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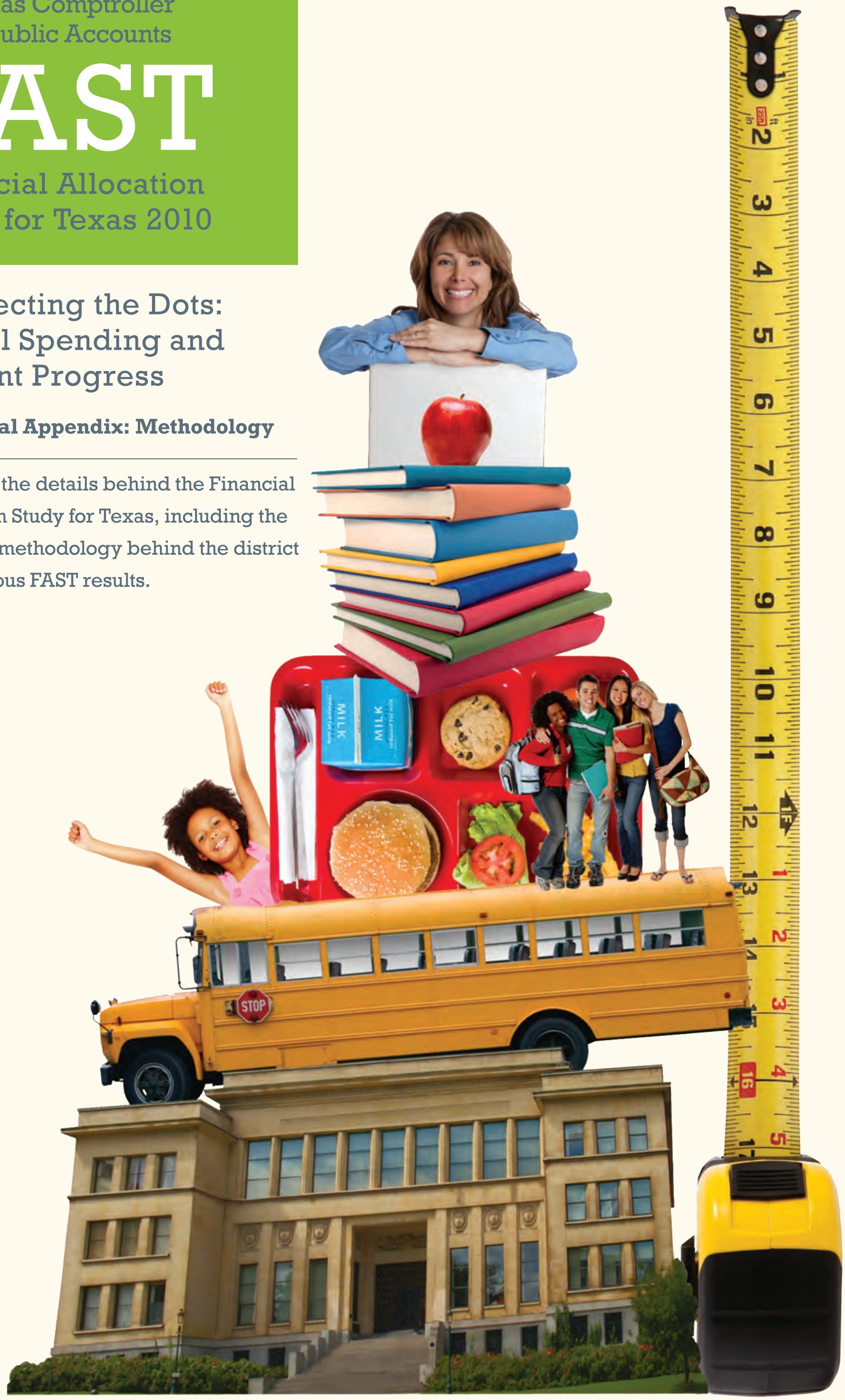
FAST

Financial Allocation Study for Texas 2010

Connecting the Dots: School Spending and Student Progress

Technical Appendix: Methodology

Get all of the details behind the Financial Allocation Study for Texas, including the in-depth methodology behind the district and campus FAST results.



FAST

FINANCIAL ALLOCATION STUDY FOR TEXAS

APPENDIX: BACKGROUND, METHODOLOGY AND EXPANDED DATA FOR RECOMMENDATIONS

This is the Appendix of the Financial Allocation Study for Texas (FAST) report. The complete version is available online at **www.FASTexas.org**.

View the FAST report's other sections online, including:

PART 1: EXECUTIVE SUMMARY

PART 2: SCHOOL DISTRICT LISTINGS

PART 3: SMART PRACTICES FOR MINIMIZING COSTS

PART 4: COST EFFICIENCIES IN HIGHER EDUCATION

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TECHNICAL APPENDIX 1: FAST ACADEMIC PROGRESS METHODOLOGY

Legislation establishing the FAST report requires the Comptroller to evaluate school resource allocation by integrating existing academic and financial data.

Economists perform similar exercises to study the productivity of businesses and industries through various modeling techniques. These models study the relationship between "inputs" — the goods and services that go into a product — and "output" — the product itself. A drink manufacturer, for instance, might combine water, fruits and sweeteners with labor and machinery to produce a juice drink sold at grocery stores.

In education, the inputs combine to form a more elusive product. Financial contributions to education, such as teacher salaries and textbook purchases, can be measured in annual dollar expenditures. These inputs, however, combine to produce student achievement, which is measured by test scores rather than currency.

To complicate matters further, the learning process is cumulative. Achievement in any grade reflects the achievements of prior grades. This represents another challenge: evaluating the impact of one year's worth of educational resources requires an assessment of *that year's* academic progress, rather than the accumulated achievement of previous years.

Furthermore, numerous factors that influence student achievement are beyond the school's control, such as natural aptitude, parental involvement, family income and community values.

The FAST study attempted to resolve these measurement issues by using what is often called a *value-added model* (VAM). Instead of measuring levels of student achievement, VAMs measure *growth* in achievement by controlling for the varying characteristics of students, campuses and districts to determine the annual impact of each factor.

Adjusting for such characteristics puts each student, campus and district on equal footing for comparisons across the state. For each school year, each student receives a score representing how much he or she "learned" in relation to students throughout the state; each campus receives a score representing its contribution to student learning as measured against campuses statewide, and each district receives a score representing its contribution to student learning as measured against districts statewide.

House Bill 3, which directed the Comptroller to conduct the FAST analysis, seeks only campus and district-level results. This report, therefore, does not examine progress by classroom and can draw no conclusions about individual teacher performance.

FAST MODEL: FUNDAMENTALS

The FAST project's VAM, the Academic Progress Model, was used to measure annual academic growth and produce Academic Progress scores in math and reading for each campus and district included in the study. FAST researchers then combined progress in math and reading to create a composite academic progress score.

Like most such models, the FAST model uses statistical methods based on *linear regression*. Linear regression analysis allows researchers to quantify relationships between an item of interest and the factors that affect or are associated with it.

For example, agricultural researchers might use regression analysis to study the relationship between crop yields and rainfall. The regression model might account for other factors associated with crop yields, such as average temperature and soil composition. These other factors are known as "controls" that help isolate the relationship between crop yields and rainfall.

The objective in this case is to measure only what students learned in a given year. The model achieves this by controlling for factors selected based on research and consultation with experts and peer reviewers. By including these control factors, their influence is effectively removed from the Academic Progress scores:

- prior-year TAKS math score
- prior-year TAKS reading score
- gender
- English proficiency
- ethnicity
- family income (measured by those receiving free or reduced-price lunches)
- Special Education status
- Gifted and Talented program status
- language of TAKS administration (English or Spanish for grades 4-6)
- grade level

The model also includes "interaction terms," or other control variables made from combinations of the factors above.

INTERPRETATION

Appropriate conclusions can be drawn from the results only by carefully understanding what is being estimated. This report's Academic Progress percentiles represent math or reading growth relative to campuses or districts statewide, with adjustments for fair comparison that put all campuses or districts at the same starting line. These measures are presented as three-year averages of annual progress, to reduce volatility. Annual progress is calculated for each of the three years and then averaged. Scores are reported in percentiles ranging from one to 99, with 50 as both mean and median.

Scores have the same interpretation as any percentile number. A campus Math Progress score of 60 means that during the last three school years, the campus's students showed as much or more progress on math TAKS than 60 percent of campuses statewide. Control variables adjust the results to isolate the campus contribution. In other words, a campus's Math Progress score attempts to remove student socioeconomic factors that may affect learning.

Annual Progress scores for districts can be interpreted similarly, as representing the amount of learning made by the district's students, and controlled for the socioeconomic characteristics of each student in the district. A Composite Academic Progress Percentile (CAPP) is calculated as the average of math and reading progress. This represents a summary academic rating with equal weights given to math and reading.

A campus CAPP of 60, for instance, means that during the last three school years, the campus's students showed as much or more progress in math and reading combined than 60 percent of campuses statewide. Similarly, a district Composite Academic Progress Percentile of 60 means that during the last three school years, the district's students showed more progress in math and reading combined than 60 percent of districts statewide.

DATA CONSIDERATIONS

TEA provided all student-level data used in this analysis to the UT-Dallas Education Research Center. Student-level data came from TEA's PEIMS; campus and district-level data are from TEA's annual AEIS reports.

The study determined which students to include in the analysis based on advice of the Technical Advisory Team and others (see Part 1 (Executive Summary) for a list of the technical team members). The model included all students with two consecutive years of TAKS scores. Other students were included if they:

- were included in TEA's "Campus Accountability Subset";
- took either the English or Spanish versions of the regular TAKS reading/language arts or math test;
- had valid indicators for race/ethnicity, eligibility for free or reduced-price lunches, Limited English Proficiency (LEP) status, Special Education status or Gifted and Talented status, and were gender-identified in the current year;
- were Special Education students who took either TAKS-Accommodated or TAKS-Modified; or
- took TAKS Linguistically Accommodated Testing.

Students who took TAKS-Alternative tests were not included, due to significant differences in these versions of the test.

The study also followed rules for including campuses and districts. Only campuses and districts that received a Texas Accountability System rating were included; those without TAKS scores were excluded, as were any campuses or districts with fewer than 10 students.

FAST MODEL: TECHNICAL DESCRIPTION

The FAST Academic Progress model was used to measure annual academic growth and produce Academic Progress Scores and Percentiles in math and reading for each campus and district in the study. This model was derived from a model developed by the Dallas Independent School District that has been evaluated extensively over the years.[1]

Academic literature offers a variety of alternative VAMs, some focused on estimating teacher effects instead of, or in addition to, campus effects.[2] The FAST model is based on the Dallas ISD model because of its long track record, its Texas origins, its use of a number of TEA data elements and its use in TEA's own assessment approaches.

The FAST model uses statistical methods based on linear regression, specifically a regression technique called mixed-modeling methodology, to accommodate students, campuses and districts.[5] This approach measures academic growth by modeling current student achievement on TAKS reading or mathematics, known as the "post-test," by how the student performed in the previous year ("pre-test"), and by other characteristics of students. These other factors, called "control" variables or "covariates," were modeled to remove their influence on the Academic Progress Scores.

Dallas ISD's assumptions and methodology were modified to accommodate advances in computational technology. The Dallas ISD model uses a two-stage process, with the first stage adjusting for fair comparisons of all students and the second stage separating out the contributions of students, campuses and districts to academic growth. The FAST model, by contrast, consolidates the two stages into one incorporating students, campuses and districts, while making "fairness" adjustments for equal comparison. This technique is known as *multi-level, random intercepts mixed modeling*, with students, campuses and districts each represented by a level.

The FAST methodology uses both a three-level campus model and a two-level district model. The first level represents students, and the next levels represent districts and/or campuses. Each level has its own equation and the components of each equation depend on the others. To produce estimates for each model, the levels were algebraically combined into a single equation called the mixed model. Estimates then were produced from statewide TEA data, with effects partitioned between districts, schools and individual students.

The first level in both models has each student's post-test score regressed on his or her pre-test score, and any characteristics important to maintaining fairness. For interpretation and numerical stability, the level-one variables are grand-mean centered. The second and third levels only include random intercepts and do not include any covariates. This allows for the clustering of students within campuses, and campuses within districts, so that only the campus or district effect is measured.

The district model includes a second level that predicts the district effect as the residual over the level-one variables. The campus model includes second and third levels, which together provide value-added predictions at the campus level.

CAMPUS MODEL

The campus model uses the notation of Raudenbush and Bryk (2002), where the student-level math or reading TAKS outcome is:

$$Y_{ijk} = \pi_{0jk} + \sum_{p=1}^{P} \pi_{pjk} a_{pjk} + e_{ijk},$$

i = 1,…,m students (m varies by year)
j = 1,…,n campuses (n varies by year)
k = 1,…,o districts (o varies by year)
p = 1,…,34 student-level variables

Y_{ijk} = student TAKS reading or math score
π_{pjk} = student-level coefficients
a_{pjk} = student-level control variables
e_{ijk} = student-level random error, with $e_{ijk} \sim N(0; \sigma^2)$

Based on the Dallas ISD model, and with advice of the technical review team and other stakeholders, the following student-level control variables were included:

a_1 = Math pre-test score
a_2 = Math pre-test score squared
a_3 = Reading pre-test score
a_4 = Reading pre-test score squared
a_5 = African American (1 if African American)
a_6 = Hispanic (1 if Hispanic)
a_7 = Limited English Proficient (1 if LEP)
a_8 = Gender (1 if Male)
a_9 = Free or Reduced Lunch (1 if on Free or Reduced-Price Lunch)
a_{10} = African American x LEP
a_{11} = Hispanic x LEP
a_{12} = African American x Gender
a_{13} = Hispanic x Gender
a_{14} = African American x Free or Reduced-Price Lunch
a_{15} = Hispanic x Free or Reduced-Price Lunch
a_{16} = LEP x Free or Reduced-Price Lunch
a_{17} = Gender x Free or Reduced-Price Lunch
a_{18} = African American x Gender x Free or Reduced-Price Lunch
a_{19} = Hispanic x Gender x Free or Reduced-Price Lunch
a_{20} = LEP x Gender x Free or Reduced-Price Lunch
a_{21} = Spanish-language test current, grades 4-6 (1 if Spanish TAKS)

a_{22} = Spanish-language test prior-year reading, grades 4-6 (1 if Spanish TAKS)
a_{23} = Spanish-language test prior-year math, grades 4-6 (1 if Spanish TAKS)
a_{24} = Spanish-language test prior-year reading, grades 4-6 x Reading pre-test score
a_{25} = Spanish-language test prior-year math, grades 4-6 x Math pre-test score
a_{26} = Gifted class (1 if Gifted)
a_{27} = Special education class (1 if Special Education)
a_{28}–a_{34} = Grade binaries for grades 5 – 11 (reference grade is 4)

The campus-level is:

$$\pi_{0jk} = \beta_{00k} + r_{0jk},$$
$$\pi_{ljk} = \gamma_{l00}, \qquad l = 1,\ldots,P$$

β_{00k} = campus-level coefficients
γ_{l00} = non-randomly varying intercepts
r_{0jk} = campus-level random effect, with r_{0jk} ~N(0; $\tau_2^{\,2}$)

The district level allows for the clustering of campuses within school districts:

$$\beta_{00k} = \gamma_{000} + \mu_{00k},$$

γ_{000} = non-randomly varying intercept
μ_{00k} = district-level random effect, with μ_{00k} ~N(0; $\tau_3^{\,2}$)

DISTRICT MODEL

The district model uses the same structure for the student level, but without terms for campuses. Thus, student-level notation is the same as in the campus model without the "j" terms:

$$Y_{ik} = \pi_{0k} + \sum_{p=1}^{P} \pi_{pk} a_{pk} + e_{ik},$$

The district level is:

$$\pi_{0k} = \gamma_{00} + \mu_{0k},$$
$$\pi_{lk} = \gamma_{l0}, \qquad l = 1,\ldots,P$$

γ_{00} = non-randomly varying intercept
γ_{l0} = non-randomly varying intercepts for student covariates
μ_{0k} = district-level random effect, with μ_{0k} ~N(0; $\tau_2^{\,2}$)

DIAGNOSTICS, ESTIMATION AND RANDOM EFFECTS

With more than 200,000 observations for each grade and year, the statistical power of the model is very strong, making statistical tests less practical than estimates with fewer observations. In reviewing the pattern of significance, the focus was more on residual diagnostics from the different levels of the model. In particular, the model assumes normality of the residuals at each of the three levels. This assumption was explored using the (standardized) estimated residuals at level one, and the (standardized) empirical Bayes residuals at levels two and three.

The model was estimated using maximum likelihood. The (unadjusted) campus effects, r_{0jk}, and district effects, μ_{0k}, were predicted based on estimated variance components. These campus and district effects were constructed to minimize the expected mean-squared error and were reliability-weighted composites of, essentially, the ordinary least squares estimate for the relevant group (campus or district) and an estimate for the overall model.[6]

These calculated effects were best linear unbiased predictions, often termed empirical Bayes residuals, and formed the basis for estimating campus (or teacher) effects in most of the models previously cited. The unadjusted campus effect is relative to its district. The campus effect was summed with the district effect to compare across all campuses. Standard errors were also calculated for both the (adjusted) campus and district predictions.

TECHNICAL APPENDIX 2: FAST SPENDING INDEX METHODOLOGY

Legislation establishing the FAST report requires the Comptroller to evaluate school resource allocation by integrating existing academic and financial data.

In comparing districts, however, it is important to note that these data do not take into account the different costs of providing educational services in various Texas communities. The cost of education in any given school district is a function of the outcomes produced, the prices of inputs, the characteristics of students and parents and other features such as school district size.

Schools that operate in areas with a high cost of living, for instance, generally face higher costs, as do those serving more challenging student bodies. Large school districts can rely on economies of scale to reduce their per-pupil education costs much more than small districts.

To fulfill the requirements of H.B. 3, the FAST project must identify efficient school expenditure practices that advance student achievement. The existing data are informative, but lack the nuance needed for this analysis. For this report, the research team used these indicators to create new cost measures.

In light of the widely varying cost environments in which school districts function, direct financial comparisons among Texas districts would not be fair or appropriate. Instead, this study evaluates each district and campus against those identified as fiscal "peers," districts and campuses that operate in a similar cost environment, are of similar size and serve similar students.

INPUT PRICES

The education sector is labor-intensive, requiring professional staff such as teachers and administrators as well as support staff such as clerks, educational aides and maintenance workers.

To measure the price of professional staff, the FAST study used an extension of the National Center for Education Statistics' Comparable Wage Index (CWI), which measures regional variations in the prevailing wage for college graduates. In other words, the CWI accounts for higher wages in areas with higher costs of living or that lack important amenities.

For example, if Dallas engineers receive 15 percent more than the average Texas engineer, and Dallas nurses receive 15 percent more than the average nurse, the CWI predicts that Dallas teachers and principals also should be paid 15 percent more than the average teachers and principals.

The study also adapted the CWI methodology to measure the price for non-professional staff using the High School Comparable Wage Index (HS CWI).

SCHOOL DISTRICT SIZE

Previous research has demonstrated that school district enrollment is a primary cost factor in public education. Districts with small enrollments face much higher per-pupil costs than larger districts, most notably due to administrative and classroom costs being spread across smaller student bodies. The Texas school finance formula recognizes the inherent cost disadvantage smaller districts face by providing them additional revenue.

Districts encompassing large geographic areas also may face higher costs because their students and schools are widely dispersed, entailing much higher transportation costs. For this reason, the state provides additional funding to small districts covering more than 300 square miles.

To reflect these factors, the FAST analysis includes two measures of school district size — the number of students in fall enrollment and the number of square miles in the district.

STUDENT NEED

To capture variations in student needs that lead to cost variations, the FAST study considered district and campus shares of students who were:

- high-needs special education students,
- other special education students,
- limited English proficient (LEP) and
- economically disadvantaged.

All four cases require additional resources per student, including smaller required class sizes and specialized teachers and supplies.

In all cases, the study employed data averaged from the 2007, 2008 and 2009 school years.[7] Using a three-year average reduces the influence of one-time events. **Exhibit 1** describes the cost factors used in this analysis.

EXHIBIT 1

DISTRICT COST FACTORS

	MEAN	MINIMUM	MAXIMUM
INPUT PRICES			
COMPARABLE WAGE INDEX	1.23	0.94	1.58
HIGH SCHOOL COMPARABLE WAGE INDEX	1.18	0.95	1.47
SCHOOL DISTRICT SIZE			
ENROLLMENT	3,783	16	199,524
SQUARE MILES	263	5	3,822
STUDENT NEED			
PERCENT LIMITED ENGLISH PROFICIENT	8.1	0.0	50.0
PERCENT ECONOMICALLY DISADVANTAGED	55.5	0.0	100.0
PERCENT HIGH NEEDS SPECIAL EDUCATION	3.7	0.0	70.9
PERCENT OTHER SPECIAL EDUCATION	7.5	0.0	33.4

Sources: Texas Education Agency, National Center for Education Statistics, Bureau of Labor Statistics, U.S. Census Bureau and Texas Comptroller of Public Accounts.

IDENTIFYING FISCAL PEERS

Information from research and stakeholders suggests that district and campus resource allocation should be evaluated through a number of lenses and using a variety of performance measures.

The FAST study achieves this by grouping each district and campus with up to 40 others that are similar to it with respect to an array of significant cost factors. The methodology matches most districts and campuses with fiscal peers using a well-regarded research strategy called propensity score matching.

PROPENSITY SCORE MATCHING

The FAST study uses propensity score matching, a well-regarded research strategy, to identify fiscal peers for each school district. Propensity score matching is used to construct comparison groups from data observed outside of the experiment and beyond the control of the researchers.[8] For example, if you want to know the effect of a jobs training program, you must compare program participants to nonparticipants who are as similar as possible to be confident that differences in employment outcomes are the result of the training.

Propensity score matching identifies the best available control group (the comparison group) for any given member of a group. For the FAST project, propensity-score matching was used to identify up to 40 peers for each district that are most similar with respect to the common determinants of school district cost — input prices, school district size and student demographics.

Because each school district needed a control group, and the only possible members of that group were other Texas school districts, there are no "treatment" or "control" districts to compare against each other for this project. Instead, school districts were divided into subgroups based on their core operating expenditures per pupil.[9] Each subgroup was assigned to a treatment group and a probit regression model was used to calculate the corresponding propensity scores (see the "District Level Matches" section for more).

For each treatment school district, all of the school districts (treatments and controls) with propensity scores within a two-standard-deviation band were identified around the district's own propensity score. Then up to 40 districts with the closest propensity scores (i.e. the 40 nearest neighbor matches) that were also within the band were designated as fiscal peers for that school district.

The research team also identified fiscal peers for individual schools using a similar methodology and campus-level data. Any differences between the district-level and campus-level analyses were driven by differences in data availability and by the need to reflect wide variations in organizational structure among elementary, middle school and high school campuses.

DISTRICT-LEVEL MATCHES

Most Texas school districts have many plausible fiscal peers. Some, however, are unusual enough in at least one cost dimension to limit their number of potential peers. For example, 10 Texas districts had a three-year average share of special education students exceeding 39 percent. No other district had a share exceeding 28 percent. Arguably, then, these 10 districts should be matched only with one another. Similarly, while most school districts serve a full range of grade levels, some have no high school and others have no elementary schools. It seems most appropriate to match these restricted grade-level districts only to districts offering similar grade ranges.

Still another group, districts in the alternative education accountability system serving at-risk youth, seems to match poorly with other K-12 districts. Finally, a handful of districts in Texas are very large — more than 1,000 times larger than some other districts. It seems inappropriate to match a very large district with a very small one, no matter how similar they are in other respects.

To accommodate these unusual cases, the districts were stratified before applying the propensity score matching technique (**Exhibit 2**). Each district was assigned to one of seven strata based on various student population characteristics, and propensity score matching was used as needed to identify fiscal peers within each stratum. If the stratum contained no more than 41 districts, then all districts in the stratum were designated as fiscal peers, and propensity score matching was not used.

The 12 smallest K-12 districts — those with no more than 100 students on average over the last three years — comprised their own stratum and were matched accordingly. It seems unreasonable, however, to exclude possible matches with slightly more than 100 students; the best possible match for a district with 99 students could be a district with 101 students, for instance. Therefore, districts with 100 or fewer students were matched with any K-12 district having fewer than 120 students. Twenty-three K-12 districts had an average of fewer than 120 students in fall enrollment, so each of the smallest K-12 districts had 22 fiscal peers.

The 16 largest Texas school districts — those with an average of more than 50,000 students over the last three years — also comprised their own stratum. These districts also were matched with any district having at least 40,000 students. Therefore, each of the largest districts also had 22 fiscal peers.

The smallest stratum contained 10 school districts specializing in special education (i.e. those with at least a 39 percent share of special education students). Eight of these 10 districts also were Alternative Education Accountability (AEA) charter school districts. No other districts had a special education share within 10 percentage points of these districts, so they represent an independent stratum, giving each nine fiscal peers.

AEA districts serve students at high risk of dropping out and are subject to different accountability standards. TEA classifies 20 K-12 districts with less than a 30 percent share of special education students as AEA districts. These 20 charter school districts represent an independent stratum in which each school has 19 fiscal peers.

Similarly, 41 school districts have no elementary grade levels. All but one of these are charter school districts and most are AEA districts. All of the districts in this stratum were designated as fiscal peers, so each had exactly 40 fiscal peers.

The largest stratum, and the primary focus of this analysis, consists of districts serving both elementary and secondary school children. Propensity score matching was used to identify fiscal peers for each of the districts in this stratum, "All Other K-12." To estimate the propensity scores, districts were divided into metropolitan and nonmetropolitan districts and then subdivided into quintiles based on core operating expenditures per pupil.[10] By grouping campuses and districts by metropolitan status, and then by core operating expenditures per pupil, the designated fiscal peers are ensured to be similar to one another with respect to the two primary determinants of educational cost, economies of scale and geographic variations in labor costs.

EXHIBIT 2

TEXAS SCHOOL DISTRICTS BY STRATUM

	NUMBER OF TRADITIONAL SCHOOL DISTRICTS	NUMBER OF CHARTER SCHOOL DISTRICTS	TOTAL NUMBER OF DISTRICTS	UNIQUE PEER GROUPS
ALL OTHER K-12	941	40	981	769
NO HIGH SCHOOL GRADES	59	91	150	77
NO ELEMENTARY GRADES	1	40	41	1
AEA K-12	0	20	20	1
VERY LARGE K-12	16	0	16	1
VERY SMALL K-12	12	0	12	1
SPECIAL EDUCATION DISTRICTS	0	10	10	1
TOTALS	1,029	201	1,230	851

Note: "Very small" K-12 school districts have no more than 100 students. "Very large" K-12 districts have more than 50,000 students. Alternative Education Accountability (AEA) school districts serve both elementary and secondary grade levels.
Source: Texas Comptroller of Public Accounts.

Each of the 10 subgroups then was assigned to a treatment group. The research team estimated the corresponding probability model using the eight cost factors, their squares and selected interaction terms as control variables.[11] Regardless of size, all non-AEA K-12 school districts are eligible matches and included in the set of possible control schools for each of the 10 subgroup analyses. Therefore, while there were 981 possible treatment districts in the stratum, there were 1,009 observations for each regression model.[12]

For each model, a corresponding distribution of propensity scores was calculated. These 10 sets of propensity scores were used to identify fiscal peers for all but the smallest and largest of the state's K-12 school districts. The research team identified the 40 school districts with the nearest propensity scores to that of each treatment district. Thus, propensity scores from model 1 were used to find the nearest neighbors for districts in the first metropolitan quintile, while the propensity score from model 10 identified the nearest neighbors for the districts in the fifth nonmetropolitan quintile.

It is important to note that each district's peers were drawn from the other 1,008 districts. Each district can have a unique peer group, so that the peer groups of a particular district's peers will not necessarily be the same. **Exhibit 3** presents descriptive statistics on those propensity scores, while **Exhibit 4** illustrates Spearman correlations among them.

Spearman correlations emphasize consistency in ranking across various score distributions, and therefore are a better metric for these comparisons than the more familiar Pearson correlations. Because the propensity scores were used for nearest-neighbor matching, it did not matter if the scores ranked districts from highest to lowest or from lowest to highest, so the sign of the correlation coefficient across rankings was irrelevant.

What *does* matter is the magnitude of the coefficient. Coefficients close to one indicate rankings that are highly consistent with one another. As **Exhibit 4** illustrates, the scores were significantly correlated across all of the various models, indicating that the different propensity score models yielded reasonably consistent rankings.

Potential matches with propensity scores more than two standard deviations away from the district's own score were discarded. If 40 neighbors were not within a two-standard-deviation radius, then the district has fewer than 40 fiscal peers.

Some districts, however, had only a handful of matches. For example, Valley View ISD, the K-12 district with the state's highest percent of students identified as Limited English Proficient, has only six neighbors within a two-standard-deviation radius, and therefore has only six propensity score matches. **Exhibit 5** shows the number of districts corresponding to each number of fiscal peers matches within "all other K-12" strata.

EXHIBIT 3

DESCRIPTIVE STATISTICS FROM K-12 PROPENSITY SCORE MODELS

	OBSERVATIONS	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
METROPOLITAN MODELS					
PROPENSITY SCORE MODEL 1	1009	0.10	0.17	0.00	0.84
PROPENSITY SCORE MODEL 2	1009	0.10	0.12	0.00	0.49
PROPENSITY SCORE MODEL 3	1009	0.10	0.11	0.00	0.56
PROPENSITY SCORE MODEL 4	1009	0.10	0.13	0.00	0.88
PROPENSITY SCORE MODEL 5	1009	0.10	0.15	0.00	0.95
NONMETROPOLITAN MODELS					
PROPENSITY SCORE MODEL 1	1009	0.10	0.16	0.00	0.79
PROPENSITY SCORE MODEL 2	1009	0.10	0.10	0.00	0.55
PROPENSITY SCORE MODEL 3	1009	0.10	0.11	0.00	0.46
PROPENSITY SCORE MODEL 4	1009	0.10	0.12	0.00	0.60
PROPENSITY SCORE MODEL 5	1009	0.10	0.20	0.00	0.96

Source: Texas Comptroller of Public Accounts.

EXHIBIT 4

SPEARMAN CORRELATIONS OF K-12 PROPENSITY SCORES

	METROPOLITAN					NONMETROPOLITAN				
	QUINTILE1	QUINTILE2	QUINTILE3	QUINTILE4	QUINTILE5	QUINTILE1	QUINTILE2	QUINTILE3	QUINTILE4	QUINTILE5
METROPOLITAN										
QUINTILE1	1.00									
QUINTILE2	0.88	1.00								
QUINTILE3	0.70	0.82	1.00							
QUINTILE4	0.55	0.69	0.75	1.00						
QUINTILE5	0.08	0.00	0.17	0.47	1.00					
NONMETROPOLITAN										
QUINTILE1	-0.31	-0.30	-0.42	-0.43	-0.18	1.00				
QUINTILE2	-0.39	-0.40	-0.50	-0.49	-0.15	0.92	1.00			
QUINTILE3	-0.67	-0.73	-0.72	-0.67	-0.12	0.70	0.81	1.00		
QUINTILE4	-0.80	-0.84	-0.81	-0.67	-0.05	0.58	0.66	0.93	1.00	
QUINTILE5	-0.78	-0.90	-0.85	-0.67	0.10	0.40	0.52	0.81	0.90	1.00

Note: All of the correlations are statistically significant at the 5 percent level.
Source: Texas Comptroller of Public Accounts.

EXHIBIT 5

NUMBER OF PROPENSITY MATCHES FOR K-12 DISTRICTS

NUMBER OF MATCHES	NUMBER OF TRADITIONALSCHOOL DISTRICTS	NUMBER OF CHARTER SCHOOL DISTRICTS
6	1	0
9	2	0
11	1	0
14	1	0
16	1	0
23	1	0
26	1	0
32	1	0
35	2	0
36	0	1
40	930	39

Source: Texas Comptroller of Public Accounts.

The final remaining stratum contains the 150 school districts with no high school.[13] Because the stratum is not small, the research team used propensity score matching to find fiscal peers for each of these districts. The stratum is not large enough, however, to be divided into quintiles, as was done with the K-12 stratum. Furthermore, a third of these districts (56) do not serve middle-school students. Therefore, the districts were divided into three groups — low-spending K-8 districts, high-spending K-8 districts and K-6 districts — based on their enrollment patterns and core operating expenditures per pupil.

As with the stratum of 981 K-12 districts, each of the three subgroups were assigned as a treatment group, and the corresponding probability model was estimated using the eight cost factors and their squares as control variables. **Exhibit 6** presents marginal effects from the three models.

Again, the 40 school districts with the nearest propensity scores to those of each designated treatment district were identified, and potential matches outside of a two-standard-deviation band were discarded. All 150 districts had at least 39 viable propensity score matches.

ASSESSING MATCH QUALITY

The peer groups identified by the propensity score analysis appear generally plausible. Districts in high-wage areas generally were matched with other districts in high-wage areas, and the same held true for high-poverty districts.

For a more formal appraisal of peer group quality, however, a frame of reference is needed. In other words, alternative groups for comparison must be generated.

EXHIBIT 6

DESCRIPTIVE STATISTICS FROM K-8 PROPENSITY SCORE MODELS

	OBSERVATIONS	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
PROPENSITY SCORE MODEL 1	150	0.31	0.24	0.00	0.92
PROPENSITY SCORE MODEL 2	150	0.31	0.27	0.00	1.00
PROPENSITY SCORE MODEL 3	150	0.38	0.24	0.00	0.96

Source: Texas Comptroller of Public Accounts.

Two alternative grouping strategies were developed. First, an alternative set of fiscal peers was constructed by randomly assigning a propensity score to each school district, and then groups based on those random scores were generated. These randomly assigned groups provided a baseline for comparison, but are no better than drawing the names of fiscal peers out of a hat.

The second alternative was a *cost-function analysis* used to assign a cost projection to each school district. Cost function analysis is a strategy used to find the relationship between specific outputs and inputs, and is widely used in educational contexts. When properly specified and estimated using *stochastic frontier analysis* (SFA), the educational cost function is a theoretically and statistically reliable method for estimating cost variations between districts, given designated performance goals.[14]

SFA was used to estimate a translog cost function with two outputs (Annual Reading Progress Scores and Annual Math Progress Scores), two input prices, and the same array of student demographics and other cost factors included in the propensity score matching analysis.[15] The cost function estimates were used to predict the cost of producing the state average level of annual progress in each school district. The 40 school districts with the closest cost predictions for each school district, then, were its alternative fiscal peers.

Exhibit 7 illustrates the Spearman correlations among the scoring variables (propensity scores, cost function predictions and random rankings) used to generate the three sets of peer groups. In all three cases, nearest neighbors with respect to the scoring variable were chosen. As the exhibit illustrates, the propensity scores are well correlated with the cost predictions, and badly correlated with the randomized scores.

The only cases in which cost function predictions were not significantly correlated with the propensity scores were the first nonmetropolitan quintile and the K-6 schools model. In the first case, the lack of correlation was driven by a large number of school districts with propensity scores near zero. Those districts are "outside the region of common support," meaning that they were not in the least-cost nonmetropolitan quintile and had a very low estimated probability of belonging there. If attention is restricted only to the region of common support, the correlation between the propensity score and the cost function projection rises to -0.4918.

The lack of correlation between the propensity scores and cost projections for the K-6 model (which persists even if attention is restricted to the region of common support) could cast doubt on the propensity score matches, but could also indicate that the instructional technology used in districts with elementary schools only is so different that the cost function model (which

EXHIBIT 7

SPEARMAN CORRELATIONS ACROSS SCORING VARIABLES

	COSTFUNCTION SCORES	RANDOM SCORES
K-12 METROPOLITAN MODELS		
PROPENSITY SCORE MODEL 1	-0.81	-0.04
PROPENSITY SCORE MODEL 2	-0.82	-0.04
PROPENSITY SCORE MODEL 3	-0.66	-0.01
PROPENSITY SCORE MODEL 4	-0.45	0.01
PROPENSITY SCORE MODEL 5	0.16	0.04
K-12 NONMETROPOLITAN MODELS		
PROPENSITY SCORE MODEL 1	0.02	0.00
PROPENSITY SCORE MODEL 2	0.11	-0.01
PROPENSITY SCORE MODEL 3	0.49	0.00
PROPENSITY SCORE MODEL 4	0.68	0.02
PROPENSITY SCORE MODEL 5	0.80	0.03
K-8 MODELS		
PROPENSITY SCORE MODEL 1	-0.54	-0.14
PROPENSITY SCORE MODEL 2	0.39	0.12
PROPENSITY SCORE MODEL 3	-0.02	-0.02

Source: Texas Comptroller of Public Accounts.

was estimated using data on K-12 districts) cannot fully reflect important cost differences for this subset of schools, thereby casting doubt on the cost function matches.

Another strategy for comparing peer groups generated by the three matching strategies is to simply count the number of matches they have in common. In doing so, the assumption is that the alternative strategies would be applied only to districts that were matched using propensity scoring, and that matches for districts in the other strata would remain unchanged.

Despite significant correlations among the underlying score variables, the cost function and propensity score modeling strategies yield very different sets of fiscal peers (**Exhibit 8**). Fewer than 10 percent of the districts identified as fiscal peers by the propensity score matching technique were also identified as peers based on cost function matching. One explanation could be that most Texas school districts are highly similar to more than 40 other districts and that the alternative strategies are finding different but equally plausible matches.

EXHIBIT 8

NUMBER OF MATCHES IN COMMON

	COSTFUNCTION MATCHES	RANDOM MATCHES
K-12 METROPOLITAN DISTRICTS		
NUMBER OF PEERS IN COMMON	1,320	615
TOTAL NUMBER OF PEERS	19,266	19,266
K-12 NONMETROPOLITAN DISTRICTS		
NUMBER OF PEERS IN COMMON	1,613	616
TOTAL NUMBER OF PEERS	19,746	19,746
K-8 DISTRICTS		
NUMBER OF PEERS IN COMMON	293	195
TOTAL NUMBER OF PEERS	5,998	5,998

Source: Texas Comptroller of Public Accounts.

Because the three strategies yielded different sets of fiscal peers, another metric for deciding among these sets was necessary. The goal of the matching strategies is to identify up to 40 peer districts that are highly similar to each individual district. Match quality evaluation is based on the extent to which the designated peers differ from the district itself with respect to each of the eight cost factors.

The mean squared error (MSE) for each cost factor measures the sum of squared differences between the district value for a cost factor and the peer values for that cost factor.[16] It represents the average deviation from baseline for the districts in the peer group. **Exhibits 9** and **10** illustrate the distribution of mean squared errors for each of the eight cost factors across each of the three alternative grouping strategies.

Exhibit 9 presents mean squared errors for K-12 school districts. As expected, the average MSE for propensity score matching was lower than for random assignment in all cases. Somewhat surprisingly, the average MSE also was lower for propensity score matching than for cost function matching in all but one case, and in that one case, percent low income, the MSEs were not statistically different at the 1 percent level. The evidence, then, suggests that propensity score matching yields more homogeneous groupings than cost function matching.

Exhibit 10 presents mean squared errors for K-8 school districts. Here, the evidence was more mixed. For the size-related cost factors (enrollment and square miles) and the special education cost factors, the propensity score-based groups were more internally similar, but for the share of low-income students and the share of LEP students the cost function-based groups were more internally similar. There were no differences in means for the MSEs of the other cost factors. As such, the evidence suggests that propensity score matching yielded fiscal peer groups that were no more or less internally consistent than those arising from cost function analysis.

DISTRICT SPENDING INDEX

To fairly assess each district's financial disposition, each fiscal peer group was sorted into quintiles by a CWI-based spending measure. The spending measure consisted of core operating expenditures per pupil, adjusted for geographic wage variations using the CWI measure.[17]

Each district then received a rating according to its quintile within the peer group. Ratings range from "very low" to "very high," representing the lowest and highest spending quintiles of each district's peer group. A rating of "average" indicates that at least 40 percent of the peers spent more than the district, and at least 40 percent of the peers spent less. **Exhibit 11** compares spending measures broken down by spending index rating.

CAMPUS-LEVEL MATCHES

The Texas public school system includes nearly 8,000 campuses that differ widely with respect to size and student demographics. The FAST analysis focused on campuses with an average of at least 25 students in fall enrollment from 2007 through 2009.

EXHIBIT 9

MEAN SQUARED ERRORS FOR ALTERNATIVE GROUPING STRATEGIES, K-12 STRATA

	OBSERVATIONS	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
ENROLLMENT					
PROPENSITY SCORE	981	27.01	25.69	2.75	215.54
COST FUNCTION	981	33.42*	32.77	2.31	328.07
RANDOM ASSIGNMENT	981	63.54*	43.97	17.37	308.17
LEP					
PROPENSITY SCORE	981	16.65	26.08	1.41	240.92
COST FUNCTION	981	22.51*	29.83	1.16	256.82
RANDOM ASSIGNMENT	981	22.68*	28.60	2.51	227.32
LOW INCOME					
PROPENSITY SCORE	981	10.15	8.95	1.25	56.86
COST FUNCTION	981	10.62	7.59	2.23	74.59
RANDOM ASSIGNMENT	981	14.10*	9.26	4.77	66.21
HIGH NEEDS SPECIAL ED.					
PROPENSITY SCORE	981	1.03	1.96	0.09	42.19
COST FUNCTION	981	1.23*	2.15	0.17	45.48
RANDOM ASSIGNMENT	981	6.10*	10.38	0.31	51.88
OTHER SPECIAL ED.					
PROPENSITY SCORE	981	1.26	1.49	0.17	25.00
COST FUNCTION	981	1.62*	1.66	0.28	27.13
RANDOM ASSIGNMENT	981	1.93*	1.85	0.47	29.89
SQUARE MILES					
PROPENSITY SCORE	981	38.42	34.79	4.76	294.03
COST FUNCTION	981	65.73*	41.35	17.23	351.56
RANDOM ASSIGNMENT	981	73.40*	45.03	14.82	360.45
HS-CWI					
PROPENSITY SCORE	981	1.12	1.27	0.03	11.20
COST FUNCTION	981	2.95*	1.76	0.11	11.50
RANDOM ASSIGNMENT	981	3.89*	1.81	1.22	10.40
CWI					
PROPENSITY SCORE	981	1.42	1.54	0.06	16.05
COST FUNCTION	981	4.06*	2.37	0.22	15.31
RANDOM ASSIGNMENT	981	5.40*	2.50	1.70	13.21

* indicates that the difference in means from propensity score matching is statistically significant at the 1 percent level.
Source: Texas Comptroller of Public Accounts.

EXHIBIT 10

MEAN SQUARED ERRORS FOR ALTERNATIVE GROUPING STRATEGIES, K-8 STRATA

	OBSERVATIONS	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
ENROLLMENT					
PROPENSITY SCORE	150	17.71	17.33	4.93	155.12
COST FUNCTION	150	35.24*	28.93	2.54	170.13
RANDOM ASSIGNMENT	150	78.68*	52.32	21.34	296.85
LEP					
PROPENSITY SCORE	150	52.36	48.69	9.25	240.52
COST FUNCTION	150	40.65	57.27	2.69	225.63
RANDOM ASSIGNMENT	150	42.90	59.12	2.37	233.14
LOW INCOME					
PROPENSITY SCORE	150	26.06	16.51	9.43	97.37
COST FUNCTION	150	20.40*	15.53	4.05	89.11
RANDOM ASSIGNMENT	150	22.46*	13.91	4.38	67.11

EXHIBIT 10 CONTINUED

	OBSERVATIONS	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
HIGH NEEDS					
PROPENSITY SCORE	150	1.92	2.71	0.29	27.08
COST FUNCTION	150	3.14*	5.33	0.24	39.37
RANDOM ASSIGNMENT	150	7.26*	11.35	0.41	52.12
OTHER SPECIAL					
PROPENSITY SCORE	150	2.99	2.37	0.73	15.52
COST FUNCTION	150	3.78*	3.13	0.34	15.39
RANDOM ASSIGNMENT	150	3.47	2.39	0.50	10.39
SQUARE MILES					
PROPENSITY SCORE	150	47.75	61.51	4.82	574.33
COST FUNCTION	150	120.81*	52.26	29.14	315.78
RANDOM ASSIGNMENT	150	120.61*	52.89	17.39	255.98
HS-CWI					
PROPENSITY SCORE	150	3.59	1.98	1.14	10.08
COST FUNCTION	150	3.82	2.85	0.20	12.02
RANDOM ASSIGNMENT	150	4.24*	1.97	1.44	9.13
CWI					
PROPENSITY SCORE	150	4.96	3.15	1.35	17.95
COST FUNCTION	150	5.30	3.91	0.56	16.27
RANDOM ASSIGNMENT	150	5.84*	2.78	2.03	12.23

* indicates that the difference in means from propensity score matching is statistically significant at the 1-percent level.
Source: Texas Comptroller of Public Accounts.

EXHIBIT 11

DISTRICT EXPENDITURES BY SPENDING INDEX

SPENDING INDEX	DISTRICTS	CORE SPENDING*	ADJUSTED CORE SPENDING**
VERY LOW	181	$7,037	$7,280
LOW	262	7,970	8,608
AVERAGE	328	8,532	9,669
HIGH	287	9,247	10,708
VERY HIGH	152	11,968	14,144
N/A***	25	—	—

* Core operating expenditures per pupil.
** Cost-adjusted core operating expenditures per pupil.
*** Insufficient data to receive a Spending Index.
Source: Texas Comptroller of Public Accounts.

It seemed most appropriate to match schools that serve similar grade levels. Therefore, the campuses were stratified according to the grade levels served (early elementary, elementary, middle, secondary and multi-level).[18] The secondary campuses also were divided into very large high schools and other high schools. (The very large high schools have at least 2,000 students in fall enrollment, and are roughly analogous to the division 5A high school classification used for interscholastic athletics. No other type of campus is this large.) Finally, the model separated out AEA residential and nonresidential campuses. Propensity score matching then was applied within each stratum. **Exhibit 12** displays the number of campuses in each stratum.

Despite the large number of campuses, a few were highly unusual and could not be matched using propensity scoring. These include two early elementary campuses and one elementary campus with a student body of at least 70 percent special education students. No other school at similar grade levels serves more than 50 percent. These three campuses were designated as a separate stratum and served as peers for one another. Similarly, the non-elementary campuses with at least 70 percent special education students were designated as a separate stratum.

As with the district-level analysis, campuses were sorted into expenditure subgroups within each stratum. In this case, however, the sorting was based on operating expenditures per pupil for campus-related activities instead of the broader definition employed in the district-level analysis.[19] Operating expenditures for campus-related activities (instruction, instructional services, instructional leadership, school leadership and student support services) are more consistently defined across campuses due to the way districts allocate administrative costs. Some districts allocate most of their central administration activities to specific campuses, while others do not. Virtually all districts allocate their campus-related expenditures.

EXHIBIT 12

TEXAS PUBLIC SCHOOL CAMPUSES BY STRATUM

TYPE OF CAMPUS	NUMBER OF CAMPUSES
EARLY ELEMENTARY SCHOOLS	332
ELEMENTARY SCHOOLS	4,059
MIDDLE SCHOOLS	1,578
VERY LARGE SECONDARY SCHOOLS*	228
OTHER SECONDARY SCHOOLS	990
MULTI-LEVEL SCHOOLS	293
AEA RESIDENTIAL SCHOOLS	
SECONDARY SCHOOLS	29
OTHER SCHOOLS	33
AEA NON-RESIDENTIAL SCHOOLS	
ELEMENTARY AND EARLY ELEMENTARY SCHOOLS	14
MIDDLE SCHOOLS	15
SECONDARY SCHOOLS	198
MULTI-LEVEL SCHOOLS	44
SPECIAL EDUCATION ELEMENTARY SCHOOLS	3
SPECIAL EDUCATION NON-ELEMENTARY SCHOOLS	29
TOTAL	7,845

* "Very large" secondary schools have more than 2,000 students.
Source: Texas Comptroller of Public Accounts.

EXHIBIT 13

CAMPUS COST FACTORS

	MEAN	MINIMUM	MAXIMUM
INPUT PRICES			
COMPARABLE WAGE INDEX	1.33	0.94	1.58
HIGH SCHOOL COMPARABLE WAGE INDEX	1.26	0.95	1.47
SCHOOL DISTRICT SIZE			
ENROLLMENT	596	1	4,572
STUDENT NEED			
PERCENT LIMITED ENGLISH PROFICIENCY	15.9	0.00	100.0
PERCENT ECONOMICALLY DISADVANTAGED	58.5	0.00	100.0
PERCENT SPECIAL EDUCATION	10.7	0.00	100.0

* Comparable Wage Index for professional workers and High School Comparable Wage Index for support staff.
Sources: Texas Education Agency, National Center for Education Statistics, Bureau of Labor Statistics and Texas Comptroller of Public Accounts.

The elementary, middle and secondary campuses then were divided into two groups — metropolitan and nonmetropolitan schools — and then subdivided into subgroups based on their instructional operating expenditures per pupil. There were too few nonmetropolitan schools in the multi-level schools, early elementary schools, large secondary schools and AEA strata, so these strata are not divided into regional groups before subdividing by instructional expenditures per pupil.

Once divided into strata and subgroups, propensity score matching was used to identify the fiscal peers for each stratum with more than 40 campuses. The matching analysis used campus-level versions of most of the cost factors included in the district-level analysis. Geographic size is not relevant at the school level and was not included. High-needs special education students and other special education students cannot be differentiated at the campus level, and so those two groups were combined. The other six cost factors from the district-level model, as well as their squares and selected interaction terms as control variables, remained. Interaction terms were selected on a case-by-case basis to ensure that all propensity score distributions satisfied the necessary balancing conditions.

Again, the 40 campuses with the closest propensity scores (i.e. the 40 nearest-neighbor matches) within two standard deviations of the campus's own propensity score were designated as its fiscal peers. If 40 neighbors were not within a two-standard-deviation radius, the campus has fewer than 40 fiscal peers. The vast majority of campuses, however, have 40 viable, nearest-neighbor matches. **Exhibit 13** displays the descriptive statistics on the six variables used in the campus-level matching analysis.

Exhibit 14 presents MSEs for the fiscal peer groups generated by propensity score matching. Each MSE represents the average percentage deviation from baseline for the campuses in the peer group with respect to a specific cost factor. As the exhibit illustrates, MSEs generally were low across all six cost factors, indicating that the peer groups were highly similar in all six dimensions.

Some outlier campuses, however, did not have very good matches. Generally, the campuses with less-precise matches were those at either end of the cost factor distribution where the number of potential close matches was limited; the most precise matches were in the middle of the distribution, where there were many potential peers. Tightening the

EXHIBIT 14

MEAN SQUARED ERRORS FOR PROPENSITY SCORE MATCHES BY CAMPUS TYPE

	OBSERVATIONS	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
EARLY ELEMENTARY SCHOOLS					
ENROLLMENT	332	9.70	12.86	0.43	87.35
LEP	332	54.95	51.51	4.91	335.27
LOW INCOME	332	10.81	12.36	1.55	98.22
SPECIAL ED.	332	2.81	4.47	0.36	46.41
HS-CWI	332	3.76	1.74	1.04	10.18
CWI	332	5.06	2.55	0.88	14.54
ELEMENTARY SCHOOLS					
ENROLLMENT	4,058	4.50	6.80	0.00	129.05
LEP	4,058	48.07	42.76	0.29	368.04
LOW INCOME	4,058	20.93	16.07	0.24	114.22
SPECIAL ED.	4,058	1.40	1.36	0.12	20.88
HS-CWI	4,058	1.64	1.27	0.01	8.73
CWI	4,058	1.80	1.37	0.02	11.97
MIDDLE SCHOOLS					
ENROLLMENT	1,577	11.42	12.66	0.51	140.17
LEP	1,577	8.26	13.68	0.15	203.12
LOW INCOME	1,577	11.69	10.85	0.26	89.11
SPECIAL ED.	1,577	2.39	2.71	0.11	40.51
HS-CWI	1,577	1.48	1.26	0.03	8.60
CWI	1,577	1.70	1.41	0.06	11.48
VERY LARGE SECONDARY SCHOOLS					
ENROLLMENT	228	0.79	0.87	0.14	8.42
LEP	228	2.96	4.41	0.19	44.37
LOW INCOME	228	11.77	10.11	1.78	78.31
SPECIAL ED.	228	1.22	0.97	0.31	7.84
HS-CWI	228	1.53	1.21	0.21	8.22
CWI	228	1.74	1.30	0.20	8.94
SECONDARY SCHOOLS					
ENROLLMENT	1,217	14.34	17.47	0.88	212.53
LEP	1,217	8.90	32.01	0.12	515.60
LOW INCOME	1,217	13.70	12.01	0.76	83.57
SPECIAL ED.	1,217	6.87	15.08	0.29	260.41
HS-CWI	1,217	1.55	1.43	0.03	10.92
CWI	1,217	1.87	1.81	0.07	18.93
MULTI-LEVEL SCHOOLS					
ENROLLMENT	369	12.98	13.34	0.77	82.71
LEP	369	16.78	33.64	0.66	320.77
LOW INCOME	369	17.48	16.12	2.33	108.70
SPECIAL ED.	369	15.49	29.97	0.61	175.00
HS-CWI	369	2.58	1.94	0.28	12.52
CWI	369	3.39	2.52	0.63	17.09

Source: Texas Comptroller of Public Accounts.

bands around the propensity scores would reduce the MSEs for campuses in the tails of the distribution, but also would reduce the number of fiscal peers.

As with the district-level peer groups, the majority of campuses had 40 fiscal peers (**Exhibit 15**). Match quality was assessed using the same techniques employed in the district analysis, arriving at the same conclusions.

EXHIBIT 15

PROPENSITY SCORE MATCHES FOR TEXAS PUBLIC SCHOOL CAMPUSES

NUMBER OF MATCHES	EARLY ELEMENTARY	ELEMENTARY	MIDDLE	VERY LARGE SECONDARY	OTHER SECONDARY	MULTI-LEVEL
0	0	1	1	0	0	0
1	0	1	0	0	0	0
2	0	3	0	0	0	0
3	0	3	0	0	0	0
4	0	2	0	0	0	0
7	0	0	0	0	1	0
8	1	0	1	0	0	0
9	0	1	0	0	1	0
10	0	1	0	0	1	0
11	0	2	1	0	0	1
12	0	2	0	0	0	0
13	0	1	0	0	2	0
16	0	0	3	0	0	0
17	0	1	0	0	1	0
18	0	3	1	0	0	0
19	0	1	0	0	0	0
20	0	1	1	0	0	0
21	0	1	0	0	0	0
22	1	0	0	0	1	2
23	2	1	1	1	0	1
24	1	0	0	0	0	2
25	2	5	0	1	1	0
26	0	0	1	1	2	1
27	0	0	0	0	0	1
28	0	3	0	2	0	2
29	0	2	0	0	0	1
30	0	1	0	0	1	1
31	0	2	0	2	0	0
32	0	3	1	0	0	2
33	1	1	0	0	1	0
34	0	1	0	1	0	6
35	0	1	0	2	3	2
36	1	0	0	0	1	0
37	0	1	2	0	3	5
38	1	1	1	2	3	6
39	1	3	1	1	0	5
40	321	4,010	1,563	215	1,166	299

Source: Texas Comptroller of Public Accounts.

CAMPUS SPENDING INDEX

As with the district analysis, each campus fiscal peer group was sorted into quintiles by a CWI-based spending measure. The spending measure consisted of campus-related activities per pupil, adjusted for geographic wage variations using the CWI measure.[20] Each campus then received a rating according to its quintile within the peer group. Ratings range from "very low" to "very high," representing the lowest and highest spending quintiles of each campus's peer group. A rating of "average" indicates that at least 40 percent of the peers spent more than the campus, and at least 40 percent of the peers spent less.

Exhibit 16 shows spending measures broken down by spending index rating.

Exhibits 17 and 18 show results from the propensity score models. The top number in each row is the estimated coefficient, and the bottom number in parenthesis is the estimated t-statistic value.

EXHIBIT 16

CAMPUS EXPENDITURES BY SPENDING INDEX RATING

SPENDING INDEX	CAMPUSES	CORE SPENDING*	ADJUSTEDCORE SPENDING**
VERY LOW	1,186	$4,848	$4,756
LOW	1,630	5,488	5,557
AVERAGE	1,772	5,917	6,160
HIGH	1,591	6,300	6,817
VERY HIGH	1,048	7,202	8,033
N/A***	1,095	—	—

* Campus-related activities per pupil.
** Cost-adjusted campus-related activities per pupil.
*** Insufficient data to receive a Spending Index.
Source: Texas Comptroller of Public Accounts.

EXHIBIT 17

MARGINAL EFFECTS FROM PROBIT, K-12 DISTRICTS

	METROPOLITAN					NONMETROPOLITAN				
	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ENROLLMENT (LOG)	0.006	0.108	-0.014	0.057	0.110	0.001	0.138	0.016	0.000	0.000
	(1.91)	(2.91)**	(0.34)	(1.61)	(1.99)*	(4.25)**	(3.62)**	(3.84)**	(3.15)**	(3.61)**
HIGH NEEDS SP. ED.	0.035	1.478	1.274	2.296	1.035	-0.001	1.011	-0.004	0.000	0.000
	(0.24)	(0.79)	(1.23)	(1.57)	(1.48)	(0.27)	(0.90)	(0.08)	(0.90)	(0.95)
LEP	-0.001	-0.156	0.108	-0.100	-0.356	0.000	-0.006	-0.002	-0.000	0.000
	(0.09)	(1.06)	(0.60)	(0.83)	(2.32)*	(1.15)	(0.05)	(0.20)	(0.39)	(1.70)
LOW INCOME	-0.031	-0.161	-0.259	0.499	-0.607	0.001	0.296	0.010	0.000	-0.000
	(1.00)	(0.57)	(0.75)	(1.75)	(2.20)*	(0.55)	(0.67)	(0.21)	(0.12)	(1.72)
OTHER SP. ED	-0.329	-0.247	-7.039	3.058	2.742	0.005	0.596	0.012	0.000	0.000
	(2.43)*	(0.13)	(3.56)**	(1.74)	(1.39)	(1.24)	(0.60)	(0.19)	(0.75)	(0.02)
SQUARE MILES (LOG)	-0.004	-0.015	0.089	-0.014	0.010	0.000	0.088	-0.001	-0.000	0.000
	(1.85)	(0.67)	(2.55)*	(0.73)	(0.42)	(2.73)**	(2.32)*	(0.41)	(0.94)	(1.75)
HS-CWI	0.352	0.875	-2.561	2.823	4.702	0.017	-1.759	0.001	0.001	-0.000
	(1.69)	(0.51)	(1.21)	(1.51)	(2.72)**	(1.78)	(0.93)	(0.00)	(1.84)	(0.50)
CWI	-0.076	0.643	2.624	0.923	-0.762	0.012	3.082	0.178	0.000	0.000
	(0.55)	(0.53)	(1.67)	(0.74)	(0.61)	(2.15)*	(2.03)*	(1.12)	(0.03)	(0.63)
ENROLLMENT (LOG), SQUARED	-0.000	-0.006	-0.002	-0.004	-0.009	-0.000	-0.009	-0.001	-0.000	-0.000
	(2.71)**	(3.27)**	(0.96)	(2.31)*	(2.65)**	(3.60)**	(3.37)**	(3.87)**	(3.39)**	(4.00)**
HIGH NEEDS SP. ED., SQUARED	-0.898	-28.213	-5.390	-29.761	-1.732	-0.030	-14.580	-0.125	-0.001	-0.000
	(0.47)	(1.13)	(0.59)	(1.62)	(0.30)	(0.56)	(1.01)	(0.21)	(0.93)	(0.88)
LEP, SQUARED	-0.010	0.228	-0.187	0.464	0.622	-0.002	0.377	0.015	0.000	-0.000
	(0.16)	(0.67)	(0.46)	(1.78)	(1.77)	(1.17)	(1.31)	(0.63)	(0.51)	(1.86)

EXHIBIT 17 CONTINUED

	METROPOLITAN					NONMETROPOLITAN				
	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
LOW INCOME, SQUARED	-0.029 (2.95)**	-0.229 (2.32)*	0.044 (0.37)	-0.119 (1.47)	0.268 (2.59)**	-0.000 (0.79)	-0.111 (0.83)	-0.019 (1.55)	-0.000 (1.03)	0.000 (1.11)
OTHER SP. ED, SQUARED	-0.287 (0.44)	-1.843 (0.25)	11.501 (1.70)	-8.317 (1.60)	-9.356 (1.68)	-0.026 (1.21)	-3.458 (0.61)	-0.096 (0.28)	-0.000 (0.71)	0.000 (0.84)
SQUARE MILES (LOG), SQUARED	0.000 (1.45)	0.001 (0.39)	-0.011 (2.82)**	0.000 (0.18)	0.001 (0.27)	-0.000 (3.06)**	-0.009 (2.44)*	0.000 (0.12)	0.000 (1.10)	-0.000 (1.11)
HS-CWI, SQUARED	-0.166 (2.04)*	-0.338 (0.49)	1.400 (1.66)	-0.788 (1.08)	-1.565 (2.16)*	-0.008 (1.83)	0.702 (0.85)	-0.042 (0.33)	-0.000 (1.99)*	0.000 (0.52)
CWI, SQUARED	0.049 (0.98)	-0.249 (0.55)	-1.290 (2.21)*	-0.507 (1.11)	-0.018 (0.04)	-0.005 (2.16)*	-1.297 (1.98)*	-0.059 (0.82)	0.000 (0.07)	-0.000 (0.93)
LOW INCOME * CWI	-0.048 (0.64)	0.164 (0.26)	1.473 (1.78)	0.785 (1.44)	2.204 (3.13)**	-0.001 (0.84)	-0.525 (0.98)	-0.092 (1.95)	-0.000 (0.77)	0.000 (1.59)
LOW INCOME* HS-CWI	0.090 (1.04)	0.021 (0.03)	-1.439 (1.61)	-1.283 (2.11)*	-1.969 (2.52)*	0.001 (0.23)	0.330 (0.46)	0.107 (1.50)	0.000 (0.65)	-0.000 (0.17)
LOW INCOME*LOG ENROLLMENT	-0.001 (0.46)	0.018 (1.09)	0.010 (0.58)	0.030 (2.26)*	-0.002 (0.08)					
OTHER SPECIAL ED* LOG ENROLLMENT	0.043 (2.80)**	0.046 (0.24)	0.711 (3.49)**	-0.199 (1.16)	-0.216 (0.98)					

Absolute value of t-statistics in parentheses: * p<0.05 ** p<0.01
Source: Texas Comptroller of Public Accounts.

EXHIBIT 18

MARGINAL EFFECTS FROM PROBIT, K-8 DISTRICTS

	LOW-SPENDING K-8	HIGH-SPENDING K-8	K-6
ENROLLMENT (LOG)	-0.707 (1.92)	2.080 (2.44)*	-0.104 (0.24)
HIGH NEEDS SP. ED.	0.497 (0.06)	2.557 (0.35)	0.457 (0.06)
LEP	-1.525 (1.58)	1.470 (1.28)	0.632 (0.54)
LOW INCOME	-0.474 (0.31)	1.222 (0.78)	-1.227 (0.77)
OTHER SP. ED	9.712 (1.83)	-17.734 (3.21)**	5.116 (0.92)
SQUARE MILES (LOG)	0.344 (0.72)	0.582 (2.70)**	-0.549 (2.15)*
HS-CWI	-15.801 (1.22)	2.100 (0.16)	16.822 (0.96)
CWI	13.925 (1.67)	-3.051 (0.36)	-15.560 (1.50)
ENROLLMENT (LOG), SQUARED	0.081 (2.32)*	-0.189 (2.36)*	-0.013 (0.32)
HIGH NEEDS SP. ED., SQUARED	-81.966 (0.68)	64.088 (0.69)	-62.352 (0.62)
LEP, SQUARED	2.455 (1.20)	-3.104 (1.28)	-0.523 (0.22)
LOW INCOME, SQUARED	-0.950 (1.59)	-0.260 (0.36)	1.132 (1.66)
OTHER SP. ED, SQUARED	-53.071 (1.83)	64.807 (2.13)*	-1.107 (0.03)
SQUARE MILES (LOG), SQUARED	-0.069 (1.00)	-0.056 (2.19)*	0.065 (2.16)*
HS-CWI, SQUARED	6.838 (1.24)	-1.699 (0.30)	-6.463 (0.88)
CWI, SQUARED	-6.267 (1.81)	2.155 (0.60)	5.891 (1.37)
LOW INCOME * CWI	1.257 (1.26)	-1.249 (1.27)	0.284 (0.26)
LOW INCOME * OTHER SPECIAL ED.	-2.825 (0.51)	14.285 (2.51)*	-9.542 (1.62)

Absolute value of t-statistics in parentheses: * p<0.05 ** p<0.01
Source: Texas Comptroller of Public Accounts.

DATA LIMITATIONS

FAST researchers found the data quality of district-level financial data to be significantly better than campus-level data.

TEA requires school districts to submit data for their campuses as well as for the district as a whole. The agency, however, only audits the district-level data. Districts report campus-level data with much more flexibility, and do not adhere to the same reporting standards as they use for district-level data. For example, not all districts allocate central administration expenses to their campuses, rendering campus-level operating expenditures unreliable for comparison.

In the 2008-09 AEIS report, campus per-pupil operating expenditures ranged from *$1 to $4.1 million*, with median spending at $6,476. Such a wide range raises questions of data reliability. Many campuses showed missing data for various financial components, with 373 campuses showing no data for operating expenditures and 509 showing no data for operating expenditures per pupil. Among those reporting data, 35 campuses showed operating expenditures of less than $1,500 per pupil, and eight reported spending less than $100 per pupil. At the other extreme, 268 campuses showed operating expenditures exceeding $15,000 per pupil, while 10 reported spending more than $100,000 per pupil.[21]

To account for campus inconsistencies, the FAST analysis only compares campus spending on operating expenditures for "campus-related" activities, averaged over three years and adjusted for geographic wage differences. This category consists of expenditures on instruction, instructional services, instructional leadership, school leadership and student support services.

When using adjusted "campus-related" activities, the number of campuses with expenditures of less than $1,500 per pupil drops to 13, while the number with expenditures exceeding $15,000 per pupil drops to 141 (**Exhibit 19**). These 154 campuses were excluded from the FAST financial analysis in accordance with National Center for Education Statistics practices.

EXHIBIT 19

FINANCIAL OUTLIER CAMPUSES

	2008-09 AEIS REPORT	2007-2009 PEIMS AVERAGE
	Operating Expenditures, All Funds Per Pupil	FAST Campus-Related Activities, Per Pupil
ALL CAMPUSES	8,322	8,355
CAMPUSES WITHOUT DATA	509	973*
CAMPUSES SPENDING GREATER THAN $15,000	268	141
CAMPUSES SPENDING LESS THAN $1,500	35	13

* Missing data for any year from 2007-2009 will result in a missing value for the three-year average.
Source: Texas Education Agency and Texas Comptroller of Public Accounts.

ENDNOTES

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4 Texas Education Agency, *Growth Model Pilot Application for Adequate Yearly Progress Determinations Under the No Child Left Behind Act* (Austin, Texas, January 12, 2009), pp. 34-37, http://ritter.tea.state.tx.us/students.assessment/resources/growth_proposal/011209_USDE_Growth_Proposal_Texas.pdf (last visited November 29, 2010); and William J. Webster and Robert L. Mendro, "The Dallas Value-Added Accountability System."

5 Tom A.B. Snijders and Roel J. Bosker, *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling* (Thousand Oaks, California: Sage Publications, 1999); Stephen W. Raudenbush and Anthony S. Bryk, *Hierarchical Linear Models: Applications and Data Analysis Methods*, 2nd ed., (Thousand Oaks, California: Sage Publications, 2002); Anders Skrondal and Sophia Rabe-Hesketh, *Generalized Latent Variable Modeling: Multilevel, Longitudinal, and Structural Equation Models* (Boca Raton, Florida: Chapman & Hall/CRC, 2004); and William H. Greene, *Econometric Analysis*, 6th ed. (Upper Saddle River, New Jersey: Prentice Hall, 2007.)

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7 Boys Ranch Independent School District has been excluded from the analysis because it is so dissimilar from other Texas school districts. Boys Ranch is a special-purpose ISD that serves a residential facility for at-risk youth.

8 Rajeev H. Dehejia and Sadek Wahba, "Propensity Score Matching Methods for Nonexperimental Causal Studies," *The Review of Economics and Statistics* (February 2002), pp. 151-161, http://www.personal.ceu.hu/staff/Gabor_Kezdi/Program-Evaluation/Dehejia-Wahba-2002-matching.pdf; Rajeev H. Dehejia, "Practical Propensity Score Matching: A Reply to Smith and Todd," *Journal of Econometrics* (No. 125, 2005), pp. 355-364, http://www-personal.umich.edu/~econjeff/Papers/dehejia_practical_pscore.pdf; and Marco Caliendo and Sabine Kopeinig, *Some Practical Guidance for the Implementation of Propensity Score Matching* (Bonn, Germany: IZA, May 2005), pp. 1-29, http://www.acoes.org.co/pdf/Documentos%20HFTF/30.pdf. (Last visited November 29, 2010.)

9 Core operating expenditures are current operating expenditures, except for functions 34, 35, 92 and 95. Functions 34 (student transportation) and 35 (food service) are excluded because they represent additional functions of local school districts not directly related to student achievement. Functions 92 (the incremental costs associated with the chapter 41 purchase or sale of WADA) and 95 (payments to juvenile justice alternative education programs) are excluded because they do not represent operating expenditures of the district itself.

10 Metropolitan school districts are those located in a county that is part of a metropolitan statistical area as defined by the U.S. Office of Management and Budget. For a list of metropolitan counties, visit http://www.census.gov/population/www/metroareas/metroarea.html.

11 The interaction terms were selected to ensure that the resulting propensity scores satisfied the "balancing property," the requirement that within a stratification block, there should be no statistical difference in means between the treatment group and the controls with respect to the explanatory variables (in this context, the cost factors). The selected interactions were the interaction between percent of low income and the HS-CWI; the interaction between the percent of low income and the CWI; and, for metropolitan districts, the interactions between district sizes and the percent of low-income and percent of other special education students.

12 All 10 models yield propensity score distributions satisfying the balancing property. In other words, there were no statistically

significant differences in cost factor means between treatment and control districts within each stratification block.

13 Four of these districts are AEA districts. Because there are so few K-8 AEA school districts, they were not analyzed separately.

14 Drawn from a forthcoming paper by Timothy J. Gronberg, Dennis W. Jansen and Lori L. Taylor, Texas A&M University.

15 The translog specification is a flexible functional form that is a second-order approximation to any cost function. For the FAST project, the research team estimated

$$\ln(E) = a_0 + \sum_{i=1}^{2} a_i q_i + \sum_{i=1}^{2} b_i w_i + \sum_{i=1}^{6} c_i x_i + 0.5 \sum_{i=1}^{2}\sum_{j=i}^{2} d_{ij} q_i q_j + \sum_{i=1}^{2}\sum_{j=i}^{2} e_{ij} q_i w_j$$
$$+ 0.5 \sum_{i=1}^{2}\sum_{j=i}^{2} f_{ij} w_i w_j + \sum_{i=1}^{6}\sum_{j=i}^{2} g_{ij} x_i w_j + \sum_{i=1}^{2}\sum_{j=i}^{6} h_{ij} q_i x_j + 0.5 \sum_{i=1}^{6}\sum_{j=i}^{6} k_{ij} x_i x_j$$
$$+ a_4 x_1^3 + \nu + \mu$$

Where E is core current operating expenditures per pupil, there are two outputs (qi), two input price measures (wi) and six other cost factors (xi). The natural log of school district enrollment (x1) also enters cubically, to accommodate the unusually large range in this variable. The estimation includes data on K-12 school districts for the 2006, 2007, 2008 and 2009 school years, so year indicators have also been added to the regression. Only traditional school districts with at least "Acceptable" accountability ratings were included in the estimation subset.

16 The research team calculates the mean squared error for school district j as where xj is the value of the cost factor for school district j, xi is the value of the cost factor for peer district i, is the statewide mean value of the cost factor and n is the number of school districts in the peer group. Dividing the squared errors by the statewide mean makes the scaling consistent across the eight cost factors, allowing for comparisons among them.

17 Core operating expenditures consists of operating expenditures excluding transportation and food services, consisting of functions 11-53 (excluding 34 and 35), 81 for charters, 92, 95 and objects 6100-6400.

18 Early elementary campuses serve students through the second grade.

19 Campus-related activities are all operating expenditures in functions 11-33, and objects 6100-6400.

20 Campus-related activities are all operating expenditures in functions 11-33, and objects 6100-6400.

21 Texas Education Agency, "2008-09 Academic Excellence Indicator System Download of All Data," http://ritter.tea.state.tx.us/perfreport/aeis/2009/DownloadData.html <http://ritter.tea.state.tx.us/perfreport/aeis/2009/DownloadData.html> . (Last visited September 16, 2010.) Custom queries created and calculations by Texas Comptroller of Public Accounts.