
Number of Individuals		23,619		72,125		219,690

All models also include individual fixed effects and 25 metropolitan-area fixed effects. The asterisks indicate coefficients that are significant at the 1-percent (***), 5-percent (**) and 10-percent (*) levels, respectively. All standard errors are corrected for clustering by metropolitan area.